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OPTIMIZING THE SUSTAINMENT NETWORK FOR EXPEDITIONARY ADVANCED BASE OPERATIONS

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THESIS

OPTIMIZING THE SUSTAINMENT NETWORK FOR EXPEDITIONARY ADVANCED BASE OPERATIONS

by

Lane M. Johnson

December 2022

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13. ABSTRACT (maximum 200 words)

The Marine Corps' Expeditionary Advanced Base Operations (EABO) concept places small, distributed forces within a contested environment to achieve strategic effects. However, current sustainment platforms and infrastructure lack the ability to provide required support in the context of EABO. As such, the Marine Corps must develop a novel resilient and robust distribution network capable of providing responsive sustainment to forces conducting EABO. To solve this problem, we develop a two-stage stochastic mixed integer linear program that seeks to minimize the cost of instantiating and operating a sustainment network across a range of possible in-context scenarios. Among the network's constraints are demand, cost, capacity, risk, and supply considerations. Of these constraints, demand introduces the most uncertainty. Fluctuations in demand come from a variety of factors to include intensity of conflict, attrition, and other combat dynamics. Through the explicit and judicious modeling of such uncertainty, our model provides solutions that are robust to a wide range of demand scenarios. By implementing our model in a notional operational scenario in the South China Sea, we provide results and insights that ultimately assist the Marine Corps by providing an analytical basis for determining an optimal network comprised of locations, capacities, and prepositioning quantities for sustaining forces conducting EABO in the western Pacific.

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OPTIMIZING THE SUSTAINMENT NETWORK FOR EXPEDITIONARY ADVANCED BASE OPERATIONS

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The Marine Corps' Expeditionary Advanced Base Operations (EABO) concept places small, distributed forces within a contested environment to achieve strategic effects. However, current sustainment platforms and infrastructure lack the ability to provide required support in the context of EABO. As such, the Marine Corps must develop a novel resilient and robust distribution network capable of providing responsive sustainment to forces conducting EABO. To solve this problem, we develop a two-stage stochastic mixed integer linear program that seeks to minimize the cost of instantiating and operating a sustainment network across a range of possible in-context scenarios. Among the network's constraints are demand, cost, capacity, risk, and supply considerations. Of these constraints, demand introduces the most uncertainty. Fluctuations in demand come from a variety of factors to include intensity of conflict, attrition, and other combat dynamics. Through the explicit and judicious modeling of such uncertainty, our model provides solutions that are robust to a wide range of demand scenarios. By implementing our model in a notional operational scenario in the South China Sea, we provide results and insights that ultimately assist the Marine Corps by providing an analytical basis for determining an optimal network comprised of locations, capacities, and prepositioning quantities for sustaining forces conducting EABO in the western Pacific.

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Table of Contents

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List of Figures

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List of Tables

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List of Acronyms and Abbreviations

A2AD	Anti-access/Area Denial
BFC	Bulk Fuel Cache
CPG	Commandant's Planning Guidance
DOD	Department of Defense
EAB	Expeditionary Advanced Base
EABO	Expeditionary Advanced Base Operations
ESD	Expeditionary Transfer Dock
FIC	First Island Chain
MAGTF	Marine Air Ground Task Force
MCPP-N	Marine Corps Prepositioning Program-Norway
MCWP	Marine Corps Warfighting Publication
MILP	Mixed Integer Linear Program
MPF	Maritime Prepositioning Force
MPSRON	Maritime Prepositioning Ship Squadron
NPS	Naval Postgraduate School
PRC	People's Republic of China
SCS	South China Sea
SIF	Stand-in Forces
U.S.	United States

USMC United States Marine Corps

USNS United States Naval Ship

WEZ Weapon Engagement Zone

Executive Summary

The United States Marine Corps' operational concept, termed Expeditionary Advanced Base Operations (EABO), was developed in response to increased enemy anti-access/area denial capabilities in the western Pacific. EABO place friendly sensing, shooting, and sustaining forces within an adversary's targeting range in a smaller, more distributed fashion when compared to conventional practices. Through a network of expeditionary advanced bases (EABs), friendly forces achieve greater situational awareness, lethality, and impose a greater cost upon the adversary while decreasing their own signature as targets.

Sustaining EABO, however, is difficult for two primary reasons. One shortcoming in the Marine Corps' ability to support EABO is that current resupply platforms, locations, and routes are not capable of persisting in a contested environment. The assumption of all-domain superiority that the United States has enjoyed in recent conflicts is eroded by its adversaries' advances in long-range precision fires. Moreover, the need to define a sustainment network in the near-term, capable of supporting future EABO, is also complicated by the fact that the demand across expeditionary advanced bases is unknown and variable. Without knowledge of exact demand quantities, or even an underlying demand distribution, developing an optimal sustainment network is not easy. However, by considering a range of possible conflict scenarios, logistics planners can better address the uncertainty of the future. Furthermore, by exploring a host of potential prepositioning sites and network architectures, planners can gain a better understanding of the optimal sustainment network.

Given the requirement to identify network locations and prepositioning quantities to satisfy demand, we first model the problem as a basic minimum cost flow problem. From this baseline model, we add extensions to incorporate various aspects of reality until we arrive at the final two-stage stochastic mixed-integer linear program. Since planners will likely be constrained by available resources when defining a sustainment network, the first extension we consider is the ability to include or exclude certain nodes from the network. Another aspect of reality that we consider is the fact that the future operating environment is unknown. Major drivers in the uncertainty of future demand in EABO are geopolitical events, conflict intensity, attrition and other combat dynamics. With the notion of uncertainty in mind, we develop possible demand scenarios, each with a probability of being realized in the

future, to represent a variety of demand signals across EABs. Defining a sustainment network capable of satisfying demand for every possible scenario is likely to be extremely expensive, wasteful, or even infeasible. That said, the next extension we introduce is related to logistical responsiveness and is termed Q% satisfaction. The aim of this extension is to provide decision makers with a wide range of candidate networks that achieve varying degrees of demand satisfaction based on the subset of scenarios for which each network is optimized. In this extension, we first generate a power set of the possible demand scenarios where each power set element is a different set of scenarios which we define to be active scenarios. Then, for each element of the power set, our model produce a network solution capable of satisfying demand for each of the current active scenarios. The sum of the current active scenarios' realization probabilities is that particular network's Q% satisfaction, or responsiveness. Those scenarios not in the current set of active scenarios are termed inactive scenarios, and one of those scenarios will occur 1-Q% of the time in the future. At this point in our modeling, we only optimize each network for the active scenarios, and as such, we have no idea how well each network satisfies demand in the inactive scenarios. We refer to the final extension as hedging which, through defined gap values, ensures a certain level of demand satisfaction for the inactive scenarios. Allowing a decision maker to declare their acceptable gap value guarantees complete demand satisfaction for the active scenarios while also ensuring their desired demand satisfaction in the inactive scenarios.

Through decisions made in two stages, the model seeks to find the minimum expected cost of instantiating and subsequently flowing supplies through the network to satisfy demand across a range of possible scenarios. In the first stage, we make long-term decisions such as which nodes to include or exclude from the network, as well as prepositioning quantities at the nodes. These decisions, like determining where to construct a new facility, cannot easily be undone once they are made. Furthermore, these decisions are made prior to the demand being realized. Once a demand scenario is realized, the model makes second stage decisions which are the optimal amounts of supplies to flow from node to node for the demand scenario that has been realized.

We begin analysis by implementing the model in a toy scenario to showcase the model's functionality before introducing a notional operational scenario for which we conduct experiments and what-if analysis. The model's results provide decision makers with numerous candidate networks, each optimized under certain conditions, and allow them to decide which network they deem best given their risk tolerance and desired level of responsiveness. We find that our model allows planners to consider a variety of possible demand scenarios, locations, and routes for analysis, ultimately enabling decision makers to derive actionable insights for developing a sustainment network in support of EABO. We also find that when multiple demand scenarios are considered, risk-pooling takes effect. Specifically, by holding back supplies at intermediate nodes, risk-pooling enables the network to provide more responsive support while simultaneously reducing waste. Furthermore, while our model guarantees complete demand satisfaction in active scenarios, hedging in the inactive scenarios affords decision makers the ability to guarantee a desired level of satisfaction in those scenarios as well.

The success of the Marine Corps in the future operating environment is dependent upon its ability to make the right decisions today to sustain its forces tomorrow. By utilizing the proposed model, planners can determine prepositioning locations, quantities, and resupply routes to best support the force conducting EABO across the competition continuum, with minimum expected cost.

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CHAPTER 1:
Introduction

The future military operating environment of the western Pacific is characterized by enemy long-range precision fires capable of denying regional access to the U.S. military and its allies. Traditional forces and platforms that rely on their physical presence to ensure freedom of navigation and power projection are placed at risk when in range of long-range precision fires. In order to meet enduring strategic objectives despite new threats, the United States Marine Corps (USMC) developed an operational strategy called Expeditionary Advanced Base Operations (EABO). EABO place friendly sensing, shooting, and sustaining forces within an adversary's targeting range in a smaller, more distributed fashion when compared to conventional practices. Through a network of expeditionary advanced bases, friendly forces achieve greater situational awareness, lethality, and impose a greater cost upon the adversary while decreasing their own signature as targets.

Sustaining EABO is challenging for several reasons. The distributed nature of Expeditionary Advanced Bases (EABs) means that resupply platforms must disperse and traverse great distances in and around contested environments. Being within an enemy's Weapon Engagement Zone (WEZ) places resupply platforms at extreme risk as they travel on air, land, or sea to support forward units. Furthermore, uncertainty places a greater strain on supply chain operations and requires a novel logistics network. Sources of uncertainty include: demand uncertainty, personnel and equipment attrition, non-stationary demand locations, and other combat dynamics. The aim of this thesis is to develop models and demonstrate their implementations to ultimately assist Marine Corps planners in constructing a logistics network capable of sustaining forces conducting EABO in the western Pacific, with minimum expected cost.

1.1 Background

In 2019, General Berger, the 38th Commandant of the USMC, released the strategic direction of the Marine Corps in his Commandant's Planning Guidance. In the publication, General Berger identifies the evolving environment of future conflicts and the necessary adjustments required of the Navy-Marine Corps team to remain competitive. In light of long-range precision fires and ambitious territorial claims by the People's Republic of China (PRC), maintaining a forward presence in the western Pacific emerges as the chief concern and requirement (United States Marine Corps [USMC] 2019).

The PRC's long-range precision weapon systems, designed to deny regional access to competitors and maintain sea control, threaten the U.S. military's ability to protect its interests and those of its allies. The stand-off distance generated by the PRC's long-range munitions affords them the ability to influence a region without physically being present. Moreover, by employing land and sea-based fires such as anti-ship ballistic missiles, the PRC is capable of targeting U.S. naval platforms and infrastructure thousands of miles from their shores. The combination of their long-range sensing and shooting capabilities creates an Anti-access/Area Denial (A2AD) environment. Traditional methods of power projection and maneuver place U.S. forces tasked with pursuing strategic aims at extreme risk. Figure 1.1 depicts various operational missiles in the PRC's arsenal that help create the A2AD dilemma. The vast quantity of short-range ballistic missiles, capable of targeting forces within the First Island Chain (FIC), poses a credible threat to friendly forces in a period of conflict. As such, the Commandant calls for smaller and more "risk-worthy" surface platforms to operate within the contested environment as to impose a greater asymmetric cost upon the PRC for choosing to launch their missiles (USMC 2019).

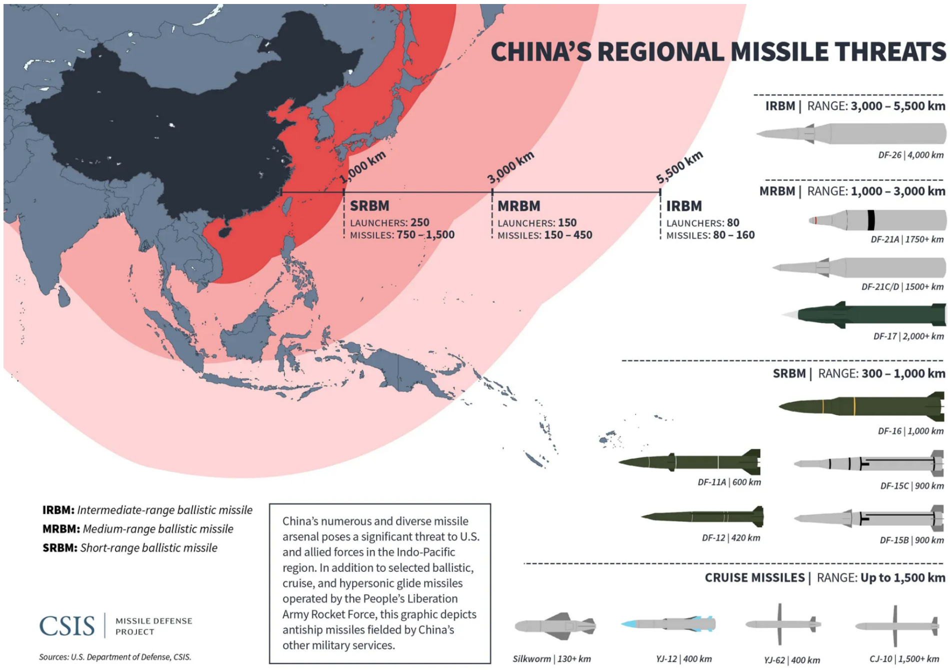

Figure 1.1. PRC missile threats and ranges. Source: CSIS (2021).

In addition to improving its strike capability, the PRC continues to assert territorial claims that contradict those of other nations in and around the South China Sea (SCS). The boundary of the PRC's claimed territorial waters is shown in Figure 1.2. A quick glance reveals the fact that PRC assertions overlap numerous countries' boundaries declared by the United Nations Convention on the Law of the Sea. PRC claims challenge the exclusive economic zones and sovereignty of other nations and leave access to the global commons at risk. Furthermore, traditional freedom of navigation operations, which place high-value platforms within disputed waters, become increasingly precarious. Without the ability to project power and influence in the FIC, many of the adversary's claims go uncontested.

Figure 1.2. Disputed territorial claims in the South China Sea. Source: Singh (2019).

The Marine Corps' response to remain competitive in the changing operating environment is to persist forward as Stand-in Forces (SIF). SIF are defined as "low signature, mobile, relatively simple to maintain and sustain forces designed to operate across the competition continuum within a contested area as the leading edge of a maritime defense-in-depth in order to intentionally disrupt the plans of a potential or actual adversary" (USMC 2021, p. 4). Instead of operating outside of the enemy's weapon engagement zone, SIF conduct operations well within the targeting range of enemy weapon systems. Emplacing low-signature forces that are optimally task-organized to operate within an A2AD environment disrupts the adversary's strategy of "counter-intervention" directed against the U.S. and allies. Since SIF are required to operate in a distributed manner to maintain their low signature, the Commandant identified EABs as a means to support SIF. Support in this context means that EABs will "host, secure, sustain, and maintain warriors and their weapons systems on a more amorphous and difficult to target forward-basing infrastructure" (USMC

2018, p. 27).

Operations that take place in and around EABs and in conjunction with SIF are EABO. Through EABO, the Marine Corps "creates a more resilient forward force posture that circumvents the efforts and obviates the investments of aspiring peer competitors employing long-range precision fires directed at dislodging U.S. forces dependent upon legacy bases, fixed infrastructure, and large targetable platforms" (USMC 2018, p. 5). EABO bring three primary capabilities to bear against adversaries: sensing, shooting, and sustainment. Sensing conducted by SIF on the inside provides greater situational awareness, of the enemy and environment, to outside forces with strategic assets. SIF on the EABs possess shooting capabilities and utilize a host of weapons to employ against land, air, and seaborne threats in the area of operations. Lastly, EABO sustainment includes support required beyond what the host nation can provide. While foraging, water purification, and the use of host nation vessels are an integral part of sustaining the force, weapons and vehicle parts, ordnance, and other equipment that is not readily available in host nations needs to be planned for and prepositioned in close proximity to SIF (USMC 2018).

1.2 Motivation

The motivation behind this thesis is the Marine Corps' need to define an optimal (i.e. with minimum expected cost) sustainment network capable of providing responsive logistics to forces conducting EABO in light of the adversary's increased capabilities. Traditional methods of sustainment rely on large, vulnerable surface platforms, and infrastructure that are required to operate outside the enemy's weapon engagement zone for their own safety.

Currently, expeditionary operations are enabled by the Marine Corps Prepositioning program, which "consists of afloat and ashore programs that provide Combatant Commanders the equipment, supplies, and sustainment to support scalable, tailorable, Marine Air Ground Task Force (MAGTF) to address crises and contingencies ranging from major combat to steady state operations" (USMC 2013, ch. 1, p. 3). The two programs included in the overall Marine Corps Prepositioning program are the Maritime Prepositioning Force (MPF) and the Marine Corps Prepositioning Program-Norway (MCPP-N). The MPF is organized into two Maritime Prepositioning Ship Squadrons (MPSRONs), as shown in Figure 1.3. MPSRON 2 is located Diego Garcia and consists of one BOB HOPE Class T-AKR, United

States Naval Ship (USNS) SEAY; one WATSON Class T-AKR, USNS SISLER; two BOBO Class T-AKs, USNS BUTTON and USNS LOPEZ; one modified SHUGHART Class T-AK, USNS STOCKHAM; and one Expeditionary Transfer Dock (ESD) Class ship, USNS MONTFORD POINT. (Prepos handbook). MPSRON 3 is located in Guam and consists of one BOB HOPE Class T-AKR, USNS PILILAAU; one WATSON Class T-AKR, USNS DAHL; three BOBO Class T-AKs, USNS BOBO, USNS WILLIAMS, and USNS LUMMUS; one LEWIS & CLARK Class T-AKE, USNS SACAGAWEA, and one ESD, USNS JOHN GLENN (USMC 2015). While the combined effects of each squadron's ships are capable of providing a wide range of support to deployed MAGTFs, their lack of defensive capabilities and large signature relegate them to operating far beyond the point of demand for their supplies in a contested environment.

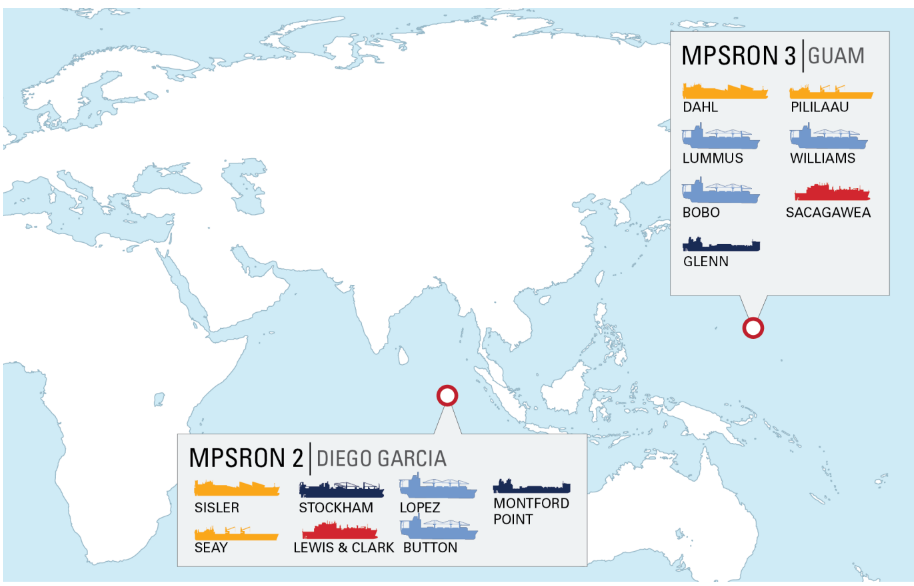

Figure 1.3. Location and composition of two active MPSRONs. Source: (USMC 2015).

The other piece of the Marine Corps' overall prepositioning effort is MCPP-N, which is a program responsible for the storage, maintenance, and prepositioning of equipment and supplies for a MAGTF in caves and other storage facilities in Norway (USMC 2015). The stockpiling of large quantities of commodities and materiel at such places is commonly referred to as an "iron mountain." While there are some advantages to theater-level supply methods, their targetability, rigid nature, and poor responsiveness make them obsolete for EABO in an A2AD environment. The EABO Handbook states that "moving commodities from distribution hubs, be they afloat or ashore, across contested seas directly to EABs supporting distributed naval forces, is the crux of the new logistics challenge" (USMC 2018, p. 62). Furthermore, the Marine Corps' Force Design 2030 calls for planning teams to conduct research to "develop, resource and implement a service-directed Global Positioning Network as an integrated afloat/ashore capability enabling day-to-day campaigning, rapid response to crisis and contingency, and deterrence" (USMC 2020). As opposed to the high value target that is the iron mountain ashore, a more robust and distributed logistics network that leverages multiple prepositioning sites, or "iron hills," and greater flexibility avoids single point of failure facilities (USMC 2018). The Marine Corps' lack of low-signature afloat and ashore prepositioning assets in the western Pacific capable of providing responsive support to EABO in a contested environment necessitates a change in logistics operations.

1.3 Mathematical Approach

We represent the logistics supply chain as a network composed of nodes and arcs. Nodes are comprised of supply, demand, and transshipment locations within the theater of operations. Supply nodes can be thought of as major military installations and other sources of supply far beyond a contested environment. Demand nodes are the forward deployed units at EAB that lie within the contested environment. Transshipment nodes are the intermediate locations between the supply and demand nodes. These locations typically lie just beyond the enemy's WEZ or contested environment. The arcs, or edges, of the network represent resupply lanes between two nodes. Our goal is to find the minimum expected cost of instantiating and subsequently flowing supplies through the network to satisfy demand across a range of possible scenarios.

Given the uncertainty of demand location and quantity, we model the problem as a two-stage stochastic Mixed Integer Linear Program (MILP). In the first stage, we make long-term decisions such as facility location and prepositioning quantities. These decisions, like determining where to construct a new facility, cannot easily be undone once they are made. Furthermore, these decisions are made prior to the demand being realized. Once the demand is realized, the second stage decisions are the optimal amounts of supplies to flow from node to node. We start the analysis by formulating a two-stage stochastic MILP as a standard minimum-cost flow model and defining it as the base model. From there, we iteratively extend the base model to incorporate more realistic factors and account for a range of possible scenarios in an A2AD environment. Among the network's constraints are demand, cost, risk, capacity, and supply considerations. Of these constraints, demand is the most uncertain. The unpredictability in demand comes from a variety of factors including intensity of conflict, attrition, and other combat dynamics. Through the explicit and judicious modeling of such uncertainty, we aim to provide solutions that are robust to a wide range of demand scenarios.

1.4 Organization

Chapter II of this thesis is a literature review that covers logistics concepts as well as previous work related to our research. In Chapter III, the basic minimum-cost flow model is introduced before various extensions to the model are discussed. Chapter IV introduces both a toy scenario, as well as a notional operational scenario, which both provide the necessary inputs for subsequent analysis and experimentation. Finally, Chapter V addresses findings, recommendations, and suggestions for future studies on this topic.

CHAPTER 2: Literature Review

This chapter is organized into two sections: logistics operations and related work. Section 2.1 covers logistics concepts and practices from both military and business contexts that we incorporate in our model. Section 2.2 is a review of previous work related to our research. We draw commonalities as well as distinctions between our work and that of others.

2.1 Logistics Operations

The following subsections provide background information for logistics concepts and practices that are implemented in our model.

2.1.1 Responsiveness

Marine Corps Warfighting Publication (MCWP) 4-1 details seven principles of logistics operations: responsiveness, simplicity, flexibility, economy, attainability, sustainability, and survivability. These principles serve as guidelines during planning to ensure operational success. MCWP 4-1 highlights the importance of the principle of responsiveness in stating that "among the logistics principles, responsiveness is the keystone. All other principles become irrelevant if logistics support does not support the commander's concept of operations" (USMC 1999, Ch 1., p. 6). Providing responsive support ensures that operations are not hindered by a lack of support, and instead are enhanced by the support provided. Logistics units can provide more responsive support to consumers in several ways: preposition supplies in caches on land or afloat, geographically place themselves closer to forward forces, utilize a "push" replenishment method, or employ different transportation platforms. Ideally, supplies are prepositioned at the demand locations for immediate distribution as needed, but for a variety of reasons including storage security, capacity, and spoilage, this solution is typically untenable. By considering the different logistics principles in our optimization techniques, we are able to provide insights into selecting optimal prepositioning locations and distribution routes to construct a more responsive logistics network.

2.1.2 Demand Uncertainty

While responsiveness focuses on having "the right stuff at the right time," logistics operations must also ensure that "the right amount of stuff" is provided to the consumer. Describing the challenge of perfectly meeting a consumer's demand, Kress states "the uncertainty in the theater of operations and the prevailing friction in the battlefield affect the extent at which responsiveness can be attained." (Kress 2016, p. 71) Prior to executing an operation, logistics planners consult with operational planners to devise a support plan. The logistics planners use information such as anticipated conflict intensity, duration, and scheme of maneuver to estimate the amount of supplies they should be prepared to deliver. These are, however, only estimates and the uncertainty of combat leads to scenarios in which the demand for supplies sometimes exceeds the amount available. While supporting units can sometimes fall short of perfectly meeting demand, there also exists the risk of providing too much supplies. Kress refers to these threats as under-responsiveness and over-responsiveness, respectively. A common approach to mitigating the uncertainty of combat is to design a more flexible logistics network that is able to provide timely support when needed. We incorporate the stochastic nature of demand in Chapter 3 by considering a wide range of potential demand scenarios.

2.1.3 Risk Pooling

In an effort to mitigate the impacts of demand variability in logistics operations, supply chain managers implement a concept known as risk pooling, or inventory pooling. Risk pooling is realized through "using centralized inventory instead of decentralized inventory to take advantage of the fact that if demand is higher than average at some retailers, it is likely to be lower than average at others" (Du 2007, lecture). By holding the retailers' demand variance at a central location, a lower expected cost of satisfying demand across all retailers' is achieved (Eppen 1979). In supply chain networks where risk pooling is not practiced, large variations in demand often result in some sort of additional cost to retailers. Specifically, when forecasted demand exceeds actual demand, retailers typically incur an inventory or holding fee to house the residual supply. Conversely, when forecasted demand is less than actual demand, retailers are unable to satisfy their consumers resulting in unrealized profit. We introduce risk pooling into our model in Chapter 3 by allowing for supplies to be prepositioned at intermediate nodes. In doing so, we are able to reduce the impacts of demand variability and uncertainty at the demand locations.

2.1.4 Hedging

When demand is uncertain, it can be very costly to ensure complete demand satisfaction regardless of future demand realization. Supply chain disruptions and extreme demand cases prevent the complete satisfaction of all possible consumer demand scenarios in a network. As such, consumers may relax their demand satisfaction requirement to a level that is "good enough." That is, a consumer understands that their demand cannot be fully met in every possible future scenario and is willing to accept demand satisfaction Q% of the time. Doing so necessarily implies that in the remaining 1-Q% of time, no level of satisfaction is guaranteed. By reducing their requirement to only Q% of scenarios, the consumer assumes risk in the 1-Q% scenarios. Ideally, the 1-Q% of scenarios are rarely, if ever, realized, but in the event that such scenarios emerge, the cost of satisfying demand can be quite expensive. Moreover, since the supply network is not designed to accommodate these rare demand scenarios that occur 1-Q% of the time, satisfying their demand may even be infeasible. To manage the impact of the risk assumed, many consumers opt to hedge against the 1-Q%. Van Mieghem describes hedging in an operational context as a subset of risk management that "refers to the adjustment of strategies and the structuring of resources and processes to proactively reduce, if not eliminate, future risk exposure" (Van Mieghem 2011, p. 6). We introduce hedging into our model in Chapter 3.

2.2 Related Work

With the goal of determining optimal prepositioning locations under uncertainty in the first stage of our two-stage modeling approach, we are essentially dealing with a facility location problem. Snyder (2006) conducts a review of facility location under uncertainty and illuminates various approaches to problems like ours as well as some of their accompanying limitations. Snyder discusses stochastic optimization and highlights two techniques to account for random parameters. He notes that describing randomness in a parameter such as demand can be done either through a probability distribution or through the use of discrete scenarios as proposed by Sheppard (1974). Since we are unaware of the underlying probability distribution for future demand in EABO, we opt for the latter and construct discrete scenarios that each have an accompanying probability of being realized. Snyder addresses two primary drawbacks in our selected scenario approach noting that generating scenarios and associated probabilities is not easy, and that computational restrictions limit the range of future scenarios that can be evaluated. He goes on to explain that the scenario approach does lend itself to more tractable models and that "it has the advantage of allowing parameters to be statistically dependent, which is often not practical when parameters are described by continuous probability distributions" (Snyder 2006, p. 4).

Sheppard (1974) proposes a discrete scenario approach to accounting for uncertainty in facility location problems. Sheppard suggests that forecasting a range of possible outcomes and their assigned probabilities provides the input necessary to derive policies, or strategies, to satisfy demand. The policy that results in the smallest expected cost would be selected as the optimal strategy. We leverage Sheppard's work by calculating an expected cost of instantiating and operating a network for a discrete set of future demand scenarios, however, we depart from his research by making a distinction between active and inactive scenarios as discussed in Chapter 3.

Daskin et al. (2005) incorporate Sheppard's findings in their Stochastic Location Model with Risk Pooling, which aims to find solutions that minimize the expected total cost of defining and operating a supply chain network across possible future scenarios. Included in the total cost are costs associated with locating distribution centers, inventory costs, and transportation costs. Rather than optimizing their network for demand following a probability distribution, they allow the modeler to define a discrete set of possible scenarios with different demand quantities as proposed by Sheppard. While their research is closely aligned with ours, we improve upon their work by providing insight into the ability of the network to satisfy demand in scenarios for which it is not optimized.

Gardner (2015) develops the Asset Allocation Optimization Model which is a two-stage stochastic mixed-integer linear program that optimizes humanitarian assistance disaster relief efforts before and after a disaster. In the first stage, the model determines optimal locations for relief assets near a disaster-affected area. In the second stage, the model determines how to route aircraft in support relief efforts. Although Gardner also uses a scenario-based approach to account for uncertainty, her model's objective minimizes the expected number of deaths across scenarios, whereas our model minimizes expected cost. Her work also differs from ours in that she applies design of experiments in her model as another way of incorporating uncertainty and variability, and she successfully demonstrates that design of experiments can be used in optimization models.

The fog of war leads to uncertainty in all aspects of combat. Enemy actions, weather, and chance all play a role in generating unforeseen circumstances on the battlefield. Ng (2003) approaches the reality of uncertainty in military operations by developing a modeling framework that determines the optimal deployment of transportation assets and supplies at the operational level, with possible interdiction by enemy forces. Ng implements a two-level, multiple time period scenario-based stochastic model that uses a combination of optimization, scenario-based simulation, and statistical analysis. By optimizing a network for a set of reference demand scenarios, Ng's model aims to define a deployment strategy that can satisfy a range of arbitrary demand scenarios with a predefined responsiveness probability. Our work is similar to Ng's in that we also use a two-stage approach to optimize our network for certain scenarios, but rather than determining how many scenarios should be included in our reference set to achieve responsiveness in arbitrary scenarios, we generate a power set of all possible future scenarios and determine the optimal network for each subset in the power set. Our approach affords the decision maker more say in determining demand scenarios for which the network is optimized, as previously discussed. Furthermore, rather than modeling time using a multiple-period approach like Ng, we handle time implicitly as described in Chapter 3.

In many supply chain operations, materiel is prepositioned closer to the demand locations to enable greater responsiveness. Kasdan (2020) studies this practice using the Navy's Bulk Fuel Cache (BFC) concept. Specifically, Kasdan investigates the BFC concept as an alternative to current methods for sustaining forward deployed forces in contested environments when conducting distributed maritime operations or expeditionary advanced operations. With the First and Second Island Chains as bounds for his analysis, Kasdan's model seeks to minimize the distance between BFCs and operational Navy and Marine Corps units. He incorporates uncertainty in the form of stochastic demand and dynamic locations. Through modeling such uncertainty, he determines optimal BFC locations, quantities, and storage capacities for sustaining the operational force. Our research varies from Kasdan's in that we optimize a network with static facility location in mind. Ultimately, Kasdan's work, like ours, informs future planning and acquisition efforts.

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CHAPTER 3: Methodology

The purpose of a logistics network is to flow supplies from some source location(s) to consumers who demand these resources. Figure 3.1 depicts an example of a logistics network comprised of source nodes, intermediate nodes, and destination nodes. As shown, the source nodes represent strategic facilities and depots where vast quantities of resources are housed. These facilities are typically located at major bases and installations beyond the reach of enemy weapons systems. The intermediate nodes represent facilities and units within the theater of operations that are emplaced for the duration of an operation. Furthermore, the intermediate nodes, as the name implies, serve as an intermediary between the major sources of supply and the ultimate consumer. For that reason, they are much closer to the combat units than are the source nodes. Finally, the destination nodes represent the combat units that actually consume the supplies. Each type of node represents a different level of logistics: activity concerning source nodes is considered strategic logistics, units and facilities involved with intermediate nodes perform operational logistics, and the flow of goods to the combat unit constitutes tactical logistics. This thesis focuses on operational logistics by considering the units and facilities represented by intermediate nodes. Specifically, we consider facility location, prepositioning of supplies, and route determination for sustaining forces conducting EABO, at the lowest possible cost, in the western Pacific.

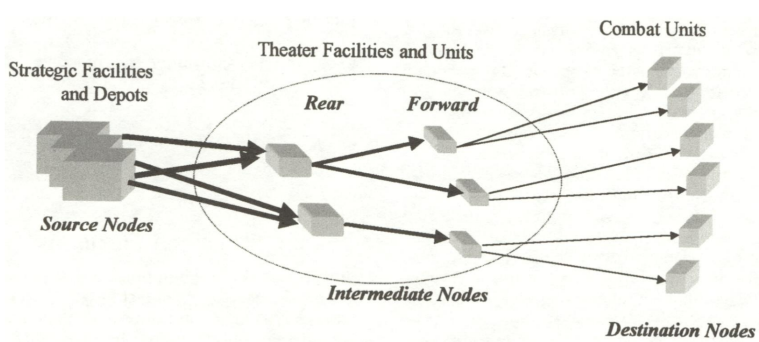

Figure 3.1. Basic logistics network composed of source nodes, intermediate nodes, and destination nodes. Source: Kress (2016).

This chapter first introduces a basic minimum-cost (min-cost) network flow model. From there, we introduce additional layers of complexity by incorporating the possibility of including or excluding certain nodes from the network as well as other concepts such as prepositioning, demand uncertainty, risk pooling, and hedging. While the aspect of time is not explicitly represented in our models, we do incorporate time implicitly by using data on a "per time unit" basis. For example, we consider the cost of flowing supplies per month, and the capacity an arc can support per month.

3.1 Basic Min-Cost Flow Model

A basic min-cost flow problem is composed of nodes and arcs, which together form a network. Each of the nodes in a basic min-cost flow network has a supply quantity, which may be non-positive or non-negative, that is associated with the type of node. A node with a positive supply quantity is classified as a supply node, whereas a node with a negative supply quantity is classified as a demand node. Nodes associated with a supply quantity of zero are intermediate nodes. Network arcs connect pairs of nodes and serve as a medium to flow supplies between nodes. Each arc has an associated cost and capacity. An arc's cost represents the cost of flowing one unit of supplies from the arc's originating node to its ending node. An arc's capacity represents the maximum amount of supplies that can flow on that arc between two nodes. The network's costs and capacities are not time dependent. The objective in a min-cost flow problem is to minimize the cost of flowing supplies throughout the network to satisfy all demand. Consider the network in Figure 3.2. The network is comprised of five nodes, A, B, C, D and E, as well as the arcs that connects them. As an example, the arc between nodes B and E is referred to as arc (B, E) and its associated cost and capacity are \$5 and 10 units, respectively. Furthermore, since node A has a positive supply quantity it is classified as a supply node, and since node E has a negative supply quantity it is classified as a demand node. Note that since nodes B, C, and D all have supply quantities of zero, they are classified as intermediate nodes. The objective is to minimize the cost of flowing 10 units of supplies from node A to node E to satisfy $E's$ demand, subject to the network's flow balance and capacity constraints.

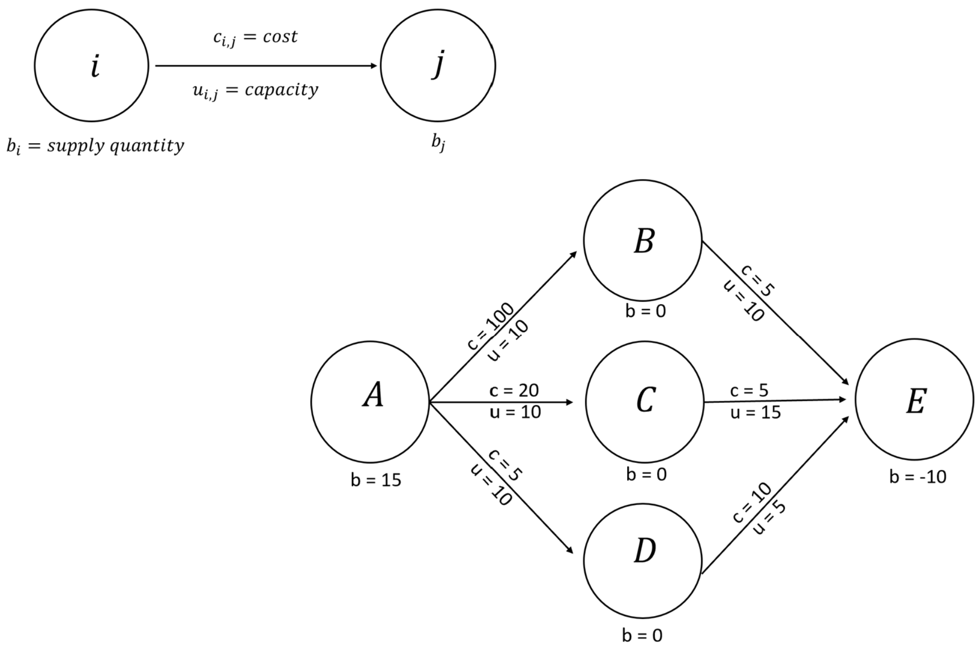

Figure 3.2. Basic min-cost flow problem network. Nodes have supply or demand values, and arcs have cost and capacity values.

The min-cost flow problem depicted by the network in Figure 3.2 is formulated as follows.

Indices and Sets

$n \in N$	Network nodes
$(i, j) \in A$	All arcs

Data

$c_{i,j}$	$(i, j) \in A$	Flow cost of arc (i, j)
$u_{i,j}$	$(i, j) \in A$	Flow capacity of arc (i, j)
b_n	$n \in N$	Supply at node n. Negative values represent demand

Decision Variables

$x_{i,j}$ $(i, j) \in A$ Units of supplies flowed on arc (i, j)

Formulation

$$\min_{x_{i,j}} \sum_{(i,j)\in A} c_{i,j} x_{i,j} \tag{3.1}$$

subject to

$$\sum_{j\in N:(n,j)\in A} x_{n,j} - \sum_{i\in N:(i,n)\in A} x_{i,n} \leq b_n \qquad \forall n \in N \tag{3.2}$$

$$x_{i,j} \leq u_{i,j} \qquad \forall (i, j) \in A \tag{3.3}$$

$$x_{i,j} \geq 0 \qquad \forall (i, j) \in A \tag{3.4}$$

The objective (3.1) represents the cost of flowing supplies throughout the network to meet demand as a function of the decision variables $x_{i,j}$.

Constraints (3.2) are flow-balance constraints that ensure the flow out of a node n must be less than the flow into node n plus/minus any supply or demand modifications. For example, the flow-balance constraint in the context of node A in Figure 3.2 ensures that the amount of supplies that flows out of node A must be less than the amount that flows into node A (0) plus node $A's$ supply (15). Conversely, the same constraint for node E ensures that the flow out of node E (0) minus the flow in has to be less than or equal to node $E's$ demand (-10).

Constraints (3.3) limit the amount of supplies that can flow along each arc in the network. For arc (A, C) in the network in Figure 3.2, the constraint restricts the arc flow, $x_{A,C}$, to the arc's capacity which is less than or equal to 10 units.

Lastly, constraints (3.4) ensure that all arc flow values are non-negative.

Looking at Figure 3.2 we can see that there are three paths from A to E. ABE has a total cost of 105, ACE has a total cost of 25, and ADE has a total cost of 15. Without any capacity constraints, the optimal solution routes 10 units of supplies through ADE. Once we incorporate arc capacities, however, we see that ADE is constrained by DE which can only flow 5 units of supplies. This issue forces us to flow a portion of the demand through the next cheapest path ACE.

Solving the problem by inspection results in optimal flows of:

$x_{A,B} = 0, \quad x_{A,C} = 5, \quad x_{A,D} = 5, \quad x_{B,E} = 0, \quad x_{C,E} = 5, \quad x_{D,E} = 5$

As previously mentioned, we route 5 units of supplies via ADE and the remaining 5 units via ACE. Multiplying each of the flow values by their respective arcs' per unit flow cost yields an objective value of 200. Our objective function value tells us that a cost of 200 is optimal in terms of satisfying the demand at node E. In other words, no other flow routing combination results in a lower cost.

3.2 Min-Cost Flow Model with Extensions

To capture various aspects of reality, we incorporate extensions to the basic model.

In Sections 3.2.1-3.2.3, we introduce our extensions to the base model. We begin the following sections by first introducing each extension conceptually before describing the associated notation and changes to the base model formulation. By presenting the model in pieces, the evolution from base model formulation to final formulation with extensions is easier to understand.

3.2.1 Choosing Nodes and Handling Uncertain Demand

The first extension we introduce is the ability to include or exclude certain nodes when constructing an optimal sustainment network. Our model considers a wide range of possible supply, demand, and intermediate nodes, and, depending on possible future demand scenarios, it may be suboptimal to include all possible nodes in the network. Specifically, budgetary constraints will likely limit the number of nodes we can include in the network. We define a binary variable, y_n, as a decision variable to determine whether or not node n is included in the network. Terminal, or demand, nodes where supplies are shipped to are always included in the network, so they are assigned a y_n value of 1. The supply and intermediate nodes, however, can be either 0 or 1, depending on whether or not it is optimal to include them in the network.

For each node we include in the network there is an associated cost of setting up and maintaining the node. Infrastructure, manpower, and security costs are some of the factors that must be considered when determining whether or not to include a node in the network. We assume that we have a total budget, H, and that each node has a cost, h_n, to include in the network. As an example, suppose we have a budget, H, of \$100, and suppose each potential node has a cost, h_n, of \$20 to include in the network. Under these conditions the maximum number of nodes that we could include in the network is 5.

We allow supplies to be prepositioned at various nodes throughout the network. From an operational perspective, prepositioning allows the logistics network to provide more timely support. By centralizing supplies, the network can respond to demand variability across different nodes more efficiently. The per-unit cost of prepositioning supplies at node n is captured by γ_n, and due to capacity constraints at the nodes, the maximum amount of supplies that can be prepositioned at node n is V_n. Prepositioning supplies at supply and intermediate nodes promotes the concept of risk pooling which is discussed in Section 2.1.3.

The next extension aims to model uncertain demand quantities. Since we do not know what the demand will be in future operations, we define a finite set, F, of possible demand scenarios that includes the amount of supplies required at each node in the network. For each scenario $f \in F$ we define the demand at node n to be $d_{n,f}$. Moreover, exactly one demand scenario will be realized in the future. Scenario $f \in F$ occurs with probability p_f, and cumulatively, the scenario probabilities sum to 1, $\sum_{f \in F} p_f = 1$.

Next, we introduce the flow variables $x_{i,j,f}$ which represent the amount of supplies shipped from node i to node j if scenario f is realized. In addition to determining which nodes to include in the network, y_n, and how much supplies to preposition at each node, s_n, we must also determine the optimal amount of supplies to flow along the (i, j) arcs within the network for each scenario f. In order to do so, we break our decision making process into two stages. Given the long-term nature of establishing a node in the network and dedicating resources to preposition supplies at that node, we determine y_n and s_n prior to any one of the demand scenarios being realized. These are our first stage decisions and once they are made, they cannot be easily, or cheaply, undone. Next are the second stage decisions in which we determine the $x_{i,j,f}$ quantities. Only after scenario f is realized can we determine the optimal $x_{i,j,f}$ values. It is important to note that after we make the first stage decisions, the y_n and s_n values remain constant regardless of which demand scenario is realized. The second stage decisions, however, depend on which scenario is realized, hence the f subscript presence in second stage decisions and absence in first stage decisions.

Consider the toy example provided in Figure 3.3. Here, we define three demand scenarios which we refer to as Scenario 1, Scenario 2, and Scenario 3, respectively. Each scenario, f, has a probability, p_f, of being realized in the future, and since their probabilities sum to 1 they represent all possible demand scenarios. For now, we will ignore the probabilities and assume that Scenario 1 will be realized with certainty. If we look solely at Scenario 1, we see the demand at EAB 1 is 100 units and the demand at EAB 2 is 20 units. In the context of our base min-cost flow model, the objective is to find the minimum cost of sending supplies from Okinawa to each of the EAB nodes to satisfy each of their demands. Without any constraints on the amount we can preposition, we would simply place 100 units at EAB 1 and 20 units at EAB 2 to satisfy their demands without having to flow any supplies from Okinawa. While this strategy is optimal for Scenario 1, a quick glance at the nodes' demands in Scenarios 2 and 3 will reveal the fact that the same strategy results in either too much or too little supplies being sent to each of the EABs in those scenarios. To account for the demand variability across scenarios, we can leverage the idea of risk pooling, described in 2.1.3, and preposition most of the supplies at Okinawa so that when one of the 3 scenarios occurs, we can flow the required amounts to the two EABs. If we preposition 20 units of supplies at EAB 2 and 100 units at Okinawa, then we can optimally support any demand scenario that is realized. Our model makes first and second stage decisions that satisfy the demand in all three scenarios.

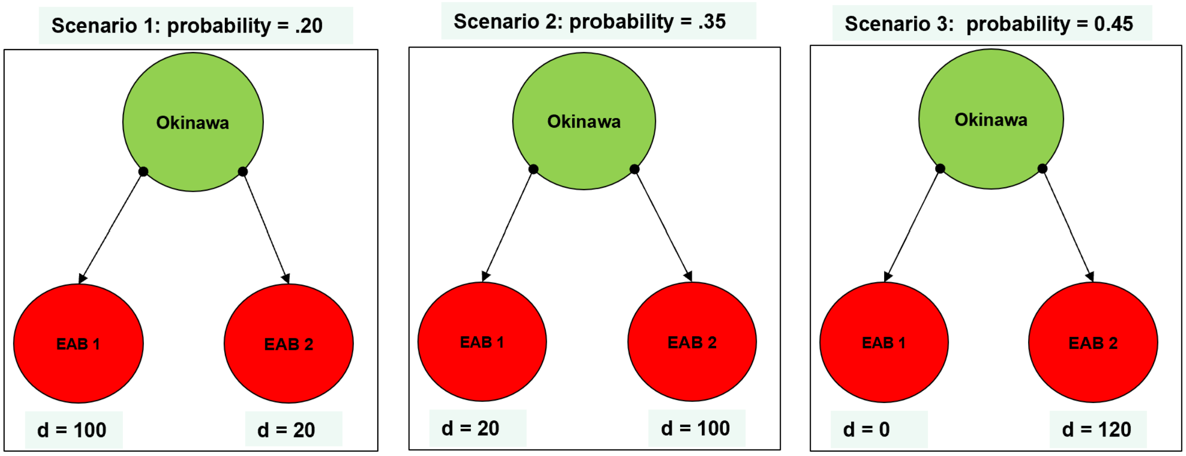

Figure 3.3. Toy example of demand scenarios. Included are demand quantities for each demand node across different scenarios as well as the scenarios' respective probability of being realized.

The following formulation includes all of the extensions mentioned to this point. With this extension, our model chooses nodes and flow values that satisfy 100% of demand across all possible scenarios at the lowest cost. In the context of Figure 3.3, our model generates a solution capable of satisfying 100% of demand across scenarios 1, 2, and 3.

Indices and Sets

$t \in T$	Terminal nodes
$m \in M$	Non-terminal nodes
$n \in N = T \cup M$	All nodes
$(i, j) \in A$	All arcs
$f \in F$	Set of all possible future scenarios

Data

$c_{i,j}$	$(i,j) \in A$	Flow cost of arc (i,j)
$u_{i,j}$	$(i,j) \in A$	Flow capacity of arc (i,j)
$d_{n,f}$	$n \in N, f \in F$	Demand at node n in scenario f
p_f	$f \in F$	Probability scenario f occurs, $\sum_{f \in F} p_f = 1$
γ_n	$n \in N$	Per-unit cost to preposition at node n
h_m	$m \in M$	Resources required to include node m in network
V_n	$n \in N$	Max amount we can preposition at node n
$bigM$		Big M trick to turn on/off constraints
H		Resource budget to constrain nodes in the network

Decision Variables

$x_{i,j,f}$	$(i,j) \in A, f \in F$	Flow on arc (i,j) in scenario f
y_n	$n \in N$	Binary variable set to 1 if node n is in network
s_n	$n \in N$	Amount of supplies to preposition at node n

Formulation

$$\min_{x_{i,j}} \quad \sum_{(i,j)\in A} c_{i,j} \sum_{f\in F} p_f x_{i,j,f} \tag{3.5}$$

$$+ \sum_{n\in N} \gamma_n s_n \tag{3.6}$$

subject to

$$y_t = 1 \qquad \forall t \in T \tag{3.7}$$

$$\sum_{m\in M} h_m y_m \leq H \tag{3.8}$$

$$s_n \leq V_n y_n \qquad \forall n \in N \tag{3.9}$$

$$\sum_{i\in N:(i,n)\in A} x_{i,n,f} \leq bigM y_n \qquad \forall n \in N, f \in F \tag{3.10}$$

$$\sum_{j\in N:(m,j)\in A} x_{m,j,f} - \sum_{i\in N:(i,m)\in A} x_{i,m,f} \leq s_m \qquad \forall m \in M, f \in F \tag{3.11}$$

$$\sum_{j\in N:(t,j)\in A} x_{t,j,f} - \sum_{i\in N:(i,t)\in A} x_{i,t,f} \leq s_t - d_{t,f} \qquad \forall t \in T, f \in F \tag{3.12}$$

$$x_{i,j,f} \leq u_{i,j} \qquad \forall (i,j) \in A, f \in F \tag{3.13}$$

$$x_{i,j,f} \geq 0 \qquad \forall (i,j) \in A, f \in F \tag{3.14}$$

$$s_n \geq 0 \qquad \forall n \in N \tag{3.15}$$

Objective function components:
Component (3.5) includes each scenario's probability of occurring to capture the cost of the expected flow across all scenarios.
Component (3.6) represents the total cost of prepositioning supplies at each node in the network.

Constraints:
Constraints (3.7) ensure that all terminal nodes are in the network. Since y_n is a binary decision variable, explicitly assigning each terminal node a value of one ensures that that node is included in the network.

Constraint (3.8) controls how many nodes are in the network. Available USMC resources will limit the number of nodes.

Constraints (3.9) ensure that the amount of prepositioned supplies at node n is zero if that node is not in the network and is limited by max-supply capacity of the node otherwise.

Constraints (3.10) allow flow into any node n to be turned on or off. If on, there is no constraint since bigM is practically infinity. These constraints apply for all scenarios $f \in F$. Controlling flow out of a node is captured in other constraints.

Constraints (3.11) ensure flow-balance for non-terminal nodes such as supply or intermediate nodes. Like Constraints (3.2) in the basic model, flow out of a node, m, minus flow into the same node cannot exceed the node's supply. These constraints apply for all scenarios $f \in F$.

Constraints (3.12) ensure flow-balance for terminal nodes, $t \in T$. Since this model allows nodes to possess supply as well as demand, flow out of a node, t, minus flow into the same node now has to satisfy the difference between the node's supply and demand requirements. These constraints apply for all scenarios $f \in F$.

Constraints (3.13) ensure flow along an arc does not exceed that arc's capacity. These constraints apply for all scenarios $f \in F$.

Constraints (3.14) ensure flow on an arc is non-negative. These constraints apply for all scenarios $f \in F$.

Constraints (3.15) prevent the prepositioning of negative supplies at nodes in the network.

3.2.2 Q% Satisfaction

The model in Section 3.2.1 takes a conservative approach to satisfying demand across potential scenarios by prepositioning, and subsequently flowing, enough supplies to satisfy demand across all possible demand scenarios. While this strategy meets the objective of demand satisfaction, it typically results in either extremely high operating costs, or worse, infeasibility due to arc and node capacity constraints. To develop a more practical solution, we extend the base model to introduce the idea of Q% satisfaction. We define this satisfaction percentage to be the decision maker's required level of demand satisfaction, or more generally, rate of responsiveness. For example, if a decision maker recognizes that it is infeasible to strictly satisfy all demand across all possible scenarios, they may relax their required level of responsiveness to 90%. In that case, Q% would be equal to 90%. That is, the decision maker now requires demand to only be fully satisfied 90% of the time. In practice, we implement Q-satisfaction by solving the model for all minimal subsets of scenarios with a cumulative probability that is equal to or exceeds Q, and choose the solution that minimizes expected cost.

Specifically, for any value of Q, we first define a power set that is composed of all subsets of possible demand scenarios with accumulated probabilities that equal or exceed Q. Each element of the power set is a list of scenarios, which we define as the *active scenarios*, F_a. A list of all elements of the power set and the corresponding active scenarios appears, for example, in Table 3.1. Each active scenario list has a corresponding probability associated with it, which is the accumulated probabilities of the active scenarios. We denote the scenarios not in the active scenario list as *inactive scenarios*. We modify the model such that we only require complete demand satisfaction in the active scenarios. The only Q% values we solve for are the Q% values associated with each set of active scenarios in the power set. For example, in Table 3.1, we only need to consider the seven Q% values in the last column generated by the different active scenario lists.

Table 3.1. Q% scenario table for Figure 3.3.

Active Scenarios	**Inactive Scenarios**	**Q%**
{Scenario 1}	{Scenario 2, Scenario 3}	20%
{Scenario 2}	{Scenario 1, Scenario 3}	35%
{Scenario 3}	{Scenario 1, Scenario 2}	45%
{Scenario 1, Scenario 2}	{Scenario 3}	55%
{Scenario 1, Scenario 3}	{Scenario 2}	65%
{Scenario 2, Scenario 3}	{Scenario 1}	80%
{Scenario 1, Scenario 2, Scenario 3}	{}	100%

The Q% associated with each subset of active scenarios is equal to the proportion of time that any one of the scenarios, f, in a given subset, F_a, is realized in a future operational setting. For example, the proportion of time that either Scenario 1 or Scenario 2 is realized is equal to 55% as indicated by the fourth row in Table 3.1.

We incorporate the possibility of various scenarios being realized by instantiating and solving a new model for each element of the power set. That is, the model returns a network with selected nodes as well as prepositioning and arc flow quantities that can fully satisfy any of the scenarios in the current set of active scenarios. For each Q% value in Table 3.1, we solve a separate instance of the model that generates a different solution and different cost, for a total of seven solutions. Again, consider row four of Table 3.1. When Scenario 1 and Scenario 2 are active, we instantiate and solve a new model that generates a solution that can satisfy the demands at EAB 1 and EAB 2, given in Figure 3.3, regardless of whether Scenario 1 or Scenario 2 is realized.

Since the model requires that the demand across all scenarios in a given set of active scenarios is satisfied, any set of active scenarios whose Q% is greater than or equal to the decision maker's desired Q% necessarily meets the required level of satisfaction.

Modifying the model from 3.2.1 to incorporate Q% Satisfaction requires only minor modification. We introduce active scenarios and modify constraints 3.12 to now only hold for active scenarios.

Indices and Sets

Same as in 3.2.1

$f \in F_a \subset F$ Set of active scenarios

Data

Same as 3.2.1

Decision Variables

Same as 3.2.1

Formulation

Same as 3.2.1 except constraint 3.12 now only applies to active scenarios. It is modified to the following:

$$\sum_{j \in N:(t,j) \in A} x_{t,j,f} - \sum_{i \in N:(i,t) \in A} x_{i,t,f} \leq s_t - d_{t,f} \qquad \forall t \in T, f \in F_a \tag{3.16}$$

Objective Function Components:
Same as 3.2.1.

Constraints:
Constraints (3.16) now ensure flow-balance for terminal nodes in active scenarios only. Since this model allows nodes to possess supply as well as demand, flow out of a node minus flow into the same node now has to satisfy the difference between the node's supply and demand requirements. These constraints apply for scenarios $f \in F_a$.

3.2.3 Hedging

While we require demand to be fully satisfied in the active scenarios, there is no degree of satisfaction guaranteed in the complementary inactive scenarios, F_a^c. Since we do not impose any demand satisfaction constraints on the inactive scenarios, there exists the risk of catastrophically failing to meet demand in the event that one of the inactive scenarios is realized. To encourage our model to satisfy demand in the inactive scenarios we introduce the concept of hedging as defined in Section 2.1.4.

We incorporate hedging in our model through the use of what we define as an allowable demand satisfaction gap, or simply, *gap*. The *gap* is a percentage of demand across terminal nodes that the decision maker is willing to leave unsatisfied in inactive scenarios. By allowing a demand satisfaction gap at demand nodes in inactive scenarios, our model ensures that in the event an inactive scenario is realized, the amount of supply delivered to each demand node is at least (1-*gap*)% of the node's demand. In the context of our running example, when Scenario 1 and Scenario 2 are active Scenario 3 is inactive. Moreover, while the model ensures complete satisfaction at EAB 1 and EAB 2 for Scenarios 1 and 2, we also guarantee at least (1-*gap*)% satisfaction at EAB 1 and EAB 2 in the event that the inactive Scenario 3 is realized. By including hedging we limit the impact of an inactive scenario being realized. When the gap = 0, we must satisfy demand completely across all scenarios, as was done in 3.2.1. Conversely, when the gap = 1.0, we satisfy active scenarios with no guarantees on the amount of demand satisfied in the inactive scenarios, as was done in 3.2.2.

The following formulation with hedging is similar to 3.2.2, but we now include a flow balance constraint similar to 3.16 for inactive scenarios. This new constraint includes the gap variable.

Indices and Sets

Same as in 3.2.2

$f \in F_a$	Set of active future scenarios for current combination
$f \in F_a^c$	Set of inactive future scenarios for current combination
$f \in F = F_a \cup F_a^c$	Set of all possible future scenarios

Data

Same as in 3.2.2

gap	Percentage of demand across terminal nodes that the decision maker is willing to leave unsatisfied in inactive scenarios

Decision Variables

Same as in 3.2.2

Formulation

Same as in 3.2.2 constraints with the addition of the following which enforces hedging in the inactive scenarios:

$$\sum_{j \in N:(t,j) \in A} x_{t,j,f} - \sum_{i \in N:(i,t) \in A} x_{i,t,f} \leq s_t - (1 - gap) d_{t,f} \qquad \forall t \in T, f \in F_a^c \tag{3.17}$$

Objective function components:
Same as in 3.2.2.

Constraints:
Constraint (3.17) enforces hedging by requiring at least (1-*gap*)% of demand to be satisfied for each terminal node in inactive scenarios. This constraint applies for all inactive scenarios in F_a^c.

3.2.4 Complete Model

For completeness, we present the complete model in its entirety below.

Indices and Sets

$t \in T$	Terminal nodes
$m \in M$	Non-terminal nodes
$n \in N = T \cup M$	All nodes
$(i, j) \in A$	All arcs
$f \in F_a$	Set of active future scenarios for current combination
$f \in F_a^c$	Set of inactive future scenarios for current combination
$f \in F = F_a \cup F_a^c$	Set of all possible future scenarios

Data

$c_{i,j}$	$(i,j) \in A$	Flow cost of arc (i,j)
$u_{i,j}$	$(i,j) \in A$	Flow capacity of arc (i,j)
$d_{n,f}$	$n \in N, f \in F$	Demand at node n in scenario f
p_f	$f \in F$	Probability scenario f occurs, $\sum_{f \in F} p_f = 1$
γ_n	$n \in N$	Per-unit cost to preposition at node n
h_m	$m \in M$	Resources required to include node m in network
V_n	$n \in N$	Max amount we can preposition at node n
$bigM$		Big M trick to turn on/off constraints
H		Resource budget to constrain nodes in the network
gap		Percentage of demand across terminal nodes that the decision maker is willing to leave unsatisfied in inactive scenarios

Decision Variables

$x_{i,j,f}$	$(i,j) \in A, f \in F$	Flow on arc (i,j) in scenario f
y_n	$n \in N$	Binary variable set to 1 if node n is in network
s_n	$n \in N$	Amount of supplies to preposition at node n

Formulation

$$\min_{x_{i,j}} \quad \sum_{(i,j)\in A} c_{i,j} \sum_{f\in F} p_f x_{i,j,f} \tag{3.18}$$

$$+ \sum_{n\in N} \gamma_n s_n \tag{3.19}$$

subject to

$$y_t = 1 \qquad \forall t \in T \tag{3.20}$$

$$\sum_{m\in M} h_m y_m \leq H \tag{3.21}$$

$$s_n \leq V_n y_n \qquad \forall n \in N \tag{3.22}$$

$$\sum_{i\in N:(i,n)\in A} x_{i,n,f} \leq bigM y_n \qquad \forall n \in N, f \in F \tag{3.23}$$

$$\sum_{j\in N:(m,j)\in A} x_{m,j,f} - \sum_{i\in N:(i,m)\in A} x_{i,m,f} \leq s_m \qquad \forall m \in M, f \in F \tag{3.24}$$

$$\sum_{j\in N:(t,j)\in A} x_{t,j,f} - \sum_{i\in N:(i,t)\in A} x_{i,t,f} \leq s_t - d_{t,f} \qquad \forall t \in T, f \in F_a \tag{3.25}$$

$$\sum_{j\in N:(t,j)\in A} x_{t,j,f} - \sum_{i\in N:(i,t)\in A} x_{i,t,f} \leq s_t - (1-gap) d_{t,f} \qquad \forall t \in T, f \in F_a^c \tag{3.26}$$

$$x_{i,j,f} \leq u_{i,j} \qquad \forall (i,j) \in A, f \in F \tag{3.27}$$

$$x_{i,j,f} \geq 0 \qquad \forall (i,j) \in A, f \in F \tag{3.28}$$

$$s_n \geq 0 \qquad \forall n \in N \tag{3.29}$$

3.2.5 Assumptions and Limitations

This model is constructed under a couple of key assumptions. First, we assume that the EAB locations are available and that they are stationary. By definition, EABs are expeditionary and forces conducting EABO will most likely conduct operations for a limited amount of time before displacing to another EAB. Not to mention, afloat EABs may never be completely stationary. We also assume that arc flows are not susceptible to any form of interdiction or attrition. This assumption is optimistic and not indicative of reality. The threat of enemy interdiction exists, especially in the conflict phase of operations. Attrition due to natural disasters or spoilage is also very much a concern.

Our model also has some limitations. Our primary limitation is that our model is commodity and connector agnostic, meaning we don't specify classes of supply transported or connectors used. Section 3.2.6 addresses these limitations, but we do not perform any analysis on specific classes of supply or connectors. Another limitation of our model is that time is not handled explicitly. Instead, we aggregate demand and arc flow values across a specified time period and ensure that the total flow into a node satisfies the node's total demand for that time period. Although we choose to construct our model and conduct analysis under these assumptions and limitations, we propose methods in which they can be challenged and addressed in Chapter 5.

3.2.6 Multi-commodity Model

The models presented previously handle only a single commodity. In this section we present a multi-commodity model capable of minimizing the expected cost of instantiating and operating a network throughout which multiple commodities flow. This formulation is similar to the model presented in Section 3.2.4 with minor changes. We introduce a commodity index k that applies to a number of parameters and decision variables. We slightly modify the objective function and constraints to now hold for all commodities $k \in K$.

Although we do not conduct experiments with this model, we present it here to highlight the possibility of extending our model to incorporate more than one commodity.

Indices and Sets

$t \in T$	Terminal nodes
$m \in M$	Non-terminal nodes
$n \in N = T \cup M$	All nodes
$(i, j) \in A$	All arcs
$k \in K$	Set of commodities (e.g. food, water, fuel, ammunition)
$f \in F_a$	Set of active future scenarios for current combination
$f \in F_a^c$	Set of inactive future scenarios for current combination
$f \in F = F_a \cup F_a^c$	Set of all possible future scenarios

Data

$c_{k,i,j}$	$(i, j) \in A$	Commodity k per-unit flow cost on arc (i, j)
$u_{k,i,j}$	$(i, j) \in A$	Commodity k flow capacity on arc (i, j)
$d_{k,n,f}$	$n \in N, f \in F$	Demand for commodity k at node n in scenario f
p_f	$f \in F$	Probability scenario f occurs, $\sum_{f \in F} p_f = 1$
$\gamma_{k,n}$	$n \in N$	Per-unit cost to preposition commodity k at node n
h_m	$m \in M$	Resources required to include node m in network
$V_{k,n}$	$n \in N$	Max amount of commodity k we can preposition at node n
$bigM$		Big M trick to turn on/off constraints
H		Resource budget to constrain nodes in the network
gap		Percentage of demand across terminal nodes that the decision maker is willing to leave unsatisfied in inactive scenarios

Decision Variables

$x_{k,i,j,f}$	$k \in K, (i, j) \in A, f \in F$	Commodity k flow on arc (i, j) in scenario f
y_n	$n \in N$	Binary variable set to 1 if node n is in network
$s_{k,n}$	$k \in K, n \in N$	Amount of commodity k to preposition at node n

Formulation

$$\min_{x_{k,i,j}} \sum_{k\in K}\sum_{(i,j)\in A} c_{k,i,j}\sum_{f\in F} p_f x_{k,i,j,f} \tag{3.30}$$

$$+\sum_{k\in K}\sum_{n\in N}\gamma_n s_{k,n} \tag{3.31}$$

subject to

$$y_t = 1 \qquad \forall t\in T \tag{3.32}$$

$$\sum_{m\in M} h_m y_m \le H \tag{3.33}$$

$$s_{k,n} \le V_{k,n} y_n \qquad \forall k\in K, n\in N \tag{3.34}$$

$$\sum_{i\in N:(i,n)\in A} x_{k,i,n,f} \le bigM y_n \qquad \forall k\in K, n\in N, f\in F \tag{3.35}$$

$$\sum_{j\in N:(m,j)\in A} x_{k,m,j,f} - \sum_{i\in N:(i,m)\in A} x_{k,i,m,f} \le s_{k,m} \qquad \forall k\in K, m\in M, f\in F \tag{3.36}$$

$$\sum_{j\in N:(t,j)\in A} x_{k,t,j,f} - \sum_{i\in N:(i,t)\in A} x_{k,i,t,f} \le s_{k,t} - d_{k,t,f} \qquad \forall k\in K, t\in T, f\in F_a \tag{3.37}$$

$$\sum_{j\in N:(t,j)\in A} x_{k,t,j,f} - \sum_{i\in N:(i,t)\in A} x_{k,i,t,f} \le s_{k,t} - (1-gap_k)d_{k,t,f} \qquad \forall k\in K, t\in T, f\in F_a^c \tag{3.38}$$

$$x_{k,i,j,f} \le u_{k,i,j} \qquad \forall k\in K, (i,j)\in A, f\in F \tag{3.39}$$

$$x_{k,i,j,f} \ge 0 \qquad \forall k\in K, (i,j)\in A, f\in F \tag{3.40}$$

$$s_{k,n} \ge 0 \qquad \forall k\in K, n\in N \tag{3.41}$$

Objective function:

The objective function is now weighted by the cost of flowing commodity k on arc i, j, as shown in 3.30.

Constraints:
Constraints 3.34-3.41 are the same as constraints 3.22-3.29 except they now hold for each $k \in K$.

CHAPTER 4: Analysis and Results

In this chapter, we present implementation results for a variety of scenarios. First we discuss some technical details concerning the implementations. For the first scenario, we revisit the toy example in Figure 3.3 and analyze various network configurations to highlight trade-offs for a decision maker to consider. We then present a notional operational scenario to analyze the model and its outputs on a larger scale. The terms solution and network are used interchangeably throughout this chapter as they both refer to the model's output.

4.1 Implementation Details

We implement our model using a variety of tools. We begin by organizing our data in a Microsoft Excel workbook. Each of the workbook's worksheets contains information, provided by the user, that is fed into the model. Tables 4.1–4.3 detail the nomenclature contained within each worksheet of the input file. The first column lists the worksheet terms, the second column lists how each term is represented in Section 3.2.4, and the third column lists the description of each term.

Table 4.1. Description of scenario nodes worksheet.

***Scenario_Nodes* Worksheet**		
Term	**Model Representation**	**Description**
$NODE$	N	Column of all nodes in the network
$DEMAND\_x$	$d_{n,f}$	Column of demand quantities for demand scenario x
$RESOURCE\_REQ$	h_m	Resources required to include each node in network
$PREPOS\_PUC$	γ_n	Per-unit cost of prepositioning supplies at each node
MAX_PREPOS	V_n	Maximum amount of supplies that can be prepositioned at each node n

Table 4.2. Description of scenario arcs worksheet.

***Scenario_Arcs* Worksheet**		
Term	**Model Representation**	**Description**
$FROM$	i	Node of origin, i, in arc (i, j)
TO	j	Destination node, j, in arc (i, j)
$COST$	$c_{i,j}$	Cost of traveling on arc from node i to node j
$CAPACITY$	$u_{i,j}$	Maximum amount of supplies that can be transported on arc (i, j)

Table 4.3. Description of scenario data worksheet.

***Scenario_Data* Worksheet**		
Term	**Model Representation**	**Description**
$SCENARIOS$	F	Column of demand scenario names
$PROBS$	P_f	Column of probabilities that correspond to the probability that each scenario will be realized
$BUDGET$	H	Resource budget that limits the number of nodes in network
$GAPS$		Column of allowable gap values used in trade-off analysis

After organizing the inputs in an Excel workbook, we read in the Excel inputs using Python's Pandas package. Once the data are read in, we implement the optimization model using Python's Pyomo package. Lastly, we leverage the COIN-OR Branch and Cut solver to solve the model. All experiments are conducted on a laptop with Intel(R) Core(TM) i7-1065G7 processor running at 1.3 GHz, 16.0 GB RAM, and Windows 10 operating system.

4.2 Toy Model Revisited

Recall the example from chapter 3 shown again in Figure 4.1. In this figure, there are 3 scenarios, each with a probability of being realized. Our goal is to minimize the cost of defining a network and its expected flow values. Since the network consists only of 1 supply node and 2 demand nodes, there is no need to determine which nodes will be in the network, assuming supplies can only be prepositioned at Okinawa. In other words, our stage 1 decisions are already made, and all nodes will be included in the network. We do, however, still need to make stage 2 decisions.

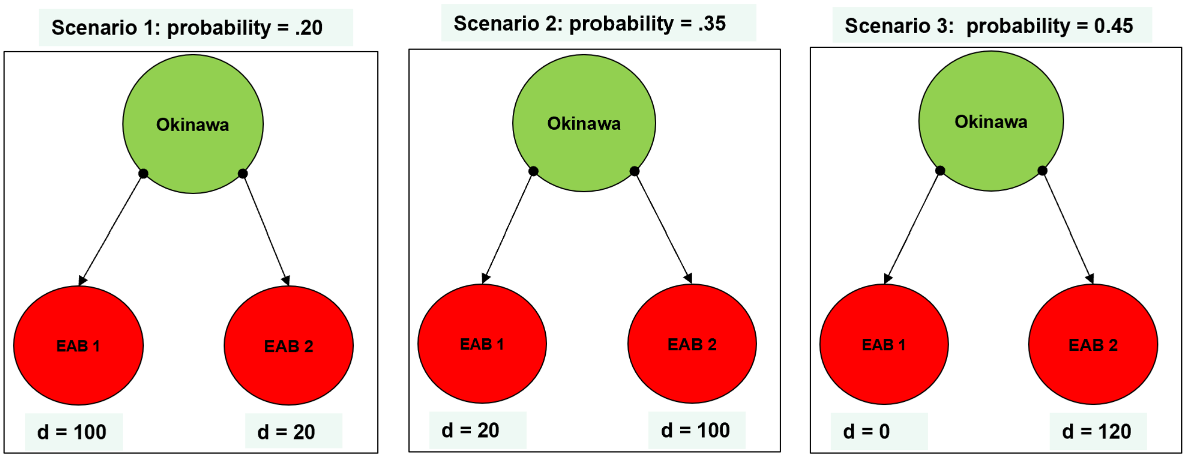

Figure 4.1. Toy example of demand scenarios. Included are demand quantities for each demand node across different scenarios as well as the scenarios' respective probability of being realized.

4.2.1 No Prepositioning at Terminal Nodes

In the first case for analysis, we assume all arc flow per-unit costs are 10, arc capacities are 150, the per-unit prepositioning cost is 15, but that prepositioning is not allowed at the terminal nodes. That is, all supplies resides in Okinawa and must be routed to the terminal nodes. Additionally, we do not incorporate hedging, meaning we set the allowable gap equal to 1, so there is no guarantee on the model's ability to satisfy demand in the inactive scenarios; we only require complete satisfaction in the active scenarios. The demand scenarios' respective probability of occurrence and demand values appear in Figure 4.1. We instantiate and solve a new (3.2.2) model for each subset of active scenarios in Table 3.1. After solving each of the seven model instances, we plot their respective objective function values against the various Q% satisfaction values shown in Figure 4.2. Since prepositioning is not allowed at the terminal nodes in this test case, the objective values are comprised of the cost of prepositioning supplies at Okinawa plus the cost of the expected arc flows. Furthermore, since each of the scenarios has a total demand of 120 units, the cost of prepositioning supplies at Okinawa is constant across all scenarios, and as a result, the objective values are driven primarily by the cost of the expected arc flows. As expected, we see that it costs more to satisfy more demand. When Q% is equal to 100, meaning all scenarios are active, we see the highest cost. This makes sense because when all scenarios are active, we require the demand across all scenarios to be satisfied, resulting in the greatest total flow values.

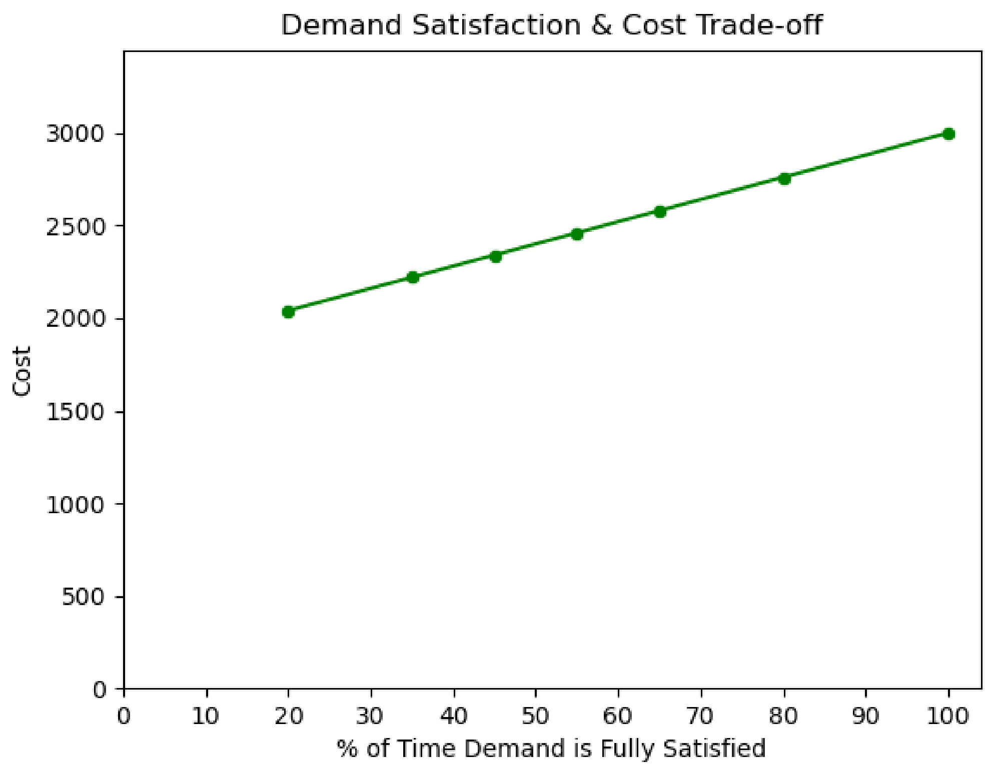

Figure 4.2. Plot showing the trade-off between complete demand satisfaction in active scenarios and cost. No prepositioning allowed.

We observe a linear relationship between Q% values and costs in Figure 4.2. We attribute the linearity observed to the network's unique structure. Specifically, there are 120 units of supplies prepositioned and 120 units of supplies shipped in all three scenarios. Since the flow cost along each arc in Figure 4.1 is identical and our gap is 1, the Q% values map directly to total demand satisfied. Following this logic, as Q% increases, total demand satisfied increases, which means total flow increases, which ultimately leads to increased costs. This relationship is modeled as:

$$cost = (units\ prepositioned)*(prepositioning\ cost) + Q*(amount\ flowed\ in\ active\ scenarios)*(flow\ cost)$$

Assuming scenarios 2 and 3 are active with the data from Figure 4.1, the total cost is:

$$cost = 120*15 + 0.8*120*10 = 2760$$

Next, we consider the network's ability to satisfy demand in the inactive scenarios by enforcing various gap quantities. In the example above, we set the gap equal to 1.0, meaning there is no requirement to satisfy any demand in the inactive scenarios. We now consider gaps of 0, 0.2, 0.4, and 1.0 as shown in Figure 4.3. Note that when the gap value is 0.0, as indicated by the blue horizontal line, the decision maker requires all demand to be satisfied in all scenarios - active and inactive. In other words, a gap of 0.0 in the inactive scenarios is the same as all scenarios being active which is why the cost for any network on that line is the same cost as the network associated with a Q% of 100.

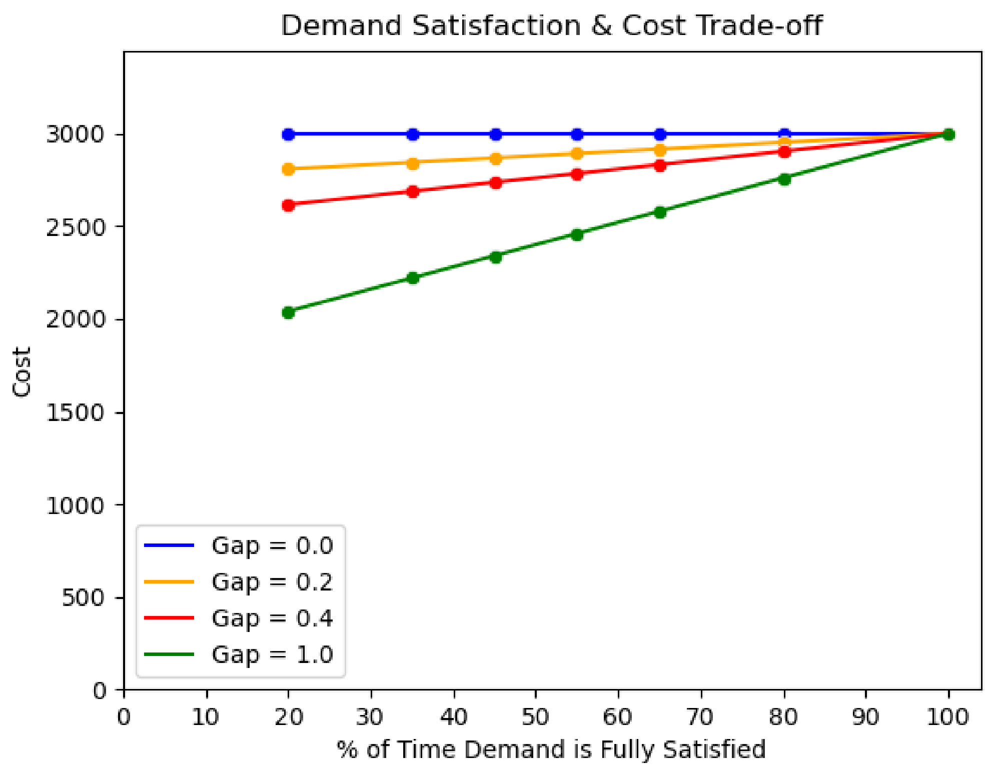

Figure 4.3. Plot showing the trade-off between demand satisfaction, cost, and gap. No prepositioning allowed.

In Figure 4.3 we observe, once again, a linear relationship between Q% values and cost for each gap value due to the network's unique structure. Note that the jump between the first points of the red and green lines is due to the jump in gap values. When we set the gap equal to 1.0, we observe the same green line as in Figure 4.2. The new relationship can be modeled as:

cost = (units prepositioned)(prepositioning cost) + Q*(amount flowed in active scenarios)*(flow cost) + (1-gap)*(1-Q)*(amount flow in inactive scenarios)*(flow cost)*

The total cost is now composed of prepositioning costs, active scenario flow costs, as well as inactive scenario flow costs. Moreover, we observe in Figure 4.3 that as we reduce the gap value, and require more demand to be satisfied in inactive scenarios, the overall cost increases.

4.2.2 Expected Demand Prepositioning at Terminal Nodes

In the previous section, prepositioning was not allowed at the terminal nodes. In this section, the maximum amount of supplies that can be prepositioned at each terminal node is that node's expected demand across scenarios. Specifically, the maximum amount of supplies allowed to be prepositioned at EAB 1 is 27 units while the maximum allowed at EAB 2 is 93. After instantiating and solving the model for each of the seven Q% values, we get the resultant plot in Figure 4.4. At this point in the analysis, there are still 120 units of demand across all three scenarios.

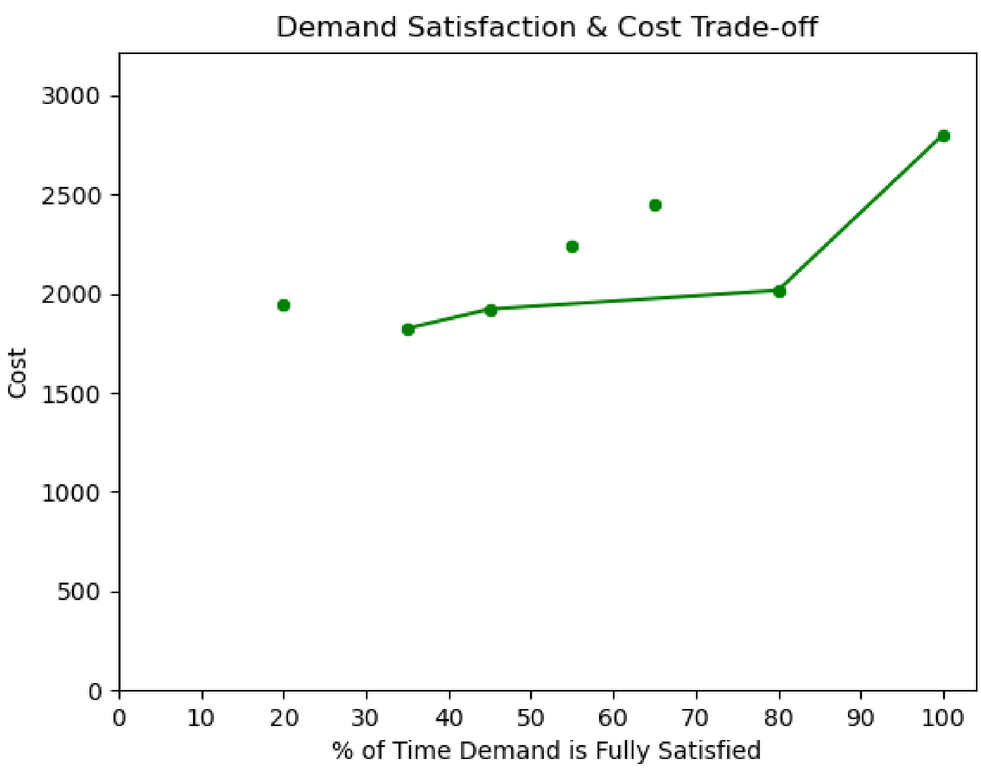

Figure 4.4. Plot showing the trade-off between demand satisfaction and cost. In this case, the maximum amount of supplies that can be prepositioned the terminal nodes is the expected demand across scenarios.

We now observe points that lie off of the lower envelope curve. We refer to this lower envelope curve as the *Pareto efficiency curve*, or *efficient frontier*. Note that in Figure 4.2 the set of all points makes up the efficiency curve. Efficiency curves are typically generated and analyzed in multi-objective problems such as ours; we aim to minimize the expected cost of satisfying as much demand as possible. Each point, therefore, is a tuple (Q, c) where Q represents the probability that the demand is fully satisfied and c represents the cost of instantiating and operating the network. A (Q, c) is on the efficient frontier if, for any other point (Q', c') such that $Q' > Q$, $c' > c$. The set of points on an efficient frontier are said to be *Pareto optimal* since we cannot improve Q% without incurring a higher cost, and likewise, we cannot achieve a lower cost without sacrificing responsiveness. Any points not on the efficient frontier represent inefficient networks, because there exist other candidate networks that achieve greater Q% values at lower costs. As such, we say that these networks are dominated by those on the efficiency curve. In other words, there are networks that lie on the efficiency curve that can satisfy more demand at a cheaper cost than the networks not on the efficiency curve.

To illustrate this notion, consider the first two points from the left in Figure 4.4. We present their decision variable values in Table 4.4.

Table 4.4. Decision variable values for toy model scenario.

Network	Q%	Active Scenario	$s_{Oki.}$	s_{EAB1}	s_{EAB2}	$x_{Oki.,EAB1}$	$x_{Oki.,EAB2}$	**Obj Val**
1	20	1	73	27	20	73	0	1946
2	35	2	7	20	93	0	7	1824.5

The first point, corresponding to a candidate logistic network, represents the case where Scenario 1 is active, resulting in a Q% value of 20%. The cost, shown in Table 4.4, associated with prepositioning and shipping supplies through this network is 1946, whereas the cost associated with the second point is 1824.5. Although the second point, or network generated when Scenario 2 is active, has a greater Q%, it achieves a lower cost by prepositioning more supplies at the EABs and shipping less supplies in the network. Due to the prepositioning limits defined for this example, a total of 73 units of supplies are shipped from Okinawa to the EABs in Scenario 1, whereas 7 units are shipped to the EABs in Scenario 2. The fact that the first point, or network, only satisfies demand 20% of the time at a higher cost than the second point means that it is an inefficient network and should not be considered as a viable solution. Upon further inspection, we find that the three points that lie off of the efficiency curve are all networks in which Scenario 1 is active. The first point, when Q% is 20%, represents the network solution for the case when Scenario 1 is active. The second point, when Q% is 55%, represents the network solution for the case when Scenarios 1 and 2 are active. Lastly, the third point in Figure 4.4, when Q% is 65%, represents the network solution for the case when Scenarios 1 and 3 are active. Since Scenarios 2 and 3 have relatively similar demands at the EABs, a network that satisfies one of these scenarios can satisfy the other for little added cost as shown in Figure 4.4. We observe that an increase in Q% from 35%, when Scenario 2 is active, to 80%, when Scenarios 2 and 3 are active, comes at a minor increase in cost, whereas including Scenario 1 to achieve a Q% of 100% is significantly more expensive. For example, prepositioning the maximum allowable (93) units of supplies at EAB 2 can satisfy 77.5% of Scenario 2 demand and 77.5% of Scenario 3 demand while the same strategy only satisfies 16.67% of demand in Scenario 1. Satisfying the remaining demand in Scenarios 2 and 3 comes at a much cheaper cost than satisfying the remaining 83.33% of demand in Scenario 1.

Next, we examine the model's ability to satisfy demand in inactive scenarios by analyzing the cost-demand satisfaction trade-off for various gap values. Figure 4.5 captures the results.

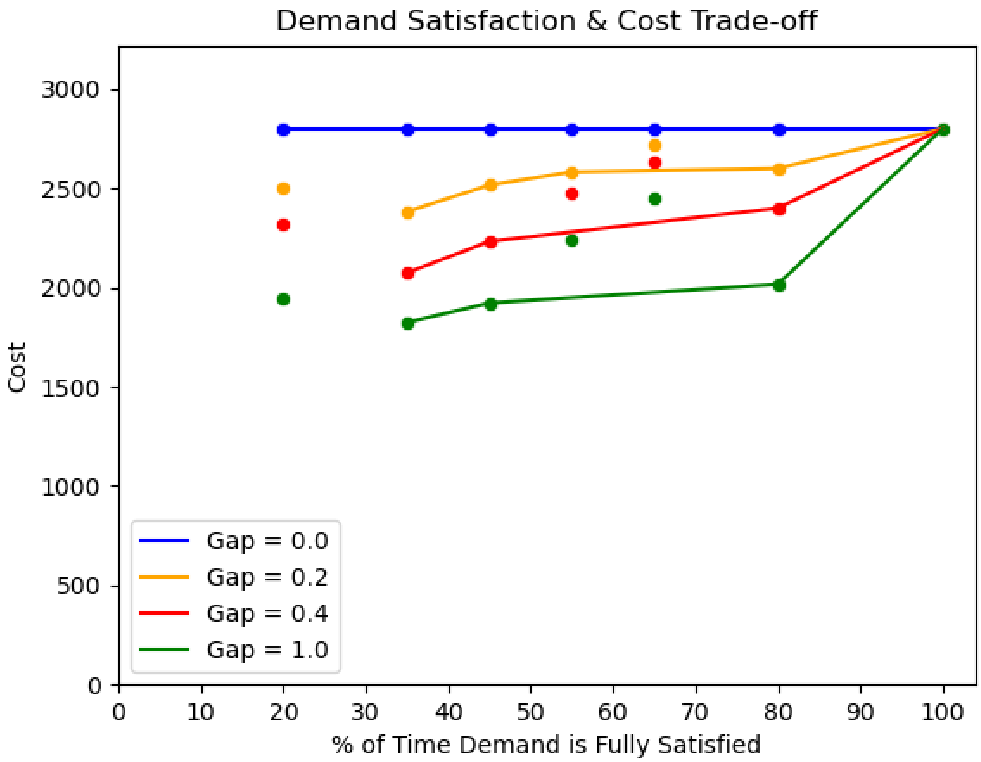

Figure 4.5. Plot showing the trade-off between demand satisfaction and cost for different gap values. The maximum amount of supplies that can be prepositioned the terminal nodes is the expected demand across scenarios.

Setting the gap equal to 1.0 results in the same plot as shown in Figure 4.4. Each point represents a different network produced by the model. As previously discussed, any point that does not lie on one of the efficiency curves is an inefficient network since there exists at least one other network that satisfies demand more often at an equal or cheaper cost. For each Q% value, we see an increasing cost associated with decreasing gaps. That is, as the gap value decreases, we require more demand to be satisfied in the inactive scenarios, which results in greater flow values and ultimately greater costs.

We interpret the results from Figure 4.5 from the decision maker's standpoint as follows. First, we assume the decision maker cares only about selecting a network that is optimized to satisfy demand in active scenarios, and that they are unconcerned with the network's ability to satisfy demand in the event that an inactive scenario is realized. Under this assumption, they most likely turn their attention to the green line representing a set of networks with a gap value of 1.0. Furthermore, the decision maker would only consider the candidate networks that lie on the efficiency curve for reasons discussed previously. The 4 candidate networks Q% and cost are shown in Table 4.5.

Table 4.5. Candidate network solutions.

Network	Q%	Active Scenario(s)	**Obj Val**
1	35%	2	1824.5
2	45%	3	1921.5
3	80%	2,3	2016.0
4	100%	1,2,3	2800.0

By looking at Table 4.5 and Figure 4.5, a reasonable network selected by the decision maker is network 3 due to its drastic improvement in Q% over network 2 coupled with only a marginal cost increase. While satisfying demand 100% of the time, which network 4 guarantees, is appealing, it may not be worth the significant cost increase. Furthermore, it is clear that Scenario 1 is problematic. We observe that any time Scenario 1 is included as an active scenario, the resultant network solution is inefficient. This finding indicates that the sustainment network should be optimized for Scenarios 2 and 3, and that the decision maker should accept the risk associated with the relatively low percent of time that Scenario 1 is realized.

4.2.3 Unlimited Prepositioning at Terminal Nodes

Next, we remove prepositioning capacities and allow an infinite amount of supplies to be prepositioned at each of the nodes in the network. Since the demand across each scenario is equal, the first three points in Figure 4.6 have the same cost. We observe that this plot is nearly identical to Figure 4.4 with the exception of the first three points in which only one scenario is active for each. This finding is attributed to the fact that once we begin including multiple demand scenarios risk pooling takes effect. That is, even though an infinite amount of supplies can be prepositioned at the terminal nodes, it is typically more efficient to pool supplies at supply or intermediate nodes.

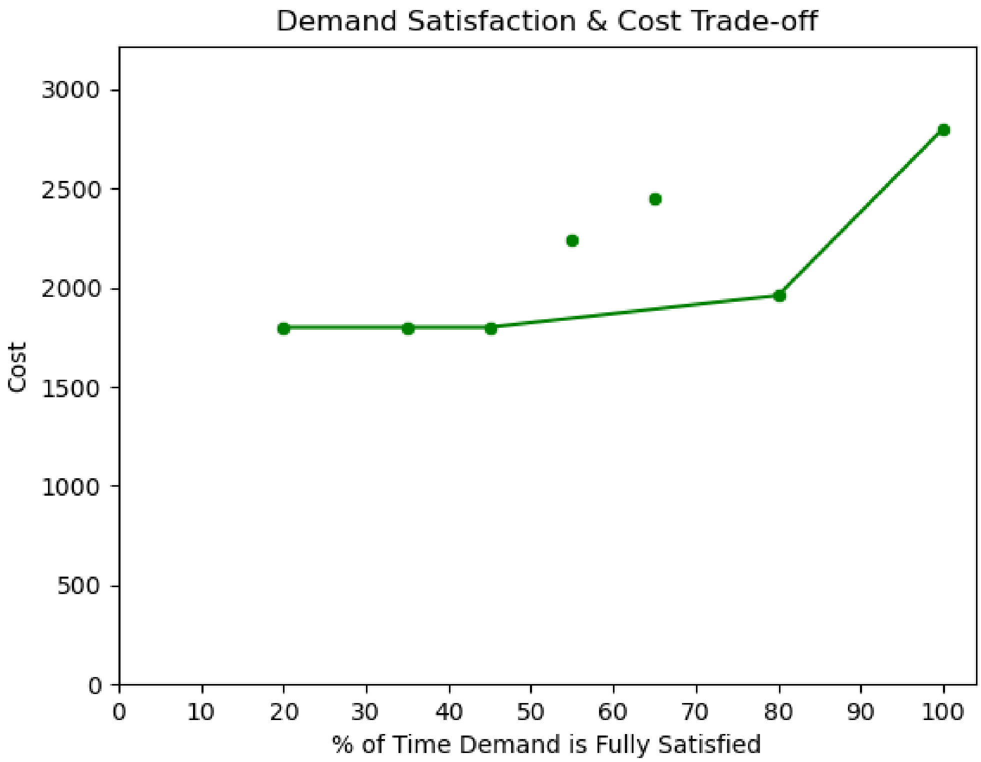

Figure 4.6. Plot showing the trade-off between demand satisfaction, cost, and gap. No prepositioning limit at terminal nodes.

Table 4.6 provides the decision variable values of the networks associated with the first three solution points in Figure 4.6 along the efficiency curve. Note that since prepositioning is not limited at the terminal nodes, the optimal strategy, given this example's cost parameters and gap value, is to preposition a node's entire demand at that node. Under this strategy, no supplies are prepositioned at Okinawa and no supplies are shipped from Okinawa to either EAB. Moreover, the cost associated with each network is composed solely of the cost to preposition supplies at each of the EABs. The first and second stage decisions are combined in Table 4.6 since the only scenario that can be realized for each network is the active scenario associated with a given Q% meaning there is only one flow value associated with each arc. In other examples, the tables are split into first stage decisions and second stage decisions.

Table 4.6. Decision variable values for candidate network solutions.

Network	$Q\%$	Active Scenario	$s_{Oki.}$	s_{EAB1}	s_{EAB2}	$x_{Oki.,EAB1}$	$x_{Oki.,EAB2}$	**Obj Val**
1	20	1	0	100	20	0	0	1800
2	35	2	0	20	100	0	0	1800
3	45	3	0	0	120	0	0	1800

The remaining solution points in Figure 4.6, however, have a different prepositioning strategy. Now, when multiple scenarios are active, we observe risk pooling. Since the demand across EABs varies by scenario, it is no longer optimal to preposition a node's demand for a single scenario at that node. For example, if Scenarios 1 and 2 are active, and the EAB demands from Scenario 1 are set as the prepositioned supply values, then when Scenario 2 is realized there will be an excess of 80 units of supply at EAB 1 and a deficit of 80 units of supply at EAB 2. Under risk pooling, the optimal strategy is to preposition a node's minimum demand across scenarios at that node and to preposition the remaining supply at Okinawa. Once a scenario is realized, the required amount of supply can be shipped from Okinawa to the appropriate EAB. Now that multiple scenarios are active, there are different flow values in the network depending on which scenario is realized. We break the solution into two tables. Table 4.7 provides the first stage decision variable values of the fourth solution point from Figure 4.6 when Scenarios 1 and 2 are active. Table 4.8 shows the second stage decision variable values of the fourth solution point from Figure 4.6 when Scenarios 1 and 2 are active.

Table 4.7. First stage decision variable values for candidate network.

Network	$Q\%$	Active Scenario	$s_{Oki.}$	s_{EAB1}	s_{EAB2}	**Obj Val**
4	55	1,2	80	20	20	2240

The risk pooling effect is evident as only 20 units of supply are prepositioned at each EAB even though there is no prepositioning limit. The remaining supply is prepositioned at Okinawa. Once a scenario is realized, the required supplies are shipped to the appropriate EAB to meet demand according to the flow values in Table 4.8.

Table 4.8. Second stage decision variable values for candidate network.

Realized Scenario	$x_{Oki.,EAB1}$	$x_{Oki.,EAB2}$
1	80	0
2	0	80

Next, we examine the model's ability to satisfy demand in inactive scenarios by analyzing the cost-demand satisfaction trade-off for various gap values under limitless prepositioning. The results in Figure 4.7 are nearly identical to those in Figure 4.5. Again, we attribute this finding to risk pooling as it is suboptimal to preposition excess supply at terminal nodes when considering multiple demand scenarios. Although we allow for an infinite amount of supplies to be prepositioned at the EABs, our model never prepositions more than necessary to satisfy the minimum possible demand at an EAB. The remaining demand variability is prepositioned at nodes further away from the demand nodes in order to provide better responsiveness.

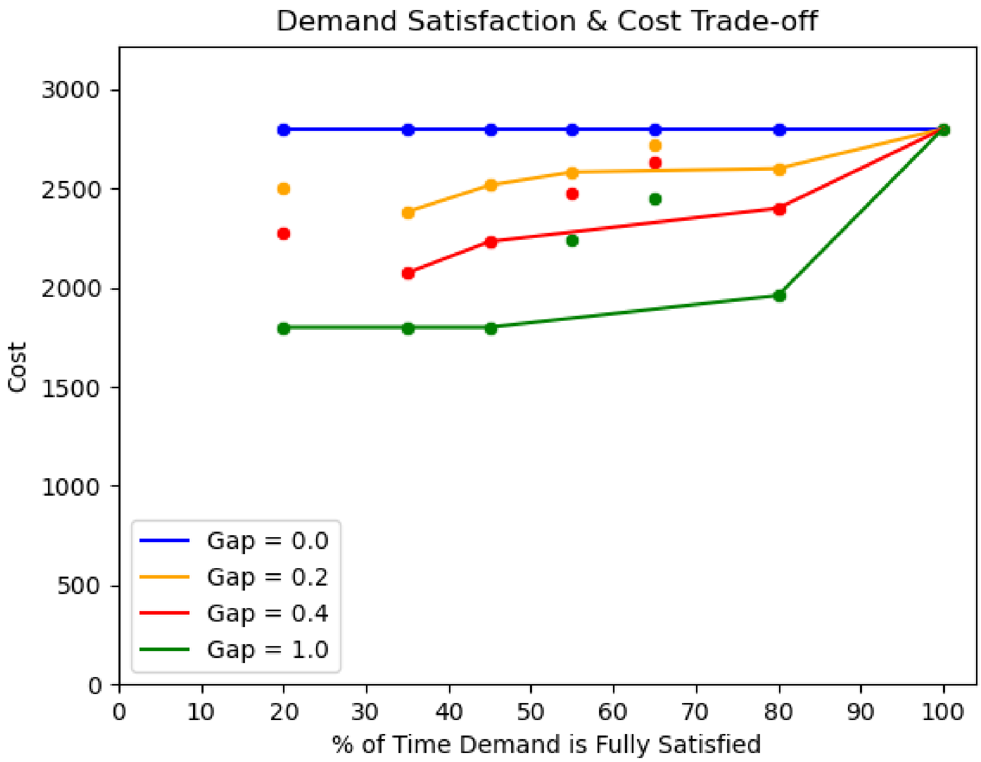

Figure 4.7. Plot showing the trade-off between demand satisfaction, cost, and gap. No prepositioning limit at terminal nodes.

4.3 Operational Scenario

In this section we introduce a notional operational scenario using the Naval Postgraduate School Joint Campaign Analysis Global War 2045 scenario (Kline 2022). The scenario is summarized as follows. The year is 2045 and tensions are rising in the SCS. Taiwan's president recently called for the declaration of complete independence from China to which China responded with a close blockade. While the U.S. military and Taiwan view this as an act of war, China argues that Taiwan is a Chinese territory and that they have the right to act as they deem appropriate. As a result of the blockade, the U.S. Navy begins providing flags and escorts to merchant ships heading toward Taiwanese ports. Meanwhile, the U.S. military also continues to increase the frequency and scale of exercises with Philippine and Indonesian armies. One of the exercises involves coalition forces placing land-based anti-ship missiles along various access points to the SCS. China threatens to occupy the Indonesian island of Natuna Besar if coalition forces continue to arm locations in the FIC. Tensions reach an all time high as a series of attacks take place in the SCS. A U.S.-flagged tanker ship is struck by an underwater explosion while approaching Kaohsiung. One week later, a Chinese deep-sea exploration ship is sunk just north of Natuna Besar. Following the attack on the Chinese ship, China sinks a Vietnamese patrol boat using a land-based missile from Woody Island in the Paracels. At this time, China reasserts its threat of invading Natuna Besar and embarks the Chinese 1st Marine Brigade at Zhanjiang, Guangdong on the South China amphibious flotilla.

Using this notional operational scenario, we construct five demand scenarios to be used as input in our model. Each demand scenario is unique and contains different demand locations and quantities as depicted in Table 4.9. Included in the table are the scenarios and their respective probabilities of being realized. The task is to define an optimal sustainment network to support the possible demand generated by friendly forces conducting EABO across EABs. Figure 4.8 displays all possible nodes and arcs that can be included in the optimal sustainment network. Hawaii is not shown, but there are three arcs coming from the right side of the figure that connect Hawaii to other nodes in the network. Green pins represent supply and intermediate nodes. Red pins represent EABs with varying demand across scenarios. The results produced by the model provide decision makers with information to aid in the determination of which nodes to include in the network as prepositioning sites, prepositioning quantities at different nodes, and arc flow values between nodes in the network.

Table 4.9. Demand scenario data.

SCENARIO (f)	**DEMAND_1**	**DEMAND_2**	**DEMAND_3**	**DEMAND_4**	**DEMAND_5**
PROBABILITY (p_f)	0.35	0.22	0.05	0.21	0.17
NODE (n)	$d_{n,DEMAND_1}$	$d_{n,DEMAND_2}$	$d_{n,DEMAND_3}$	$d_{n,DEMAND_4}$	$d_{n,DEMAND_5}$
Singapore	0	0	0	0	0
Cam Ranh Bay	0	0	0	0	0
Manila	0	0	0	0	0
Cebu	0	0	0	0	0
Yokosuka	0	0	0	0	0
Okinawa	0	0	0	0	0
Zuoying	0	0	0	0	0
Pattaya	0	0	0	0	0
Palau	0	0	0	0	0
Sasebo	0	0	0	0	0
Darwin	0	0	0	0	0
Guam	0	0	0	0	0
Hawaii	0	0	0	0	0
Zamboanga	0	0	0	0	0
EAB1	25	10	15	10	10
EAB2	10	25	15	0	25
EAB3	0	0	0	15	0
EAB4	25	15	0	50	25
EAB5	10	35	200	0	125
EAB6	10	15	315	50	125
EAB7	100	0	200	0	150
EAB8	100	15	300	50	150
EAB9	15	0	325	15	150
EAB10	0	35	300	50	150
EAB11	0	15	0	15	15
EAB12	50	15	0	50	0

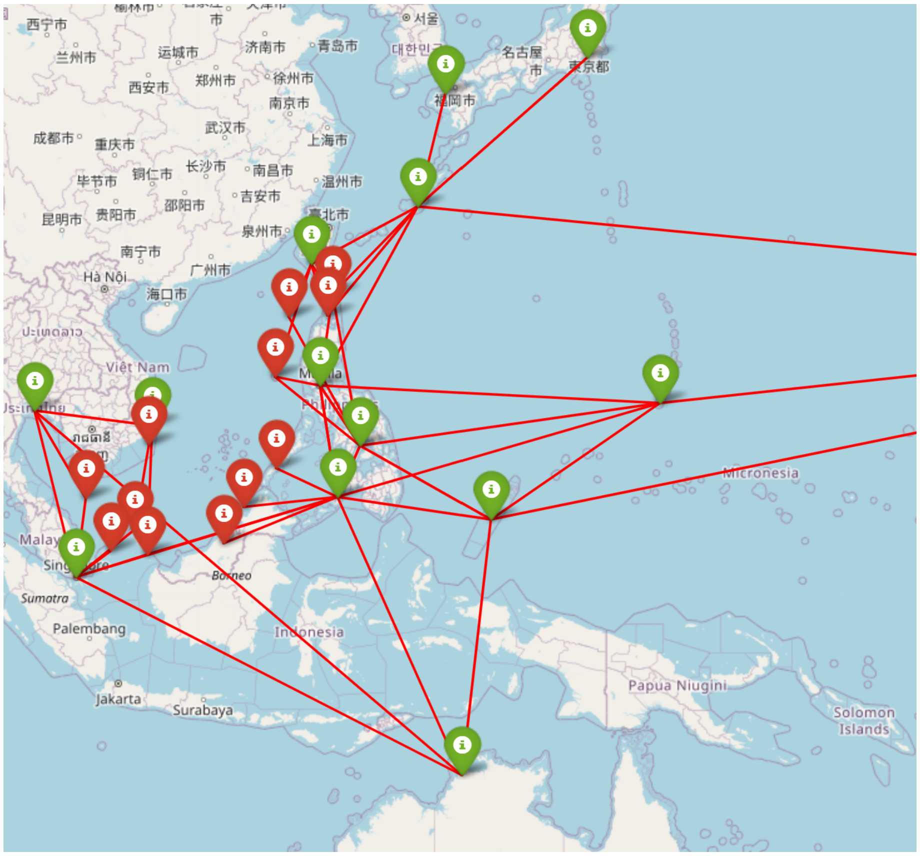

Figure 4.8. All possible nodes and arcs in consideration when determining optimal sustainment network.

In addition to the information contained in Table 4.9, we provide more scenario input data. In this example, we limit the number of intermediate and supply nodes that can be included in the network by enforcing a budget. This resembles reality because there typically exists some financial constraints that limit the amount of nodes you can establish in a sustainment network. We simplify the problem and say the cost to include each intermediate or supply node is one. We then set a budget of eight, so the maximum number of intermediate and supply nodes allowed in each candidate network is eight. Furthermore, we select five gap values to use in our analysis. Those gap values are: 0.0, 0.20, 0.35, 0.50, 1.0. Of note, the cost to flow supplies on each arc is proportional to the arc's distance. We present more details on the parameters associated with each node and arc, which are also required as input, in Tables A.2 and A.1, respectively.

The power set generated by the five demand scenarios contains 31 elements. Crossing the power set with the five gap values results in 155 model instances. The 12 possible EAB nodes, 14 possible supply nodes, and 49 arcs, equates to 297 decision variables, 26 of which are binary, and 815 constraints for each model instance. It takes roughly 30 seconds to solve all 155 instances.

4.3.1 Operational Scenario Assumptions

In addition to the modeling assumptions stated in 3.2.5, there are assumptions associated with the operational scenario. For the purposes of our analysis, we picked locations in and around the SCS as potential EABs, assuming they are accessible to U.S. forces. In reality, special permissions and authorities must be negotiated by the United States and host nations to occupy foreign territory. Another assumption we make is that EABs cannot conduct lateral resupply. That is, each EAB is purely a demand node and cannot be used as an intermediate node for supplying another EAB. This is a pessimistic assumption because when it is removed or relaxed, and lateral resupply is permitted, we expect to see a more efficient network.

4.3.2 Base Case Results

In this section, we produce results for the notional scenario and showcase them in the demand satisfaction and cost trade-off plot shown in Figure 4.9. Given the number of possible nodes, arcs, demand scenarios, and gaps, we solve 155 different model instances. Recall that each of the points in the plot represents a solved model instance, or candidate logistic network. That is, each point contains stage one decision values, or prepositioning locations and quantities, as well as stage two decision values, or arc flows for each scenario. The optimal prepositioning locations and quantities for a model instance are shown in Table 4.10.

Table 4.10. Partial stage one decision variable values.

NODE (n)	**PREPOS AMOUNT (s_n)**
Cam Ranh Bay	100
Cebu	100
Darwin	950
EAB1	15
EAB10	15
EAB11	15
EAB12	15
EAB2	15
EAB3	15
EAB4	15
EAB5	15
EAB6	15
EAB7	15
EAB8	15
EAB9	15
Manila	100
Pattaya	100
Singapore	100
Zamboanga	100
Zuoying	10

Given the amount of supplies prepositioned at Darwin, it appears to be a critical node in the network. Figure 4.9 is interpreted in the same manner as the trade-off plots produced in Section 4.2. We remove all points not on the Pareto frontiers for simplicity. A decision maker analyzes the plot by first drawing their attention to the Pareto frontiers associated with different gap values. From there, the analyst conducts a cost-benefit analysis to determine how much they are willing to pay to achieve a certain Q%, or responsiveness. Lastly, they determine how much they wish to hedge in the inactive scenarios. For example, a gap of 0.0, shown in blue, ensures complete demand satisfaction in the inactive scenarios, but it comes at a much greater cost than a gap of 0.2, shown in orange, which guarantees 80% demand satisfaction in the inactive scenarios. As expected, we observe that as the gap value decreases, the cost increases since more demand satisfaction is required in the inactive scenarios.

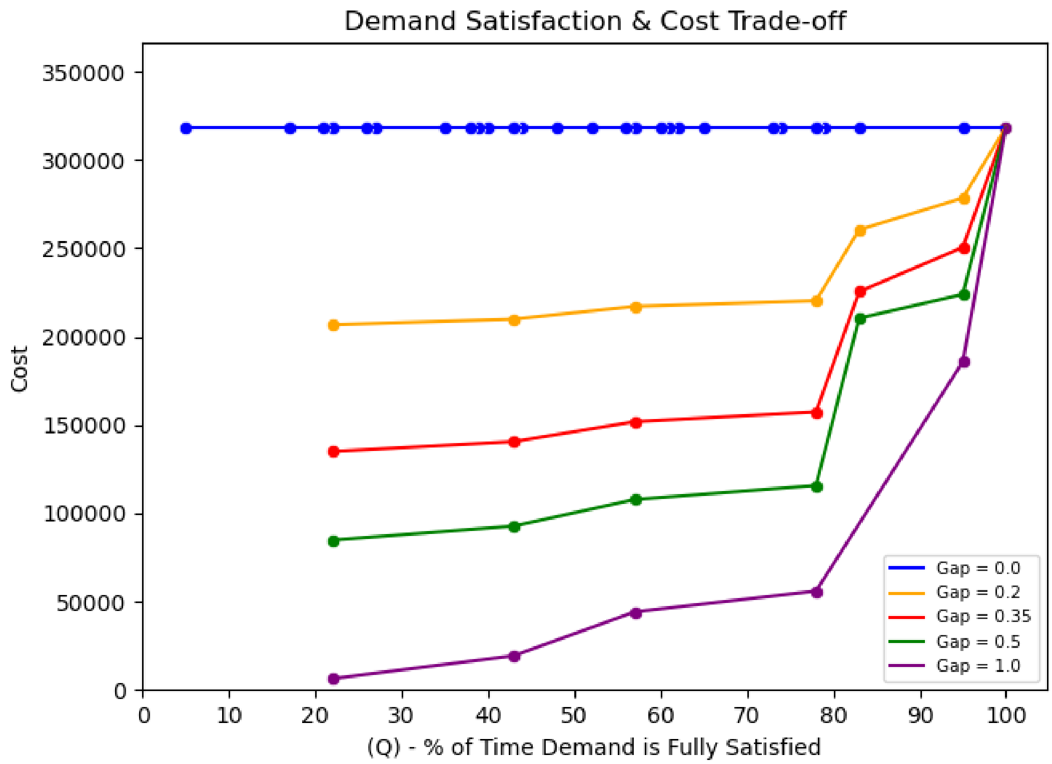

Figure 4.9. Demand satisfaction and cost trade-off plot for five gap values.

To further illustrate this thought process, imagine a decision maker wants to achieve a Q% of at least 80%. There are three elements of the power set whose accumulated probabilities sum to at least 80% and satisfy the decision maker's requirement as shown in Table 4.11.

Table 4.11. Scenario combinations with at least 80% responsiveness.

Q%	Active Scenarios	Inactive Scenarios
83	{DEMAND_1, DEMAND_2, DEMAND_3, DEMAND_4}	{DEMAND_5}
95	{DEMAND_1, DEMAND_2, DEMAND_4, DEMAND_5}	{DEMAND_3}
1	{DEMAND_1, DEMAND_2, DEMAND_3, DEMAND_4, DEMAND_5}	{}

For each row in Table 4.11, there are five network solutions, each with a different gap value. While each network for a given Q% achieves the same responsiveness, they vary in cost and demand satisfied in the inactive scenarios. Given these trade-off considerations, the decision maker must determine what they are willing to pay, in terms of cost and performance in the inactive scenarios, to achieve a desired Q%. That said, given the decision maker's desire to achieve a Q% of at least 80%, they initially settle on the green curve at the point corresponding to a Q% of 83% that guarantees 50% satisfaction in the inactive scenarios. They notice a network on the red curve, however, that still achieves a Q% of 83% while also guaranteeing 65% satisfaction in the inactive scenarios for only a minor cost increase. The decision maker then sees that if they are willing to accept a Q% of only 77%, with a gap of 0.35, the cost decreases from 225,428 to 157,336, for a savings of 30%. This calculus is repeated until the decision maker arrives at a network solution that they deem to be the best.

Furthermore, the results in Figure 4.9 contain plateaus at various cost values for each gap. While not strictly flat, these plateaus showcase the fact that there are some networks that achieve roughly 60% more responsiveness for essentially the same cost. The decision maker should only consider those networks on the right end of the plateaus.

To show an example of the results produced for each model instance, we display the decision variable values for the solution network associated with a Q% of 83% and gap of 0.5 in Tables A.3, A.4, and A.5.

4.3.3 Removing Node From Network

In this section, we remove a node from the network to study the changes in the solution and objective function value. Analyzing the base case results in Table 4.10 from an adversary's perspective, it appears that Darwin is a critical node. The amount of supplies prepositioned at Darwin coupled with its connectedness to intermediate nodes makes it a high-value target for adversaries. Therefore, in the first case, we remove Darwin from the set of possible nodes and run the model again to determine the impact of an adversary eliminating Darwin. The results are shown in Figure 4.10.

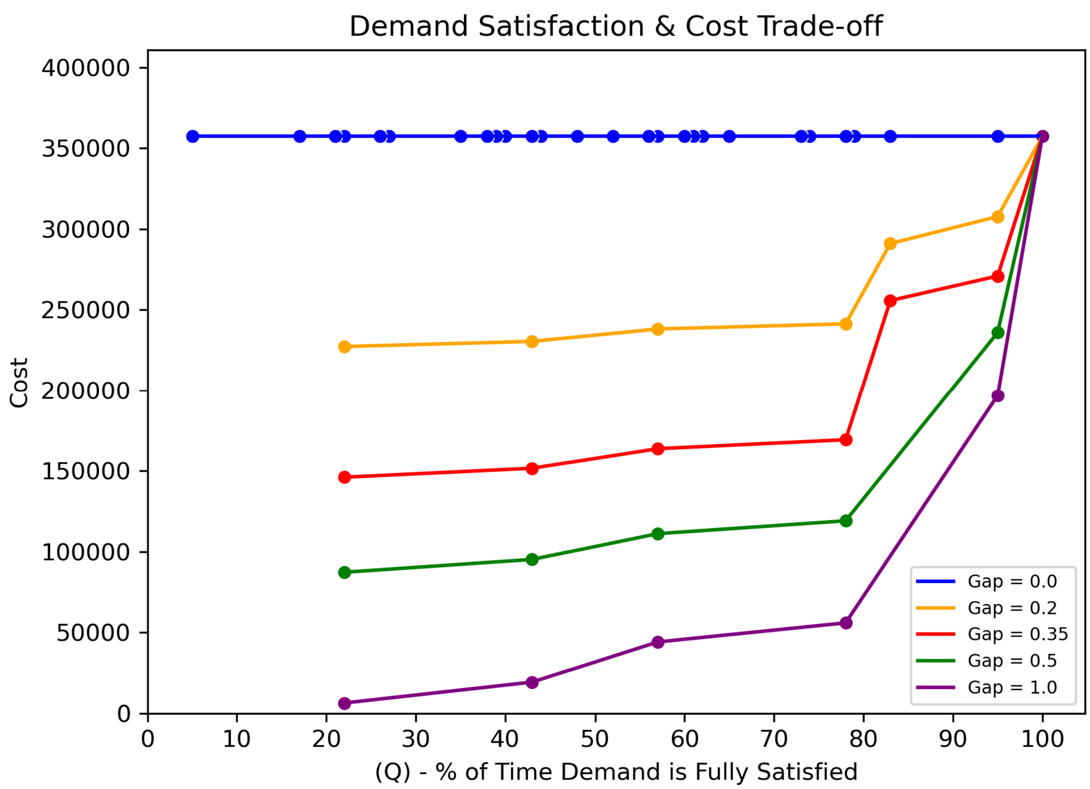

Figure 4.10. Demand satisfaction and cost trade-off plot after removing Darwin. It is more expensive to satisfy demand without Darwin in the network.

When we compare these results to the base case results in Figure 4.9, we notice that by removing Darwin the cost of each candidate network increases. When the gap value is greater than 0.2, the cost increase is marginal. For gap values 0.0 and 0.2, however, the cost increases are more pronounced. Specifically, when the gap value is 0.0, the cost for any network increases by more than 12% as shown in Table 4.12.

Table 4.12. Cost increase after removing Darwin.

	s_{Darwin}	**Obj Val (cost)**	**% change**
With Darwin	950	318532	-
Without Darwin	0	357294	+12.2

Furthermore, among all nodes, the greatest amount of supplies is prepositioned at Darwin when it is included in the network. In fact, the 950 units of supplies prepositioned at Darwin equates to 54.6% of all supplies in the network, highlighting its importance as a supply node. When Darwin is removed from consideration and no supplies are able to be prepositioned at Darwin, we find that Okinawa becomes the major prepositioning node in the network. Looking at Figure 4.8, we observe that Okinawa is located in close proximity to EABs and intermediate nodes. When demand resides at EABs in the northern end of the SCS, supplies can be shipped from Okinawa in a timely and cost-effective manner. In this operational scenario, however, the preponderance of the demand, across demand scenarios, resides in the southern end of the SCS near the island of Natuna Besar. As such, when most of the supplies are prepositioned at Okinawa, they must be shipped through numerous intermediate nodes in and around the SCS which comes at an increased cost. Based on our analysis, it appears that Darwin is an important node to consider incorporating in our network due to its cheap arc flow cost, prepositioning capacity, and connectedness to other nodes.

Our analysis in this section serves as a basis from which more rigorous attacker-defender modeling and analysis can be conducted in future research. Furthermore, while we only explore a single what-if scenario, this section demonstrates the capability that our model provides planners to conduct this type of analysis.

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CHAPTER 5: Conclusion and Future Work

5.1 Conclusion

The success of the Marine Corps in the future operating environment is dependent upon its ability to make the right decisions today to sustain its forces tomorrow. What makes this a challenging endeavor is two-fold; planners do not know what the operational demand will be in the future, and current prepositioning and sustainment networks are not capable of sustaining EABO. Without knowledge of exact demand quantities, or even an underlying demand distribution, developing an optimal sustainment network is not easy. By considering a range of possible conflict scenarios, however, logistics planners can better address the uncertainty of the future. Furthermore, by exploring a host of potential prepositioning sites and network architectures, planners can gain a better understanding of the optimal sustainment network.

The model allows planners to include a variety of possible demand scenarios, locations, and routes for analysis enabling decision makers to derive actionable insights for developing a sustainment network in support of EABO. We find that when multiple demand scenarios are considered, risk-pooling takes effect. By holding back supplies at intermediate nodes, risk-pooling enables the network to provide more responsive support while simultaneously reducing waste. Furthermore, while the model guarantees complete demand satisfaction in active scenarios, hedging in the inactive scenarios also allows decision makers to guarantee their desired level of satisfaction in those scenarios as well. Our tool enables quick trade-off analysis for planners to explore a wide range of what-if scenarios as demonstrated in Section 4.3.3.

The proposed model addresses the Marine Corps' challenge of designing an optimal sustainment network capable of supporting EABO by determining prepositioning locations, quantities, and routes. The model provides decision makers with numerous candidate networks, each optimized under certain conditions, and allows decision makers to decide which network they deem best given their risk tolerance and required level of responsiveness.

5.2 Future Work

Our generic modeling approach provides a solid foundation for future research. As such, we propose the following topics for follow-on work.

Since the model is connector and supply agnostic, the first recommendation we have for future research involves exploring different connectors. In order to fully develop our preliminary model with multiple commodities in Section 3.2.6, it should be extended to match different commodities with different connectors. The Marine Corps is currently investigating various ship-to-shore and shore-to-shore connectors for employment in an EABO context. Current resupply platforms are too large, and assume too much risk in a contested environment. Smaller platforms with smaller signatures are attractive alternatives, but their limited capacity implies a requirement for numerous platforms to satisfy demand. This area of research should examine specific connectors that either exist, or are in development. Platform parameters such as capacity, speed, signature, and cost could all inform various research questions posed by a sponsor. Another area of possible work is in the analysis of different classes of supply. The size, weight, storage, and compatibility concerns of individual classes of supply are significant. For example, current connector prototypes cannot transport large vehicles and are better suited for bulk liquids. Additionally, there are a number of security concerns and requirements associated with the storage of ammunition that cannot be overlooked. Analysis into one or more classes of supply provides planners with a much more realistic understanding of possibilities and limitations.

Several of our modeling assumptions can be challenged and investigated in future work. The assumption that EAB locations are stationary is not likely to hold up in an actual conflict scenario. The expeditionary nature of EABs and the requirement to displace after shooting to avoid counter-fire is something we choose not to incorporate in our model. A Markovian approach to modeling demand locations, or EABs, over time can help determine an optimal network, or can provide valuable insight into the responsiveness of a predetermined network.

Lastly, we recommend that future work consider the reality of risk in the form of attrition and interdiction. Our model's assumption that there is no enemy interdiction or loss of supplies along resupply routes is optimistic. Given the enemy's increased sensing and shooting capabilities, planners must account for loss of supplies, connectors, and even nodes in the network. Enemy attacks and network operator defenses can be modeled in a more rigorous attacker-defender analysis than what is done in Section 4.3.3. By modeling interdiction of various arcs or nodes, network operators can gain a better sense of network vulnerabilities as well as network elements that should be hardened against attacks. Incorporating this aspect of reality and defining a resilient network capable of handling such losses provides great value to forces reliant upon timely resupply.

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APPENDIX: Operational Scenario Inputs and Results

Tables A.1–A.5 in this appendix contain the input parameters, as well as the base case and what-if results, for the notional operational scenario explored in Section 4.3.

Table A.1. Operational scenario arc data.

FROM (i)	**TO** (j)	**COST** ($c_{i,j}$)	**CAPACITY** ($u_{i,j}$)
Hawaii	Guam	3971.60	10000
Hawaii	Okinawa	4844.55	10000
Hawaii	Palau	4907.17	10000
Guam	Manila	1598.54	10000
Guam	Cebu	1438.75	10000
Guam	Zamboanga	1602.82	10000
Guam	Palau	980.35	10000
Yokosuka	Okinawa	935.97	10000
Sasebo	Okinawa	485.20	10000
Okinawa	Zuoying	535.17	10000
Okinawa	Manila	921.62	10000
Okinawa	EAB1	539.93	500
Okinawa	EAB2	628.75	500
Palau	Cebu	720.74	10000
Palau	Zamboanga	749.10	10000
Darwin	Palau	1233.98	10000
Darwin	Zamboanga	1463.01	10000
Darwin	Singapore	2083.20	10000
Darwin	Pattaya	2696.05	10000
Zuoying	EAB1	167.12	500
Zuoying	EAB2	244.24	500
Zuoying	EAB3	257.88	500
Zuoying	EAB4	540.83	500
Manila	EAB1	427.29	500

Manila	Zamboanga	529.27	10000
Manila	EAB4	220.02	500
Manila	Cebu	337.52	10000
Cebu	Manila	337.52	10000
Cebu	Zamboanga	264.37	10000
Cebu	EAB1	716.40	500
Cebu	EAB4	517.77	500
Cebu	EAB3	687.37	500
Zamboanga	Cebu	264.37	10000
Zamboanga	Manila	529.27	10000
Zamboanga	EAB5	320.98	500
Zamboanga	EAB7	452.82	500
Zamboanga	EAB11	958.33	500
Zamboanga	EAB12	591.19	500
Zamboanga	Singapore	1320.08	10000
Singapore	EAB8	379.09	500
Singapore	EAB9	366.91	500
Singapore	EAB10	207.75	500
Singapore	EAB11	361.60	500
Singapore	Pattaya	822.08	10000
Pattaya	EAB8	485.78	500
Pattaya	Cam Ranh Bay	565.72	10000
Cam Ranh Bay	EAB6	93.91	500
Cam Ranh Bay	EAB9	325.84	500
Cam Ranh Bay	EAB11	619.55	500

Table A.2. Operational scenario node data.

NODE (n)	**RESOURCE_REQ** (h_n)	**PREPOS_PUC** (γ_n)	**MAX_PREPOS** (V_n)
Singapore	1	10	100
Cam Ranh Bay	1	10	100
Manila	1	10	100
Cebu	1	10	100
Yokosuka	1	1	1000
Okinawa	1	1	1000
Zuoying	1	25	100
Pattaya	1	10	100
Palau	1	10	100
Sasebo	1	1	1000
Darwin	1	1	1000
Guam	1	1	1000
Hawaii	1	1	1000
Zamboanga	1	10	100
EAB1	1	15	15
EAB2	1	15	15
EAB3	1	15	15
EAB4	1	15	15
EAB5	1	25	15
EAB6	1	25	15
EAB7	1	25	15
EAB8	1	25	15
EAB9	1	25	15
EAB10	1	25	15
EAB11	1	25	15
EAB12	1	25	15

Table A.3. Operational scenario prepositioning decision values.

NODE (n)	PREPOS AMOUNT (s_n)
Cam Ranh Bay	100
Cebu	100
Darwin	950
EAB1	15
EAB10	15
EAB11	15
EAB12	15
EAB2	15
EAB3	15
EAB4	15
EAB5	15
EAB6	15
EAB7	15
EAB8	15
EAB9	15
Guam	0
Hawaii	0
Manila	100
Okinawa	0
Palau	0
Pattaya	100
Sasebo	0
Singapore	100
Yokosuka	0
Zamboanga	100
Zuoying	10

Table A.4. Operational scenario node selection decision values.

NODE (n)	**INCLUDE NODE (y_n)**
Cam Ranh Bay	1
Cebu	1
Darwin	1
EAB1	1
EAB10	1
EAB11	1
EAB12	1
EAB2	1
EAB3	1
EAB4	1
EAB5	1
EAB6	1
EAB7	1
EAB8	1
EAB9	1
Guam	0
Hawaii	0
Manila	1
Okinawa	0
Palau	0
Pattaya	1
Sasebo	0
Singapore	1
Yokosuka	0
Zamboanga	1
Zuoying	1

Table A.5. Operational scenario arc flow decision values.

FROM (i)	**TO** (j)	**SCENARIO** (f)	**FLOW VALUE** ($x_{i,j,f}$)
Cam Ranh Bay	EAB6	DEMAND_3	300
Cam Ranh Bay	EAB6	DEMAND_4	35
Cam Ranh Bay	EAB6	DEMAND_5	47.5
Cam Ranh Bay	EAB9	DEMAND_5	52.5
Cebu	Zamboanga	DEMAND_1	20
Cebu	Zamboanga	DEMAND_3	100
Cebu	Zamboanga	DEMAND_5	7.5
Darwin	Pattaya	DEMAND_3	100
Darwin	Singapore	DEMAND_3	780
Darwin	Zamboanga	DEMAND_3	70
Manila	EAB4	DEMAND_1	10
Manila	EAB4	DEMAND_4	35
Manila	Zamboanga	DEMAND_3	100
Pattaya	Cam Ranh Bay	DEMAND_3	200
Pattaya	EAB8	DEMAND_5	27.5
Singapore	EAB10	DEMAND_2	20
Singapore	EAB10	DEMAND_3	285
Singapore	EAB10	DEMAND_4	35
Singapore	EAB10	DEMAND_5	60
Singapore	EAB8	DEMAND_1	85
Singapore	EAB8	DEMAND_3	285
Singapore	EAB8	DEMAND_4	35
Singapore	EAB8	DEMAND_5	32.5
Singapore	EAB9	DEMAND_3	310
Singapore	EAB9	DEMAND_5	7.5
Zamboanga	EAB12	DEMAND_1	35
Zamboanga	EAB12	DEMAND_4	35
Zamboanga	EAB5	DEMAND_2	20
Zamboanga	EAB5	DEMAND_3	185

Zamboanga	EAB5	DEMAND_5	47.5
Zamboanga	EAB7	DEMAND_1	85
Zamboanga	EAB7	DEMAND_3	185
Zamboanga	EAB7	DEMAND_5	60
Zuoying	EAB1	DEMAND_1	10
Zuoying	EAB2	DEMAND_2	10

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