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EXPLORING PHARMACEUTICAL LOGISTICS REQUIREMENT FORECASTS FOR CONTESTED ENVIRONMENTS

December 2023

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In NEAR-PEER contested logistics, accurate pharmaceutical estimation and inventory management are crucial for military readiness. Amidst diverse threats across combatant commands, logistics and resource efficiency gain significance. Our research aligns with the Secretary of the Navy's directives, emphasizing efficient resupply and projecting warfighting capabilities from maritime environments. Our study employs a simulation-based model for pharmaceutical estimation in contested environments. Analyzing historical data, we categorize consumable demands by patient categories. Simulation assesses stockout risks, revealing pitfalls in using averages and neglecting variability, even with real patient data-based inventory policies.

The study's insights benefit medical professionals, operational logisticians, and military planners, enhancing inventory management, supply chain logistics, and risk mitigation. Planning and allocating pharmaceuticals proactively based on demand predictions considering uncertainty ensure timely medication access. This improves operational medicine capabilities in distributed maritime operations, aligning with the military's evolving needs and strategic directives.

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LIST OF ACRONYMS AND ABBREVIATIONS

AIREX	Air Explosion
AMAL	Authorized Medical Allowance List
CMS	Centers for Medicare and Medicaid Services
DHA	Defense Health Agency
DOD	Department of Defense
GSA	General Services Administration
ICD	International Classification of Diseases
JMPT	Joint Medical Planners Toolkit
MARCORLOGCOM	Marine Corps Logistics Command
MARCORSYSCOM	Marine Corps Systems Command
MEDLOG	Medical Logistics
mg	milligrams
MHS	Military Health System
mL	milliliters
NDS	National Defense Strategy
Neb	Nebule
NHRC	Naval Health Research Command
PRC	People's Republic of China
SME	Subject Matter Expert

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EXECUTIVE SUMMARY

The U.S. President, Secretary of the Navy, and Chief of Naval Operations have emphasized the strategic significance of addressing challenges posed by NEAR-PEER competitors and the critical importance of contested logistics. Given the national security concerns with the supply chain of pharmaceuticals, it is vital to consider the accessibility, affordability, and security of essential medicines. We aim to strengthen the pharmaceutical supply chain in contested environments, ensuring a resilient and reliable system.

In military operations, maintaining a reliable supply chain for pharmaceuticals is challenging. The limitations on resupply and evacuation opportunities require a forward-thinking approach to ensure the availability of critical medications when they are needed most. Recognizing the importance of medical support in various scenarios, it is critical to gain a comprehensive understanding of the potential pharmaceutical requirements that may arise during deployments.

PURPOSE AND OBJECTIVES

The core objective of this study was to identify potential pharmaceutical logistics requirements while assessing the potential risk of stockouts and managing stockpiles for a given inventory. Our aim was to develop a tool capable of estimating the requisite quantities of pharmaceutical supplies to address specific patient categories most likely to occur in military operations. This information can be used to inform policy on pharmaceutical inventory for contested logistics planning. We analyzed two scenarios to gauge the likelihood of stockouts, which have the potential to trigger critical shortages of essential healthcare products.

METHODOLOGY AND APPROACH

To meet these demands efficiently and effectively, the development and upkeep of a dependable and predictive model are essential to the development of adequate policy. This model utilized real patient data from the Military Health System (MHS) to analyze length of stay and pharmaceutical demand, then used this data to simulate the patient-to-

patient variability that may be experienced in theater. By using Monte-Carlo simulations, this project was able to predict a range and relative likelihood of possible demand quantities for select medications and simultaneously measure the risk of stockout of starting inventories.

Current models in place for projecting medical materiel requirements have notable limitations. Previous identification of pharmaceutical inventory items has typically been based on the recommendations of Subject Matter Experts (SME), both for addition and removal of line items. We believe there has been no concerted effort by the MHS to correlate previous patient demand data for the expected patient types in planning scenarios with expected pharmaceutical requirements.

To our knowledge, existing planning tools and procedures do not estimate the likelihood of an item reaching a critical zero inventory level before resupply. This is a crucial consideration when determining the necessary quantity required.

IMPACT AND IMPLICATIONS

The insights yielded by this study hold the promise of informing military planners and commanders as they strategize to optimize inventory management, enhance supply chain efficiency, and mitigate risks. The introduction of simulation into this process is a strategic advancement that can pinpoint readiness gaps. For instance, using average medication demand with values derived from Monte Carlo simulation service levels revealed an elevated risk of stockouts or increased potential for waste and unnecessary expenditure, compared with a policy of stocking at a 95th percent service level.

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In addition to our professional acknowledgments, we extend heartfelt thanks to our families for their support. Their sacrifices of time and continuous encouragement allowed us to dedicate ourselves to this research.

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I. INTRODUCTION

Our aim was to develop a tool capable of estimating the requisite quantities of pharmaceutical supplies to address patient categories most relevant to conflict and NEAR-PEER contested logistics. Furthermore, two scenarios were analyzed to gauge the likelihood of stockouts, which have the potential to trigger critical shortages of essential healthcare products.

This study was motivated by the potential for shortages in pharmaceuticals that could occur in operational environments, particularly in contested areas or areas with limited opportunity for resupply or casualty evacuation. Our assumption is that in these environments, is that an appropriate makeup and quantity of pharmaceuticals would need to be on hand in advance (prepositioned or co-deployed with fighting forces) to provide appropriate medical care until resupply or casualty evacuation opportunities can be realized. As outlined in the Amphibious Operations, force regeneration is vital, ensuring timely medical support and replenishment of critical pharmaceuticals to "restore units to a desired level of combat effectiveness" in alignment "with mission requirements and available resources" (Joint Chiefs of Staff, 2021).

In May 2023, General David Berger, former Commandant of the Marine Corps, emphasized the necessity for a shift in prepositioning strategies, stating that the current posture was designed for a different era. He highlighted the critical importance of logistics in the evolving landscape. Additionally, he specifically pointed out that the Pentagon's foremost priority should be advancements in logistics to effectively respond to China's growing influence. During war games alongside Admiral Harry Harris, the former commander of United States Pacific Command, General Berger identified a requirement for an alternative to land-based forces. This insight highlights the strategic significance of reevaluating and optimizing logistics operations in contemporary military planning and preparedness (Grady, 2023).

Military operations in contested environments may present challenges in maintaining adequate pharmaceuticals for treating casualties due to restricted resupply and casualty evacuation opportunities. To address the evolving needs of military operations, it is critical to proactively identify and preposition or co-deploy pharmaceuticals alongside our forces. Given the importance of medical support in various scenarios, it is essential to have a comprehensive understanding of the possible pharmaceutical requirements that may arise during deployments. The Department of Defense (DOD) must proactively enhance the readiness and operational effectiveness of our forces while safeguarding the health and well-being of military personnel in diverse operational environments by developing and maintaining a reliable and predictive model that can anticipate the demand for pharmaceuticals in conflict. By establishing accurate prediction methods, the military can strategically stockpile, allocate, and preposition the necessary pharmaceutical resources, ensuring timely access to critical medications for both routine healthcare needs and emergency situations.

Current methods have gaps, such as reliance on SME input instead of real patient data, and do not account for variability of medication demand for a given patient category.

A. RESEARCH QUESTIONS

The purpose of this study was to assess the pharmaceutical logistics requirements and evaluate the potential stockout risk along with managing stockpiles.

The primary research question is as follows: In situations where resupply or patient evacuation is not feasible, what pharmaceutical resources should be on hand in theater to address specific patient categories?

The secondary research question is as follows: What quantity of each medication would be required to achieve a <5% risk of stockout for the patient categories and medications analyzed?

We also compare the above inventory policy based on <5% risk of stockout with a more conventional inventory policy.

B. RESEARCH METHODS

Data was requested from Marine Corps Systems Command (MARCORSYSCOM), via Naval Health Research Center (NHRC) to identify patient categories of interest for this project. Corresponding patient data was then requested from the Defense Health Agency. The available patient data was then reviewed, with further patient data selection taking place. Once the included patients in the study were finalized, patient length of stay distributions and daily pharmaceutical demand distributions were created, to inform these uncertainties. The model was built to allow for user-inputs for personnel deployed, casualty rate, casualty proportions across 12 patient categories, and the number of days until resupply/evacuation. Our model generated simulated casualties for each day of the mission, up to 500 casualties per patient category. It also generated patient medication demand and length of stay, using parameters estimated from the real patient data received from DHA. Two scenarios were then simulated 1000 times via Monte Carlo simulations. The results of these simulations were then compared to two potential inventory policies.

C. FINDINGS

We identified the most common medications for patient categories of interest, as well as length of stay and patient medication demands, and approximated exponential distributions that informed the construction of our model (identified in Table 8). Utilizing an inventory policy that provided for a specific service level outperformed an inventory policy based on average patient demand. The findings of this study can provide valuable insights for planners, logisticians, and commanders in designing effective strategies for inventory management, supply chain optimization, and risk mitigation.

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II. BACKGROUND (LITERATURE REVIEW)

Senior leaders anticipate that the next fight the United States military may find itself in will be with a NEAR-PEER competitor. According to the 2022 *NDS*, "Even as we focus on the People's Republic of China (PRC) as our pacing challenge, the NDS accounts for the acute threat posed by Russia" (Department of Defense, 2022, p. 2). With that expectation, there has been a planning shift to focus on supporting operations in contested environments which is mentioned in the NDS "to ensure our future military advantage, we will build a resilient Joint Force and defense ecosystem" (Department of Defense, 2022, p. 1). The same challenges met for resupply of items like fuel will apply to patient movement and medical materiel resupply.

Within the DOD, the provision of comprehensive medical support is a critical component of implementing the overarching force health protection policy. This responsibility is outlined in the DOD Directive 6200.04, which mandates the delivery of appropriate medical support, training, equipment, and supplies (Department of Defense, 2004). This directive serves as a guiding document that emphasizes the importance of ensuring the well-being and health of military personnel. It directs the DOD to establish and maintain robust medical capabilities to effectively respond to the medical needs of service members and promote force readiness. The DOD is tasked with providing medical support that is tailored to the unique operational requirements of the military. This includes the development and implementation of comprehensive training programs to equip medical personnel with the necessary skills and knowledge to deliver high-quality care in operational environments. It also emphasizes the acquisition and maintenance of appropriate medical equipment and supplies to ensure medical readiness in various operational environments.

The Defense Health Agency (DHA) works in collaboration with various entities, including the Office of the Joint Staff Surgeon, Combatant Commands, and the Department of Health and Human Services, to ensure the strategic stockpiles of medical countermeasures are adequately prepared to address potential threats and operational requirements.

Marine Corps Logistics Command's (MARCORLOGCOM) primary focus is on ensuring the seamless supply, maintenance, distribution, and prepositioning of resources and equipment necessary for the expeditionary force to contribute to the operational readiness and effectiveness of the Marine Corps. Their knowledge and skills enable efficient and effective logistics operations, ensuring that Marines have the necessary resources at the right place and time, enabling the Marine Corps' mission success and maintaining its expeditionary capabilities.

A. MEDICAL LOGISTICS

Effective Medical Logistics (MEDLOG) practices are critical to overall mission readiness and success. Kress (2015) highlights "the unique nature of medical support in a campaign, with respect to its effect on the combat activities, its scale and its characteristics" (Kress, 2015, p. 207). Medical support has a distinctive role, and ethical considerations while saving warfighters lives in military operations, which affect operational success through morale and readiness.

One of the key responsibilities of MEDLOG is the development of the Joint Deployment formulary in collaboration with the senior pharmacy officer and other relevant stakeholders (Joint Chiefs of Staff, 2017). By developing a theater pharmaceutical formulary, the military aims to ensure the availability and appropriate use of essential medications in theater, ultimately supporting the delivery of quality healthcare to service members and promoting mission success in diverse operational environments. Our project hopes to improve upon this process.

Forecasting medical materiel requirements for contingency operations, Moroney (2004) highlighted the limitations of relying on individual tools for accurate forecasting. He points out that multiple tools demonstrate potential in improving forecasting accuracy for the NHRC's Estimating Supplies Program and resupply Validation Program along with the Army Medical Research and Materiel Command's Joint Medical Materiel Modeling Tool. Moroney's research emphasizes the need for a comprehensive approach that combines multiple tools and strategies to address the challenges of accurate forecasting in medical operations.

Effective inventory control enables the military to strike a delicate balance between minimizing costs and ensuring operational readiness (Jaw, 1995). By accurately forecasting demand and carefully managing inventory levels, military organizations can optimize their resource allocation and reduce unnecessary expenditures.

Simulation can be helpful in preparing for combat. Researchers have previously used simulation to examine outcomes of various combat scenarios and the dynamics of warfare, carefully evaluating the impact of evolving technologies and tactics. Peng et al. (2022) stated, "Through simulations of this combat mode and comparative analysis with previous combat data, the results were found to be highly consistent and reflect the nature of attrition in a modern war as compared to traditional combat."

Previous medical teams deployed to combat zones caring for mass casualties and combat trauma were only set up for 72 hours of care, by design. (Williams, 2020). With no guarantee of air dominance for patient evacuation and resupply in the next fight, longer stays are likely to be required, with greater inventory on hand to also be necessary. The unpredictable nature of operational environment demand characteristics requires the supply chain employ innovative means to ensure Class VIII(a) medical supplies are readily available (Williams, 2020).

According to Commander Kellye Donovan (personal communication, April 24, 2023), there is currently a gap in the availability of a planning tool that can estimate the number and type of pharmaceuticals required per casualty type based on medication administration data. This limitation can be a challenge in forecasting pharmaceutical needs and the absence of such a tool hinders the ability to optimize readiness or identify inefficiencies or potential shortages. Addressing this gap and developing a planning tool that incorporates medication administration data would increase medical efforts for commanders at all levels of warfare and optimize pharmaceutical support for various casualty scenarios.

B. CLASS VIII(A) MEDICAL LOGISTICS IN DISTRIBUTED MARITIME OPERATIONS

Military operations in contested environments present challenges in maintaining adequate pharmaceuticals for treating casualties due to restricted resupply and casualty evacuation opportunities. According to Williams (2020), “the unpredictable demand of an operational environment creates challenges for logistics managers seeking to identify all the required Class VIII(a) supplies and have them available, not expired, and in the right quantity” (p. 41). To effectively plan for patient care in these scenarios, medications will need to be co-deployed alongside military forces or prepositioned in accessible locations. Recognizing the importance of medical support in various scenarios, it is essential to have a comprehensive understanding of the possible pharmaceutical requirements that may arise.

The Navy Medicine and USMC Health Services Support currently uses the Joint Medical Planners Toolkit (JMPT) to forecast casualty data for specific scenarios. According to Kellye Donovan (personal communication, April 24, 2023), the toolkit is capable of providing an output of ICD codes anticipated in a given scenario. However, instead of providing the mix of line items and quantities needed for pharmaceuticals, it recommends a standard Authorized Medical Allowance List (AMAL) by which to treat the patient population. Standardized AMALs rely on Subject Matter Expert (SME) review to “generate medical materiel requirements based on user defined mission type” (Defense Logistics Agency, PowerPoint slides, April 21, 2017), but this review does not necessarily adequately project the needs that will be met (Hupfl, 2018).

Previous iterations of planning tools only provide expectation of patient management for limited timeframes (Williams, 2020). In contested environments, with patient movement and resupply limited, the quantity of medications present alongside forces will increase. To our knowledge, current planning tools and processes do not include risk estimation for the likelihood of an item hitting an inventory level of zero before resupply, in determining the quantity required. Introducing simulation into this process is a strategic move that can identify gaps in readiness.

A Gap in the Planning Process: There is not currently a planning tool that estimates the required number and type of pharmaceuticals needed per casualty type based on medication administration data according to Kellye Donovan (personal communication, April 24, 2023).

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III. METHODOLOGY

A. DATA

To pursue our research questions, we first needed to identify patient categories of interest to the organization and medication demands. We began by soliciting data from the Marine Corps Systems Command (MARCORSYSCOM) (via JPMT and the Naval Health Research Center (NHRC)), which provided us with two listings of patient categories that were relevant to future planning tools and scenarios. NHRC provided these codes to MARCORSYSCOM based on their existing planning tools. Subsequently, we utilized this compilation of patient categories to request the DHA's Enterprise Integrated Analytic Solutions section for de-identified patient data related to those patient categories. This data included the patients treated within the MHS over the past year.

B. DATA COLLECTION – PATIENT

MARCORSYSCOM via Naval Health Research Center (NHRC) furnished us with a set of 179 ICD-9 codes, a provision aligned with the requirements of two exercises: Air Explosion (AIREX) and NEAR-PEER output from the MPTk. These codes are of particular interest to planners within the organization and are aligned to potential threats defined in the National Defense Strategy (NDS).

We evaluated data accessibility through three potential sources of data on medication demand paired with patient categories, with the Defense Health Agency (DHA) being the primary source from which we obtained our dataset. We received data on patient age, military status, and diagnosis codes corresponding to their hospitalization. Additionally, the length of stay and the quantities of medications administered throughout their hospitalization period were received. Although information regarding "other required interventions" was not included in the dataset, we were able to gather comprehensive data, including breakdowns for each day of hospitalization and additional length-of-stay information categorized by the tier of care received.

While ICD-9 served as the standard for medical coding for several decades since its introduction in the 1970s, its limitations in capturing the intricate nuances of modern diagnoses and procedures became evident as healthcare practices advanced. By the mid-2010s, the global healthcare community recognized the need for a more comprehensive and adaptable coding system, leading to the replacement of ICD-9 with ICD-10 (Centers for Medicare & Medicaid Services, n.d.). This newer framework proved better equipped to handle the dynamic landscape of medical information. However, as the AIREX and NEAR-PEER patient distributions from MARCORSYSCOM were provided in ICD-9 format, obtaining current data from the DHA necessitated a mapping process from ICD-9 to ICD-10, which, to our knowledge, is not standardized.

Our research team developed a comprehensive mapping process, which we then executed for all ICD-9 codes available in the data sets from MARCORSYSCOM (results shown in Table 1). This procedure entailed navigating code structure differences and ensuring congruence with the varying levels of detail in the two systems. A secondary verification was then performed to ensure accuracy of the mapped codes. As ICD-10 codes are more precise, the corresponding descriptions of each code were compared side-by-side with the descriptions of the ICD-9 codes to ensure a match, based on clinical experience of the project team. Certain ICD-9 codes were found to lack corresponding ICD-10 counterparts, often due to advances in scientific understanding or changes in coding processes. For these examples, an alternative resource (ICD10data.com), was used to identify the closest corresponding ICD-10 code to the original ICD-9 code. Such determinations were administered by the Centers for Medicare and Medicaid Services (CMS). This evaluation also laid the groundwork for the future reverse mapping and translation of codes, accommodating the enhanced granularity provided by ICD-10 back into the ICD-9 codes for simulation.

C. DATA COLLECTION – MEDICATION DEMAND

The data received from MARCORSYSCOM provided patient categories as a list of ICD-9 codes. Our team then transmitted the relevant list of ICD-10 codes after conversion from the NHRC ICD-9 codes (Table 1) to the DHA's Enterprise Integrated Analytic Solutions division. We requested de-identified patient data relevant to the identified patient categories within the MHS over the preceding year. The data was received in spreadsheet format, organized in split tabs due to the coexistence of a legacy and a newer Electronic Healthcare Record (EHR) within the MHS. Further analysis proved that the newer system's data held greater relevance to our team's objectives.

Table 1. ICD-9 to ICD-10 Mapping Table

ICD-9 to ICD-10 Mapping Table		
ICD-9 Code	Description	ICD-10 Codes Included
812.31	Open fracture of shaft of humerus	S42.399B
823.92	Open fracture of unspecified part of fibula with tibia	S82.201B, S82.401B, S82.202B, S82.402B
853.1	Other and unspecified intracranial hemorrhage following injury with open intracranial wound, unspecified state of consciousness	S01.90XA, S06.360A
860	Traumatic pneumothorax without mention of open wound into thorax	S27.0XXA
863.9	Injury to gastrointestinal tract, unspecified site, with open wound into cavity	S31.609A, S36.90XA
864	Injury to liver without mention of open wound into cavity, unspecified injury	S36.119A
865	Injury to spleen without mention of open wound into cavity, unspecified injury	S36.00XA
866	Injury to kidney without mention of open wound into cavity, unspecified injury	S37.009A
866.1	Injury to kidney with open wound into cavity, unspecified injury	S31.001A, S37.009A
873.8	Other and unspecified open wound of head without mention of complication	S01.90XA, S09.90XA
910.1	Abrasion or friction burn of face, neck, and scalp except eye, infected	L08.90, S00.90XA, S10.91XA
943	Burn of unspecified degree of upper limb, except wrist and hand, unspecified site	T22.00XA, T22.40XA

Summary of Mapping from ICD-9 to ICD-10

D. PATIENT SELECTION/EXCLUSION

We first omitted data for patients aged 0–17 years old and 65 years old and above. We then selected a subset of patient categories that were well represented in our dataset based on their ICD-10 codes that would most closely align with the ICD-9 codes present in the patient proportions represented in AIREX and NEAR-PEER scenarios.

The 46 most common patient categories from the scenario were reviewed, and categories with 20 or more patients were retained, resulting in a final selection of 12 patient categories. Certain patients were encountered multiple times during our review due to conversions between ICD-10 and ICD-9 codes. This observation led to a situation where the total number of unique patients for some categories was less than 20. Due to some patients being represented in multiple categories (ex: individual patient with both diagnosis code 860 and 873.8), the number of unique patients in the analysis was 247.

In this process, we excluded cases related to burns and diagnoses deemed outside the scope of our study. However, we did include more specific diagnoses for cases with vague initial diagnoses. For example, "unspecified metatarsal" conditions were expanded to encompass patients with any specified metatarsal condition.

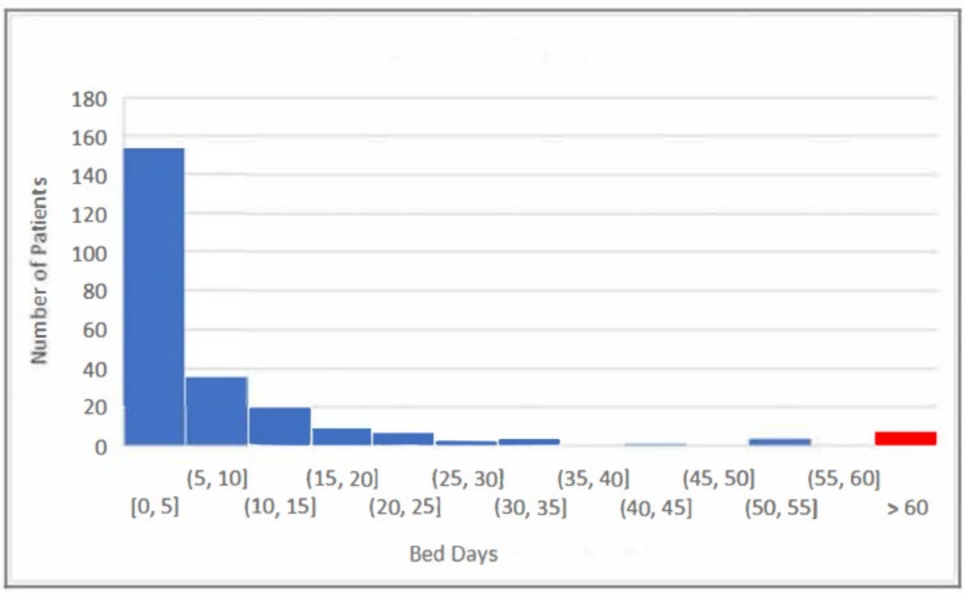
E. MEDICATION SELECTION AND STANDARDIZATION

Based on frequency of administration in the data set and clinical judgement, we selected 27 medications for use in our model. The 27 medications selected for inclusion represented 3,071 administered doses out of 34,042 total administered doses in this patient subset.

Based on our experience with the military medical record and how doses are recorded, we standardized and reported quantities for each medication. In the process of dose interpretation, we identified a crucial consideration: a recorded '0' may not necessarily signify a complete absence of dosage. For instance, '0/ 100' denoted the administration of 100mL. Similarly, '1/ 100' indicated a 100mL dosage. '1/ 200' signified a single dose administered within a 200mL volume, while '2/ 100' represented two doses, each at 100mL. In cases involving medication forms, such as a vial of furosemide listed at 20mg/ mL, if a patient received a dosage indicated as '1/.--', we inferred this to signify the utilization of a full vial (commonly available in 2mL vials), resulting in a 40mg administration. When faced with multiple vial sizes available in the market, we opted for the most frequently represented size within our dataset. In instances where no reference point was available in the dataset, we exercised discretion in selecting the largest reasonable dose for a single administration. This judgement could limit the accuracy of our eventual forecasts, given the uncertainty of the dose actually received.

F. MODELING

Once the patient categories and medications were selected, the length of stay and daily medication demands were analyzed across the patients included in the project. The daily medication demands for each patient were calculated by dividing their total quantity administered by their length of stay. This daily medication demand was found to approximate the shape of an exponential distribution across all 27 medications in our study and be inversely correlated to length of stay. The length of stay was also found to approximate the shape of an exponential distribution across these patients (Figure 1). Therefore, we used exponential distributions to represent these variables when creating assumptions for our model.



The distribution of the duration of a patient's stay for 247 retained patients.

Figure 1. Length of Stay

We developed a model representing casualties of different types occurring during a mission, each with a length of stay and medication demands, and estimating the total demand for each medication across all patients (Tables 2–5). The model (Figure 2) presumes a scenario with no constraints on medical personnel and processes or non-pharmaceutical material types, fluids, and financial resources. Implicitly, the model assumes perfect utilization of package sizes and a meticulous allocation of resources, ensuring the prevention of waste and redundancy in inventory. Additionally, it assumes all medications were strategically prepositioned or co-deployed, effectively managing prescriber variability within the broader spectrum of patient variability in demand and consumption.

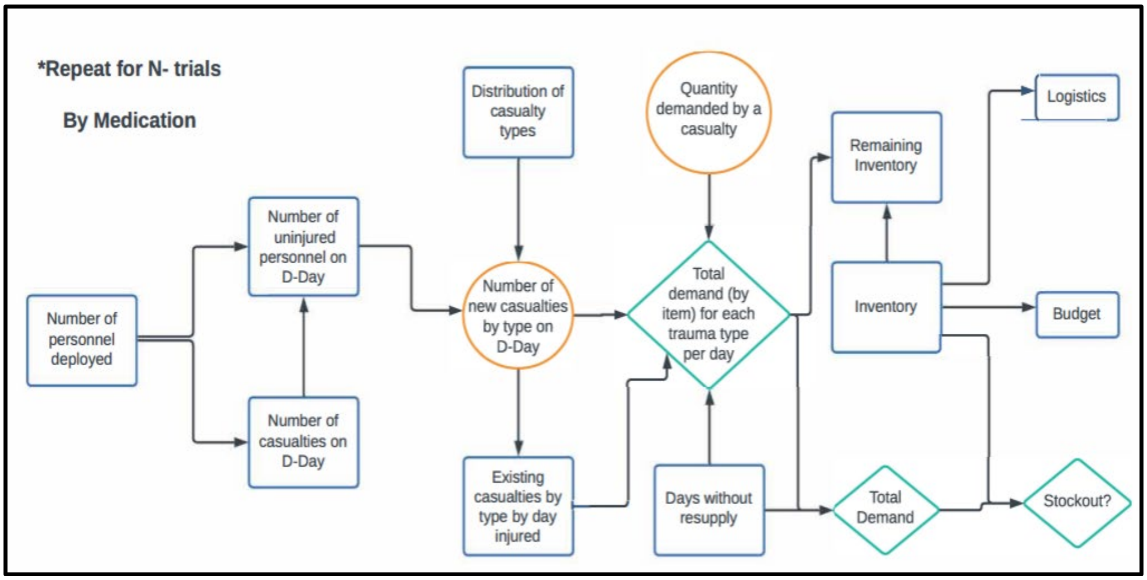


Figure 2. Map of Our Model

We calculated starting inventory using two policies, an "average" policy (A_m) that uses average daily demand and length of stay to determine the inventory for each medication (with a 20% safety stock) and a 95th percentile of simulated demand.

Table 2. Parameters of Model

Day of Mission	
h	Indexes day of mission, h= 1 , … , K
K	Length of mission in days
Casualty Type	
D	Average length of stay for all patient types (days)
S	Number of casualty types in model
g	Indexes trauma type (Figure 1), g = 1 , … , S
L_g	Probability that a casualty is of type g (Table 1). These values are a user input in the model.
O_g	Average length of stay of a given casualty type g (Table 1)
C	Total number of casualties expected for mission, a user input (see Table 7)
F_h	Number of new casualties on day h, a user input
g(i)	Patient type for ca
Medication Demand	
B_m $B_{m,g}$	Average patient demand for all patients of medication (m) Average quantity demanded for a given medication (m) for a given trauma type, g
m	Indexes medication type, m = 1 , … , 27
Q_g,m	Proportion of patients of type g from the DHA data set that had zero demand for medication m

These are the parameters within our model.

Table 3. Variables

Casualties	
$J_{h,g}$	Number of new casualties on day h
Medication Demand	
$P_{i,m,h}$	Quantity of medication demanded by a casualty (i) for a given medication on day h
$R_{m,h}$	Quantity of medication demanded (m) across all patient types on day h
Medication Consumption	
T_m	Quantity of medication demanded (m) across all patient types for all days of mission (k)
Inventory Policies	
A_m	Quantity of a Medication stocked for average inventory policy of a given medication (units vary by medication type- see Figure 7)
95th SL inventory policy	
F_m	Quantity of medication m stocked in the 95th SL inventory policy
Quantity of a medication demanded by a given casualty	
$P_{m,g(i),h}$	Quantity of medication m demanded on day h by a casualty (i) of type (g) 1. Exponential distribution 2. If value from step 1 is below threshold, zero, otherwise X_{mi}
Aggregation of medication demands for a given day	
$R_{m,h}$	Quantity of medication (m) demanded across all patient types on day h
Aggregation of medication demands for the mission	
T_m	Quantity demanded for a given medication across all patient types across all days of the mission

These are the variables within our model.

Table 4. Equations

"Average" inventory policy
$A_m = B_m \times C \times D \times 0.5 \times 1.2$
95th SL inventory policy
F_m = 95th percentile of demand quantity of medication m, from the simulation output
Number of new casualties by each type
$J_{h,g} \sim Bin\ (F_h, L_g)$
Quantity of a medication demanded by a given casualty
$X \sim EXP\left(\frac{1}{B_{m,g(i)}}\right)$ $P_{m,g(i),h}\begin{cases} 0\ if\ patient\ no\ longer\ admitted \\ 0\ if: X < -LN\left(1-Q_{m,g(i)}\right)/\left(1/B_{m,g(i)}\right) \\ X, o.w. \end{cases}$
Aggregation of medication demands for a given day
$R_{m,h} = \Sigma_i\ (P_{i,m,h})$
Aggregation of medication demands for the mission
$T_m = \Sigma\ (R_{m,h})$

Table 5. 10 Day Scenario

10 Day Scenario		
	NEAR-PEER	**AIREX**
Number of Days before Resupply/Evacuation	10	10
Day of mission	**New Casualties each day**	
1	1	8
2	6	1
3	15	1
4	5	400
5	5	1
6	1	1
7	1	1
8	51	1
9	8	1
10	1	1

These values were provided by NHRC and entered directly into the model. The model allows for this to function as a user input.

Crystal Ball in Microsoft Excel generated simulated casualties for each day of the mission, up to 500 casualties per patient category. It also generated patient medication demand and length of stay, using parameters estimated from the real patient data received from DHA as detailed in Tables 3 and 4. Since an exponential distribution was used, appropriate minimum demands were employed once the assumption generated demand to ensure the appropriate proportion of "zero demand" fields was present in the final aggregation of patient demand by day as shown in Table 5. Since our 12 patient categories did not represent all patient categories in the scenarios provided by MARCORSYSCOM, we also normalized the distribution of patient categories to account for 100% of all casualties generated by summing the user inputs for patient category probabilities (Table 6). We built a Crystal Ball Monte Carlo simulation model in Microsoft Excel. The first tab of the workbook allows for user-inputs for personnel deployed, casualty rate, casualty proportions across the 12 patient categories, and the number of days until resupply/ evacuation (Table 6).

Table 6. Comparison Parameters of Two Scenarios

		Single MEU	Single CSG	
		2200	7500	
Possible casualties within 60 days (from JMPT)	7500	Scenario 1	Scenario 2	
Number of Days before Resupply/Evacuation	14	Near Peer Proportion	Airex proportion	Description
Proportion of 812.31	0.0019	0.010484938	0.0019	Open fracture of shaft of humerus
Proportion of 823.92	0.0028	0.003173254	0.0028	Open fracture of unspecified part of fibula with tibia
Proportion of 853.10	0.0006	0.00301555	0.0006	Other and unspecified intracranial hemorrhage following injury with open intracranial wound, unspecified state of consciousness
Proportion of 860.0	0.0051	0.006035152	0.0051	Traumatic pneumothorax without mention of open wound into thorax
Proportion of 863.90	0.0053	0.014355519	0.0053	Injury to gastrointestinal tract, unspecified site, with open wound into cavity
Proportion of 864.0	0.0053	0.018867314	0.0053	Injury to liver without mention of open wound into cavity, unspecified injury
Proportion of 865.00	0.0053	0.025770899	0.0053	Injury to spleen without mention of open wound into cavity, unspecified injury
Proportion of 866.00	0.0053	0.014417531	0.0053	Injury to kidney without mention of open wound into cavity, unspecified injury
Proportion of 866.10	0.0053	0.046069706	0.0053	Injury to kidney with open wound into cavity, unspecified injury
Proportion of 873.8	0.0356	0.02905683	0.0356	Other and unspecified open wound of head without mention of complication
Proportion of 910.1	0.0038	0.004483177	0.0038	Abrasion or friction burn of face, neck, and scalp except eye, infected
Proportion of 943.00	0.0126	0.004808217	0.0126	Burn of unspecified degree of upper limb, except wrist and hand, unspecified site

Table 6 represents user inputs for the casualty proportions from the two scenarios tested.

Once each patient was generated, with a corresponding length of stay, day of admission, day of discharge, and daily demand for each 27 medications, the totals for each day across all patient categories in the mission, were calculated and summed to get total demand over the mission (T_m). The model then identifies the day of mission and returns the cumulative sum to that point as the crystal ball forecast cell. This setup allows for each “mission” to be simulated repeatedly in a Monte Carlo fashion, returning aggregate demand for each medication for each trial. 1000 trials were conducted for both the AIREX and NEAR-PEER scenario, with their results exported and saved for further analysis.

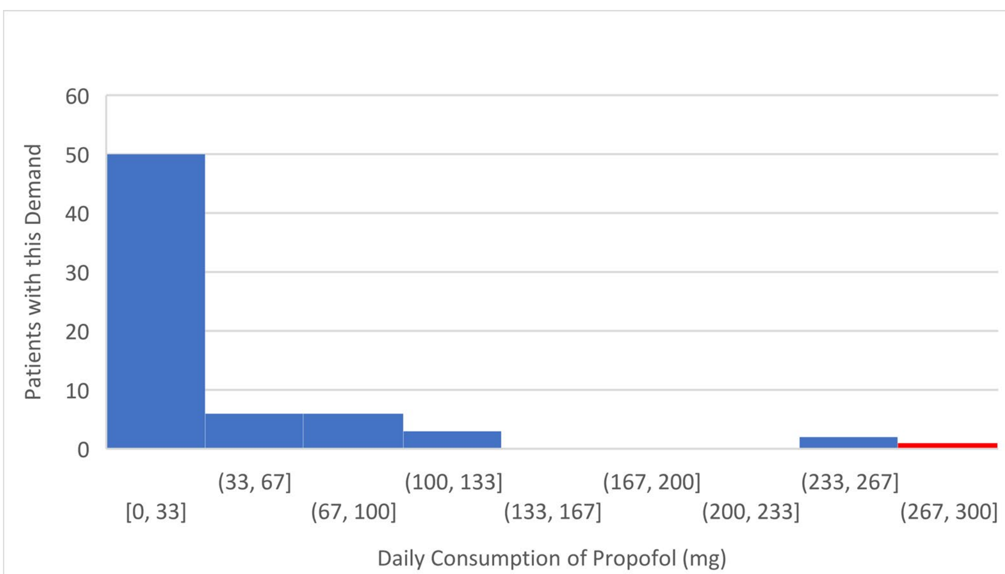
IV. RESULTS AND ANALYSIS

This section describes the data received from MARCORSYSCOM and DHA that was analyzed to build our model. We then will discuss the simulation results and analysis and compare the potential results of two inventory strategies against the simulated demand.

A. ANALYSIS OF PATIENT DATA

Initial data receipt from MARCORSYSCOM provided 183 patient categories for the two scenarios of interest. Of these, 12 were found to have at least 20 results within the patient data from DHA. Among the patients included in our project, 27 essential medications were identified, crucial for any preposition or co-deployment of pharmaceuticals with deploying forces or resupply. Demands for all of these were found to approximate exponential distributions. An example is included in Figure 3. Table 7 summarizes patient consumptions of each of the 27 medication types identified by patient category.

1. Medication Consumption



Depicting patient medication consumption values from DHA, for propofol. It roughly approximates an exponential distribution.

Figure 3. Propofol Demand Histogram

Table 7. Patient Consumption from DHA

Patient Consumption from DHA	812.31		823.92		853.1		860		863.9		864	
	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD
Acetaminophen oral (mg)	641.44	1196.00	628.96	1309.31	484.35	1558.02	348.65	1024.79	248.31	706.65	34.38	80.18
Albumin Inj (g)	0.72	1.67	0.21	0.66	0.56	2.25	0.54	2.32	0.53	1.96	0.00	0.00
Albuterol Inh (mg)	0.18	0.40	0.10	0.32	0.00	0.02	0.02	0.10	0.01	0.03	0.00	0.00
Amikacin Inj (mg)	0.00	0.00	0.00	0.00	0.00	0.00	0.50	3.55	5.72	16.43	0.00	0.00
Calcium ChlorideInj (mg)	1.01	3.82	0.70	2.52	1.27	3.59	0.57	2.49	1.91	5.14	0.96	4.90
Cefazolin Inj (mg)	219.51	398.95	599.69	993.19	396.80	1473.19	118.81	528.77	210.64	839.04	38.46	196.12
Dexamethasone (mg) [With and without preserva	0.43	1.03	1.43	4.12	0.60	2.49	0.77	3.70	0.19	0.75	0.19	0.98
Epinephrine Inj (mg)	0.00	0.01	0.01	0.02	0.00	0.00	0.00	0.01	0.01	0.04	0.00	0.00
Fentanyl [Preservative-Free] Inj (mg)	64.46	90.09	97.33	132.37	76.78	147.30	69.88	162.17	40.59	82.95	26.44	79.40
Fursomide Inj (mg)	0.09	0.35	0.88	2.77	0.27	0.89	0.08	0.49	0.26	0.85	0.10	0.49
Hydromorphone Inj (mg) [With and without prese	0.14	0.17	0.35	0.53	0.37	0.84	0.18	0.51	0.20	0.38	0.00	0.00
Hydromorphone Inj (mg) [Preservative Free]	0.04	0.11	0.03	0.10	0.14	0.27	0.06	0.23	0.11	0.33	0.19	0.47
Ipratropium/Albuterol (nebules)	0.00	0.00	0.00	0.00	0.02	0.09	0.02	0.08	0.03	0.10	0.02	0.10
Ketamine Inj (mg)	17.33	58.00	21.79	66.21	56.09	294.16	33.18	183.47	143.11	426.07	14.42	53.93
Ketorolac Inj (mg)	2.40	5.61	7.96	19.26	1.04	4.13	4.46	17.55	1.19	5.32	0.58	2.94
Lidocaine Inj (mg) [Preservative Free]	0.91	2.49	1.89	3.42	0.58	1.62	1.84	8.39	0.73	2.49	0.00	0.00
Midazolam Inj (mg) [With and without preservativ	0.15	0.18	0.32	0.36	0.16	0.28	0.15	0.37	0.16	0.31	0.01	0.03
Morphine Inj (mg) [With and without preservative	0.03	0.13	0.38	1.39	0.00	0.00	0.27	1.04	0.35	1.21	0.72	1.77
Norepinephrine Inj (mg)	0.07	0.17	0.03	0.11	0.16	0.53	0.05	0.25	0.13	0.47	0.00	0.00
Ondansetron (mg) [Preservative Free]	0.81	2.33	0.32	0.56	1.11	2.71	0.68	1.63	0.21	0.64	1.22	2.54
Oxycodone Oral (mg)	0.30	1.21	0.60	2.16	0.01	0.03	0.80	2.91	1.27	3.47	0.38	1.96
Phenylephrine Inj (mg)	0.41	0.69	1.11	1.54	0.53	1.81	0.32	1.16	0.29	0.54	0.00	0.00
Propofol Inj (mg)	13.12	27.65	21.59	31.85	56.46	129.68	37.74	117.98	58.55	165.62	3.85	19.61
Rocuronium Inj (mg)	1.88	3.61	6.41	13.77	5.11	13.92	3.75	12.15	2.37	4.16	0.96	4.90
Sodium Chloride Inh (mg)	0.06	0.15	0.03	0.08	0.07	0.19	0.06	0.26	0.08	0.27	0.00	0.00
Vancomycin Inj (mg)	19.54	38.29	90.80	156.72	154.59	506.31	39.40	236.09	180.33	555.91	0.00	0.00
Vasopressin Inh (units)	0.15	0.52	0.04	0.14	0.10	0.59	0.11	0.63	0.50	2.16	0.00	0.00

	865.00		866.00		866.10		873.80		910.10		943.00	
	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD
Acetaminophen oral (mg)	162.63	455.48	354.87	642.31	322.61	619.82	321.30	1203.40	524.85	1574.05	309.18	626.02
Albumin Inj (g)	0.27	0.86	0.44	1.19	0.40	1.14	0.53	2.05	0.51	1.71	0.60	1.23
Albuterol Inh (mg)	0.04	0.21	0.02	0.05	0.02	0.05	0.01	0.07	0.02	0.09	0.01	0.02
Amikacin Inj (mg)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.05	4.41	14.47	22.47
Calcium ChlorideInj (mg)	1.16	3.99	0.45	2.03	0.41	1.94	0.72	2.74	0.00	0.00	2.93	6.17
Cefazolin Inj (mg)	69.14	172.26	115.47	354.17	115.07	338.63	307.74	1280.91	128.85	459.80	11.87	48.56
Dexamethasone (mg) [With and without preserva	0.02	0.06	0.02	0.05	0.07	0.24	0.44	1.97	0.29	0.97	0.07	0.16
Epinephrine Inj (mg)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.08
Fentanyl [Preservative-Free] Inj (mg)	40.78	56.39	59.75	100.26	60.54	95.51	136.17	600.57	26.50	51.59	53.69	58.71
Fursomide Inj (mg)	0.13	0.72	0.07	0.33	0.07	0.31	0.15	0.68	2.02	10.60	1.29	4.37
Hydromorphone Inj (mg) [With and without prese	0.23	0.50	1.72	5.76	1.64	5.49	0.21	0.65	0.17	0.67	0.23	0.36
Hydromorphone Inj (mg) [Preservative Free]	0.07	0.22	0.05	0.13	0.04	0.12	0.08	0.21	0.01	0.03	0.15	0.40
Ipratropium/Albuterol (nebules)	0.00	0.01	0.00	0.01	0.01	0.02	0.01	0.07	0.01	0.05	0.05	0.13
Ketamine Inj (mg)	10.32	23.61	12.21	30.28	12.11	29.01	32.03	220.60	1.57	8.44	118.27	229.95
Ketorolac Inj (mg)	0.00	0.00	2.71	8.34	2.47	7.97	5.45	16.09	2.34	8.39	0.28	0.79
Lidocaine Inj (mg) [Preservative Free]	0.78	2.34	0.00	0.00	0.51	2.37	0.36	1.26	0.00	0.00	0.57	2.42
Midazolam Inj (mg) [With and without preservativ	0.14	0.37	0.21	0.48	0.22	0.47	0.19	0.69	0.16	0.62	0.31	0.55
Morphine Inj (mg) [With and without preservative	0.25	1.35	0.02	0.07	0.02	0.07	0.01	0.11	0.13	0.44	0.48	1.54
Norepinephrine Inj (mg)	0.05	0.25	0.00	0.00	0.00	0.00	0.09	0.40	0.00	0.02	0.23	0.62
Ondansetron (mg) [Preservative Free]	0.66	1.86	0.07	0.17	0.10	0.24	0.96	2.33	0.34	0.88	0.29	0.90
Oxycodone Oral (mg)	2.47	6.92	2.53	6.85	2.38	6.54	0.01	0.06	0.41	2.19	1.79	3.46
Phenylephrine Inj (mg)	0.10	0.35	0.15	0.43	0.28	0.80	0.34	1.38	0.36	1.00	0.30	0.46
Propofol INj (mg)	30.41	85.50	8.70	28.17	8.92	27.02	148.94	655.58	43.59	111.96	38.38	58.79
Rocuronium Inj (mg)	1.05	3.39	1.54	3.57	2.15	4.70	2.75	10.62	2.00	4.32	3.59	4.25
Sodium Chloride Inh (mg)	0.09	0.25	0.08	0.27	0.07	0.26	0.04	0.15	0.05	0.25	0.03	0.08
Vancomycin Inj (mg)	107.92	525.14	170.75	651.47	160.28	620.84	90.25	384.35	235.65	560.54	97.60	124.95
Vasopressin Inh (units)	0.00	0.00	0.02	0.11	0.02	0.10	0.06	0.44	0.02	0.09	1.59	3.82

Summary of medication consumption by patient category. Columns reflect patient categories from Table 1.

2. Length of Stay

In regard to our primary research questions, the initial data from DHA is relevant, particularly for answering the question of "what medications should be stocked?" While this list is not conclusive, it represents items that would certainly be needed in either scenario. Figure 3 provides insight about the quantities demanded per patient, especially in regard to their variability. Not all patients have the same demand, and some patients rarely can require significantly more medications than the majority of patients, making demand of the "next casualty" uncertain. Table 8 provides insights in the relative demands across casualty types. The demands patterns vary from casualty type to casualty type. This means that even for the same number of expected casualties in a given scenario, changing the proportion of patient types could change the expected overall pharmaceutical demand for the mission.

Table 8. Statistics of Length of Stay by Patient Categories

Length of Stay			
Patient Category	**Number of Patients Included**	**Average Length of Stay (Days)**	**Standard Deviation of LOS (Days)**
812.31	17	21.47	21.77
823.92	13	16.61	16.21
853.1	32	14.59	20.72
860	101	8.74	13.44
863.9	46	14.59	23.43
864	26	2.96	2.46
865	31	14.06	13.32
866	20	11.15	11.4
866.1	22	11.18	10.87
873.8	57	10.26	16.65
910.1	29	10.03	18.68
943	21	26.57	34.77

Table 8 depicts relative length of stay by each patient category. This can be insightful for planning purposes when resupply/evacuation opportunities are limited, as it illustrates how long a patient can be expected to require hospital/inpatient level medication attention (and resource consumption).

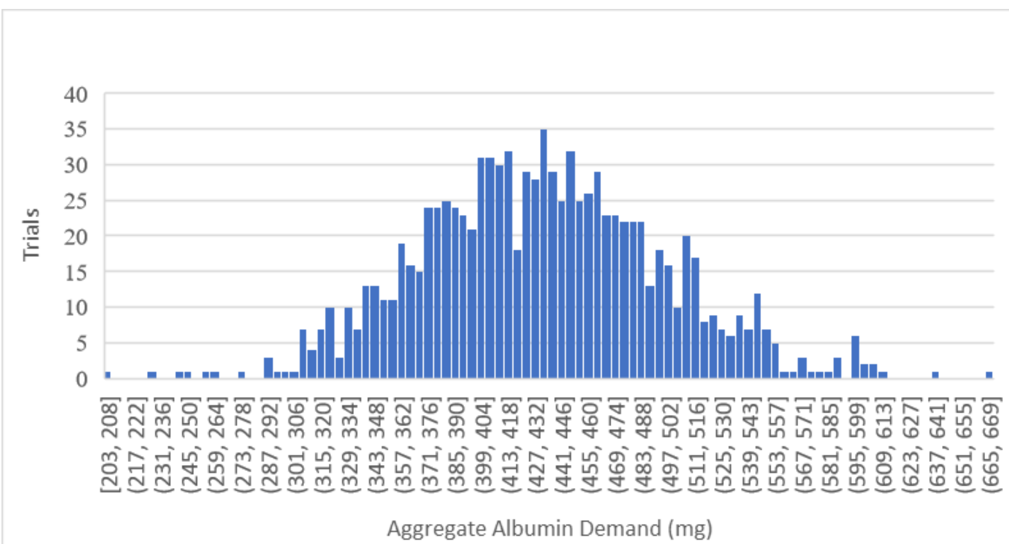
B. SIMULATION RESULTS AND ANALYSIS

1. Demand Distributions

We ran the simulation model for two scenarios provided by MARCORSYSCOM. The first was titled "AIREX" and represented an airborne explosion near a collection of Naval assets. The second was "NEAR-PEER" and represented a ground-based combat scenario against a NEAR-PEER competitor. The number of personnel and casualties both differed in these scenarios, as well as the proportion of patient categories (Tables 6 and 7).

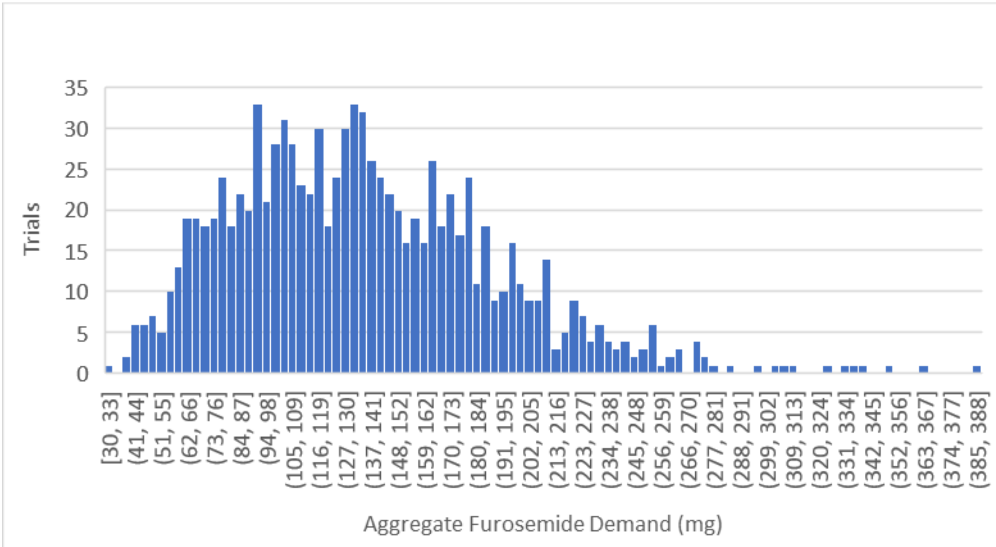
The generated demand quantities, especially when casualty numbers were higher, exhibited mostly normal distribution shapes. However, unusual shapes were observed for specific medications, likely contingent on the expected number and types of casualties. Running individual simulations, considering the number and types of casualties along with available patient data, is recommended over relying on static results from a single trial.

Most medications exhibited a normal distribution of aggregate demand. An example is provided by Albumin, in Figure 4. However, some, such as amikacin, furosemide, norepinephrine, lidocaine, calcium chloride, vasopressin, and epinephrine, displayed a skewed distribution. Furosemide's demand distribution is shown in Figure 5.



T_m for Albumin across 1000 simulations.

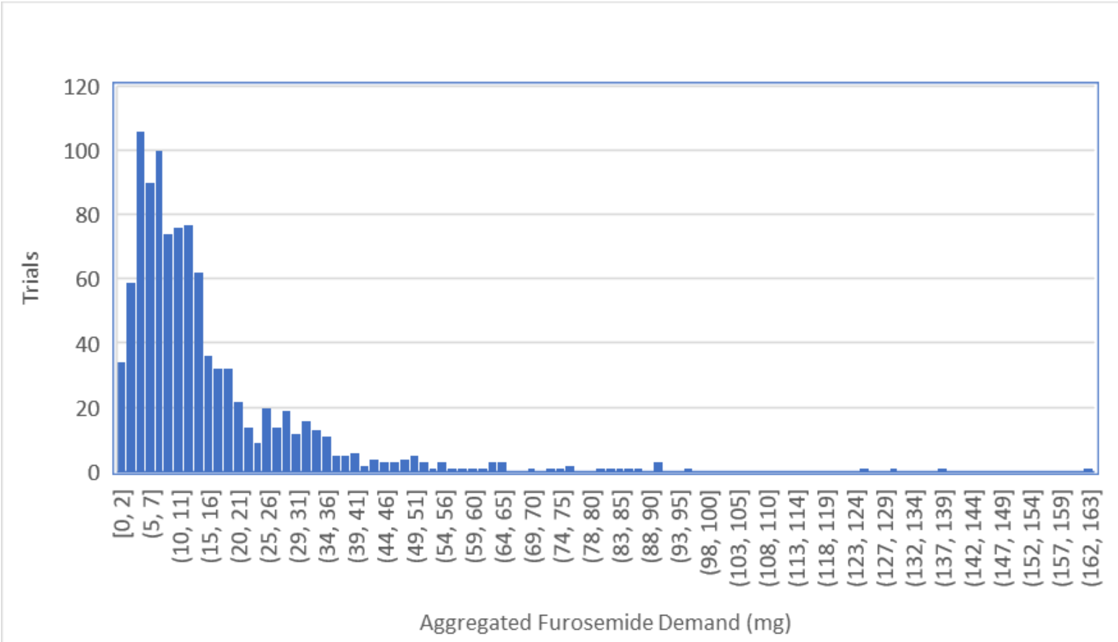
Figure 4. Albumin Demand (AIREX)



T_m for Furosemide across 1000 simulations.

Figure 5. Furosemide Demand (AIREX)

Conversely, in the NEAR-PEER scenario, medications tended to exhibit a slightly right-skewed distribution, indicative of an overall lower average demand, aligning with the lower number of casualties in this scenario, as in Figure 6. An important note regarding the shapes of the distributions is that right-skewed distributions contain many values that are less than the average value of the distribution. If an inventory policy were only based on the average demand of patients, there would be a higher chance (than a normal distribution) of demanding less medication than the averaged value. If an inventory policy was based on this average for a medication with a skewed demand distribution, it would have a higher likelihood of carrying excess inventory compared to a demand that was normally distributed.



Representative of a right-skewed distribution of the T_m of furosemide across 1000 trials.

Figure 6. Furosemide Demand (NEAR-PEER)

Table 9 encapsulates summary statistics derived from the simulation that is a comprehensive overview of the demand dynamics across the two scenarios. These statistics serve as an insightful portrayal of the simulated demand for each specific scenario.

Table 9. Simulation Output

1000 simulation output	AIREX			
	Mean	Median	95th Percentile	St Dev
Acetaminophen oral (mg)	429509	428239	512836	49154
Albumin Inj (g)	433	432	543	64
Albuterol Inh (mg)	23	22	37	7
Amikacin Inj (mg)	1371	1349	2269	498
Furosemide Inj (mg)	136	131	234	54
Hydromorphone Inj (mg) [With and without preservative]	1189	1186	1456	157
Midazolam Inj (mg) [With and without preservative]	293	293	341	28
Morphine Inj (mg) [With and without preservative]	131	131	188	32
Norepinephrine Inj (mg)	41	41	59	10
Phenylephrine Inj (mg)	297	295	367	41
Vancomycin Inj (mg)	154569	153019	188288	20066
Ketamine Inj (mg)	39408	39127	53020	7841
Ketorolac Inj (mg)	2188	2181	2864	403
Oxycodone Oral (mg)	1636	1609	2084	256
Lidocaine Inj (mg) [Preservative Free]	426	421	571	82
Ondansetron (mg) [Preservative Free]	780	777	946	98
Propofol Inj (mg)	63148	62739	81069	10352
Rocuronium Inj (mg)	2599	2584	3178	342
Vasopressin Inj (units)	106	100	197	48
Calcium ChlorideInj (mg)	687	675	952	145
Cefazolin Inj (mg)	188185	186804	237723	27155
Dexamethasone (mg) [With and without preservative]	224	220	301	42
Epinephrine Inj (mg)	3	3	6	1
Ipratropium/Albuterol (nebules)	8	8	12	2
Fentanyl [Preservative-Free] Inj (mg)	122761	122257	141990	11578
Hydromorphone Inj (mg) [Preservative Free]	82	82	101	12
Sodium Chloride Inh (mg)	57	56	73	10

1000 simulation output	NEAR-PEAR			
	Mean	Median	95th Percentile	St Dev
Acetaminophen oral (mg)	69081	68027	102646	19381
Albumin Inj (g)	65	62	106	23
Albuterol Inh (mg)	4	4	10	3
Amikacin Inj (mg)	83	60	268	86
Furosemide Inj (mg)	15	11	44	16
Hydromorphone Inj (mg) [With and without preservative]	186	183	286	56
Midazolam Inj (mg) [With and without preservative]	46	45	64	10
Morphine Inj (mg) [With and without preservative]	20	19	41	11
Norepinephrine Inj (mg)	5	5	11	3
Phenylephrine Inj (mg)	51	49	83	17
Vancomycin Inj (mg)	23882	23248	36728	7107
Ketamine Inj (mg)	5117	4729	9015	2328
Ketorolac Inj (mg)	378	358	668	158
Oxycodone Oral (mg)	247	235	407	92
Lidocaine Inj (mg) [Preservative Free]	78	73	148	36
Ondansetron (mg) [Preservative Free]	127	124	185	34
Propofol Inj (mg)	9524	9061	15886	3457
Rocuronium Inj (mg)	417	408	652	129
Vasopressin Inj (units)	7	5	21	7
Calcium ChlorideInj (mg)	87	82	163	43
Cefazolin Inj (mg)	33945	32684	52933	10879
Dexamethasone (mg) [With and without preservative]	43	42	77	19
Epinephrine Inj (mg)	0	0	1	0
Ipratropium/Albuterol (nebules)	1	1	2	1
Fentanyl [Preservative-Free] Inj (mg)	19306	19150	26335	3997
Hydromorphone Inj (mg) [Preservative Free]	12	12	19	4
Sodium Chloride Inh (mg)	9	9	14	3

Represents summary statistics of simulated demand for each scenario.

Despite having a higher number of overall casualties, the demand results were not proportional to the number of casualties. Despite having 4.4 times the number of patients in the AIREX scenario (416/94), only five medications had more than twice the average demand of the NEAR-PEER scenario. This is likely due to the differences in distribution of casualty types between the two scenarios. This is illustrated in Table 10.

Table 10. AIREX Per-patient Values Divided by NEAR-PEER Patient Values

AIREX per-patient values Divided by NEAR-PEER Per-Patient Values			
	Mean	Median	95th Percentile
Acetaminophen oral	1.40	1.42	1.13
Albumin Inj	1.50	1.57	1.15
Albuterol Inh	1.23	1.40	0.82
Amikacin Inj	3.73	5.04	1.91
Furosemide Inj	2.02	2.80	1.19
Hydromorphone Inj [With and without preservative]	1.44	1.47	1.15
Midazolam Inj [With and without preservative]	1.45	1.48	1.21
Morphine Inj [With and without preservative]	1.47	1.57	1.04
Norepinephrine Inj	1.87	2.03	1.26
Phenylephrine Inj	1.31	1.36	0.99
Vancomycin Inj	1.46	1.49	1.16
Ketamine Inj	1.74	1.87	1.33
Ketorolac Inj	1.31	1.38	0.97
Oxycodone Oral	1.50	1.54	1.16
Lidocaine Inj [Preservative Free]	1.24	1.30	0.87
Ondansetron [Preservative Free]	1.39	1.42	1.15
Propofol Inj	1.50	1.56	1.15
Rocuronium Inj	1.41	1.43	1.10
Vasopressin Inj	3.32	4.28	2.13
Calcium Chloride Inj	1.78	1.87	1.32
Cefazolin Inj	1.25	1.29	1.01
Dexamethasone [With and without preservative]	1.16	1.19	0.89
Epinephrine Inj	3.89	5.13	2.34
Ipratropium/Albuterol	2.10	2.23	1.46
Fentanyl [Preservative-Free] Inj	1.44	1.44	1.22
Hydromorphone Inj [Preservative Free]	1.50	1.55	1.20
Sodium Chloride Inh	1.45	1.48	1.15

Represents the demand values per patient from AIREX divided by the demand values per patient from NEAR-PEER, resulting in a unit-less ratio of demand between the two simulations. Higher values are shown in green and lower values in red.

2. Evaluating Inventory Policies

In our experience, once one has data for a given demand, one can be tempted to just use the "average" value to forecast future demand. For comparative analysis in our project (Table 11), we assessed a policy of stocking 95th percent service level value (F_m) of each medication in the two scenarios against an inventory policy we will refer to as the average inventory policy (A_m). The average inventory policy involved estimating the expected number of casualties over a 10-day period, multiplying this by the average daily demand per patient for all patient categories, and then further multiplying by the average length of stay derived from the patient distributions, divided by two. A 20% safety stock was added to this calculation.

The average risk of stocking out of at least one medication for the 95% service level policies was 0.636 and 0.642 for AIREX and NEAR-PEER, respectively. For every simulation in both scenarios, the average inventory policy always had at least one stockout.

In both scenarios, the average inventory policy exhibited inferior performance compared to an inventory policy based on the service levels derived from the simulations. Specifically, in the AIREX scenario, 8 out of the 27 medications would have been stocked at insufficient levels for any of the 1000 trials—a zero percent service level. Conversely, 16 out of the 27 medications would have been stocked at levels exceeding the demand required for all 1,000 trials—a 100% service level.

In the NEAR-PEER scenario, the average inventory policy indicated that six medications would have been inadequately stocked for any of the thousand trials, while 17 medications would have been stocked at levels surpassing the demand for all 1,000 simulations.

Customizing the risk of stockouts based on cost and other logistical constraints is feasible through this approach. This opens the possibility of employing linear programming or other optimization methods. This could aid in identifying the most valuable medications within the available subset, akin to solving a traditional "knapsack problem" where certain minimums are obligatory given that the other necessary information (product dimensions, weights, prices, etc.) are already available to MARCORSYSCOM.

Table 11. AIREX and NEAR-PEER Inventory Comparison

	AIREX 0.95 SL Inv		NEAR-PEER	
Demand Results	**Airex 0.95 SL Inv**	**Airex Avg Inv**	**NP 0.95 SL Inv**	**NP Avg Inv**
Acetaminophen oral (mg)	512850	663494	102647	151238
Albumin Inj (g)	543	949	107	216
Albuterol Inh (mg)	37	51	10	12
Amikacin Inj (mg)	2270	2993	268	682
Furosemide Inj (mg)	234	1598	44	364
Hydromorphone Inj (mg) [With and without preservative]	1457	384567	286	87659
Midazolam Inj (mg) [With and without preservative]	341	1272	64	290
Morphine Inj (mg) [With and without preservative]	188	11	41	3
Norepinephrine Inj (mg)	59	182918	11	41695
Phenylephrine Inj (mg)	367	1027	83	234
Vancomycin Inj (mg)	188292	623	36728	142
Ketamine Inj (mg)	53030	177	9015	40
Ketorolac Inj (mg)	2864	38	669	9
Oxycodone Oral (mg)	2085	85220	408	19425
Lidocaine Inj (mg) [Preservative Free]	571	8296	148	1891
Ondansetron (mg) [Preservative Free]	946	2271	185	518
Propofol Inj (mg)	81084	406	15889	93
Rocuronium Inj (mg)	3178	774	652	176
Vasopressin Inj (units)	197	130	21	30
Calcium ChlorideInj (mg)	952	1569	163	358
Cefazolin Inj (mg)	237741	1981	52940	452
Dexamethasone (mg) [With and without preservative]	301	710	77	162
Epinephrine Inj (mg)	6	139527	1	31804
Ipratropium/Albuterol (nebules)	12	6654	2	1517
Fentanyl [Preservative-Free] Inj (mg)	141993	116	26335	27
Hydromorphone Inj (mg) [Preservative Free]	101	189982	19	43305
Sodium Chloride Inh (mg)	73	430	14	98

Compares the inventory for each need between the two inventory policies for both scenarios (Am and Fm), based on the simulation results. Higher values are shown in green and lower values in red.

Table 12 allows for some conclusions to be drawn regarding inventory policies. In general, the service level policies provide less quantity of medication than the average inventory policies (18 out of 27 and 19 out of 27). However, this trend is sometimes inverted, likely due to the patient distribution within the simulated scenario compared to the raw proportions from the patient data. Of particular interest is vasopressin, which yields a higher inventory level for the average policy in one scenario, but a higher inventory level for the service level policy in the other scenario. This could indicate that further research may not yield predictable patterns on which inventory policy is more likely to yield a higher inventory level for a given medication.

Table 12. Probability of Stockout

Probability of stockout				
	AIREX		NEAR-PEER	
	0.95 SL inventory policy	"Averages" Policy	0.95 SL inventory policy	"Averages" Policy
Acetaminophen oral (mg)	0.049	0	0.049	0
Albumin Inj (g)	0.049	0	0.049	0
Albuterol Inh (mg)	0.049	0.001	0.049	0.02
Amikacin Inj (mg)	0.049	0.004	0.049	0
Furosemide Inj (mg)	0.049	0	0.049	0
Hydromorphone Inj (mg) [With and without preservative]	0.049	0	0.049	0
Midazolam Inj (mg) [With and without preservative]	0.049	0	0.049	0
Morphine Inj (mg) [With and without preservative]	0.049	1	0.049	0.989
Norepinephrine Inj (mg)	0.049	0	0.049	0
Phenylephrine Inj (mg)	0.049	0	0.049	0
Vancomycin Inj (mg)	0.049	1	0.049	1
Ketamine Inj (mg)	0.049	1	0.049	1
Ketorolac Inj (mg)	0.049	1	0.049	1
Oxycodone Oral (mg)	0.049	0	0.049	0
Lidocaine Inj (mg) [Preservative Free]	0.049	0	0.049	0
Ondansetron (mg) [Preservative Free]	0.049	0	0.049	0
Propofol Inj (mg)	0.049	1	0.049	1
Rocuronium Inj (mg)	0.049	1	0.049	0.984
Vasopressin Inj (units)	0.049	0.3	0.049	0.012
Calcium ChlorideInj (mg)	0.049	0	0.049	0
Cefazolin Inj (mg)	0.049	1	0.049	1
Dexamethasone (mg) [With and without preservative]	0.049	0	0.049	0
Epinephrine Inj (mg)	0.049	0	0.049	0
Ipratropium/Albuterol (nebules)	0.049	0	0.049	0
Fentanyl [Preservative-Free] Inj (mg)	0.049	1	0.049	1
Hydromorphone Inj (mg) [Preservative Free]	0.049	0	0.049	0
Sodium Chloride Inh (mg)	0.049	0	0.049	0

Illustrates the probability of a stockout of each individual medication. A lower number is typically better, unless the inventory getting that low number is excessive. High numbers indicate poor performance. Highlighted values indicated high likelihood of stockout.

It is worth mentioning that Table 13 identifies 100% stockout risk by using the average policy in the same medications for both scenarios. Upon review, there does not seem to be a clear link between these medications that would put them at a particular risk of stockout (e.g., they are not in the same therapeutic class). Our best assumption is that the proportionality of patient categories within the simulations led to this trend, but it warrants further analysis.

Table 13. Expected Unmet Demand, Given a Stockout Occurred

Inventory Policy Performance				
	Expected Excess inventory, when given no stockout occurs			
	AIREX		NEAR-PEER	
	0.95 SL inventory policy	"Averages" Policy	0.95 SL inventory policy	"Averages" Policy
Acetaminophen oral (mg)	89002	233985	35951	82156
Albumin Inj (g)	117	516	44	151
Albuterol Inh (mg)	15	28	6	8
Amikacin Inj (mg)	959	1629	198	599
Furosemide Inj (mg)	104	1462	32	349
Hydromorphone Inj (mg) [With and without preservative]	285	383377	107	87472
Midazolam Inj (mg) [With and without preservative]	51	979	19	244
Morphine Inj (mg) [With and without preservative]	60	N/A	22	1
Norepinephrine Inj (mg)	19	182877	6	41690
Phenylephrine Inj (mg)	74	730	34	183
Vancomycin Inj (mg)	35991	N/A	13717	N/A
Ketamine Inj (mg)	14550	N/A	4198	N/A
Ketorolac Inj (mg)	721	N/A	312	N/A
Oxycodone Oral (mg)	479	83584	173	19178
Lidocaine Inj (mg) [Preservative Free]	155	7870	75	1813
Ondansetron (mg) [Preservative Free]	178	1491	63	391
Propofol Inj (mg)	19182	N/A	6808	N/A
Rocuronium Inj (mg)	619	N/A	251	18
Vasopressin Inj (units)	97	48	15	23
Calcium ChlorideInj (mg)	282	882	82	271
Cefazolin Inj (mg)	52823	N/A	20380	N/A
Dexamethasone (mg) [With and without preservative]	82	487	36	118
Epinephrine Inj (mg)	3	139524	0	31804
Ipratropium/Albuterol (nebules)	4	6646	1	1516
Fentanyl [PreservativeFree] Inj (mg)	20469	N/A	7500	N/A
Hydromorphone Inj (mg) [Preservative Free]	21	189900	7	43292
Sodium Chloride Inh (mg)	17	373	6	89

Table 14 represents the average value of unmet demand in the event of a stockout. A smaller value is better in this case, indicating a better inventory level.

Table 14. Inventory Policy Performance

Expected Unmet Demand, Given a Stockout Occurred				
	AIREX		NEAR-PEER	
	0.95 SL inventory policy	"Averages" Policy	0.95 SL inventory policy	"Averages" Policy
Acetaminophen oral (mg)	24708	N/A	12001	N/A
Albumin Inj (g)	28	N/A	14	N/A
Albuterol Inh (mg)	4	9	2	2
Amikacin Inj (mg)	247	189	60	N/A
Furosemide Inj (mg)	38	N/A	25	N/A
Hydromorphone Inj (mg) [With and without preservative]	66	N/A	32	N/A
Midazolam Inj (mg) [With and without preservative]	14	N/A	5	N/A
Morphine Inj (mg) [With and without preservative]	15	120	7	18
Norepinephrine Inj (mg)	6	N/A	2	N/A
Phenylephrine Inj (mg)	20	N/A	11	N/A
Vancomycin Inj (mg)	9540	153945	3782	23740
Ketamine Inj (mg)	4090	39231	1845	5077
Ketorolac Inj (mg)	184	2151	107	369
Oxycodone Oral (mg)	132	N/A	67	N/A
Lidocaine Inj (mg) [Preservative Free]	49	N/A	21	N/A
Ondansetron (mg) [Preservative Free]	56	N/A	19	N/A
Propofol Inj (mg)	5844	62742	2098	9432
Rocuronium Inj (mg)	184	1826	77	245
Vasopressin Inj (units)	26	35	7	8
Calcium ChlorideInj (mg)	58	N/A	31	N/A
Cefazolin Inj (mg)	12763	186203	7466	33494
Dexamethasone (mg) [With and without preservative]	23	N/A	13	N/A
Epinephrine Inj (mg)	1	N/A	0	N/A
Ipratropium/Albuterol (nebules)	1	N/A	0	N/A
Fentanyl [PreservativeFree] Inj (mg)	4364	122644	1970	19280
Hydromorphone Inj (mg) [Preservative Free]	6	N/A	2	N/A
Sodium Chloride Inh (mg)	4	N/A	2	N/A

Table 15 gives excess inventory when the medication did not stockout. A smaller value is better here, as large values indicate wasted space, money, and effort. The average policies tended to have larger relative excess values in the event of no stockout.

As illustrated (see Figure 7), the "averages policy" had significantly more items stock out on each simulation, but the two scenarios had similar number of stockouts. The x-axis represents the number of medications stocked out. The y-axis represents how many simulations stocked out its corresponding number of medications. After analyzing unmet demand in the event of a stockout, and excess inventory in the event of no stockout, the average policy was outperformed by the service level policy in both regards (Tables 14 and 15). This policy performance has the possibility to translate into wasted resources (dollars, manpower, effort, storage space) for excess inventory and potential patient harm or suffering in the unmet demands. The inventory policy performance of the service level policy also outperformed the average policies in the number of line items stocked out in both scenarios.

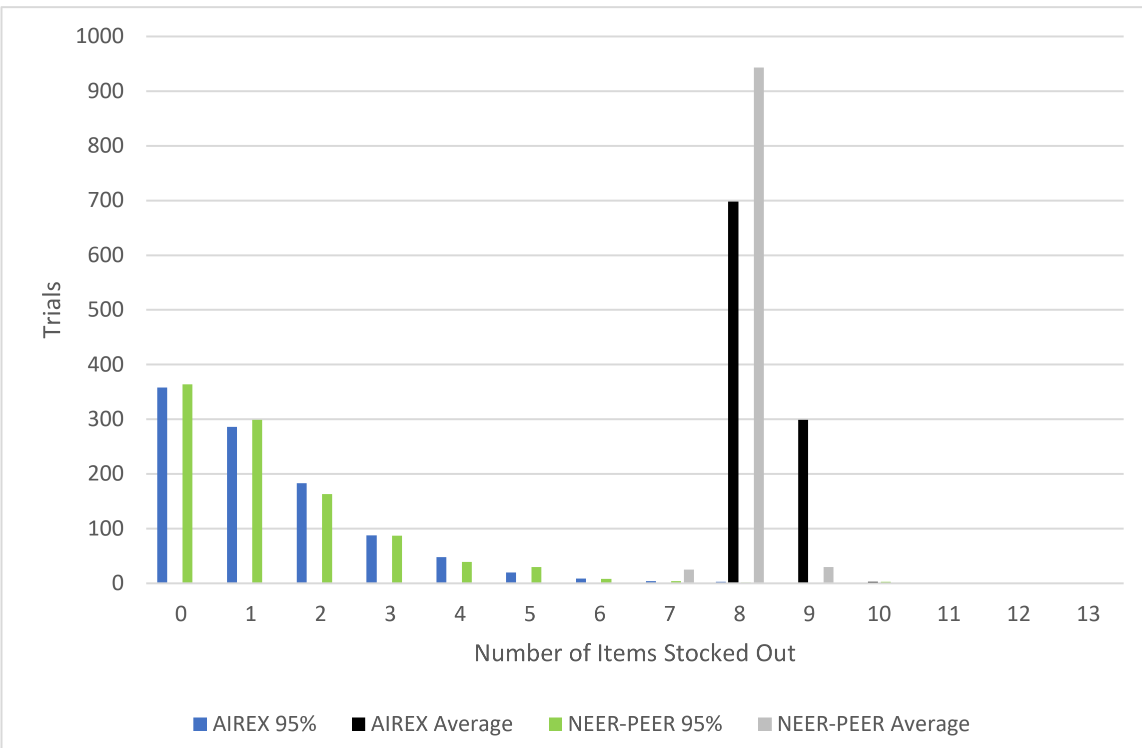


Figure 7. Inventory Policy Comparison

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V. SUMMARY AND RECOMMENDATIONS

The purpose of this study was to assess the pharmaceutical logistics requirements and evaluate the potential stockout risk along with managing stockpiles.

Our primary findings were:

- Identifying the most common medications for patient categories of interest.
- The length of stay and patient medication demands.
- Approximated exponential distributions that informed the construction of our model (identified in Table 8).
- The differences in results for the two scenarios show that planning for specific casualty (patient) types anticipated on a mission can substantially affect the medication demand.

Utilizing an inventory policy that provided for a specific service level outperformed an inventory policy based on average patient demand. Through simulation, we were able to model a variety of scenarios and assess the likelihood of inventory depletion, or "stockouts," which could lead to critical shortages of essential healthcare supplies. We created a model that can estimate the requisite quantities for pharmaceutical supplies to support specific patient categories (selected by interest to MARCORSYSCOM and NHRC, then further refined by data availability). Furthermore, by using simulation, we analyzed various scenarios and assessed the likelihood of stockouts, which could result in critical shortages of essential healthcare products.

We have developed a pharmaceutical demand forecasting model that demonstrates advantages over existing models, particularly in the context of risk management for contested logistics planning. This model facilitates the creation of demand forecasts by simulating the number of casualties received, the duration without resupply, and the types of casualties encountered. Our intent was to structure our research in a manner rooted in actual patient data, that would add to medical planning capabilities and possibly exert influence on higher-level decision-making regarding the selection and quantity of provisions. It bridges a critical gap in planning factors applicable to the U.S. Military. The utilization of actual patient data, as opposed to solely relying on subject matter expertise, significantly enhances the reliability of models that intend to quantify needs.

The data utilized in building the Monte Carlo simulation model was previously unavailable in the format received for this project. Legacy electronic healthcare records lacked comprehensive capture of medication quantities received during patient admissions. The more recent electronic healthcare record system, while still in need of standardization and exhibiting limitations, holds the potential for additional insights and ongoing analysis of treatment and consumable requirements once standardized.

However, merely using real patient data does not ensure the formulation of a quality inventory policy; it does not eliminate planners' need to consider risk. For instance, using average medication demand with values derived from Monte Carlo simulation service levels revealed an elevated risk of stockouts or increased potential for waste and unnecessary expenditure, compared with a policy of stocking at a 95th percent service level.

Prevailing tools suffer from limitations stemming from the absence of genuine patient data and estimation of stockout risk. Furthermore, there is a compelling need for additional analysis targeting additional medications and differing patient casualty types. The integration of real patient data with Monte Carlo simulation provides insights into medication demand within a context that aligns with gaps in existing planning tools.

By using Monte Carlo simulations, we can effectively estimate the risk associated with relying solely on averages in the presence of uncertainty and mitigate the risk by developing inventory policies that consider demand uncertainty.

Despite this, inherent risks persist within the current inventory and financial policies. These unexplored risks include considerations such as transportation and storage hazards. Given the potential diversity of missions, the simulation of daily casualty arrival, patient intake, and discharges would yield valuable insights for policymakers, contractors, and planners alike.

Our study encountered a range of constraints and challenges, including limited data availability, and concerns about data quality. Furthermore, because the data set represents prescriber variability, there may have been overestimates with a smaller number of prescribers. The study was constrained by a limited number of disease states based on available data, and the analysis of medications was also limited by the available dataset. Imperfect matching for ICD-9 to ICD-10 codes is another data quality limitation. If future planning tools were to utilize ICD-10 codes, the challenges associated with ICD-9 code conversions could be avoided. Our modeling assumption that 100% of casualties were in 12 patient categories presented inherent challenges. Other constraints imposed by Crystal Ball, such as limitations on the number of days, patients, and medications, highlighted the necessity for alternative software or a stepwise approach in the face of larger models. However, opportunities for optimization or efficiency in data extraction and analysis are promising with the advent of artificial intelligence, which may make this type of analysis easier and more accurate.

A. AREAS FOR FURTHER RESEARCH

This study estimated the pharmaceuticals needed to treat casualties in deployed and contested environments assuming no substitution. However, there's significant opportunity for consolidation of pharmaceuticals to reduce the logistics footprint now that the demand patterns have been identified. Options for this consolidation could include elimination of similar pharmaceuticals such as those in the same American Hospital Formulary Service medication category, grouping of pharmaceuticals could also potentially be applied along with a continuous inventory review system as data changes to ensure the most accurate and efficient inventory system is in place (Galka 2016). Prioritization of medications that do not require special handling or storage, such as refrigeration, controlled substances, hazardous materials, or hazardous waste. There could also be an effort to reduce overall volume and weight of the medications required in an application of the "knapsack problem." One example of this could play out by substituting dexmedetomidine for propofol where clinically appropriate, for example, potentially yielding decreased storage weight and volume on hand to treat the same casualty.

There are remaining distribution challenges remaining that could affect the quantity of medications required. Continued investigation is warranted to assess the redundancy of medications, considering the challenge of accounting for unknown geographic locations of the point of injury—a scenario analogous to the strategic placement of crash carts in hospitals or fire extinguishers in buildings. This exploration should involve a comprehensive comparison against existing AMALs to evaluate stockout risks associated with the current inventory levels. Additionally, addressing the "knapsack problem" is essential, involving strategic decision-making on what supplies to include in a push package, considering the constraints of limited space and other pertinent factors.

As Medical Service Corps Officers, we have all operated in remote locations where casualty evacuation or resupply is difficult. Without assumed air superiority or clear sea lines of communication, evacuation or resupply could be impossible for extended periods of time. Before consideration of rationing, triage modification, or inventory optimization via cost, transportation, or other constraints, its important to address the fundamental question: "what and how much do we need to preposition?" The aim is to ensure that we never face stockouts in remote environments. We hope that this project has contributed positively toward this goal.

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