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# Emergency Logistics Stochastic Network Optimization with Prepositioning and Distribution Center Support

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**EMERGENCY LOGISTICS STOCHASTIC NETWORK OPTIMIZATION WITH PREPOSITIONING AND DISTRIBUTION CENTER SUPPORT**

THESIS

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## Abstract

The purpose of this study is to examine the Air Force Medical Service's (AFMS) War Reserve Materiel (WRM) supply chain management through the use of the supply chain optimization software, anyLogistix. The goal is to illuminate potential improvements to policies that effect inventory management and test the effects of specific inputs, such as an influx of network support and capacity expansion, into the models. Network optimization shows the cost benefit analysis of these factors and if demand is satisfied through all the demand points.

This study specifically looks at the supply chain management of five pre-hospital analgesic medications: ketamine, morphine, fentanyl intravenous (IV), fentanyl oral and hydromorphone. Through two recent studies covering combat care in the Middle East, this thesis projects demand and builds it into the network. To illustrate the effectiveness of the supply chain, this study looks at a potential conflict in the Korean region. Through three different wartime scenarios and ten different inputs, this study examines 30 models and the effects of inputs on these scenarios.

Through the scope of transportation cost, carrying cost, supply cost, expansion cost and satisfied demand, this research evaluates all 30 models. The research shows that given the predicted demand for warfare in Korea, it will be difficult to meet the needs of certain products with AFMS assets, such as ketamine and fentanyl oral. Expansion of the network capabilities will lessen this demand shortfall and the introduction of suppliers with the necessary resources will eliminate these shortfalls completely.

## Acknowledgments

I would like to express my deepest gratitude to my thesis advisor, Dr. Frank Ciarallo for his guidance, invaluable insight and putting up with my exasperating questions for as long as he did. I also would like to thank my reader Dr. Seong-Jong Joo for his support and patience with me throughout the thesis process. I could not have completed this thesis without their undying support and mentorship. Finally, I would like to thank my classmates and friends as the jokes and snarky comments made my time at the Air Force Institute of Technology fly by. Despite the difficulties of coming to school in the midst of pandemic restrictions, my classmates and committee members carried me to the end, for which I will forever be thankful and look back cherishing the moments.

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# I. Introduction

**Background**

The United States Air Force Medical Service (AFMS) War Reserve Materiel (WRM) program is vast and spreads across multiple continents and regions. Figure 1 shows the current structure of the medical WRM network as built in anyLogistix. Its efficient and effective deployment is key to preserving war fighting capabilities and providing lifesaving resources to US armed forces both at home and abroad. These resources serve as a vital component of warfare that demand the integration of policies that use efficiency as a foundation, but within the program's implementation there lies much uncertainty. Key questions for the WRM network include: what quantities of products should be prepositioned at regional locations and what missions these strategically placed resources assist? Answers to these questions offer insight into what inventory policies offer the most value to enhance network efficiency.

Complicating this further is that these questions do not offer standardized solutions and can differ greatly by a region's geopolitical factors. Solving such a dilemma as network optimization for WRM inventory therefore requires a dynamic approach with the flexibility required to adapt to an ever-changing environment. There are no ubiquitous answers to how to respond to a disaster situation (Kovacs & Moshtari, 2017). The uncertainty of a response calls for a multi-pronged academic approach that accounts for a multitude of variables. Emergency logistics has led to the increased demand for development of multi-

disciplinary models (Hoyos et al., 2015). A failure to adequately adapt and strive for efficiency has grave consequences to both the network utilization and the warfighters requiring medical products in the midst of a conflict.

With an understanding of the questions surrounding network efficiency, it's key to dive into the purpose of the WRM program. Air Force WRM is an enterprise-wide program to support operations across the full spectrum of military operations. These are the supplies and equipment deemed necessary to reduce the amount of time required to achieve a certain level of operational capability, according to the National Security Strategy (AFI 25-101, 2019). Medical WRM is a dynamic program based off the expected consumption of resources and the ability of the supply chain to resupply critical materiel (AFMAN 41-209, 2019). It is a buffer to support and maintain operations in a time of high uncertainty and dynamic variables.

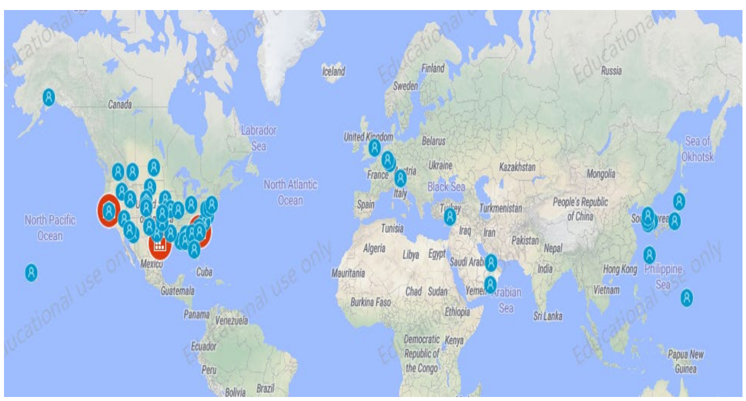



**Figure 1 - War Reserve Materiel Network**

Modern medical warfare has seen enormous changes and improvements over the last decades. The survivability rate for those in battle has greatly increased, which can

partially be attributed to several factors including advancements in technologies and approaches to battlefield medicine, such as tourniquets and pre-hospital patient transport (Howard et al., 2019). Crucial to these advancements is the rapid deployment and use of critical resources. A failure to efficiently move medical resources within the network to demand points can result in human suffering or death. Resilience is an important concept within logistics capabilities as the uncertainty of war puts strains on the volume and timing of supplies. A system is further challenged when dealing with perishable items, something prevalent with medical products (Chang et al., 2017).

Emergency logistics is a field with growing interest due to the cataclysmic effects of natural disasters, which impact nearly 220 million people and lead to $120 billion in economic losses on average per year (DAT, 2017). The objectives of emergency logistics models are to enhance responsiveness and support a supply pipeline that aligns with demand (Banomyong & Sopadang, 2010). The increased potency of these disasters across the globe must be addressed using technological advances and network designs that optimize objectives focused on saving costs and lives. The economic impact of such disasters can greatly effect a nation and its citizens. The 2011 Japan earthquake and tsunami accounted for an estimated economic loss of 4.1% of the country's Gross Domestic Product (GDP) of that year (Hoyos et al., 2015). When implemented as a tool, effective emergency logistics management brings critical resources to those most impacted and in need.

Prepositioning is a fundamental component of both the WRM program and the broader field of emergency logistics. These forward deployed assets help reduce response times by shortening transportation and decreasing reliance on the supply chain (Galindo &

Batta, 2013). Strategies like lean supply chain management or just-in-time (JIT) purchases are designed to be responsive, but can struggle to meet sudden demand without a well-established supply chain (Jahre & Fabbe-Cotes, 2015). Prepositioning also comes with an increased level of carrying and maintenance costs. Optimization of staging supplies should balance the likelihood of an event to occur in a location (Alem et al., 2016). Depending on the network's capabilities and resource availability, staging supplies in a region must account for the probability and the costs of maintenance.

When working in an emergency logistics environment, strong leadership skills are imperative as those in decision making positions work with great uncertainty. Disaster management is unique in comparison to other fields of study as the measuring stick of success lies in the ability to save lives and reduce suffering within this uncertain environment. The improbability surrounding emergency logistics causes the setting, time and demand signals to vary greatly by the scope of the operation (Kovacs & Moshtari, 2017). Many leaders fail to adapt to changing environments, technologies and resource requirements. Leaders in disaster management encounter numerous self-inflicted roadblocks including a dedication to solutions based on their past experiences and the assumptions and confidence in their own decision-making abilities (Alem et al., 2016).

As the world has become more globalized over the decades, so have the demands for a swift and efficient logistics response. The WRM network must incorporate the principles of flexibility with a globalized response framework. The United States carries an important leadership role in responses to humanitarian and global conflicts. With that responsibility comes the awareness that not all situations are uniform. A health system's compatibility to a global perspective greatly differs across the demographics and diversity

of the host nation’s populace (Jahre & Fabbe-Cotes, 2015). Delivering medical and logistics support to impoverished countries will greatly differ from those with well-established institutions and infrastructure already in place to assist in a response. Logistics planners have many moving parts and must also account for both geographic and political stability and behavior of the local populace (Kovacs & Moshtari, 2017). The goal of this research is to apply emergency logistics principles to network optimization and the medical WRM program using the supply chain optimization program, anyLogistix.

**Problem Statement**

The AFMS WRM program is massive and built on the same principles as emergency logistics. Uncertainty can hamper efficient deployment, preparation and prepositioning during a response. WRM deployment is vital to the warfighting mission. The survivability rate of those fighting in combat can be improved when medical intervention is quick with well-positioned critical medical resources.

**Purpose Statement**

The purpose of this study is to examine the AFMS’s WRM supply chain management through the supply chain optimization software, anyLogistix. The goal is to illuminate potential improvements to policies that effect inventory management and test the effects of specific inputs, such as an influx of network support and capacity expansion, into the models. Network optimization shows the cost benefit analysis of these factors and if demand is satisfied through all the demand points.

## Research Questions

1) Which factors help reduce costs while meeting or exceeding demand satisfaction?

2) Will adding factors effect model performance?

3) Is anyLogistix a useful platform for answering network questions?

## Research Focus

This research will focus on three components: building the WRM network, adapting the network to certain parameters and an examination of outputs. Due to the complexity of analyzing dynamic environments such as those in warfare, this study looks at three unique scenarios and ten different inputs to test the responsiveness and costs of the network on five different pain medications: ketamine, morphine, fentanyl IV, fentanyl oral and hydromorphone. These pain medications are used to treat pre-hospital combat casualty patients. They are all scheduled drugs and require special handling, but do not require any extreme temperature storage. The time period for each model is 30 months. These three components give a clearer picture of where the network lies and how it can be adapted to build a better response.

## Methodology

The approach in this study utilizes the network optimization module of anyLogistix. Using the system outputs associated with costs and responsiveness, this study builds a comparative analysis of the three scenarios and 30 models. This research also examines those models meeting 100% demand satisfaction.

## Assumptions

In this study the main assumption is that the only resources in the network are those within the AFMS WRM program. There is no support from other services such as the United States Army or our NATO counterparts. Storage points, or bases in this study, are able to support an expanded role within the network. Demand signals and points are constant through the model's 30 month duration. Transported materiel arrives to the location without damage or major interruptions. Since this network is operating in a time of war, the concept of perfect transportation is ideal but may not be realistic. Each medication dosage goes to one patient, there is no mixing of different medications. Products in the network are bought, sold and shipped as individual units. There is no bundling or bulk purchases in the network. There is an unlimited production of resources when incorporating suppliers. This study does not account for certain costs such as product in-processing or out-processing, preparation costs, or special handling such as the additional security surrounding drug inventories.

## Limitations

Limitations in this thesis revolve around the effects of a narrow scope of using only five medications and the constraints built into the network. These medications come from different unit type codes (UTCs) and are deployable with those specific packages. The focus of this study is on showing the costs and benefits associated with different inputs, but this does not place a bound on one of the most imperative factors, the budget. Since the US government constantly deals with budget constraints, it is in reality one of the most vital factors to deploying necessary resources.

## Implications

This research has two implications: framework design and operational planning. Network optimization can help leaders construct an adaptable WRM framework for cost-efficient inventory storage and transportation. The anyLogistix program can run an optimized network capable of adjusting to the geopolitical needs associated with conflicts in different regions. This can give logistics planners the ability to adjust the network until it reaches an appropriate cost and responsiveness threshold. Expanding the network in anyLogistix by incorporating operational planning can build a more realistic scenario. These operational plans have greater insight into the demands and needs of a conflict region. This creates a better link between these models and military medicine operational planning, which ultimately builds a better representative model.

# II. Literature Review

## Overview

WRM asset deployment is analogous to the field of emergency logistics. Emergency logistics research garnered heightened attention with the increased visibility and the devastation caused by natural disasters, such as Hurricane Katrina in 2005 (Afshar & Haggani, 2012). This section examines four unique categories of analysis covering emergency logistics: general characteristics of emergency logistics, metrics, strategies and tactics and models. General characteristics of a response looks at the objectives associated with emergency logistics and how different models take different approaches to define their objectives. The metrics section focuses on some of these objectives and further breaks down the components of each objective. Strategies and tactics dives into previous approaches within the military that addresses the optimization of WRM location and ordering. Lastly the research examines modeling and simulations to both better define and enhance the logistical response.

## General Characteristics of Emergency Logistics

Emergency logistics expanded as a field of study with a populace demanding improved disaster logistics mechanisms as a result of devastation from disasters like Hurricanes Katrina, Hurricane Rita and Superstorm Sandy. The system's infrastructure built at the time of these disasters was not sufficient to sustain a complementary response. Models and concepts correlate restructuring such a disaster response to the efficient deployment and use of emergency logistics. Researchers are shifting their focus to the numerous complexities that exist within the field of disaster response. The increased

number and impact of natural disasters led researchers to seek a comprehensive model integrating supply chain operations in response to natural disasters (Afshar & Haggani, 2012). The proposed model incorporates operational details such as vehicle routing and location optimization for facilities to accelerate a more comprehensive logistics delivery system. It also includes capacity constraints not only for each facility, but also the whole transportation system in a disaster scenario (Afshar & Haggani, 2012). A distinctive characteristic within the field of emergency logistics is the reliance on public support, especially during the initial stages of a response. Dealing with the bureaucracies and organizations associated with government present its own set of challenges, which the authors explore through the government's supply chains. Much of this involves intricacies of the response system both relying on and dealing with the US government Federal Emergency Management Agency (FEMA) (Afshar & Haggani, 2012). The intricacies of government reliance in a disaster and the uncertainty of structural integrity further complicate emergency logistics operations.

The complexities of emergency logistics and humanitarian disaster responses led researchers to examine a way of separating and standardizing responses to maximize adaptability to any situation. Modularity and standardization have emerged as possible strategies for bolstering humanitarian operational responses (Jahre & Fabbe-Cotes, 2015). Jahre & Fabbe-Cotes conducted a longitudinal study of the Emergency Response Unit (ERU) concept practiced by the International Federation of Red Cross (IFRC). The ERU utilizes a standardized response to emergency management with an emphasis on quality, responsiveness and a focus on adjusting to the standards in any affected country (Jahre & Fabbe-Cotes, 2015). Emergency logistics presents high operational ambiguity and a

massive organization such as the IFRC gives a global perspective on adapting responses to meet differentiated demands. Modularity creates independence between component designs by standardizing interface specifications and can be viewed as a system's components ability to be separated and recombined. When examining the humanitarian field of study, both practically and academically, standards garner more attention than modularity. An appropriate response would take the focus that standards and modularity complement each other (Jahre & Fabbe-Cotes, 2015). Emergency logistics must embrace the flexibility required to respond by integrating both standards and modularity in the field.

Any response relies on the efficient movement and storage of resources critical to logistics support in an uncertain environment. The use of stochastic models is an important tool while studying the storage, distribution and risk surrounding a logistics response due to this uncertainty (Mete & Zabinsky, 2010). Establishing multiple supply points and storage areas is a tactic to combat uncertain demand, a policy that is observable throughout the WRM program. Mete & Zabinsky develop a case study of an earthquake scenario in the Seattle area, with an objective to minimize transportation time and unsatisfied demand by incorporating the priorities of medical supplies, transportation and demand estimates (Mete & Zabinsky, 2010). A unique feature of this model is that numerous scenarios were run to consider times with possibly higher demands. For example, downtown hospitals during working hours will have a higher need for resources than during the evening. Facility location selection in this model considers operating cost, capacity and distance to the demand points. The first step of this model selects and stocks a location; the second step remedies the demand unsatisfied by the resources amassed during the first step (Mete & Zabinsky, 2010). Prepositioning is a key component of a response as it serves as a buffer

until emergency logistics supply chains can kick in and the delivery system is operational. Just as important is the transportation system and its ability to move scarce resources efficiently through the affected areas.

The impact natural disasters have on a larger more concentrated global population has sparked an increased interest in efficient delivery systems to impacted populations. This enthusiasm has led to studies aimed at enhancing both the methodological rigor of the research as well as the practical relevance within the field of humanitarian operations. When conducting humanitarian research, key characteristics include: problem structuring, understanding relative factors, recognizing uncertainties, integrating that uncertainty into the model, utilizing appropriate technology into the model's development, and utilizing suitable data (Kovacs & Moshtari, 2017). Humanitarian operations models that fail to be grounded in practical relevant conditions are in danger of overlooking relevant constraints. Identifying and incorporating practical constraints leads to both realistic and innovative models. Researchers need to build a bridge between themselves and practitioners, allowing more meaningful evaluation of models and long term coordination with responders in the field. Many studies use limited objectives or impractical real-world assumptions and offer solutions with limited validity in execution (Kovacs & Moshtari, 2017). Building and maintaining the relationship between academics and practitioners is especially important in a field with such dire circumstances.

Disaster Operations Management (DOM) provides tools and support to a response and consists of four stages: mitigation, preparedness, response and recovery. With models and research emerging on DOM, a literature review on Operations Research (OR) models addresses how different researchers are approaching the subject. The ultimate goal of this

research is finding better measures and practices to reduce the human and economic loss associated with disasters (Hoyos et al., 2015). One of the first thorough literature reviews of DOM revealed that most of the literature in OR focused on the mitigation phase, with mathematical programming as the main tool to address it. This study, conducted from 2006 to 2012, revealed a focus on mathematical programming models for the preparedness and response phases, with many incorporating a simulation component (Hoyos et al., 2015). Researchers should better understand and analyze the inputs and assumptions in these models. Simulation-based research focuses on the development of models that help to process and analyze input data for the response phase. Hoyos et al. calls for more focus on inventory planning for distribution, mostly because of the uncertainty in both supply and demand of commodities. Issues mentioned by multiple researchers include a desire for more studies on the recovery phase of DOM (Hoyos et al., 2015). The transitional stages between response and recovery present the largest challenges when the impacted area's demands are high, resources limited, infrastructure degraded and individual behaviors unpredictable (Holguin-Veras et al., 2013).

With the recent COVID-19 response, there has been a greater association with public health emergencies and emergency medical logistics. Public health emergencies require novel models incorporating medical demand forecasting and relief distribution centers (He & Liu, 2015). Future research will significantly focus on the impact of an efficient framework on public health's emergency medical logistics, which has three characteristics that increase the complexity of solving logistical problems in comparison to normal daily logistics: limited information surrounding demand, the spread of a disaster and the substitutability of available remedies (He & Liu, 2015). In public health, the rate

of the spread is shaped by a population's characteristics such as cultural norms and the overall health attributes. A linear programming approach is then applied to facilitate logistics distribution decision-making, where the objective function minimizes the physical fragility and applies weights to different prioritized groups. This model includes extensions for incorporation of spatial interactions and psychological fragility during emergencies (He & Liu, 2015).

Inventory decisions can have a large impact on the cost and preparedness associated with military battlefield operations. Predictive analytics and data should be used to create decision support tools that reinforce mission objectives and logistic demands (Chang et al., 2017). Surgical Critical Care Initiative (SC2i), a military health and research program, developed a physician's tool to evaluate the demand for massive blood transfusions. A model simulated a conflict between NATO and Russian forces. This tool gives physicians the ability to rapidly identify patients requiring a blood transfusion given their specific health data. With more effective prepositioning and planning of blood resources identified through the use of this model, the medical network would waste 71,459 fewer units of blood products leading to MEDEVAC helicopters flying 110 fewer blood resupply missions, freeing up capacity for 770 more patient movements. This study quantified what one decision support tool used alongside a simulation model could accomplish by supporting military logistics and reducing waste in a common medical product: blood (Chang et al., 2017).

Risk management is an essential aspect of leadership within an emergency logistics response. Incorporating risk into a two-stage stochastic model (Alem et al., 2016) helps guide leadership through some of the self-inflicted roadblocks they may encounter. The

first stage considers both prepositioning and vehicle capacity then the second stage makes operational decisions surrounding inventory to ultimately determine aid supply in emergency logistics. The model addresses an immediate supply crisis with sudden large demands and short lead times contrasting with periods of low demand. These are spurred by a disaster and are managed with prepositioning as well as procurement during a disaster. Alem et al. uses seventeen scenarios to test a range of cases. Analysis of these scenarios demonstrates the importance of prepositioning for emergency logistics, especially as it pertains to different levels of risk aversion. Leaders must balance the rise in prepositioning cost with their risk tolerance (Alem et al., 2016).

**Metrics**

Welfare economic principles should be incorporated into the logistics models as a means to leading to the greatest good for the greatest number of people. Some models incorporate a social cost as the preferred objective function for post-disaster operations (Holguin-Veras et al., 2013). The degradation of social constructs and logistical networks during disasters leaves relief as the only roadblock to increased social costs. A key provision of the paper is an approach to assigning economic value to non-traditional goods and services. Holguin-Veras et al. uses deprivation costs as the economic value of human suffering. This disaster response model is unique in that it accounts for opportunity costs, where a reduction in deprivation costs for beneficiaries leads to an increase in deprivation costs for those not receiving aid (Holguin-Veras et al., 2013).

Warfare can be unpredictable and many models fail to account for the possibility of interruption in the supply chain. Galindo and Batta's model designed for prepositioning

supplies to assist in the recovery stage, also incorporates the possible destruction of facilities with prepositioned materials (Galindo & Batta, 2013). Logistics planners must acknowledge that warfare is not easily predictable and build around such uncertainty, balancing the risk of storing supplies in potentially affected areas with the increased responsiveness of prepositioning (Galindo & Batta, 2013).

Monte Carlo simulation is a technique best used to model where uncertainty exists. To better understand the highly uncertain field of emergency logistics, an evaluation of the use of Monte Carlo simulation is warranted. Emergency logistics can gain great insight by developing a framework for models that use a probability distribution to represent uncertainty and informing researchers about the possibility of various outcomes (Banomyong & Sopadang, 2010). The theoretical nature of research into emergency logistics makes it prone to unforeseen constraints or inefficient practice when encountering practical application. Emergency logistics planners must accept that realities are far more complex than any simple model can portray. Monte Carlo based model's use of sets of random numbers as inputs help represent this complexity (Banomyong & Sopadang, 2010). Monte Carlo simulation allows for a systematic evaluation of emergency logistics models with uncertain inputs. It creates outputs with an associated probability distribution, which helps logistics planners better characterize the impact of decisions in an environment flush with uncertainty.

Transportation is key to a disaster response and finding a reliable model to address efficient use of assets can greatly improve the responsiveness of emergency logistics. Infrastructure in a disaster environment is unreliable and planning requires flexibility around routing. This uncertainty can be addressed by an algorithm focused on supply

delivery that addresses potential delay risks (Hamedi et al., 2012). This research determined that the optimal objective function for transportation routing includes: cost, response time and reliability. This paper uses a mathematical integer programming model to build a shortest path solution for an emergency logistics delivery system. In this approach, if problems lead to a node failure, a vehicle may return to a preceding node and select another route (Hamedi et al., 2012).

**Strategies and Tactics**

The connection between emergency logistics strategies and WRM tactics is clear. Both are shrouded by uncertain demand and require strategic planning to meet the numerous challenges of a dynamic environment. In Whitson (2013), consolidation of medical WRM UTC assemblages was explored to minimize cost and prevent fracturing of the UTCs. Consolidation has numerous benefits when it comes to inventory, including a reduction in cost, locations and manpower (Whitson, 2013). Consolidation of resources better prepares a strategic foothold for WRM and helps posture future deployments.

The WRM program, with a large prepositioned component, is prone to dormant demand signals that hurt the logistics ordering system. One of the key components of a WRM response is the pharmaceutical supply chain. WRM demand can result in non-recurring demand, which can affect fulfillment through suppliers (Brubakken, 2020). Shortfalls are an issue that plague stagnant demand as suppliers take time to fill orders that lack a predictable demand pattern. In these situations, shortfalls can be minimized by considering pharmaceutical availability within the constraints of a budget. The research looks at centralized ordering of items prone to shortages, which can lead to a greater than

20 percent increase in availability of pharmaceuticals (Brubakken, 2020). Pharmaceuticals comprise a large portion of any emergency logistics response and strengthening the availability of these crucial products through supply chain delivery system improvements will bolster the WRM program.

**Modeling**

Optimization models are a key mathematical tool for building solutions to complex problems. There are many components within emergency logistics that can be modeled mathematically and optimized, leading to an efficient response. Emergency logistics optimization models fall under the umbrella of two main categories, pre and post-disaster operations. Facility location and prepositioning are commonly considered in models for pre-disaster. Supply distribution is the primary focus in models for post-disaster operations. A content analysis on emergency logistics optimization models can bring the hope of identifying research gaps and future research scope (Caunhye et al., 2012). Most facility location optimization models in emergency logistics combine the process of location with stock prepositioning, evacuation, or relief distribution. Most objective functions seek a mathematical solution to cost and responsiveness, neglecting other areas such as manpower. Two limitations of optimization models in emergency logistics are human behavior and the availability of dependable data (Caunhye et al., 2012). Optimization models developed academically and used in the field, give insight into the current view of emergency logistics as well as suggest improvements that may guide future data-driven research.

The uncertainty surrounding the use of WRM and emergency logistics warrants an examination of simulation as a tool to enhance and verify policies. Simulation is a powerful tool to tackle the uncertainty in life as it presents an imitation of a real-world system without the consequences of failure or the commitment of resources (Banks, 1999). The consequences of a faulty disaster response model can be devastating on recovery operations. Simulation modeling is a tool that can bridge the uncertainty and identify the negative consequences of unleashing a novel model in a life-altering situation (Banomyong & Sopadang, 2010). This form of modeling allows for observation of an artificial system to infer answers to the questions surrounding specific actions and consequences. Simulation also expands to the conceptual so researchers can test and observe events or scenarios that have not occurred yet (Banks, 1999). There are risks in using these capabilities: they must truly capture the system they wish to test and represent it accurately enough to address the problem as it occurs in the real-world. In the case of emergency logistics, this requires researchers to maintain a relationship and verify scenarios and results with first responders (Banks, 1999).

Wargaming is a type of simulation model designed to show possible outcomes of conflict between two or more forces. Wargames have historically neglected logistics mechanisms as this may overcomplicate or elongate the scenario. In fact this omission can create an unrealistic simulation and give a false understanding of real outcomes. Specifically key constraints for military operations, such as a budget, may be disregarded (Cardenas, 2016). Historically, most wars require logistics support over a long duration of time. Logistics has taken a larger role within wargames, but there are still aspects within simulations that affect the reality of logistics, such as the limitless use of ammunition

(Cardenas, 2016). Wargaming should strive to achieve realism in many aspects of its simulation, as neglecting logistics components could greatly reduce the practical application of simulation results in an actual war.

A simulation framework helps forecast events which may interrupt logistics operations (Golroudbary et al., 2019). This paper discusses three simulation methods: agent-based modeling (ABM), discrete-event simulation (DS) and system dynamics (SD), with researchers searching for optimized actions using a combination of these methods, especially for the more complex systems. This research looks at creating a hybrid of these methods as an approach to the complexities of the logistics delivery system (Golroudbary et al., 2019). A hybrid simulation approach can tackle the different aspects of a complicated logistics delivery system, including the field of emergency logistics.

There are similarities between other fields of study and emergency logistics in the quest to further develop simulation to achieve a better understanding of operations amongst uncertainty. One of these fields being cyber operations. There is a lack of reliable data in the cyber operations field of study due to cyber security and the risks associated with disclosure. Simulation of sensitive data can help overcome a gap in information (Hamman et al., 2020). Without access to operational data, academic contributions remain inhibited, but can be bridged by creating a simulation environment strong enough to give academics the ability to research and improve operations, while also protecting sensitive cyber procedures (Hamman et al., 2020). While emergency logistics does not suffer from the same disclosure issues associated with cyber operations, it shows that a clear partnership between academics, first responders and logistics planners goes a long way towards supporting relevant simulations and solutions that are applicable to the field.

# III. Methodology

## Chapter Overview

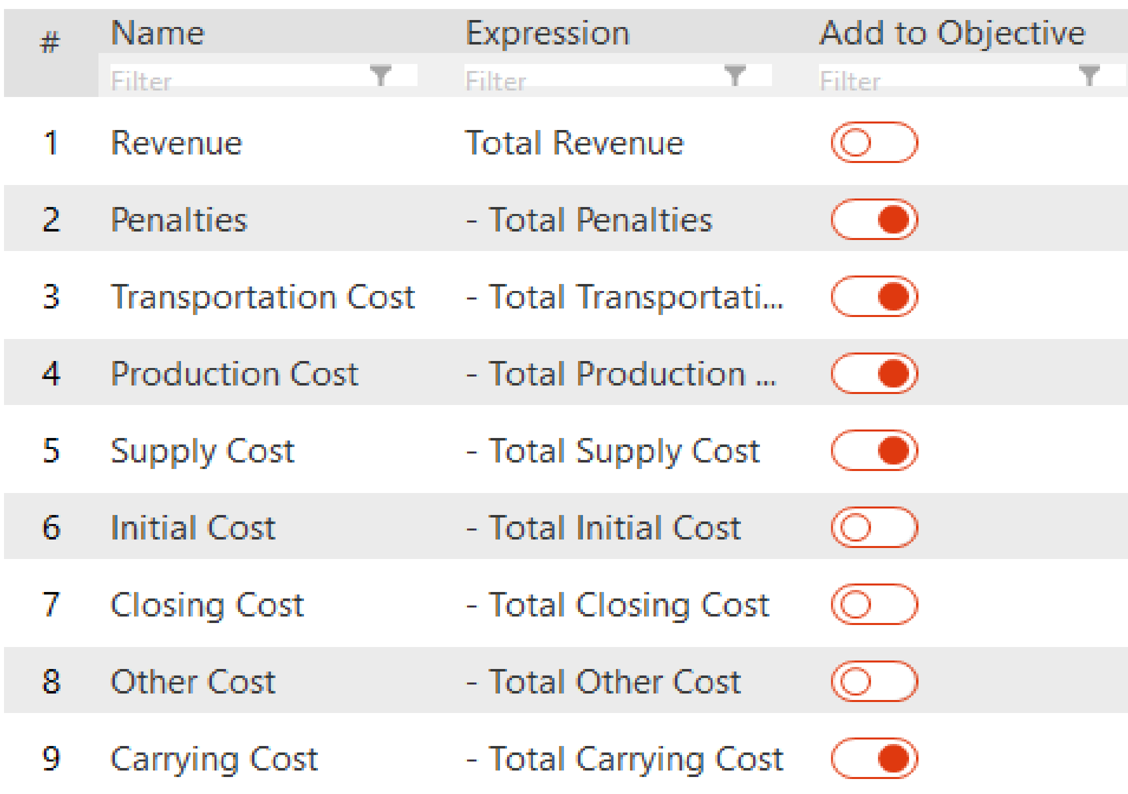
The research method used for this study is a comparative analysis on network design and WRM inventory placement. Substitute medications and those used by joint warfighters were not included in this study. Different doses of similar products were combined to remove clinical decisions from this study and its impact on the network design. For example, this study combines the 4 mg/mL dosage of morphine with the 10 mg/mL dosage, only recognizing one unit of morphine no matter what the concentration. This study utilizes three different scenarios of warfare: protecting the homeland, creating a military front along the Demilitarized Zone (DMZ) and forward deploying demand points. Based on those three notional scenarios, ten models were developed in anyLogistix with similar inputs and tested them for all three scenarios. This led to a total of 30 models. The network design models were driven by a demand model for each of the five medications, each with associated costs. The major outputs from this model are total cost, responsiveness and level of satisfied demand for each product after optimization. Focusing on only one of cost or response can negatively affect practical responses, as was done with the 2004 Indian Ocean tsunami and 2010 Haiti earthquake (Caunhye et al., 2012). All scenarios were run for a total of 30 months, broken into ten different three month periods.

Data supporting model parameters related to inventory came from the joint medical data repository, Logicole, which is an information website that pulls data daily from the Air Force operational logistics system. The data utilized for this study was pulled from the system on 20 January 2022. This data does not represent the capabilities of the United

States or allied militaries. Substitute medications or those used by joint warfighters were not included in this study.

**Network Objective Functions**

Numerous factors were considered in the objective for our models. Figure 2 is a display of the anyLogistix network optimization objective function inputs. For this study, we included all available costs in the anyLogistix network optimization level, outside of carbon emissions, tariffs and a facility opening and closing. This research incorporated both cost and responsiveness to the objective function.



| # | Name | Expression | Add to Objective |
|---|---|---|---|
| | Filter | Filter | Filter |
| 1 | Revenue | Total Revenue | |
| 2 | Penalties | - Total Penalties | |
| 3 | Transportation Cost | - Total Transportati... | |
| 4 | Production Cost | - Total Production ... | |
| 5 | Supply Cost | - Total Supply Cost | |
| 6 | Initial Cost | - Total Initial Cost | |
| 7 | Closing Cost | - Total Closing Cost | |
| 8 | Other Cost | - Total Other Cost | |
| 9 | Carrying Cost | - Total Carrying Cost | |

**Figure 2 - AnyLogistix Objective Function**

## Scenario Creation

To capture the efficiency of the WRM network, given specific parameters, this study created three notional scenarios to test the system's capabilities. Scenario 1 involves a situation where demand points are located within the South Korean border. The demand points were chosen based off of prior Korean War battles (Bloody Hill, Incheon), the country's largest concentration and most likely largest demand point center (Seoul) and points with access to both the East and West coasts of the country (Mokpo-si and Busan). Figure 3 shows the unmapped scenario 1, with the red dots representing the Air Force (AF) warehouse locations and the blue dots are the demand points. Figure 4 represents the mapped version, which shows the blue connecting lines between bases and demand points. Transportation modes must travel these blue lines when moving to and from locations.

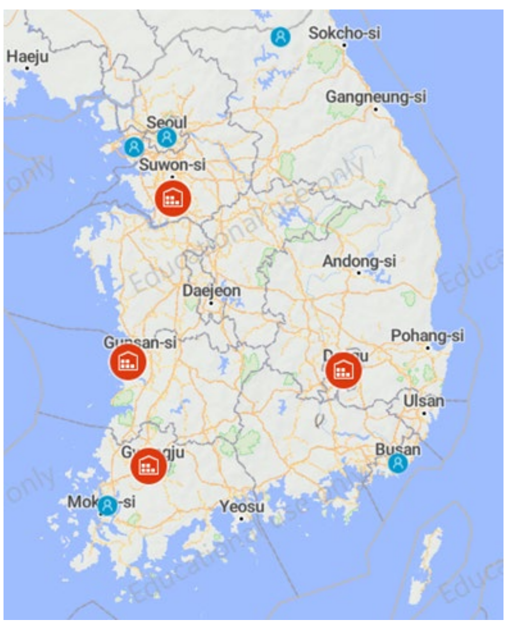



**Figure 3 - Scenario 1 Unmapped**

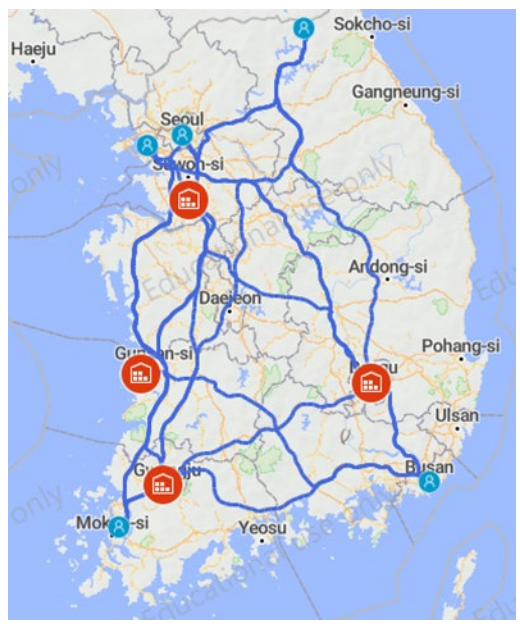



**Figure 4 - Scenario 1 Mapped**

Scenario 2 involves a situation where demand points are all along the Demilitarized Zone (DMZ).  The six demand points were chosen based off an even spread across the DMZ. Figure 5 shows the unmapped scenario 2, with the red dots representing the AF warehouse locations and the blue dots are the demand points. Figure 6 represents the mapped version, which shows the blue connecting lines between bases and demand points. Transportation modes must travel these blue lines when moving to and from locations.

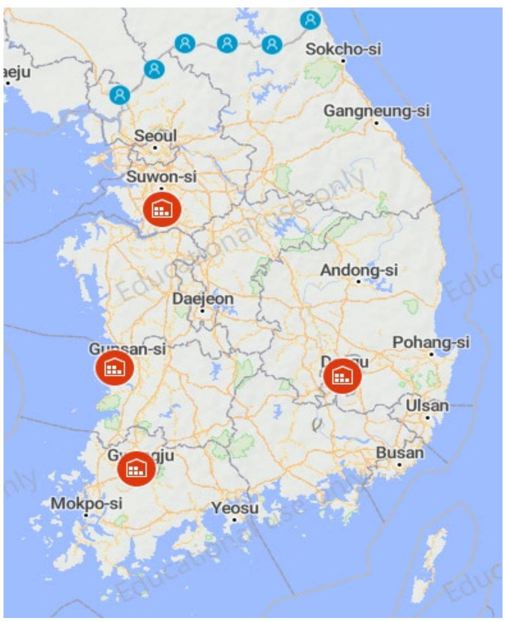



**Figure 5 - Scenario 2 Unmapped**

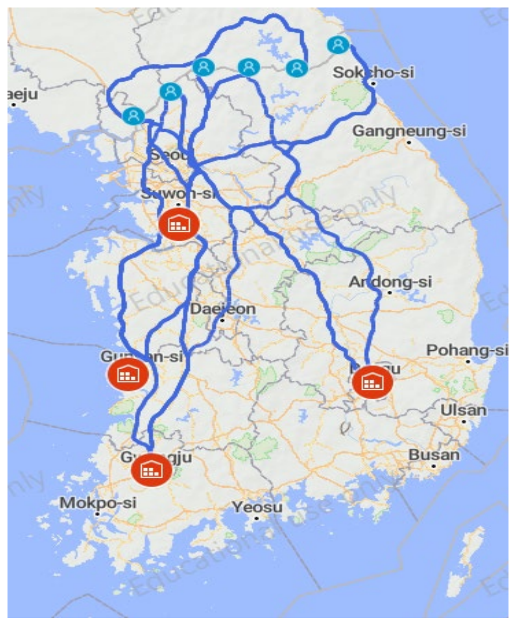



**Figure 6 - Scenario 2 Mapped**

Scenario 3 involves a situation where demand points are all forward deployed across the DMZ. The demand points were chosen based off the ten cities with the highest population within North Korea. These cities include: Pyongyang, Hamhung, Chongjin, Nampo, Wonsan, Sinuiju, Kaechon, Kaesong, Sariwon and Sunchon (World Population Review, 2022). Figure 7 shows the unmapped scenario 3, with the red dots representing the AF warehouse locations and the blue dots are the demand points. Figure 8 represents the mapped version, which shows the blue connecting lines between bases and demand points. Transportation modes must travel these blue lines when moving to and from locations.

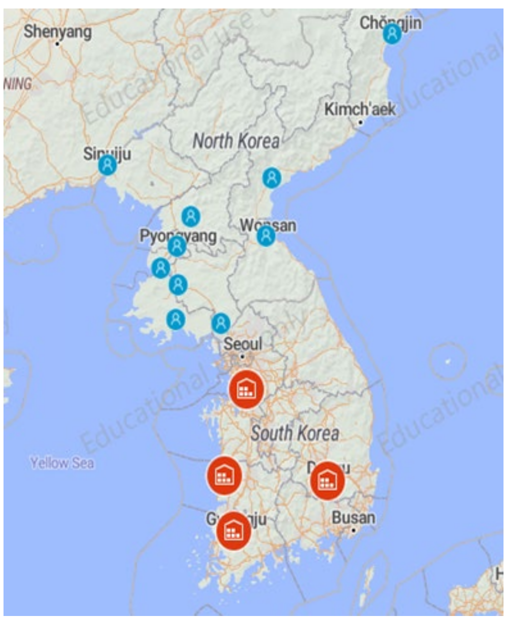



**Figure 7 - Scenario 3 Unmapped**

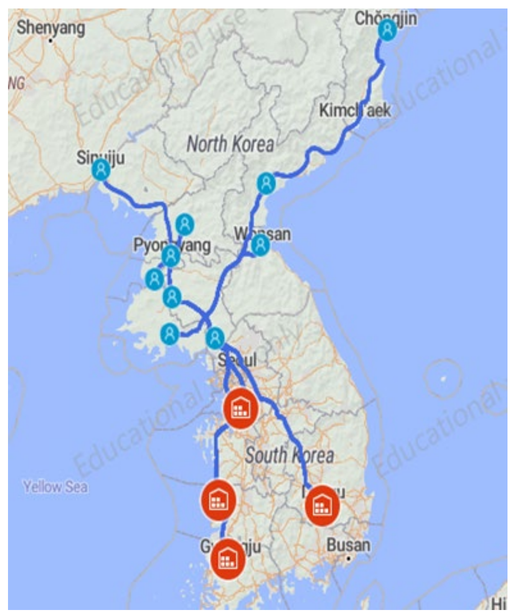



**Figure 8 - Scenario 3 Unmapped**

## Models

In testing the three scenarios, this study analyzes ten unique sets of inputs to evaluate their impact across all scenarios, leading to the creation of 30 different models. The inputs remain consistent through all three scenarios, allowing a consistent basis of comparison for costs and responsiveness. There are seven different inputs to test model performance: adding suppliers, adding United States Consolidated Storage and Deployment Centers (CSDC) support, adding Pacific Air Forces (PACAF) support, altering initial inventory, altering minimum inventory, altering maximum inventory and adding CSDCs to either PACAF or Europe. Table 1 lists the details of each model.

The US CSDCs are large distribution centers that consolidate supplies of WRM products, reducing the network footprint. There are three CSDCs located on the East coast, West coast and central United States. The benefit of these centers in the models is that they offer an influx of supply, but their use comes with added transportation costs. PACAF support in the models comes from six bases: Andersen Air Force Base in Guam, Hickam Air Force Base in Hawaii, Kadena Air Base in Japan, Joint Base Elmendorph in Alaska, Misawa Air Base in Japan and Yokota Air Base in Japan. Another input revolves around adding CSDCs to the network. These potential CSDC locations are Osan Air Base, Kadena Air Base and Yokota Air Base for PACAF and Lakenheath Air Base, Ramstein Air Base and Aviano for Europe. These locations will be stocked at the same levels as the US CSDCs. The last sets of inputs revolve around the stocking levels. For most models, we utilized the varied levels obtained from LogiCole. Initial stock is the amount in the system from day one of the model, minimum is the minimal stock of a product allowed at each

location and the maximum is the most stock allowed at each location. Solutions for models 1 – 10 are summarized graphically in Appendix F - Appendix O.

**Table 1 - Model Factor Breakdown**

| | | | | | | | Stocking Levels | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model Number | Scenario | Period | Suppliers | CSDC Support | PACAF Support | Customers | Initial | Min | Max | Added CSDCs | Trials |
| Model 1 | Homefront | 30 Months | No | No | No | 5 | 1000 | 0 | 10000 | No | 250 |
| Model 2 | Homefront | 30 Months | No | Yes | No | 5 | 1000 | 0 | 10000 | No | 250 |
| Model 3 | Homefront | 30 Months | No | No | Yes | 5 | Varied | 0 | Varied | No | 250 |
| Model 4 | Homefront | 30 Months | No | Yes | Yes | 5 | Varied | 0 | Varied | No | 250 |
| Model 5 | Homefront | 30 Months | No | Yes | Yes | 5 | Varied | 0 | Varied | Yes | 250 |
| Model 6 | Homefront | 30 Months | No | Yes | Yes | 5 | Varied | 0 | Varied | Yes + E | 250 |
| Model 7 | Homefront | 30 Months | Yes | Yes | Yes | 5 | Varied | 0 | Varied | Yes | 250 |
| Model 8 | Homefront | 30 Months | Yes | Yes | Yes | 5 | Varied | 0 | Varied | Yes + E | 250 |
| Model 9 | Homefront | 30 Months | Yes | Yes | Yes | 5 | 1000 | 1 | 10000 | Yes | 250 |
| Model 10 | Homefront | 30 Months | Yes | Yes | Yes | 5 | 0 | 100 | 10000 | Yes | 250 |
| Model 11 | DMZ | 30 Months | No | No | No | 5 | Varied | 0 | Varied | No | 300 |
| Model 12 | DMZ | 30 Months | No | Yes | No | 6 | Varied | 0 | Varied | No | 300 |
| Model 13 | DMZ | 30 Months | No | No | Yes | 6 | Varied | 0 | Varied | No | 300 |
| Model 14 | DMZ | 30 Months | No | Yes | Yes | 6 | Varied | 0 | Varied | No | 300 |
| Model 15 | DMZ | 30 Months | No | Yes | Yes | 6 | Varied | 0 | Varied | Yes | 300 |
| Model 16 | DMZ | 30 Months | No | Yes | Yes | 6 | Varied | 0 | Varied | Yes + E | 300 |
| Model 17 | DMZ | 30 Months | Yes | Yes | Yes | 6 | Varied | 0 | Varied | Yes | 300 |
| Model 18 | DMZ | 30 Months | Yes | Yes | Yes | 6 | Varied | 0 | Varied | Yes + E | 300 |
| Model 19 | DMZ | 30 Months | Yes | Yes | Yes | 6 | 1000 | 1 | 10000 | Yes | 300 |
| Model 20 | DMZ | 30 Months | Yes | Yes | Yes | 6 | 0 | 100 | 10000 | Yes | 300 |
| Model 21 | Forward Deployed | 30 Months | No | No | No | 10 | Varied | 0 | Varied | No | 500 |
| Model 22 | Forward Deployed | 30 Months | No | Yes | No | 10 | Varied | 0 | Varied | No | 500 |
| Model 23 | Forward Deployed | 30 Months | No | No | Yes | 10 | Varied | 0 | Varied | No | 500 |
| Model 24 | Forward Deployed | 30 Months | No | Yes | Yes | 10 | Varied | 0 | Varied | No | 500 |
| Model 25 | Forward Deployed | 30 Months | No | Yes | Yes | 10 | Varied | 0 | Varied | Yes | 500 |
| Model 26 | Forward Deployed | 30 Months | No | Yes | Yes | 10 | Varied | 0 | Varied | Yes + E | 500 |
| Model 27 | Forward Deployed | 30 Months | Yes | Yes | Yes | 10 | Varied | 0 | Varied | Yes | 500 |
| Model 28 | Forward Deployed | 30 Months | Yes | Yes | Yes | 10 | Varied | 0 | Varied | Yes + E | 500 |
| Model 29 | Forward Deployed | 30 Months | Yes | Yes | Yes | 10 | 1000 | 1 | 10000 | Yes | 500 |
| Model 30 | Forward Deployed | 30 Months | Yes | Yes | Yes | 10 | 0 | 100 | 10000 | Yes | 500 |

### Demand Model

Given the amount of uncertainty involved in warfare, demand for medical care can be complicated to predict. The demand model is based on a triangular distribution, which

requires a specification of low, high and median values. In my implementation, we assumed the mode of the triangle distribution was equal to the median.

A Department of Defense (DoD) assessment of a potential Korean conflict states that military casualties could total 200,000–300,000 within the first 90 days (Hanson et al., 2021). Defining a casualty as both a fatal and nonfatal injury, this study uses the figure of 100,000 as a casualty predictor for a 90 day period. Given this, total casualties per day amount to 1111 service members. This value was used to drive demand for the individual items in the model.

Two studies analyzed the usage and demand for five medications used during enroute patient care: ketamine, morphine, fentanyl IV, fentanyl oral and hydromorphone. These studies evaluated military medical care and give a glimpse into their prospective demands during warfare. The first of these sources is a secondary analysis conducted from 2007 until 2016 of the DoD trauma registry that examined over 28,000 subjects. This study was used for the low value for the triangular distribution. It observed a range of percentages from 15.3% usage (morphine) to 2.1% (fentanyl oral) (Schauer et al., 2018). However this study was missing observed demand for two of the medications, fentanyl IV and hydromorphone. This study estimated the demand given the other percentages to be 3% and 1% respectively. The second source is a short term pre-hospital combat study at medical treatment facilities (MTF) in Afghanistan between October 2012 and September 2013 (Petz et al., 2015). Information from this study was used as the high numbers for the triangular distribution. Table 2 shows the percentages taken from the two studies.

**Table 2 - Expected Demand Percentage**

| | Estimated Usage | |
|---|---|---|
| Medication | High | Low |
| Ketamine IV | 52.0% | 5.4% |
| Morphine IV | 34.0% | 15.3% |
| Fentanyl IV | 22.0% | 3.0% |
| Fentanyl Oral | 20.0% | 2.1% |
| Hydromorphone | 6.0% | 1.0% |

Using the percentages in Table 2, low, high and median values for all five medications are computed using Equation 1. These numbers were added to anyLogistix with factoring in a five day ordering period.

d = low or high demand of triangular distribution

e = estimated casualties

p = percent demand (taken from two sources)

n = number of demand locations

o = order interval

$$d = \frac{\left(\frac{e * p}{90}\right)}{n} * o$$

**Equation 1 - Calculated Triangular Distribution Demand**

For example, the low value (d) for ketamine demand in scenario 3 is computed as follows:

$$d = \frac{\left(\frac{100000 * 5.4\%}{90}\right)}{10} * 5 = 30 \text{ vials of ketamine demanded per site per ordering period}$$

Table 3 shows the results of this calculation for the low, high and median values for each of the five medications included in the models.

**Table 3 - Estimated Demand Calculations Scenarios 1 to 3**

| Estimated Demand - Scenario 1 | | | |
|---|---|---|---|
| **Medication** | **Low** | **High** | **Median** |
| Ketamine IV | 60 | 578 | 319 |
| Morphine IV | 171 | 378 | 274 |
| Fentanyl IV | 33 | 244 | 139 |
| Fentanyl Oral | 23 | 222 | 123 |
| Hydromorphone | 11 | 67 | 39 |
| **Estimated Demand - Scenario 2** | | | |
| **Medication** | **Low** | **High** | **Median** |
| Ketamine IV | 50 | 481 | 266 |
| Morphine IV | 143 | 315 | 229 |
| Fentanyl IV | 28 | 204 | 116 |
| Fentanyl Oral | 19 | 185 | 102 |
| Hydromorphone | 9 | 56 | 32 |
| **Estimated Demand - Scenario 3** | | | |
| **Medication** | **Low** | **High** | **Median** |
| Ketamine IV | 30 | 289 | 159 |
| Morphine IV | 86 | 189 | 137 |
| Fentanyl IV | 17 | 122 | 69 |
| Fentanyl Oral | 12 | 111 | 61 |
| Hydromorphone | 6 | 33 | 19 |

**Travel Cost Calculation**

In a network optimization, transportation costs are essential for tracking because unlimited travel costs would give an unrealistic approach to optimization and skew results.

For transportation costs this study utilized three modes of transport: C-17 aircraft, High Mobility Multipurpose Wheeled Vehicle (HMMWV) and commercial trucks. The availability of these modes is crucial to the network. Location of emergency vehicles represents a crucial resource supporting product movement (Mete & Zabinsky, 2010). AnyLogistix incorporates a straight line option, where the model allows for a straight connection (shortest linear distance) between two points. Alternatively, the model can be directed to use actual roadways (which are typically longer than the linear distance). The C-17 utilizes the straight line model of transport. Both the HMMWVs and commercial trucks follow roadways. Modal restrictions were built into each model: C-17 aircraft were the only ones allowed to travel across oceans, commercial trucks were the only mode of transportation from suppliers to US CSDCs and HMMWV travel was the only mode for transport within both North and South Korea.

In all three scenarios, the military is in a state of war, so priorities must be balanced between real world mission and military needs at that time of the conflict. Therefore, this study takes into account capacity limitations and costs associated with each mode of transportation. The capacity is as follows: 5000 individual units for both C-17 and commercial trucks and 500 units for the HMMWVs. Another cost factor is the speed of each mode. For the C-17, this study uses 517 miles per hour (mph) (United States Air Force, 2018). The HMMWV speed will use a triangular distribution to calculate their speed, with the minimum speed being five mph, maximum 55 mph and mode 40 mph (United States Army Acquisition Center, 2021). The commercial truck speed was also calculated using a triangulation distribution with a minimum speed of five mph, maximum 70 mph and mode 55 mph.

The final inputs in this study for transportation cost involves the fuel cost per gallon (HMMWV, commercial truck) and cost per hour of flight (C-17). The diesel fuel cost was obtained through the Armed Forces Network Pacific website as of 5 February 2022. The cost of diesel fuel used was $3.93 (Armed Forces Network Pacific, 2022). For the cost of commercial trucks, this study took the national average of gasoline prices as of 5 February 2022 at $3.77 (AAA, 2022). The cost of a flight hour for a C-17 was determined to be $24,562 (United States Air Force, 2016). Since this study assumes that these five medications will not take up the entire aircraft, the costs associated with C-17 travel will amount to one quarter of the total cost of flight per hour. Only one quarter of the plane is dedicated to medical transportation, so only one fourth of the cost will be utilized in our network optimization.

Given these transportation cost inputs, the dollar per unit per mile was calculated and added into anyLogistix. Equation 2 shows the cost (a) dollar per unit per day for HMMWV travel and Equation 3 shows (a) for C-17s.

w = miles per gallon

x = miles per hour

y = units of capacity

z = dollars per gallon

b = dollars per hour

a = dollar per unit per mile

Route cost for HMMWV:

$$a = z * \frac{1}{w} * \frac{1}{y}$$

**Equation 2 - HMMWV Dollar per Unit per Mile Calculation**

For example, a trip from Osan Air Base to Kunsan Air Base is 88.75 miles. Using the HMMWV as the only source of transportation within Korea, the total cost is:

88.75 miles x 500 units x 0.0013100 dollars per unit per mile = $58.13

Route cost for C-17:

$$a = b * \frac{1}{x} * \frac{1}{y}$$

**Equation 3 - C-17 Dollar per Unit per Mile Calculation**

For example, a trip from Travis Air Force Base to Osan Air Base is 5627 miles. Using the C-17 aircraft as the only source of transportation from the United States to Korea, the total cost is:

5627 miles x 5000 units x 0.002375435 dollars per unis per mile = $66,832.72

**Carrying Costs**

Another input calculated for network optimization is the carrying cost of inventory. Prepositioning an unlimited amount of these crucial supplies carries a cost. Logistics planners must balance the costs and benefits of storage locations and inventory levels with swift distribution to beneficiaries (Mete & Zabinsky, 2010). First this study looked at what

annual carrying cost factor to use in determining the carrying cost for these items. The typical industry wide cost factor is around 20 – 25%, but this figure would be higher for forward deployed bases. For the bases within the continental United States (CONUS), this study assigned a cost factor of 20%. For forward bases in Korea and those bases assisting in the PACAF region, this study assigned an annual carrying cost factor of 30%. Each individual item has a different carrying cost based on the product price, storing requirements and annual flow of each product. This study aggregates the different carrying costs by taking the median price of our five medications and using that as a universal cost across items for simplicity. These carrying cost factors are used in Equation 4 and Equation 5. The final step of determining the daily carrying cost rate takes these values and divides by the number of working days in a year. For this study we are utilizing all 365 days, due to the constant demand during warfare. The variable added to anyLogistix is (c) the carrying cost dollars per unit per day.

c = carrying cost dollars per unit per day

d = annual carrying cost factor CONUS

e = annual carrying cost factor PACAF

f = median price for 5 items

Carrying cost of bases within CONUS:

$$c = \frac{d*f}{365} = \frac{0.2*1.54}{365} = 0.000843836$$

**Equation 4 - Carrying Cost CONUS Bases**

Carrying cost of bases outside CONUS:

$$c = \frac{e*f}{365} = \frac{0.3*1.54}{365} = 0.001265753$$

**Equation 5 - Carrying Cost OCONUS Bases**

### Facility and Inventory Expansion

In testing the different models, this study added inputs that would drive additional facility and expansion costs for inventory. These models with additional costs included 5-10, 15-20 and 25-30. There are three expansion cost components added to these models: the cost to procure the stock at the added facilities, the cost of expansion at these facilities and the transportation costs to deliver to these facilities. The stocking levels at added CSDCs in Europe and PACAF mirror the levels at the US CSDCs. Therefore, using the procurement costs of the five medications, this research is able to calculate the added costs. The total comes to $11.8K to stock all five medications in the three PACAF CSDCs and $23.6K to stock at both PACAF and Europe CSDCs. For facility expansion, this study assumes a $10K cost to expand at these locations to support storage of the medications (e.g., the inclusion of all six CSDCs would incur an extra $60K cost). The final cost component is the shipment of these medications to the CSDCs. For this figure the study

took the time traveled between the US CSDCs and our potential CSDCs from the anyLogistix output and used the flying cost per hour to estimate the cost of transportation.

**Suppliers**

Suppliers play a prominent role when included in the models. Suppliers feed the five medications into the network, boosting resource availability and the added cost of procurement. This study alludes to the recent US government response to COVID-19 as an inspiration to include suppliers. The government has the ability to use the Defense Production Act as a means to propel manufacturing in support of the country in times of national security. The Defense Production Act was used to produce vital resources such as vaccines, masks and ventilators during the COVID response. The Defense Production Act can also be justified in dire times of war, which all three scenarios encompass. This study notionally uses five of the top pharmaceutical companies in the United States as a means to produce our five products. These suppliers are: Pfizer Incorporated in Massachusetts, AbbVie in Illinois, Johnson & Johnson in Florida, Merck & Co Incorporated in North Carolina and Gilead Services in California. Figure 9 shows the mapped out locations of these suppliers. Each supplier was assigned production of a specific product. Looking at the capabilities and size of each facility, the product assignment is as follows: Pfizer Incorporated (ketamine), AbbVie (hydromorphone), Johnson & Johnson (morphine), Merck & Co Incorporated (fentanyl IV) and Gilead Services (fentanyl oral).


**Figure 9 – Supplier Locations**

## Network Objective Function

Network optimization utilizes mathematical functions for the objectives and the constraints to help guide the path to the ultimate optimal solution. These functions are embedded within the anyLogistix software and dependent upon this study's specific parameters. To help visualize these functions, the model inputs, model variables, objective function and constraints are summarized below.

Model Inputs

$t_m$ = Transportation cost through mode m

$s_p$ = Supply cost of product p

$c_l$ = Carrying cost at location l

$x_l$ = Inventory at location l

$x_{Max_l}$ = Max inventory at location l

$x_{Min_l}$ = Min inventory at location l

$k_{C17}$ = Capacity C-17

$k_{HMV}$ = Capacity HMMWV

$k_{TRK}$ = Capacity CONUS Trucks

$m_{uk}$ = Mode of transport between CSDCs and Korea

$m_{sk}$ = Mode of transport between Supporting bases and Korea

$m_{kd}$ = Mode of transport between Korea and Demand Points

$m_{su}$ = Mode of transport between Suppliers and CSDCs

Model Variables

| | |
|---|---|
| Locations: | $l \in$ {u, s, k, d} |
| Products: | $p \in${Ketamine, Hydromorphone, Fentanyl Oral, Fentanyl IV, Morphine} |
| Transportation Modes: | $m \in$ {C-17, HMMWV, Commercial Trucks} |

Objective Function

The objective is to minimize the sum of transportation costs (through all modes m) and supply and carrying cost (of all products p at all locations l)

$$\text{Min} \quad \sum_{\forall m} t_m + \sum_{\forall l} \sum_{\forall p} (s_{lp} + c_{lp})$$

Constraints for the objective function include maximum and minimum inventory stock levels, modal capacity limitations and mode selection between destinations.

s.t.

| | |
|---|---|
| $x_{Min} \le x_l \le x_{Max}$ | [Inventory Limit] |
| $C\text{-}17 \le k_{C17} \le 5000$ | [C-17 Capacity Limit] |
| $HMV \le k_{HMV} \le 500$ | [HMMWV Capacity Limit] |
| $TRK \le k_{TRK} \le 5000$ | [Truck Capacity Limit] |
| $m_{uk}$ = C-17 | [Mode Selection CSDCs to Korea] |
| $m_{sk}$ = C-17 | [Mode Selection Support Bases to Korea] |
| $m_{kd}$ = HMMWV | [Mode Selection Korea to Demand Points] |
| $m_{su}$ = CONUS Trucks | [Mode Selection Suppliers to US CSDCs] |
| All Variables $\ge 0$ | [Non Zero Constraint] |

**Summary**

This study utilizes the anyLogistix software, but integrates calculations for costs, constraints associated with the WRM network and assumptions. The triangular distribution within anyLogistix determines an estimated demand. Travel costs are calculated through three predetermined modes of travel, with the variable dollar per unit per mile. Carrying costs are different by home versus overseas locations. Expansion costs are calculated and added to models to account for a base to hold extra inventory and the costs associated with this purchase. The model's inputs and constraints contribute to the objective. This research runs 30 different models across three scenarios with the goal of quantifying the impact of inputs on costs and responsiveness.

# IV. Results and Analysis

## Overview

This results and analysis section will consolidate the results of the study's network optimization and give a stronger picture of the costs and benefits associated with each of our 30 models. These results are extracted from the data exported from anyLogistix. This data is summarized and displayed using tools from JMP and Excel. The results will focus on determining the efficiency of factors included in the various models for the three scenarios given certain inputs. In particular, the trade-offs.

## Demand Satisfied vs. Costs

The primary metric this study evaluates is how much demand is satisfied. This is traded-off against the costs needed to reach a particular level of demand satisfaction. This trade-off drives the analysis of model performance. The focus on cost intensifies when different models achieve 100% demand satisfaction within a particular scenario. The analysis is separated for each of the five medications: the results for ketamine are shown in Figure 10. This graph focuses on models 1-10, but 11-30 have similar shapes and characteristics. Model 9 is the best performing model on this chart, as it is the lowest cost option to reach 100% demand satisfaction. This is the model that is stocked with an initial inventory of 1000 at the start of the conflict. Model 1 performs the worst as there is no resupply and resources are limited in relation to demand. Figure 10 shows the results just for ketamine, but this graph has the same best of fit line, minimum performing and maximum performing models as three of our other medications: fentanyl oral, fentanyl IV and morphine.

Figure 11 shows the graph of hydromorphone demand satisfied vs costs for scenario 1. Hydromorphone is the one medication that differs from the other four in performance overall and best performing model. This graph has the steepest rise of any of the five medications, showing that it costs the least amount of money to reach 100% demand satisfaction in comparison to other medications. The best performing model in Figure 11 is model 5, where the PACAF CSDCs are added. The CSDCs boost inventory in the immediate conflict region. The worst performing model for hydromorphone in scenario 1 is model 1. This is for similar reasons as the other medications: no resupply and limited resources in the region. The graphs broken down by scenario and medication are shown in: Appendix A (ketamine), Appendix B (hydromorphone), Appendix C (fentanyl oral), Appendix D (fentanyl IV) and Appendix E (morphine).

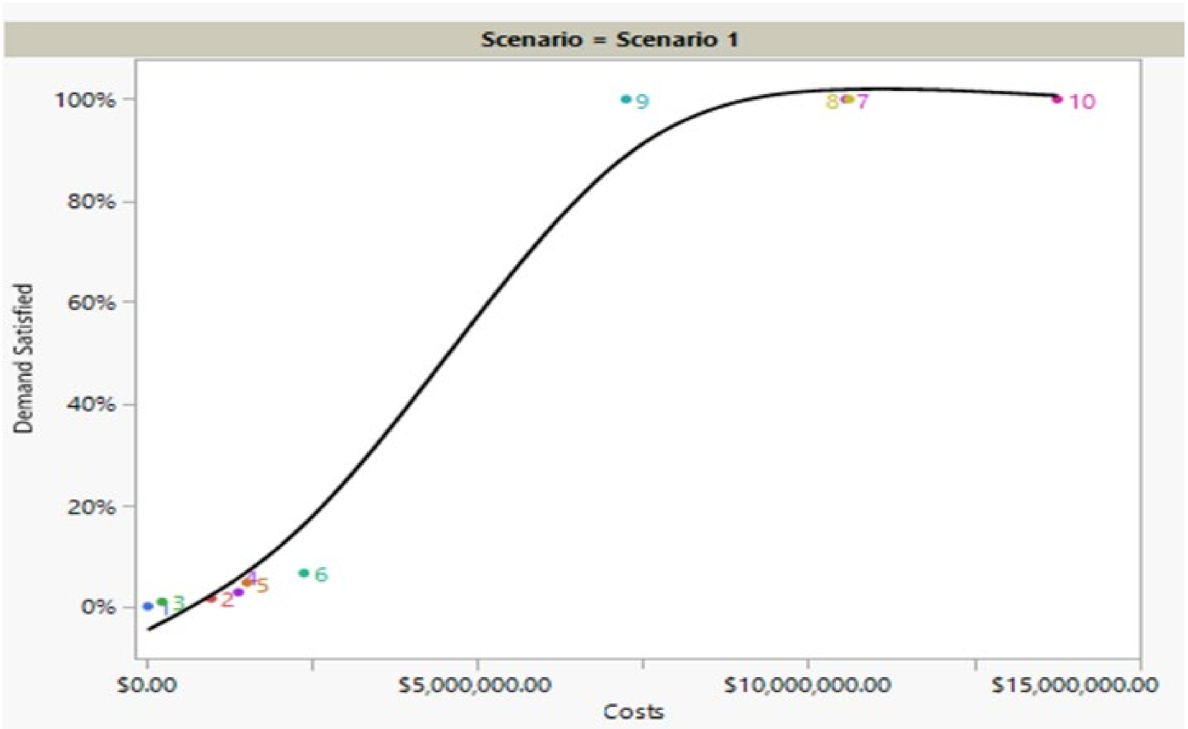



**Figure 10 – Scenario 1 Ketamine Demand Satisfied vs. Costs: Each point is labeled with the model number**

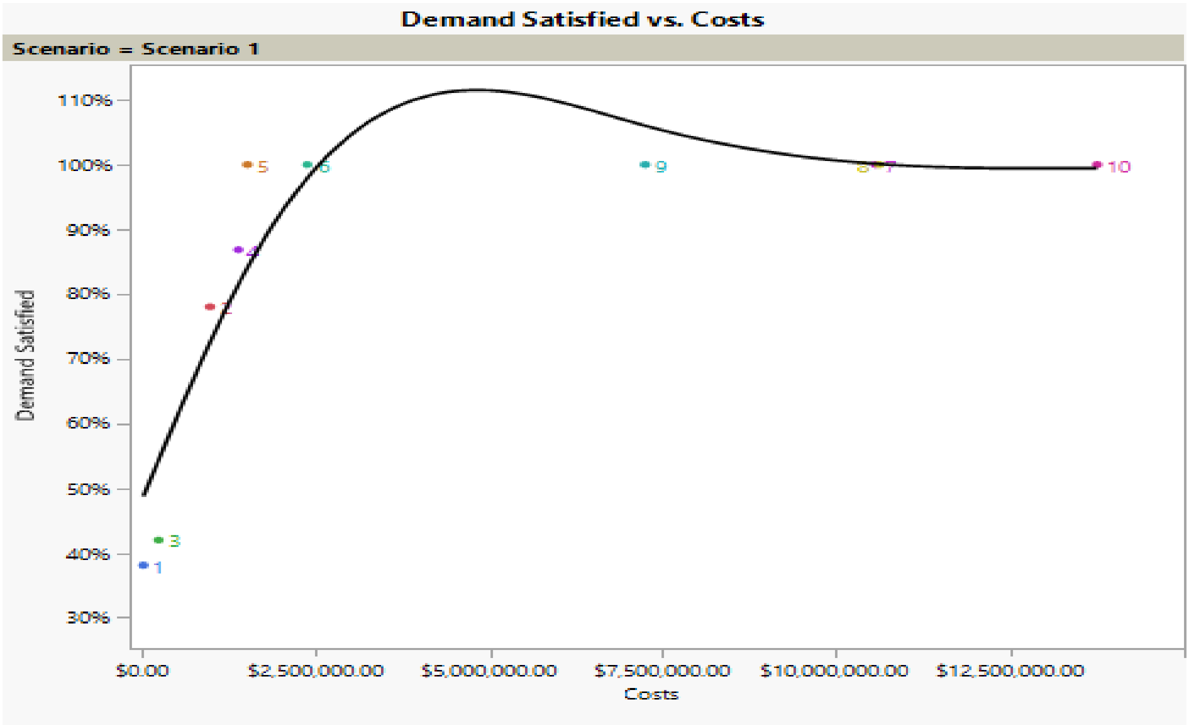



**Figure 11 – Scenario 1 Hydromorphone Demand Satisfied vs. Costs: Each point is labeled with the model number**

## Spending Efficiency

For this study, it’s imperative to find ways to separate and understand the impact of parameters within the objective function. To illustrate the efficiency of spending, this study developed a metric to determine the percent demand satisfaction per $100K dollars spent. Metric calculation is shown in Equation 6. Costs are incurred in the models from transporting the medications, carrying the medications in the network, procurement of the medications and expansion of the network to support additional medications.

$$Demand\ Satisfied\ Per\ \$100K\ Spent = \frac{Satisfied\ Demand\ of\ Product\ p}{\frac{Costs\ (Transportation + Carrying + Supply + Expansion)}{\$100{,}000}}$$

**Equation 6 – Demand Satisfied per $100K Spent**

The percent demand satisfied per $100K dollars spent metric shows the efficiency of dollars spent not the efficiency of meeting network requirements. This metric is used in this study as a comparative tool. For the purpose of comparison, we focus on the top and bottom three performing models in this metric for each medication. The results are shown in Table 4. Models 1, 11 and 21, those with no resupply, appear most often as the top performing models in demand satisfied per $100K spent. This is due to the low costs associated with these models. With inventory already located in South Korea and no transportation costs associated with resupply, these models are shown as efficient with respect to costs. Models 10, 20 and 30, those with no initial stock, appear the most as the bottom three due to the high costs, especially in transportation, in relation to demand satisfaction.

**Table 4 - Top & Bottom Performing Models**

| | | Demand Satisfied per 100k Spent | Model | | | Demand Satisfied per 100k Spent | Model |
|---|---|---|---|---|---|---|---|
| Ketamine | Top 1 | 1.38% | Model 9 | | Bottom 1 | 0.17% | Model 22 |
| | Top 2 | 1.36% | Model 19 | | Bottom 2 | 0.18% | Model 12 |
| | Top 3 | 1.34% | Model 29 | | Bottom 3 | 0.18% | Model 2 |
| Hydromorphone | Top 1 | 227.22% | Model 1 | | Bottom 1 | 0.72% | Model 30 |
| | Top 2 | 118.15% | Model 11 | | Bottom 2 | 0.72% | Model 20 |
| | Top 3 | 92.59% | Model 21 | | Bottom 3 | 0.73% | Model 10 |
| Fentanyl Oral | Top 1 | 2.06% | Model 3 | | Bottom 1 | 0.00% | Model 1 |
| | Top 2 | 1.87% | Model 13 | | Bottom 2 | 0.00% | Model 11 |
| | Top 3 | 1.77% | Model 23 | | Bottom 3 | 0.00% | Model 21 |
| Fentanyl IV | Top 1 | 116.35% | Model 1 | | Bottom 1 | 0.72% | Model 30 |
| | Top 2 | 59.61% | Model 11 | | Bottom 2 | 0.72% | Model 20 |
| | Top 3 | 46.70% | Model 21 | | Bottom 3 | 0.73% | Model 10 |
| Morphine IV | Top 1 | 164.42% | Model 1 | | Bottom 1 | 0.72% | Model 30 |
| | Top 2 | 84.76% | Model 11 | | Bottom 2 | 0.72% | Model 20 |
| | Top 3 | 65.46% | Model 21 | | Bottom 3 | 0.73% | Model 10 |

Figure 12 shows the demand satisfied per $100K spent vs models. This graph demonstrates the effect of low spending on the models. The high points are models 1, 11 and 21 with spikes at 3, 13 and 23. These models do not utilize help from the United States and lack a big influx of supply.

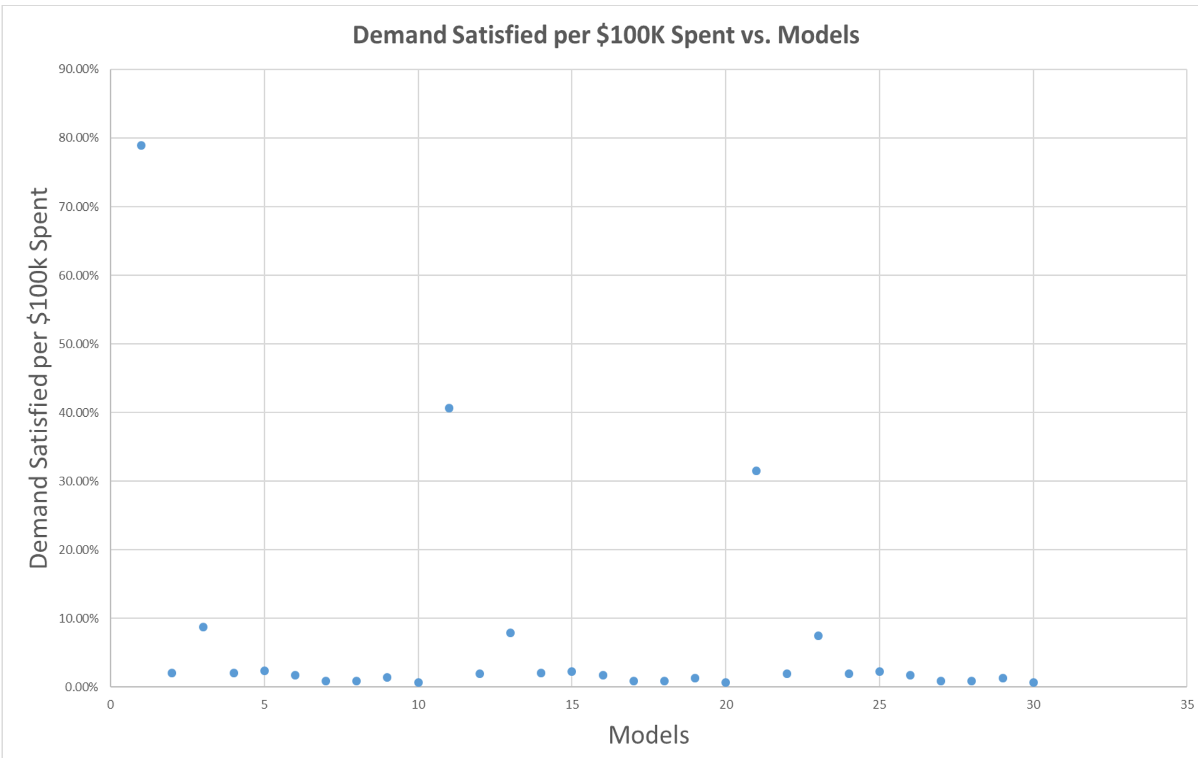



**Figure 12 - Demand Satisfied per $100K Spent vs. Models**

The demand satisfied per $100K spent is focused on spending efficiency and less so in the success of the supply in the model to meet medication demands. Figure 13 overlays this metric with total demand satisfied for each model. This allows a more direct comparison between the two metrics. The total demand satisfied per model is the total satisfied demand within the model's 30 month period divided by the total demand in that

same 30 month period. The two lines show that for models 1, 11 and 21 costs are low (generally a good thing) for the statistic demand satisfied per $100K spent (blue line chart), but total demand satisfied (green line chart) is less than 100% (generally a bad thing). Every peak on the demand satisfied per $100K spent line corresponds to a low value for the total demand satisfied.

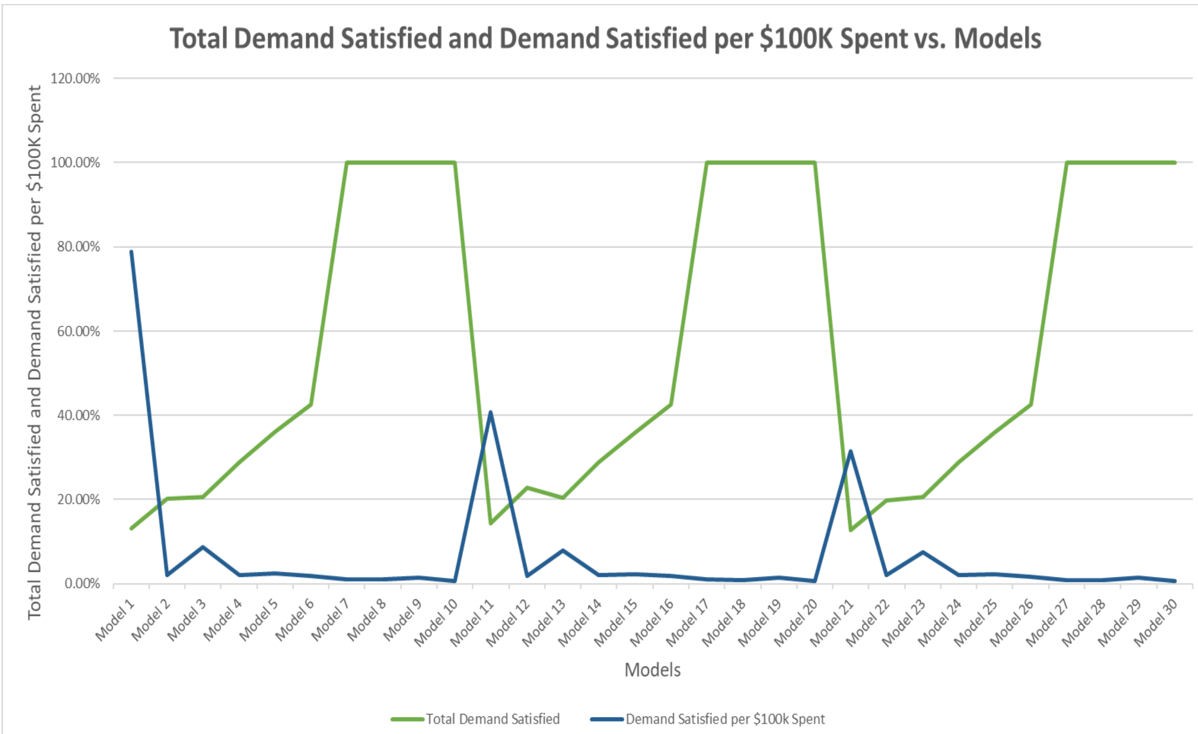



**Figure 13 - Total Demand Satisfied and Demand Satisfied per $100K Spent vs. Models**

## Demand Points Supplied

A vital model comparative discriminator is the number of demand points supplied. A network that fails to meet demand at all locations is not meeting level of service goals and causing harm to patients unable to receive medications. Figure 14 shows the percent demand met per $100K spent versus the number of demand locations supplied. Models 1-

10 have a maximum of five demand points, models 11-20 a maximum of six demand points and models 21-30 a maximum of ten demand points. Any model that falls below these maximums in demand points supplied was unable to supply all the demand points in the scenario and deliver critical resources to our casualties. The models failing to reach maximum demand points supplied are: 1, 3, 11, 13, 21, 23 and 24. Figure 14 illustrates that every time there is a spike in demand satisfied per $100K spent there is a decrease in the number of demand points supported. The decreased spending, visible through the spikes in demand satisfied per $100K spent, correlates to the decrease in demand points supplied.

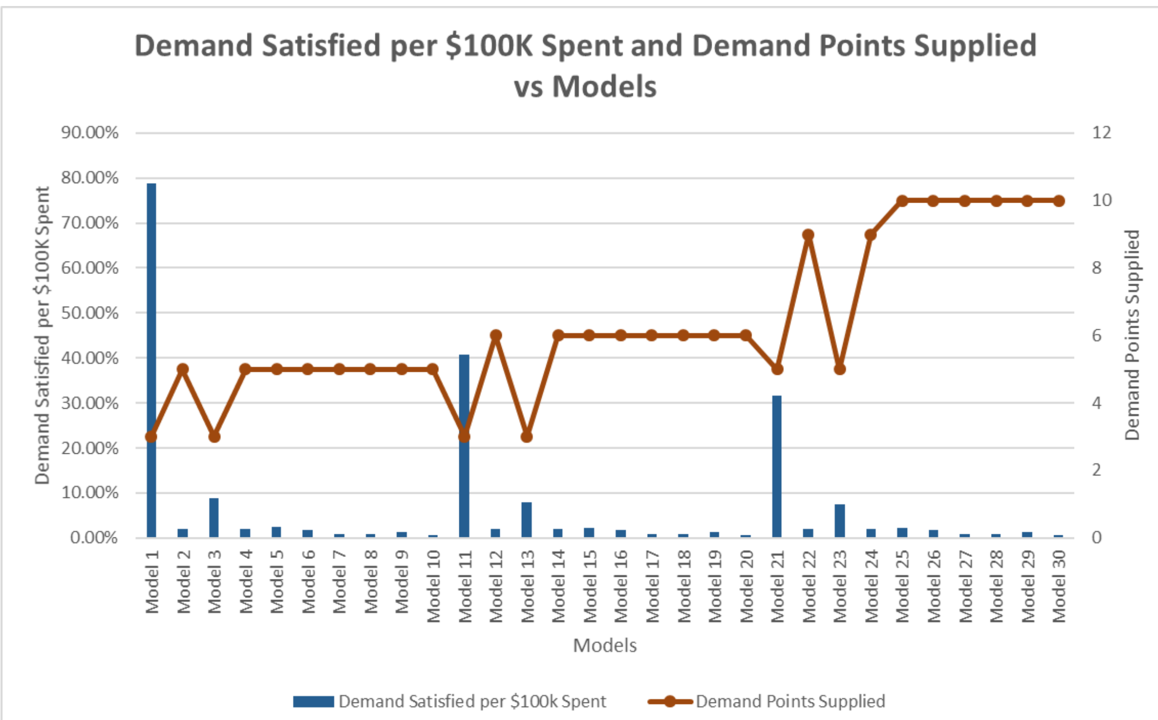



**Figure 14 - Demand Satisfied per $100K Spent and Demand Points Supplied vs Models**

Product flow is a metric tracked within anyLogistix. This number quantifies the movements of medications within the network for each model. Figure 15 shows the product flow versus demand points supplied, which visualizes the effects of product flow, measured in units used in servicing demand. The number of demand points supplied is maximized for each location and reaches stability after models 4, 14 and 25. For this study, models 4, 14 and 24 is where both the PACAF and US CSDC were integrated for network support. Following the pattern in previous scenarios, model 24 should have reached the maximum number of demand points supplied for scenario 3, which is ten, but this was not the case as only nine demand points were supported. This shows that there were still not enough resources within the network to support all demand locations when expanded to ten. Chongjin, the furthest demand point in the Northeast corner of North Korea, was the demand point that went unsupplied in model 24. By looking at the flow, this study also shows the changes occurring between the first three models in every scenario. Models 1, no resupply, and 3, PACAF support, do not have enough resources and flow within the network to support all demand points, which is similar for models 11, 21, 13 and 23. Model 2, which incorporates US CSDC support, introduces enough resources into the network to support all demand points, which is the same for model 12. Model 22 is unable to support all ten demand points due to the lack of resources in the system. These results indicate that the US CSDC support boosted resupply and capacity better than just including PACAF support.

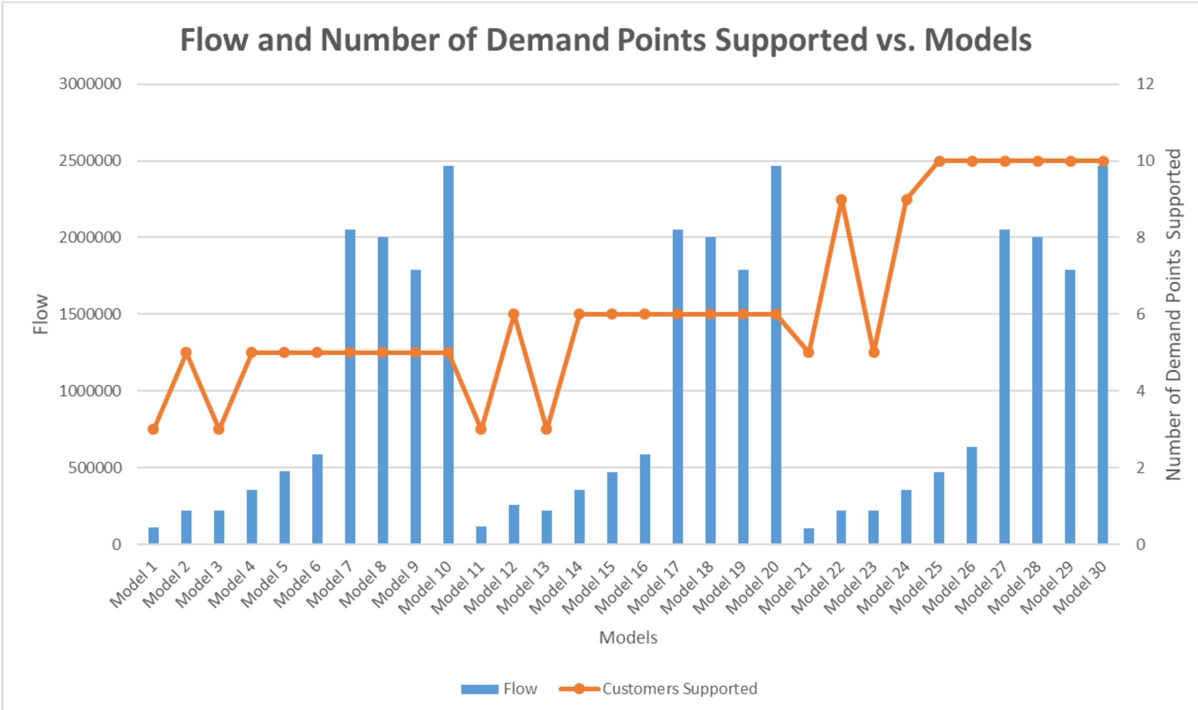



**Figure 15 - Product Flow and Demand Points Supplied vs Models**

## Model Comparison 100% Demand Satisfaction

100% demand satisfaction for a model occurs when all five medications are delivered on time with the correct quantity to all demand locations, in that particular scenario. These network optimization problems are complex, with numerous inputs and constraints, so there is no universal path to achieve 100% demand satisfaction. Models 7 – 10, 17 – 20 and 27 – 30 all achieve 100% demand satisfaction with different inputs. This study seeks to answer the questions surrounding what models and inputs display the most cost efficiency while reaching an acceptable percentage of demand satisfied. Comparing high performing models can help shed clarity on the effects of these different inputs. To compare these alternative solutions, the following analysis studies the descriptive statistics

for all similar models (e.g., 7, 17 and 27) to help differentiate the inputs and models across the three scenarios and answer key questions. This form of comparison will also give clarity to some of the risks vs rewards of inventory management for the five medications. The mean is used as the comparative metric from the descriptive statistics.

Table 5 shows the percent change from the mean of one similar model to another. This is shown for each of transportation, carrying, and supply cost, as well as flow. The largest percentage increase, at 377.4%, occurs for carrying cost for the mean of models 7, 17 and 27 to models 9, 19 and 29. This large percentage increase is best explained by looking at the inputs of these models. Models 9, 19 and 29 are differentiated from the rest by the introduction of 1000 units of inventory for every product at every location. There is also an additional supply procurement and transportation cost associated with this new inventory policy. Introducing this inventory policy in these models skyrockets carrying costs in relation to models 7, 17 and 27. Larger inventories in the network drive the larger carrying costs in models 9, 19 and 29.

The largest percent decrease, at 93.64%, occurs for carrying cost between models 9, 19 and 29 to 10, 20 and 30. This large decrease is partly due to the network inventory policy. In models 9, 19 and 29, high levels of inventory will remain in place until the demand signals exceed the amount at storage locations. This increases carrying costs. It's important to notice the relationship between carrying and transportation costs in any model. Models 10, 20 and 30 have no initial inventory and a minimum of 100 units of every medication at every location. With this inventory policy (minimum 100 units with no initial inventory) product orders occur in the early periods of models 10, 20 and 30. This establishes a network with high transportation costs focused on getting products from the

US suppliers out to the customers through the supporting bases and CSDCs. This is further evident in Figure 16 which shows the mean transportation, supply and carrying costs aggregated by similar models. Both Table 5 and Figure 16 show that transportation costs are highest with low levels of prepositioned materiel (models 10, 20 and 30) and carrying costs are highest in a network that is well stocked at the start of the conflict (models 9, 19 and 29).

**Table 5 - Mean Comparison Similar Models**

| **100% Demand Satisfied Models Cost and Flow Comparisons** | | | | | |
|---|---|---|---|---|---|
| | | **% Change** | | | |
| **Original Models** | **New Models** | **Transportation Cost** | **Carrying Cost** | **Supply** | **Flow** |
| Mean of Models 7, 17, 27 | Mean of Models 8, 18, 28 | 0.01% | 54.41% | -4.77% | -2.29% |
| Mean of Models 7, 17, 27 | Mean of Models 9, 19, 29 | -30.94% | 377.40% | -64.06% | -12.87% |
| Mean of Models 7, 17, 27 | Mean of Models 10, 20, 30 | 31.43% | -69.63% | 25.51% | 20.21% |
| Mean of Models 8, 18, 28 | Mean of Models 9, 19, 29 | -30.95% | 209.18% | -62.26% | -10.82% |
| Mean of Models 8, 18, 28 | Mean of Models 10, 20, 30 | 31.43% | -80.33% | -62.26% | 23.03% |
| Mean of Models 9, 19, 29 | Mean of Models 10, 20, 30 | 90.31% | -93.64% | 25.51% | 37.96% |

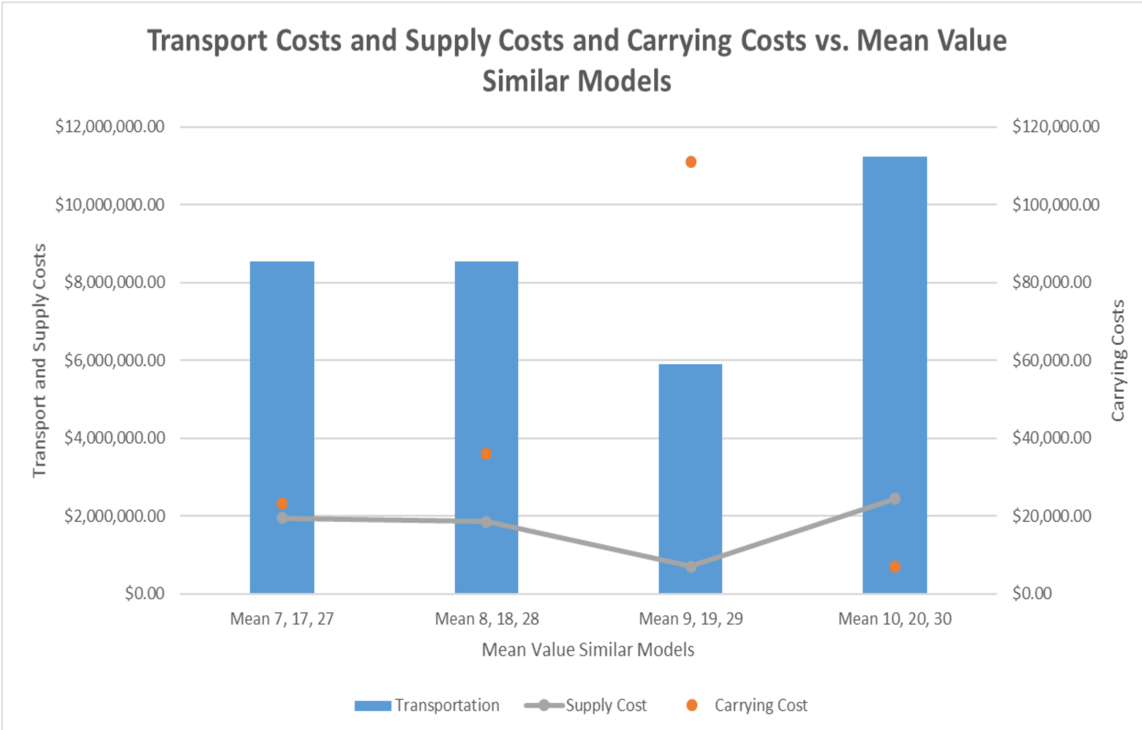



**Figure 16 - Mean Cost Comparison of Similar Models**

## Scenario Comparison

When comparing the descriptive statistics of scenarios 1, 2 and 3, they all have similar numbers. The largest increase in percent change, at 3%, occur with transportation costs from scenario 1 to 2. With more demand points in the network, transportation cost increases are anticipated given the growth of movements within the system. There are also increases for the amount of flow in the network, as more demand locations require a greater amount of flow in the network.

# V. Conclusion and Recommendations

## Conclusions

This study focused on assessment of the effects of inputs on a notional WRM network. AnyLogistix is a tool that enlightens the risk vs reward of decision making policies related to inventory and product location. This study shows that as demand points increase it becomes harder to service all locations. Breaking this conclusion down by scenario, 92% of demand points were supplied through all the models in scenario 1 with five different demand points, 90% in scenario 2 with six different demand points and 88% in scenario 3 with ten different demand points. Incorporating the demand satisfied per $100K spent metric, the scenarios that spend little money appear effective, but in comparison to statistics showing total demand satisfaction, are actually weak. When little money is spent, as with models 1, 11 and 21, it shows that these models are exerting few resources to achieve demand satisfaction. The lack of resources and spending within the network boosts these numbers. From this it is clear that demand satisfaction and efficiency of spending must be considered together.

This study also shows that with added inputs and expanded capacity, the WRM network can achieve 100% demand satisfaction across all medications. Medical inventory expansion improves demand satisfaction in network optimizations: greater network inventory leads to more resources and higher demand satisfaction. The results show that unconstrained suppliers ensure 100% demand satisfaction in the network. Infinite resources without constraints and in a fixed environment produce desired results, albeit with an added element of cost that fluctuates with different inputs. The network

optimization components of anyLogistix can test the effects of new policies and procedures before their implementation is carried out.

## Research Questions

In concluding this study, it's important to revisit our key research questions and use the results and analysis to help answer them.

1) *Which factors are useful in reducing cost while meeting a demand satisfaction threshold?*

   Within our models, there was much success in minimizing cost while reaching 100% demand satisfaction when prepositioning materiel. This was most evident in models 9, 19 and 29, where the combination of costs were $3.3 million cheaper than the next closest models (7, 17 and 27) that met 100% demand satisfaction. This study also shows the effects of adding well-stocked storage centers and boosting inventory on specific medications. Hydromorphone was the quickest medication to reach 100% demand satisfaction, which occurred after adding the three PACAF CSDCs in South Korea and Japan (models 5, 15 and 25). Another key factor in both cost and demand satisfaction was the introduction of suppliers into the network. These unconstrained suppliers increased supply costs, but with the benefit of reaching 100% demand satisfaction to all demand points. Across all scenarios, these suppliers supported an effective network.

2) *Will adding factors effect model performance?*

Per Figure 10 and Figure 11, inventory management plays a key role in costs and demand satisfaction. The higher the inventory of a medication in the network, the quicker it is to reach 100% demand satisfaction. Prepositioning materiel leads to higher carrying costs and is associated with increasing supply availability (models 9, 19, 29). An increase in the number of demand locations decreases the number of demand points supplied. This is evident in models 22 and 24, where only nine out of the ten locations were supplied. Finally, this study observed that a decreased number of resources in the network reduces the number of demand points supplied. When moving from model 2, US CSDC support, to model 3, PACAF support, there is a decrease in resource availability and the number of demand points supplied. This is also true for the other scenarios: models 12 to 13 and 22 to 23. The network is hampered by going from the well-stocked CSDC support to PACAF support.

3) *Is anyLogistix a useful platform for answering network questions?*

The use of a supply chain optimization software in evaluating the network performance must produce fruitful information to return value for substantial modeling effort. The question then becomes how can a software be evaluated? Network adaptability and abundant reliable data are two critical metrics for a software's performance. AnyLogistix is a unique tool that if utilized correctly can give great insight and be adaptable with the proper time and effort by the user dedicated to building an accurate network. Much effort must be made to accurately

capture the nature of a network, with storage centers, warehouses and suppliers linked appropriately. An accurate network allows for adaptability in considering logistical needs across varied geopolitical situations. Network optimization efforts can mimic many of the details of the analysis in this thesis based on notional South Korean scenarios and apply similar analysis to other countries and regions wherever the needs should arise. Ultimately, yes, when accounting for applicable costs and constraints, anyLogistix is a good software tool to tackle crucial network questions related to cost, inventory and demand satisfaction.

**Recommendations**

This study creates several recommendations from the network designs created through anyLogistix and the utilization of the data produced from the system. The models created in this study utilize the current WRM network and three notional scenarios produced for this study. Operational planning is not incorporated into these situations. If there is greater intelligence on a specific conflict region, this should be incorporated into the logistics planning through additional modeling constructs within anyLogistix. Travel restrictions or limitations across vast regions may limit a logistics response. Planners should incorporate an enemy's expected reactions and our allied capabilities in the region, something that must be integrated into military operational planning. This linkage between current operational plans and our constructed networks will build a more realistic response.

The use of anyLogistix can also assist in finding the optimal inventory levels given the WRM network's structure and our study's inputs. This research only focuses on five individual medications. Studying a wider variety of products in the network allows the

researcher to build a response that multiplies medical capabilities. In this study universal figures were used for the initial, minimum and maximum inventory numbers at all locations in the network. Models 9, 19, and 29 had initial, minimum and maximum inventory levels of 1000, 0 and 10000 respectively. Models 10, 20, and 30 had initial, minimum and maximum inventory levels of 0, 100 and 10000 respectively. Varying these numbers based off of the expected demand of individual items or packages allows more flexibility for logistics planners to reduce costs and decrease response times. AnyLogistix provides a collection of tools to support this additional analysis.

**Future Research**

This study is limited in scope and an expansion of the optimization models could bring a greater applicability to solutions for operational combat medicine. The network could be expanded to focus on entire Air Force WRM packages, additional medical products and equipment, locations or incorporated joint capabilities. Looking only at specific medications, as this study does, eliminates the ability to analyze by Unit Type Code (UTC) and an item's impact to the mission (e.g., if the item is critical or not). The inclusion of UTC packages could add great applicability as there may be support equipment or supplemental medications within the continuum of care that are important to overall effectiveness. By expanding the models to capture the stocking levels of entire UTCs, which may contain dozens of different medical products, researchers can gain insight into important interactions inherent in the WRM network. Models expanded in this way can guide how to properly preposition these packages to reach a desired demand satisfaction in a cost efficient manner. With potential conflicts in Europe, South America and even within

the United States, this study can look at other Major Commands (MAJCOMs) in assisting WRM logistics planning and deployment tactics. Additionally, this study can help guide facility location decisions within the network. Expanding or building CSDCs is an expensive and extensive process that may be simplified by utilizing tools such as Greenfield Analysis within anyLogistix.

Practical decisions regarding initial inventories are most often in a budget constrained environment. Although this study did not consider such constraints, incorporating these in well within capabilities of anyLogistix.

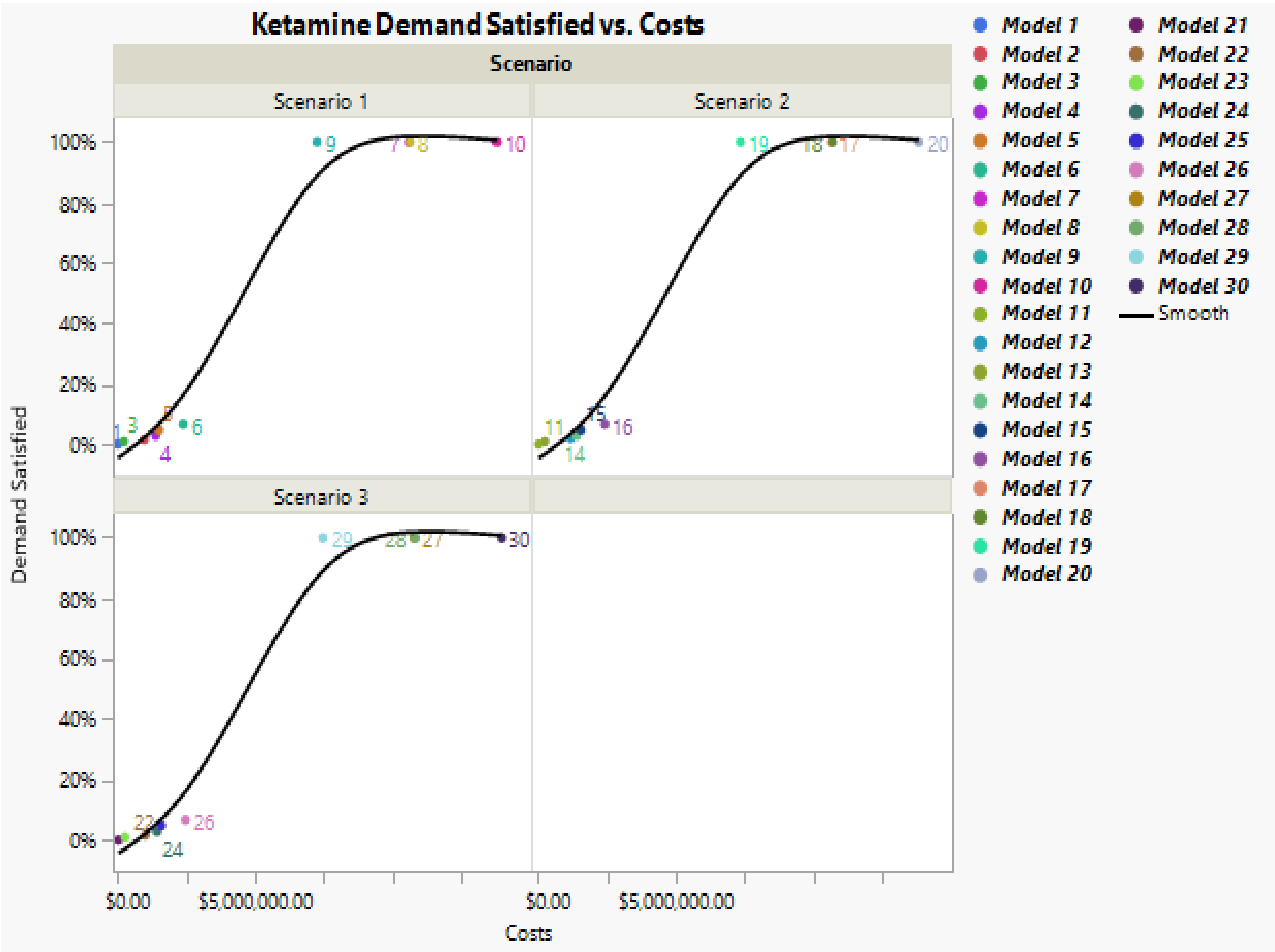
Any network optimization is reliant on accurate constraints to enforce the problem's realities. Future research should look to expand on the constraints, including: incorporating both unloading and processing costs and time constraints, the possibility of facility or mode degradation within the network or interruptions in the supply chain. Logistics in a contested environment is unpredictable. Future studies into logistics capabilities should involve a form of randomness due to contested situations to confirm facility sustainment or effective delivery. This study assumed there were no interruptions to the transport of medications, but integrating the possibility of facility destruction or failed deliveries, whether it be by enemy attack or interrupted infrastructure, gives a realistic approach to combat logistics.

Finally, future research should look to expand models based on the other features and tools within anyLogistix: specifically Greenfield Analysis and simulation. Greenfield Analysis can determine optimal location for future warehouses or medical storage points. This supports building updated and new networks to deal with changing circumstances and future conflicts. During warfare, locations may be altered depending on the nature of the

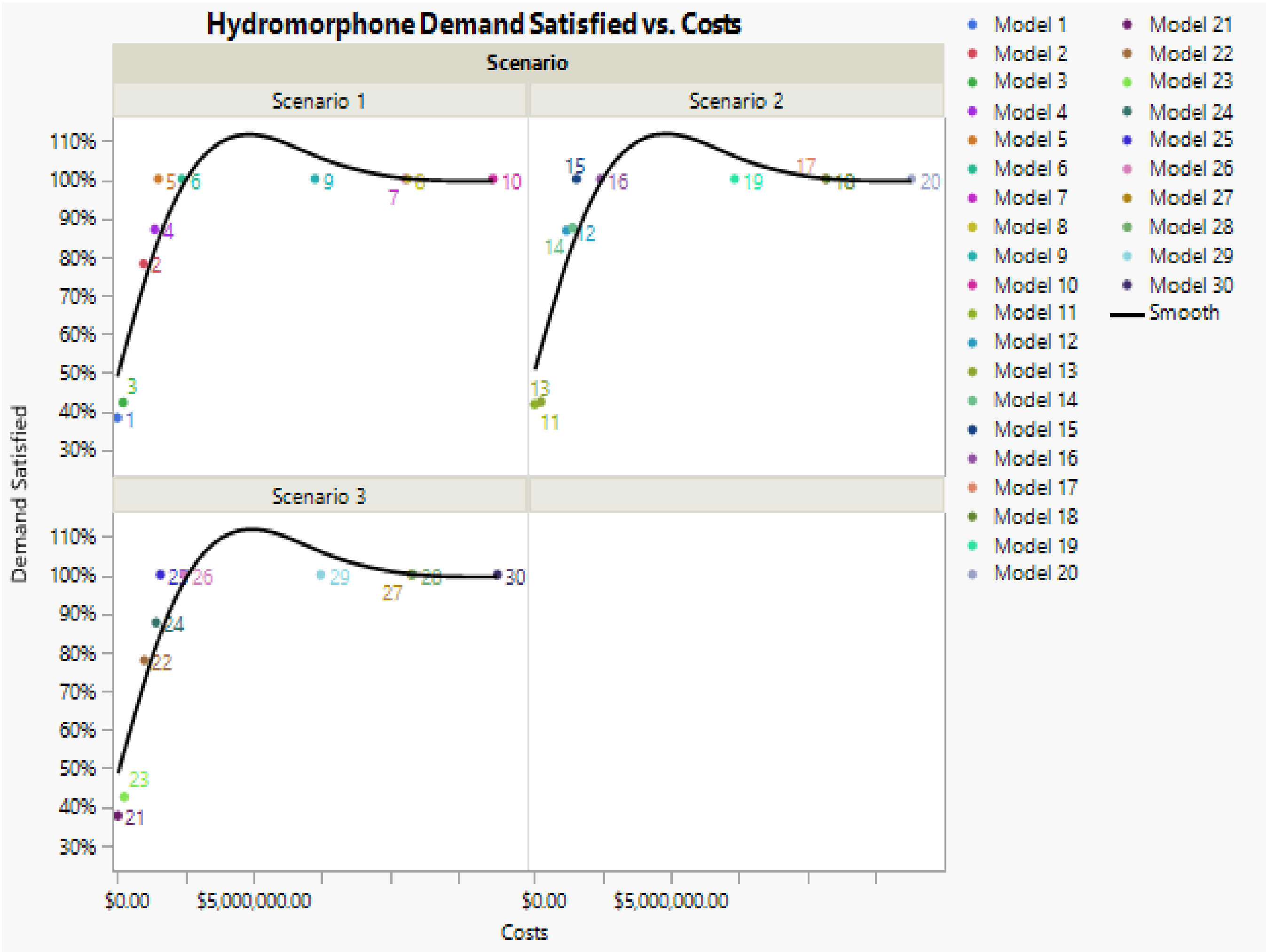
conflict and the position of friendly forces. This study utilizes the network already in place for medical WRM, but this assumes that the current network is built to support a future conflict. Simulation is a tool that can show outcomes associated with our network optimization at a finer grained level of detail. It can give insight and specific statistics on model performance. This feature also allows for expanded information to be placed in the system, with the number of vehicles and vehicle locations being some additional features in the simulation module.

## Appendices

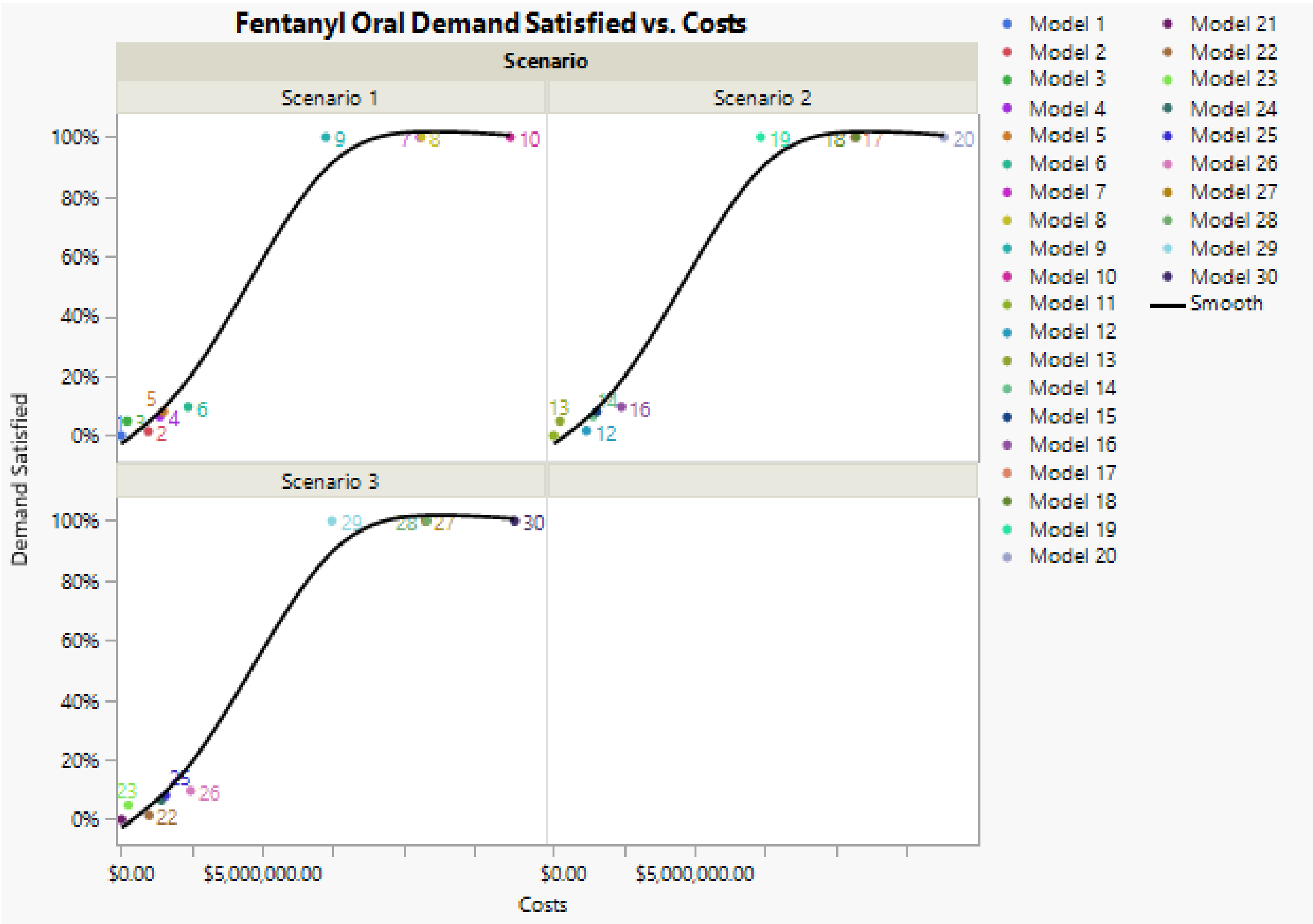
### Appendix A. Ketamine Demand Satisfied vs. Costs Scenarios 1 – 3



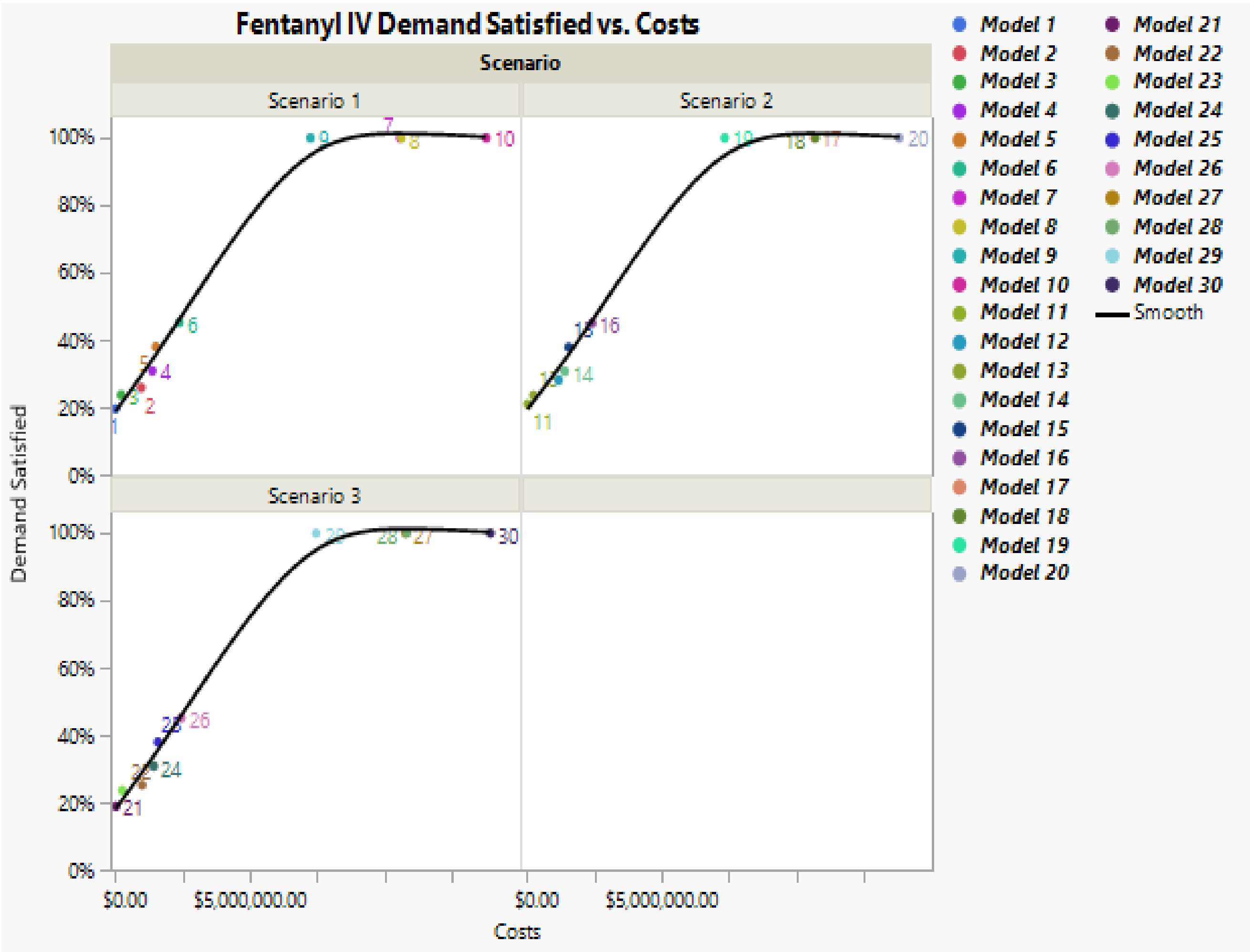
**Appendix B. Hydromorphone Demand Satisfied vs. Costs Scenarios 1 – 3**



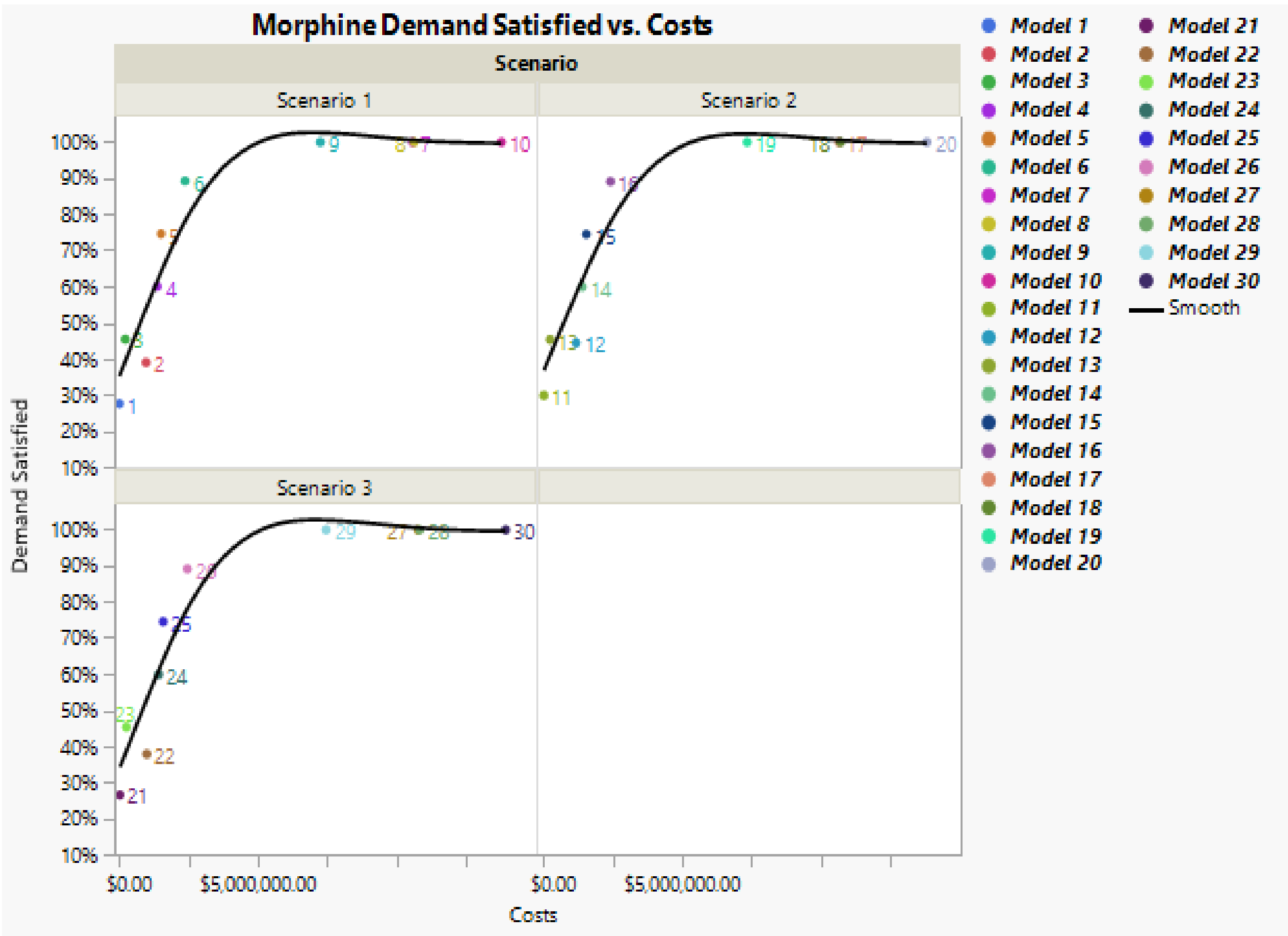
## Appendix C. Fentanyl Oral Demand Satisfied vs. Costs Scenarios 1 – 3



## Appendix D. Fentanyl IV Demand Satisfied vs. Costs Scenarios 1 – 3

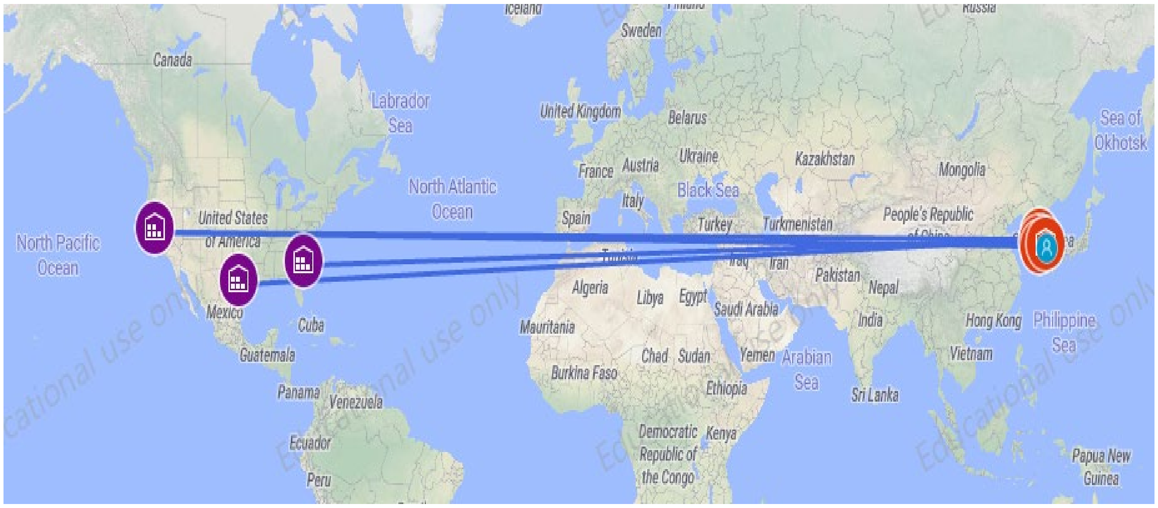


## Appendix E. Morphine Demand Satisfied vs. Costs Scenarios 1 – 3

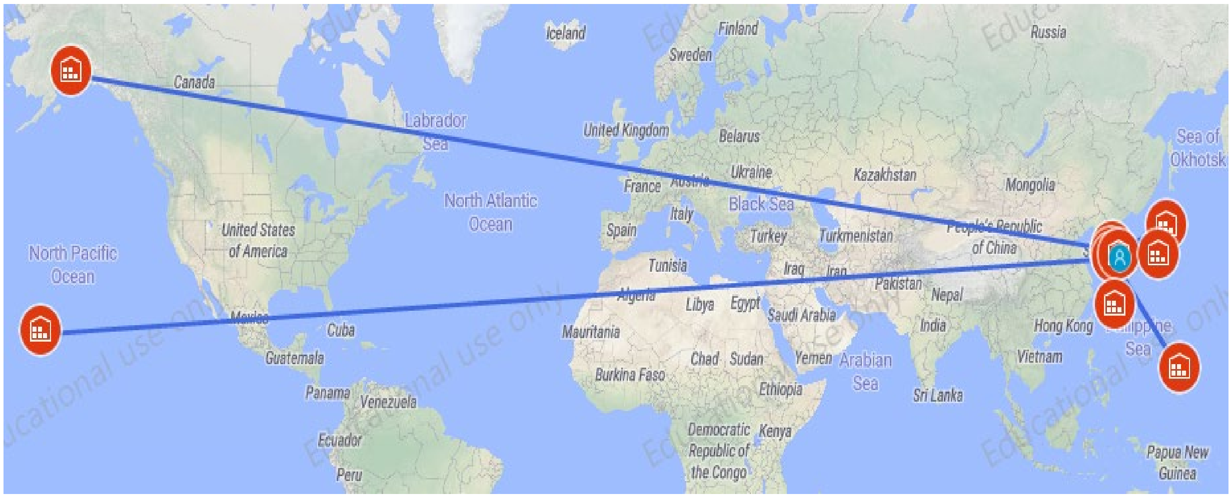


# Appendix F. Solution to Model 1 Scenario 1

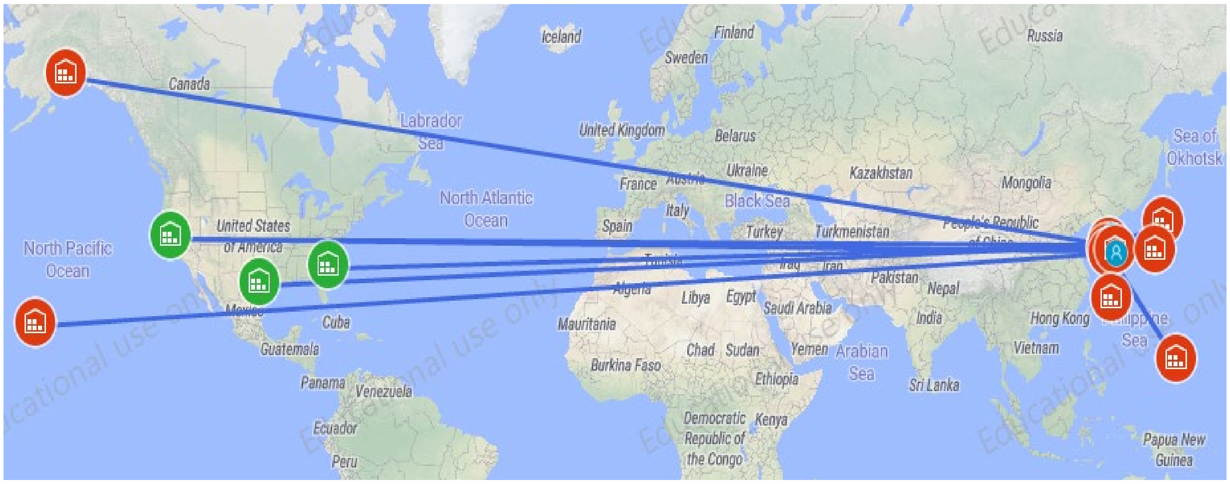
## Appendix G. Solution to Model 2 Scenario 1



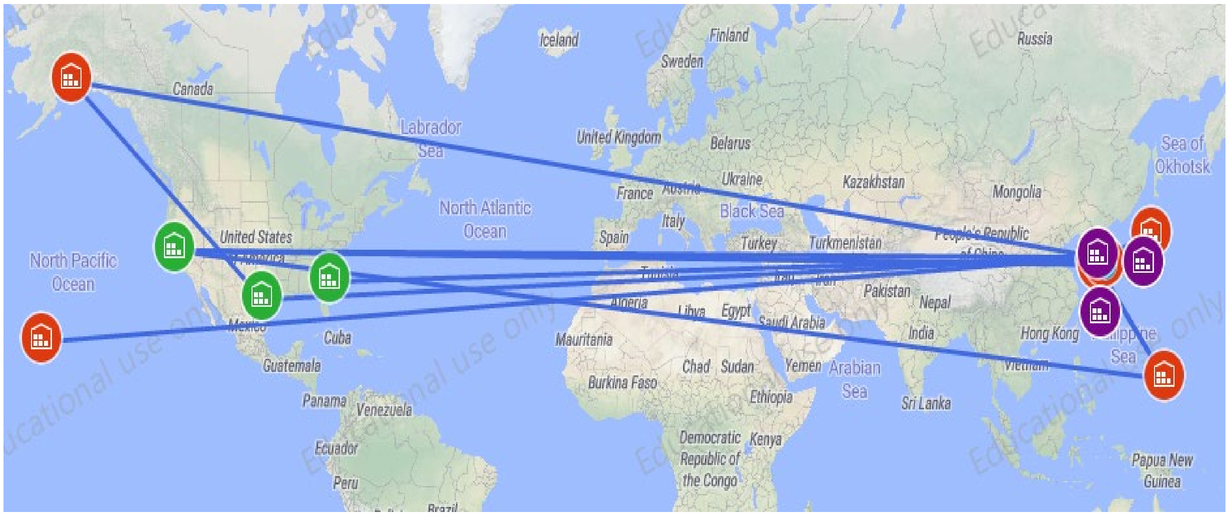
## Appendix H. Solution to Model 3 Scenario 1



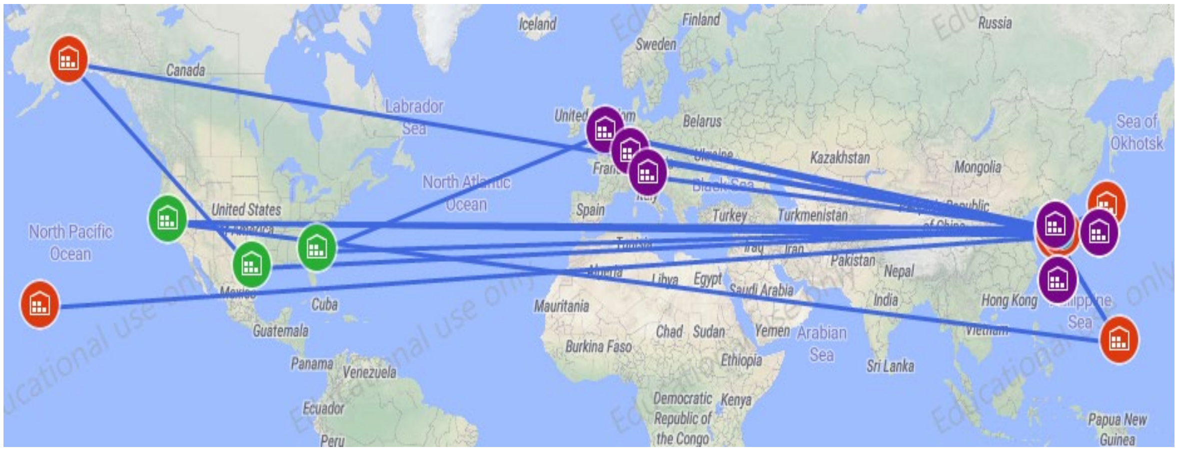
## Appendix I. Solution to Model 4 Scenario 1



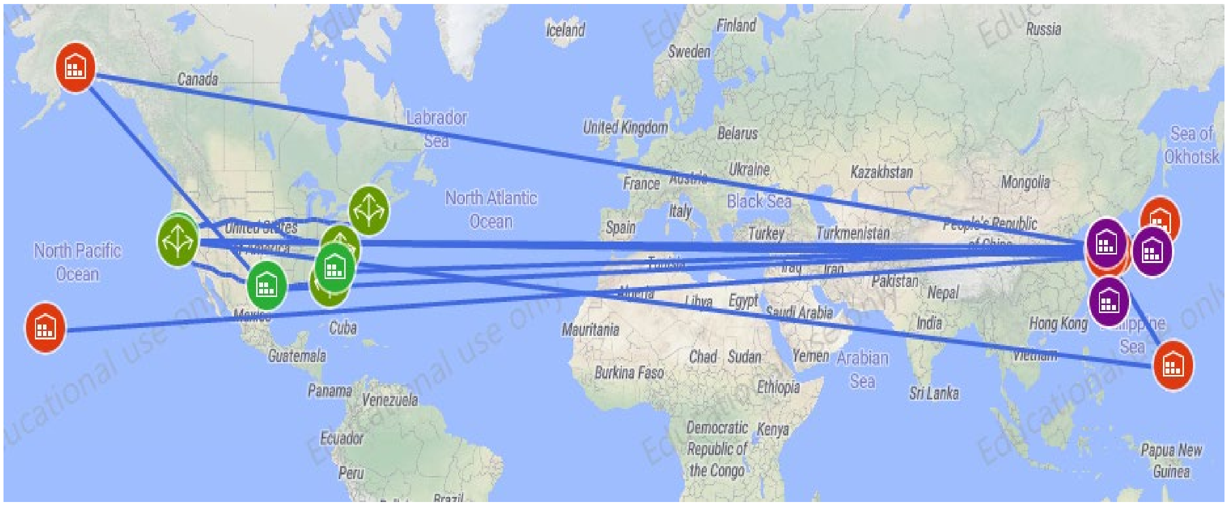
# Appendix J. Solution to Model 5 Scenario 1



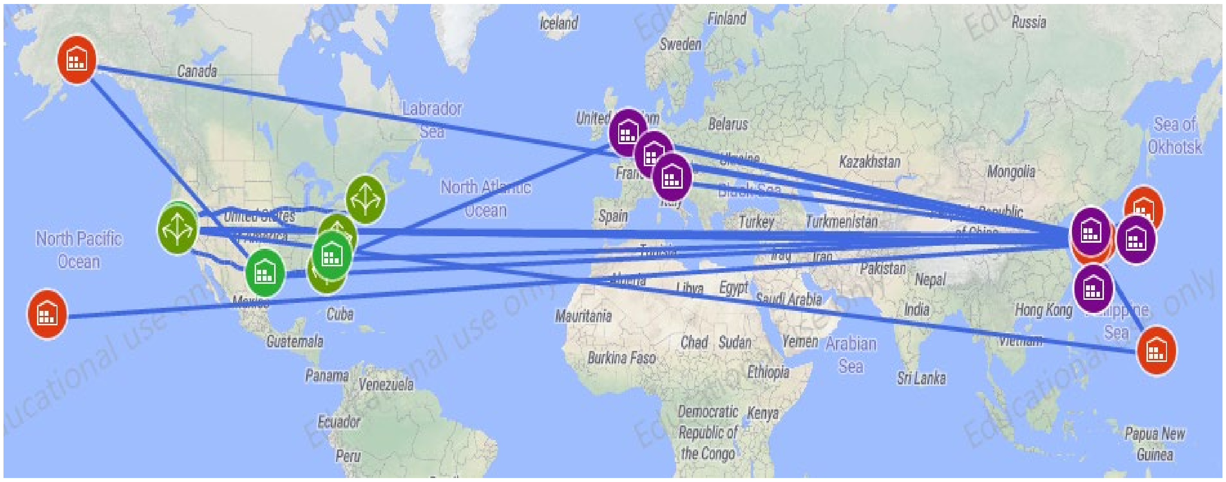
## Appendix K. Solution to Model 6 Scenario 1



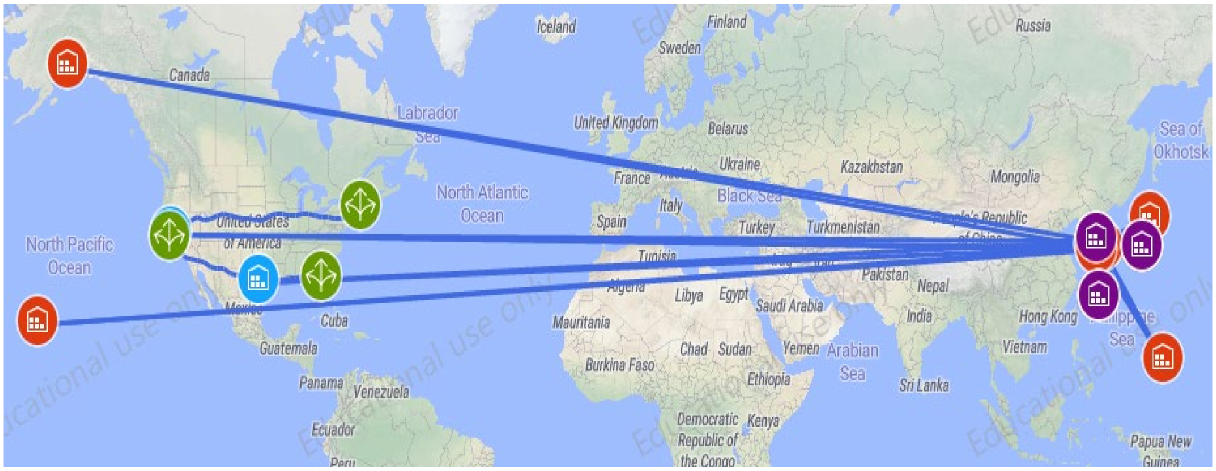
# Appendix L. Solution to Model 7 Scenario 1



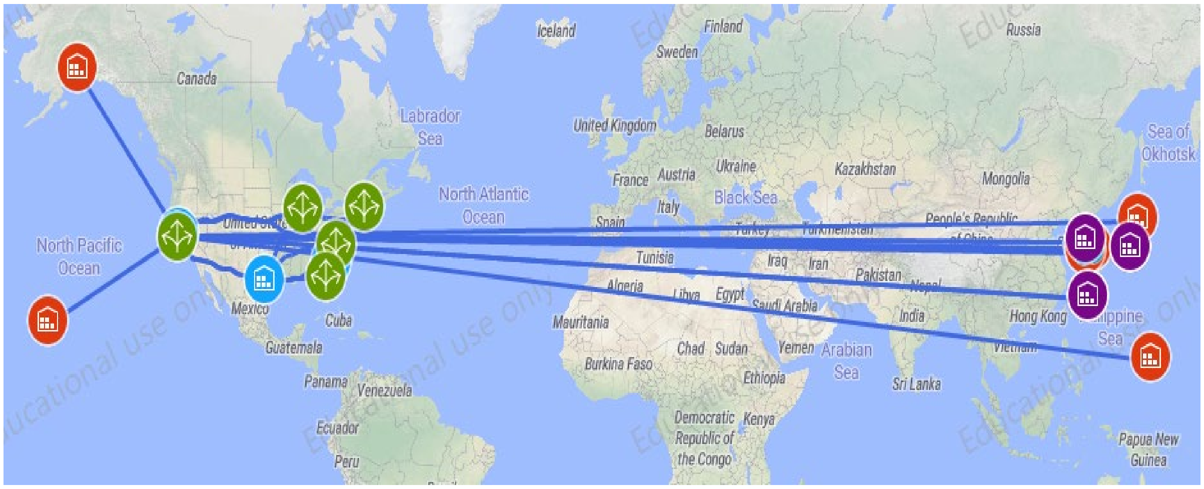
# Appendix M. Solution to Model 8 Scenario 1



## Appendix N. Solution to Model 9 Scenario 1



# Appendix O. Solution to Model 10 Scenario 1



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## Vita

Captain Christian J. Graves was born in Wyncote, Pennsylvania in 1991. He received his High School diploma from Cheltenham High School in June 2009. Captain Graves entered undergraduate studies at the University of Scranton, where he graduated with a Bachelor of Science degree in Healthcare Administration and received his commission in December 2013. His first assignment was as Deputy Medical Readiness Flight Commander at Travis Air Force Base until 2016. He then became the Medical Logistics Flight Commander at Kunsan Air Base, South Korea from 2016 until 2017.

Captain Graves then served as the Medical Logistics Element Leader from 2017 until 2018 in the 43rd Aeromedical Evacuation Squadron at Pope Army Airfield, NC. He deployed in support of the Aeromedical Evacuation Liaison Team in 2018, forward deploying to the Baghdad Diplomatic Support Center in Baghdad, Iraq. After the deployment, Captain Graves transitioned back to Pope Army Airfield, working as the Resource Management Element Leader until 2020. He entered the Graduate School of Engineering and Management, Air Force Institute of Technology in September 2020, graduating with a Masters Degree in Logistics and Supply Chain Management in March 2022. Upon graduation, he will be stationed at Montgomery, Alabama.

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This study examines the Air Force Medical Service War Reserve Materiel supply chain management through the use of the supply chain optimization software anyLogistix. The goal is to illuminate potential improvements to policies that effect inventory management and test the effects of specific inputs, such as an influx of network support and capacity expansion, into the models. Network optimization shows the cost benefit analysis of these factors and if demand is satisfied through all demand points. Through three unique wartime scenarios, this study looks at the supply chain management of five pre-hospital analgesic medications: ketamine, morphine, fentanyl intravenous, fentanyl oral and hydromorphone.

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