ABSTRACT

McCONNELL, BRANDON MARK. Assessing Uncertainty and Risk in an Expeditionary Military Logistics Network. (Under the direction of Thom J. Hodgson & Russell E. King).

Uncertainty is rampant in military expeditionary operations spanning high intensity combat to humanitarian operations. These missions require rapid planning and decision-support tools to address the logistical challenges involved in providing support in often austere environments. The U.S. Army's adoption of an enterprise resource planning (ERP) system provides an opportunity to develop automated decision-support tools and other analytical models designed to take advantage of newly available logistical data. This research presents a tool that runs in near-real time to assess risk while conducting capacity planning and performance analysis designed for inclusion in a suite of applications dubbed the Military Logistics Network Planning System (MLNPS) which previously only evaluated the mean sample path. Logistical data from combat operations during Operation Iraqi Freedom (OIF) drives supply requisition forecasts for a contingency scenario in a similar geographic environment. A nonstationary queueing network model is linked with a heuristics logistics scheduling methodology to provide a stochastic framework to account for uncertainty and assess risk.

A case study demonstrates the capabilities of the MLNPS for analyzing the logistics requirements of an expeditionary operation. In the case study, an Infantry Brigade Combat Team (IBCT) and a Stryker Brigade Combat Team (SBCT) conduct operations from South Sudan into Sudan against the Islamic State of Iraq and Syria (ISIS). Particular focus is placed on the requirements for the last tactical mile (LTM) trucks. New graphical and risk-analysis tools support (i) comparing alternative courses of action, and (ii) evaluating the performance of a selected course of action under a complete disruption of the sustainment vehicles.

Assessing Uncertainty and Risk in an Expeditionary Military Logistics Network

by
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DEDICATION

To R. Dale Fink, the most educated man I have ever known (and one hell of a grandfather).

BIOGRAPHY

Brandon McConnell graduated from the United States Military Academy at West Point in 2006 with a Bachelor of Science in Operations Research and was commissioned as a Second Lieutenant in the United States Army as an Infantry officer. Following his Infantry training and completion of the US Army Ranger School, he served as a platoon leader with the 101st Airborne (Air Assault) Division's 2nd Brigade Combat Team at Fort Campbell, Kentucky. Deploying in support of Operation Iraqi Freedom (2007-2009) to Baghdad, Iraq, he lead an infantry platoon and later an infantry reconnaissance platoon.

After promotion to Captain and completion of the Maneuver Captain's Career Course, he began his second assignment at Schofield Barracks, Hawaii, serving with 1st Battalion, 21st Infantry Regiment, 2nd Brigade Combat Team, 25th Infantry Division. Deploying in support of Operation Iraqi Freedom (2010)/ Operation New Dawn (2010-2011), he served as the Battalion Assistant Operations Officer and led the battalion's targeting efforts before taking command of Charlie Company—an Infantry Rifle Company—while deployed. After redeployment, Brandon finished his command assignment and became the Brigade Deputy Operations Officer where he remained until 2013 when he joined the Operations Research graduate program at North Carolina State University.

Brandon is exceptionally proud to be from East Tennessee and suffers from a chronic surfing addiction.

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I must first thank my family and friends whose unwavering support throughout my graduate school journey was vital to my success even though my communications were sporadic at times. Thank you to all the friends, classmates, my parents, brothers, and others that tolerated and believed in me through all stages of this process.

I am extraordinarily blessed with a talented and highly-engaged committee; without their time, ideas, and especially their patience, this dissertation would not exist. At the heart of this team are my two co-chairs – I could not ask for better guidance or better mentors than these two professionals. Never accused of being completely sane, Dr. Thom Hodgson kept me moving in the right direction and aware of the bigger picture; the constant combination of humor and harassment kept my spirits up when things were bleakest. Dr. Russell King provided a steady supply of keen insight, mentorship, ideas, and basic civilian life coaching. Much of the data analysis and modeling is the fruit of Dr. James Wilson's labors and I am indebted to him for any skills I have acquired. I started this research project as the world's worst programmer – not much has changed there but I have grown tremendously from Dr. Michael Kay's willingness to teach practical problem-solving with computer code and share his logistics acumen. Dr. Kristin Barletta enthusiastically helped turn my ideas for abusing the Virtual Factory into reality. The research greatly benefited from Dr. Yunan Liu's eager interest and his relentless positive attitude – somehow he made it possible for me to achieve my goal of "stochastic-themed" research. Finally, COL (ret.) Greg Parlier, Ph.D., provided the go-to Army logistics expertise that kept this connected to reality and always made time to provide feedback. His experience and instincts have been invaluable.

This project originally started as a collaboration with LTC Matt Rogers, Ph.D., and I benefited greatly from our professional partnership as well as our continued friendship. Thanks for taking this infantryman on as your academic Ranger buddy.

I would like to thank the skilled professionals located at ERDC, TRAC-LEE, and TRAC-MRY for taking time to showcase their analytical tools as well as provide invaluable feedback for both this paper and our military logistics research. Our project was fortunate to receive engaged comments and interest from the Military Operations Research (MORS) community; a special thank you to Walt DeGrange for his time and talents.

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LIST OF ACRONYMS & ABBREVIATIONS

AH	Attack Helicopter
AMP	Analysis of Mobility Platform
ABCT	Armored Brigade Combat Team
APOD	Airport of Debarkation
APOE	Airport of Embarkation
BCT	Brigade Combat Team
CJCS	Chairman, Joint Chiefs of Staff
COA	Course of Action
CONUS	Continental United States
DANTE	Deployment Analysis Network Tool Extended
DDJC	Defense Depot, San Joaquin, California
DDSP	Defense Depot, Susquehanna, Pennsylvania
DEPSECDEF	Deputy Secretary of Defense
DIS	Delayed Infinite Server
DIS-FF	Delayed Infinite Server - Feed Forward network
DIS-VF	Delayed Infinite Server - Virtual Factory
DLA	Defense Logistics Agency
DOD	Department of Defense
DP	Decision Point
DRID	Defense Reform Initiative Directive
DSAT	Deployment Scheduling Analysis Tool
ERDC	Engineer Research and Development Center
ERP	Enterprise Resource Planning
FEU	Forty Foot Container Equivalent Unit
FM	Field Manual
GCSS-A	Global Combat Support System - Army
GDAS	Global Deployment Analysis System
GIS	Geographical Information System
HBCT	Heavy Brigade Combat Team
HQDA	Headquarters, Department of the Army
IBCT	Infantry Brigade Combat Team
ID	Infantry Division
ITV	In-Transit Visibility
JFAST	Joint Flow and Analysis System for Transportation
JOPES	Joint Operation Planning and Execution System
JP	Joint Publication
LBC	Logistics Battle Command
LD	Line of Departure
LMI	Logistics Management Institute

LTM	Last Tactical Mile
MBF	Mission-Based Forecasting
MCO	Major Combat Operations
MDMP	Military Decision Making Process
MIDAS	Model for Intertheater Deployment by Air and Sea
MLNPS	Military Logistics Network Planning System
MTOE	Modified Table of Organization and Equipment
MobSim	Mobility Simulation model
NHPP	Non-Homogeneous Poisson Process
NSN	National Stock Number
ODDP	Operations-Driven Demand Patterns
OIF	Operation Iraqi Freedom
PEU	463L Pallet Equivalent Unit
PH	Phase
PLANS	Planning Logistics Analysis Network System
RFID	Radio-Frequency Identification
SBCT	Stryker Brigade Combat Team
SO	Stability Operations
SPOD	Seaport of Debarkation
SPOE	Seaport of Embarkation
TDC	Theater Distribution Center
TEU	Twenty Foot Container Equivalent Units
TPFDD	Time-Phased Force and Deployment Data
TRAC	Training and Doctrine Command Analysis Center
TRAC-LEE	Training and Doctrine Command Analysis Center - Fort Lee
TRAC-MRY	Training and Doctrine Command Analysis Center - Monterey
TRANSCOM	Transportation Command
UH	Utility Helicopter
US	United States
VF	Virtual Factory
VF-DIS	Virtual Factory-Delayed Infinite Server
WWX	World Wide Express

Chapter 1: The Problem

Chapter 1 begins with a brief introduction to the problem setting and the context to motivate our research. This problem description walks the reader through the military structure which imposes various challenges on the problem and sets the stage for a more detailed look. This formally introduces the problem of military sustainment planning for expeditionary operations. Next, a survey-styled section (1.2) catalogs senior leader expectations for military sustainment tools and then reviews the current models. Section 1.2 will further highlight the motivation for the remainder of the research. Following Section 1.2, the end of the chapter presents a guide for how the dissertation proceeds.

1.1 Problem Overview

This research develops tools to assist the United States (US) Army and military decision makers with sustainment planning for expeditionary operations. Joint Publication (JP) 1-02 (Department of Defense Dictionary of Military and Associated Terms) defines an expeditionary force as an "armed force organized to accomplish a specific objective in a foreign country." For the purposes of this research we define an expeditionary operation as a sequence of military actions, whether tactical, operational, or strategic, with a common purpose or unifying theme (see *operation*, JP 1-02; see Field Manual (FM) 3-0 Operations, chapter 6 for *levels of war*). Supporting US forces on foreign soil requires both significant planning and logistical infrastructure. We seek to contribute efficient decision support tools for military planners and decision-makers to rapidly assess alternatives, develop feasible plans, and identify logistical capacity requirements to support expeditionary operations.

1.1.1 Defense Logistics Agency (DLA)

The Defense Logistics Agency (DLA) is the United States' "largest logistics combat agency" providing worldwide support, in peace and war, to the US military (http://www.dla.mil/).

DLA provides almost all consumable items such as uniforms, medical supplies, construction materials, food, and fuel. Based on the DLA fact sheet, 86 percent of all spare parts are provided by DLA; they manage over 5.1 million items, operate in 48 states and 28 countries, and manage 24 distribution centers worldwide (http://www.dla.mil/).

Commensurate with their responsibilities, DLA's network is extensive. In 2014, DLA fulfilled "12.5 million orders for 1.4 billion pounds of materiel to 33,213 customers across 86 countries" (Faris presentation, 2014). Logistical problems of this size, scale, and importance clearly require efficient solutions that highlight performance tradeoffs to the decision-maker. Whether planning for a contingency, assessing options, or determining required capacities at supporting logistics hubs, these processes need to be performed as quickly as possible with near-real time being the obvious goal.

1.1.2 Motivation

The US military invasion of Iraq in 2003 achieved tactical success but was accomplished in spite of very real logistical challenges as described in Peltz et al. in their RAND study (Peltz et al., 2005ab). "Within a week or so after the fall of Baghdad, the 3rd Infantry Division's (ID) reported equipment readiness dropped from about 90 percent for key ground combat systems to under 70 percent due to continuing distribution problems…Across V Corps, all combat systems fell below 80 percent readiness by early July" (Peltz et al., 2005a).

The RAND study concluded that there is a significant need for automated planning and decision-support tools to better support expeditionary operations. Specifically, these tools must be capable of identifying logistics resources needed to support a given operation. Additional requirements include an increased ability for the Army and DLA to rapidly assess distribution capabilities, enhanced capability for planners to assess required logistics resource

capabilities during deliberate and contingency planning, and the ability to consider uncertainty and evaluate impacts of resource shortages (Peltz et al., 2005a).

The US Army recognizes that while the "bravery and sacrifice of Soldiers is essential to victory it can rarely overcome poor decisions against a competent, adaptive enemy. The side that forecasts better, adapts more rapidly, thinks more clearly, decides and acts more quickly, and is comfortable operating with uncertainty stands the greatest chance to seize, retain, and exploit the initiative over an opponent" (Army Doctrine Publication 1-01: Doctrine Primer, 2014).

1.2.3 Research Objective

This research seeks to provide logistical models that can serve both as decision-support tools as well as provide value to planners. As it seems unlikely that the United States will significantly reduce its active role in global security and protection of its interests (and those of its allies) across the world, we focus on logistics as it relates to sustaining expeditionary operations. Specifically, the research requirement is that these tools run in near-real time, support comparisons between multiple courses of actions, conduct feasibility checks, and are capable of determining resource requirements throughout the network across some planning horizon. Figure 1.1 depicts the broad research objective – specifically this dissertation concerns itself with these objectives to assess risk and enable risk-based decision-making.

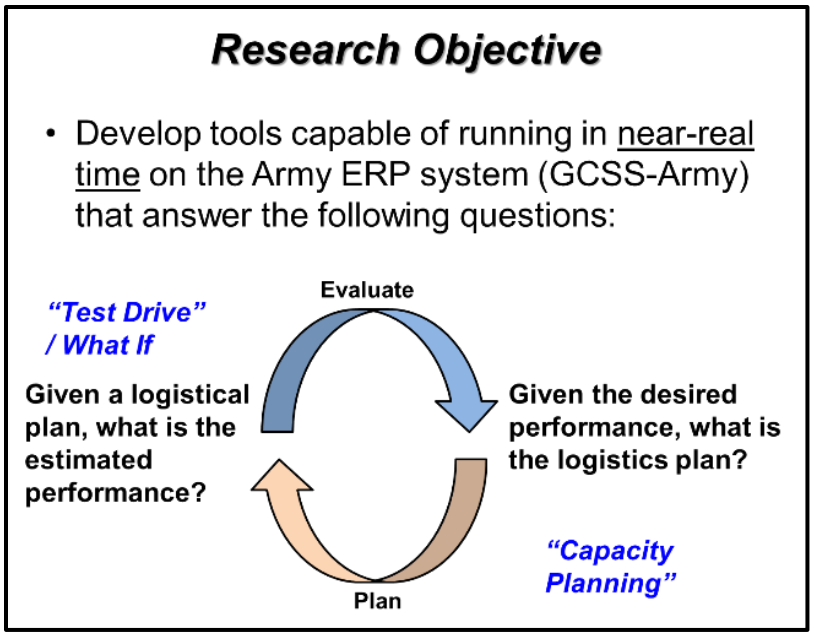

Figure 1.1: Research Objective.

Computation time is an important consideration in order to operationalize the tool so that decisions can be made rapidly based on the information it provides. Many military modeling tools require extensive time to setup—sometimes 2-3 weeks or more—and then also suffer from long run times. These tools often model many granular details and while excellent tools for certain contexts (e.g. certain studies where time is not a major factor and current operations are not affected), these are not practical for operational use. The battlefield has always evolved rapidly but modern warfare occurs in a data-rich environment; this underscores the need for rapid operational tools since the data is available but dynamic.

1.2 Senior Leader Expectations

1.2.1 Background

The battle is fought and decided by the quartermasters before the shooting begins.

–Field Marshal Erwin Rommel

When the United States of America decides to take a military action, or even consider a potential action in a response to a contingency, that mission belongs to the combatant command that is responsible for that geographic sector of the world. These commanders identify the mission requirements for these operations and may need to rely on the generating forces to provide military units if the combatant commanders do not have enough to meet the mission requirements. In addition, combatant commands coordinate with the US Transportation Command (TRANSCOM) to plan, synchronize, and execute the physical transportation of these units into the required area of operations to conduct their mission.

This can be done as part of a very thorough process, referred to as "the deliberate planning process," or as part of a rapid and expedited response to a world event, denoted "crisis action planning" (Bates, 2004). In either event, several problems present themselves to be solved. First, there is the problem of planning and executing the physical movement of the personnel and equipment of the required military units from their home stations to the required location to execute the mission. If this is an expeditionary operation, a second and immediate problem is determining what logistical capabilities and resources must be installed to facilitate the entry into and opening of the area of operations. And finally, military units conducting operations will require ongoing support, or sustainment, throughout the duration of their mission which requires the continued focus of the logisticians. Most of the literature focuses on the problem of moving the personnel and equipment to the deployed area of operations.

In the US military, the plan that orchestrates the initial movement of units and their equipment relies on a database known as the Time-Phased Force and Deployment Data (TPFDD) (Bates, 2004). The TPFDD contains a myriad of data governing when units and equipment will become available, depart, and arrive at the various locations along the way from their homestation into theater. Hodgson et al. (2001) provide a high-level network flow-based optimization tool to rapidly conduct sensitivity analysis for the TPFDD problem with the Deployment Analysis Network Tool Extended (DANTE). DANTE minimizes the time to transport units and equipment from their home bases in the United States to their forward destinations and provides a real-time tool to evaluate deployment decisions. The required inputs are the units and associated equipment to deploy, transportation assets available, and logistical infrastructure (Hodgson et al., 2001). It is noteworthy that DANTE does not provide a meticulous TPFDD; its purpose is the rapid evaluation of a course of action for sensitivity analysis. DANTE's output provides identification of choke points, queueing times, along with backlogs and clearance information for each node.

Hodgson et al. (2004) offer the Deployment Scheduling Analysis Tool (DSAT) as a personal-computer based tool that rapidly assesses courses of action and creates the deployment schedule (TPFDD) using a heuristically optimized discrete event simulation approach. Unlike DANTE, DSAT does not aggregate the required equipment and personnel to transit the network which results in a higher fidelity solution.

Akgun and Tansel (2007) present a mixed integer programming model to solve this problem but on a very limited scale. Yildirim et al. (2009) present a geographical information system (GIS)-integrated application, with user interface, that runs a discrete-event simulation

using listener event graph objects (LEGOS). All of the models mentioned are multi-modal to account for the various transportation options available.

This paper provides an updated survey of the current models in use that address the sustainment-themed problems rather than the TPFDD problem. To the best of our knowledge, the last related survey was McKinzie and Barnes (2004) which focused on legacy systems, primary strategic mobility models, supporting models, and the TPFDD problem specifically. Their survey provides an excellent treatment of four principal models: the global deployment analysis system (GDAS), Joint Flow and Analysis System for Transportation (JFAST), Model for Intertheater Deployment by Air and Sea (MIDAS), and the mobility simulation model (MobSim). For a detailed description of model setup, input data, and other characteristics for these and the TPFDD problem, we refer the reader to the McKinzie and Barnes (2004) survey as well as the following papers. Bates (2004) provides a good introduction to the Joint Operation Planning and Execution System (JOPES) which is the electronic information system used to track, store, and process the data used mobilizing and deploying the joint forces. In addition, Boukhtouta et al. (2004) provide a survey of planning tools the reader may find useful.

This chapter proceeds with a discussion of the requirements and wishes for tools to plan and evaluate military logistics systems to support expeditionary operations with an emphasis on sustainment. Section 1.2.2 highlights these themes and identifies the source documents for these requirements. Section 1.2.3 introduces the Army's Enterprise Resource Planning (ERP) system and the importance of this new technology. Section 1.2.4 explores the various models used by military planners and evaluates them in light of the stated requirements and the other models. In some instances, there is some overlap with the

systems mentioned in McKinzie and Barnes (2004) as a few models mentioned there are also capable of evaluating logistics networks and conducting "end-to-end" analysis. Even with this overlap, the focus remains on the sustainment portion. Section 1.2.5 concludes with current gaps and avenues for further research.

1.2.2 What Senior Leaders Want

My logisticians are a humorless lot […] they know if my campaign fails, they are the first ones I will slay. – Alexander the Great

Before surveying currently used sustainment planning tools, it is important to review what characteristics and capabilities these tools should possess. Much of the literature focuses on characteristics of a logistics system – some of the calls for change are quite general, others specifically address a needed decision support tool. We find it useful to approach this collection of literature by looking at both desired characteristics of the logistics system as a whole—it is reasonable to presume that automated decision support tools should be nested with these features—as well as consider what specific functions must be performed by these tools.

Looking at the literature for major themes, the need for the tools to possess an "end-to-end" perspective reigns paramount. In March of 2000, Deputy Secretary of Defense John J. Hamre published Defense Reform Initiative Directive (DRID) # 54 –Logistics Transformation Plans as part of the ongoing pursuit of the hailed revolution in military logistics (Hamre, 2000). Three months later, the Joint Chiefs of Staff released Joint Vision 2020 to conceptually guide the continuing transformation into a dominant force to meet the nation's needs as envisioned for the year 2020. This is the earliest surveyed reference to the need for an "end-to-end set of information capabilities" (Shelton, 2000). As depicted in

Figure 1.2, this is echoed four years later following the invasion of Iraq by the Army G-4, the Army's most senior officer relating to logistics.

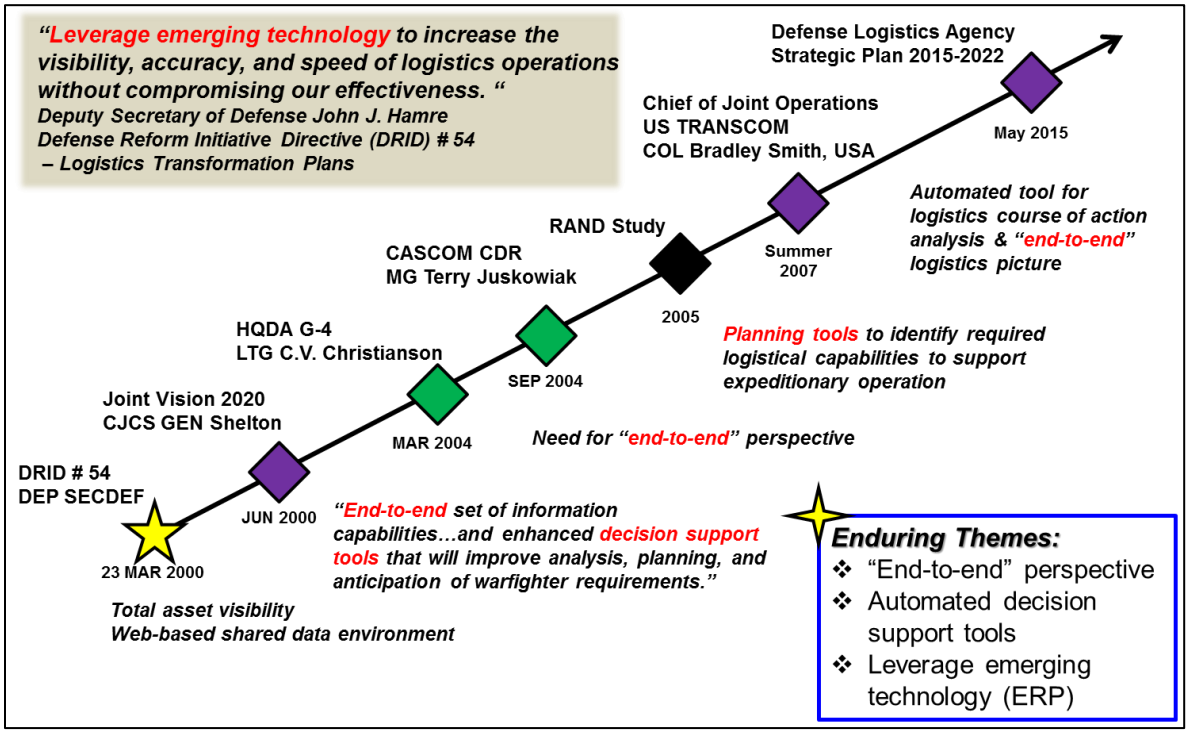

Figure 1.2: Timeline of Senior Leader Comments. This research regards GCSS-Army as the "emerging technology."

The call for an end-to-end perspective, often explained as from the point of supply to the point of consumption, in Joint Vision 2020 proved to be quite prescient as a 2005 RAND study identified some of the major challenges to the US class of supply nine (CL IX) distribution system (repair parts) during the invasion of Iraq were specifically linked to the military's failure to consider the plan's impact on the US-based distribution centers (Peltz et al., 2005). Clearly there is an appetite for decision support tools that consider the entire supply pipeline, from the continental US (CONUS) depots all the way to the combat units, to aid logistics planners. Trying to optimize or improve one portion of this chain without regard to the whole can lead to increased, or at least unconsidered, inefficiencies. For example, identifying the required capacity of the theater distribution center to support the

expeditionary forces might be irrelevant if the CONUS-based depots are unable to keep up with the demand which will pass on the delays downstream to the rest of the supply chain.

	Type	Issue	Schrady 1999	DRID #54 (2000)	JV 2020 (2000)	Hodge 2001	Christianson 2004	Juskowiak & Wharton, 2004	RAND Study (2005)	Kauffman 2005	Dail & Jones 2007	Smith 2007	Jackson 2009	DLA Strategic Plan 2015-2022 (2015)
System Features	Characteristics	End-to-end perspective (point of supply to end user)			X		X	X	X	X	X	X		X
		In-Transit Visibility (ITV)	X			X				X	X	X		
		Web-based shared data environment		X	X	X						X		
		CONUS ability to sustain expeditionary forces						X	X			X		
		Leverage emerging technologies		X	X	X								
		Time Varying Nature	X						X					
		Operates in near-real time			X							X		
		Repair parts identification, availability, & expected delivery dates				X		X						
		Time Definite Delivery Schedules					X							
		Consider uncertainty							X					
		Information vs. Data	X											
Functionality	Evaluation	COA Analysis	X						X			X		
		What-If Analysis (Test Drive)	X						X			X		
		Sensitivity Analysis							X				X	
	Planning	In Theater Distribution	X											
		Sustainability of the Force	X											
	Prediction	Sustainment	X						X					
		Closure	X											
		Movement Capacity	X						X					
		Forecasting demand								X				

Figure 1.3: Literature Summary for Logistics Decision Support Tools.

While the literature is quite clear that any suite of sustainment planning tools must have an end-to-end perspective, it also provides some descriptions on what functions these tools must be able to perform. In 1999, Schrady outlined three general functions for logistics models: Evaluation, Planning, and Prediction. We have used this breakdown to also review the literature's comments on what the models should help planners accomplish. The first and most direct use of these tools is in evaluation of a given planned scenario.

In the military decision making process (MDMP), a commander's staff will generate multiple courses of action (COA) which essentially comprise multiple feasible solutions.

Before a commander makes a decision, the staff typically enters the COA analysis phase to identify tradeoffs and impacts between the options they have presented to the commander. Sustainment planning tools should possess the functionality to assist with such tasks (Shrady, 1999; RAND, 2005; Smith, 2007). This process clarifies the options for the commander, assists with visualization, and ultimately aids the decision-making process especially in complex scenarios.

In addition, these models should also be capable of assessing the impact of an event or set of events as part of "what-if" analysis (Shrady, 1999; Peltz et al., 2005; Smith, 2007). This may be something as simple as answering what the impact would be of a seven day sandstorm on the logistics network, as experienced in March 2003 during the invasion of Iraq. These tools also need to be capable of assessing how sensitive the logistics system is to a set of changes to the operational and logistic plan, a component marked important by both the 2005 RAND study and the Department of Defense's model for evaluating sustainment tools (Jackson, 2009). Sustainment tools need to be capable of evaluating a specific plan and set of circumstances to understand the likely impacts as they relate to logistics under a range of reasonable assumptions.

Sustainment tools are not solely needed for evaluation; there is a real need for tools to directly assist in the planning process in two keys areas. Schrady (1999) asserts that an enhanced tool is needed to plan in-theater distribution. As previously discussed, models that address the TPFDD problem look at how to get forces into theater but do not address in detail how to distribute supplies to those forces once established in theater. Schrady further mentions that there is a "need to plan for the replenishment and therefore the sustainability of the force." He identifies several variables these models must account for including the

specific force composition, missions, level of contact with the enemy, and climate. Models that can account for specific units and missions could greatly assist planners in determining what operational decision might fit a specific contingency and help identify the required logistics capabilities needed to support the operation.

Schrady also stated that tools to assist with prediction were necessary. Specifically he identifies the need to predict closure, sustainability, and transportation capacity. Closure refers to the "information of material received and on the way, and planned shipment dates" (Schrady, 1999). Predicting sustainability is necessary to understand what supplies are available in theater, how rapidly they can flow into theater, and how quickly they are consumed by the supported forces. These functions both require an understanding of the resources available to transport these supplies between locations and how this transportation capacity will evolve over time as the operation continues. It is also noteworthy that the Institute for Defense Analyses maintains a report detailing the accreditation standards for mobility models in use by the Department of Defense; we refer the reader to this for a more formalized look into how the government assesses various mobility and transportation models (Jackson, 2009).

Multiple senior leaders have called for logistics models and sustainment tools that provide an end-to-end perspective that considers the entire supply chain from the point of supply to the end user. Schrady called for tools that can evaluate multiple options from a logistics perspective, assist in the planning process, and predict the logistical performance of a plan. Figure 1.3 summarizes both the characteristics and functions called for by the literature. These tools must be accessible via a shared platform and must run in near-real time to support the rapid decision-making cycle required in dynamic, quickly-changing

scenarios (Hamre, 2000; Shelton, 2000; Peltz et al., 2005). As emphasized by both the Deputy Secretary of Defense and the Chairman of the Joint Chiefs of Staff, these tools must leverage emerging technologies to meet these demands in ways not previously available (Hamre, 2000; Shelton, 2000).

1.2.3 The New Technology

GCSS-Army has come ashore and we are burning the ships.

–LTG Raymond Mason, Deputy Chief of Staff, HQDA G-4

The Army has spent over $4 billion to invest in a new logistics information technology, the Global Combat Support System—Army (GCSS-A) (Mason, 2013). To enable transition away from mass stockpiles into a lean and responsive logistics system, the Army has been working for years to implement a commercial Enterprise Resource Planning (ERP) system based on the mySAP Business Suite from the German software company SAP; the intent is to have one integrated system that covers both the national and tactical domains within Army Logistics (Coker & Hallinan, 2006; NRC, 2014). GCSS-Army replaces numerous outdated legacy systems, each with their own disparate databases and processes, and streamlines them into one single system database accessible to commanders, decision-makers, and other users at all levels.

The specific functions of GCSS-Army are many, including equipment accountability features, unit supply ordering, and dispatching vehicles –all of which significantly assist tactical units (Huckabee & Smoot, 2012; Wyche, 2014; McGill & FitzGerald, 2015; Williams, 2015; Fogg, 2017). In the context of sustainment tools, it is not the functionality of GCSS-Army that makes it so important but the data that it stores in one accessible place. GCSS-Army provides units the in-transit visibility (ITV) to know where their ordered parts are and when they will arrive. The new system enables the customer-focused metrics to fully

become reality, measuring logistics success "at the last tactical mile with the Soldier" using customer wait time and lateness measures of performance (Christianson, 2004; DoDI 4140.61, 2000; FY2000 DoD Strategic Logistics Plan, 1999; Deaton, 2016; Fogg, 2017).

GCSS-Army was fielded in 2012 with phased roll-outs of additional functionality continuing to emerge. It is the largest web-based ERP in the world, consolidating over forty thousand databases (Mason, 2013). While it also reduces the workflow to units in areas such as maintenance and supply status, the data it houses is replete with possibilities. Sustainment models and logistical planning tools should not simply use this ERP data because of the great investment of time and treasure in its fielding, although there is a modicum of sense in that. If GCSS-Army really is, as the Army's Deputy Chief of Staff for G-4 puts it, "the most significant positive change in Army logistics this decade," then sustainment models and tools should tap into this data resource because of the enhanced capabilities GCSS-Army provides (Mason, 2013; NRC, 2014; Powell, 2014; Fogg, 2017). With such unprecedented access to data, GCSS-Army truly offers the potential to change Army logistics in ways that were not possible before. Turning this data into usable information using operations research techniques and decision-support tools provides an unprecedented opportunity to enhance and alter how the Army conducts logistics (for more details, see Chapter 6 of NRC, 2014; Fogg, 2017).

1.2.4 Current Tools & Models for Sustainment

The line between disorder and order lies in logistics… - Sun Tzu

As previously mentioned, McKinzie and Barnes (2004) provide an in-depth survey of military mobility models. Among the principal strategic mobility models in this survey—GDAS, JFAST, MIDAS, and MobSim—none of them interface with the GCSS-Army to the

best of our knowledge. These models have various features that make them attractive to specific users. McKinzie and Barnes (2004) discuss these in detail and provide an excellent comparison of these models in their survey. These models are extremely robust and comprehensive in their functionality and provide course of action analysis, evaluation of "what-if" scenarios, and provide useful outputs that are ready to be used. Each can accommodate a JOPES TPFDD file as an input. These models assist with mobilizing and deployment units. They are not end-to-end models per se—to achieve an end-to-end analysis using the most capable of these requires running several separate models consecutively to obtain an end-to-end approximation.

While JFAST is able to do some limited sustainment analysis, these tools are not designed for ongoing sustainment planning or determining the required logistical capacities (e.g., pallets per day) at critical nodes over time to support an expeditionary operation. Since the 2004 survey, there have been several new models developed that specifically address sustainment of expeditionary forces. This paper presents an overview of these models in light of the senior leader guidance covered. Figure 1.4 below summarizes the current sustainment models for comparative purposes.

	Type	Issue	LBC	PLANS	AMP	SupplyGuru
System Features	Characteristics	End-to-end perspective (point of supply to end user)				
		Interfaces with ERP system (GCSS-Army)				
		Web-based shared data environment				
		CONUS ability to sustain expeditionary forces				X
		GIS integrated				
		Time Varying Nature				
		Operates in near-real time				
		Consider uncertainty				
Functionality	Evaluation	COA Analysis				
		What-If Analysis (Test Drive)				
		Sensitivity Analysis				
	Planning	In Theater Distribution				
		Sustainability of the Force	X	X		
	Prediction	Sustainment	X	X		X
		Closure				
		Movement Capacity	X	X		
		Forecasting demand				X

*X - Somewhat Provides Feature

Figure 1.4: Summary of Current Sustainment Models.

1.2.4.1 Logistics Battle Command (LBC)

Developed by the Army's Training and Doctrine Command Analysis Center – Monterey (TRAC-MRY) and currently in use at the TRAC-LEE Logistics Analysis Center at Fort Lee, Virginia, the Logistics Battle Command (LBC) is a discrete event simulation written in Java that uses the Naval Postgraduate School's Simkit application to manage its event list. Currently LBC is used for comparative assessments of force designs, weapon systems, vehicles, or concepts of support with respect to their impact on military logistics but is being developed into a decision support tool for planners and logisticians with a target rollout date of 2018.

LBC provides some distinct modeling advantages in that it can be run deterministically or use probability distributions to obtain stochastic results. It is capable of scaling to different levels of fidelity and can model all classes of supply at a chosen level of detail. Distribution focused, LBC can produce a schedule of resupply convoys based on a

specific operation and desired levels of supply. The model can test various task organizations and assist with both COA analysis and "what-if" style questions. One particularly novel feature is that it can conduct Threat Impact Assessments to account for attrition and loss of supplies and supply distribution assets as a result of enemy action (Hayes, 2015).

Specifically, LBC is suited for assessing the feasibility of a logistics distribution plan up to the theater level and whether the planned sustainment force is sufficient for the demands of the operation. The model assumes that all required supplies are available at a starting node or logistics hub such as an intermediate staging base (ISB) or a theater distribution center (TDC). Based on a discussion with the principal developer of LBC, the software can accommodate the full "end-to-end" supply chain but such a perspective would necessitate lengthy run times, especially during stochastic analysis (Hayes, 2015; Jackson, 2016).

Another key feature of LBC is that it can identify shortages and surpluses of both supplies and distribution assets (trucks, capacity, man-hours) in the plan. This ability, along with its easy transition to sensitivity analysis, makes it an excellent tool for analyzing theater distribution in detail. The input requirements are also structured as user-friendly as possible, allowing an analyst to construct scenarios using Microsoft Excel, an Access database, with LBC's graphical user interface, or directly through Extensible Markup Language (XML) if desired.

Using a one hour resolution for the simulation, LBC is capable of achieving a runtime for a single replication of 2-3 hours. Using the probabilistic attrition features, it can achieve 45 replications in about 5 days. Model setup can take 1-2 weeks depending on the

complexity of the scenario (Hayes, 2015). In short, LBC is an excellent tool for distribution modeling. However, it is not practical for rapidly answering questions requiring an end-to-end perspective and LBC does not interface with the Army's new ERP system.

1.2.4.2 Planning Logistics Analysis Network System (PLANS)

A division of the US Army Corps of Engineers, the US Army Engineer Research and Development Center (ERDC) is finalizing the development of a web-based tool known as the Planning Logistics Analysis Network System (PLANS). PLANS is designed to assess multiple early entry options taking into account terrain, weather, sea conditions, and bathymetry. It is capable of projecting multi-modal logistics performance, even at high levels of fidelity. PLANS has the ability to answer what-if questions, identify logistic bottlenecks, and estimate transportation throughputs on various modes. The tool conveniently features web-based secured access and a geographic information system (GIS)-integrated user interface. The model assumes the supplies start at an offshore location, though it could start the supplies at an onshore node if desired, and then use discrete event simulation to model the resulting logistics processes.

PLANS is capable of very high-fidelity modeling – including individual theater distribution center components such as forklifts and accounting for soil and weather when simulating travel over a road network. The web-based user interface is also very user-friendly and the GIS-integration is particularly helpful. For all that it is, PLANS is not an end-to-end model; it provides an easy-to-use high-fidelity tool for a specific piece of the expeditionary problem but cannot be used to look at the entire supply chain supporting an expeditionary operation. Last, PLANS is unable to pull data from GCSS-Army and instead relies on consumption rates and planning factors.

1.2.4.3 Analysis of Mobility Platform (AMP)

Analysis of Mobility Platform (AMP) is a high level modeling and simulation tool focused on determining transportation capacity of the DOD network. It is used to identify the required transportation assets for the joint services such as number of trucks, aircraft, and ships. While technically it does provide an end-to-end perspective, AMP requires the analyst to run a series of models sequentially (one mode at a time) to achieve this perspective. It is not appropriate for our problem as it primarily looks at much longer time horizons (2 – 3 years) for strategic level planning than an expeditionary operation might call for. Last, AMP does not integrate with the ERP system (Rogers, 2016, Anonymous, 2016).

1.2.4.4 SupplyGURU

Created by the supply chain software company Llamasoft, SupplyGURU is a highly versatile supply chain and inventory software package boasting a suite of tools to assist with facility location, supply chain optimization, and other related problems. It comes with its own mixed-integer linear program (MIP/LP) solver as well as a discrete event simulation package. Though a commercial product, SupplyGURU has gained the attention of military logisticians, including the Defense Logistics Agency (DLA). Its use of a MIP/LP solver may result in limitations to our problem when modeling the supply requisitions from CONUS depots all the way to units operating in theater. While SupplyGURU could model this end-to-end problem with discrete event simulation, the sheer size and complexity make it likely to require long run times to get stochastic-based results. To the best of our knowledge, SupplyGURU does not interface with GCSS-Army (Llamasoft, 2016; Rogers, 2016).

1.2.5 Conclusion

As the US military continues to transform its logistics processes, new and more capable tools will be both needed and available. With the complexity of twenty-first century warfare and

the evolving trends at the tactical, operational, and strategic levels, leaders rely on analysts and planners equipped with updated tools outfitted to answer logistical questions in the new environment. Likewise, new technologies such as ERP systems provide copious amounts of new data that may be harnessed like never before to enhance old ways of solving logistics problems and support entirely new logistics tools.

We are unaware of any current Army decision support tool or model that uses the ERP data. A recent dissertation by LTC Rogers used Operation Iraqi Freedom data to demonstrate that analytical tools can use ERP data and provide timely, actionable information to decision-makers (Rogers, 2016). While a promising proof-of-concept, Rogers' model remains an academic demonstration and there are no official efforts underway to build an ERP-based logistics toolset of this scope.

The current array of logistics models and tools are highly vetted and quite capable but do not individually meet the senior leader guidance for logistics tools. Modelers, analysts, and planners require logistics tools that are both end-to-end in scope and interface with the treasure trove of data stored in the ERP system (GCSS-Army). In order to address the rapidly changing circumstances that are commonplace on the modern battlefield, these tools must run in near-real time to transform data into information in time for leaders to exploit. Armed with data like never before, analysts can use these new tools to better support the decision process of key leaders.

1.3 Organization of Dissertation

The rest of the dissertation is organized as follows. Chapter 2 reviews a recent model that serves as a deterministic proof of concept to address these sustainment challenges. Chapter 3 discusses the existence of risk in the expeditionary military logistics planning problem and

provides a stochastic framework to perform capacity planning and predict logistic performance while considering risk; to accomplish this a novel combination of scheduling and nonstationary queueing networks leads to a computationally efficient stochastic model. Chapter 4 presents a data-driven approach to forecasting supply requisition demand. Chapter 5 applies the stochastic framework (Ch. 3) and requisition forecasting approach (Ch. 4) to a notional expeditionary operation in Africa demonstrating the ability to assess and consider risk while conducting capacity planning and performance analysis. Chapter 6 summarizes the research and discusses directions for future work.

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Chapter 2: Deterministic Proof of Concept (Relevant Literature)

Our wars have not been one size fits all, and neither have our logistics. We need to remain flexible in planning for future logistics…We need to sense, anticipate, respond, and do logistics better. *—General Paul Kern, commanding general, Army Materiel Command*

In order to develop a model that answers the senior leader expectations presented in Chapter 1, we need to expand the toolbox with which to attack these logistics problems. A natural starting point is deterministic models not only due to the modeling practice of working from simple towards complex but by the sheer size and nature of the system.

This chapter reviews relevant literature focusing on a practical demand forecasting methodology and a recent dissertation work –the Military Logistics Network Planning System (MLNPS)—which is designed to exploit both this new forecasting technique in conjunction with the Army's ERP system.

2.1 Relevant Literature

2.1.1 Mission-based Forecasting (MBF)

One very promising and relatively recent approach to military sustainment demand forecasting is mission-based forecasting (MBF)—also known as operations-driven demand patterns (ODDP)—which was born out of a Logistics Management Institute (LMI) study on Army aviation units completed in 2005. The study used stratified sampling to analyze the Class IX repair part demand patterns to see if those patterns could be characterized by the operational mission and the geographic location of the unit. The study looked at Class IX ordering for AH-64 Apache and UH-60 Blackhawk helicopters for training in CONUS, major combat operations (MCO) during Operation Iraqi Freedom (OIF) in Iraq, and stability operations (SO) during OIF in Iraq (Parlier, 2011, 2016, 2017).

The results for the AH-64 Apache are summarized below in Figure 2.1; it should not be a surprise that the total repair part demand for parts during major combat operations in Iraq was 4.4 times the demand during CONUS-based training. We would expect aircraft to be logging more flight hours during OIF and the impact of the dry, desert environment with blowing dust and sand naturally affects aircraft maintenance. What might surprise the reader is that the specific parts used differ greatly across operational mission sets and geographic locations. This disparity is illustrated in Figure 2.1 using the Venn diagrams (Parlier, 2011). The authors observed that of all the repair parts used in CONUS by the AH-64D, only 12 percent were needed in Iraq during major combat operations. Of these parts required during major combat operations during OIF, 29 percent were not traditionally needed while in CONUS.

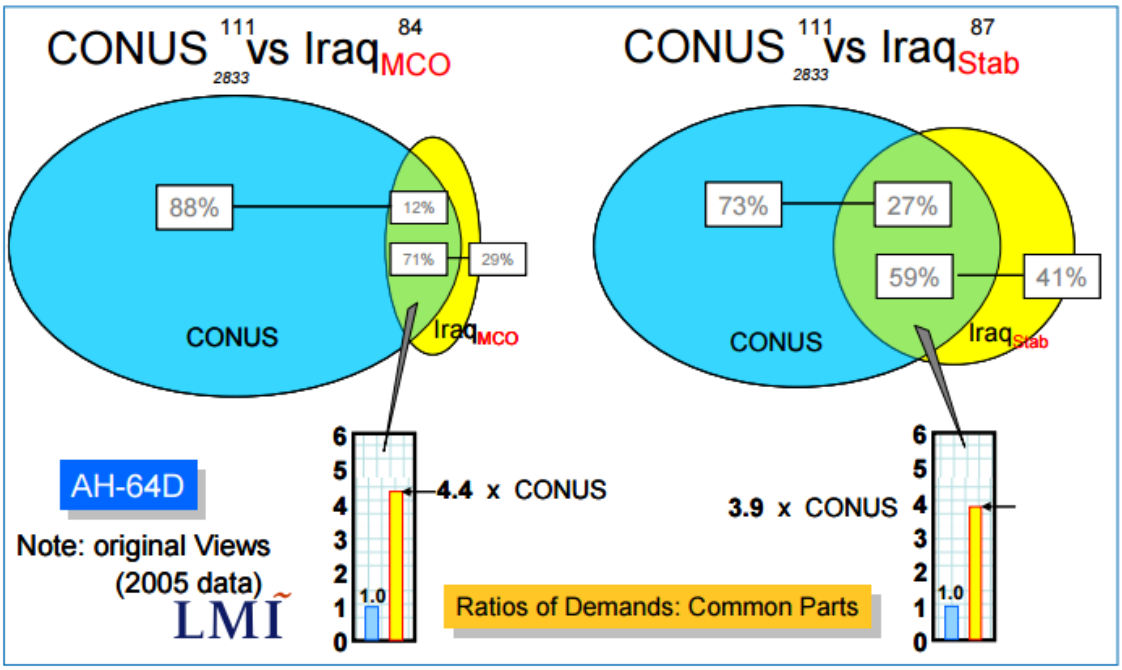

Figure 2.1: 2005 Repair part demand for AH-64 Apache helicopters (Parlier, 2011) during major combat operations (MCO) and stability operations (Stab).

The research team went on to use MBF in an aviation unit to assess the impact this methodology could have on the unit budget and forecast accuracy relative to other Army forecasting methods. The results were astounding – MBF consistently achieved close to an order of magnitude improvement (100%) in the forecast accuracy for both type of parts and part quantities (Parlier, 2011). MBF forecasts are 70-100% more accurate than current forecasting methods and if coupled with GCSS-Army, would provide a powerful predictive tool for Army logistics. While MBF applied to operational units can reduce demand uncertainty and directly assist normal logistics functions, MBF can also dramatically assist military planners seeking to plan for expeditionary operations, evaluating a contingency plan, or attempting to solve an anticipated logistical challenge.

While MBF proved to be both accurate and practically viable, it is unfortunately not developed enough to extend to other units outside of the Apache and Blackhawk units in the Army aviation community. In November 2013, the Deputy Assistant Secretary of Defense for Maintenance Policy & Programs, Mr. John B. Johns, sanctioned a project called the Maintenance Value Chain (MVC) to confirm the LMI results. The validation phase (Phase I) was completed in September 2014, with comparable findings. Mr. Johns expanded the study to other services and platforms (air and ground) (Rogers, 2016). To our knowledge, these additional studies have not yet finished. If successful across other platforms, such as the M1 Abrams main battle tank or the M1126 Stryker infantry carrier vehicle, the MVC project may provide the impetus for MBF to be officially adopted by the Department of Defense (Rogers, 2016). In any event, its fundamental approach of accounting for unit type, specific mission, and the environmental conditions makes a lot of sense as the Army has modularized the force into Brigade Combat Teams (BCTs) with the aim of increasing its expeditionary capabilities.

MBF seems structurally designed for an intuitive integration with how Army planners look at operational missions and contingency scenario requirements. For further details on MBF, readers should consult Parlier (2011, 2016).

2.1.2 Military Logistics Network Planning System (MLNPS)

In 2016, Rogers et al. proposed a Military Logistics Network Planning System (MLNPS) that harness both GCSS-Army and MBF to assist decision makers and planners with several aspects of military logistics. A non-exhaustive list includes identifying required capacities across the logistics network to support an expeditionary operation, anticipating bottlenecks, conducting what-if analysis, and course of action analysis. MLNPS is a significant contribution as it is the only known model that is designed to use the Army's ERP data.

To date, the MLNPS fundamentally models the logistics network as a large factory with each logistics node represented as a machine in the factory. A logistics node might be a location or a specific process at a location. Supply requisitions (e.g. CL IX) act as jobs that must be processed through this factory. With this approach, MLNPS exploits an engine known as the Virtual Factory (VF) to near-optimally schedule these jobs in near-real time to minimize the maximum lateness. The VF was initially reported on by Hodgson et al. in 1998 and has sustained a number of improvements, most notably, the addition of batch processing by Thoney et al. (2002).

The ability to handle batch processing allowed the VF to schedule for multiple factory networks while also accounting for transportation between the factories since a truck may be modeled as a batch processor itself. Melendez (2002) and Trainor (2001) used batch processing in conjunction with the VF to address military deployments (also see Hodgson et al., 2004). Rogers et al. (2016) extended this idea by focusing on repair parts transiting the military logistics network by using nested batch processors to model requested repair parts

being loaded into pallets which are loaded into containers then shipped via surface (ocean) vessels.

The MLNPS is designed to run as an application (app) on the Army's ERP system. Using the VF to process this data along with a MBF for future demand, the MLNPS terminates with a near-optimal sequence to essentially maximize customer (ordering units) satisfaction. Rather than focus on the sequencing, Rogers et al. realized this provided a forecast of when, where, and how much queuing will occur at various nodes across the logistics network. They were able to validate their model against real performance data from the invasion of Iraq in 2003 during OIF which demonstrated the MLNPS could approximate the real logistics network performance. Using this model and mean value parameters, they developed a trial-and-error method to test drive a logistics plan and assess how well it will support a planned expeditionary operation using deterministic outputs from the VF. The approach was used in assessing the logistics network both for the invasion of Iraq and for a notional intervention scenario set in Africa.

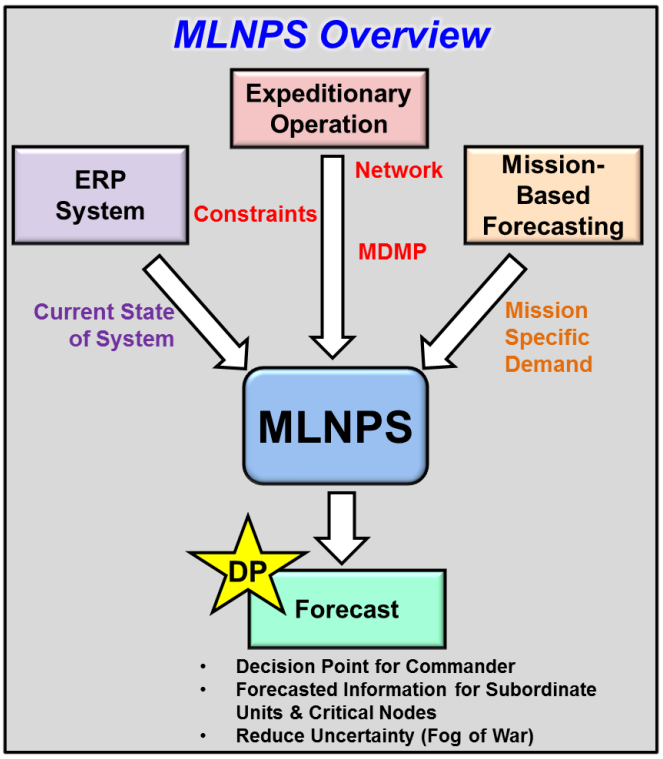

Figure 2.2: MLNPS Overview.

MLNPS has tremendous potential as a military logistics model for several key reasons: it supports end-to-end analysis in near-real time and is designed to incorporate both GCSS-Army and MBF. As illustrated by Figure 2.2, GCSS-Army can provide the model with the current location and status of all requisitions currently in the system; Rogers et al. (2016) focus on CL IX repair parts but also model food and water (CL I) and ammunition (CL V). The model requires the planned logistics network and necessary constraints as an input from the planner/analyst. Mission-based forecasting provides the best forecast possible based on the units, environment, and planned operational mission set. MLNPS then forecasts how well the network will perform, where significant queuing will exceed thresholds causing sustainment problems, and provides a decision-maker with information to adjust the plan or notify subordinate units of what to expect as the operation unfolds.

	Type	Issue	LBC	PLANS	AMP	SupplyGuru	MLNPS
System Features	Characteristics	End-to-end perspective (point of supply to end user)					
		Interfaces with ERP system (GCSS-Army)					
		Web-based shared data environment					P
		CONUS ability to sustain expeditionary forces				X	
		GIS integrated					
		Time Varying Nature					
		Operates in near-real time					
		Consider uncertainty					
Functionality	Evaluation	COA Analysis					
		What-If Analysis (Test Drive)					
		Sensitivity Analysis					
	Planning	In Theater Distribution					X
		Sustainability of the Force	X	X			X
	Prediction	Sustainment	X	X		X	
		Closure					
		Movement Capacity	X	X			
		Forecasting demand				X	X

*X - Somewhat Provides Feature, P - Possible

Figure 2.3: MLNPS vs. Current Sustainment Models.

Conceptually, MLNPS provides many of the features senior-leaders have repeatedly asked for in logistics decision-support tools. Echoing Chapter 1, Figure 2.3 highlights MLNPS's attributes in light of current military sustainment models. Again, key features are the end-to-end perspective and the integration with the ERP system all in a computationally efficient way. While MLNPS can analyze the uncertainty, obtaining stochastic results requires significant computation time that is highly inefficient and time consuming. As an aside, MLNPS does not currently consider alternate routing despite that this capability has been added to the Virtual Factory (Weintraub et al., 1999; Hodgson et al., 2004).

MLNPS is designed to rely on MBF to estimate future repair part needs based on the unit types, the mission, and the operating environment. As previously mentioned, MBF is not currently an option for units outside of Army aviation units (specifically, the AH-64 and UH-60 platforms). Based on the results of the initial LMI study and the validation by MVC, it seems likely that MBF will be effective across multiple unit types and platforms.

However, the lack of MBF for other unit types poses a short-term obstacle for MLNPS and requires a “surrogate MBF” for use as a decision-support and planning tool.

Using data from the RAND study on OIF logistics (Peltz et al., 2005a), Rogers et al. (2016) probabilistically characterized key aspects of the supply requisitions to include the weight, volume, origin distribution center, ordering unit, routing, and mode of transportation. This allowed them to generate representative datasets given a particular mission and task organization (forces to participate in an operation) while respecting the original correlations among these various characteristics. As noted by Rogers, this was only a surrogate for MBF.

We take time to note that an important modeling challenge when using MLNPS is a lack of dynamic reallocation of shared resources. While the VF has a spectrum of processors (logic blocks to handle different types of processes), it currently cannot reassign shared resources. Consider a simple example where there are 10 trucks located at Warehouse A which sends orders via truck to Location 1 and Location 2 and that for security reasons these trucks travel in protected daily convoys. In reality, Warehouse A can adjust the number of trucks sent to each location based on the daily delivery requirements. The VF requires this allocation (by day) to be a pre-specified user input; however, the impacts of the queueing are unknown prior to running the VF. In practice, it is often simpler to model this with two pools of resources, the trucks dedicated to go to Location 1 and 2, respectively (e.g. 4 trucks for Location 1, 6 for Location 2). This static assignment (albeit daily) still allows for underutilized resources that are needed elsewhere. If a dynamic reallocation remedy is tractable, it is likely an open research problem on how to integrate this into the VF logic without compromising the computational advantages the VF provides. LTC Rogers (2016)

overcame this challenge by establishing a permanent division of those resources as explained above and used sensitivity analysis to justify the split allocation of resources.

Table 2.1: MLNPS Pros and Cons.

Key Features	Primary Limitations
End-to-end perspective	Limited stochastic information
Interfaces with ERP system (GCSS-Army)	No shared resource reallocation
Operates in near-real time	MBF currently limited to AH-64/UH-60 units

As MLNPS well-addresses the senior-leader requirements for a military logistics decision-support tool, particularly for expeditionary operations, this research seeks to enhance and augment its functionality. Table 2.1 summarizes the key features and primary limitations of MLNPS. Though MLNPS is quite efficient, Rogers et al. (2016) used an iterative procedure to identify required logistical capacities over time. This amounted to informed guessing by looking at the queuing output and adding capacity at a point in time; then they reran the model with the updated capacity and observed the resulting impact on performance. Their approach provided a great capability but the process can be improved and automated. Appendix A proposes an automated approach to the MLNPS' task of finding required capacities for a particular logistics node.

2.2 Need for Stochastic Insights

This research centers on refining and expanding the capabilities of the Military Logistics Network Planning System (MLNPS), proposed by Rogers et al. (2016), especially as it relates to uncertainty and understanding risk. In the language of Rogers et al., these refinements and expansions should serve as additional tools to be integrated in to the MLNPS app for use with the Army's ERP system (GCSS-Army).

Currently, MLNPS has been essentially synonymous with a Virtual Factory (VF) model of the military logistics network. This work seeks to expand the scope of the MLNPS such that the VF model remains a portion but increasing the utility and functionality of the MLNPS as a suite of tools rather than a single modeling approach. It is the fundamental, underlying problem that unifies the MLNPS, not the thought process taken by the analyst. Prior to proposing additional tools, we first recall the VF framework and examine what the current VF-based MLNPS provides upon termination.

Since the MLNPS has proved useful in test-driving a logistics network to obtain a forecast for performance, it is worthwhile to reexamine everything that is accessible to an analyst given the MLNPS as it currently stands. As explained in Section 2.1.2, the MLNPS models the supply requisitions as jobs to be processed by machines in a factory where the machines are the logistical nodes of the military network. Figure 2.4 highlights these inputs which are ostensibly obtainable via GCSS-Army and a specific planning or operational scenario. The principal outputs are the lateness, queue length, sojourn time, and the number of jobs started. Lateness statistics are available by job and by mode of transportation; all other metrics are available by machine and by day. The term *sojourn time* refers to a job's queuing time plus its processing time at a particular node.

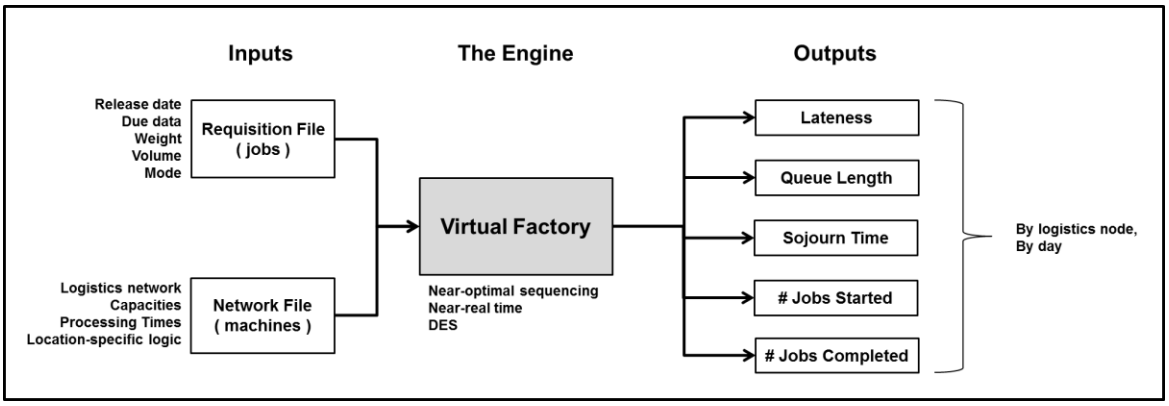

Figure 2.4: Virtual Factory (VF) Inputs & Outputs.

We may presume any or all of this is available for use in the development or enlightenment of other tools and models. This also serves as a "base case" for a model both in terms of computation time and performance. With regards to computation time, additional tools should either make it faster (and/or easier) to answer a particular question than with the VF directly or do so in a way that answers a question the VF cannot answer directly. As to performance, these tools are all abstractions which provide approximations of system behavior – additional tools for inclusion in the MLNPS should match or exceed the VF's output information in terms of accuracy.

Understanding what the VF does not provide is also useful. As it stands, the MLNPS relies on forecasting the mean-value sample path. Processing times are input as expected values rather than defined by statistical distributions. As a consequence, the VF outputs are insufficient to conduct statistical inference regarding a performance measure. Providing a sense of the uncertainty in the VF forecast is then difficult, especially regarding any variation imposed by the network (as opposed to the jobs) itself. This will be discussed in later chapters.

Using average values as parameters in a deterministic procedure is a good first step for this large complex problem. Even so, the resulting analysis is unable to make probabilistic evaluations necessary to assess risk or understand uncertainty. Using average input values to generate average performance still generates analysis that will underestimate risk largely due to Jensen's Inequality; for an excellent discussion of this problem, see Savage (2009). Probabilistic analysis is not simply academic concern but a useful deliverable to end users such as military planners and senior leaders making decisions in

these contexts. These stakeholders would benefit from an understanding of how robust their logistics plan is to the uncertainties that persist throughout the operation.

Chapter 3 discusses risk in this context and develops a modeling framework to provide the stochastic insights necessary for risk analysis in the MLNPS application.

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Chapter 3: A Stochastic Framework That Permits Risk Analysis

Friction…is the force that makes the apparently easy so difficult…friction…is everywhere in contact with chance, and brings about effects that cannot be measured….The good general must know friction in order to overcome it whenever possible, and in order not to expect a standard of achievement in his operations which this very friction makes impossible.

–Carl von Clausewitz

Carl von Clausewitz first related the concept of friction to the formal analysis of war in his classic *On War* (Wilhelm, 2010). Understanding the role of friction as it relates to the uncertainties that persist on the modern battlefield remains an important responsibility of the military commander. Historically, new processes and technological solutions have often tempted leaders into underestimating the residual friction and uncertainty inherent in military operations; the Army's new ERP system (GCCS-Army), with its ability to provide data on demand, certainly bolsters US information superiority but by no means equates to perfect information or lifts the fog of war (Shelton, 2000; Wilhelm, 2010). GCSS-Army provides unprecedented access to data – the Army must harness that data and transform it into useful, actionable information for decision-makers (Perna, 2015; Fogg, 2017).

Section 3.1 motivates this chapter by discussing the importance of uncertainty in military decision-making. Section 3.2 revisits what is available to the analyst using the MLNPS. Section 3.3 discusses what risk is and associated risk literature in a military logistics planning context. Section 3.4 introduces some advances in queueing theory that provide some fresh approaches for this problem and for MLNPS. Section 3.5 exploits the queueing theory by establishing a modeling framework to capture the uncertainty in the military logistics network and then identify the required capacities for a given operation.

3.1 Motivation

As discussed in Chapter 2, the MLNPS currently forecasts the mean-value sample path based on its Virtual Factory (VF) engine. Using the VF, processing times are input as expected values rather than defined by statistical distributions (Rogers et al. (2016) extended this using parameter sampling in the job file; see Section 3.4 for more details). As a consequence, the VF outputs from the mean-value sample path are insufficient to conduct statistical inference regarding a performance measure. Providing a sense of the uncertainty in the VF forecast is then difficult, especially regarding any variation imposed by the network (as opposed to the requisitions) itself. While deterministic outputs from MLNPS (obtained with the VF) provide planners and decision-makers with actionable insights, it fails to communicate the uncertainty inherent in the information and the process. More simply, these outputs do not provide a sense of how bad things could be (severity) or their likelihoods. In short, the outputs do not support risk analysis. This chapter seeks to provide a tool to take GCSS-Army data and provide stochastic insights regarding the logistics network so that decision-makers can understand the uncertainty and risks inherent in their decisions.

This capability is absolutely needed for several reasons. GCSS-Army interfaces with imperfect humans who make mistakes and sometimes (perhaps even often if the reader is a cynic) act irrationally. Humans drive the logistics system – GCSS-Army helps keep track of the system itself. This military logistics system is mind-bogglingly complex with many dynamic interactions and dependencies that make complete understanding of these effects between workers, resources, and policies a pipedream. This complexity itself can create its own risks (Perrow, 1999). Finally, this logistics system is designed to do one thing – support friendly operations; these operations are being opposed, disrupted, or otherwise thwarted by

adversarial entities (Wilhelm, 2010). The old adage "the enemy gets a vote" applies and provides an unstoppable source of uncertainty. While the uncertainty cannot be altogether eliminated, GCSS-Army makes it possible for tools to account for this uncertainty.

3.2 Connecting the Virtual Factory with Risk Analysis

The Virtual Factory (VF) is deterministic but can be used to analyze risks and gauge uncertainty to support a military planner seeking to make the logistics network resilient enough to withstand the risks facing both the network and the risks inherent in the supported operation.

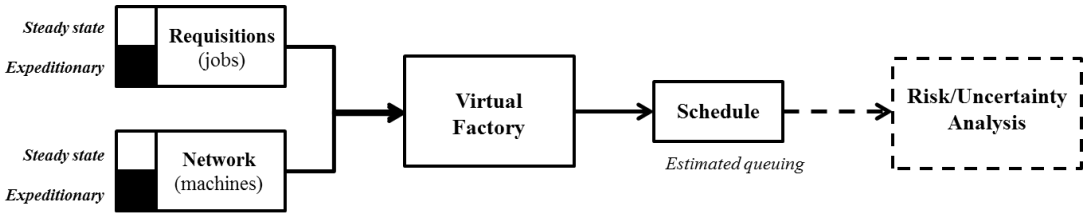

Figure 3.1: Post-Virtual Factory Risk Analysis Module.

Along with the queuing estimates for each requisition along every node in the logistics network, the VF also provides a schedule. This schedule can be used in conjunction with some stochastic modelling to conduct risk analysis without requiring the VF to be run repeatedly (see Figure 3.1). There is a tremendous amount of uncertainty in the problem, much of it coming from the supported operation. The network itself is prone to uncertainty which governs the processing times for the logistical nodes. It seems reasonable to assume that flight times for air transportation may be approximated with deterministic values but using the mean-value times for container ships travelling via surface may not be appropriate depending on the context (see Appendix B for details). Table 3.1 provides a list of some of the sources of uncertainty inherent in this problem and how these may affect the model's

representation. To provide a complete toolset, the MLNPS should include a "Risk Analysis" functionality to assess the impact of these 'risks.'

Table 3.1: Uncertainty Sources & Impact on Model.

Source of Uncertainty	**Primary Impact on VF Model**	
	Requisitions	**Network**
Performance	√	√
Demand	√	
Enemy		√
Terrain/Weather	√	√

It is apparent based on work by Rogers (2016) that the Military Logistics Network Planning System (MLNPS) provides insight that would be otherwise unavailable to military joint planners and analysts. While useful, as presented it is a deterministic tool that could benefit from a module capable of stochastic-based analysis. The potential questions a planner might wish to answer for a decision-maker follow directly from the questions posed by LTC Rogers (2016). Planning a military operation involves tremendous uncertainty and it is natural to wish to understand the uncertainty inherent in various aspects of the planned operation whether it is logistics performance or the estimated staffing and capacities required to support the operation. Some questions that require stochastic analysis are include below:

1. What are the required capacities (over time) at a particular logistics node needed to adequately support an operation? What is a (1-α) confidence interval for this capacity?
2. What is the required capacity at a certain node that will ensure that the queuing will not exceed some threshold?
3. What is the required capacity at a certain node that will ensure the average queuing is kept to some target?

4. What is the impact of not opening a particular logistics node until a specific point in time?
5. What is the impact of minimally resourcing a particular logistics node until a specific point in time (providing needed resources there from then on)?
6. For a given logistical support plan, what is the uncertainty on various performance metrics (lateness, probability of lateness, queuing, etc.) for various types of supply requisitions and nodes?

In order to address the stochastic nature of the problem, we first review what information we have prior to conducting the stochastic analysis. Using MLNPS, planners will have access to the input files to the Virtual Factory (VF); these consist of the projected supply requisitions (job file) and the logistics network (machine file). It is reasonable to assume the planners also have the output files obtained by running the VF on the mean value problem; these output files describe the mean value sample path and contain the queuing at each node, lateness, and the near-optimal sequencing. We can also safely assume that for a given logistics network structure, we have the directed graph structure, or adjacency matrix, to describe this feed-forward system.

We obtain this feed-forward structure through several important assumptions. First, we assume all requisitions are appropriately handled, routed, and moved along the required path from the point of supply to the point of consumption – in other words, we are not modeling lost, misrouted, or frustrated cargo. This is reasonable due to the sheer size of the network and the immense requisition flow volume. In addition, the military is actively embracing interconnected technologies such as radio frequency identification (RFID), two dimensional bar codes, satellite-based communications, and others that help prevent these logistical mishaps (Hodge, 2001; Kross, 2003; Juskowiak & Wharton, 2004; Cholek & Anderson, 2007; NRC, 2014). For now, these tools are designed to model repair parts,

known as Class IX, along with food and water (CL I) and ammunition (CL V); we do not model major end items (CL VI) such as a vehicle hulk which may require depot level maintenance where it would be sent out of theater to a special maintenance facility. This process is called reverse logistics and can be readily modeled with the Virtual Factory but is beyond the scope of this research (the addition of reverse logistics changes the network structure from a feed-forward system to a feedback system). This idea is discussed in Section 6.2.4.

3.3 Risk in Military Logistics Planning

3.3.1 Risk Concepts

The term *risk* is rampant in both military and nonmilitary applications; to construct a framework for risk analysis with the MLNPS, it is vital to clarify what constitutes risk. This research is not the first to contend with this term that is so easily understood yet so difficult to precisely define. In their survey in supply chain risk literature, Heckmann et al. (2015) lament the lack of clarity on the use of the term *risk* in general and as it applies to supply chains; they note "the term risk is still vague and often ill-defined" despite its frequent use in vernacular communication. Historically, the concept of risk itself has included the notion of *what-if* analysis since at least the 14th century when maritime merchants assessed the dangers that could result in lost ships. The idea of risk included reductions in asset value, catastrophic or total losses, and decreased business performance (Heckmann et al., 2015). Even in its early stages, risk analysis was already a multidimensional concept.

In the 17th century, the idea of risk capitalized on new mathematics to address the probability of events that cause a loss. This affinity for probability governs modern risk analysis though "definitions of supply chain risk are often vague, ambiguous, and defy quantification" (Heckmann et al., 2015). This criticism is especially relevant to risk

assessment in a military logistics planning context where risk itself is multidimensional. Parlier (2011) identifies operational risk and organizational risk; of these terms, operational risk is the most relevant to the MLNPS as the military supply chain faces operational risk in the unanticipated requirements and disruptions from events such as enemy, terrain, or weather. Beyond these considerations, a commander faces risks that address timing, performance, or other concerns. These may be measured by any number of qualitative or quantitative metrics that frame how the commander views risk. The framework for risk analysis must be flexible to accommodate different notions of risk and address various sources of risk, even if only through what-if functionality. Further complicating the analysis is the fact that risk has both time and location components that greatly increase the dimensionality – risk can evolve over time as the operational plan unfolds and might be concentrated in different logistic nodes as a function of time.

There is no common definition of supply chain risk; in the literature the supply chain objectives drive the risk assessment. The purpose of the military supply chain is to supply readiness to the supported units (Parlier, 2016; Parlier, 2017) yet Heckmann et al. (2015) find that only 1 in 33 surveyed papers address an effectiveness-driven supply chain – the lone paper seeks to increase customer satisfaction via service level (Kull & Closs, 2008). Most of the literature is concerned with efficiency-driven supply chains focused on optimizing costs, profit, or inventory. While important, these considerations are not driving decisions for expeditionary military logistics.

There are many concepts of risk and how to assess it. The US Army's Techniques Publication (ATP) 5-19 Risk Management and Department of the Army Pamphlet (DA PAM) 385-30 Mishap Risk Management dissect risk management into the five step cyclical

process provided by Figure 3.2 which identifies two steps pertaining to assessment. These documents are focused on operational risk and safety, respectively, and do not apply directly to the supply chain; however, any risk analysis included in MLNPS will invariably end up supporting a decision-maker using this framework.

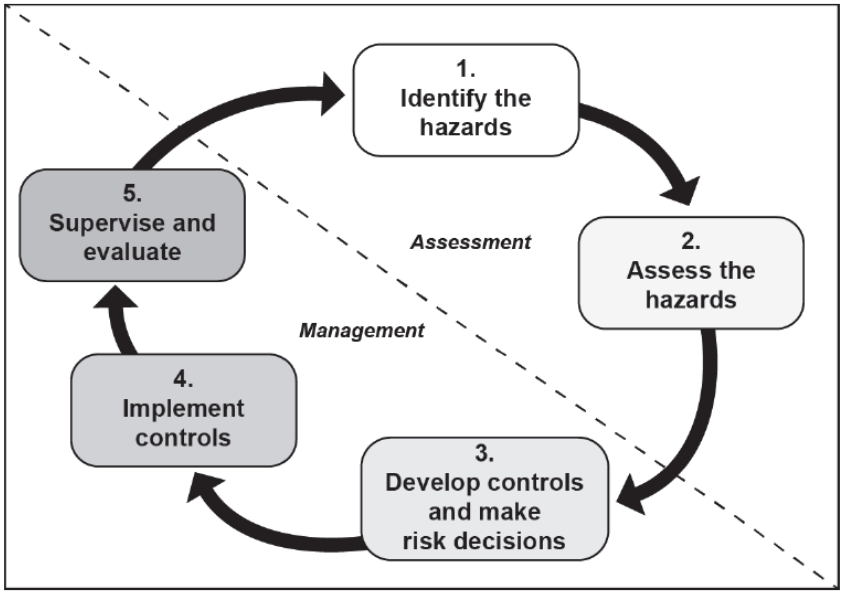

Figure 3.2: The US Army Risk Management Process (ATP 5-19).

The risk management process uses a *risk assessment matrix* displayed in Figure 3.3 below which relates the severity of the consequence with the probability of occurrence of disruptive events or scenarios. Military planners use the risk level derived from the risk assessment matrix to allocate appropriate resources, assign decision-making authorities, and evaluate courses of action. Kaplan and Garrick (1981) quantitatively define risk as a set of triplets that describe (Scenario, Likelihood, and Consequence). Misapplications of this construct often lead to faulty assessments of risk, especially when a multiplicative definition of risk (i.e. Risk = Probability x Consequence) is used – this is especially evident when inputs to the risk assessment exhibit negative correlations (Kaplan & Garrick, 1981; Cox, 2008; Ball & Watt, 2013; Alderson et al., 2015). Despite criticism from the National

Research Council, this approach is still widely used by others including the US Department of Homeland Security (Alderson et al., 2015).

		Probability (expected frequency)				
		Frequent: Continuous, regular, or inevitable occurrences	**Likely:** Several or numerous occurrences	**Occasional:** Sporadic or intermittent occurrences	**Seldom:** Infrequent occurrences	**Unlikely:** Possible occurrences but improbable
Severity (expected consequence)		**A**	**B**	**C**	**D**	**E**
Catastrophic: Death, unacceptable loss or damage, mission failure, or unit readiness eliminated	**I**	**EH**	**EH**	**H**	**H**	**M**
Critical: Severe injury, illness, loss, or damage; significantly degraded unit readiness or mission capability	**II**	**EH**	**H**	**H**	**M**	**L**
Moderate: Minor injury, illness, loss, or damage; degraded unit readiness or mission capability	**III**	**H**	**M**	**M**	**L**	**L**
Negligible: Minimal injury, loss, or damage; little or no impact to unit readiness or mission capability	**IV**	**M**	**L**	**L**	**L**	**L**
Legend EH – extremely high risk H – high risk L – low risk M – medium risk						

Figure 3.3: US Army Risk Assessment Matrix (ATP 5-19).

The quantification of risk presents a key challenge for risk assessment (Haimes, 1991). In the literature, the discussion of risk invariably leads to different aspects of how an event affects the system (here system refers to the military logistics system). In all of these contexts, risk assessment must be in accordance with the system objective (here, military readiness) but also system properties (Park et al., 2013; Alderson et al., 2015, Heckmann et al., 2015). Figure 3.4 groups relevant literature from military, government, transportation

infrastructure, and supply chain sources into a concept map illustrating how risk itself is framed and defined. Some discussions center on *robustness*—the system's ability to withstand different types of adverse events (Levina & Tirpak, 2006) or maintain stability (Maguire & Cartwright, 2008; Durach et al., 2015). Robustness itself is now conceptualized as a subcategory of *resiliency* (discussed below) and is subject to numerous definitions in supply chain contexts (Durach et al., (2015). Others evaluate risk in terms of the *response* to a disruptive event (Vugrin et al., 2010; Choi et al., 2016) by observing the magnitude and duration of the impact. Some authors focus on the *recovery* after the event by noting the resources required to respond (Hughes & Healy, 2014), the ability to transform post-event as part of the recovery (Levina & Tirpak, 2006; Maguire & Cartwright, 2008; Manyena et al., 2011), or predicting the trajectory of the recovery time itself (Haimes et al., 2008).

Many authors focus on system *resilience* to address risk. Haimes (2009) and Park et al. (2013) discuss multiple definitions of resilience in the literature. A common feature in resilience discussions is the notion of adapting in the face of disruptive events and bouncing back (Zolli & Healy, 2012; Alderson et al., 2015). Indeed, the lines between resilience and previously mentioned notions of risk seem blurry. Presidential Policy Directive 21 (PPD21) defines *resilience* as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions [and] includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" (The White House, 2013). The US Government Accountability Office (GAO) devotes considerable effort to reporting on the use and definition of *resilience* in official US Department of Homeland Security (DHS) documents (GAO, 2010). Clearly, "*resilience* is a family of related ideas, not a single thing" (Westrum, 2006). The same is true of *risk*.

This research's perspective on resilience most closely aligns with the definition of *operational resilience* as "the ability of a system to adapt its behavior to maintain continuity of function (or operations) in the presence of disruptions" used by Alderson et al. (2015). Their work links infrastructure resilience to system operation (function), focuses on disruptions, and warns risk analysts to be wary of correlated inputs (these correlated inputs are a fundamental flaw of the multiplicative Risk = Probability x Consequence approaches). A go-to tool to assess resilience is the resiliency curve which plots measures of interest for various options against an increasingly disruptive impact (Alderson et al., 2013; Alderson et al., 2015). These resiliency curves provide intuitive visualizations of system resilience and which options dominate under disruptive effects.

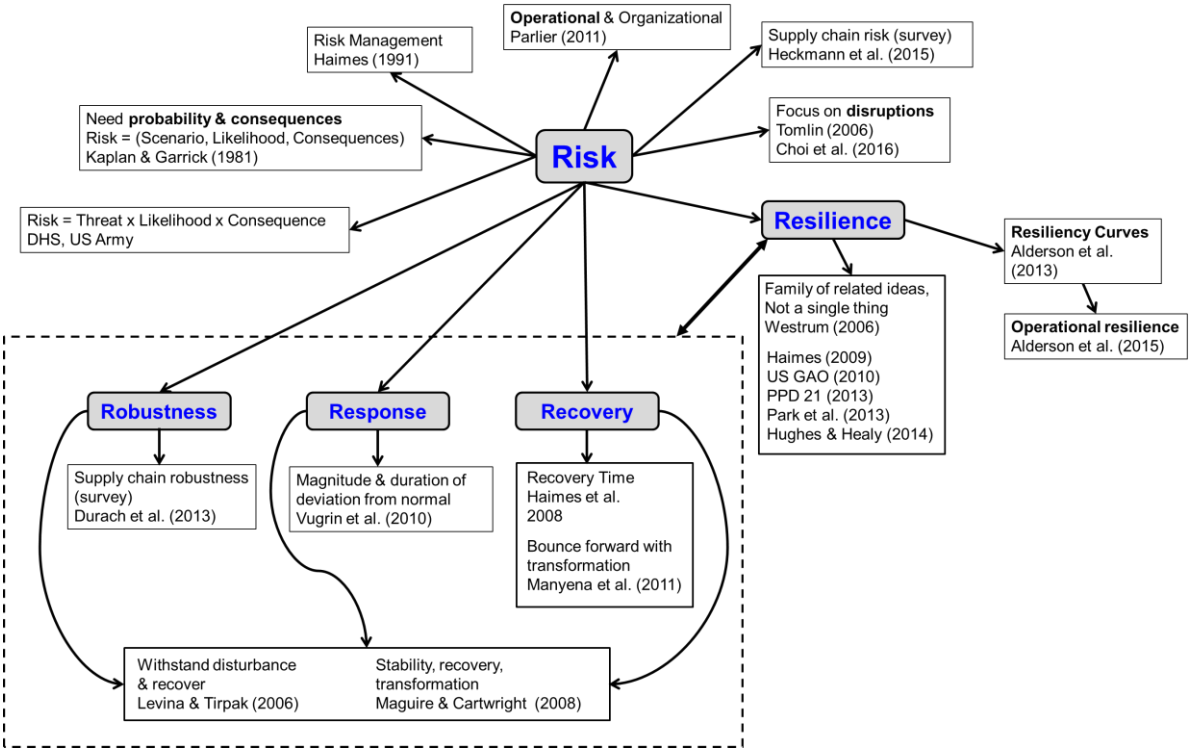

Figure 3.4: Concept Map for Risk-themed Literature

3.3.2 Risk Attitudes

In utility theory and financial contexts, specifying risk requires an understanding of the decision maker's risk attitude which is usually assessed as risk-averse, risk-seeking, or risk-neutral. Interestingly, supply chain risk literature does not even consider risk-seeking attitudes (Heckmann et al., 2015). It is difficult to assess what risk attitude is most appropriate for military logistics planning purposes precisely because risk is both so multidimensional and such a personally interpreted concept. Risk attitudes vary greatly during an operation based on geopolitical situation, enemy action, timing, weather, echelon, unit, mission, and even the individual commanders.

3.3.3. Risk Measures

There is no universal supply chain risk measure championed by the literature though authors using both probabilistic and scenario approaches attempt to quantify risk by measuring both likelihood and severity of adverse effects. Many authors have applied risk measures from finance such as deviation (including one-sided, absolute, expected, or standard), value at risk, and conditional value at risk. Others directly apply probability as the risk measure; still others do not further quantify risk beyond an uncertainty in input parameters (Heckmann et al., 2015; especially §5 and Fig. 5).

Despite widespread use, it is clear that expected value metrics are fundamentally flawed and present a false assessment to decision makers by equating high impact, low probability events with low impact, high probability events (Parlier, 2011). Heckmann et al. (2015) observes "the real challenge in the field of supply chain risk management is still the quantification and modeling of supply chain risk." The lack of clear and adequate measures results in authors using the inadequate expected value or turning to finance-based measures.

There are some finance risk measures that can be helpful if framed correctly for a decision maker. The value at risk (VaR) approach is a start point and is fundamentally just a quantile; as a quantile, VaR assists in assessing both severity and likelihood of adverse effects. Suppose X is the loss (or in our context, backlog or even capacity shortage) in a situation subject to uncertainty so that X is a random variable with probability density function (p.d.f.) $f_X(\bullet)$ and cumulative distribution function (c.d.f.) $F_X(\bullet)$. Hence for an arbitrary upper limit x on the loss X, $F_X(x) = P(X \le x)$ is the probability that the loss will not exceed that limit. Given $\alpha \in (0,1)$, the 100α% value at risk (VaR$_\alpha$) is the upper limit on loss that X will exceed with probability $1-\alpha$:

$$P(X > VaR_\alpha) = 1 - F_X(VaR_\alpha) = 1 - \alpha . \tag{3.1}$$

For example, if α = 0.95 and the 95% value at risk VaR$_{0.95}$ = \$2,000, then the loss X will exceed \$2,000 with probability $1-\alpha = 0.05$ (i.e., 5%). Formally, the value at risk is defined as

$$VaR_\alpha = F_X^{-1}(\alpha) = \min\{x : F_X(x) \ge \alpha\} \text{ for } \alpha \in (0,1). \tag{3.2}$$

Informally, VaR$_\alpha$ may be interpreted as a "reasonable" worst-case loss limit that will be "breached" (exceeded) with probability $1-\alpha$ as specified in Equation (3.1) and illustrated by Figure 3.5. Unfortunately, this measure only defines the "best" of the worst-case outcomes that can occur with $1-\alpha$ probability. It marks the beginning of the risk zone but does not provide insight into how bad things can really get. Instead conditional value at risk (CVaR) is used to portray the expected worst-case loss. Often used for attractive mathematical properties that lend themselves to optimization, CVaR can be intuitively understood as the expected loss when "VaR breach" occurs:

$$CVaR_\alpha = E\left[X \mid X > VaR_\alpha\right] \text{ for } \alpha \in (0,1)$$

$$= \int_{VaR_\alpha}^{\infty} x f_X(x)/(1-\alpha)\,dx, \tag{3.3}$$

where $x f_X(x)/(1-\alpha)$ is the conditional p.d.f. of X given that $X > \text{VaR}_\alpha$.

CVaR seems to be the more useful and easily understood of these two finance risk measures for military logistics planning if instead of loss we consider relevant logistics-based metrics (e.g., backlog or capacity shortage) but there is value in using multiple quantiles to describe the severity and likelihood of adverse impacts. This is related to the use of histograms by Savage (2009) who emphasizes focusing on the shape of the distribution. If quantiles illustrate the severity and likelihood for what can happen, CVaR is a natural augmentation to describe the average worst case scenario. Other conditional expectations may be appropriate (e.g. something of the form $E\left[X \mid X > 0\right]$) if accompanied by a measure of how often or likely the condition occurs.

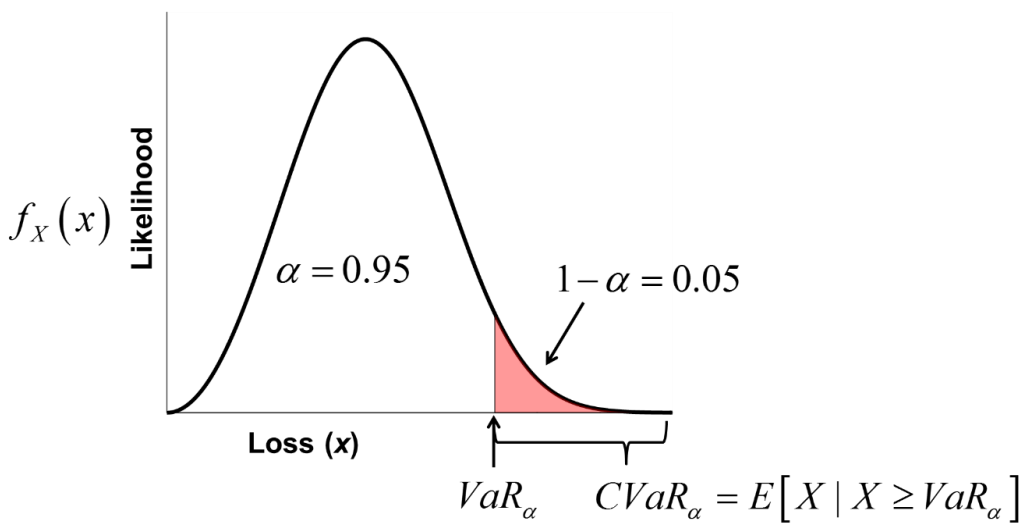

Figure 3.5: Graphical Depiction of Value at Risk (VaR_α) and Conditional Value at Risk (CVaR_α). VaR_α is the "best" of the worst-case losses. CVaR_α is the average worst-case loss given that a "VaR breach" has occurred. The graph arbitrarily depicts larger values of X as worse for illustration purposes; this distinction is context dependent.

However useful CVAR because of its mathematical properties (which are beyond the scope of this chapter), it is still just an average given a "VaR breach." It would be even better to also understand the worst-case outcomes in terms of severity and loss themselves. Select $0 < \beta_1 < \beta_2 < \cdots < \beta_k < 1$ to enable consideration of the $\beta_1, \ldots, \beta_k$ quantiles of the conditional distribution of the loss X—we use loss here as an example, the metric may vary—given that $X > \text{VaR}_\alpha$; take $k = 3$ with $\beta_1 = 0.25, \beta_2 = 0.50,$ and $\beta_3 = 0.75$ so that we wish to know the quartiles of this conditional distribution (describing the worst case outcomes). In this example, we would define the condition c.d.f. of X given $X > \text{VaR}_\alpha$,

$$F_{X,\alpha}(x) = P(X \le x \mid X > VaR_\alpha), \tag{3.4}$$

with the corresponding p.d.f.

$$f_{X,\alpha}(x) = \tfrac{1}{1-\alpha} f_X(x). \tag{3.5}$$

Then for $i = 1, \ldots, k$, we have the (α, β_i)–conditional quantile of the value of risk,

$$CQVaR_{\alpha,\beta_i} = F_{X,\alpha}^{-1}(\beta_i), \text{ for } i = 1, \ldots, k, \text{ which simplifies,} \tag{3.6}$$

$$CQVaR_{\alpha,\beta_i} = \min\{x : F_{X,\alpha}(x) \ge \beta_i\}, \text{ for } i = 1, \ldots, k. \tag{3.7}$$

3.3.4. Risk Analysis for the MLNPS

This research agrees with Perrow (1999) in that expeditionary military operations are highly complex affairs and as a result the supporting logistics are prone to operational risks from the complexity and system structure alone. Providing risk analysis tools for the MLNPS requires a framework that can inform the leader through default risk analysis outputs as well as equip the analyst with a structure to assess both severity and likelihood of outcomes; this structure should enable the analyst to find and present risk insights in the form relevant to the situation and the leader's perspective on risk. The dimensionality of the military logistics planning

problem does not provide a clear direction for establishing a single (or small set of) risk measure(s).

It seems evident from the literature, particularly Alderson et al. (2015), that risk (or resiliency) analysis should reflect the operation and function of the system during and after the disruptive event. Focusing on disruptions and an ability to facilitate systematic exploration of disruptive events and consequences is vital – in other words, old fashioned what-if analysis functionality is critical.

3.4 Relevant Queueing Literature

Queuing theory provides a rich and convenient source of tools to apply to this problem as it can account for uncertainty in both arriving requisitions and processing time through a network. Recent advances also integrate time-varying properties while relaxing the mathematically convenient Markovian assumptions from classical textbooks. Queuing theorists are largely concerned with two basic questions which align with our stated research objectives: (1) given a stochastic system's properties, estimate its performance (performance analysis) and (2) given a performance target, estimate the system properties required to achieve the desired performance (capacity planning).

Recognizing that the number of servers at a queue is analogous to the capacity of a logistics node, it is clear that queuing theory can assist MLNPS in setting capacities (or estimating required capacities) to achieve better performance. Figure 3.6 (mimicking Mandelbaum & Momčilović, 2008) demonstrates that by increasing the system scale, it is possible to increase quality of service without loss of efficiency – in other words, properly setting the capacity can benefit both quality and efficiency.

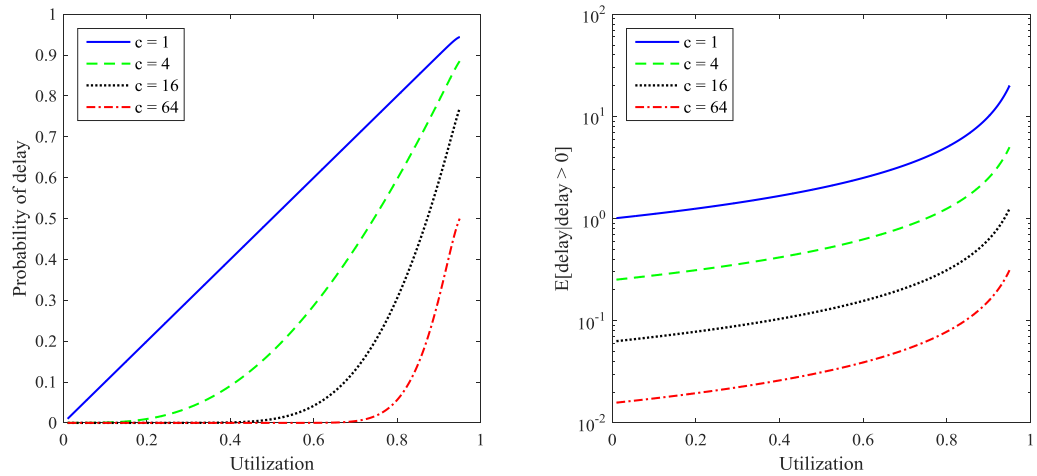

Figure 3.6: Performance of *M/M/c* queues (for c = 1, 4, 16, 64) demonstrating it is possible to increase efficiency and quality through staffing; utilization (ρ) is the arrival rate (λ) divided by the total service rate ($c\mu$), $\rho = \lambda / c\mu$.

The rest of this section presents selected literature most relevant to our problem focusing on staffing time-dependent (nonstationary) queueing systems and non-Markovian properties for both single queues and networks of queues. For a broader review, we encourage the reader to examine a state-of-the-art survey on staffing service systems with nonstationary demand by Defraeye and Nieuwenhuyse (2016) which covers literature from 1991-2013 (see §1 for scope and alternate surveys in the field). Green et al. (2007) and Whitt (2007) provide excellent reviews of techniques for staffing service systems including those with time-varying demand. Readers completely unfamiliar with queueing theory will find Appendix E contains introductory information and identifies queueing regimes.

3.4.1 Single Server with Time-Varying and/or Non-Markovian Processes

Modeling a queue is often complicated as many real world systems experience arrival rates that vary over time. This time-varying (nonstationary) difficulty implies the system never reaches a steady-state. Many studies have found evidence of this in everything from

hospitals, telephone call centers, and even trucks at a seaport (Buffa et al., 1976; Fig. 5, Gans et al., 2003; Green et al., 2007; Chen, et al., 2011; Izady & Worthington, 2012). Models using Markovian arrival processes with exponential interarrival times, even the time-varying version with a non-homogeneous Poisson process (NHPP), and exponential service times provide mathematical convenience, yet many systems experience more significant variation in both the arrival process and service time distribution than is accounted for via Markovian models. To see empirical evidence of these phenomena in our context, refer to Appendix B. Many of the results relying on a stationary model or a system's steady-state will provide poor approximations to the non-stationary (time-varying) case. If enough variation exists in either the arrival process or the service time distribution—particularly in the arrival process—Markovian-based results similarly perform poorly (Liu & Whitt, 2012b; Aras, 2016; He et al., 2016). The nonstationary non-Markovian nature of the military logistics problem is motivation to look for more advanced tools; Figure 3.7 shows selected relevant literature for nonstationary capacity planning (staffing) including model, techniques or features, and the performance metric stabilized for single queues.

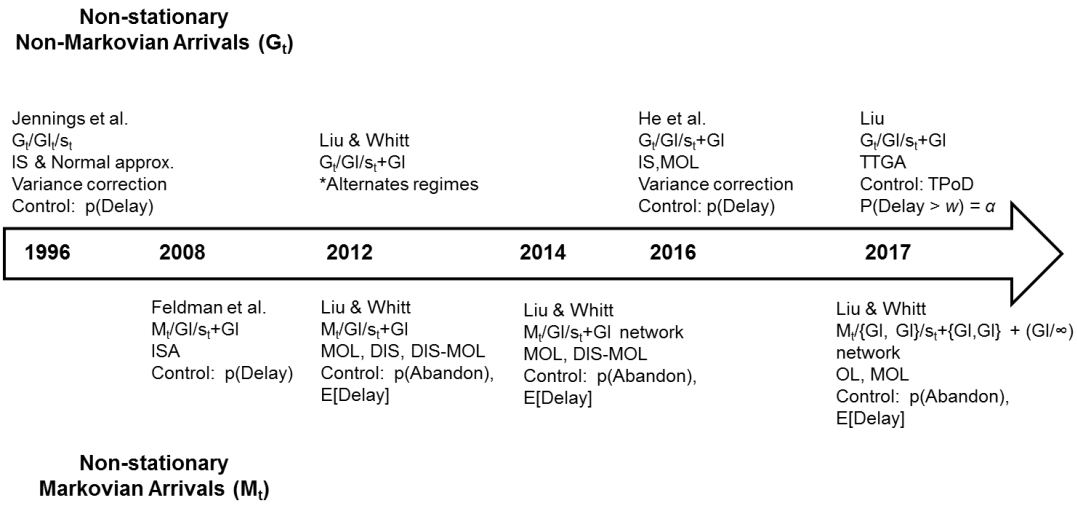

Figure 3.7: Nonstationary Capacity Planning (Staffing) literature for single queues and networks.

These papers address various features that are present in the military logistics planning problem including time-varying (nonstationary) arrivals, non-Markovian (non-exponential) service times, and operate in the overloaded regime (efficiency driven) regime where all arrivals are expected to experience a non-zero delay. A more detailed discussion of queueing regimes is found in Appendix C.

		MLNPS Requiremetns	Jennings et al., 1996	Whitt 2006	Feldman et al., 2008	Liu & Whitt, 2012a	Liu & Whitt, 2012b	He et al., 2016	Liu 2017
Purpose	Performance Analysis	X				X	X		X
	Capacity Planning	X	X	X	X	X	X	X	X
Features	Time-Varying Arrivals	X	X		X	X	X	X	X
	Non-Markovian Arrival Process	X	X				X	X	X
	Non-Markovian Service Times	X	X	X	X	X	X	X	X
	Abandonment (from queue)			X	X	X	X	X	X
Stabilization Targets	Expected Delay, E[Delay]	X				X			
	Probability of Delay, p(Delay)		X		X			X	
	Tail Probability of Delay (TPOD)	X							X
	p(Abandon)					X			
Regimes	Efficiency Driven (ED)	X	X	X		X	X		X
	Quality and Efficiency Driven (QED)								
	Quality Driven (QD)						X		
Asympotic Limit	Many-Server Heavy-Traffic (MSHT)	X	X	X		X	X	X	X
Approximation Techniques	Infinite Server (IS)		X						
	Delayed Infinite Server (DIS)					X			
	Iterative Staffing Algorithm (ISA)				X				
	Offered Load (OL)					X			
	Modified Offered Load (MOL)					X			
	Delayed Infinite Server - Modified Offered Load (DIS-MOL)								
	Two Term Gaussian Approximation								X
	Normal Approximation to Poisson		X					X	
Other	Variance Correction	X	X						
	Model Uncertainty			X					

Figure 3.8: Literature Comparison for Single Queue Nonstationary Capacity Planning

Jennings et al. (1996) use an infinite server (IS) model and a Normal approximation to choose the time-varying staffing function, $s(t)$, such that the probability of delay is approximately equal to some target value for the $G_t / GI_t / s_t$ queue. Feldman et al. (2008) develop an iterative staffing algorithm to find the staffing function for the $M_t / G / s_t + G$ queue with the goal of stabilizing the delay probability. Feldman et al. show their algorithm also stabilized average waiting times, along with other metrics, and converged exactly for the $M_t / M / s_t + M$ special case.

Whitt (2006a) uses a deterministic fluid approximation to determine the performance and required near-optimal staffing levels for the $M / GI / s + GI$ model with uncertainty both in the arrival rate and staffing. In the paper, Whitt assumes the arrival rate is changing and its value is random; the staffing level is affected by a random percentage of assigned staff that do not show up for work. Whitt's results are relevant in that they establish a framework

for assessing both process and model uncertainty in one model and the results essentially hedge against arrival rate uncertainty.

Liu and Whitt (2012a) use IS models to develop offered-load (OL) and modified offered-load (MOL) approximations for the time-dependent staffing level required to stabilize the abandonment probabilities and expected delay for the $M_t / GI / s_t + GI$ queue. Though they conclude with a formula-based algorithm, their MOL approach requires the queue to have abandonment for the algorithm to work. Liu and Whitt show their use of two infinite servers in series, the delayed infinite server (DIS) model, is asymptotically correct in an efficiency-driven (ED), or overloaded, many-server heavy-traffic regime. This DIS model is discussed in more detail later in Chapter 3.

Liu and Whitt (2012b) develop a deterministic fluid model to approximate the many-server $G_t / GI / s_t + GI$ queue and calculate the time-dependent performance functions. The paper assumes the system alternates between being underloaded and overloaded which is motivated by the idea that staffing will never be exactly correct due to process uncertainty; it presents an algorithm and solution for obtaining the performance functions (Aras, 2016). This extends the $G / GI / s + GI$ fluid model in Whitt, 2006b, to the time-varying transient case.

Recent work by He et al., (2016) extends established staffing algorithms to allow for non-Markovian arrival processes. Their staffing under a heavy-traffic limit is effective in stabilizing the time-varying probability of delay at set targets. Further, section 4 provides insight into the impact and interplay between arrival process variability and service time distributions (He et al., 2016). Specifically, they study the suitability of their staffing

algorithm, as well as the established procedure, under various levels of variability in the arrival process and different service time distributions.

Liu (2018) presents a staffing method to stabilize the tail probability of delay (TPOD) in nonstationary queues with non-Markovian arrivals, service and patience-time distributions ($G_t / GI / s_t + GI$). This allows capacity planning to ensure $(1-\alpha)\%$ of arrivals are processed within *w* days, or alternatively, $P(Delay > w) = \alpha, \alpha \in (0,1)$. This control target is highly relevant as it is easily understood by policymakers and we believe more useful for the MLNPS.

3.4.2 Networks of Queues

There has been significant work in performance analysis using the fluid approximations in Liu and Whitt (2012b) for networks of queues. Liu and Whitt (2011) develop performance approximations for an open $(G_t / M_t / s_t + GI)^m / M_t$ network with *m* individual $G_t / M_t / s_t | GI$ queues each with proportional Markovian routing. They extend this to include a similar network but with general service time distributions for the $(G_t / GI / s_t + GI)^m / M_t$ model (Liu & Whitt, 2014b).

Liu and Whitt (2014a) extend their previous work with the delayed infinite server (DIS) and delayed infinite server modified offered load (DIS-MOL) approximations (Liu & Whitt, 2012a) to appropriately staff a network of $M_t / GI / s_t + GI$ queues in a feed forward structure which has the most direct relevance to the MLNPS problem though Section 3.8 illustrates the arrival processes in the MLNPS model is not Markovian. Izady and Worthington (2012) present an application of the infinite server (IS) and square root staffing rule (SRS) from Jennings et al. (1996) to use the maximum offered load to staff an accident

and emergency department in the United Kingdom; though less general than Liu and Whitt (2012a), their $\left(M_t / GI / s_{mt}\right)^m / M$ model is especially important.

Most of the queuing theory cited is largely focused on call center applications – Izady and Worthington (2012) apply the theory to staff a system where the process itself is a network of tasks that require disparate but often shared resources such as nurses, doctors, and other categories of specialized personnel. After finding the ideal time-dependent staffing plan, they formulate an integer programming model to best implement this idealized staffing under real-world staffing level and legal constraints by penalizing the total over and understaffing.

3.5 Virtual Factory Delayed-Infinite Server Feed Forward Model

3.5.1 Modeling Problem as Queueing Network

The military logistics network stretching from CONUS depots to the expeditionary theater of operations can be modeled as a queueing network where logistical nodes (or processes) are queues and the requisitions are arriving as orders via GCSS-Army. These orders are sourced, picked and packed, then shipped to the ordering unit as the simplified model in Figure 3.9 illustrates.

The model is a feed-forward queuing network as supply requisitions move from the sourcing depot across the network to the ordering unit and do not require rework or depart the network through some lateral exit (Section 6.2.4 discusses relaxing this assumption). In the simplified network shown, requisitions are arrivals in the queuing theory terminology and arrive according to a schedule obtained from the requisition forecast. There are multiple classes of arrivals based on the mode of transportation to be used whether military air, world-wide express (WWX), or ocean (surface). Within each arrival class are many subclasses

defined by the specific route that requisition must take through the network, largely defined within a class by the sourcing node and the ordering unit.

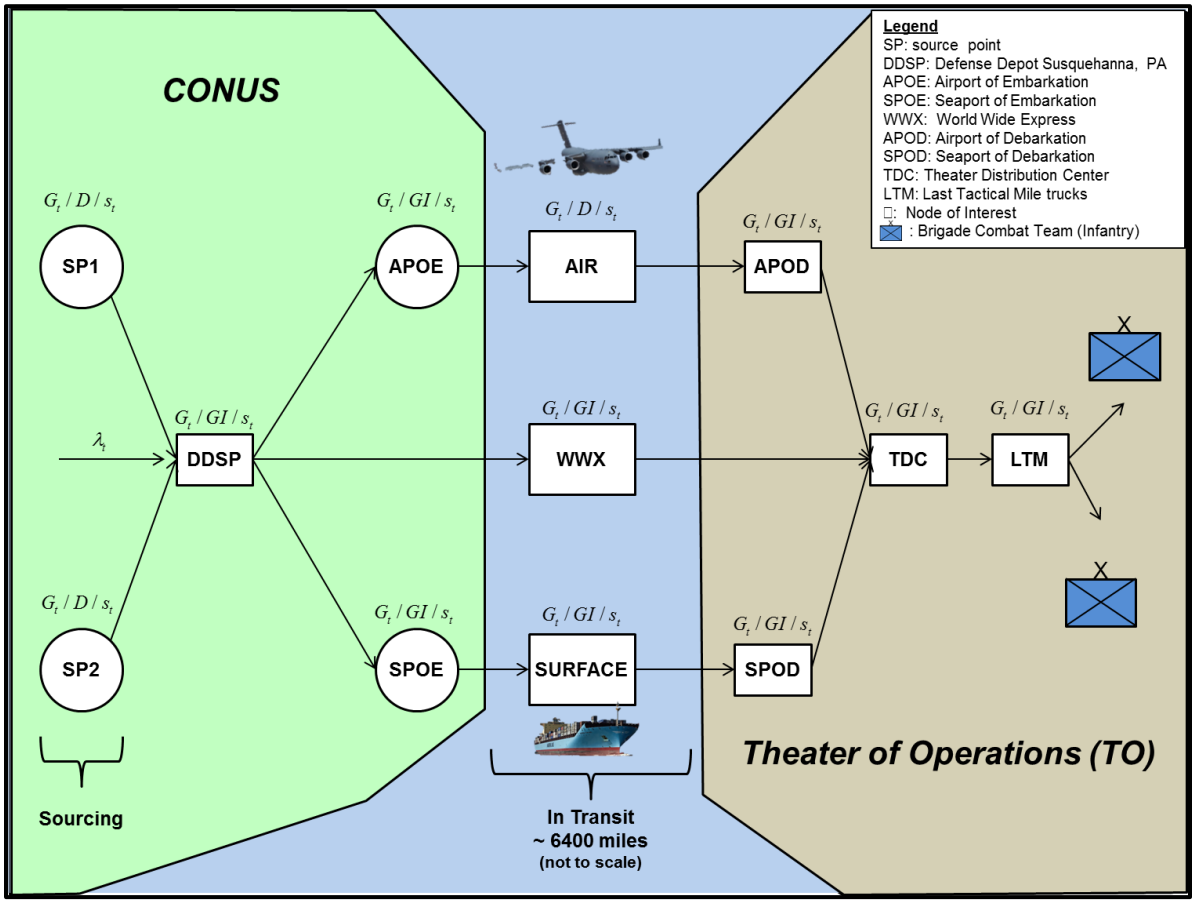

Figure 3.9: Military Logistics Network as Queueing Network (simplified for illustration).

The feed-forward structure implies that by estimating the performance or capacity required at an upstream location, if the departure process is obtainable it also provides the arrival process to the downstream nodes so the analysis can be repeated for downstream locations. Consider the simplified military logistics network depicted as a feed-forward queuing network in Figure 3.9; supply requisitions arrive at either DDSP or to an alternative depot acting as a sourcing point (SP1 or SP2). The requisitions from alternative depots still move to DDSP as it is the primary container collection point (CCP) for palletizing and containerizing shipments. As Rogers (2016) discusses, most requisitions travel via military

aircraft, world-wide express (a contracted point to point service), or surface shipment (ocean freight). Shipments traveling on military aircraft (ocean freight) are palletized (containerized) at DDSP then loaded onto military aircraft (container ships) at the airport (seaport) of embarkation, or APOE (SPOE) for movement into theater where they are offloaded at the airport (seaport) of debarkation, or APOD (SPOD). These shipments are then transported to the theater distribution center (TDC). Requisitions being shipped via world-wide express (WWX) travel directly to the TDC. At the TDC, pallets and containers are broken down and moved forward via military transportation to the ordering units. This final process is often referred to as the last tactical mile (LTM) due to the transportation occurring through a designated combat zone.

Using mission-based forecasting (MBF) and the data from GCSS-Army, it is possible to estimate the arrival processes to the network shown in Figure 3.9. Since MBF is not available for all unit types, Chapter 4 presents a data-driven approach to forecasting requisitions for a given scenario. This forecast provides estimated nominal time-varying arrival rate to the upstream sourcing nodes.

While the feed-forward structure imparts computational efficiency and suggests a simple sequential approach, the time-varying (nonstationary) property and presence of non-Markovian (non-exponential) arrival and service processes greatly complicate the analysis. The reader will notice the fundamental modeling unit traversing the network is changing as well and there is no common unit for capacity (number of servers); Rogers (2016) used number of requisitions per day for DDSP, 463L pallets per day for the APOE, and forty foot container equivalents per day (FEU) for surface freight, and even the number of medium

truck companies as a capacity unit. Queueing theory has no easy way of accounting for these unit changes.

To simplify the analysis, avoid tedious empirically-based unit conversations, and dodge task organization disputes, the model employs a 463L pallet equivalent unit (PEU) as the base unit of capacity to be used throughout the network. For reference, Figure 3.10 portrays airmen loading 463L pallet holding multipack containers into a military aircraft. This is reasonable as it readily converts to twenty foot container (TEU) and forty foot container (FEU) equivalent units widely used in the logistics practitioner community. The CCP packs requisitions and multipack boxes into containers. The TDC requires an equivalency unit as it breaks down both pallets and containers and organizes them with individual requisitions for onward transport. Given a particular Army truck company equipment list, known as the modified table of organization and equipment (MTOE), it is possible to convert between PEU and a collection of logistics distribution resources.

Figure 3.10 Depiction of 463L pallet with multipack containers (Lavender, 2009)
Al Taqqadum, Iraq (Jan. 9, 2009) Seabees assigned to Naval Mobile Construction Battalion (NMCB) 7 and Air Force airmen of Expeditionary Logistics Readiness Squadron Detachment 4 maneuver 463L pallets with Seabee equipment into an Air Force C-17 for transportation. (U.S. Navy photo by Mass Communication Specialist 2nd Class Michael B. Lavender).

Establishing the PEU unit also provides an opportunity to account for the tare weight. One can calculate the number of PEUs arriving (or departing) location *m* on day *t* by taking the total weight and volume for that day and location and dividing by the effective maximum capacity of the 463L pallet given by Equation (3.8) below. The larger of the two determines the 463L pallet equivalent capacity required; note for resources the smaller of the two is the offered resource capacity. Table 3.2 lists the 463L maximum and effective capacity. The use of cubic inches preserves integrality in the model for computational efficiency and adequately models requisitions with less than a unit cubic foot volume.

$$P_{mt} = \max\left\{\frac{TotalWT_{mt}}{95\%\ PEU\ WT},\ \frac{TotalCU_{mt}}{85\%\ PEU\ CU}\right\}$$

$$= \max\left\{\frac{TotalWT_{mt}}{9500}\ \text{lbs},\ \frac{TotalCU_{mt}}{712368}\ \text{in}^3\right\} \tag{3.8}$$

Using 95% of the maximum weight accounts for tare weight. Using 85% of the maximum volume accounts for inevitable voids between contents that prevent using all of the physical container volume. Whether a tractor trailer or a shipping container, spaces are considered full at the 85% volume utilization point.

Table 3.2: Maximum and Effective Capacity of the 463L Pallet.

	Weight (lb)	**Volume (cu in)**
100% 463L Capacity	10000	838080
Effective PEU	9500 (95%)	712368 (85%)

3.5.2 Technical Overview

To assess risk and answer the research objectives, this research uses a tandem Virtual Factory Delayed Infinite Server (VF-DIS) offered load approximation for each location; the model alternates between using the VF and the DIS approximations for each location moving across the network from upstream to downstream. The appeal lies in leveraging each submodel's strengths. The Virtual Factory is efficient and can handle nested batch processing (think multipack inside a pallet on a truck) as well as a number of realistic constraints, and with small refinements, the DIS model (Liu, 2012a) provides a computationally efficient method to evaluate performance and predict capacity requirements while communicating a sense of the uncertainty in the predictions. This tandem approach uses each model to the maximum potential while avoiding each model's weaknesses.

The Virtual Factory (VF) can already address the unit change without the PEU and is also capable of modeling location-specific policies via its processor logic; these are important as some locations do not work weekends or resources vary according to specific schedules driven by real-world considerations. Another example stems from a working policy used by a container packing location (one of several batch processes) – a container is considered full

when it reaches its effective capacity, reaches the minimum capacity to send and there are no orders left to pack, or when it has been sitting open (and partially filled) for at least three days. These nuances are conveniently incorporated through the VF's processor logic.

The approach starts with the data-driven requisition forecast and the performance target of average delay desired for each of the network locations. These performance targets are obtained from stakeholders, proposed for the sake of continued analysis, or derived from senior leader interaction. The forecast conforms to requirements described in Chapter 4 but in general is both nonstationary and non-Markovian. We assume an empirical or fitted theoretical distribution is available for the processing time at each location in the network to account for stochastic variation; these may be general (non-exponential).

Figure 3.11 gives a visualization of the VF-DIS process with a small portion of the network. It depicts the network as two competing models, the DIS and the VF approaches, with the bold (blue) line representing the solution approach for an analyst conducting risk analysis and military logistics planning. Taking the logistics network, processing logic, and requisition forecast, the $\lambda(t)$, as inputs, VF-DIS first uses the VF at the upstream nodes to assess the arrival process in PEU and the resulting departure process (also in PEU) given the default time-dependent capacity plan, the s_t , which can be initialized via a simple constant capacity. With the average delay targets for the upstream nodes, the DIS model calculates the time dependent capacity required to meet the targets by providing both a time dependent average (the S_t) and the stochastic variability around that average. These capacity plans (functions over time) are used as inputs to the VF which accounts for location-specific policies, logic, and schedules; the VF then returns the time dependent departure process in PEU represented as $\sigma(t)$. Since the network is feed-forward, the departure process is the

downstream arrival process so the model advances downstream once the upstream planning is complete and repeats the process until it reaches the most downstream nodes.

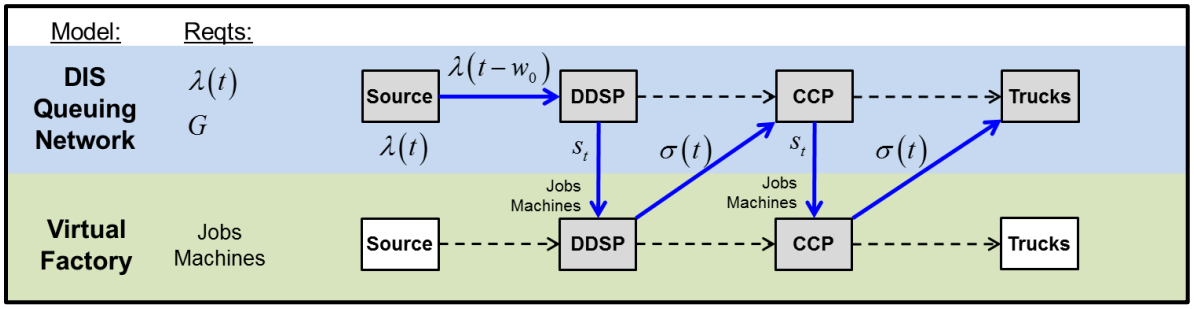

Figure 3.11 Visualization of the Virtual Factory Delayed Infinite Server (VF-DIS) offered load network model.

The performance targets for each node may be obtained from senior leader guidance, experts, or simply a staff estimate as part of the planning process. If not derived from successful historical performance or leader guidance, staff planners may choose to use a range of targets they believe to be feasible and present them with their resulting impacts to the staff and/or leadership for analysis and decision. The calculations this choice permits is the science but choosing an appropriate performance target is clearly part of the art of the method described here.

3.5.3 Technical Details: What Happens at Every Node

The VF-DIS performs the same steps at every location. If that location is not of interest or cannot be impacted by available decisions, there is no need to linger performing analysis once the departure process is obtained. However, when the VF-DIS model reaches a node of interest such as the theater distribution center (TDC) or the LTM trucks, it may be desirable to identify a logistics plan for that location to meet senior leader performance guidance and assess the associated risk. This section provides the technical details for this process.

Consider an arbitrary node in the logistics network. Let w be the average delay taken as the performance target for this node and denote the average arrival rate (in PEU per day)

on day t as $\lambda(t)$; this nonstationary arrival rate is obtained using the VF and the data-driven requisition forecast discussed in Chapter 4. Assume an estimate of the dispersion of this arrival process; this may be available from the data-driven requisition forecast using multiple sample paths or acquired by parsing historical data. The logistics node is represented as a $G_t / GI / s_t$ queueing model where the processing time, S, at this location is independent and identically distributed according to the general distribution F_S. The arrival process is a nonstationary non-Poisson process (NNPP). Figure 3.12 labels this Model 1. Define $\sigma(t)$ as the average departure rate on day t for the associated departure process.

Model 1 can be approximated by a $M_t / GI / s_t$ queue (Model 2 in Figure 3.12) as it captures the time-dependent fluctuations in the arrival process with the same deterministic mean function while retaining Model 1's non-exponential service time distribution and time-varying capacity. The only difference is in the arrival process variability. The transition to Model 2 is motivated by convenience and requires a correction to account for the arrival variability. There is no reliable method to obtain analytical approximations for the capacity required over time to meet performance targets for Model 1 and use of simulation will not permit the analysis to be performed in near-real time. From the network perspective, Model 2 enables Poisson superposition as an approximation at a downstream node that receives requisitions from multiple upstream nodes; the aggregate arrival process is then approximately a nonhomogeneous Poisson process (NHPP).

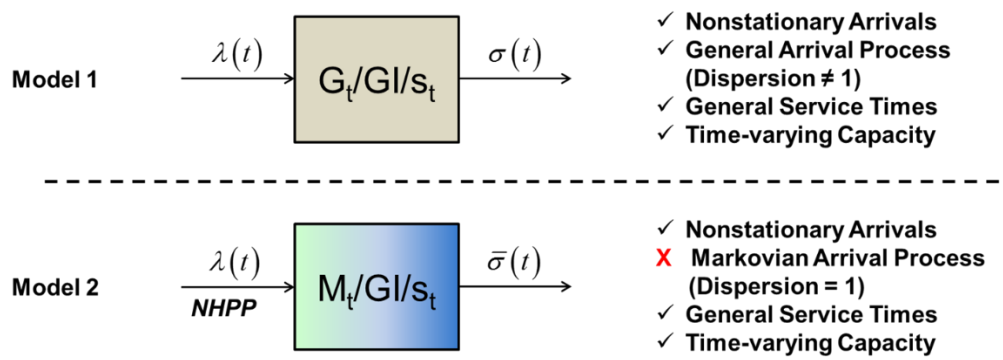

Figure 3.12: Queueing Models for a Location—Model 2 approximates Model 1 by focusing on the time-dependent behavior. In general, the departure process for Model 2 is a nonstationary non-Poisson process.

To identify the capacity to achieve the average delay target for Model 2, Liu and Whitt (2012a) show that the Delayed Infinite Server (DIS) offered load approximation works well for systems such as the military logistics system where requisitions may be expected to wait for some (even small) amount of time before being processed. The DIS model, depicted as Model 3 in Figure 3.13, approximates Model 2 by using two infinite capacity queues in series. This presentation of the DIS model is modified to remove the abandonment process implying the assumption that there is no lost, misrouted, or frustrated cargo. The first queue represents the waiting space in Model 2; the second queue represents the service facility of Model 2.

The infinite capacity implies the departure process from each queue in Model 3 is also a NHPP which is computationally and mathematically critical in the feed-forward network. The idea behind Model 3 is simple. Requisitions arrive to the first queue (waiting area) and wait a deterministic amount of time equal to the target average delay, *w*, before continuing to the second queue. This implies an average arrival rate of $\beta(t) = \lambda(t-w), t \geq w,$ at the second queue which is just a deterministic time shift.

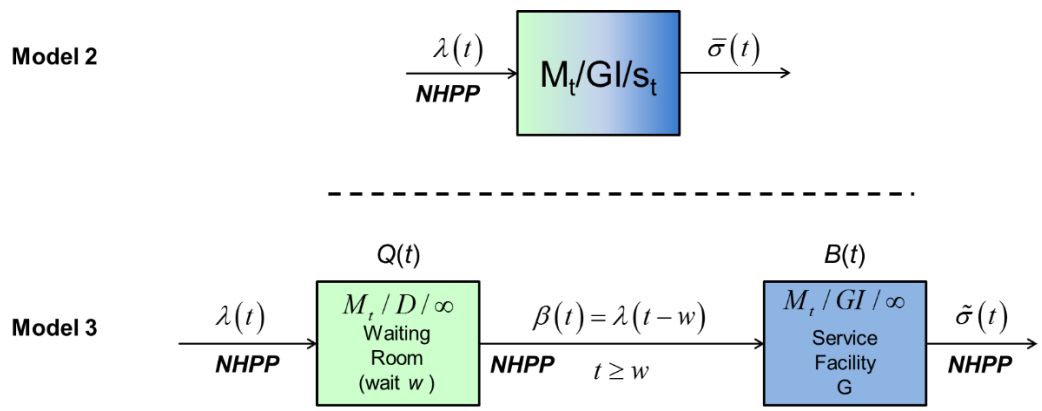

Figure 3.13: The Delayed Infinite Server (DIS) offered load approximation for the $M_t/GI/s_t$ queue (Model 3). Liu and Whitt (2012a) show Model 3 approximates Model 2. The contents of the first two queues, $Q(t)$ and $B(t)$ respectively, are independent Poisson random variables for a fixed *t*. See Table 3.3 for departure rate $\tilde{\sigma}(t)$.

At the second queue, requisitions immediately begin processing according to the general service time distribution F_S. The objective is to determine the number in the second queue at time *t*, $B(t)$, which serves as the first order approximation of the number of busy servers in Model 2 while maintaining an average delay of *w*. In simpler terms, Model 3 approximates Model 2 by having all requisitions wait the desired average delay then simply observes how many busy servers would be in the second queue over time. Based on the mathematics of the infinite server queue, this is obtained via direct calculation applying known results for the $M_t/GI/\infty$ queue (Eick et al., 1993; notably Theorem 1). Applying these known results for a fixed *t*, $B(t)$ is a Poisson random variable with mean $E\left[B(t)\right]$ determined by Equation 3.9 (Liu & Whitt, 2012a). Note the notation, $(x)^+ = \max\{x,0\}$, and the service time complementary cumulative distribution function, $\bar{F}_S(x) = 1 - F_S(x)$.

$$E\left[B(t)\right] = \int_0^{(t-w)^+} \lambda(t-w-x)\bar{F}_S(x)\,dx \tag{3.9}$$

Equation 3.9 calculates the average capacity over time required to maintain the performance target. Even better, the mathematics of Model 3 fully specify the distribution of this predicted capacity requirement. Chapter 5 exploits this idea and underpins Monte Carlo methods to estimate what cannot be calculated analytically. Table 3.3 summarizes the remaining analytical formulas for the DIS offered load approximation.

Table 3.3: Model 3 DIS Approximations for Model 2 (without abandonment). Note that $t \wedge w = \min\{t, w\}$ and $(t-w)^+ = \max\{t-w, 0\}$.

Performance Feature	**DIS Approximation***
Queue Length, $Q(t)$	~ Poisson with mean $E\left[Q(t)\right] = \int_0^{t \wedge w} \lambda(t-x)\,dx$
Number of Busy Servers, $B(t)$	~ Poisson with mean $E\left[B(t)\right] = \int_0^{(t-w)^+} \lambda(t-w-x)\,\bar{F}_S(x)\,dx$
Departure Rate, $\tilde{\sigma}(t)$	~ NHPP with time-varying rate $\tilde{\sigma}(t) = \int_0^{(t-w)^+} \lambda(t-w-x)\,dF_S(x)$
Total Number in System, $X(t)$	$X(t) = Q(t) + B(t)$

* for a fixed *t*

This approximation predicts the required capacity over time for Model 2 as $B(t) \sim Poisson\left(E\left[B(t)\right]\right)$ however the results from Liu and Whitt (2012a) apply to the $M_t / GI / s_t$ queue in Model 2. As a Poisson random variable for a fixed *t*, $B(t)$ has a variance equal to the mean; accounting for Model 1's G_t arrival process requires a variance correction otherwise this would produce a false sense of risk. For a stochastic counting process such as $\{A(t), t \geq 0\}$ that counts the number of arrivals (events) by time *t*, the process dispersion, $I(t)$, is the variance to mean ratio of the cumulative number of arrivals (events) as given by Equation (3.10),

$$I(t) = \frac{Var\left[A(t)\right]}{E\left[A(t)\right]}, \text{ for } t > 0. \tag{3.10}$$

For any NHPP such as Model 2's M_t arrivals, $I(t) = 1 \ \forall t > 0$.

The arrival process is *overdispersed if* $I(t) > 1$ and *underdispersed* if $I(t) < 1$. If the arrival process to Model 1 is significantly overdispersed then a naïve implementation of the DIS offered load approximation will underestimate risk to the decision-maker because while the predicted average will be true the variance will be underestimated. Figure 3.14 provides an estimated dispersion for the LTM trucks in the Sudan COA 1 scenario from Rogers et al. (2016) and later described in detail in Chapter 5; with the arrival rate in PEU, the LTM arrivals are over five times more variable than a NHPP. In other applications, healthcare clinics often see underdispersion (~0.4-0.6) in appointment-based systems where arrival processes may be overdispersed (~1.5-2.5) in emergency departments or at call centers (Kim and Whitt, 2014; Kim et al. 2015, Whitt and Zhang, 2015; Liu et al., 2017).

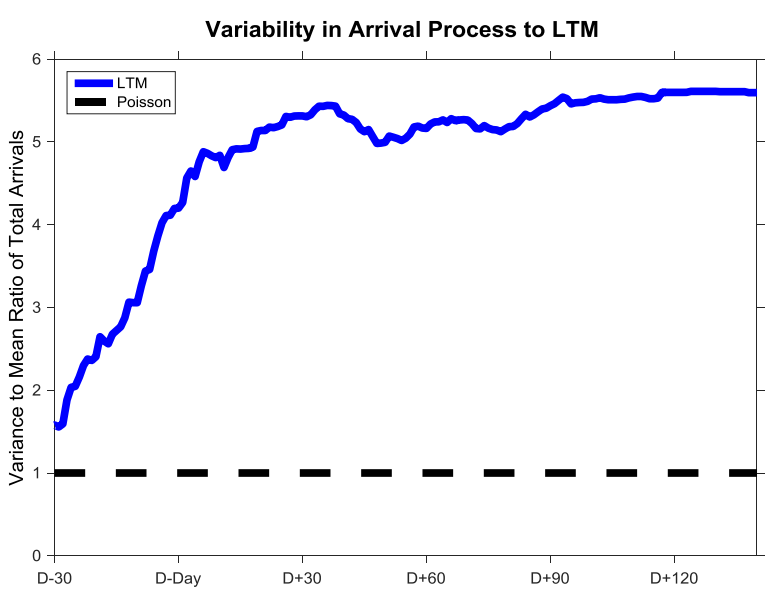

Figure 3.14: LTM Arrival Dispersion for Sudan COA 1 from Rogers et al. (2016) is over 5 times as variable as a NHPP (dashed line).

This research assumes that with GCSS-Army data an analyst can estimate the dispersion for a given location (as explained in Chapter 4, this research estimates the dispersion using multiple sample paths for the requisition forecast).

Obtaining this risk correction factor (RCF) requires applying a result from the stationary $G/G/\infty$ queueing model as a heuristic which is consistent with Jennings et al. (1996, see §6) and He et al. (2016, see §3). Let $m(t)$ and $v(t)$ be the mean and variance for $B(t)$; note in Model 3, the relation $m(t)=E\left[B(t)\right]=v(t)$ hold exactly (in Model 2, this relation holds approximately). The heuristic RCF, $\tilde{z}(t)$, used by the VF-DIS approach is to use the approximation

$$v(t)\approx\tilde{z}(t)m(t)\text{, with the RCF} \tag{3.11}$$

$$\tilde{z}(t)=\max\left\{1,\, z(t)\right\}, \tag{3.12}$$

$$z(t)=1+\frac{\left(c_a^2(t)-1\right)}{E\left[S\right]}\int_0^\infty\left[1-F_S(x)\right]^2 dx \tag{3.13}$$

$$c_a^2(t)\approx\frac{Var\left[A(t-w)-A(t-w-\eta)\right]}{\int_{t-\eta}^{t}\lambda(u-w)\,du}\ , \tag{3.14}$$

for a chosen $\eta>0$. The function $\tilde{z}(t)$ does not allow a reduction in variance (a modeling assumption due to lack of dispersion data – this avoids a false sense of certainty) and can increase the variance using the time-dependent generalization of the heavy-traffic peakedness (3.13) taken from Whitt's (1992) treatment of the stationary $G/G/\infty$ model which characterizes the variance to mean ratio of the steady-state number of busy servers. Since Model 1 is nonstationary, (3.13) is a heuristic. As written, Equation (3.13) assumes a stationary service time distribution but this can be relaxed. Equation (3.14) is a time-

dependent generalization of the asymptotic variability parameter (dispersion) and is similar in form to (3.10); this asymptotic variability parameter is also time-shifted by w to account for the DIS approximation due to the transient focus of this application. If the model is looking past initial transient conditions, the time-shift in (3.14) would be unnecessary because $\lim_{t\to+\infty} I(t) = \lim_{t\to+\infty} I(t-w)$. The parameter η determines the dispersion estimate in the local interval $[t-\eta, t]$; the model uses a timestep of one day and numerical evaluations confirmed $\eta = 1$ is a good choice for this application. The intuition is that both the arrival variability (3.14) and the service time variability (3.13) affect the variance of the capacity prediction (number of busy servers). Specifically, the tail of the service time distribution drives the impact on the variance with the term $\int_0^\infty \left[1-F_S(x)\right]^2 dx$ in (3.13).

Since the arrival variability parameter (3.14) is estimated empirically, it can be undefined when $\int_{t-\eta}^{t} \beta(u)\,du = 0$ which occurs during lulls in arrivals on η consecutive days. When this occurs, we define $c_a^2 = 0$ for this special case such that the RCF $z(t) = 1$ which aligns with engineering intuition.

This RCF (3.12) corrects the variance in the approximation for Model 2 so the final results may serve as an approximation for Model 1. The Normal approximation to the Poisson implies that instead of $B(t) \sim Poisson(m(t))$ which underestimates risk, the required capacity is actually approximated by $B(t) \sim Normal\left(m(t)+\frac{1}{2}, z(t)m(t)\right)$. Adding a half to the mean function corrects for the conversion between a discrete distribution to a continuous one but may be omitted in practice if desired. This continuity correction may lead to a positive bias in the capacity forecast when the nominal requirements are relatively

low and the continuity correction has a larger relative impact on the mean. In Chapter 5's demonstration of this technique, $B(t)$ is a Normal distribution truncated on the interval $(0, +\infty)$ to prevent the sampled $z(t)$ from pushing too much probability below zero; this is equivalent to $(B(t) \mid B(t) > 0)$. Figure 3.15 displays an overview of the entire process to predict capacity requirements for a single location. The Virtual Factory is responsible for both the arrival rate $\lambda(t)$ and determining the departure rate $\sigma(t)$ as it is designed to handle location specific packing policies, work schedules, and other realism constraints.

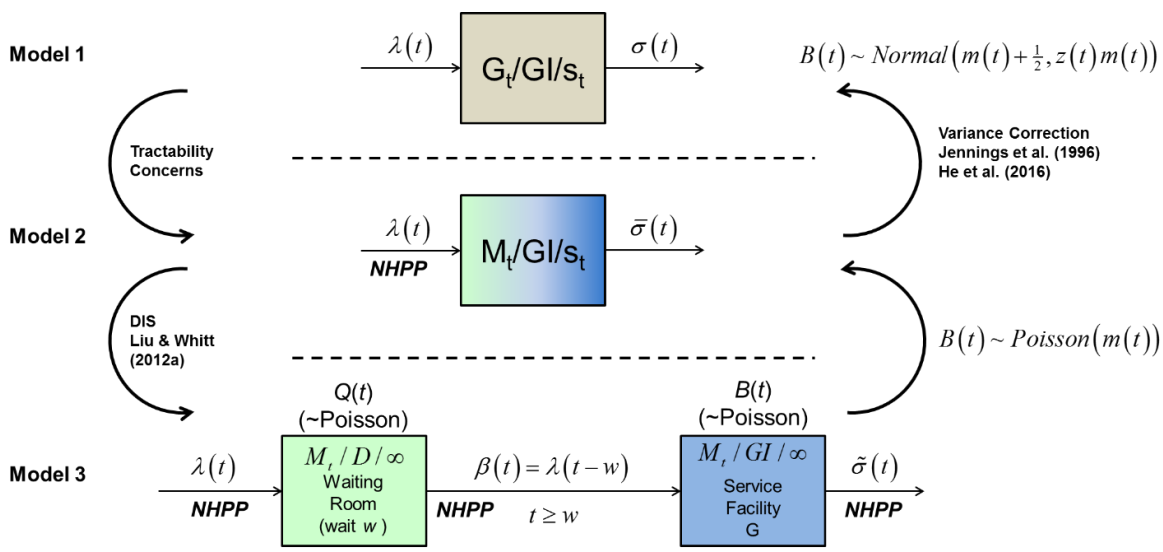

Figure 3.15: Overview of VF-DIS model for capacity planning. Though not depicted, the Virtual Factory determines the departure process due to schedules, batching, and other real-world location policies.

Combined with the tandem VF-DIS approach, this provides a framework to describe the average requirements that fluctuate over time as well as the stochastic variation around that deterministic prediction. In short, this includes both severity and likelihood in the predictions.

3.5.4 Engineering Refinement

Much of the queueing literature cited is motivated by staffing requirements for call centers where $B(t)$ is employed with a buffer over a discretized time horizon often with the square root staffing rule (SRS). The SRS establishes a buffer to hedge against stochastic variability by establishing a probability γ and associated quality of service parameter δ_γ such that $P\left(N(0,1) > \delta_\gamma\right) = \gamma$, which exploits the Normal approximation to the Poisson. Then the capacity recommendation is established by

$$s_\gamma(t) = \left\lceil E\left[B(t)\right] + \delta_\gamma \sqrt{Var\left[B(t)\right]} \right\rceil. \tag{3.15}$$

In the case of expeditionary military logistics such continuous control is not likely to be possible, even over long subintervals. Chapter 5 addresses this concern and also demonstrates a technique to use the VF-DIS model structure to generate possible capacity plans for a location given the time-varying risk information.

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Chapter 4: Generating a Data-Driven Demand Forecast

When conditions finally permitted maintenance operations, repair parts were not to be had....Shortages of predictably high-demand repair parts and vehicular fluids had the most lasting effect on fleet readiness....A valuable lesson learned during OIF was that "just-in-time" logistics does not work during continuous offensive operations.

—Third Infantry Division Operation Iraqi Freedom (OIF) After Action Report

4.1 Introduction

The MLNPS provides a convenient set of tools for analyzing performance of logistical courses of action as well as a means of identifying the capacities needed to hit performance targets. Both of these capabilities require forecasted demand from certain classes of supply such as food and water, ammunition, and repair parts (Classes I, V, IX respectively; see Table 4.1 for all) over the studied time horizon. Since mission-based forecasting (MBF), driven by consumption data, is not available for platforms outside of Army aviation, we have opted to use available modern combat data to generate the demand forecast. Acknowledging this is supply-side data and therefore a faulty signal for true demand, this data-driven process mimics some MBF techniques such as stratifying on unit type and mission intensity in order to generate the best demand forecast possible without true MBF.

This chapter presents a process to generate the demand forecast that will support analysis with the MLNPS. Section 4.2 describes the requisition datasets taken from Operation Iraqi Freedom (OIF). Section 4.3 provides a process overview of generating a demand forecast. Section 4.4 discusses the modeling specifics. Additional details may be found in Appendix D.

4.2 Data-Driven Approach

It is critical to use modern combat data to get a representative picture of modern combat repair part demand. To forecast demand for different missions in varying operational environments, the process presented here would be replicated using data generated under those conditions. While order data may not be a perfect demand signal, when properly characterized this data provides an initial approximation of the demand required in absence of the consumption-driven MBF. The model focuses on food and water, ammunition, and repair parts primarily because the data describe repair parts (CL IX) and they all share common resources across the distribution network. Table 4.1 lists the classes of supply for reference.

Table 4.1: US Classes of Supply taken from Figure C-1 in JP 4-09 Distribution Operations (Department of Defense, 2013).

Class (CL)	**Description / Examples**
I. Subsistence: Food & Water	Rations, food, water
II. General Support Items	Clothing, individual equipment, tentage, tools, administrative and housekeeping supplies
III. Petroleum, Oils, Lubricants (POL)	Fuel, oils, lubricants, coolants
IV. Construction / Barrier	Materials that support fortification, obstacle & barrier construction, and general construction material
V. Ammunition	Ammunition of all types, bombs, explosives, mines, fuses, detonators, rockets, missiles
VI. Personal Demand Items	Nonmilitary sales items, personal & official mail, postal packages
VII. Major End Items	A final combination of end-products ready for intended use (tanks, pylons, vehicles)
VIII. Medical	Medical material, repair parts to medical items, blood
IX. Repair Parts (less medical)	Repair parts, components, dry batteries

An author from the 2005 RAND study (Peltz et al., 2005) provided Operation Iraqi Freedom repair part requisitions; TRANSCOM provided data on all requisitions processed

by the Defense Depot Susquehanna, Pennsylvania, (DDSP) in 2003. Together these datasets provide the weight, volume, sourcing depot, requisition date, requesting unit and location, and other factors for all repair part orders processed by DDSP and those destined for units in Kuwait and Iraq. For specific operational characteristics, the process relies on data from the first 87 days of OIF which consists of 647,189 individual requisitions (11.6 million parts) spanning the two weeks prior to crossing the line of departure through the end of May 2003. The DDSP-specific data contains the 7.7 million requisitions from 2003. Both datasets have a time precision of days which aligns with the chosen time step for this work. Due to similar terrain and environmental factors the OIF dataset is sufficient for the analysis in Chapter 5 which considers a notional operation in Sudan.

4.3 Process Overview – A Sample Path Approach

Generating a demand forecast requires three key inputs—the task organization, concept of the operation, and the timeline—which are estimates produced out of the military planning process. The task organization lists what units are conducting the operation and may change over time. The specific tasks (missions) for these units are found in the concept of the operation. The timeline ties everything together; these products provide the analyst with the specific details (*who*, *what*, *when*, *where*, and *why*) for the operation.

The timeline is essential to breaking down the time horizon of interest into various missions for the units. The forecast must account for the fact that repair part demand is different by both unit type (think infantry versus aviation units) and type of operation (preparing for combat versus combat). This is accomplished by defining three operational intensity levels (OIL) then using the OIF invasion data to characterize each type of unit's demand under those operational descriptions to describe pre-combat (OIL 1), steady-state

operations out of an established base (OIL 2), and direct combat operations or high intensity conflict (OIL 3). Since these levels are qualitative in nature, Table 4.2 provides recommended guidelines for identifying these levels using historical data.

Table 4.2: Guidelines to Identify Operational Intensity Levels.

Operational Intensity	**Distinguishing Features**
Level 1	□ Prior to crossing line of departure. □ Not conducting combat operations. □ Preparation for combat operations.
Level 2	□ Operations conducted from established base such as a forward operating base (FOB) or at least based from a fixed location. □ Operations take on a steady-state, routine nature during this period.
Level 3	□ Conducting invasion. □ Direct combat operations / high intensity conflict.

Figure 4.1 graphically shows the process. The first requisitions generated are the food, water, and ammunition supplies that must sustain the units in the model. Then a specific workflow addresses repair part demand for every unit for every Operational Intensity Level (OIL). This workflow determines the number and timing of requisitions, how those requisitions are routed to the ordering unit, the required delivery date, order weight and volume, and the sourcing depot. Once this has occurred for every unit for every operational intensity level, the concatenation of these requisitions constitutes the forecast. Due to how the forecast employs probability distributions, the resulting forecast is a projected sample path for that time horizon.

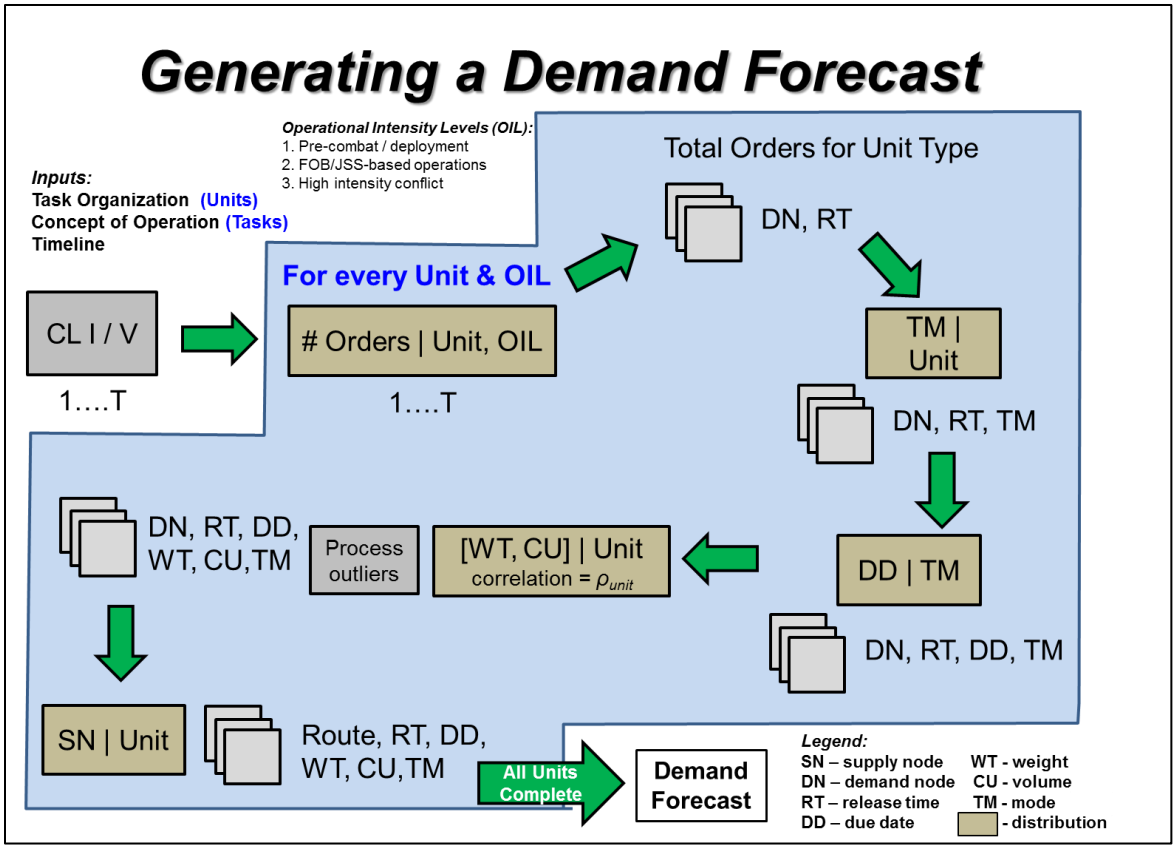

Figure 4.1: Process Overview to Generate a Demand Forecast.

4.4 Modeling the Demand Process

4.4.1 Food, Water (CL I), & Ammunition (CL V)

Unit size plays an obvious role in estimating Class (CL) I requirements. Since bottled water was the primary source of potable water during OIF (Peltz et al., 2005) and this research focuses on initial expeditionary operations, we generate pallets of bottled water to supply the units originating at the theater distribution center (Rogers, 2016). This assumption is easily changed across the time horizon as are the starting locations of those pallets depending on the logistics plan. Army Tactics, Techniques, and Procedures (ATTP) 4-41, "Army Field Feeding and Class I Operations" recommends ration cycles and feeding plan guidelines (see Section 5.3 of Rogers, 2016) to identify the capacity required to haul CL I to the units so the remaining capacity may be allocated to other classes of supply.

Assuming an average Brigade Combat Team (BCT) strength of 4,500 Soldiers with attached enablers that increase the troop count by 10% yields approximately 4,950 personnel per BCT. Consistent with doctrinal water planning guides, assume 7.27 gallons of water per person per day is required in an arid environment to account for hydration, hygiene, and feeding purposes. The standard planning factor estimates a pallet may hold up to 228 gallons of bottled water (CASCOM, 2008). Using Rogers' (2016) 10% breakage planning factor, this yields a daily water requirement of 173 pallets of water per day for a BCT. Each pallet holds 576 Meals-Ready-to-Eat (MREs) and assuming initial rations are three MREs per day, the daily food requirement is approximately 26 pallets per day. These rations are nonperishable. Based on planning factors provided by an analytical Army logistics agency, ammunition (CL V) requirements would be approximately 60% water weight and 40% of the water volume (Rogers, 2016).

4.4.2 Generating Repair Part (CL IX) Requisitions

This section describes the workflow depicted in Figure 4.1 by the irregular shaded (blue) box. This process occurs for each unit with generated requisitions being collected into a large list along with the CL I and CL V requisitions. Depending on multiple factors such as time horizon, task organization, and mission, this process can generate a significant number of requisitions. For reference, the Sudan scenario presented by Rogers et al. (2016) and also analyzed in Chapter 5 generates requisitions for 61 days prior to LD and 90 days of operations after. In addition to the almost 2.3 million requisitions that competed for DDSP resources during the OIF invasion used as a surrogate for global, non-Sudan demand, the random requisitions generated for just the Sudan operation is on the order of 294,149 requisitions on average (20 samples with sample standard deviation 11,538).

Analysis of the OIF invasion data clearly identified that the number of daily requisitions varies both with the type of unit and based on that unit's operational intensity level. For a given unit, the model assumes each day as independent and identically distributed within an operational intensity level as the data showed weak autocorrelations. This assumption is not limiting and can be relaxed (see Chapter 6). The data permits modelling a total of 8 unit types with the unit to BCT identification used for the OIF invasion data listed below in Table C.1. For each unit, the sub-timeline of operational intensity level determines the number of requisitions per day. If an IBCT has an OIL schedule as depicted in Figure 4.2, the number of requisitions released on days 1 through 14 requires the appropriate cumulative probability distribution (CDF) for OIL 1. In Figure 4.2, $Nrel^{(j)},\ j = 1, 2, 3,$ is the daily number of requisitions ordered (released by GCSS-Army). Table 4.3 lists the distributions used for unit type and OIL.

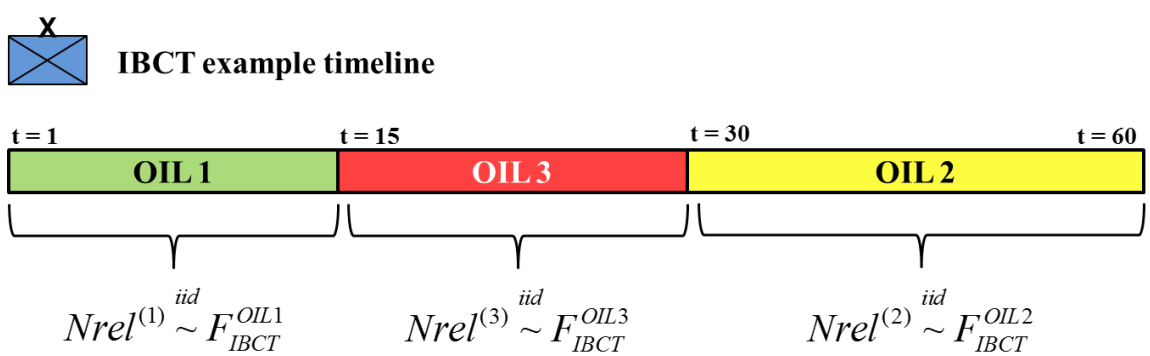

Figure 4.2: Example for Generating Number of Requisitions by Day for IBCT. See Table 4.3 for distributions organized by unit and operational intensity level (OIL).

The OIF invasion data permitted fitting three distributions that provide a convenient way to generate IBCT repair part requisitions for any given timeline (in an arid environment). Each day, the number of requisitions released is assumed to be independent and identically distributed within each unit and OIL. Table 4.3 summarizes these distributions by unit. Taking the ceiling of samples from continuous distributions ensures

integrality. All orders generated on day *t* are given a release time of *t*. For more details, refer to Appendix D.

Table 4.3: Summary of Distributions Modeling Number of Requisitions By Day

Unit	**Distribution Used for Number of Requisitions Released by Day (*n* = sample size in OIF data, 6 MAR 2003 – 31 MAY 2003)**
IBCT	OIL 1 – Loglogistic (22), *n* = 22 OIL 2 – Erlang (47)), *n* = 47 OIL 3 – Beta (18), *n* = 18
HBCT*†	OIL 1 – Empirical (14), *n* = 14 OIL 2 – Empirical (47), *n* = 47 OIL 3 – Empirical (26), *n* = 26
AVN BN	OIL 1 – Weibull (22), *n* = 22 OIL 2 – Empirical (47), *n* = 47 OIL 3 – Loglogistic (18), *n* = 18
EN BN	Empirical (87), *n* = 87
DIV HQ	Empirical (87), *n* = 87
Sustainment BDE	Gamma (87), *n* = 87
Misc Enabler BN	Empirical (87), *n* = 87
3x Truck CO	Empirical (87), *n* = 87

* now called ABCT; † used as surrogate for SBCT

After generating a unit's requisition volume across the timeline of interest, the process randomly selects each requisition's mode of transportation; this is critical in subsequent stages to identify the route. The Sudan operation provided by Rogers et al. (2016) and again analyzed in Chapter 5 employed the distribution from Table 4.4 taken from the OIF invasion data.

Table 4.4: Transportation Mode Distribution.
Taken from OIF invasion data.

Transportation Mode	**Probability**
Military Air	0.7340
World Wide Express (WWX)	0.1292
Surface (Ocean)	0.1368

The allotted time to deliver the requisition in days, known as the standard delivery time (*SDT*), is generated based a requisition's transportation mode (*TransM*). This time is added to the release time (*RT*) to calculate the due date (*DD*). Each standard delivery time

(conditional on transportation mode) is modeled with a discrete uniform distribution (denoted DU) in Equation (4.2) and Table 4.5. Since standard delivery times vary by requisition priority and service-specific processes, assuming the actual standard delivery times found in Table 2.2 from the Department of the Army Pamphlet (DA PAM) 710-2-1 (Using Unit Supply System) are the upper bounds (b_{TransM}) and allowing up to an approximate 70% reduction (a_{TransM}) to account for varying priority designations (DA PAM 710-2-1, see Table 2.2) helps to account for individual prioritization. For more details on requisition priorities, see Rogers, 2016, p. 31, and Ch 2, DA PAM 710-2-1. Due dates for requisition *i* are given by

$$DD_i = \left(SDT_i \mid TransM_i\right) + RT_i \text{, where} \tag{4.1}$$

$$\left(SDT \mid TransM\right) \overset{iid}{\sim} DU\left(a_{TransM}, b_{TransM}\right). \tag{4.2}$$

Table 4.5: Bounds for Standard Delivery Times.

Transportation Mode	$\left(a_{TransM}, b_{TransM}\right)$
Military Air	(12, 18)
WWX	(10, 14)
Surface (Ocean)	(52, 75)

The Virtual Factory requires orders to have both a weight and volume to properly capture the details of processes such as movement by truck, packing a 463L pallet, and breaking down and sorting packages in a forty foot container. The OIF invasion data provides these marginal distributions. Reality requires them to be correlated. Using a Gaussian copula allows using a different target correlation based on unit type as demonstrated in Table 4.6 (see Ross, 2013) while respecting the correct marginal distributions for weight and volume.

Table 4.6: Empirical correlation between weight (lbs) & volume (cu ft) from OIF invasion.

Unit	Correlation(WT, CU)	Sample Size
IBCT	0.7830	51381
HBCT	0.7833	23543
AVN BN	0.6338	47451
EN BN	0.3422	22747
3 x Truck Co	0.9813	9901
DIV HQ	0.7127	19890
Sustainment BDE	0.7072	85662
Misc Enabler BN	0.9865	1466

The marginal distributions for weight and volume are provided in Table 4.6; these were results of distribution fitting using the OIF dataset. Rogers et al. (2016) also use these same Lognormal distribution parameters for weight and volume. Unlike Rogers et al., this research identified that the Beta distribution (refer to Table 4.7) is an excellent fit for the base-10 logarithm of both weight and volume; Table 4.7 lists the associated parameters. Pilot experiments indicate that the distribution choice affects the ability to generate samples close to the target correlation for unit type. For some correlations, the Lognormal outperformed the Beta, though the Beta worked best for most units; for some target correlations, neither method worked well. This research uses the best result from the pilot experiments; Section 6.5 identifies this as an area for future work. Sampled weights or volumes that exceed that requisitions transportation mode get reassigned to the maximum capacity for the offending weight or volume; this is reasonable as this only occurs less than one-fifth of one percent of the time in the data.

Table 4.7: Marginal distributions for requisition weight and volume.

Quantity (units)	Lognormal*	Generalized Beta†
Weight (lbs)	WT ~ Lognormal $\mu = 0.935, \quad \sigma = 2.498$	$\log_{10}(WT)$ ~ Generalized Beta† $\alpha_1 = 9.290,\ \alpha_2 = 11.604$ $a = -4.2, \quad b = 6.1991$
Volume (cu ft)	CU ~ Lognormal $\mu = -2.04, \quad \sigma = 2.663$	$\log_{10}(CU)$ ~ Generalized Beta† $\alpha_1 = 11.078, \alpha_2 = 12.747$ $a = -6.222, \quad b = 5.319$

* Used by Rogers (2016); † Generalized Beta distribution: $a + (b-a)\,Beta(\alpha_1, \alpha_2)$

Each requisition is assigned to a sourcing depot conditional on the requesting unit according to the empirical probability mass function found for each unit type's source depot location. These empirical distributions—provided in Appendix D, Table D.2—can vary based on order content; since model does not specify individual types of repair parts, this approach permits capturing the unit type variation of supply depots while keeping the level of detail at overall requisition attributes. As explained by Rogers (2016), certain DLA distribution centers have specialized stock—such as communications equipment at Tobyhanna, Pennsylvania—and these specializations affect these sourcing distributions.

After specifying the unit (demand node), transportation mode, and sourcing depot (supply node), it is a simple lookup from the appropriate route matrix that stores the route for a requisition going from that depot to that unit with that transportation mode; collectively these route matrices comprise the route library which is an output of the logistical network modeling process. After identifying each requisitions route, the entire requisition forecast is completed by aggregating the CL I / CL V requisitions, each unit's forecast, and the forecast for global requisitions that will compete for DDSP resources. In this research, as in Rogers et al. (2016), a comparable set of requisitions that routed through DDSP in OIF provides a start point for the non-expeditionary requisitions that share CONUS resources upstream.

This procedure (see Figure 4.1) provides a data-driven approach to generating requisition forecasts since mission-based forecasting is not yet available for all Army units and platforms. The result is a sample path approach which requires replication to assess the uncertainty in the forecast itself which is the arrival process to the queueing network described in Chapter 3.

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Chapter 5: Risk-based Expeditionary Logistics Planning for a Notional Operation

You will not find it difficult to prove that battles, campaigns, and even wars have been won or lost primarily because of logistics. *–General Dwight D. Eisenhower*

Armed with the methodology from Chapter 3 providing a framework with which to analyze the logistics of an expeditionary operation, this chapter uses the VF-DIS framework on a notional operation. The chapter employs the same fictional scenario used by LTC Rogers where an Infantry Brigade Combat Team (IBCT) and a Stryker Brigade Combat Team (SBCT) are conducting operations from South Sudan into Sudan against the self-styled Islamic State in Iraq and Syria (ISIS). The SBCT will operate in the outlying Darfur region while the IBCT operates in the capital of Khartoum (Rogers, 2016). A Division Headquarters conducts command and control for the operation and the units are provided with enablers that include engineer and aviation units; Table 5.1 presents the Task Organization used to generate the forecast for supply requisitions using the procedure outlined in Chapter 4. In his analysis, LTC Rogers evaluates different courses of action (COA) based on potential locations for the Theater Distribution Center (TDC). While the techniques from this chapter could assist with evaluating the COAs presented by Rogers, this chapter focuses on LTC Rogers' selected option, Sudan COA 1, with the TDC being located in Juba, the capital of South Sudan.

Table 5.1: Task Organization for Sudan Mission (Rogers, 2016).

Task Organization
1 x Infantry Brigade Combat Team (IBCT)
1 x Stryker Brigade Combat Team (SBCT)
1 x Engineer Battalion (Construction Effects)
1 x Aviation Battalion (Attack & Lift)
1 x Sustainment Brigade
1 x Division Headquarters
3 x Battalions of Miscellaneous Enablers

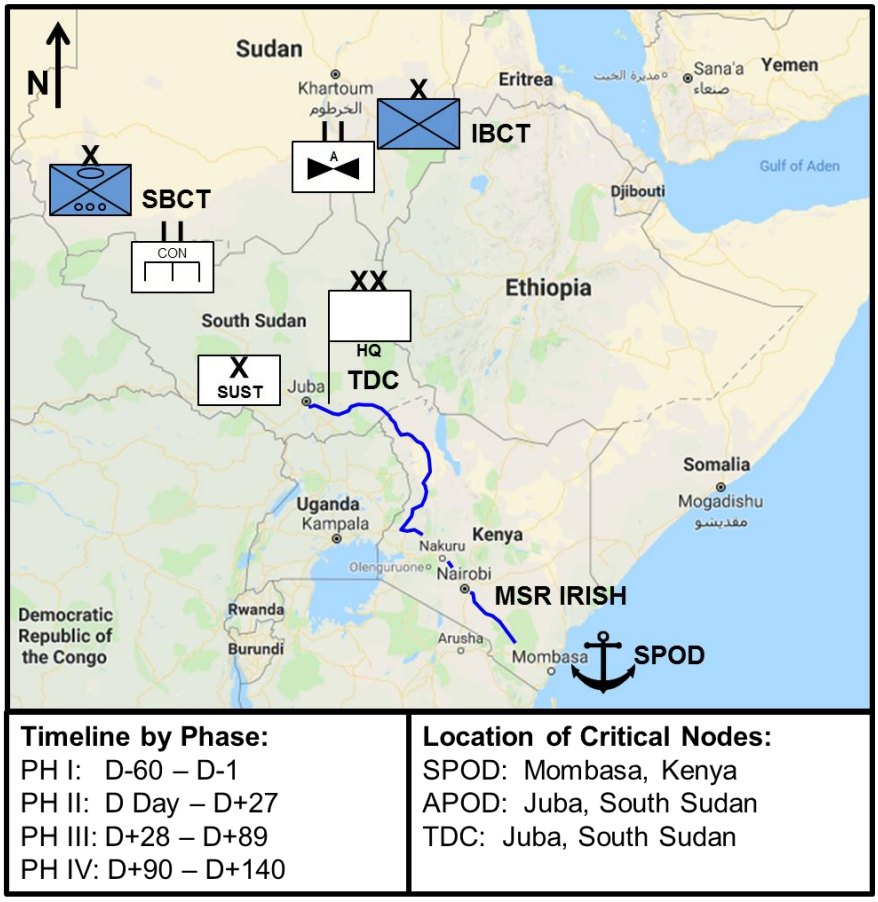
5.1 Focusing on the Last Tactical Mile (LTM)

Applying the techniques from Chapter 3 to the final plan recommended by LTC Rogers illustrates the contribution of this methodology. The Last Tactical Mile (LTM) trucks, the ground units that transport supplies from the TDC to the BCT Supply Support Activities (SSAs), are the ideal candidates for this demonstration for several reasons. The LTM trucks are the logistical link to the units which implies this may be a location where a theater commander has the most control as they are not necessarily constrained by ties to airports, seaports, or other infrastructure or process restrictions, including CONUS effects. Practically, their geographical proximity to the units also incurs more risk. Given the feed-forward structure of the network, the LTM trucks are the final node to analyze and identify the required capacity for operations; the process to analyze other nodes is almost identical except that no other node is the furthest downstream resource. This property creates a few technical challenges that are readily overcome but not present at any other place in the feed-forward network. In simpler terms, if analysis of LTM trucks is possible, it is possible to do this for any node upstream.

5.2 Overview of the Notional Operation

The operational details and timeline are identical to LTC Rogers' scenario; Figure 5.1 provides a visual summary. The seaport of debarkation (SPOD) is located in the port of Mombasa, Kenya. The TDC is located in Juba, South Sudan, with the airport of debarkation

(APOD) nearby. Though not depicted in Figure 5.1, the CONUS network is also identical to LTC Rogers' scenario.



Timeline by Phase:	Location of Critical Nodes:
PH I: D-60 – D-1	SPOD: Mombasa, Kenya
PH II: D Day – D+27	APOD: Juba, South Sudan
PH III: D+28 – D+89	TDC: Juba, South Sudan
PH IV: D+90 – D+140	

Figure 5.1: Sudan COA 1 Overview with Main Supply Route (MSR) IRISH annotated.

The logistics network in Figure 5.1 is identical to the one used by LTC Rogers to enable direct comparison with key details summarized here. For more details on the logistics network, the reader is encouraged to see Ch. 3, of Rogers (2016). To model the logistics network, we make the following assumptions consistent with LTC Rogers:

1. CONUS dedicated truck routes depart six days a week (Monday through Saturday). Trucks travel seven days a week but may not deliver on a Saturday or Sunday.
2. CONUS dedicated trucks have unlimited capacity as DLA can quickly acquire additional trucks. Similarly, there are always enough trucks to move requisitions

from source depots to Container Consolidation Points (CCPs) or from a CCP to the APODs/SPODs.

3. Restocking the sourcing depots does not require the same resources used by the distribution system.
4. All orders are sourced from a CONUS source depot then shipped to their destination.
5. Once a multipack, pallet, or container has started loading, it remains at the location until full or the maximum waiting period has been met (whichever is soonest). Pallets wait up to three days with containers waiting up to fifteen. Multipacks, pallets and containers are considered full when they reach 95% of maximum weight capacity or 85% maximum volume capacity. If these at least one of these criteria are met, prior to sending any requisitions that could fit in the remaining space are pulled from the queue and packed (on a revised slack basis) to ship forward to the next location.
6. All pallets and containers contain repair parts for different units unless the route to a unit does not support break bulk operations. This ensures the model does not ship near empty containers. Break bulk operations involve breaking down a container or pallet and sorting the packed requisitions based on their ordering units.
7. If a requisition can fill an entire multipack, pallet, or container, the logistics node builds it unit-pure (no other unit orders included). Unit pure multipacks, pallets, and containers do not require breakdown and sorting operations at the TDC and advance directly to the LTM trucks.
8. All air shipments use 463L pallets and all ocean freight employ 40 foot containers. These pallets and containers are comprised of multipack boxes and individual parts that are too large to fit in the multipacks.
9. All surface (ocean) freight travels on commercial ships. This is not a limiting assumption but fits the Sudan scenario.
10. Sudan orders are assumed to follow the same distribution of transportation modes as occurred in OIF. This is not a limiting assumption as this is an input to the forecasting procedure.

Unlike Rogers (2016), times to process requisitions are now considered stochastic and are akin to service time distributions. The mean roundtrip times from Rogers (2016) are

kept fixed but this research assumes LTM convoys may sometimes return up to one day early if there are good conditions but may be delayed significantly if adversely impacted by weather or mechanical failures. Without data to estimate these deviations, we assume the LTM roundtrip time is distributed via a generalized Beta distribution having the form $a+(b-a)Beta(\alpha_1,\alpha_2)$ with first shape parameter $\alpha_1 = 1.2$, and second shape parameter $\alpha_2 = 12$. The generalized lower and upper bounds results from the assumption that roundtrips to support the maneuver units take a minimum of 90% of the mean roundtrip time from Rogers (2016) and no more than twice the mean time. Figure 5.2 illustrates the LTM roundtrip time probability density functions.

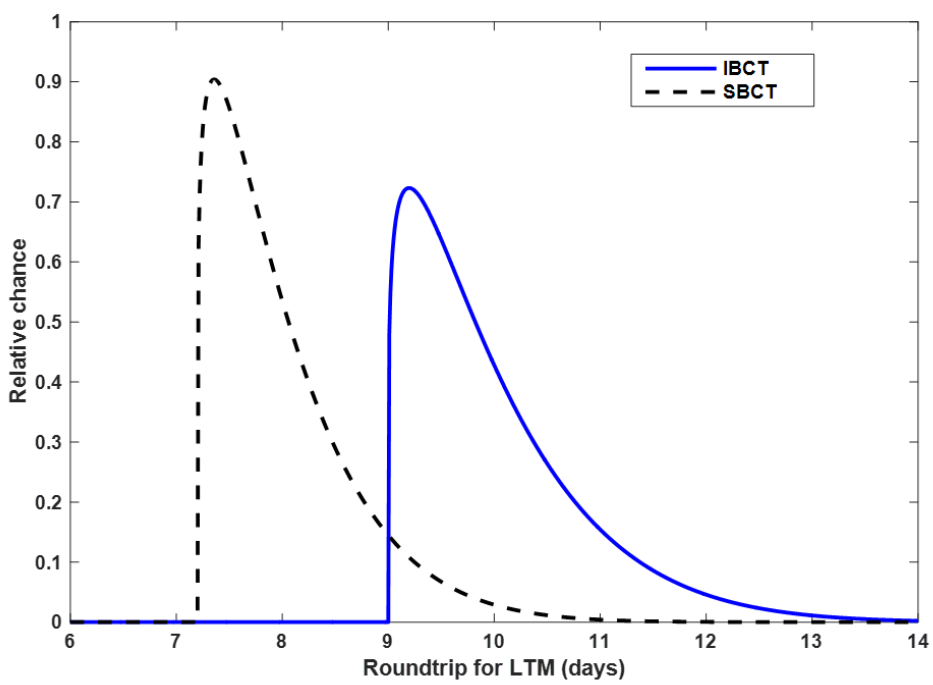


Figure 5.2: Assumed Service Time Distributions for LTM roundtrip times. Consistent with Rogers (2016), the mean roundtrip for IBCT is 10 days, 8 for SBCT. The coefficient of variation for both is 0.0839.

5.3 Forecasting Required Capability to Achieve Performance Target at Location (LTM)

With the network capacities determined by Rogers et al. (2016) for this scenario, the Virtual Factory readily provides the sample average arrival rate in 463L pallet equivalent units (PEU) to the LTM trucks using 55 MBF sample paths. The reader is reminded the multiple sample paths are necessary due to our method of forecasting repair part demand (Ch. 3); with a different and perhaps more direct forecasting method—such as consumption data-driven Mission-Based Forecasting—the average scenario demand over time might be more accessible which would require only one run of the Virtual Factory instead of the multiple runs required in this work. The analysis presented employs 55 sample forecasts.

The DIS model requires a performance target for this node. Based on LTC Rogers' findings, this chapter uses a performance target that requires the capacity needed to achieve a requisition average (not time average) delay of seven days. The sample dispersion at the LTM is both time-varying and greater than 1 (~5) which requires the risk correction factor to adjust the forecasted variance. Without this correction, the model would underestimate risk.

The forecasted requirements presented in Figure 5.3 include the risk correction for LTM required capacity given in 463L pallet equivalent units (PEU). The solid bold (blue) line marks the average with shaded regions denoting the probability the required capacity is in that range on any given day. The graph is not smooth for good reasons. The LTM node is located furthest downstream and is subject to the accumulated effects of every node's schedule nuances. Some logistics nodes in CONUS do not operate on Saturdays and Sundays. With the timeline fixed, ship schedules, dedicated trucking routes, and long convoy round trip times create a very jagged forecast.

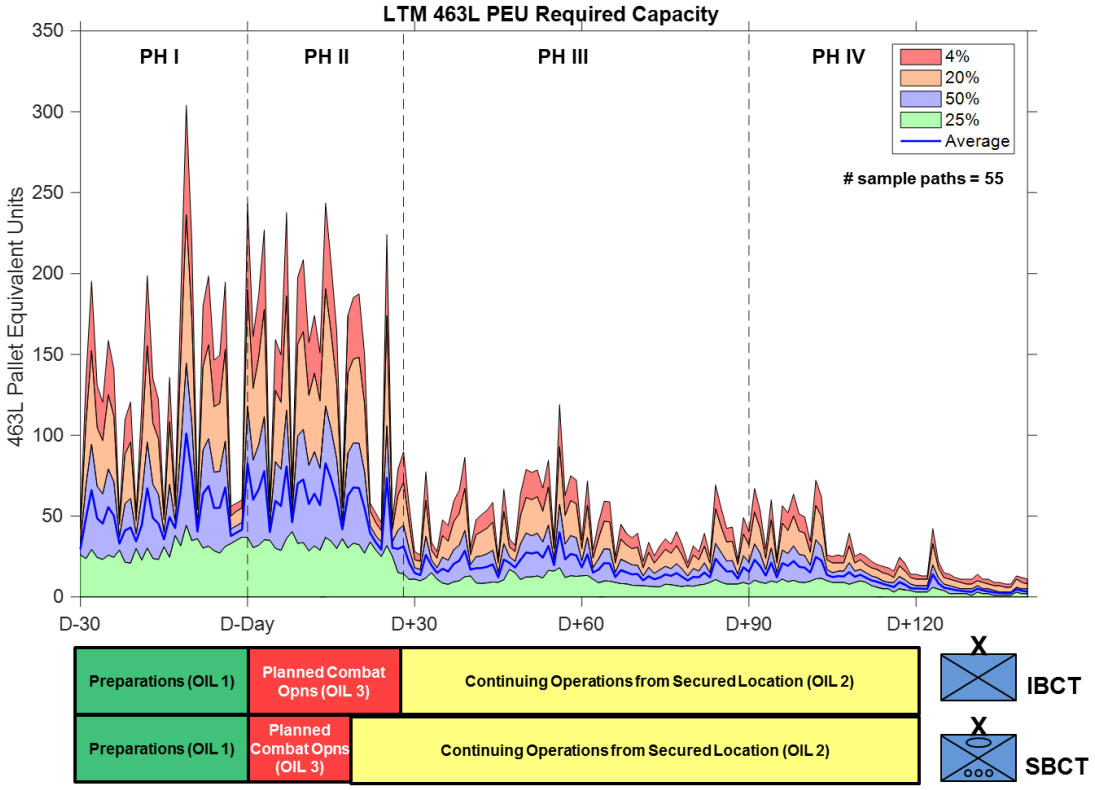


Figure 5.3: Forecasted Capacity Required at LTM in 463L PEU to Achieve Target Performance of 7 day Average Delay (55 sample paths). Dashed vertical lines denote phases of the operation. BCT operational intensity level timelines displayed below graph.

This forecast provides the framework which allows analyzing potential outcomes in a stochastic (probabilistic) sense because it provides a fully specified distribution for required capacity for every day. With this in place, it is possible to rapidly compute probabilities, calculate expectations, or even generate realizations via Monte Carlo methods. This implies that if something can be calculated or generated then it is possible to get stochastic descriptions for any metrics of interest.

5.4 Generating Courses of Action

The queueing theory that permits construction of the forecast depicted in Figure 5.3 implies a continuous or near-continuous control of that logistics node but that is hardly possible in the military logistics context, especially under expeditionary conditions. It may be possible to

plan for significant capacity changes once per phase. Perhaps a commander can adjust resources once in the planning horizon or maybe not at all. The forecast generated with the VF-DIS model is useful for generating some default capacity options for a specific location.

Developing multiple options is attractive as the computational efficiency of these models permits rapid detailed analysis of each option and permits comparing them over time. One approach is to simply look at the requirements forecasted by Figure 5.3 and visually set the capacities with intuition or external knowledge about the plan; this technique might develop a plan to ensure the LTM trucks have 70 PEU for Phase I and II then only 20 PEU for Phase III and IV (presumably freeing up some capacity for other missions including a reserve). A more detached technique would be to simply use Figure 5.3's forecast to calculate the daily value-at-risk ($VaR_{0.95}$), also known as the 95th quantile, and plan each phase to receive the capacity set to the phases's time-averaged $VaR_{0.95}$. Alternatively, a constant capacity throughout the planning horizon may be appropriate. The analysis proceeds with these three plans though any plan for LTM can be evaluated.

Figure 5.4 provides a visualization of these competing options over time with the constant option set to 78 PEU consistent with LTC Rogers' final recommended plan for the LTM trucks (Rogers, 2016). The chart overlays the three LTM options against the backdrop of average required capacity, the 75th quantile for required capacity, and the 95th quantile for required capacity to convey a sense of the stochastic variation that exists about the average.

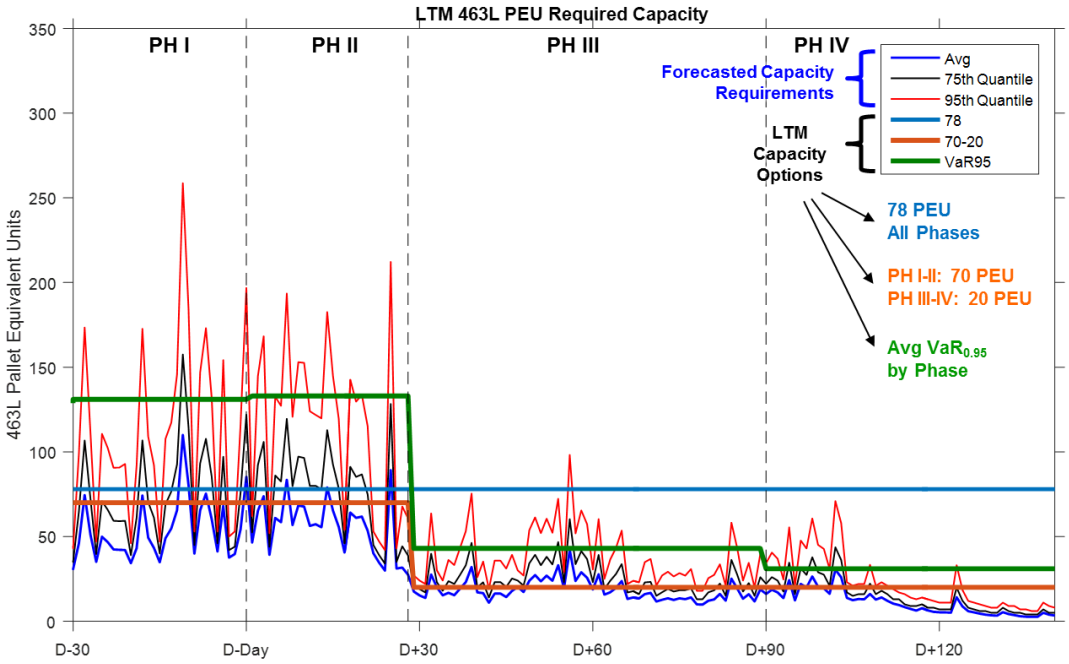


Figure 5.4: Generating Options for the LTM trucks in the Sudan scenario.

These options serve to demonstrate the flexibility of this approach and the capability to evaluate any given logistical capacity plan.

5.5 Evaluating Multiple Courses of Action

Regardless of the complexity or the number of the capacity plans, the visualization provided by Figure 5.4 is not enough. Commanders want to understand the impacts of these plans in meaningful terms that include both expected performance and an understanding of the uncertainty involved. With the Virtual Factory and the DIS models, an analyst can evaluate backlogs, delay, lateness, utilization, and other measures by location, by day, by requesting unit, transportation mode, or any combination of these. The analyst's job is to dig for specific and nuanced insights and these models certainly equip the analyst for such a task. This section provides some examples of initial insights that may be constructed by default to

inform the decision-maker. Figure 5.5 shows average backlog over time for the three options as an example.

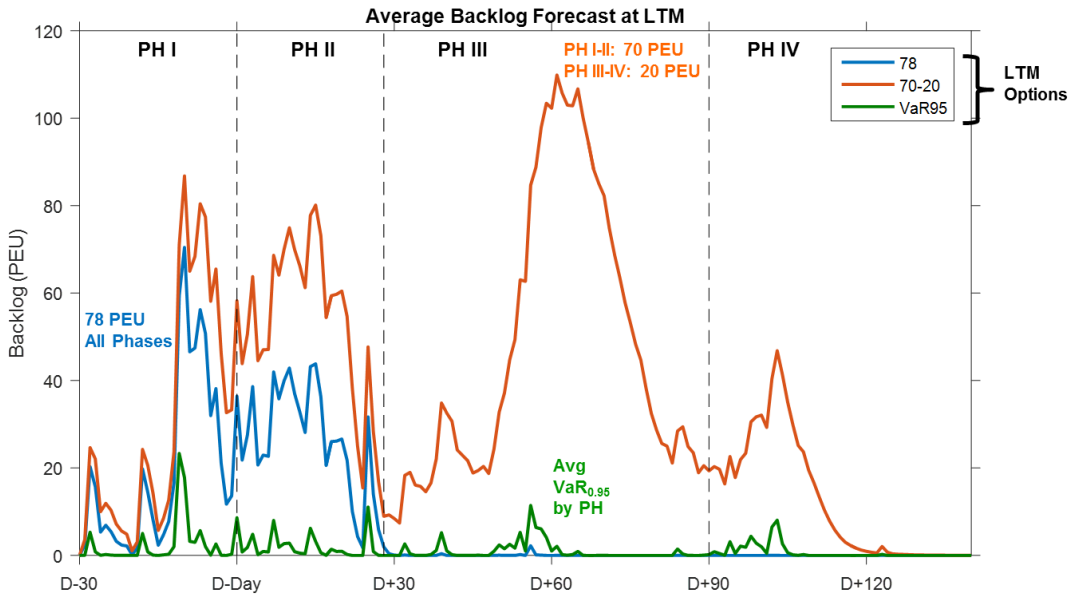


Figure 5.5 Average Backlog in PEU at LTM trucks for Multiple Courses of Action.

This approach extends Rogers et al. (2016) by not only evaluating average delay across the time horizon but also by making stochastic information available either directly calculated analytically using the distributions (by day) or via Monte Carlo methods which are both quick and accessible with modern computers. Though Figure 5.5 currently shows average backlog only, it is just as easy to present confidence intervals, quantile bands, or another stochastic visualizations for a chosen metric of interest. The entire distribution of backlog is accessible as is the distribution of the worst case outcomes each day—recall Equation (3.7). Presenting risk-based information that depicts the uncertainty coupled with delay predictions in Rogers (2016) provides a more complete understanding of the tradeoffs between multiple courses of action. Senior leaders seek to understand the risks faced and

how to mitigate them – to that end it is critical to estimate how bad things can actually get both by location and over time.

5.6 Further Evaluation of a Specific Plan

After evaluating a set of plans over time, we select the constant capacity plan taken from Rogers et al. (2016) for further analysis. With the outputs of the Virtual Factory and DIS models, an analyst can evaluate backlog, delay, lateness, and other constructed metrics over time for a specific plan and under multiple what-if scenarios. Motivated by the massive sandstorm that resulted in a seven day disruption to CL IX part resupply early in the invasion of Iraq in 2003, Rogers (2016) evaluated the impact of a complete disruption of the resupply vehicles for this Sudan scenario. It is possible to perform a risk-based analysis of the constant 78 PEU capacity plan for LTM trucks from Rogers (2016) under a complete disruption of the resupply vehicles.

First, for this constant capacity plan, it is apparent that using a simple average to measure the impacts of a disruption underestimates risk in this context; this is not a surprise based on Savage (2009). Figure 5.6 shows the total increase in the backlog in pallet-days of a complete disruption on the LTM trucks starting at D+11 in the Sudan COA 1 scenario from Rogers (2016). The impact is depicted with different measures. The average total impact increases slower than the other three risk-based measures used such as the 75th and 95th quantiles, and the conditional value at risk which is the average worst case scenario of the worst 5% of possible outcomes.

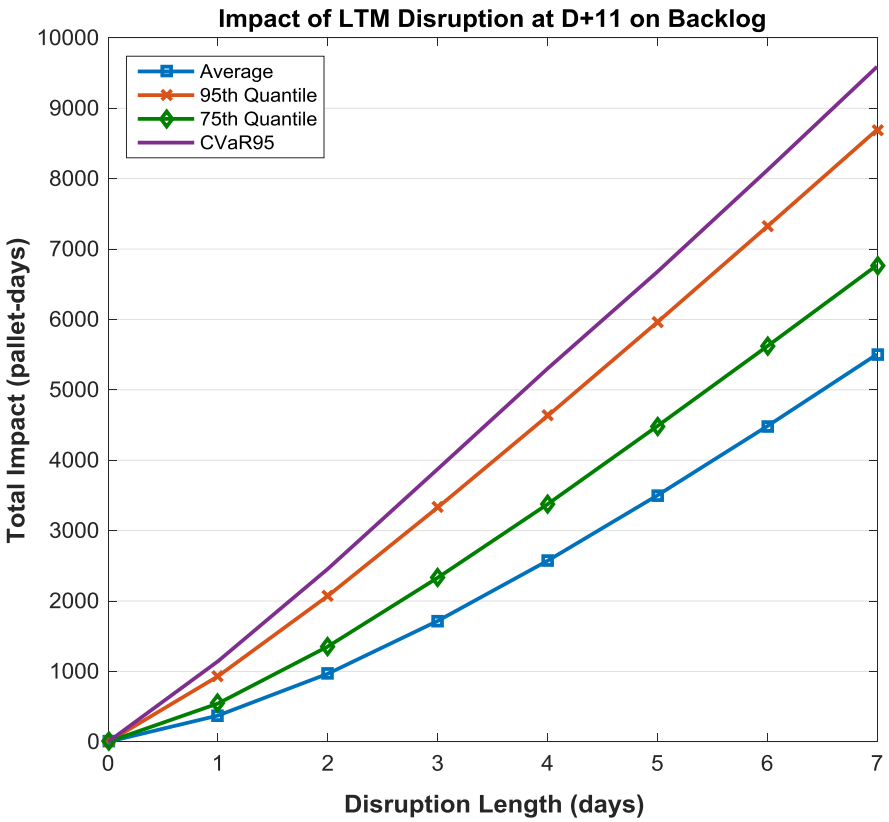


Figure 5.6 Total impact on backlog in pallet-days of a complete disruption to LTM trucks starting on D+11 in Sudan COA 1 scenario from Rogers (2016) for 78 PEU plan.

Figure 5.6 was inspired by resiliency curves from Alderson et al. (2015) that present multiple alternatives with a common measure on the vertical axis plotted over an increasing negative impact on the network. These resiliency curves also provide an alternative framework for comparing multiple courses of action.

LTC Rogers (2016) showed the value of performing what-if analysis on a given plan to assess how it performs under different potential outcomes. This VF-DIS model permits the same analysis but also shows information beyond the average by connecting potential outcomes with their likelihoods. Figure 5.7 illustrates this by showing the average backlog at the LTM trucks with and without a seven day disruption starting at D+11; the figure also

depicts how bad the backlog can get by showing the 75th and 95th quantiles. The peak backlog with a 7 day disruption will be almost 480 PEU (7.4 times the no disruption peak). By taking into account the variation around the average, an analyst can forecast there is a 75% chance the peak backlog with this 7 day disruption would be less than 550 PEU (8.7 times the no disruption peak) if the LTM trucks have 78 PEU capacity. Similarly, there is a 95% chance the peak backlog would be no more than 685 PEU (11 times the peak when there is no disruption peak). The recovery times are also available from Figure 5.7.

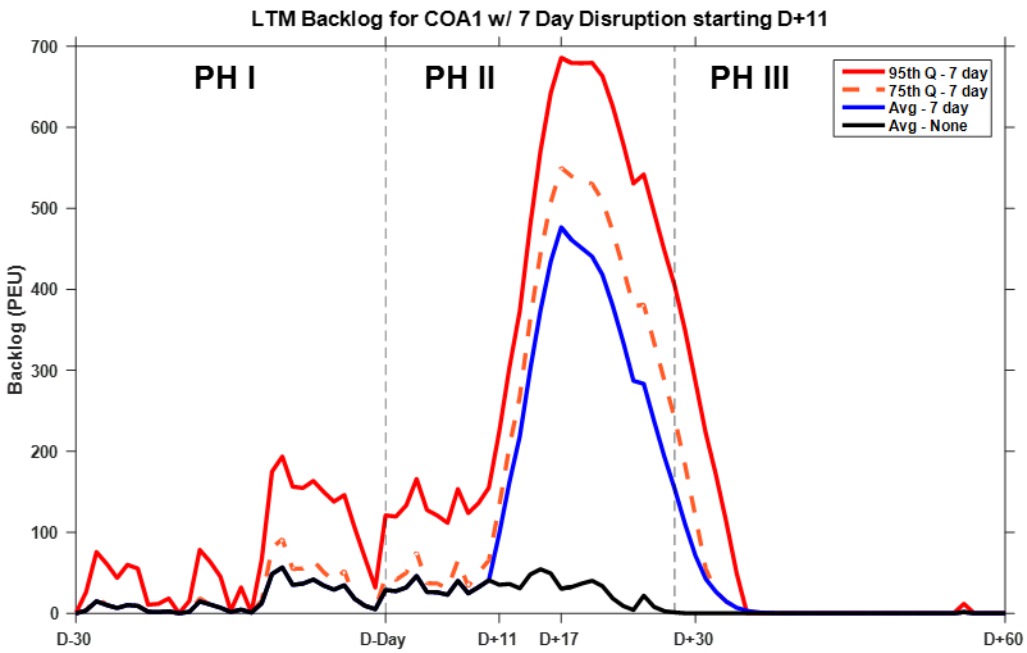


Figure 5.7 Daily LTM backlog with & without a 7 day disruption (starting D+11) for Sudan COA 1 scenario in Rogers (2016) for 78 PEU LTM plan.

5.7 Conclusion

This chapter extends Rogers et al. (2016) by demonstrating how to use the methodology from Chapter 3 and the data-driven demand forecasting process from Chapter 4 to conduct logistical planning for an expeditionary operation. Section 5.3 uses the VF-DIS model to forecast the required capacity for the LTM trucks based on a performance target for average

delay. Section 5.4 demonstrates how to use risk information from this forecast to generate a proposed capacity over time. Employing both analytical and Monte Carlo methods to analyze multiple proposed capacity plans in Section 5.5 demonstrates how this technique could apply to any given plan. Section 5.6 provides an example of how to use forecasted capacity to make risk-based detailed predictions for a single plan over time.

The utility of risk-based measures for what-if analysis cannot be overstated. These tools enhance the MLNPS and extend the depth of analysis made possible. Using multiple demand forecasts (sample paths) required multiple runs of the Virtual Factory to estimate the sample arrival rate as well as the sample dispersion. If the US Army continues to develop mission-based forecasting beyond aviation units, this analysis would require only one run with the Virtual Factory if GCSS-Army data provided the sample dispersion for the variance correction. In short, multiple sample paths are currently required to obtain Figure 5.3 but with an approach such as mission-based forecasting that does not rely on sample paths, this is obtainable with a single run of the Virtual Factory.

By exploiting the strengths of both the DIS model and the Virtual Factory as well as the feed-forward network structure, this approach maximizes its computational advantages. After obtaining the forecasted requirements to meet a logistics target (Figure 5.3), the subsequent analysis is computationally efficient using either analytical results, Virtual Factory output, or simple Monte Carlo methods which are extraordinarily fast in our experience just working with MATLAB.

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Chapter 6: Contribution Summary & Future Research

You cannot have Army readiness without materiel readiness. Soldiers cannot win on the battlefield without weapons to shoot, tanks to maneuver, food to eat and the logistics support to ensure those provisions are in place when they are needed.

—GEN Gus Perna, US Army's senior logistician; and commander, Army Materiel Command

6.1 Contribution

This research contributes to the military expeditionary logistics planning problem in several ways. First, since mission-based forecasting (MBF) does not exist for the majority of Army platforms, formations, missions, or operational environments, we use supply-side modern combat data taken from OIF and apply MBF-style techniques to generate the best forecast possible for the demand signal as described. This forecast accounts for unit type and operational mission. Based on an operational scenario, we improve the MLNPS capabilities by adding techniques to account for uncertainty and assess risk; we achieve this improvement using a sample-path based forecasting approach, incorporating recent advances in time-varying queueing networks such as the DIS approximation, and fusing these capabilities with the strengths of the Virtual Factory using the tandem approach. The Virtual Factory excels at realistic tasks such as properly packing multipacks, pallets, and containers, timing the shipments, and accommodating real-world schedules.

These enhancements to the MLNPS center on two fundamental tasks: (1) given a plan, estimate the plan's performance, and (2) given a target performance, find the required plan. Ultimately, this research provides a data-to-decision support process that yields a framework for assessing risk as both the severity and likelihood of possible outcomes become available via analytical calculation or Monte Carlo methods.

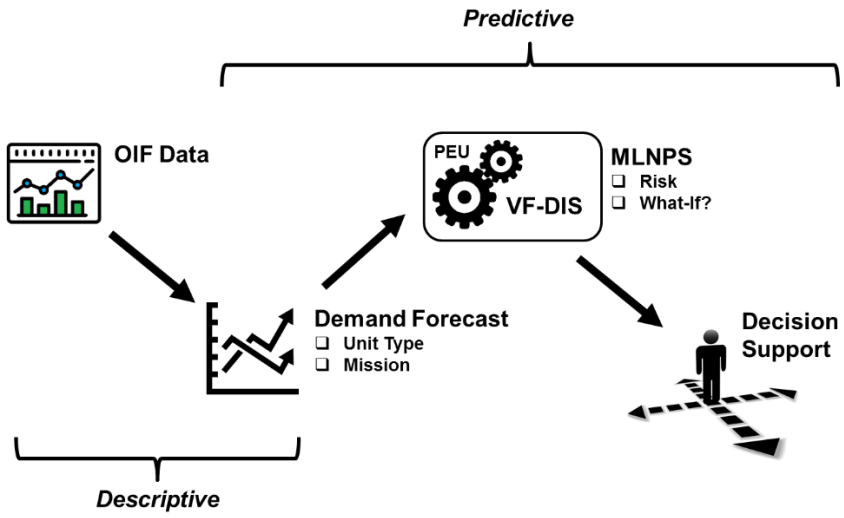

Figure 6.1: Research Contribution.

The case study presented in Chapter 5 demonstrates the capabilities of the MLNPS for analyzing the logistics requirements of an expeditionary operation. In the case study, an Infantry Brigade Combat Team (IBCT) and a Stryker Brigade Combat Team (SBCT) conduct operations from South Sudan into Sudan against the Islamic State of Iraq and Syria (ISIS). Particular focus is placed on the requirements for the last tactical mile (LTM) trucks. New graphical and risk-analysis tools support (i) comparing alternative courses of action, and (ii) evaluating the performance of a selected course of action under a complete disruption of the sustainment vehicles.

6.2 Future Work

There is much to be done to improve MLNPS and expand its utility. Some of these tasks are relatively minor and add precision while others are significant structural improvements with the potential to drastically expand the scope of MLNPS.

6.2.1 Risk

Risk is a difficult concept to quantify – it means different things to different people often depending on the context or application. From discussion in Alderson et al. (2015) it is clear

that any risk or resilience analysis should reflect the operation and function of the system continuing after the disruptive event and facilitate systematic exploration of disruptive events and consequences (what-if analysis). This research accomplishes these two tenets but does not meet the third criterion: incorporate the system's ability to change, especially under worst-case conditions (Alderson et al., 2015). This limitation exists because the model is largely predictive in nature (see Figure 6.1); to address this final tenet, Section 6.2.5 discusses feeding the outputs of this research into prescriptive models.

One practical improvement is the construction of a useful *risk dashboard* as conceptualized by Figure 6.2. The concept sketch provided shows dropdown boxes for specific logistical node locations (processors), performance measure and target for control, and course of action (COA). Check boxes allow viewing the entire operational plan or just particular phases. Such an interface would make functional demonstrations more accessible to a larger audience, especially to US Army personnel.

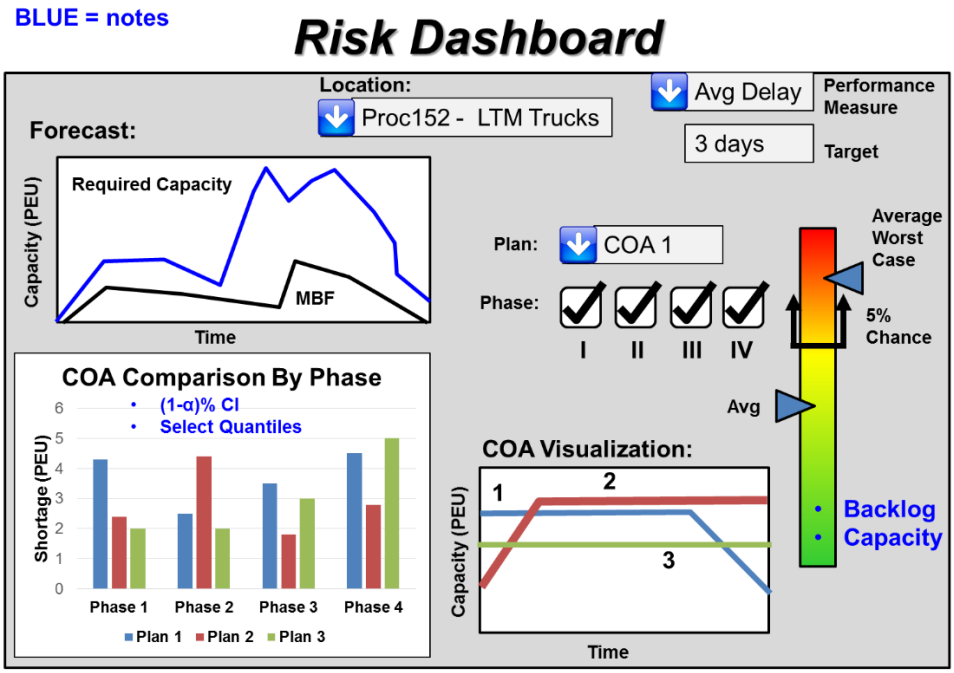

Figure 6.2: Concept Sketch for a Risk Dashboard.

6.2.2 Shared Processors

As discussed in Section 2.1.2, the Virtual Factory requires specified allocations for shared resources over the time horizon. A more realistic and detailed modeling of how to dynamically reallocate a shared resource, such as the LTM trucks supporting two units in different locations, would improve the performance forecast. To preserve the near-real time efficiency of this tool, this would likely require extensive study of the literature and test cases to provide robust heuristics for a new Virtual Factory processor.

6.2.3 Structural Improvements

Building an approximate cost model and integrating with the Virtual Factory via metaheuristics would enable exploration of tradeoffs between performance and expense though cost does not seem the key factor in expeditionary operations where readiness and lethality of the supported force are more critical. Tools using methods similar to Trainor (2001) could identify the efficient frontier based on chosen metrics of interest such as lateness, utilization, risk, or cost. Using computationally efficient approaches, possibly network models, future work might address alternate routing for critical supplies or requisitions for a specific unit or phase of the operation.

6.2.3.1 Alternate Routing

When multiple modes of transportation or alternate routes are feasible for a set of requisitions for all or a portion of the path from the supply node to the demand node, allowing for the selection of transportation mode or route could improve the model and provide actionable insights for those with real-time GCSS-Army access. Accounting for rerouting in the face of disruptions would add contingency functionality to the MLNPS and lead to more meaningful risk analysis (Tomlin, 2006). Indeed, without considering some of these alternatives this model may overstate risk in some cases.

6.2.3.2 Requisition Priority

Requisition priority plays no current role in the MLNPS performance approximation but might be useful in a more thorough risk analysis. Military logisticians use transportation priorities to indicate the criticality of repair parts to the mission. By incorporating this as an data field extracted from GCSS-Army, the MLNPS can better determine logistics risk by using this priority code in weighted measures (e.g. weighted lateness). The current model only accounts for this in the requisition forecast when generating requisition-specific standard delivery times.

6.2.4 Expanded Scope

The MLNPS currently focuses on repair parts (CL IX) and—to a limited extent—food, water, and ammunition (CL I, V). Expanding this list to include fuel (CL III) would require modeling other transportation assets and the fuel network but would be feasible with the MLNPS general approach. Currently the MLNPS only considers forward distribution but the reverse logistics process requires careful thought to integrate into the MLNPS framework. Both this work and Rogers (2016) focus on expeditionary operations where one expects minimal reverse logistics requirements. From a technical perspective, the Virtual Factory is well-suited to modeling reverse logistics but the queueing theory (DIS model) would require refinement for implementation; those interested in pursuing this feature would be well served by recent and ongoing work by Dr. Yunan Liu and Dr. Ward Whitt on nonstationary, non-Markovian queuing networks with feedback (Liu & Whitt, 2017).

The delayed infinite server presented in Chapter 3 uses average delay (by location) as a performance target for control (setting capacity). Rather than using average delay, using the two parameter control of the tail probability of delay is probably a better and more applicable way to set performance targets, especially in a risk context (Liu, 2018). This would require

engineering refinements to incorporate with the existing MLNPS VF model but would be a worthy addition.

Though motivated by a military logistics problem, the MLNPS can be used in other contexts, especially logistics planning problems with austere environments, significant uncertainty, nontrivial time-varying properties, and a network structure. Expanding its use to certain humanitarian or disaster relief efforts would provide interesting venues for extending the scope of these techniques.

6.2.5 Demand Forecasts

Both Parlier (2011, 2016) and Rogers (2016) discuss the impact of mission type on supply requisitions and the current challenges the Army faces forecasting future supply requisitions demand. The MLNPS would benefit greatly from a concerted effort by the US Army to fully adopt mission-based forecasting (MBF) or related techniques for both major platforms (such as the M1 Abrams tank or the AH-64 Apache attack helicopter) and different formations (IBCT, SBCT). In the meantime, Chapter 4 provides a data-driven approach forecasting requisitions for a given expeditionary operation in an arid or desert environment. This approach would clearly benefit from additional datasets but could improve with increased precision in modeling correlations such as the necessary correlation between weight and volume. The methods here can be improved; the nonparametric Markov bootstrap technique (Willemain & Smart, 2001; Willemain et al., 2004, 2005) and others seeking to capture autocorrelations of intermittent demand provide promising directions (Syntetos & Boylan, 2005; Syntetos et al., 2015). Modelers, researchers, and analysts seeking requiring a demand forecast and seeking use GCSS-Army data will need to continue to grapple with this challenge as long as MBF remains a vision rather than a reality.

For the method presented in Chapter 4, further study is required to select the best approach to generate sample correlations that are close (at least in expectation) to the desired targets. The naïve implementation of the Gaussian copula, for both the Lognormal and Beta distributions, used in Chapter 4 works but further comparing the current performance with Magnussen (2004) has the potential to provide a better method. Thorough numerical experimentation should provide guidance on which approach best represents the data for the full range of target correlations.

Finally, cutting-edge forecasting research is grappling with how to forecast related families of parts (Willemain, 2017). Thought not yet ready for implementation at scale (think unit types like a light infantry battalion or platforms like the M1 Abrams tank), this line of research may yield new forecasting methodologies relevant to this problem.

6.2.5 Prescriptive Models

As Figure 6.1 illustrates, current and previous work with the MLNPS focus primarily on descriptive and predictive analytics. A good direction for future efforts is to identify useful questions for which a series of prescriptive models can provide the answers. These models would be fed with the descriptive and predictive elements already manifest in the MLNPS and expand the decision-support utility of this framework.

One potential opportunity for a prescriptive model is constrained capacity decisions considering risk. Inevitably senior leaders will not have enough resources to completely remove risk, especially during expeditionary operations. With the Virtual Factory and DIS model, the MLNPS can generate the stochastic forecast for required capacities to meet senior leader performance targets. Similar to Izady and Worthington (2012), this forecast can feed a prescriptive decision model to identify and recommend where resources may be best used. Appendix E provides an example formulation in the Naval Postgraduate School (NPS)

format (Brown & Dell, 2007) as a start point for future research. A prescriptive model is critical to understanding what decisions are required to achieve the best performance under the worst-case conditions and could permit automation of the system's ability to change as discussed by Alderson et al. (2015).

6.2.6 Collaboration Targets

Eventually, to increase trust in the MLNPS, data representative of actual CONPLANS or OPLANS must be run and discussed with military planners. There remain some viable opportunities for collaboration with DLA and TRANSCOM in pursuit of this objective. To increase success, adding measures consistent with other tools would improve this interaction; an example would be adding the day-tons-late metric since Analysis of Mobility Platform (AMP) also employs this metric. Other potential collaborators would include the PLANS team at ERDC.

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APPENDICES

Appendix A – Deterministically Enhancing MLNPS

This appendix proposes an extension to Rogers (2016) that automates the capacity planning in a computationally efficient manner.

A.1 Two-stage Deterministic Tool to Find Required Capacity

In the work to date (Rogers et al., 2016), we have demonstrated how the GCSS-Army system can be used to anticipate when and where the logistical network will be inadequately resourced, what the impact will be on the system, and how to identify the required capacities along the network to ensure the logistical network is resilient enough to properly sustain a planned expeditionary operation. We have also provided an example – DDSP queuing in 2003—of how to address a backlog by finding the required capacities to prevent unacceptable requisition queueing at critical nodes. This example did not provide a unique method or even an efficient one to replicate this in future analysis. In addition, we concluded that conducting the sustainment analysis with an end-to-end perspective comes with its own challenges as the sheer volume of requisitions (jobs) flowing through the CONUS depots dwarfs the amount that will ultimately go to the expeditionary operation. This makes adjusting the expeditionary network very quick but imposes computational burdens when looking at the whole network simply because of all the non-expeditionary requisitions.

Clearly, a computationally efficient procedure to plan and adjust network capacities to some desired level of support is both needed and will facilitate subsequent analysis. With a little thought, it seems obvious that a practical capacity function (capacity over time) for a particular node is hardly unique and we only require an efficient way to discover a good capacity function in an automated fashion. We propose a two stage procedure as an additional feature for the Military Logistics Network Planning System (MLNPS). This

procedure will first adjust the CONUS-based node capacities (upstream) and record the times when the expeditionary jobs hit theater. Then we will use the theater hit times to focus the adjustments on the expeditionary network gaining computational efficiencies.

2-Stage Procedure to Plan Network Capacity Requirements

For a given set of requisitions over a given time period, here also referred to as jobs, we may divide them into two sets: the expeditionary jobs (J_E) and the steady-state jobs (J_S). Here, the term "steady-state jobs" refers to all the requisitions that are not going to the expeditionary theater of operations and would be required over a given time period regardless of such an (expeditionary) operation. The procedure is divided into two stages with a reconciliation process at the end. Stage 1 finds the CONUS node capacities and only considers the CONUS network. Stage 2 is exclusively focused on the expeditionary network and finding the required resources to meet target thresholds.

Stage 1: Set CONUS Node Capacities

Using the full set of requisitions, adjust the network as outlined in Table A.1 such that the furthest downstream nodes are the sea port of debarkation (SPOD) and the airport of debarkation (APOD). For the jobs moving by World Wide Express (WWX), simply use the theater distribution center (TDC) as their terminal node. Run the Virtual Factory (VF) using this modification from the actual problem as depicted in Figure A.1. Using the queuing results at critical nodes, primarily the major node Defense Depot Susquehanna, Pennsylvania, (DDSP) and its twin at San Joaquin, California, (DDJC), adjust the capacity of each node until the queueing is at the acceptable level. This "acceptable level" is left as a parameter to be specified or estimated based upon the specifics of the situation and the decision-makers involved. In previous research, we have used the average queuing in the months prior to the expeditionary operation as the threshold.

Table A.1: Stage 1 Modified Network.

Transportation Mode	**Terminal Node in Theater**
Air	APOD
Surface (ocean)	SPOD
WWX	TDC

For a specific node, we propose the *Stage 1 Procedure* to obtain the required capacities over time for a specific node. For this procedure we set the queuing threshold, $\omega(t)$, as the average maximum pick and pack time for the selected defense depot (e.g. $\omega = 3$ days). This may be a scalar value or a discrete function over time. Run the VF using the base capacity and obtain the estimated queuing (e.g. average pick and pack time) along with the hit times for each job at its terminal node in theater according to Table A.1. If the resulting queueing is within the acceptable limits then Stage 1 is complete. If the queuing was unacceptable at some point along the time horizon, then for the first time the threshold was violated ($\bar{t}$), increase the capacity starting at time $\bar{t} - a$ by the amount the queuing exceeded the threshold starting on from $\bar{t}$ to $\bar{t} + b$ where *a* and *b* are user parameters that govern the procedure's performance. Starting the capacity increase *a* time steps early prevents or mitigates the queuing spike occurring in the first place. Increasing it by the amount exceeded over *b* time steps prevents the procedure from being run repeatedly for small threshold violations reducing the computation required for Stage 1 where it is already the most burdensome. The user may adjust *a* and *b* as parameters.

Figure A.1: Stage 1 Model.

Rerun the VF using the updated node capacity. Once there is enough capacity, the procedure will terminate with the specific points in time where the capacity must increase along with the magnitude of the required capacity increase and the queuing time of every job at that particular node. It also outputs the estimated hit times the expeditionary jobs will arrive in theater (T_H^j). Stage 1 completes with the required capacities identified over time for all CONUS nodes of interest and the estimated theater arrival times for expeditionary jobs.

Box A.1: Stage 1 Procedure.

Stage 1 Procedure: **CONUS Network Capacity**

Given a specific discrete time horizon, $t \in \{0,...,T\}$; set of requisitions, $J = J_S + J_E$; acceptable queuing threshold, $\omega(t)$; and the modified network according to Table 2.2, determine CONUS node capacities required.

Procedure:

1. Using node *i*'s initial planned capacity, $K_i(t)$, run the VF and note the resulting queueing, $W_i(t)$, such as the average pick and pack time. For all jobs, record queuing times q_{ji}. For all expeditionary jobs, $j \in J_E$, record the theater hit times T_H^j.
2. If $W_i(t) \le \omega_i(t) \;\; \forall t$ then Stage 1 is complete. Else, go to 3.
3. Let $\bar{t} = \{\min t : W_i(t) - \omega_i(t) > 0\}$.

Then $K_i(t-a) = K_i(t) + \sum_{l=0}^{b} [W_i(\bar{t}+l) - \omega_i(\bar{t}+l)], \;\; t = \bar{t},\ldots,\mathrm{T}$. Go to 2.

Alternatively, do for $t = \bar{t},\ldots,\bar{t}+b$

Stage 2: Theater Network Analysis

Using the recorded queuing from Stage 1, the joblist requires updates. It is apparent that once the upstream effects of the CONUS network have been recorded, this portion of the network no longer affects the remaining flow of the supply requisitions. Stage 2 should be restricted to the expeditionary jobs permitting adjustments to the jobs and network to conform to the Stage 2 model. As seen in Figure A.2, the network begins with the defense depot and each job's processing time at this source node includes all the processing and queueing from all the CONUS nodes. This model may be analyzed rapidly for a variety of reasons; some examples include identifying required capacities, testing network resilience against possible disruptive events, evaluating risk, and sensitivity analysis. The VF will run significantly faster on the Stage 2 model as it does not have to account for the large volume of requisitions moving through the upstream CONUS channels to the rest of the world. VF runs in Stage 2 can occur quickly so the most critical section of the analysis—the expeditionary network—may be studied in detail but in the context of the end-to-end analysis performed in Stage 1. This Stage 2 Analysis may focus on the queuing but also on other metrics, most notably lateness.

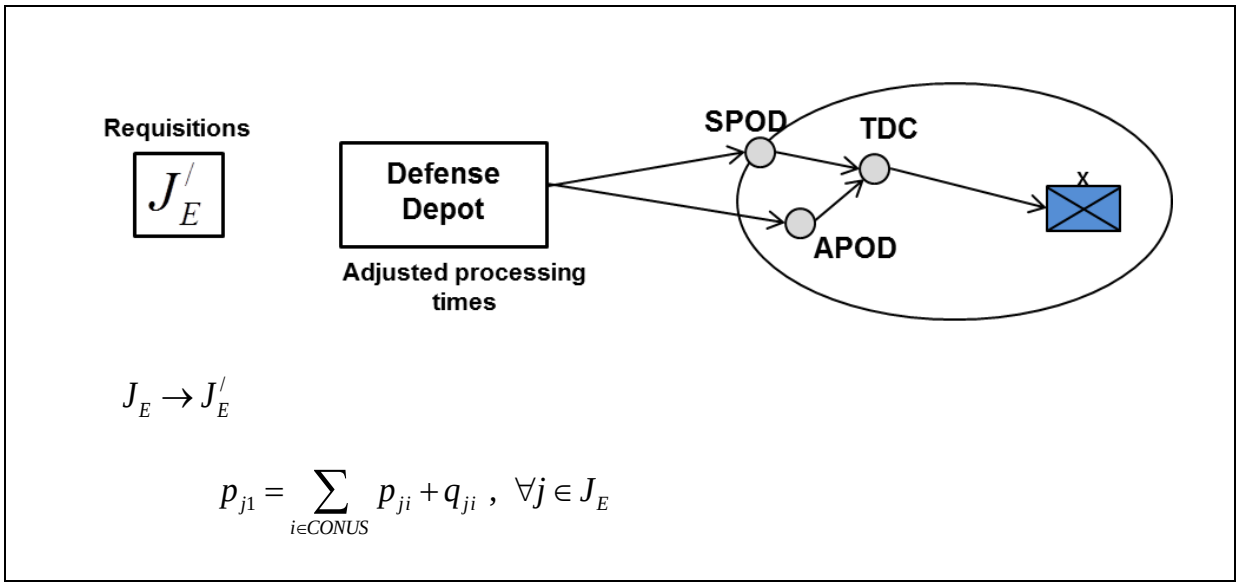

Figure A.2: Stage 2 Model.

Implementation requires experimentation to understand the impact of the model parameters and what values might be best for this application. Generating scenarios to test this procedure would follow work done by Rogers et al. (2016) and include scenarios from their work. In addition, sensitivity analysis is required to understand the impact of the parameters *a* and *b* and what values perform reasonably well.

Validation Plan for 2-Stage Procedure

While it is true that these runs in Stage 2 are all "anchored" to the final Stage 1 sequence that produced the theater hit times, we believe this will still provide value in additional to the computational savings. It is clear that a numerical study will need to be completed to assess the impact of using Stage 2 results that are anchored to a false Stage 1 sequence. The experiment would require completing Stage 1 to establish a common network. For the control, determine the expeditionary network capacities using the entire network and joblist with the VF working from upstream to downstream. This will be feasible

but almost surely computationally intensive. Then, for comparison, use the 2-Stage Procedure as outlined above to complete the analysis.

Table A.2: Validation Concept for 2-Stage Procedure.

	Method	**Network**	**Joblist**
Control	1–Stage Procedure	Full (CONUS + Theater)	All $J_S + J_E$
Test	2–Stage Procedure	Staged	Stage 1: $J_S + J_E$ Stage 2: $J_E^{/}$

To assess the impact of using this procedure, we would need to compare both the capacities identified for the network under each procedure, various performance metrics to include queuing and lateness measures at nodes of interest, and the computation time. This would allow us to validate the 2-Stage Procedure both in terms of computational efficiency as well as its accuracy as an approximation.

The results obtained from Stage 2 completion are approximations. Tables A.2 & A.3 outline the plan to assess the performance of the approximation. It is also possible to simply take the Stage 2 results for in-theater capacities and rerun the entire model with the original (true) joblist, the full network, and the capacities found by the procedure. A single run of the entire joblist on the entire network may be permissible depending on a planner's timeline – this would provide a final verification run if desired.

Table A.3: Assessment Plan for 2-Stage Procedure Validation.

Utility Criteria	Outcome Data	Victory Conditions
Accuracy	Required capacities* Queuing* Lateness metrics*	1. 2-Stage procedure results in capacities sufficiently close to control 2. 2-Stage procedure predicts downstream queuing and lateness sufficiently close to control
Efficiency	Computation time	3. 2-Stage procedure computation time significantly less than 1-Stage procedure.

* for nodes of interest

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Rogers, M., McConnell, B., Hodgson, T.J., Kay, M.G., King, R.E., Parlier, G., Thoney-Barletta, K. 2016. A Military Logistics Network Planning System (MLNPS). Paper in 2nd review at *Military Operations Research* (MORS).

Appendix B – Supplementary Data Analysis

B.1 The Requisition Arrival Process: Total Requisitions (CL IX) at DDSP in 2003

It is important to understand as much as possible about repair part requisitions as the arrival process as we intend to apply a queueing network framework to develop additional tools for the Military Logistics Network Planning System (MLNPS). To that end, we observe that the Defense Depot Susquehanna, Pennsylvania (DDSP), is a critical component of this process as it sources the majority of requisitions and servers as the container collection point (CCP) for all requisitions leaving the east coast of the United States.

This appendix presents empirically discovered structural properties of this time-varying arrival process where the Class IX repair part requisitions are modeled as arrivals to a queuing network. The purpose is to inform the reader's intuition on this process and provide insight into the model assumptions developed in the research.

Using requisition data from DDSP in 2003, we make the following observations based on the visualization in Figure A-1 which shows the total daily requisitions that DDSP processed (top) against the number of maneuver brigade combat teams (BCTs) in theater (bottom). A dashed line indicates the day of the invasion (20 Mar). It is important to note that these requisitions are supporting both Operation Iraqi Freedom (OIF) and the rest of the normal worldwide operations as well. Looking at just the repair parts requested from 6 Mar – 21 May, the same 87 day period analyzed by Rogers et al. (2016), the total value of these requisitions exceeds $3.4 billion.

It appears there is a strong weekly pattern – which validates our intuition that the work week imposes certain patterns—and indeed the autocorrelation function at a lag of seven is 0.536. Overall it appears the demand pattern is fairly constant but with a very slight

uptick over time. The total daily volume does not appear to directly relate to the number of maneuver BCTs in theater as the demand generated by the deployed BCTs is small relative to the rest of the global demand DDSP is responsible for fulfilling. There appears to be a large seasonal cycle for some quarterly effect with a period of approximately 90 days. Finally, the pattern looks quite different after day 300 (Oct 27).

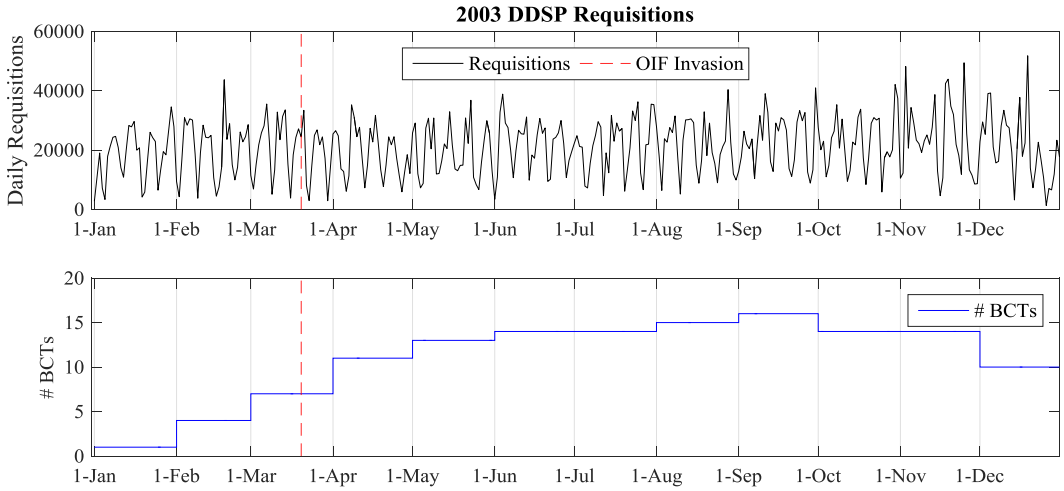


Figure B.1: 2003 DDSP Requisitions.

The requisition flow indeed follows a pattern each week as illustrated by Figure B.2. Looking at the confidence intervals for each day's average volume, the weekdays are statistically indistinguishable while the weekend days are clearly lower. The author believes this pattern is likely to be repeated again due to institutional inertia and the historical lack of synchronization between the Defense Logistics Agency (DLA) and operational planners for expeditionary operations. Rogers et al. (2016) demonstrate that through such synchronization and the resulting staffing plan for DDSP, DLA has a tremendous opportunity to prevent sustainment problems downstream in theater. Future volume patterns at DDSP may not match this entirely but are likely to have this structure (Figure B.2) simply due to the fact that most of the requisitions processed are steady-state non-expeditionary supply orders.

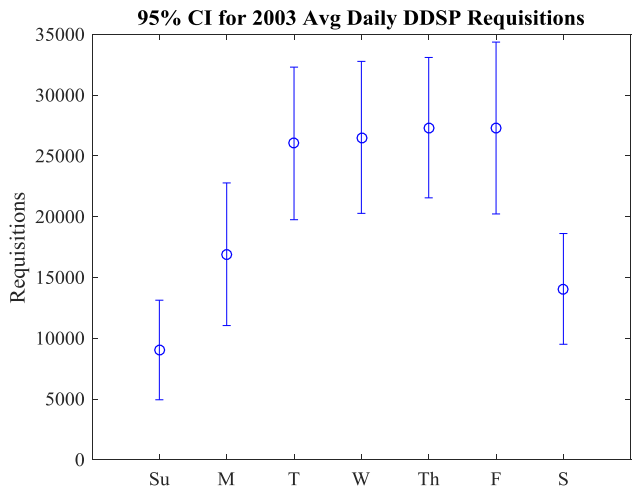


Figure B.2: 95% CI for 2003 Average Daily Requisitions at DDSP.

Though the demand volume appeared constant when looking at the daily volume at DDSP as shown in Figure B.1, a weekly perspective provides additional insights. A simple linear regression (excluding the first and last weeks due to the American holidays) reveals the average weekly number of requisitions increased by almost 720 per week (see Figure B.3). It seems apparent that any model used must be able to account for a time-varying arrival process in order to supplement the analysis already provided by the MLNPS.

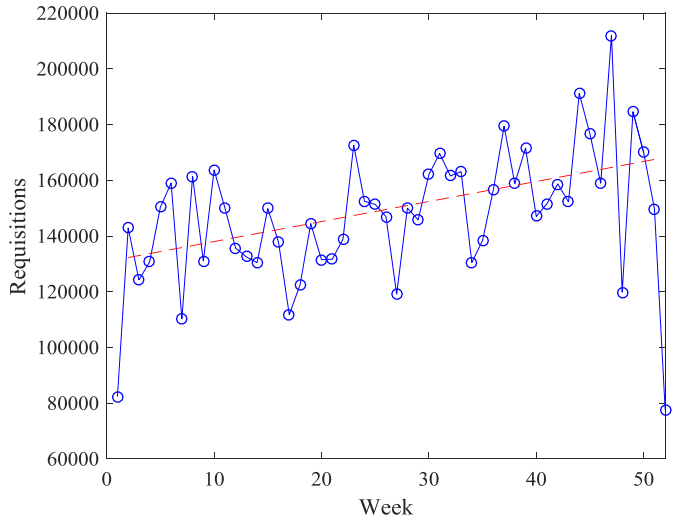
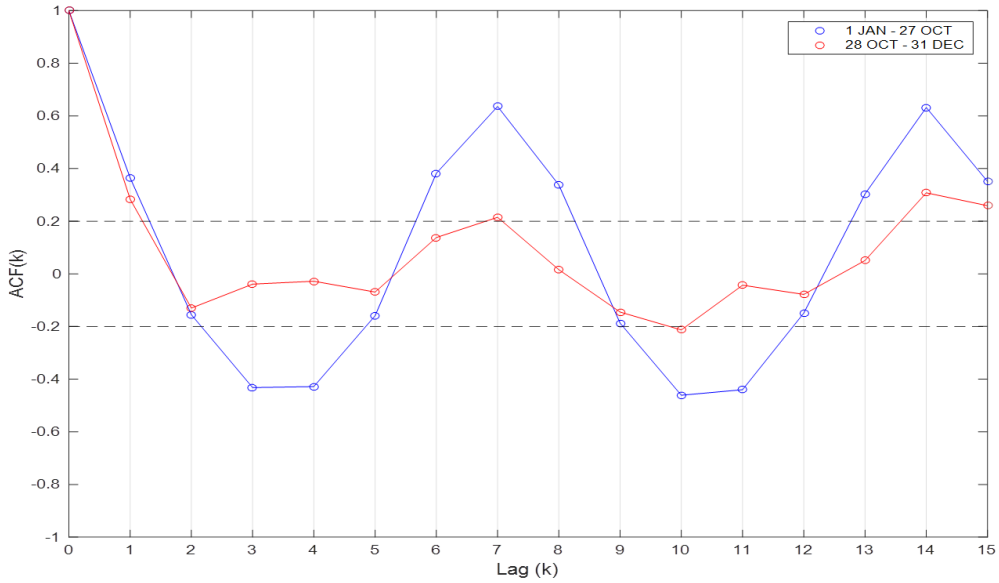


Figure B.3: 2003 DDSP Weekly Requisitions. Weeks 1 & 52 omitted from regression.

By inspection, one can see a strong pattern in Figure B.1 until day 300 (27 Oct) after which it appears there is a different regime governing the demand volume at DDSP. Looking at the autocorrelation of the total number of daily requisitions in Figure B.4, it is apparent a weekly pattern dominated prior to 27 Oct. After that, the autocorrelation function stays within ± 0.20 which indicates a regime change into what appears to be 'more random' behavior. We are unable to explain this shift without undue speculation but there are several factors that may have contributed to this change. First, deployed units adjusted their ordering needs as the operations in Iraq evolved following the successful invasion; their ordering patterns also changed as the logistical kinks were worked out of the system and CL IX repair parts became less of a challenge to obtain. Unit rotations may have also had an effect as deploying and redeploying units get eventually obtained budgetary incentives to order at certain times. A detailed investigation into this phenomena is beyond the scope of this work – we look to develop models capable of handling these time-varying properties.



Lag (k)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Nrel	0.347	-0.140	-0.312	-0.311	-0.137	0.319	0.536	0.263	-0.173	-0.377	-0.333	-0.122	0.262	0.565	0.331
Nrel[1:300]	0.365	-0.155	-0.432	-0.428	-0.159	0.382	0.636	0.338	-0.187	-0.461	-0.440	-0.149	0.304	0.632	0.351
Nrel[301:365]	0.284	-0.130	-0.039	-0.028	-0.069	0.138	0.215	0.016	-0.145	-0.213	-0.043	-0.078	0.051	0.308	0.259

Figure B.4: Autocorrelation Plot of DDSP Requisition Flow.

B.2 Transportation Times

As we aim to build in stochastic tools to enhance the Military Logistics Network Planning System (MLNPS), it is important to consider what is actually random and what may be modeled deterministically without loss of information.

B.2.1 Air Transit Times

Looking at commercial flight times (wheels up to wheels down) using *FlightAware.com* for three separate long routes, the coefficient of variation is sufficiently small in the context of our problem to call air transit times deterministic. Table B.1 presents descriptive statistics for these three routes. This is important as it may allow us to gain some computational efficiencies for deterministic portions of our queueing network model. While this may allow a simplification from modeling these times as random, there is undoubtedly some variation involved in the tasks prior to wheels up or following the wheels touching down. These "loading/unloading" tasks may introduce variation and must be considered.

Table B.1: Flight time (hrs) from 11 Oct 2015 to 10 Feb 2016.

Flight Time (hrs)	**KU 118**	**DL 837**	**DL 200**
Route	JFK – KWI	ATL – HNL	ATL – JNB
Distance (mi)*	6334	4493	8279
# Flights	53	125	121
Mean	10.62	9.35	14.57
Median	10.53	9.35	14.57
Standard Dev	0.455	0.339	0.287
Min	9.82	8.55	13.7
Max	11.77	10.07	15.58
Range	1.95	1.52	1.88
CV	0.043	0.036	0.020

* Great circle distance (http://flightaware.com)

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Appendix C – Queueing Theory Basics

This appendix provides an overview of queueing theory which more simply stated is the mathematics behind waiting in line. Not intended to be exhaustive, this appendix is included to the highly diverse set of Operations Research tools that comprise this research. For those unfamiliar with queueing theory, this provides enough background to grasp the intent of Chapter 3.

It is convenient to first review the notation used to describe a queuing model first proposed by Kendall (1953) summarized in Table C.1. This chapter uses the notation $A/S/c/K/N/D$ to describe a queue with arrival process *A*, service time distribution *S*, *c* parallel servers, system capacity *K* (queue + number in service), calling population *N*, and queue discipline *D*. In general, *K* and *N* are often assumed to be infinite, $K = N = \infty$, and the service discipline is 'first in-first out' (*D* = FIFO) unless otherwise stated; as such, queues will be abbreviated $A/S/c$. If a queue experiences abandonment in which an arrival will exit the queue foregoing service if their wait time exceeds their patience time, then the queue would be annotated $A/S/c+a$, where *a* describes the abandonment process (patience time distribution). Time-varying processes will be annotated with a subscript *t*. The capital letter *I* will be used to mark an independent and identically distributed process.

Table C.1 – Common designations using Kendall's notation.

A – Arrival process S – Service time distribution	M – Markovian: exponential interarrival times (Poisson process, PP) M_t – Time-varying rate for exponential interarrival times (non-homogenous PP) G (G_t) – General (time-varying) distribution for interarrival times (non-exponential)
c – Number of servers	1 – single server *s* (s_t) – multiple servers (time-varying number of servers)
K – System capacity N – Calling population	Assumed to be infinity unless stated otherwise (as integers).
D – Queue discipline	FIFO/FCFS – First In, First Out / First Come, First Served (default) LIFO – Last In, First Out SIRO – Service in Random Order Priority – Arrivals served according to their assigned priority.

In queuing theory, it is often useful to categorize the "staffing regime" in which the queue of study is operating; to some extent, these regimes reflect one's beliefs about the system or the philosophy regarding the system design (Garnett et al., 2002). This is important because while a single-server queue imposes an unavoidable trade-off between resource utilization (service efficiency) and the quality of service experienced by the arrivals, "large scale" queues (many-servers) are able to achieve both efficiency and quality through appropriate staffing (Mandelbaum and Momčilović, 2008). Figure C.1 (mimicking Mandelbaum and Momčilović, 2008) demonstrates that by increasing the system scale, it is possible to increase quality of service without loss of efficiency.

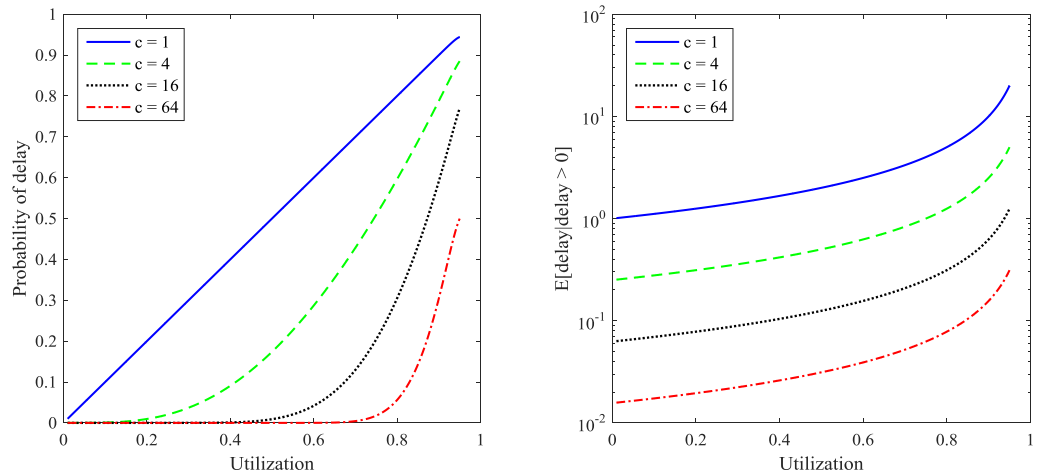

Figure C.1: Performance of *M/M/c* queues for *c* = 1, 4, 16, 64.
It is possible to increase efficiency and quality through staffing.

Consider a queue with arrival rate λ and service rate μ (the mean service time is given by μ^{-1}); our purpose is to select the number of servers , *s*, for the queue. Let the probability an arrival abandons the queue before entering service be denoted $P(Ab)$ and the steady-state waiting time in the queue (prior to entering service or abandoning) be W_q. Then the probability an arrival does not immediately enter service is $P(W_q > 0)$. One common statistic may be to calculate the average server utilization (traffic intensity) by Equation C.1. Another measure of the queue's traffic is the (average) offered load (OL), given by Equation 3.2. Garnett et al. (2002) use the limit $OL \to \infty$ to characterize the first three regimes listed in Table C.2 according to their convergence behavior in this limit then established guidelines (rules of thumb) for staffing in these regimes.

$$\rho = \frac{\lambda}{\mu s} \tag{C.1}$$

$$OL = \frac{\lambda}{\mu} \tag{C.2}$$

In the rationalized regime, staffing is set based on a positive quality of service (QoS) parameter, β, where a higher value yields a higher quality of service. Garnett et al. (2002) provide an approximation function for the delay probability and showed the convergence of the abandonment probability to zero. In the Quality-Driven (QD) regime, the system is underloaded and able to staff such that the delay and abandonment probabilities are negligible. In the Efficiency-Driven (ED) regime, the system is overloaded and does not have the resources to prevent arrivals from waiting. Delay is almost a certainty for virtually all arrivals and if the system can have abandonment, there will be a nonzero fraction leaving the queue prior to service. Garnett et al. (2002) notes that even in the ED regime "both $P(Ab)$ and $E[W_q]$ remain small if the capacity shortfall is small."

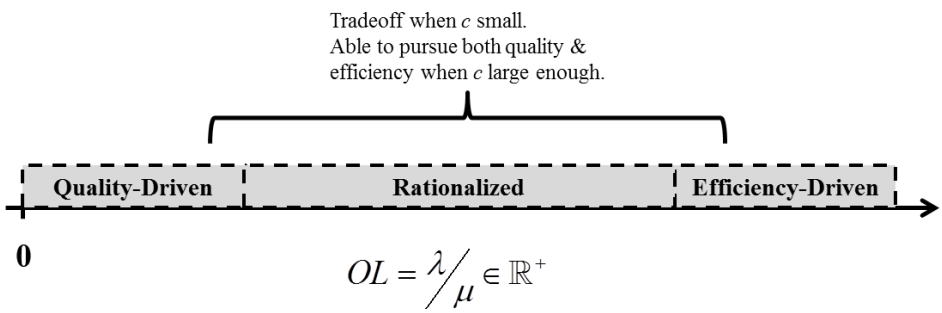

Figure C.2: Offered load visualized on the number line.

Another way to picture these regimes is by remembering that the offered load must be a positive number and thus lies on the number line pictured in Figure C.2. When the scale of the system is small, the inevitable competition for few resources forces a tradeoff between quality and efficiency; appropriate staffing is a tool to attempt to regulate this balance. When the scale is large enough, the individual impacts of each arrival are reduced and economies of scale start to apply. The forced tradeoff is less stark and one can staff such that both quality and efficiency are emphasized. In this regime, first introduced by Halfin and Whitt in 1981

and often referred to as the "Quality and Efficiency Driven" (QED) regime, some arrivals will wait and others will proceed directly to service (Halfin & Whitt, 1981; Gans et al., 2003).

Determining which regime your system is likely to be in (or shift between) is both a judgement call based on philosophy as well as an empirically driven determination. Sample statistics for various performance metrics may be used in conjunction with common sense to assess what regime most applies. As discussed later, abandonment is not a key feature of this research so there is a need for the identity presented by given in Equation C.3, where θ^{-1} is the average patience time, which permits summarizing the regime performance in terms of the expected waiting time (steady state) (Garnett et al., 2002). It is important to note that Equation C.3 holds at equality only when the patience time distribution is exponential – (Gans et al., 2003, Mandelbaum and Zeltyn, 2004).

$$\theta \cdot E\left[W_q\right] = P\left(Ab\right) \tag{C.3}$$

Mandelbaum and Zeltyn (2004) demonstrate that in both the QD and QED regimes the asymptotic relationship in Equation C.4 holds but not in an ED regime. Here the patience time cumulative distribution function (cdf) *F* is assumed to have a positive density value at the origin, $f\left(0\right)$ (Gans et al., 2003, Mandelbaum and Zeltyn, 2004).

$$f\left(0\right) \cdot E\left[W_q\right] \approx P\left(Ab\right) \tag{C.4}$$

Table C.2: Queuing Regimes (Garnett et al., 2002).

Regime	Staffing Level	Performance as $OL \to +\infty$
Rationalized	$s = OL + \beta \cdot OL$	$P(W > 0) \to \alpha(\beta)$* and $P(Ab) \to 0$
Quality-Driven (QD)	$s = OL + \varepsilon OL, \quad \varepsilon > 0$	$P(W > 0) \to 0$ and $P(Ab) \to 0$
Efficiency-Driven (ED)	$s = OL - \varepsilon OL, \quad \varepsilon > 0$	$P(W > 0) \to 1$ and $P(Ab) \to \varepsilon$
Quality and Efficient-Driven (QED)		

* See Garnett et al. (2002) for more details.

The literature on queueing theory is vast and this appendix seeks only to introduce readers unfamiliar with the vocabulary to the key notation, concepts, and the somewhat philosophical, ever mathematical idea of queueing regimes. Chapter 3 reviews relevant literature to nonstationary queues and queueing networks.

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Appendix D – Demand Forecasting Details

D.1 Empirical Data from OIF Invasion Dataset

Table D.1: Unit Type Identification in OIF Invasion Data.

Unit in Model	Unit Field	Operational Unit
IBCT	426 CSB 526 CSB 526 BSB 2BCT 526 CSB 2BCT 626 CSB 407 CSB	1-101 AASLT 2-101 AASLT 3-101 AASLT 2-82 ABN
HBCT*	3 FSB 26 FSB 203 FSB	1-3 ID 2-3 ID 3-3 ID
AVN BN	A – 101 AV B – 101 AV C – 101 AV 603 ASB	Proxy for Aviation Battalion
EN BN	ACR Grd	(1/3) Proxy for Engineer Battalion
3 x Truck CO	317 CSB	Proxy for 3 Truck Companies
DIV HQ	801 CSB	Proxy for Division Headquarters
Sustainment BDE	COSCOM (field: Div)	Proxy for Sustainment Brigade
Misc. Enabler BN	19 SC	(x3) Proxy for Misc. Enabler Battalion

* now referred to as Armored Brigade Combat Team

Table D.2: Empirical Source Depot Distributions for Selected Units.

DLA Distribution Centers	IBCT	HBCT	AVN BN	EN BN	Truck CO
DDSP	0.601270	0.654390	0.630443	0.606180	0.683181
Chrlst	0	0	0	0	0
DDAA	0.003849	0.019380	0.002061	0.018207	0.009628
DDAG	0.003409	0.005510	0.001009	0.001838	0.003711
DDBC	0.002079	0.003900	0.001703	0.002932	0.001805
DDCN	0.001419	0.000930	0.002355	0.000219	0.000802
DDCT	0.003497	0.000340	0.007381	0.000175	0.000602
DDDC	0.001639	0.001150	0.002397	0.000700	0.001504
DDHU	0.001023	0.000640	0.001535	0.000700	0.000903
DDJC	0.110763	0.100570	0.102656	0.126138	0.117039
DDJF	0.000572	0.000340	0.001072	0.000131	0.000401
DDNV	0.002717	0.002160	0.004563	0.001182	0.003209
DDOO	0.000649	0.000040	0.001241	0.000263	0.000602
DDPW	0.000715	0.000470	0.000757	0.000350	0.000501
DDRT	0.038043	0.042160	0.041866	0.057423	0.028884
DDRV	0.019049	0.020360	0.012448	0.014881	0.007321
DDTP	0.006313	0.005980	0.009420	0.004202	0.001705
DDWG	0.002541	0.000850	0.004563	0.001094	0.000401
DVD	0.079429	0.048100	0.076939	0.062500	0.064988
EBS	0	0	0	0	0
GSA	0	0	0	0	0
GSA CA	0	0	0	0	0
GSA NJ	0	0	0	0	0
OddRIC	0	0	0	0	0
OOALC	0	0	0	0	0
Other	0.118923	0.090860	0.095023	0.099746	0.071909
Sierra	0.000121	0	0	0	0
DDCO*	0	0	0	0	0
LEAD*	0	0	0	0	0
RockIs	0.001980	0.001870	0.000568	0.001138	0.000903

* Present in data but now closed. Use DDSP.

D.2 US Army Ration Guidelines

Standard	Expeditionary < 6 Months					Temporary < 24 Months	
Ration Cycle	M-M-M	U-M-M	U-M-U w/one UGR (A) meal every third day	U-M-U	U-M-U	U-M-U	21 Day CONOPS Menu
Theater Ration Mix	MRE 100%	UGR (H&S) 34%	UGR (H&S) 56%	UGR (H&S) 34%	UGR (H&S) 10%	UGR (H&S) 05%	Force Provider, LOGCAP or Direct Contract 90 % Supported by SPV Platform 10% Combination of MRE's, UGR's Condition based
		MRE 66%	MRE 33%	MRE 33%	MRE 20%	MRE 15%	
			UGR (A) 11%	UGR (A) 33%	UGR (A)+ 70%	UGR (A)+ 80%	
Facilities		MKT, KCLFF, CK, Tents, Refers			MKT, CK, Unit Tents, Force Provider, Refers		Force Provider LOGCAP & SPV
Deployment Days D+	1-20 days	21-30	31-60	61-90	91-180	181 Days to 24 Months	

Notes:
1. Ration Legend: MRE-M, UGR (H&S) or UGR (A) – U, UGR (A) with Short Order Supplemental Menus – UGR (A)+
2. Units deploying into developed areas may move directly into the temporary standard depending upon their mission and the theater logistical capabilities at that location.

Figure D.1: Army Feeding Plan Guidelines (Rogers, 2016).

D.3 Using VF-DIS Results

Define a random variable $X \sim F_X(x)$ such that $F_X(x) = P(X \le x) = p$. Let

$Q(p) = F_X^{-1}(p)$ F_X if continuous and strictly monotonically increasing or

$Q(p) = \inf\{x \in \mathbb{R} : p \le F_X(x)\}$ otherwise.

References

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Appendix E – A Stochastic Optimization Model for Capacity Decisions with Risk

The outputs from the Virtual Factory and DIS models provide ready inputs for a well-crafted prescriptive model if a useful one can be formulated. We provide a primal formulation in the Naval Postgraduate School (NPS) format (Brown and Dell, 2007) for planning LTM capacity in the Sudan COA 1 scenario and admittedly leave it as a nonlinear integer program.

E.1 Example Decision Model for LTM Trucks in Sudan COA 1

Index Use [~Cardinality]

$j \in J$ unit locations supported by LTM trucks [~2]

$t \in T = \{1, 2, \ldots\}$ day alias for planning period [~120]

$\omega \in \Omega$ scenarios sampled for required capacity at LTM [~$|\Omega|$, e.g. 100]

Given Data [Units]

$requirement_{jt}(\omega)$ capacity required at location *j* on day *t* in scenario ω [463L PEU]

$available_t$ total available LTM capacity on day *t* [463L PEU]

$lowerbound_{jt}$ minimum LTM capacity to support location *j* (CL I, V) on day *t* [463L PEU]

Decision Variables [Units]

$CAPACITY_{jt}$ LTM capacity supporting location *j* on day *t* [463L PEU]

Auxiliary Variables [Units]

$backlog_{jt}(\omega)$ LTM backlog for location *j* on day *t* [463L PEU]

Formulation

$$\underset{CAPACITY}{MIN} \quad \frac{1}{|\Omega|}\sum_{\omega}\sum_{j}\sum_{t} backlog_{jt}(\omega) \tag{E.1}$$

s.t.

$$backlog_{jt}(\omega) = \left(requirement_{jt}(\omega) - CAPACITY_{jt}\right)^{+} \qquad t = 1, \forall j, \forall \omega \tag{E.2}$$

$$backlog_{jt}(\omega) = \left(requirement_{jt}(\omega) + backlog_{j,t-1}(\omega) - CAPACITY_{jt}\right)^{+} \quad t > 1, \forall j, \forall \omega \tag{E.3}$$

$$\sum_{j} CAPACITY_{jt} \le available_{t} \qquad \forall t \tag{E.4}$$

$$0 \le lowerbound_{jt} \le CAPACITY_{jt} \qquad \forall j \forall t \tag{E.5}$$

Discussion

The objective (E.1) seeks to minimize expected total backlog. This can be modified to focus on certain phases (time periods), locations, or include a risk-based penalty term. Constraints (E.2, E.3) define the backlog by scenario as a function of the LTM capacity assignment while forcing the capacity assignments to stay below the total available LTM capacity (E.4). Note that in the currently nonlinear formulation presented that the expression $(X)^{+} = \max\{X, 0\}$. A lower bound on the assignment is possible with (E.5) to ensure enough capacity exists to supply food, water, and ammunition, though this can be relaxed or specified in detail.

E.2 Model Expansion

By adding additional indexes for other locations with shared resources, it is possible to expand the formulation from Section E.1 to a larger portion of the network or even the entire theater of operations (expeditionary portion of the network). This idea would assist in recognizing, analyzing, and managing risk decisions over time and space. Clearly the ability

to solve these decision models plays a role but even an effective local optimum provides insights not directly obtainable without significant repetitions of the predictive outputs from the Virtual Factory and DIS models.

References

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Appendix F – Virtual Factory References and User Guide

This appendix consolidates the Virtual Factory (VF) literature into a single location which encompasses 15 peer-reviewed papers from 1998–2018 not counting any that arise from this dissertation. There have been a number of VF-related dissertations over this time period. These citations are found in the references at the end of this appendix. The other purpose of this appendix is to provide a starting point for those seeking to use the Virtual Factory to solve other problems, even those outside of the military logistics realm.

Over time, the Virtual Factory has become a modeling language of its own. Previous uses have largely focused on the optimization part (seeking to minimize the maximum lateness) or on operational decisions that were directly linked to sequencing (including manpower & multiple factory transportation issues). Rogers et al. (2016) is the first to use the outputs of the final sequence as a forecast for an efficient logistics network's performance to support analysis and subsequent decisions.

The details of the Virtual Factory and how to model effectively with it are beyond the scope of this section.

F.1 Processor Formatting

Schedule Type: governs when processor is working
Availability Type: governs how capacity is changing
Change Type: governs how to/from trip times (processing times) are changing

Primary Controls:

	Always On	Weekly	Custom	Constant Capacity	Changing Capacity
Processor Type	Schedule Type 1	Schedule Type 2	Schedule Type 3	Availability Type 1	Availability Type 2
1	X	X	X		
2	X	X	X		
3	X	X	X		
4	X	X	X	X	X
5	X	X	X	X	X
6		X		X	X
7		X		X	X

Other Controls:

	To/From Trip Times Constant	To/From Trip Times Varying
Processor Type	Change Type 1	Change Type 2
7	X	X

Type 1

Index	Proc Type 1	Processing Time	Weight Cap	Cube Cap	Schedule Type	Schedule (if 2 or 3)

Type 2

Index	Proc Type 2	Processing Time	Cap Groups	Schedule Type	Schedule (if 2 or 3)

Type 3 NLT

Index	Proc Type 3	Make Group Time	Group Weight	Group Cube	Group Send Time	Send Weight	Send Cube	Pallet Equivalent	Schedule Type	Schedule (if 2 or 3)

Type 4

Index	Proc Type 4	Break Group Time	Break Number	Schedule Type	Schedule (if 2 or 3)	Availability Type

Type 5

Index	Proc Type 5	Processing Time	Capacity Requisitions per Day	Schedule Type	Schedule (if 2 or 3)	Availability Type

An example input format for a processor with type 2 availability:

Index | Proc Type 4 | Proc Time | Weight Cap |

Schedule Type 3 | # Days Proc Available | List of Dates of Proc Available in Ascending Order Availability Type 3 | # Capacity Changes | Date1 of Capacity Change | Weight Cap1 | Date2 of Capacity Change | Weight Cap2

F.2 Job Formatting

The joblist is format is below (for each job). Note that the Routing is the ordered list of processors the job must travel through.

Number of Operations | Routing | Release Time | Due Date | Weight | Volume | Transportation Mode

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