ABSTRACT

ROGERS, MATTHEW BYRNE. A Logistic Planning System for Contingency Missions to Identify a Feasible and Efficient Logistical Footprint (Under the direction of Thom Hodgson).

The United States Army is extremely well trained in planning the operational piece of war. Planning for the logistical footprint needed to sustain the operational plan often falls short. The logistical plans do not fall short because of the effort. Historically, logistical planning has not embraced the size and complexity associated with the U.S. military logistical network. This research is a proof of concept for a Military Logistic Network Planning System (MLNPS) that can be used during mission planning to quickly identify a feasible and efficient logistical footprint that can sustain the operational plan. The logistical network is treated as a large job-shop and uses a form of discrete event simulation to route jobs (requisitions for sustainment supplies) through the logistical network. The simulation identifies backlogs in the network through queuing. The queuing information is then used to help make adjustments to the network in order to improve efficiency. The process of simulation and network adjustment is continued interactively until a feasible and efficient logistical network is identified. The MLNPS can be used to identify and fix logistical problems during the planning stages of military operations instead of waiting until the backlogs are experienced and the military’s ability to sustain the fight is impacted. The MLNPS can also be used during operations to inform commanders of operational impacts on logistics. Contingency operation scenarios are used to showcase the MLNPS’s capabilities.
A Logistic Planning System for Contingency Missions to Identify a Feasible and Efficient Logistical Footprint

by
Matthew Byrne Rogers

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Industrial Engineering

Raleigh, North Carolina

2016

APPROVED BY:

Dr. Thom Hodgson
Committee Chair

Dr. Russell King

Dr. Kristin Barletta

Dr. Michael Kay

Dr. Greg Parlier
DEDICATION

This work is dedicated to the two most important women in my life; my mother and my daughter.
BIOGRAPHY

Lieutenant Colonel Matt Rogers was born on 15 August 1976 in San Jose, California. Matt graduated from the United States Military Academy in 1998 and was commissioned as a Second Lieutenant in the Corps of Engineers. Matt’s career in the Army has taken him to numerous locations throughout the country and the world, leading the finest Soldiers in the world. During his 18 years in the Army, Matt completed two combat tours in Afghanistan and one in Iraq. He also earned Masters of Science degrees from The University of Missouri-Rolla in 2002 and Arizona State University in 2008, and spent three years as an instructor in the Department of Mathematical Sciences at the United States Military Academy. Matt has one daughter, Katherine, who is 5 years old.
ACKNOWLEDGEMENTS

There are too many people to mention by name that have contributed to my research and supported me throughout the process; however, I would be remiss if I did not mention those who had the most profound impact on me during the past three years. I would like to first thank my committee chair, Dr. Thom Hodgson. He worked tirelessly to help me with a dissertation topic, built a committee that was involved in every step of my research, supported me through the many trials and tribulations, kept me on track, and most importantly cared about me as a student and person. I am forever in debt to Dr. Hodgson and hope that I can one day repay him. Until then, I will use what I learned from him to be better leader and mentor. The rest of my committee guided and supported me throughout the entire process. Dr. Thoney-Barletta spent hundreds of hours converting my military understanding of the Army’s logistical network into computer code capable of simulating the network. I could never have completed my research without the Virtual Factory “Code Queen.” Dr. King always provided valuable feedback and gave up what little free time he had to help mentor me during the challenges of research and life. Dr. Kay was instrumental in helping understand the world of shipping & transportation and always offered new ways solve nagging problems. Dr. Parlier was a stalwart source for anything dealing with military logistics and always led me to the subject matter expert if he was not.

I would like to thank Brandon McConnell for his extensive contributions to my research. Without Brandon, my PhD would have taken six years instead of three. Whether explaining a statistical concept, generating a much needed dataset, or fitting one of many datasets, Brandon worked tirelessly to help me with whatever I needed. Thank you to the many other fellow students who helped me along the way, especially the “dum dum crew.”
I would like to thank three individuals from outside of NC State University, who were catalysts for my research. Thank you to Marc Robbins from RAND Corporation for providing me with the Operation Iraqi Freedom dataset that was critical to validating my model and offered an understanding of the sustainment supplies needed to support an expeditionary operation. Thank you to Joe Farris at DLA Distribution for helping me understand and visualize the DLA logistical network. Our discussions provided the first real momentum in my research and gave me the confidence that I could actually model this overwhelmingly large logistical network. Thank you to LTC John Hiltz and his team at USTRANSCOM for providing the datasets that initially allowed me to calibrate my model using actual requisitions.

Lastly I would like to thank my family and friends. Again, too many to thank by name, but they were always there for me providing support in many different ways. Thank you to my Mom and Dad for always being on the other end of the phone providing encouragement. A special thank you to my Mom for listening to me every Monday afternoon as I drove home from school, wondering if I was going to fail out of school. She always believed, which made me believe. Finally, thank you to my amazing daughter, Katherine. Completing a PhD while being a single daddy was challenging, but would have been impossible if she were not the angel that she was. She made me smile every day and was a constant reminder that life is simple & good. She is amazing in more ways than I can describe. She is my bright shining star, the love of my life, and the motivation to always be and give my best. I hope that one day I inspire her as much as she inspires me.
# TABLE OF CONTENTS

**LIST OF TABLES** ..................................................................................................................... viii
**LIST OF FIGURES** .................................................................................................................... ix
**LIST OF ACRONYMS AND ABBREVIATIONS** ........................................................................ xi

**Chapter 1** Introduction ............................................................................................................. 1
  1.1 Motivation ................................................................................................................................. 1
  1.2 Problem Description .................................................................................................................... 6
  1.3 Outline ....................................................................................................................................... 11

**Chapter 2** Literature Review ....................................................................................................... 12
  2.1 Overview .................................................................................................................................... 12
  2.2 The Virtual Factory ..................................................................................................................... 13
  2.3 Mission-Based Forecasting .......................................................................................................... 19
  2.4 Current Planning Tools ............................................................................................................... 24

**Chapter 3** Problem Formulation ................................................................................................ 28
  3.1 Overview .................................................................................................................................... 28
  3.2 Modeling the status quo Army Supply Network (Box 5) ............................................................ 29
    3.2.1 Modeling the “Status Quo” Network (Box 5.1) .................................................................... 32
    3.2.2 Modeling Contingency Operations (Box 5.2) ..................................................................... 38
    3.2.3 Modeling the Shipping Capabilities & Constraints (Box 5.3) ................................................. 40
  3.3 The Forecast Data ....................................................................................................................... 42
    3.3.1 Using a Mission-Based Forecast (Box 2) ............................................................................ 43
    3.3.2 Using Condition Based Maintenance to Improve the Forecast (Box 3) ............................... 43
  3.4 The Current State of the System (Box 4) .................................................................................... 43
  3.5 Building and Testing the Model .................................................................................................. 44

**Chapter 4** Adapting the Virtual Factory for the MLNPS ............................................................. 45
  4.1 The Processors ............................................................................................................................ 45
  4.2 Model Bias .................................................................................................................................. 50
  4.3 Modeling the Path of a Requisition .............................................................................................. 51
  4.4 Model Inputs ............................................................................................................................... 57
    4.4.1 Processor Inputs File ............................................................................................................ 58
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.4.2 Requisition Input File</td>
<td>58</td>
</tr>
<tr>
<td>4.4.2.1 Release and Due Dates</td>
<td>58</td>
</tr>
<tr>
<td>4.4.2.2 Creating Paths for Requisitions</td>
<td>59</td>
</tr>
<tr>
<td>4.4.2.3 Physical Characteristics of Requisitions</td>
<td>61</td>
</tr>
<tr>
<td>Chapter 5 Using Operation Iraqi Freedom (OIF) as the MLNPS Test bed</td>
<td>62</td>
</tr>
<tr>
<td>5.1 Operation Iraqi Freedom and the MLNPS</td>
<td>62</td>
</tr>
<tr>
<td>5.2 The Operation Iraqi Freedom Dataset</td>
<td>63</td>
</tr>
<tr>
<td>5.3 Calibrating and Validating the Model</td>
<td>63</td>
</tr>
<tr>
<td>5.4 Using the MLNPS to plan Operation Iraqi Freedom</td>
<td>76</td>
</tr>
<tr>
<td>5.5 Sensitivity Analysis of the Improved Network</td>
<td>83</td>
</tr>
<tr>
<td>Chapter 6 Using the MLNPS to Plan a Notional Operation in Sudan</td>
<td>86</td>
</tr>
<tr>
<td>6.1 The Notional Operation in Sudan</td>
<td>86</td>
</tr>
<tr>
<td>6.2 Generating the Mission-Based Forecast</td>
<td>88</td>
</tr>
<tr>
<td>6.3 Using the MLNPS to Plan the Logistical Network</td>
<td>94</td>
</tr>
<tr>
<td>6.3.1 Course of Action 1 (TDC located in Juba)</td>
<td>96</td>
</tr>
<tr>
<td>6.3.2 Course of Action 2 (TDC Located in Wau)</td>
<td>103</td>
</tr>
<tr>
<td>6.3.3 Course of Action Comparison and Recommendation to the Commander</td>
<td>104</td>
</tr>
<tr>
<td>6.4 Sensitivity Analysis of the Plan</td>
<td>105</td>
</tr>
<tr>
<td>Chapter 7 Future Research</td>
<td>110</td>
</tr>
<tr>
<td>BIBLIOGRAPHY</td>
<td>113</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

Table 1.1: Modes of Transportation [12] ...........................................................................................................7
Table 3.1: Standard Delivery Times in Days [36].................................................................................................31
Table 4.1: Example Maersk Ship Schedule from www.maerskline.com .........................................................54
Table 4.2: Uniform Distribution by Mode of Transportation..............................................................................59
Table 4.3: Example Requisition Paths..............................................................................................................60
Table 5.1: Army Feeding Plan Guidelines [48]..................................................................................................65
Table 5.2: OIF Planned vs. Actual Conditions [14] .........................................................................................67
Table 6.1: Sudan Mission Task Organization ..................................................................................................87
Table 6.2: Mode of Transportation pmf ...........................................................................................................92
Table 6.3: Example Supply Node pmf .............................................................................................................93
Table 6.4: By Unit Correlation between Weight (WT) and Cube (CU).................................................................93
Table 6.5: Round Trip Convoy Times for each COA .........................................................................................95
Table 6.6: COA 1 Required Capacities ..........................................................................................................103
Table 6.7: COA 2 Required Capacities ..........................................................................................................104
Table 6.8: Course of Action Comparison ......................................................................................................104
LIST OF FIGURES

Figure 1.1: Network Example ............................................................................................................................................ 7
Figure 2.1: Part Demand: Relative composition and magnitude [15] .................................................................................. 21
Figure 2.2: MBF compared to current forecast methods (A, B, C & D): Part breadth (different parts) [15] ........................................... 22
Figure 2.3: MBF compared to current forecast methods (A, B, C, & D): Part depth (part quantity) [15] ......................................................... 23
Figure 3.1: Decision Support System (DSS) Flow Chart ........................................................................................................ 28
Figure 3.2: Adding Transportation Nodes ............................................................................................................................. 30
Figure 3.3: DLA Dedicated CONUS Truck Routes [12] ............................................................................................................. 33
Figure 3.4: EUCOM Dedicated Truck Routes, Frequency & Shipment Times [38] ................................................................. 35
Figure 3.5: CONUS Dedicated Truck Shipment Times [12] ........................................................................................................ 41
Figure 3.6: FedEx Shipping times from Susquehanna DC [40] ................................................................. 41
Figure 4.1: Requisition Path from CONUS to OIF ............................................................................................................. 45
Figure 5.1: Monthly Average Pick & Pack Time at DDSP ........................................................................................................ 70
Figure 5.2: Average Time in Queue at APOE ............................................................................................................................ 71
Figure 5.3: Average Time in Queue at TDC .............................................................................................................................. 72
Figure 5.4: Average Number of Requisitions in Queue to LTM Trucks .................................................................................... 74
Figure 5.5: DDSP Avg Pick & Pack Times for 2003 (As Planned) ................................................................................................. 77
Figure 5.6: DDSP Avg Pick & Pack Time as Planned vs. Actual OIF ....................................................................................... 78
Figure 5.7: 2003 DDSP Requisition Volume and BCTs in Iraq ...................................................................................................... 79
Figure 5.8: DDSP Avg Pick & Pack Time with Added Capacity – 1st Iteration (Red) ................................................................. 80
Figure 5.9: DDSP Avg Pick & Pack Time with Added Capacity – 2nd Iteration (Green) ............................................................... 81
Figure 5.10: DDSP Avg Pick & Pack Time with Added Capacity – 3rd Iteration (Blue) ............................................................... 82
Figure 5.11: Number of Requisitions in Queue for 200 LTM Trucks ......................................................................................... 84
Figure 5.12: Number of Requisitions in Queue for 300 LTM Trucks ......................................................................................... 85
Figure 6.1: Requisition Path from CONUS to Sudan ............................................................................................................. 87
Figure 6.2: Geographical Relationship between Juba and Wau ................................................................................................. 95
Figure 6.3: SPOD Queuing for COA 1 (2 Truck Companies) ....................................................................................................... 97
Figure 6.4: SPOD Queuing for COA 1 (3 Truck Companies) ....................................................................................................... 98
Figure 6.5: SPOD Queuing for COA 1 (4 Truck Companies) ....................................................................................................... 98
Figure 6.6: SPOD Queuing for COA 1 (5 Truck Companies) ....................................................................................................... 99
Figure 6.7: LTM Queuing for COA 1 (6.5 Truck Companies) ................................................................................................. 101
Figure 6.8: LTM Queuing for COA 1 (7 Truck Companies) ................................................................................................. 102
Figure 6.9: LTM Queuing for COA 1 (8 Truck Companies) ................................................................................................. 102
Figure 6.10: By Node Queuing Impact from Increased Requisition Volume ...................................................................................... 106
Figure 6.11: 7 Day Disruption Impact on SPOD Queuing ........................................................................................................ 107
Figure 6.12: LTM Queuing without Seven Day Disruption ........................................................................................................ 108
Figure 6.13: LTM Queuing with Seven Day Disruption
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAR</td>
<td>After Action Review</td>
</tr>
<tr>
<td>AESIP</td>
<td>Army Enterprise Systems Integration Program</td>
</tr>
<tr>
<td>AFRICOM</td>
<td>United States Africa Command</td>
</tr>
<tr>
<td>APOD</td>
<td>Airport of Debarkation</td>
</tr>
<tr>
<td>APOE</td>
<td>Airport of Embarkation</td>
</tr>
<tr>
<td>ATTP</td>
<td>Army Tactics, Techniques, and Procedures</td>
</tr>
<tr>
<td>BCT</td>
<td>Brigade Combat Team</td>
</tr>
<tr>
<td>CBM</td>
<td>Condition Based Maintenance</td>
</tr>
<tr>
<td>CCP</td>
<td>Consolidation and Containerization point</td>
</tr>
<tr>
<td>COCOM</td>
<td>Combatant Command</td>
</tr>
<tr>
<td>CONUS</td>
<td>Continental United States</td>
</tr>
<tr>
<td>COP</td>
<td>Combat Outpost</td>
</tr>
<tr>
<td>CTC</td>
<td>Combat Training Center</td>
</tr>
<tr>
<td>DC</td>
<td>Distribution Center</td>
</tr>
<tr>
<td>DD</td>
<td>Due Date</td>
</tr>
<tr>
<td>DLA</td>
<td>Defense Logistics Agency</td>
</tr>
<tr>
<td>DoD</td>
<td>Department of Defense</td>
</tr>
<tr>
<td>DOS</td>
<td>Days of Supply</td>
</tr>
<tr>
<td>DSAT</td>
<td>Deployment Scheduling Analysis Tool</td>
</tr>
<tr>
<td>DSS</td>
<td>Decision Support Systems</td>
</tr>
<tr>
<td>ERDC</td>
<td>Engineer Research and Development Center</td>
</tr>
<tr>
<td>ERP</td>
<td>Enterprise Resource Planning</td>
</tr>
<tr>
<td>EUCOM</td>
<td>European Command</td>
</tr>
<tr>
<td>FAD</td>
<td>Force Activity Designator</td>
</tr>
<tr>
<td>FOB</td>
<td>Forward Operating Base</td>
</tr>
<tr>
<td>GAO</td>
<td>Government Accountability Office</td>
</tr>
<tr>
<td>GCSS</td>
<td>Global Combat Support System</td>
</tr>
<tr>
<td>GFEBS</td>
<td>General Fund Enterprise Business System</td>
</tr>
<tr>
<td>GUI</td>
<td>Graphical User Interface</td>
</tr>
<tr>
<td>HSAC</td>
<td>House Armed Services Committee</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>----------------------------------------------------------</td>
</tr>
<tr>
<td>IBCT</td>
<td>Infantry Brigade Combat Team</td>
</tr>
<tr>
<td>IPG</td>
<td>Issue Processing Group</td>
</tr>
<tr>
<td>ISIS</td>
<td>Islamic State in Iraq and Syria</td>
</tr>
<tr>
<td>IT</td>
<td>Information Technology</td>
</tr>
<tr>
<td>LB</td>
<td>Lower Bound</td>
</tr>
<tr>
<td>LBC</td>
<td>Logistic Battle Command</td>
</tr>
<tr>
<td>LOGPAC</td>
<td>Logistical Package</td>
</tr>
<tr>
<td>LMP</td>
<td>Logistics Modernization Program</td>
</tr>
<tr>
<td>MBF</td>
<td>Mission-Based Forecasting</td>
</tr>
<tr>
<td>MCO</td>
<td>Major Combat Operations</td>
</tr>
<tr>
<td>MLNPS</td>
<td>Military Logistic Network Planning System</td>
</tr>
<tr>
<td>MOG</td>
<td>Maximum on Ground</td>
</tr>
<tr>
<td>MHE</td>
<td>Material Handling Equipment</td>
</tr>
<tr>
<td>MRE</td>
<td>Meal Ready-to-eat</td>
</tr>
<tr>
<td>MSR</td>
<td>Main Supply Route</td>
</tr>
<tr>
<td>OCONUS</td>
<td>Outside the Continental United States</td>
</tr>
<tr>
<td>OE</td>
<td>Operational Environment</td>
</tr>
<tr>
<td>OEF</td>
<td>Operation Enduring Freedom</td>
</tr>
<tr>
<td>OIF</td>
<td>Operation Iraqi Freedom</td>
</tr>
<tr>
<td>OIL</td>
<td>Operational Intensity Level</td>
</tr>
<tr>
<td>PACOM</td>
<td>Pacific Command</td>
</tr>
<tr>
<td>PD</td>
<td>Priority Designation</td>
</tr>
<tr>
<td>RD</td>
<td>Release Date</td>
</tr>
<tr>
<td>RDD</td>
<td>Required Delivery Date</td>
</tr>
<tr>
<td>SBCT</td>
<td>Stryker Brigade Combat Team</td>
</tr>
<tr>
<td>SO</td>
<td>Stability Operations</td>
</tr>
<tr>
<td>SPOD</td>
<td>Sea Port of Debarkation</td>
</tr>
<tr>
<td>SPOE</td>
<td>Sea Port of Embarkation</td>
</tr>
<tr>
<td>SSA</td>
<td>Supply Support Activity</td>
</tr>
<tr>
<td>TCSP</td>
<td>Theater Consolidation Shipping Point</td>
</tr>
<tr>
<td>TDC</td>
<td>Theater Distribution Center</td>
</tr>
<tr>
<td>TRANSCOM</td>
<td>U.S. Transportation Command</td>
</tr>
<tr>
<td>UGR</td>
<td>Unitized Group Ration</td>
</tr>
</tbody>
</table>

xii
<table>
<thead>
<tr>
<th>UNC</th>
<th>Urgency of Need</th>
</tr>
</thead>
<tbody>
<tr>
<td>WWX</td>
<td>World Wide Express</td>
</tr>
</tbody>
</table>
Chapter 1
Introduction

"Logistic considerations belong not only in the highest echelons of military planning during the process of preparation for war and for specific wartime operations, but may well become the controlling element with relation to timing and successful operation."

- VADM Oscar C. Badger, USN

1.1 Motivation

Prior to the start of Operation Enduring Freedom (OEF) and Operation Iraqi Freedom (OIF), budget concerns and supply chain inefficiencies led the Army to begin initiatives aimed at transforming the logistical system. As a result, in July 2005, the United States Army began an “IT Solution” project designed to replace over 200 standalone and redundant legacy logistical systems with one fully integrated modern logistical system. Some of what the single logistical system was designed to accomplish are the following: 1) Gain full visibility of assets across the entire supply chain, 2) Provide service-wide financial accounting that is synchronized with the Government Accounting Office (GAO), and 3) Optimize the flow of parts and supplies to ensure the force is properly supplied. This new database system is comprised of three different Enterprise Resource Planning (ERP) tools and is powered by the commercial-off-the-shelf enterprise software system, SAP®. The three ERPs used by the Army are the Global Combat Support System (GCSS)-Army, the Logistics Modernization Program (LMP), and the General Fund Enterprise Business System (GFEBS). All three ERPs are synchronized by the Army Enterprise Systems Integration
Program (AESIP) and together make up a web-based end-to-end system that allows the Army to see and share supply chain and financial information in real time.

The GFEBS ERP is the Army’s web-enabled financial, asset and accounting management system that standardizes, streamlines, and shares critical data across all components of the Army [1]. GFEBS manages a $110 billion annual budget and will serve nearly 80,000 users once fully fielded [2]. The purpose of GFEBS is to provide a state-of-the-art financial management system that supports soldiers as well as adheres to congressionally mandated governance procedures [2].

The LMP ERP supports the Army’s national-level wholesale logistics mission by managing approximately $22 Billion in inventory and approximately 2 million daily transactions [3]. LMP is one of the world’s largest, fully integrated supply chain, maintenance, repair and overhaul planning and execution solutions [3]. It is designed to integrate many different logistical components and allow the Army to supply and service soldiers more quickly and cost effectively [3].

The GCSS-Army ERP is the tactical unit level retail logistics and financial system for the U.S. Army. This modern day ERP replaces the outdated system and integrates 40,000 supply and logistics databases into a single, enterprise-wide system [4]. When fully fielded, GCSS-Army will serve nearly 160,000 end users across 300 plus Army locations around the world; making it the largest web-based ERP in worldwide production [5]. GCSS-Army provides many benefits over the current legacy systems, including increased service, decreased cost, decreased cycle time, asset visibility, and planning [6].

The initial fielding of GCSS-Army was to begin in Fiscal Year (FY) 2008 with a targeted completion date of 2010. The timeline however kept getting pushed to the right and
the completion date is now estimated to be the end of 2016. With the slow fielding, failure to meet performance expectations, and a price tag exceeding $4 billion, the GCSS-Army and other Armed Service ERP systems have gotten the attention of the House Armed Services Committee (HASC). The HASC is concerned about the Department of Defense’s (DoD’s) continued lack of progress in implementing sound information technology (IT) systems for business management [7]. This concern is valid. The Air Force recently scrapped its $1 billion ERP software project, citing far too much cost for too little gain [8]. Due to these concerns, the HASC “directed the Secretary of Defense to have an outside company or other entity conduct an independent analysis of DoD financial IT systems” [9]. The result was an Institute for Defense Analysis assessment that was completed in 2011. Additionally, DoD Supply Chain Management has been on the GAO “hi-risk” list since 1990 and in 2011 determined that the “DoD needs to take additional actions to address challenges in supply chain management” [10].

Another reason for concern, caused by the recent emphasis on the support of OEF & OIF and accompanied by a constantly swelling budget, is a reduced Army emphasis on supply chain management initiatives. For the past ten years, the focus has been on having an effective logistical system instead of an efficient and cost effective one because the Army has essentially been operating in an unconstrained environment. With the completion of OIF, the drawdown of OEF, and a drastically reduced budget due to sequestration, the emphasis is, as of this writing, on having a more efficient and cost effective logistical system [11]. With the returned emphasis on what is being called “cost-wise readiness” [11], the Army needs to be doing more to help the new ERP systems realize their promised goal of improved logistical performance.
One of the possible reasons the HASC may be looking askance at the Army’s new ERP systems is because the members cannot see the benefits of the system and are constantly reminded of the billion dollar price tag and slowed timelines. With a decreasing budget and inefficient supply chain management operations, HASC leaders want to see the promised improvement in performance be realized. Bottom line, the HASC wants to be able to see the benefits of the multi-billion dollar systems, not just hear predictions about what it can eventually do.

It is hard to show the benefits of the new Army ERPs when they are not yet fully fielded and when dealing with a logistic network as large as that of the U.S. Military. The military logistical network consists of 24 wholesale supply locations, and ~33,000 retail supply locations across ~86 countries [12]. It uses ~10 different modes of transportation, receives ~50,000 daily requisitions, and manages ~2.4 million lines of inventory that total ~$109 billion in inventory [12]. Managing a network this large in an efficient and cost effective manner requires enlightened management, the application of advanced analytics, and comprehensive planning. In order to apply advanced analytics, complete transparency of the entire network is required. Knowing the exact location and status of every single item in the military supply system at any snapshot in time is ideal. Fortunately, with the introduction of the new Army ERP systems, knowing the location and status of every item at any point in time is now possible. In fact it is the single most important benefit of the SAP powered system. It is this ability of the ERPs to provide real time visibility of the entire logistical network that will allow the billion-dollar “IT Solution” to improve supply chain operations.

The Army’s “IT solution” is not THE solution to the Army’s logistical problems but is the key enabler to overcoming the tremendous logistical challenges. The ERPs are an
incredible tool that get the needed data. But the real value to the logistical system is in how that data is used. The Army needs a comprehensive strategy incorporating effective analytical tools (advanced analytics) with the appropriate information technologies (ERPs) required to enable and provide the decision support systems (DSS) needed for cost-effective, performance oriented results [13].

Since the information technology system is already created and nearing full fielding, the problem lies in building the new analytical tools that will power the decision support systems. One analytical tool that could greatly assist the Army is a decision support tool to help with logistical planning. The Army does a fantastic job, at all levels, of quickly planning the operational piece of missions; however, the Army is not as good at quickly planning the logistics piece of missions. This is not to say that the Army does not plan for logistics. They just don’t have the tools needed to make that planning as comprehensive and rapid as it needs to be. Often times, a mission is planned and executed without fully understanding the impacts on the logistical system. Too often, the deficiencies in the supporting logistical system are identified once troops and equipment are in place and exercising the logistical system. The Army is then forced to spend additional funds in order to shift critical transportation assets to meet the logistical needs of the mission.

A need for the aforementioned analytical tools was identified in a study conducted by the RAND Corporation in 2005 [14]. This study of the Operation Iraqi Freedom (OIF) Logistics found significant logistical deficiencies due in part to a lack of theater distribution planning and decision-support tools [14]. The authors recommended that “Planning tools and organizational structures need to better support expeditionary operations” with “effective
automation to rapidly determine capability requirements” [14]. With ERPs, these improved planning tools can be realized.

With the future fight being the protection of American citizens and American interests from increasingly powerful terrorist organizations around the globe, logistical support for rapid long distance deployments will be paramount. The additional challenge of operating under a tighter budget, and the fact that logistical operations make up nearly 70% of all missions costs, makes it impossible to ignore the need for fast, advanced analytics to optimize logistical operations.

**1.2 Problem Description**

So why is the logistical planning so difficult and why are advanced analytics needed? As noted, the military supply network is immense and has an average of ~50,000 new requisitions on a daily basis. Each of those requisitions is for a supply item (or multiple supply items) to be shipped from one of 24 Defense Logistics Agency (DLA) distribution centers (DCs) to one of ~33,000 units (customers) located throughout the world (See Figure 1.1 for a small scale representation of the network).
Each item can be shipped via up to ten different modes of transportation depending upon the location of the customer (by geographical combatant command) and distribution center (See Table 1.1).

Table 1.1: Modes of Transportation [12]

<table>
<thead>
<tr>
<th>Mode of Shipment</th>
<th>NORTHCOM</th>
<th>PACOM</th>
<th>CENTCOM</th>
<th>EUCOM</th>
<th>SOUTHCOM</th>
<th>AFRICOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dedicated Truck</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td></td>
<td>✔️</td>
</tr>
<tr>
<td>Defense Trans Coord Initiative (DTCI)</td>
<td>✔️</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface Small Package (SSP) &gt; 150 lbs</td>
<td>✔️</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial Sea Container (JSC-06)</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Military Sealift Command (MSC Charter)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>World Wide Express (WWX)</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Commercial Air</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Theater Express</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Military Air</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Multi-Modal</td>
<td></td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
</tbody>
</table>
Each mode of transportation has an associated cost and delivery time based on the supply item being shipped.

Part of the problem is determining which mode of transportation to send each item in order for the customer to receive it on-time or as close to the due date as possible, subject to the capacities of each mode of transportation along each transportation arc. Mathematically, this is a very hard problem. Computing the least cost (optimal) solution is not guaranteed and even finding a near-optimal solution in a reasonable period of computer processing time using heuristics is challenging.

Determining how to ship each requested part in order to meet the due date of the customer and minimize associated shipping costs is just part of the problem and is already being done well by DLA distribution. What is not being done or what capability does not currently exist, is the ability for logistical planners to preemptively adapt logistical systems to meet operational needs. The structure of the Army’s logistical network is in a constant state of flux as new missions arise, old missions come to a close, and current missions change as the operational environment (OE) changes. When considering the timeline and size of a mission, decision makers need to understand the impacts on the entire logistical network. They need to be able to plan for changes in the logistical system that will allow for the seamless implementation of an operational plan. Decision makers also need to be able to determine whether or not an operational plan can be sustained logistically or if the logistical system needs to be adjusted prior to initiation of the plan.

In order to help the military with the aforementioned challenges, a decision analysis tool is designed, using advanced analytics and mission-based forecasting (MBF), that helps predict choke points in an existing logistical network and provides valuable information
about how to eliminate those choke points. The tool uses repetitive simulation to model the routing of all requested supplies from receipt of the requisition to the delivery of the supplies to the customer. It routes the supplies along the available transportation arcs subject to the available transportation assets, while satisfying the customer by minimizing the maximum lateness of all requisitions. When simulating the movement of all requisitions across the entire network, queuing occurs at logistic nodes. The identification of queuing along specific transportation routes signifies potential choke points. The choke points can be created by the status quo logistical network or, most likely, by the increased demands from global deployments and other mission sets. Once potential choke points are identified, the decision support tool allows the decision maker to shift or add transportation assets, or other logistical capabilities, to reduce or eliminate choke points. The tool can then run with the revised logistical network and once again determine potential choke points. This process can be repeated in real time until the logistical network can sustain all operational missions or the decision maker determines that an operational mission or planned mission must be adjusted.

One of the problems with a decision support tool with these characteristics is the lead time that is required for assets to be shifted. Even though a model can run extremely fast and provide valuable information, if the data is not received within the lead time needed to shift or add logistical assets, the information is useless. If the decision support tool helps identify a potential choke point that will start in four days and it takes seven days to request a truck then a decision maker cannot alter the network in time to have an impact.

The use of mission-based forecasting [15] can help provide information about problems within the network with the lead-time needed to adjust the network; it allows the tool to be an “early warning system.” Mission-based forecasting is a predictive analytic
method for forecasting logistical demands associated with specific operational missions. The logistical needs of a Brigade Combat Team (BCT) during garrison operations, combat operations in a desert environment, and combat operations in a tropical environment are very different. With mission-based forecasting, each specific operational mission has an associated logistical forecast. These forecasts can be put into the decision support tool in order to achieve the necessary lead time required to make changes to the logistical network to satisfactorily support the mission. The increase in number of days of lead time is the same as the number of days of forecasted data; therefore, if you need 14 additional days of lead time, you need 14 days of forecasted demand.

With the advanced analytics running the model and mission-based forecasting to help extend the reach of the predictive capability of the model; this decision support tool can be used in several different ways. The model can be run on a periodic basis to help keep the Army’s logistical network running in an efficient and cost-wise manner. It can be used on a day to day basis to determine the impact of weather and enemy actions on the network. The tool can be used to predict the logistical impacts of operational plans during contingency planning. This will allow Army senior leaders and planners to have logistical contingency plans “on the shelf.” Lastly, the tool will allow senior leaders and planners to have a proof of concept tool during crisis action planning. The tool will allow them to plan the logistics of a mission as quickly as they can conduct the operational planning to see if the operational plan is logistically feasible. The speed of the tool will actually allow them to plan faster than operational planning and present logistical impacts of different size missions during mission analysis.
Although a few specific functions of the proposed decision support tool have been discussed, the possibilities go far beyond just those few. The tool can be adapted to meet other logistical requirements that can further improve Army supply chain management.

1.3 Outline

The rest of the dissertation is organized as follows. Chapter 2 reviews the appropriate literature with respect to current advanced analytics and mission-based forecasting. Chapter 3 introduces the mathematical model and advanced analytics used in the Military Logistics Network Planning System. Chapter 4 covers how the Virtual factory was adapted for the needs of the MLNPS. Chapter 5 discusses calibration and validation of the model using requisition data from Operation Iraqi Freedom (OIF). Chapter 6 discusses the use of the MLNPS to plan the logistical network for a notional contingency operation in Africa. Finally, Chapter 7 discusses the ways forward to improving the functionality of the MLNPS and considers other applications for similar advanced analytic tools.
Chapter 2  
Literature Review

"The line between disorder and order lies in logistics..."

- Sun Tzu

2.1 Overview

The basis of the advanced analytics needed to solve the problem at hand is akin to what is needed to optimize the flow of jobs through a factory, with due dates. The Army logistical network can be thought of as one huge factory where parts/requisitions (jobs) need to be routed through different nodes (machines) in order to reach their final destination (complete the job) by the established due date. There is extensive literature on the routing of parts in a factory to solve many different optimization problems. Most of the literature, however, does not address problems of the same scope and size as Army logistical network. Very few of the solution techniques in the literature can solve such a problem or can come up with a good solution within any reasonable amount of time. One advanced analytics tool that can find good solutions to very large scheduling problems, in a short period of time, is the Virtual Factory discussed in Hodgson et al. [16]. With the Virtual Factory modeling the flow of parts through the Army supply network, one can forecast congestion (queuing) and use that output to help redesign the logistic network for contingency missions. Section 2.2 will cover the literature on this optimization tool called the Virtual Factory.

Forecasting is needed in order identify logistical problems in time to make effective changes. The type of forecasting needed is mission-based forecasting. There is widespread literature on forecasting but very little literature on mission-based forecasting because it is a relatively new topic. Section 2.3 will cover the current literature on mission-based forecasting.
2.2 The Virtual Factory

The Virtual Factory is the name given to an iterative simulation-based scheduling advanced analytics tool that was developed in the Department of Industrial & Systems Engineering at North Carolina State University. The computational effort of the Virtual Factory is linear in the size of the problem, and high quality solutions to large-scale problems can be obtained in seconds [17]. The uses of the Virtual Factory have grown over the years, but the initial concept of the advanced analytics used to power it was presented in Hodgson et al. [16]. They introduced the use of revised slack and a repetitive simulation-based procedure (first proposed by Lawrence and Morton [18]) to solve the N-job, M-machine, large job shop scheduling problem for minimizing maximum lateness ($L_{\text{max}}$); also known as the $N/M/L_{\text{max}}$ problem. The $N/M/L_{\text{max}}$ problem is known to be NP-hard [19]. Starting from the present state of the system (i.e., the location of every job in the system plus its residual routing), the Virtual Factory simulation is run. Jobs are sequenced on machines in order of increasing slack (the time a job can be in a queue for a machine and still meet its due date). Let $d_i$ be the due-date of job $i$ and $p_{ij}$ the processing time of job $i$ on machine $j$. The slack of job $i$ on machine $m$ is then defined as

$$slack_{im} = d_i - \sum_{j \in m^+} p_{ij},$$

where $m^+$ is the set of all operations along the route of job $i$ that are performed after completion of the job on machine $m$. Since using slack to sequence job does not account for potential queuing, revised slack (time at which a job needs to begin processing on the machine to meet its due date) is used after the first iteration to provide better results. Queuing times from the simulation are recorded for each job on each machine and then
revised slack is calculated based off the queuing times. Let \( q_{ij} \) be the queuing time for job \( i \) at machine \( j \). Revised slack is then defined as

\[
slack^{'}_{im} = d_i - \sum_{j \in m^+} p_{ij} - \sum_{j \in m^+} q_{ij},
\]

where \( m^+ \) is the set of all operations along the route of job \( i \) that are performed after completion of the job on machine \( m \) except the one immediately following \( m \). The simulation is then run with jobs sequenced on each machine in order of increasing revised slack. This process is repeated, using continually updated revised slack, until an iteration limit is reached or the lower bound (\( LB \)) for \( L_{\text{max}} \) is achieved. An effective lower bound for \( L_{\text{max}} \) introduced in Carlier and Pinson [20] is easily computed and compared to the solutions found by the Virtual Factory. To compute \( LB(L_{\text{max}}) \), the earliest start and latest finish for each job are calculated on each machine along the job’s route. Let \( m^- \) be the set of machines proceeding machine \( m \) and \( m^+ \) be the set of all machines following machine \( m \). Let \( r_i \) be the release time of job \( i \). The earliest start (ES) and latest finish (LF) on machine \( m \) are then defined as follows:

\[
ES_{im} = r_i - \sum_{j \in m^-} p_{ij},
\]

\[
LF_{im} = d_i - \sum_{j \in m^+} p_{ij}.
\]

The earliest start times are used as the release times and the latest finish times are used as the due date for each job on each machine. A preemptive earliest due date rule introduced by Baker and Su [21] is used to calculate a lower bound for each machine. The maximum of all the machine LBs is the \( LB(L_{\text{max}}) \) for the entire job shop. The Virtual Factory was tested using data from a large furniture manufacturing facility. The authors showed that the procedure achieved excellent solutions relative to the \( LB(L_{\text{max}}) \) and in little computational
time. They showed that problems tend to stabilize at an excellent \( L_{\text{max}} \) after 10 or less iterations of the simulation.

In a modification to the previously discussed publication, Hodgson et al. [22] insert idle time into machine schedules in order to allow critical jobs (those with lateness close or equal to the current \( L_{\text{max}} \)) to begin being processed upon arrival at a machine. This was done because they observed that, too often, these critical jobs were delayed because a machine was busy processing non-critical jobs when the critical job arrived. Improvement was accomplished by inserting idle time into a machine queue so when a critical job arrived to a machine it began processing immediately. The results were significant as the procedure that expedited critical jobs had solutions much closer to the \( LB(L_{\text{max}}) \), with a relatively small increase in computational time.

In another expansion of the Virtual Factory model, Weintraub et al. [23] introduced alternative routing of jobs. The goal of the research was to use tabu search to find alternate routes for jobs that would further improve the \( L_{\text{max}} \) found by the Virtual Factory. Because changing the routing of jobs can also change the cost associated with the job, the authors created a ratio between \( L_{\text{max}} \) improvement and cost of the alternate route. This ratio was then used in selecting alternate routes that have the best potential for reduction in the LB on \( L_{\text{max}} \) for the least cost. The twenty most promising alternate routes of all jobs were then inserted into the best solution found by the Virtual Factory and the simulation was run in attempt to find an improvement on \( L_{\text{max}} \). As would be expected, as the number of iterations of the tabu search increased, the computational time increased exponentially. An exponential increase in computational time is not good when looking for a quick solution, but the results also showed that little improvement on \( L_{\text{max}} \) occurred after 100 iterations of the tabu search. Near optimal
solutions were found with little additional computational time. A simple two-part alternate routing heuristic was introduced in Hodgson et al. [24] and used to solve a military deployment-scheduling problem. The work done on the Deployment Scheduling Analysis Tool (DSAT) will be discussed later in this section. Alternative routing will be an important part of the analytical decision support tool developed because it will have to look at sending parts along different modes of transportation to alleviate congestion within the Army supply network.

In order to represent the external transportation required to run multi-factory manufacturing supply chains, Thoney et al. [17] introduced the use of batch processors in the Virtual Factory. Batch processors are machines that process multiple jobs/items at the same time and all jobs remain inside the batch processor until the operation is complete. In manufacturing, batch processors traditionally include heat treat operations, painting operations, and numerous different chemical operations. Batch processors can also represent bulk transportation operations because multiple jobs can be placed in a transportation vehicle (e.g., a truck) that has a specified travel time between factories. The difference between regular machines and batch processors lies in the fact that the queuing for a job in a batch processors is impacted by the jobs that arrive after it. The batch processor cannot begin until it is full (an assumption made in Thoney et al.), so a job will queue at the batch processor until all jobs have arrived, not just while waiting for jobs ahead of it to process. The authors propose two different queuing schemes for batch processors and test each to see which ones is better. The first queuing scheme aims to start the batch processor as soon as possible and the second queuing scheme aims to place a job in the right batch. It was determined that the queuing scheme aimed at putting each job in the right batch was equal or better for all tested
scenarios and was therefore used during all experiments. Simulating multiple different scenarios (varying the number of trucks, number of factories, and size of the problem) in the Virtual Factory resulted in excellent results. The difference between $L_{\text{max}}$ & $\text{LB}(L_{\text{max}})$, and the computational time required to attain the solutions was consistent with the results from the Virtual Factory without batch processing. The use of batch processors is critical in the development of the decision support tool because the processors represent the many different modes of transportation between supply and demand nodes in the Army logistical network. This research takes batch processors one step further because batch processors are processing batch processors when multiple pallets are put on an aircraft.

Until the research presented in Thoney et al. [25], the Virtual Factory found solutions to static job shop scheduling problems (simulating the system until it is empty). Since real systems do not normally run until empty, Thoney et al. adapted the Virtual Factory to account for the introduction of new jobs as old jobs are being processed. On a continual basis, new jobs must also be scheduled based off the production schedule for the jobs already in the system (i.e., a rolling horizon). The rolling horizon scenario is much more practical for solving real industrial/military problems. The new procedure ran, releasing new jobs each day and running the best schedule found by the Virtual Factory. Results showed that the Virtual Factory in a rolling horizon environment performed well. The rolling horizon scenario is a necessary aspect of the Virtual Factory application to simulating the Army Supply network because forecasted demand will need to be added to the system on a daily basis in order to provide accurate predictive capability.

Common algorithms such as simulated annealing and genetic algorithms are often used to find good solutions to problems with large solution spaces. The challenge is finding
the balance between the “goodness” of a solution and the computational time required to find that solution. The success of these algorithms tends to hinge upon the starting location of the search. It is common practice to start search algorithms at solutions that are known to be good, to reduce computation time and increase the chances of finding near optimal solutions. These good starting solutions are called seeds. Schultz et al. [26] integrated a simulated annealing procedure with the Virtual Factory. They used solutions from the Virtual Factory as seeds for a simulated annealing procedure in attempt to improve on the solution. They tested the Virtual Factory with a simulated annealing procedure on a set of benchmark scheduling problems created by Demirkol et al. [27]. The Virtual Factory simulated annealing procedure achieved new or equivalent best solutions for 159 of the 160 benchmark problems. For industrial-sized problems, the procedure found significant improvement after 1 minute and little further improvement after 5 minutes. This research shows that, using Virtual Factory solutions as seeds, common search algorithms can be used to improve on already good solutions of the Virtual Factory.

Although the Virtual Factory was initially created as an advanced analytics tool for solving large job shop scheduling problems, it can be used to solve other large problems that have a network similar to a factory. The first proposed use to solve a military related scheduling problem was presented in Hodgson et al. [24]. The authors created a Deployment Scheduling Analysis Tool (DSAT) to help plan for Army deployments to overseas countries. DSAT schedules the movement of equipment from the home station of a unit to the final staging area in the forward deployment location. The equipment is scheduled to minimize the maximum lateness of all deploying units to ensure ground commanders have units staged and ready for combat operations as planned. The DSAT found excellent solutions with little
computational time, which is vital to conducting sensitivity analysis during deployment planning.

2.3 Mission-Based Forecasting

_If we could first know where we are and whither we are tending,

_We could better judge what to do, and how to do it._

―Abraham Lincoln, June 16, 1858

The art of aligning resource requirements with specific mission requirements is something the United States Army has historically not done well. Although we fought a war in Iraq in 1991, when we invaded Iraq in 2003 we had logistical challenges similar to those that we had in 1991 [28]. Similar logistical challenges were encountered in supporting Operation Enduring Freedom in Afghanistan (OEF). After Action reports from OEF and OIF indicated that the Army supply system was too slow and inflexible to properly support combat operations [15]. Demand forecasts used during OEF and OIF “were determined by an inflexible outdated requisition process that relied on WW II-era historical wartime and even current *peacetime* consumption rates” [15]. The Army supply network was reactive in nature instead of anticipating logistical needs and being proactive to meet those needs. It is widely understood in the Army logistical community that “reactive logistics—the old logistics—will never be able to keep up with warfare as we know it” [29]. One way to prevent reactive logistics is to have more accurate demand forecasts.

Current Army forecasting techniques involve averaging past demand over several years and across many different mission sets and geographical locations. The large variability in such averages limits forecast accuracy for the multitude of different mission sets and potential operating environments faced by today’s Army. The Army needs to have forecasts that are unique to a specific type of unit, conducting a specific type of mission, in a
specific location. Mission-based forecasting is a forecasting technique that uses stratified sampling to create forecasts for different mission sets in different environments. The concept of mission-based forecasting was first introduced in a 2005 government consulting group study by LMI and further articulated in “Transforming U.S. Army Supply Chains” [15]. Using Army aviation units as a test bed, LMI looked at repair part (U.S. Armed Forces Class of Supply IX – Class IX) demand for AH-64 Apaches during training in the continental United States (CONUS), major combat operations (MCO) in Iraq, and stability operations (SO) in Iraq. Looking at an AH-64 helicopter unit in these three scenarios resulted in homogeneous data that was broken down by mission type (Training vs. MCO vs. SO) and environment (Moderate CONUS vs. dry Iraq).

The data collected during the LMI study was the result of stratified sampling because it targeted a homogeneous sub population of the Army supply system. “Stratified sampling is a powerful variance reduction technique that enables accurate and precise estimates to be made without the need for larger and more costly sample sizes that are typically required when using random sampling of a large and diverse, heterogeneous population” [15]. This sampling technique is much different than the current sampling techniques used by the Army and lends itself to helping forecast supply demands for specific missions.

Once all of the data was collected from the AH-64 test bed, the research team developed an experimental design to test the hypothesis that, “if empirically derived Class IX usage patterns, profiles, and/or trends can be associated with various operational mission types, then operational planning, demand forecasting, and budget requirements can be significantly improved to support a capabilities-based force” [15]. The results of the experiment showed demand patterns distinctive to different operational missions and
geographical locations (environments), confirming the first (“if”) part of hypothesis (see figure 2.1) [15].

The intersection of each Venn diagram represents the part demand during CONUS operations AND operations in Iraq. The aggregated demand for all of these parts (part depth) was 4.4 times higher during Major Combat Operations in Iraq than during CONUS operations and 3.9 times higher during Stability Operations in Iraq. Additionally, the Venn Diagrams portray a large percentage of parts demand seen during CONUS operations (Blue) that is never seen in Iraq (Yellow) and vice versa (part breadth).

The research team next looked at determining whether or not the stratified data from the AH-64 test bed could be used to develop a method for improved demand forecast accuracy. They did this by looking at actual part data pulled from a unit-level maintenance database instead of from a supply requisition database as is done for current forecasting methods. The data was then used to estimate future demand for operational missions similar
to the scenarios from the test bed. This estimation of future demand based on operational mission is a mission-based forecast. The mission-based forecast was tested against and compared with current forecasting methods used by the Army. The results were remarkable. Across multiple platforms (e.g., AH-64 or UH-60) and operational settings, MBF consistently demonstrated nearly an order of magnitude (e.g., 100%) improvement in demand forecast accuracy [15]. Specifically looking at AH-64 and UH-60 forecasts, forecast accuracy for part “breadth” (figure 2.2) and part “depth” (figure 2.3) were dramatically improved across operational settings [15].

Figure 2.2: MBF compared to current forecast methods (A, B, C &D): Part breadth (different parts) [15]

Figure 2.2 compares the success of MBF to other practiced forecast techniques (A-D). The parts forecasted using MBF were only those parts that showed demand in Iraq and CONUS. While the population size of the other forecasting techniques was larger (and has different parts), it is clear that the percentage of parts correctly forecast versus over/under forecast is much higher using MBF.
Figure 2.3 shows similar results to those shown in figure 2.2, but looks at all parts from the study. In the legend, the found (predicted qty) is the number of parts that were forecasted to be used and the found (actual qty) is the number of different parts that were actually replaced.

After the completion of the LMI research in 2005, little research was done on MBF until the Deputy Assistant Secretary of Defense for Maintenance Policy & Programs, Mr. John Johns started an initiative in November 2013 to validate the LMI study. This initiative is called the Maintenance Value Chain (MVC) project. Phase I, the validation phase, of the study was completed in September 2014, and the results were similar to the results of the study completed in 2005 [30]. This validation led Mr. Johns to expand the study to other services and other test beds (e.g., air and ground systems). If this second phase of the study produces results that validate the effectiveness of MBF, it may generate the momentum needed to make mission-based forecasting the standard forecasting method for the Army and Department of Defense.
Another forecasting tool that can further improve demand forecasts for the Army supply system is Condition Based Maintenance (CBM). CBM tracks the condition of equipment, using sensors, and uses that information when deciding when to conduct maintenance [15], thus when to order parts. For example, CBM can track the number of flight hours on the rotor blades of helicopters. The number of flight hours before the blades must be replaced differs depending upon the mission set and environment (just like MBF). When rotor blades reach a specific number of flight hours, a demand signal is triggered. This gives the supply system an expectation of when new blades will be needed and allows it to get them there prior to the blades failing and in the most efficient and cost conscious manner. This helps change the maintenance operations from a break-then-fix approach to a predictive, proactive approach [15]. This predictive and proactive approach that can be based on specific mission sets and operating environments will further improve forecasting.

The combination of mission-based forecasting and condition based maintenance is a key part of the proposed decision analysis tool because it has the potential to provide the most accurate forecasts that are specific for different missions and environments. The accuracy of the forecasts increases the confidence in any predictions made about the Army logistical system. The ability to forecast for a specific mission helps the decision analysis tool predict impacts of different missions on the logistical system.

2.4 Current Planning Tools

The Department of Defense has many different planning tools at its disposable and uses different ones depending upon the agency and type of analysis needed. While each planning tool is useful and provides great analysis, research found that none of them offers end-to-end analysis of the entire sustainment logistical system. End-to-end is from the supply warehouse in the U.S., or other location in the world, to the ordering unit conducting
combat operations in a potentially hostile environment. Many of the well-known logistic planning tools have a focus outside of sustainment supplies, so will not be discussed. The following is a non-exhaustive list of planning tools, but covers some of the more widely used tools or tools more closely aligned with the capabilities of the MLNPS:

1) Analysis of Mobility Platform (AMP): The Analysis of Mobility Platform is the planning tool that is most similar to the MLNPS. Unlike many other planning tool found during research, AMP does allow end-to-end modeling. AMP is a “modeling and simulation application used for analyzing the end-to-end transportation of equipment, passengers, and supplies through the Defense Transportation System” [31]. AMP is used widely by the U.S. Transportation Command (TRANSCOM) in providing an understanding of the overall transportation capabilities needed for long term strategic planning [31]. The main differences between AMP and the MLNPS are:

a. AMP focuses primarily on transportation assets and does not look at other logistical nodes like distribution centers & theater distribution centers. The MLNPS models every aspect of the logistical network.

b. AMP is a modeling shell that integrates three other mobility models, running them in a sequential, “stovepipe,” fashion [32]. The MLNPS is one integrated model that includes all modes of transportation working interactively.

c. Initial scenario and setup time for AMP is time consuming [32]. Scenario and setup time for the MLNPS is estimated to be a maximum of 48 hours, depending upon the scenario complexity.
d. AMP does not harness the power of the Army’s ERP systems. It uses standard planning factors. The MLNPS uses the requisitions found in the ERPs.

2) Logistic Battle Command (LBC): Logistic Battle Command is a discrete event simulation capable of theater level modeling and sustainment planning & verification [33]. The model is used primarily by the Army Training and Doctrine Command’s Analysis Center at Fort Lee, Virginia. LBC is a highly flexible model that can be adapted to help answer a multitude of logistical problems/questions. It can model large scenarios with as many as 18 brigade combat teams (BCT) or help generate a schedule of resupply convoys for a single BCT. The main differences between LBC and the MLNPS are:

   a. LBC is capable of end-to-end modeling but currently is not being used in that capacity. Currently, LBC models only in-theater operations; from the ports to the customer.

   b. LBC does not harness the power of the Army’s ERP systems. It uses standard planning factors. The MLNPS uses the requisitions found in the ERPs.

3) Supply Chain Guru: Supply Chain Guru is commercial-off-the-shelf software from llamasoft ®. It is a highly adaptable software program that can be used to model, analyze, and optimize supply chains [34]. The maximum size of a network that Supply Chain Guru can model is not known; however, the Defense Logistics Agency (DLA) did a study on the network similar in size to the network discussed in Chapter 1. The scope of the model was much different than the scope of the MLNPS. The DLA study was focused on changing inventory levels and policies. It is believed that Supply Chain Guru could be
adapted to achieve goals similar to that of the MLNPS, but the software uses a MIP/LP solver. Research shows that MIP/LPs cannot solve large $N/M/L_{\text{max}}$ problems; the problem is NP-Hard. The concern is that the run-time will become too long for purposes of analysis, or the software will not have enough memory to solve the problem.

4) Planning Logistics Analysis Network (PLANS): PLANS is a logistics planning tool being designed by the U.S. Army Engineer Research and Development Center (ERDC). While still in the design phase, the model has the potential to be powerful in planning in-theater logistical operations. It is not an end-to-end model. The model takes a very detailed, micro look at all in-theater logistical operations. From weather pattern impacts on roads and soils, to the efficiency of individual forklifts in a warehouse, the strength of this model is in the details. While a micro analysis of a network is important, it is not the focus of this research. The details of PLANS would slow down the MLNPS and are not needed to achieve the desired level of analysis.
Chapter 3
Problem Formulation

3.1 Overview

In order to create the decision support system discussed in Chapter 1, the Army Supply system must first be modeled in such a manner that the structural integrity is maintained AND the Virtual Factory can properly simulate the movement of parts (requisitions). There are many components of the model, as depicted in the decision support system flow diagram shown in figure 3.1. This chapter will provide a general overview, with more specific details about the actual contingency operation networks discussed in subsequent chapters.

![Decision Support System (DSS) Flow Chart](image)

**Figure 3.1: Decision Support System (DSS) Flow Chart**

Each numbered box prior to the Virtual Factory is a different component that must be modeled individually. The formulation of each of these models and their assumptions are discussed further in this chapter. Once the model is created and mated with the Virtual Factory, situational deployment scenarios are created and used to demonstrate the Virtual
Factory as a forecasting tool. The tool is then integrated into a decision support system and used to help a decision maker understand the logistical requirements needed to support specific missions. The anecdotal example of Operation Iraqi Freedom (OIF) is used to show how the decision support tool could have been used to predict and avoid the logistical backlog that occurred in Kuwait during the early part of OIF.

3.2 Modeling the status quo Army Supply Network (Box 5)

As discussed in Chapter 1, the U.S. Military Supply Network is the largest supply network in the world. The network includes 24 DLA Distribution Centers (DCs) located around the world, which are supply nodes that store over 2.4 million different lines of inventory. These 24 DCs supply over 33,000 customers, which are demand nodes that are spread over 86 countries. Parts are shipped from supply nodes to demand nodes via 10 different modes of transportation as laid out in Table 1.1. Depending upon the mode of transportation, parts may have to pass through additional transportation nodes in order to reach the final destination. These transportation nodes consist of ports, airfields, intermediate transportation stops, and Forward Operating Bases (FOBs). Figure 3.2 depicts possible transportation nodes added to the path of a part from a supply node to a demand node.
In the scenario depicted in figure 3.2, node 1 is the supply node and node 6 is the demand node. The modes of transportation and associated routes are depicted in routes 1-3. Nodes 2 and 3 are transportation nodes that must be added to the network because they are the Sea Port of Embarkation (SPOE) and Sea Port of Debarkation (SPOD), respectively. Nodes 4 and 5 are an Airport of Embarkation (APOE) and Airport of Debarkation (APOD), respectively. In a deployed environment these could also be FOBs that supplies must pass through in order to reach their final destination. The need to pass through FOBs is discussed further in section 3.2.2.

The path each requisition takes as it moves from the supply node to the demand node depends upon the mode of transportation. Based upon the item type, location of the supply node, and location of the demand node, different modes of transportation are available for each job. A job is a requisition that has a specific due date, demand node (customer), and release date. The item to be shipped may limit some modes of transportation due to its size or composition. For example, an engine for a tank may not be able to be shipped FedEx.
because of its size, and ammunition cannot be shipped FedEx because it is hazardous. The chosen mode of transportation is determined by sourcing logic which is discussed later.

When a part is ordered, the ordering unit enters the requisition into the GCSS-Army computer system and defines the Priority Designator (PD) for the part. A part is given a PD based off the unit’s Force Activity Designator (FAD) and Urgency of Need Code (UNC) as outlined in Army Regulation (AR) 725-50 [35]. There are three different levels for the UNC and five levels for the FAD. The resulting PD dictates the standard delivery time for a requisition (see table 3.1). The required delivery date (RDD) or due date (DD) then becomes the ordering date plus the standard delivery time. The requisition is then put into three different Issue Processing Groups (IPG) which determine the mode of transportation.

<table>
<thead>
<tr>
<th>Priority Designators</th>
<th>CONUS and Intratheater</th>
<th>Unit Location</th>
<th>Europe, Mediterranean and Africa</th>
<th>Pacific</th>
</tr>
</thead>
<tbody>
<tr>
<td>.01 thru 03</td>
<td>10</td>
<td>14</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>.04 thru 08</td>
<td>14</td>
<td>18</td>
<td>18</td>
<td>19</td>
</tr>
<tr>
<td>09 thru 15</td>
<td>32</td>
<td>70</td>
<td>75</td>
<td>85</td>
</tr>
</tbody>
</table>

In order to properly model the military supply network, many assumptions are made. Each assumption must be both valid and necessary. It is also important to understand that every assumption biases the model. The bias either makes the model more efficient than the actual system (positive bias) or less efficient than the actual system (negative bias). The goal is to develop the model with positive bias so if the model identifies problems in the network, we can be confident that the problem will be seen in the actual network. If we create a model that is negatively biased, the model may identify problems that won’t occur in the actual network.
The following is a list of assumptions made in order to model the network in such a manner that the predictive tool functions as described in Chapter 1:

1. Parts are considered delivered when they reach the customer’s supply support activity (SSA) location.
2. Part priority has only three priority designations:
   a. PD-02 / IPG I (World Wide Express)
   b. PD-05 / IPG II (Air)
   c. PD-12 / IPG III (Surface)
3. FAD is limited to two levels, garrison and deployed. A deployed unit is designated a higher priority than a unit in garrison. This will happen naturally in the model, since deployed and garrison transportation should not compete.
4. All time units are in units of days.
5. The minimum travel time is one day. If a part departs the demand node and arrives at the supply node on the same day, the travel time is one day.

The remainder of section 3.2 goes into more detail about specific aspects of the network.

3.2.1 Modeling the “Status Quo” Network (Box 5.1)

The status quo network is the network with all units conducting garrison operations from their respective home bases, both CONUS and OCONUS. No units are conducting training at Combat Training Centers (CTCs) and no units are deployed from their home station. It is important to accurately portray this network because it is the base network from which all changes are made. DLA and the Army have established rules, called sourcing logic, that dictate how parts are shipped in the status quo network. The sourcing logic for CONUS and OCONUS units are different and will be discussed separately.

The CONUS Network:
CONUS based units make up the majority of the demand nodes (All but ~100 of ~33,000 demand nodes) and supply nodes (17 of 24) [12]. The majority of parts are shipped within the CONUS network. Due to the robust and reliable transportation network within the United States, the Army has dedicated truck routes that supply many of the demand nodes. The Army has mandated that if there is a dedicated truck that goes between a supply node and a demand node, a dedicated truck MUST be used regardless of priority [37]. The CONUS dedicated truck routes used by DLA, at the time of this dissertation, are depicted in Figure 3.3.

If there is not a dedicated truck, the part is shipped via World Wide Express (WWX), Defense Transportation Coordinated Initiative (DTCI), or Surface Small Package (SSP), depending upon the size and priority of the part [37]. DTCI and SSP are contracted shipment methods available within CONUS that are cheaper than using WWX but usually take longer. DTCI is used for packages that are greater than 300 pounds (a less-than-truckload contract)
and SSP is used for packages that are less than 300 pound [37]. World Wide Express is the term used for carriers like FedEx, UPS, and DHL. WWX, SSP, and DTCI are all point-to-point transportation methods, thus the carrier is responsible for pick-up at the DLA DCs and delivery to the customer. When parts are shipped via these methods, no transportation nodes must be added to the path.

As seen in Figure 3.3, dedicated trucks only originate from two CONUS DLA DCs. These two DCs are the primary suppliers for all parts in the supply system. These two DLA DCs are Susquehanna (DDSP) and San Joaquin (DDJC). The sourcing logic maps each demand node to a primary DC, which is either DDSP or DDJC; the other DC is the secondary DC [37]. If neither the primary or secondary DC has the part, the sourcing logic looks for the part at any of the other CONUS DCs.

Some parts in the supply system are managed by the military and its item managers. Each of these parts has an item manager responsible for determining from where to ship an item when a requisition is received. Unlike the source logic used by DLA, the item manager takes a holistic approach when determining how a requisition is sourced. This makes it hard to model this part of the network, thus an assumption is made to simplify the logic (see 3 below).

The following assumptions describe the CONUS supply network model:

1. Dedicated trucks depart six days a week, Monday through Saturday. Trucks travel seven days a week but cannot deliver on Saturday or Sunday.

2. There is no limit on the number of dedicated trucks that can be used daily. If additional trucks are needed, DLA can request and will receive them without any required lead-time.
3. All parts are managed by DLA. This prevents the model from having to include logic used by Army item managers and the Government Supply Agency.

4. DLA will properly re-order items with enough time to prevent any stock outs at any of the DCs.

5. Resupply of DCs does not use the same transportation network as the military supply system.

6. No parts are shipped from an OCONUS DC to a CONUS demand node.

The OCONUS Network:

Demand nodes residing OCONUS have different source logic as well as different modes of transportation. Each demand node still has a primary DC, which is usually OCONUS. If the primary DC has the part, the part can be shipped via dedicated truck if in the European Command (EUCOM), see Figure 3.4, or the Pacific Command (PACOM). If not in EUCOM or PACOM, one of the other available modes of transportation must be used. If the primary DC does not have the requested part, it can be shipped from any of the other DCs in the world.

Figure 3.4: EUCOM Dedicated Truck Routes, Frequency & Shipment Times [38]
The additional modes of transportation used for OCONUS can be found in Table 1.1.

The United States Transportation Command (TRANSCOM) coordinates military sea and air transportation, as requested by DLA. Commercial air transportation is treated the same as military air and it is up to the Air Force to determine if a pallet gets on a military or commercial aircraft. 463L pallets are used for air shipment and 20 & 40-foot containers are used for surface shipments. DLA is responsible for coordinating the transportation to get the containers from a CONUS DC to the SPOE/APOE and from the SPOD/APOD to the requesting unit or break bulk location. The additional movements require transportation nodes to be added for each port/airfield and the break bulk locations.

Commercial sea transportation is also coordinated by TRANSCOM. TRANSCOM contracts for space on commercial ships. The commercial company is responsible for point-to-point shipment from the DC to the requesting unit or break bulk location. For this mode of transportation, transportation nodes are added at the SPOE and SPOD despite the point-to-point responsibility of the carrier. This allows for better transparency of the network and understanding of delays.

Surface shipment of parts is the priority mode of transportation for all routine OCONUS requisitions coming from a CONUS DC. TRANSCOM determines whether a container is shipped on a military or commercial ship. The mandated primary mode is commercial ship, with exceptions for certain items like ammunition [39].

Air shipment of parts is the priority mode of transportation for all high priority OCONUS requisitions coming from a CONUS DC. The Army has a checks and balances system to limit the number of items shipped via air. The Army Air Clearance Authority reviews all high priority OCONUS requisitions and sends the shipments via surface if it is
determined that the cost outweighs the need [37]. Although commercial air shipment is usually faster and cheaper than military air, the primary mode is military air due to the need to meet Air Force readiness hours [39].

If a part is going to be shipped surface or air, it must be put in a container (surface) or on a 463L pallet (air) at a Container Consolidation Point (CCP). CCPs are located, primarily, at DDSP and DDJC. Supplies show up at CCPs from the DCs in multi-pack boxes unless the part is too large to fit in a multi-pack. Pallets and containers are then built from these multi-pack boxes and individual (large) parts. These containers/pallets can be built for a specific unit or for break bulk. Break bulk containers are ones that have parts for numerous different demand nodes. Once the container reaches the Theater Consolidation Shipping Point (TCSP), the containers must be broken down and the parts sorted by unit. The parts are then shipped from the TCSP to the final destination. TCSPs are usually located at OCONUS DCs or sites that are co-located or near the SPOD/APOD. The rate at which containers can be broken down and sorted is critical to a smooth flowing network. These rates are a key component of the model and are discussed later.

Once a container/pallet is started, it remains at the CCP until full or a specified waiting period is met [37]. The waiting period is three days for air pallets and 15 days for surface containers [37]. The waiting period is used to try and ship full, or almost full, containers/pallets without waiting so long that the parts are late getting to the customer. The following assumptions describe the “status quo” OCONUS supply network model:

1. All air pallets and surface containers are built as break bulk unless the route to a unit does not support break bulk operations. This prevents the model from shipping pallets and containers that are near empty.
2. If a single requisition can fill an entire pallet/container, a unit pure pallet/container is built. The pallet/container then bypasses the TCSP and travels directly to the demand node.

3. If a break bulk container is filled with parts all designated for the same demand node, it bypasses the TCSP and travels directly to the demand node.

4. Army Air Clearance Authority does not have any downgrade authority. This prevents the model from needing to include human logic that is not easily represented mathematically.

5. Only 40-foot containers are used for surface transportation.

6. 100% of surface containers shipped in the status quo networked are shipped on commercial ships.

7. There is no limit on the number of trucks that can be used to move pallets and containers between CONUS DCs or from the CONUS CCPs to the APODs/SPODs. As many trucks as are required by DLA will show up and transport the cargo.

3.2.2 Modeling Contingency Operations (Box 5.2)

There are many contingency missions the Army could be called upon to assume. These missions may be peacekeeping operations, disaster relief operations, humanitarian operations, or combat operations; to name a few. These operations take place anywhere in the world and each one has a unique structure. These operations add new demand nodes and transportation nodes to the overall network. Unlike most transportation nodes in the status quo network, transportation nodes added due to contingency operations are often severely capacitated. Many contingency operations occur in countries with airfields and ports that are
small, under-developed, or non-existent. This cripples the movement of supplies into the area of operations because ships and planes queue up waiting to get into a port or airfield.

Every port has a specific number of berths where ships can be loaded and unloaded. The number of berths in a port limits the rate at which ships can be downloaded. Airfields have a Maximum on Ground (MOG) number that limits the number of aircraft that can land and be loaded/unloaded at any given time. The MOG of an airfield limits the daily number of aircraft that can be scheduled to land.

Each port and airfield has Material Handling Equipment (MHE) that load & unload containers and moves them to holding areas. Usually, this same MHE then loads the containers onto other transportation assets for onward movement. Each piece of MHE has a specific rate at which it can move containers. The total MHE capability at a port or airfield limits the amount of containers that can be processed daily. The military and DLA have differently sized elements than can deploy to help with material handling, and each one has a different capability.

Contingency operations also add other transportation nodes and eliminate many of the point-to-point services offered by commercial carriers. The nodes that are added are usually different Forward Operating Bases (FOBs) that supplies must pass through in order to reach their final destination. In a combat environment, point-to-point delivery is not available because carriers will not risk the lives of their personnel to transport supplies in a combat zone. When this is the case, commercial shipping services (WWX, commercial sea, and commercial air) commonly end at the SPOD or APOD.
Assumptions:

1. Parts are considered delivered when they reach the FOB that is the first stop after the APOD/SPOD or Theater Distribution Center (TDC).

Network details and assumptions for specific contingency operations modeled during the research will be discussed in subsequent chapters.

3.2.3 Modeling the Shipping Capabilities & Constraints (Box 5.3)
The following assumptions are used when modeling the transportation assets:

1. There are no capacity constraints on the commercial sea assets available.

   TRANSCOM can put as many containers as needed on the scheduled ships. Ship schedules are based on commercial carrier schedules between ports.

2. There are no capacity constraints on the number of parts that can be shipped WWX, SSP, and DTCI.

3. A container/pallet is considered full when it reaches 85% of cubic capacity and 95% of weight capacity.

4. CONUS Dedicated truck route shipping times are according to the times in Figure 3.5.
5. CONUS WWX shipping times are determined by FEDEX generated maps like the one in Figure 3.6 that shows the shipping times from the Susquehanna DC.
6. SSP and DTCI shipping times are calculated by adding 2 days to shipping times used for CONUS WWX.

7. OCONUS WWX shipping times are calculated using global DHL shipping times for a 10 kg package [41].

8. Commercial and military sea travel times are calculated using SeaRates.com [42].

9. Commercial and military air travel times are calculated using Airplane Manager using a heavy jet and no winds [43].

10. It takes a commercial ship four days to load and download at the port.

11. Aircraft load and download times are insignificant given time unit increments are in days.

12. Five 463L pallets are the equivalent of one Forty Foot Equivalent (FEU) container.

13. A 40-foot container can hold 40 multi-boxes and a pallet can hold 8 multi-pack boxes.

14. A multi-pack box has a usable load capacity of 1,250 lbs. or 50 cubic feet.

Facts used in the model:

1. A 463L Pallet usable load capacity is 10,000 lbs. or 485 cubic feet [44].

2. A 40-foot container usable load capacity is 44,000 lbs. or 2,000 cubic feet [45].

3.3 The Forecast Data

Forecasted requisition data is a critical component of the model because it is used to represent the load put on the network. The model is only as good as the forecasted data. Care must be made to ensure that an overestimated forecast is not used because that will negatively bias the model.

The following assumptions are used when modeling the requisitions received by DLA:
1. DLA receives requisitions once a day, at the end of the day.

2. Requisitions arrive sorted by unit.

3. Requisitions cannot be shipped until the day after they are received.

3.3.1 Using a Mission-Based Forecast (Box 2)

Mission-based forecasts (MBF) properly adjust the number of requisitions to match the change in demand due to different types of operations. The base forecast used for every unit is a garrison forecast that uses an average demand based on previous years’ data. When a unit deploys to a Combat Training Center (CTC) or on a contingency operation, the garrison forecast is replaced with a forecast that is specific to the mission. These demands enter the model beginning at time equal zero, with release dates dictated by the mission-based forecast. Forecast details for specific contingency operations modeled during research will be discussed in subsequent chapters.

3.3.2 Using Condition Based Maintenance to Improve the Forecast (Box 3)

Condition Based Maintenance (CBM) can be used to improve the forecast because it adds low variance demand to the model as sensors predict when a part on a vehicle will need to be replaced. Knowing when a part needs to be replaced provides information on when the part will be ordered. The challenge in introducing CBM into the current model is the fact that it is not yet implemented in the military. Thus, the CBM forecast will not be used in the model.

3.4 The Current State of the System (Box 4)

The current state of the system is all of the parts that are already moving through the supply network. This consists of parts waiting to be shipped as well as all of the parts that are in-transit to customers. Theoretically, with the full integration of the Army retail ERP system (GCSS-Army), the current location and status of every part in the supply system is
known. Therefore, to initiate the model, the full current state of the system would be downloaded and entered into the model.

### 3.5 Building and Testing the Model

Using the “status quo” network described above, a model was built using the Virtual Factory as the engine and the network specifics as the input parameters. Initially, historical sustainment supply requisition data was provided by USTRANSCOM in order to test the validity of the model using the European Command network. This allowed for a rough calibration of the model to compare model results to statistical results from that USTRANSCOM data. Due to the lack of a size or weight associated with the requisitions as well as no contingency operation data, a different dataset was needed.

The 2005 RAND Corporation study conducted on the logistical challenges faced during Operation Iraqi Freedom (OIF) presented great statistics on the significant queuing seen at many of the critical logistic nodes. Knowing tremendous data was behind the statistics, the authors of the study were contacted and the data was obtained. This data paved the way for modeling the OIF network and validating the ability of the model to closely replicate the actual logistical network. This model calibration and validation will be discussed in the next Chapter.
Chapter 4
Adapting the Virtual Factory for the MLNPS

4.1 The Processors

As discussed in Chapter 2, the Virtual Factory was first used to solve a military related scheduling problem in Hodgson et al. [24]. The C++ code had to be adapted so machines processing jobs could be adjusted to represent aircraft and ships processing military equipment across the world. For this research, the C++ code had to again be adjusted to represent the different logistical nodes and transportation assets that are required to move sustainment supplies around the world. The logistic nodes and transportation assets are referred to as processors and are assigned a processor number. Each processor number is assigned a processor type where each type of processor represents a specific function within the logistical network. The path a requisition must take from point of supply to point of consumption in Iraq is shown in Figure 4.1.

Figure 4.1: Requisition Path from CONUS to OIF

Each one of the logistical elements seen in figure 4.1 is represented by one of seven different types of Virtual Factory processors. Each processor has unique characteristics but can
represent more than one type of logistical element in the network. The following is a list of these processors and their specific characteristics:

**Type 1 Processor (Center Vehicle Parts):** This processor models a vehicle that transports individual requisitions, multi-packs, containers, or pallets or any combination thereof from a specific origin to a specific destination. The travel time is a fixed value and there is no return travel time. The capacity, in terms of weight and cube, of each vehicle may or may not be finite each day (If a value of -1 is given, there is an unlimited capacity each day; else the cube and weight capacities are entered). If anything is placed onto a vehicle on a given day, the vehicle leaves to transport the items, regardless if the vehicle is full or not. This processor has three possible schedule types.

**Processor Schedule Types:** A Type 1 schedule means the processor operates 7 days a week, 365 days a year. A Type 2 schedule allows the processor to operate on a weekly schedule but one that does not have the processor available every day of the week. A Type 3 schedule allows for a schedule that is not the same week to week. This allows the user to dictate the days the processor does operate by entering a schedule length and the day the processor is available.

**Type 2 Processor (Center Vehicle Groups):** Like a Type 1 Processor, this processor models a vehicle that transports individual requisitions, multi-packs, containers, or pallets from a specific origin to a specific destination. The travel time is a fixed value and there is no return travel time. The difference between Type 1 and Type 2 processors is that the capacity of a Type 2 processor is in terms of items on the vehicle, not cube and weight. Since the capacity can be in requisitions, multi-packs, containers, or pallets, a combination
thereof is not possible. This processor has the same three schedule types as the Type 1 processor.

**Type 3 Processor (Center Machine Make Groups):** This processor models the building of groups; a pallet OR a container OR a multi-pack. Pallets and containers can be filled with individual requisitions (BIG requisitions that could not fit into a multi-pack) or multi-packs. Multi-packs can only be filled with individual requisitions. Each type of group built AND destination requires a separate Type 3 processor. An unlimited number of groups can be built; however, this can be adjusted if there needs to be a daily capacity. Only full groups can proceed to the next processor in the schedule, unless a specific number of days have passed since the first requisition was placed in the group. This is accomplished by assigning a maximum cube & weight, a send cube & weight, and a maximum time that a group can be open. If the send cube or weight for a group is reached, this processor attempts to reach the maximum cube or weight by looking at each requisition in the queue, in attempt to fit more in the group. If no parts remaining in the queue can fit in the group, it is closed and a new group is opened. At the end of each day, if a group has not reached the maximum send cube or weight, but has reached the maximum time, it will proceed to the next processor.

Regardless of the cube of the built group, before moving to the next processor, the maximum cube is assigned to the group; a partially full container still takes up the full cube of a container when it is placed on a ship. Because there are two different sized groups (Pallet and Container) that will eventually get broken down by a Type 4 processor, the groups must be in similar units. The equivalent unit is pallets because pallets are smaller than containers. Each group is therefore assigned a number of pallet equivalents. This processor can operate on any of the three types of schedules previously discussed.
Type 4 Processor (Center Machine Break Groups): This processor models the breaking down of groups that were built by a Type 3 Processor. It breaks groups down one level; a pallet is broken down into BIG parts and multi-packs, but since a multi-pack is another group, they are not broken down. A fixed number of pallet equivalents can be broken down per day and is an input value for this processor. Since multi-packs are always unit specific, only pallets and containers are broken down by this processor. This could be adjusted to also break down multi-packs into requisitions, but the equivalency unit in the Type 3 processor would have to be changed to multi-packs. Because the number of pallet equivalents that can be broken down may change over time, a break down availability schedule is added to this processor. A Type 1 availability results in a processor that operates at a constant break down rate. A Type 2 availability allows for a fluctuating break down rate and requires input values of the day the rate changes as well as the new rate. This processor can operate on any of the three types of schedules previously discussed.

Type 5 Processor (Center Machine Parts Number): This is a processor that models the stationary operation of filling requisitions from a distribution center. It models the personnel and equipment that take supplies off of shelves and places them in queue for unit specific multi-pack boxes, if they can fit in one. Capacity per day is in terms of number of requisitions and can have an unlimited or finite capacity. This processor can operate on any of the three types of schedules and two types of availabilities previously discussed.

Type 6 Processor (Center Vehicle Roundtrip Individually): This processor models vehicles that transport pallets and containers from a specific origin to a specific destination. The processor models a specific number of individual vehicles. Each vehicle has a fixed forward trip time, when the vehicles are full, and a fixed return trip time, when the vehicles
are empty. Although the return trip is modeled with this processor, the pallets/containers are moved onto the next processor on the route once they reach the destination. Each vehicle has a capacity, in terms of pallet equivalents, that can be transported. Individual vehicles leave only when they are full. Any upload/download time or crew rest time is included in one of the fixed travel times. The schedule is such that vehicles operate 7 days a week. The availability can be Type 1 or Type 2; A Type 2 availability allows the number of vehicles to change over time.

**Type 7 Processor (Center Vehicle Roundtrip Together):** This processor models vehicles that transport individual requisitions, multi-packs, pallets, or containers or any combination thereof. This center models one large vehicle. The large vehicle represents a group of vehicles moving together, with a maximum capacity in terms of weight and cube. Each vehicle has a forward trip time, when the vehicles are full, and a return trip time, when the vehicles are empty. Vehicles leave according to when they are available; they do not wait until full. Any upload/download time or crew rest time is included in one of the fixed travel times. The trip time for this processor can change over time depending upon the change type designated. A Change Type 1 means the forward and return trip times do not change for the duration of the simulation. A Change Type 2 allows the forward and return trip times to fluctuate over time. When forward and return travel times are changed, only subsequent trips are affected. The schedule is such that vehicles operate 7 days a week. The availability can be Type 1 or Type 2; A Type 2 availability allows the maximum cube and weight of the vehicle to change over time.

One of the most significant adaptations of the Virtual Factory was the need to model batch processors within batch processors. As a requisition transits the network it may have to
be grouped in a multi-pack box, or a container/pallet, or a ship/aircraft or any combination thereof; all of which are batch processors. When a requisition is put in all three batch processors, there is a point where the simulation has a batch processor inside a batch processor, inside a batch processor. This required new rules for prioritizing and sequencing batch processors in a queue. This was handled by nesting the original rules from the Virtual Factory at each level of the batch processors from the lowest level up.

4.2 Model Bias

As discussed in previous sections and chapters, all models are biased; however, a model can be built to ensure it is correctly biased. This model uses queuing to predict network performance. It is the presence of queuing that signals potential problems with the network. In order to predict network backlogs with any degree of confidence, the network must be modeled in such a manner that any bias results in less queuing than expected. For example, if the average flight time between an APOE and APOD is 36 hours, using one day as the flight time will properly bias the model. Having a flight time of two days will bias the model the wrong way because it may result in queuing at the APOE when there probably won’t be any in real life. When queuing is seen in the network, we must be confident that the queuing will be there in real life; this is done by managing the bias.

The heuristics inherent to the Virtual Factory properly biases the model, but each processor must also be properly biased. The bias is managed by choosing deterministic values, for capacities & processing times, which correctly bias the model. Correct bias is also inherently built into the model with the way multi-packs, pallets, containers, and vehicles are filled. The cubic size of each requisition is treated as liquid when being packed into any container. This results in containers that fit more requisitions than would be able to
be packed into any container due to the dimensional challenges of packing boxes of different shapes and sizes.

4.3 Modeling the Path of a Requisition
From order to delivery, the path of a requisition encompasses transit on several different vehicles and handling & waiting at numerous logistical nodes (See Figure 4.1). Each step of the journey must be modeled as accurately as possible in order to correctly predict network performance. The modeling of each process is outlined in the rest of this section.

When a requisition is entered into GCSS-Army, there is a period of time where DLA determines the proper mode of transportation, and from which DC the requisition should be sourced. This is called the order & source time. It is represented with a Type 1 Processor and has a processing time equal to the mean processing time from historical data. It is assumed that there is an unlimited number of requisitions that can be processed each day; thus there is no queuing at this node. Each requisition is processed for a specific period of time and then is ready for pick & pack at the DC.

Once a requisition is sourced to a specific DC, those supplies must be pulled from the warehouse shelves and packaged for shipment. This is referred to as pick & pack operations. This process is modeled using a Type 5 processor for the primary DC and a Type 1 processor for all other DCs. The Type 1 processor is used to model low volume distribution centers that are able to pick and pack requisitions within one day of being selected as the sourcing DC. Once packaged at a low density DC, the requisition is ready for shipment to the consolidation and containerization point (CCP). The Type 5 processor is used to model the primary DC because the volume of requisitions can surpass the capacity, causing queuing. If not too large, requisitions are placed in a multi-pack box before being moved to the CCP. If a requisition is too large to fit in a multi-pack box, it is sent on to the CCP as a separate item.
For those requisitions that can fit in a multi-pack box, a Type 3 processor is used to model the packing of requisitions into the box. This is a subcomponent of the pick and pack process. There is a different processor for each unit, making the multi-pack boxes unit pure. Once a multi-pack box is full or has been open for three days, it is moved to the CCP.

Requisitions that are sourced at a DC not co-located with the CCP must be shipped on a commercial truck to the CCP. This processed is modeled using Type 1 processor. The processing time is determined based off the mean travel time from each DC to the CCP based on historical data. Due to the robust nature of the CONUS trucking network, it is assumed that an unlimited amount trucks are available to transport to the CCP. The only queuing occurs due to trucks not being loaded on Sundays. Once the trucks arrive at the CCP, the requisitions await palletization or containerization based off the overseas mode of transportation.

Placing individual requisitions or unit specific multi-pack boxes on 463L pallets and in 40-foot containers is modeled using a Type 3 processor. In order to maintain the proper bias of the model, all requisitions that are waiting at the beginning of the day to be processed, will be processed that day. The processing time is one day, placing all requisitions in a container or pallet at the end of the day. All containers are loaded for a specific destination but are not dedicated to a specific unit. This results in needing a different processor for each Theater Distribution Center (TDC) in the model. Pallets can be built unit pure or with different units on the same pallet. If the pallets are unit pure, there is a different pallet processor for each unit. If the pallets are built with mixed units, there is one processor that makes pallets destined for the TDC. At the end of each day, if a container/pallet is full or reached the maximum time, it is moved forward to be trucked to the A/SPOE.
Pallets and containers are shipped from the CCP to the A/SPOE on commercial trucks. This process is modeled using a Type 1 processor. The processing time is determined based off the mean travel time from the CCP to the A/SPOE based on historical data. Due to the robust nature of the CONUS trucking network, it is assumed that an unlimited amount of trucks are available to ship to the A/SPOE. The only queuing occurs due to trucks not being loaded on Sundays. Once the trucks arrive at the A/SPOE, the pallets/containers await loading onto an aircraft or ship. The time to download the truck is considered negligible because the smallest time unit is in days.

Loading of ships and aircraft are treated differently in the model. The time to load a pallet onto an aircraft is considered negligible compared to the flight time, which is in days. Thus, once a pallet arrives at the APOE it goes in the queue for departure and will depart the next day a plane and pallet position are available for it, subject to priority.

The time to load a container onto a ship is not negligible and is determined based off historical data from either DLA or port operations/capabilities. Ships are loaded according to a ship schedule. This schedule is determined by using the actual ship schedules for the top carriers used to ship supplies to the destination port. Historic data is used to determine the major carriers used between the SPOE and SPOD. Major carriers, such as Maersk and Hapag-Lloyd, publish annual route schedules. For each port of origin, these schedules have the day of the week the ships depart as well number of number of trips annually. An example schedule from the port of Norfolk to European ports is presented in Table 4.1.
Table 4.1: Example Maersk Ship Schedule from www.maerskline.com

<table>
<thead>
<tr>
<th>DESTINATION</th>
<th>SERVICE</th>
<th>DEPT.</th>
<th>ARRIVAL</th>
<th>2015</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALGECIRAS</td>
<td>TA5</td>
<td>SAT</td>
<td>FRI</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>ANTWERP</td>
<td>TA1</td>
<td>THU</td>
<td>SAT</td>
<td>8</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>TA2</td>
<td>SAT</td>
<td>FRI</td>
<td>14</td>
<td>20</td>
</tr>
<tr>
<td>BREMERHAVEN</td>
<td>TA1</td>
<td>THU</td>
<td>TUE</td>
<td>11</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>TA2</td>
<td>SAT</td>
<td>TUE</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>BUSAN</td>
<td>TP12</td>
<td>SAT</td>
<td>MON</td>
<td>44</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>TP12</td>
<td>SAT</td>
<td>SAT</td>
<td>27</td>
<td>37</td>
</tr>
<tr>
<td>COLOMBO</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TP12</td>
<td>SAT</td>
<td>SAT</td>
<td>27</td>
<td>37</td>
</tr>
<tr>
<td>FELIXSTOWE</td>
<td>TA2</td>
<td>SAT</td>
<td>WED</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>GENOA</td>
<td>TA5</td>
<td>SAT</td>
<td>MON</td>
<td>22</td>
<td>22</td>
</tr>
</tbody>
</table>

Once a schedule is determined, it dictates when containers can begin to be loaded onto a ship. If a container is waiting to be loaded when a ship is scheduled to begin loading, the container is loaded. If a container enters the queue after the loading process has begun, it must wait for the next ship. A Type 2 processor is used to model this loading process. A Type 3 schedule is used to schedule ships out as far as needed for the simulation. The capacity is assumed to be unlimited on each ship, resulting in the container queue being emptied every time a ship is loaded. Once a ship is loaded, it departs the following day.

The transit of ships and aircraft from the A/SPOE to the A/SPOD is modeled using a Type 2 processor. The processing time is determined using either average transit times from historic data or using www.searates.com for ship transit times and www.airplanemanager.com for aircraft transit times. As discussed previously, ships depart immediately following the loading period. Aircraft are modeled differently because it is assumed that the loading time is negligible and a there are limited number of pallet positions. Aircraft schedules are created using historical data that has the number and type of aircraft transiting between APOEs and SPODs. The Air Mobility Command (AMC) air channel
sequence listing can also be used. From this data and the knowledge of how many 463L pallets can fit on each aircraft, a schedule is created for how many pallets can be transported each day from an APOE to an APOD. These schedules are rough estimates but could be extremely accurate using an actual Air Tasking Order (ATO). An ATO is an Air Force schedule that lists all sorties for a 24-hour period. This is usually locked-in 72 hours out from execution of the sorties. Without an ATO, it is important to make sure the deterministic number of pallet positions properly biases the model. Since we want the model to be biased in favor of network efficiency, a value should be selected that results in pallets waiting at the APOE for less time than they historically have on average. Once the ship or aircraft reach the S/APOD, the containers and pallets are downloaded before follow-on movement.

The unloading of ships and aircraft is also modeled differently. Just as in loading aircraft, the unloading time of an aircraft is assumed to be negligible and thus moves straight to the queue for follow-on movement once the transit is complete. The unloading of the containers on ships is modeled using a Type 2 processor with a Type 1 schedule. The Type 1 schedule assumes unloading and customs are conducted 7 days a week. This can be changed to a Type 2 schedule if port operations are not 7 days a week. The processing time for the download of a ship is the half of the mean time it takes to download an entire ship. This accounts for the fact that some containers are unloaded right away and others must wait until unloading is almost complete. Once a container is downloaded, it is placed in the queue for the trucks that will transport it to the theater distribution center (TDC).

The trucks that move containers and pallets from the A/SPOD to the TDC are modeled using either a Type 2, Type 6, or Type 7 processor with loading/unloading times assumed to be negligible. If the trucking network is robust and has commercial trucks that
can be contracted, a Type 2 processor with unlimited capacity is used. This assumes that a
truck is always available when needed. A Type 1 schedule is used if trucks operate 7 days a
week and a Type 2 schedule if anything other than 7 days a week. The processing time is the
time it takes a truck to move from the A/SPOD to the TDC. This is calculated using the
mean travel time from historical data or Google Maps and an estimated rate of march. If
there are a limited number of trucks that can operate autonomously, in a secure environment,
a Type 6 processor is used. The number of processors is equal to the number of available
trucks and the capacity of each truck is the cubic and weight capacity. The cube & weight or
pallet capacities of each type truck is determined using ATP 4-11, “Army Motor Transport
Operations” [46].” If there are a limited number of trucks that must move as a secured
convoy, a Type 7 processor is used. The capacity is equal to the sum of the capacity of all
the trucks in the convoy. The number of trucks available and the logistical battle rhythm
usually dictate the schedule. The logistical battle rhythm is the weekly schedule for the
Logistical Package (LOGPAC) operations that resupply combat units. LOGPAC Operations
are a grouping of multiple classes of supplies and supply vehicles under the control of a
single convoy commander [47]. Once the trucks arrive at the TDC, the pallets and containers
are put in the queue to be broken down. If a pallet or container is unit pure, it bypasses the
TDC processor and moves to the queue for the trucks to the unit.

TDC operations, the process of breaking down pallets and containers and re-sorting
requisitions by unit, is modeled using a Type 4 processor. The processing time is one day
and the capacity is the number of 463L pallet equivalents that the center can break down per
day. A Type 1 or Type 2 schedule is used depending upon whether or not the TDC operates
7 days a week. Once requisitions are sorted by unit, they are placed in the queue for the trucks to transport them to the location of the ordering unit.

The trucks, or other modes of transportation, that move requisitions from the TDC to the final destination are modeled using either a Type 2, Type 6, or Type 7 processor. Just like the trucks between the A/SPOD and the TDC, the type of processor used depends upon the maturity of the transportation network and security situation. In a wartime environment, these are the last tactical mile trucks and are therefore modeled using a Type 7 processor. The trucks move full, or partially full, from the TDC to the final destination and deadhead, are empty, on the return trip. The schedule is usually dictated by the planned number of days of supply that are put on each convoy or according to the unit’s logistical needs. Although requisitions may have to be transported to further locations within a Brigade Combat Team, it is not modeled in this research. The last tactical mile trucks are the last leg of the shipment that is modeled.

Other transportation assets, such as rail, can be modeled using one of the seven processors discussed previously. Rail was not used during this research because it was not a common mode of transportation for the locations and operations used.

4.4 Model Inputs

Prior to the simulation starting, two input files are read-in by the Virtual Factory. These two files contain all of the information needed for the simulation. The first file read-in by the Virtual Factory is the Processor Input File. This file is a list of all processors and the specific characteristics of each processor as outlined in Section 4.1. This input file is discussed in more detail in Section 4.4.1. The second file read-in by the Virtual Factory is the Requisition Input File. This file is a list of all requisitions to be simulated through the logistical network. This input file is discussed in more detail in section 4.4.2.
4.4.1 Processor Inputs File

This file is a list of all processors and the specific characteristics of each processor as outlined in Section 4.1. This is the file that is adjusted as the characteristics of the network change. How each value is determined will be discussed in detail for each specific scenario.

4.4.2 Requisition Input File

Generating the requisition input file is a complicated and often a lengthy process. Computation time is usually longer than the computation time for the simulation; however, it is usually created only once for a scenario. The computation time would be significantly less if mission-based forecasting were a more mature concept. The file consists of three major components for each requisition; release & due dates, the requisition path, and physical characteristics of the actual item/items. Each of these will be discussed in more detail in subsequent sections. Because mission-based forecasting is not yet a reality in the capacity needed for the MLNPS, much of the specifics about the requisitions are randomly generated. Random generation will be discussed for specific scenarios.

4.4.2.1 Release and Due Dates

The release date (RD) for each requisition is determined differently depending upon the mission and data available. If a mission-based forecast is available, the release date for each requisition is a part of that forecast. If historical data is used as a surrogate mission based forecast, the release date for a requisition is the date the requisition was actually established in the supply system. Without a true mission-based forecast or a surrogate mission-based forecast, the release dates must be randomly generated. Historical data is used to fit a distribution that models the release date frequency. A different distribution is fit for different phases or operational intensities of a scenario. For example, if historical data is available for major combat operations as well as stability operations, a different distribution
is used to model each. More details about data fitting will be discussed for each specific scenario modeled.

The due date for each distribution is based upon standard delivery times found in table 3.1; however, due to differences in service (Navy, Air Force, etc.) priorities and the need to expedite some requisitions, the delivery times are randomly generated. A uniform distribution is used to model the due date. The standard delivery times in table 3.1 are the upper-bounds and the lower-bounds are 70% of the upper-bounds. A summary of the uniform distribution used, by mode of transportation, for requisitions going to Europe is presented in Table 4.2.

<table>
<thead>
<tr>
<th>Mode of Shipment</th>
<th>a (70% of UB)</th>
<th>b (Standard Delivery Time)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WWX</td>
<td>10</td>
<td>14</td>
</tr>
<tr>
<td>MilAir</td>
<td>12</td>
<td>18</td>
</tr>
<tr>
<td>Ocean</td>
<td>52</td>
<td>75</td>
</tr>
</tbody>
</table>

The uniform distribution generates an allowable delivery time (\( ADT \)) for each requisition. That allowable delivery time determines the due date (\( DD \)):

\[
DD = RD + ADT
\]

Due dates can be modeled many different ways and can easily be adapted as needed for specific scenarios.

4.4.2.2 Creating Paths for Requisitions

Prior to the start of the simulation in the Virtual Factory, each requisition must have a pre-determined path. This path consists of the processors that each requisition must pass through and the order of processors. The path for each requisition depends upon the supplier, customer/destination, mode of travel, size of the requisition, and whether or not pallets are
built unit pure or not. Each combination of the aforementioned factors results in a different path for a requisition. All possible combinations and the corresponding paths are created in Excel and then called when creating the requisition input file. Using the details of each requisition, the excel file is searched for the matching details. Once matched, the corresponding path is pulled out and put into the requisition input file.

When simulating the OIF logistical network, there were 8,873 different combinations of requisition details. A small sample of different combinations and the corresponding path is presented in Table 4.3.

Table 4.3: Example Requisition Paths

<table>
<thead>
<tr>
<th>Req Num</th>
<th>Supply Node</th>
<th>Demand Node</th>
<th>Big Part</th>
<th>Mixed or Pure</th>
<th>Mode of Transpo</th>
<th>Path</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>149</td>
<td>No</td>
<td>Mixed</td>
<td>MilAir</td>
<td>1-2-33-50-14-52-53-54-55</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>149</td>
<td>Yes</td>
<td>Mixed</td>
<td>MilAir</td>
<td>1-2-50-14-52-53-54-55</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>149</td>
<td>No</td>
<td>Pure</td>
<td>MilAir</td>
<td>1-2-33-42-14-52-53-55</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>149</td>
<td>No</td>
<td>Mixed</td>
<td>Surface</td>
<td>1-2-70-87-14-51-88-89-53-54-55</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>150</td>
<td>No</td>
<td>Mixed</td>
<td>MilAir</td>
<td>1-2-34-50-14-52-53-54-56</td>
</tr>
</tbody>
</table>

Treating requisition number one as the baseline, requisitions two through five have slightly different characteristics, in bold, and require a different path. Requisition number two is too big to fit in a multi-pack box thus does not need to pass through the multi-pack building processor (Processor 33). Requisition number three is designated for a unit pure pallet so has a different pallet building processor (Processor 42 instead of 50) and does not need to be broken down at the TDC (Processor 54). Requisition number four is going Surface instead of MilAir, so must go in a different multi-pack box (Processor 70), travel in container (processor 82) instead of a pallet, and go on a ship instead of an aircraft which requires loading and unloading (Processors 51, 88 & 89). Requisition number five is going to a
different supply node so must go in a different multi-pack box (Processor 34) and has
different vehicles that deliver it to the final destination (Processor 56).

Depending upon the mission, the number of variations for a requisition may increase
which will increase the number of possible paths a requisition can take. This does not impact
the computation time of the simulation because the paths are generated and searched when
creating the requisition input file and not during the simulation.

When a mission-based or surrogate mission-based forecast is not available, the supply
node, demand node, and mode of transportation must be randomly generated. These must be
randomly generated sequentially because some of the distributions are conditioned on
specific characteristics. For example, a supply node distribution may be conditioned on the
demand node. Specifics on the use of distributions to randomly generate requisition values
will be explained in more detail for specific scenarios.

4.4.2.3 Physical Characteristics of Requisitions

The physical characteristics of a requisition are the cube and weight. In the absence
of a mission-based forecast, the weight and cube of a requisition are randomly generated
while maintaining a similar correlation as is found in existing data. Details on specifics of
the distribution will be explained in more detail for specific scenarios.
Chapter 5
Using Operation Iraqi Freedom (OIF) as the MLNPS Test bed

Once the Virtual Factory was adapted to meet the needs of the Military Logistics Network Planning System, the model had to be validated. Without validating the model, the model has no credibility that it can simulate the performance of the Army’s logistical network. The model needed to be validated by running the model and comparing the model results to results from an actual network. If the model could come close to matching the performance of the actual logistical network, then research to use the MLNPS as a credible planning tool could continue. In order to run the validation, a dataset was needed that had all of the requisition information, as discussed in chapter 4, needed to run the model. Data was also needed on network performance. A dataset with all of these requirements was obtained. The dataset contained all requisitions for Operation Iraqi Freedom as well as the data points on network performance in transporting those requisitions through the network. With this dataset, validation could begin.

5.1 Operation Iraqi Freedom and the MLNPS

The acquisition of the dataset from Operation Iraqi Freedom was a research catalyst. The dataset allowed for calibration and validation of the model. Before the model could be credibly used to plan a logistical network, it needed to be shown that it could accurately model the military logistical network. This was done by simulating the movement of the requisitions during OIF and comparing the actual queuing seen in the network with the queuing from the model. Calibration and validation of the model is discussed further in section 5.3. Once validated, the model was used to show how logistics could have been planned for OIF using the MLNPS; this is discussed in section 5.4.
5.2 The Operation Iraqi Freedom Dataset

The dataset obtained from the RAND study covered all 2003 requisitions with customers in Iraq and Kuwait as well as all requisitions that were processed by the Defense Logistics Agency (DLA) Distribution Center (DC) in Susquehanna Pennsylvania (DDSP). The requisitions that were processed by DDSP were vital because DDSP was the primary DC serving Operation Iraqi Freedom (OIF). This means DDSP requisitions going to CONUS units and requisitions going to OIF units competed against each other for DDSP resources. The dataset had the following critical fields:

1) Cube of the requisition
2) Weight of the requisition
3) Date the requisition was ordered (release date)
4) Mode of transportation
5) DC that supplied the requisition
6) Requesting unit and location (Usually by SSA)
7) Travel time along critical arcs (Processing time)
8) Queuing time at critical nodes
9) A/SPOE & A/SPOD locations

Hundreds of other fields were in the dataset but were not used for this research.

This dataset acts as a surrogate for a mission-based forecast in the MLNPS. Each component of the requisition input file is found in the OIF data set, except the due date; thus no information had to be randomly generated other than the due date. The due date was generated as discussed in section 4.4.2.1.

5.3 Calibrating and Validating the Model

Only a portion of the OIF dataset was used when calibrating and validating the model. Requisitions with release dates two weeks prior to forces crossing into Iraq through the end of May 2003, were simulated. This sub-dataset consisted of approximately 1.96
million requisitions with release dates spanning an 87-day period. Approximately 647,000 of these requisitions were destined for units in Iraq or Kuwait, with the remaining approximately 1.3 million requisitions destined for units in the Continental United States (CONUS) or elsewhere in the world. The 1.3 million requisitions not going to OIF were included in the simulation because they went through the same primary DC, DDSP, as those that went to OIF; thus they competed for the same resources. All of the 1.96 million requisitions competed for resources from the DCs through the trucks moving containers and pallets to the A/SPOE. Because requisitions may consist of more than one part, the approximately 647,000 requisitions were actually approximately 11.6 million parts.

What the dataset did not include is Class I (food and water – CL I) and Class V (ammunition – CL V). Since CL I and CL V supplies use a significant amount of transportation assets, they had to be added to the model. It was assumed that all water supplied during the first 90 days of operations was bottled water. This is a valid assumption because bottled water was the primary source of potable water during OIF [14]. Army Tactics, Techniques, and Procedures (ATTP) 4-41, “Army Field Feeding and Class I Operations,” provides recommendations for ration cycles during sustained expeditionary operations. A summary of the feeding plan guidelines is presented in Table 5.1.
Table 5.1: Army Feeding Plan Guidelines [48]

<table>
<thead>
<tr>
<th>Standard</th>
<th>Expeditionary &lt; 6 Months</th>
<th>Temporary &lt; 24 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ration Cycle</td>
<td>M-M-M</td>
<td>U-M-M</td>
</tr>
<tr>
<td>Theater Ration Mix</td>
<td>MRE 100%</td>
<td>UGR (B&amp;S) 34%</td>
</tr>
<tr>
<td></td>
<td>MRE 66%</td>
<td>UGR (A) 11%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>UGR (A) 70%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>UGR (A)+ 80%</td>
</tr>
<tr>
<td>Facilities</td>
<td>MKIT, KCLFF, CK, Tents, Refers</td>
<td>MKIT, CK, Unit Tents, Force Provider, Refers</td>
</tr>
<tr>
<td>Deployment Days D+</td>
<td>1-20 days</td>
<td>21-30</td>
</tr>
</tbody>
</table>

Notes:
1. Ration Legend: MRE-M, UGR (H&S) or UGR (A) – M, 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.

Table 5.1, coupled with the physical characteristics of each type of ration, allows for the computation of haul assets required to move the food needed for the troops. When modeling OIF, it was assumed that only MREs were provided for the first 90 days of operations. This does not follow the guidelines from table 5.1, but is a good estimator that maintains proper bias of the model. As a 90-day operation transitions from an all MRE ration cycle to a mix of MREs and Unitized Group Rations (UGRs), the burden on the logistical network increases. With all other factors remaining constant, this will decrease the efficiency of the network. The max decrease in efficiency is approximately 17%; properly biasing the model but not over biasing. Two other CL I assumptions are that there is a water bottling plant and a large wartime supply of MREs and UGRs in Kuwait. These two assumptions lead to the origin of all CL I being at the theater distribution center in Kuwait.

Calculating the daily amount CL I needed to sustain the forces in Iraq was required to determine the number of last tactical mile (LTM) trucks needed to transport just CL I from
the TDC to the tactical units fighting in Iraq. The three pieces of information needed for the
calculation are the number of troops in Iraq, the CL I consumption rates per person, and the
amount of CL I that fits on a pallet. Using the brigade combat teams (BCTs) found in the
OIF dataset, the dates those BCTs entered Iraq, and the number of soldiers per BCT, a by day
troop strength in Iraq was estimated. An average BCT has approximately 4,500 soldiers. An
assumption was made that units attached to a BCT for combat operations would increase
troop strength by approximately 10%; resulting in planning a factor of 4,950 soldiers per
BCT. According to the Combined Arms Support Command (CASCOM) Water Planning
Guide [49], 7.27 gallons per person per day is required in an arid environment. The 7.27
gallons is for consumption, personal hygiene, and field feeding. The CASCOM water
planning guide has a planning factor of approximately 228 gallons of bottled water per pallet.
Assuming a planning factor of 10% for breakage of bottled water [14], the daily water
requirement for a BCT is:

\[
\frac{4,950(7.27)(1.1)}{228} \approx 173 \text{ pallets}
\]

Assuming 3 meals a day and the fact that a pallet can hold 576 MREs, the daily food
requirement for a BCT is:

\[
\frac{4,950(3)}{576} \approx 26 \text{ pallets}
\]

CL V planning factors used was 60% of water weight and 40% of water cube, which is in
line with planning factors used by the Training and Doctrine Command Analysis Center at
Fort Lee (TRAC-LEE). These daily CL I and CL V consumption rates are used to determine
the capacity of last tactical mile trucks taken up by CL I and CL V. Class III, fuel, was not
modeled during this research. Fuel is a major portion of logistical operations and requires
extensive planning; however, the assets used to transport fuel are different that those assets
used to transport other sustainment supplies. The MLPNS could easily be used to plan a fuel network, but was not because the dataset did not contain fuel.

The first step in validating the model is to run the model under “actual” conditions and compare the model with network performance from the OIF dataset. Before continuing, it is important to distinguish between what will be referred to as “actual” conditions and “originally planned” conditions. The logistical plan for OIF and what actually happened differ in multiple areas. A summary of the major differences between planned and actual conditions is presented in Table 5.2.

Table 5.2: OIF Planned vs. Actual Conditions [14]

<table>
<thead>
<tr>
<th>Network Node</th>
<th>Originally Planned</th>
<th>Actual*</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDSP Pick &amp; pack</td>
<td>No Increase needed</td>
<td>Increased Capacity</td>
</tr>
<tr>
<td>Capacity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kuwait TDC</td>
<td>Established 60 days prior to LD and properly manned</td>
<td>- TDC established day of LD and severely undermanned</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Thousands of on ground containers</td>
</tr>
<tr>
<td>Pallet Configuration</td>
<td>Unit-Pure Pallets</td>
<td>Unit-Mixed Pallets until OCT ’03</td>
</tr>
<tr>
<td>LTM Trucks</td>
<td>965 Trucks</td>
<td>191 Trucks</td>
</tr>
<tr>
<td></td>
<td>Uninterrupted capacity</td>
<td>- Troop movement requirements</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Sand Storm</td>
</tr>
</tbody>
</table>

During planning, logisticians determined that 965 (originally planned) military trucks were needed to transport supplies from the TDC in Kuwait to troops in Iraq [14]. When forces crossed the line of departure (LD) into Iraq, there were only 191 (“actual”) trucks available. This shortage was due in part to decision makers allowing the deployment of transportation companies to be delayed for more combat troops. Unplanned events had additional impacts on the LTM trucks. The trucks were needed for unexpected troop movements and a three-
day sandstorm prevented any tucks from moving early in the operation (“actual”). Another area where what was originally planned and what actually happened differ was in the organization of 463L pallets. OIF planners wanted pallets to be built unit pure [14]. This means each pallet has only requisitions from a single customer. This allows pallets to bypass processing at the TDC because they are already sorted by unit. Due to problems with deployment unit designation, pallets were built with requisitions from multiple units on the same pallet. This led to the pallets needing to be broken down, by unit, at the TDC.

Originally planned and “actual” conditions differed at DDSP because there was not a plan to have to increase the capacity at the DC; however, as will be discussed later, significant queuing caused DDSP to hire additional workers to meet the demand. Although the exact plan for the TDC was not found, it is reasonable to assume that the plan was to have the TDC running, at least at partial capacity, prior to the start of OIF. What actually happened was staff did not arrive at the TDC until the day OIF began. The staff only consisted of 200 of the approximately 1,000 personnel needed to run the TDC. Additionally, the TDC began as a plot of open desert [14].

Different techniques were used to determine the many deterministic values needed for the processor inputs file. The mean processing time from the OIF dataset was used for the processing time for many of the processors in the network. The processors that used mean processing times were order & source time, travel time to the CCP, and transit time between A/SPOE & A/SPOD. For those processors that were based on a daily capacity, the processor times are one day. This essentially makes the processing time equal to the queue time plus one day. The processors that have a one day processing time are pick & pack, pallet build, and TDC operations. Processing times for transit time to the A/SPOD and transit time from
the A/SPOD to the TDC are each one day as determined using www.google.com. The round trip transit time for the LTM truck processor is based on the distance traveled and the planned rate of march [50]. Capacities for the processors were determined using historical documents [50] [14] or by using the MLNPS to determine the capacities that resulted in similar queuing as was in the OIF dataset. No matter the method used for determining the deterministic values, care was taken to try and use the best possible values; fully understanding that not all times or capacities are strictly deterministic.

The model was run with “actual” planning conditions and compared to how the network actually performed (reality). This is done by comparing the model results with either the empirical evidence from the OIF dataset or using anecdotal evidence from OIF After Action Reviews (AARs). Queuing at critical nodes along the network path, found in figure 4.1, was compared. All of the nodes were analyzed but only those with measurable queuing are discussed. The nodes are analyzed in order of how parts transit the network. A total of four nodes will be discussed during validation of the model. The first two nodes compared will be done so using empirical evidence from the OIF dataset. The first statistic compared is the queuing, commonly referred to as pick & pack time, at the DLA distribution center in Susquehanna (DDSP). DDSP was the primary distribution center for supplies going to OIF. The by-month average pick & pack time comparison for March to May, 2003, is presented in Figure 5.1.
The average pick & pack times from the model and dataset are quite similar, with a maximum difference of 0.24 days for any month. Considering the smallest time unit of the simulation is in days, this shows that the model very closely represent what really happened at DDSP.

The next node that had significant queuing was the airport of embarkation (APOE). The comparison of by-month average time in the queue at the APOE is presented in Figure 5.2.
The difference in APOE queue time between the model and dataset is more significant than at DDSP, but is no more than a little over a day for any of the three months. As discussed in section 4.3, estimating the number of daily pallet positions available for sustainment supplies is extremely difficult; therefore, a difference of a little over a day is not surprising or concerning. It is also not concerning because the Air Force can adjust the Air Tasking Order (ATO), on an almost daily basis, to meet the pallet position requirements. For this model, a constant number of pallets were used; although the model can handle fluctuating capacities. The results do show that the selected number of pallet positions correctly biased the model. Without the details provided by the ATO, the number of pallets positions must be estimated. It is important to keep in mind the estimated value needs to properly bias the model.

The last two nodes discussed are compared using anecdotal evidence, because the in-theater queue times were not available in the OIF dataset due to the difficulties in tracking
the supplies once they arrived in Kuwait. The anecdotal evidence comes from AAR comments stating that repair parts did not start arriving, uninterrupted, into Iraq until around 1 May, 2013 [50].

The first node that showed significant queuing during the first 90 days of OIF was the theater distribution center (TDC) in Kuwait. The by-day average time a requisition was in queue at the TDC is presented in Figure 5.3.

In addition to the by-day average time in the queue, figure 5.3 also shows the staffing level of the TDC with a secondary axis and line plot superimposed on the graph [14]. The day that coalition forces crossed the line of departure (LD) from Kuwait into Iraq, is also depicted on the graph to understand when forces were actually in Iraq waiting for supplies. The yellow
star marks the approximate day requisitions began consistently arriving at ordering units. It is important to point out that queue times do not include any requisitions for CL I or CL V. The graph shows that there is not any significant queuing until a little over a week after forces entered Iraq. This can be explained by the fact that few supplies were ordered until forces had a tactical pause in fighting and were able to put supplies on order. Once the ordering began, around the end of March, requisitions were in the TDC queue for a significant amount of time. This significant queuing can likely be explained by the fact that there were only 200 personnel working in the TDC and their primary focus was getting CL I and CL V into Iraq. The model had queuing that reached nearly 45 days before the TDC was able to start working off the backlog and reduce the queuing time. The point at which the model begins to show a significant drop in average queue time coincides with the 1 May date that AAR comments suggested parts began arriving uninterrupted to forces in Iraq. The TDC was able to finally begin working off the backlog of requisitions because of the increase in staffing. Although a direct comparison to the actual queuing at the TDC was not possible, the queuing from the model seems to mimic what actually happened based off the available anecdotal evidence.

The last node that showed significant queuing during the first 90 days of OIF was the processor that represented the last tactical mile trucks (LTM); the trucks that moved supplies from the TDC to units located in Iraq. The by-day average NUMBER of requisitions waiting to be moved by the LTM trucks is presented in Figure 5.4.
In addition to the by-day number of requisitions in the queue for LTM trucks, figure 5.4 shows the number of LTM trucks on hand for operations with a secondary axis and line plot superimposed on the graph [14]. The line of departure and approximate day requisitions began arriving in Iraq are again denoted just as figure 5.3. It is again important to point out that queue times do not include any requisitions for CL I or CL V. The graph shows that from the point when forces crossed into Iraq, the number of requisitions in the queue increased steadily until approximately 10 April. A series of events were contributors to the extensive queuing. First, as already discussed, 191 of the required 965 trucks were available when forces crossed into Iraq on 20 March 2003. Next, on 23 March, a sandstorm crippled logistics for a three-day period [14]. No trucks or aircraft were able to provide any type of resupply to troops in Iraq.
When the sandstorm finally cleared on 26 March, the last tactical mile trucks were re-tasked. Due to fierce enemy resistance along the major supply lines to Baghdad, brigade combat teams from the 101st and 82nd Airborne Divisions were needed to secure the terrain surrounding the main supply routes (MSRs) [14]. The brigade combat teams were all light infantry brigades, which do not have the transportation assets needed to move the required distance into Iraq. The last tactical mile trucks were therefore needed to transport the units. The troop movements consumed all of the available trucks from 26 to 30 March [14]. Once trucks were finally available for resupply operations on 31 March, troops in Iraq were in dire need of CL I and CL V resupply. They had gone a long period of time without any resupply, and their on-hand stockage of supplies was almost completely depleted [14]. In order to bring unit on-hand supply up to the appropriate levels, the available LTM trucks were filled almost exclusively with CL I and CL V. This helps explain why the backlog of requisitions was not immediately worked off in the model. According to the model, it was not until approximately 11 April until there was enough room on the LTM trucks to haul queued requisitions. This resulted in the queue of approximately 5,000 requisitions being delivered to units in Iraq. This did not, however, lead to an uninterrupted delivery of supplies. The TDC was still not operating at full capacity on 11 April (see figure 5.3), which resulted in requisitions only trickling out. As seen in figure 5.4, this period of time where LTM truck capacity far exceeded demand, due to a continued backlog at the TDC, continued until approximately 5 May. Soon after, the model shows more steady state operations with requisitions only queuing due to the resupply schedule and not due to a lack of resources. This is the point at which the model shows uninterrupted delivery of requisitions to units in
Iraq. Just as with the TDC queuing, LTM truck queuing from the model seems to mimic what actually happened based off the available anecdotal evidence.

As presented in figures 5.1-5.4, comparing model network performance under “actual” conditions to results from the OIF dataset showed that the model is capable of closely mimicking an actual logistical network. This gave the model the credibility needed to use the MLNPS to plan the logistical network for a contingency operation.

5.4 Using the MLNPS to plan Operation Iraqi Freedom

Again using the OIF dataset, the MLNPS was next used to show its value in planning the logistical network for a contingency operation. Since many of the planning factors for OIF are known, the MLNPS is used to model the OIF network under originally planned conditions (see table 5.2). The originally planned factors are what OIF planners determined were needed, using the planning tools they had at the time and the tactical plan for OIF. The model is run with the originally planned input values and the network performance is analyzed. The network performance from the model is compared to how the network was performing, in terms of queuing, prior to the start of OIF. This queueing occurring prior to OIF is referred to as acceptable queueing. This acceptable queueing is the mean queue time for the three months, in 2003, leading up to the start of OIF. When the queue time is not available from the OIF dataset, an acceptable queue time is estimated.

Acceptable queuing at each node was compared to the queueing from the model. For the first 90 days of operations, the model did not show significant queuing at any node. This shows that if the OIF logistical network had been established as planned, it would have run without any excessive queuing for the first 90 days of operations; as was actually seen and discussed in section 5.3.
The model was then run for a 365 day period using all of the requisitions from 2003; from the OIF dataset. This was done to see if the model would show any significant queuing later in the operation. Initially, only the first 90 days were modeled because the operational plan tends to change significantly after the first 90 days and the computation time for the model increases; however, with a tool like the MLNPS the model could be run for 365 days without running out of memory.

The dataset used to model all of the requisitions entering the supply system in 2003 consisted of 7.67 million requisitions; approximately 4 times larger than the 90 day dataset. The model was run, and significant queuing was seen for the pick & pack operations at DDSP. The queuing did not occur in the first 90 days, but shortly after began to steadily increase until queuing exceeded 25 days in December 2003. The queuing the model predicted is presented in Figure 5.5.

![Figure 5.5: DDSP Avg Pick & Pack Times for 2003 (As Planned)](image-url)
As planned, it was thought that DDSP capacity at the start of OIF would be sufficient to handle the requirements of OIF. What actually happened? At some point during OIF, DDSP received indicators that the demand was exceeding the capacity. DDSP had to hire 400 additional workers to try and work off the requisition backlog and prevent further backlogs [14]. The indicators were not seen with enough time to hire the 400 workers needed to prevent significant queuing. By the time the additional 400 workers were able to start working off the backlog of requisitions, the queuing had reached almost 12 days in August. Figure 5.6 shows the comparison of monthly queuing predicted by the model (without any increase in capacity) and the actual queuing from the OIF dataset (with the increase in capacity from 400 additional workers).

![Figure 5.6: DDSP Avg Pick & Pack Time as Planned vs. Actual OIF](image)

As seen in figure 5.6, the hiring of 400 additional workers resulted in DDSP eventually getting the queuing under control by the end of 2003; however, the peak queuing of 12 days was unacceptable and had profound downstream network impacts [14]. Ideally, DDSP gets
bottleneck indicators earlier and can hire workers in time to prevent queuing from exceeding 3-4 days. The MLNPS is a tool that CAN forecast significant queuing in time for capacity to be properly adjusted.

In order to show how the MLNPS could have been used to plan capacity needs at DDSP, the model is run under original planning conditions using the entire 2003 OIF dataset. With the understanding that the OIF dataset has the actual increase in requisitions as OIF matured, one may question whether or not this could have actually been forecasted; without being able to forecast that increase in volume, the MLNPS would not be value added. Figure 5.7 helps answer that question whether or not the actual increase in requisition volume could have been forecasted.

![Figure 5.7: 2003 DDSP Requisition Volume and BCTs in Iraq](image-url)

The primary axis of figure 5.7 shows the monthly volume of requisitions arriving at DDSP and the secondary axis shows the steady increase in the number of brigade combat teams.
fighting in Iraq. A positive correlation between the number of brigade combat teams and the number of requisitions is clear. DDSP may or may not have been privy to the number of BCTs planned for Iraq, but if they had, they would have been able to forecast the increase in requisition volume.

Moving forward with the assumption that DDSP could have forecasted the increase in volume, the model was run with the entire 2003 OIF dataset; however, this time the capacity at DDSP was incrementally changed at different points in time. First, the capacity was increased by 2,000 requisitions per day starting the end of May. Figure 5.8 shows how the average pick & pack time at DDSP decreased from the original plan.

![Figure 5.8: DDSP Avg Pick & Pack Time with Added Capacity – 1st Iteration (Red)](image)

The model shows the pick & pack time leveling out to acceptable levels through September, but then steadily increasing to almost ten days.

With pick & pack times still at unacceptable levels, the capacity was increased by an additional 1,000 requisitions per day (3,000 total increase) starting the end of May. Figure
5.9 shows how the average pick & pack time at DDSP decreased compared to the previous iterations.

The model shows the pick & pack time now leveling out to acceptable levels through the beginning of November, but then increasing beyond acceptable levels.

Noticing that unacceptable queuing was not present until the end of the year, for the third iteration, additional capacity was added later in the year. An additional capacity of 500 requisitions per day was added to the model in November. Figure 5.10 shows the average pick & pack times at DDSP compared to the previous iterations.
After the third iteration of capacity adjustments, the model queuing appears to be under control. With additional capacity of 3,000 requisitions per day (15% increase in capacity) added in May and 500 added November, DDSP would be able to handle the volume of requisitions associated with the increase of BCTs fighting in Iraq. There could be more efficient solutions, and working with DDSP to plan a more phased hiring plan would almost certainly be better than the incremental capacity changes used in the three iterations. This does however illustrate how the MLNPS could be used to forecast and then eliminate queuing at a distribution center. What is not shown, but needs to be mentioned, is the potential downstream network improvements created by reduced queuing at DDSP.

Having used the MLNPS to test and improve the logistical plan for OIF, the next step is to determine the resiliency/robustness of the plan.
5.5 Sensitivity Analysis of the Improved Network

Common practice during operational planning is to determine the resiliency of a plan. A commonly used quote during operational planning, credited to Helmuth Moltke the Elder, is “No plan survives first contact with the enemy.” While the enemy is often a contributing factor to a change in plans, many other factors can also affect a plan. The premise of the quote is that war is extremely complicated and rarely plays out as envisioned during planning. Sensitivity analysis is therefore conducted in attempt to make a plan robust enough to withstand potential changes. The MLNPS can be used to conduct such sensitivity analysis. For OIF, the MLNPS was used to determine how sensitive the planned network (with adjusted DDSP capacity) was to an increase in requisition volume and a decrease in the number of last tactical mile trucks.

What if the mission based forecast used for the OIF mission was not accurate? What if the volume of requisitions was underestimated by as much as 15%? The MLNPS can be used to help determine how sensitive the plan is to such an increase in volume of requisitions. The volume of requisitions was increased by 15% and the MLNPS was run. The 90-day average pick & pack time increased from 3.37 days to 4.24 days. With an increased pick & pack time of less than one day, it does not appear that the network is very sensitive to the increased requisition volume; however, a decision maker would determine whether or not the increase in pick & pack time is acceptable. If unacceptable, the capacity at DDSP could be increased to maintain an acceptable pick & pack time.

The original OIF plan called for 965 trucks to move supplies from Kuwait to Iraq. At some point in time, planners cut or delayed the deployment of truck companies. The exact reason is not known; however, it is believed that the deployment of truck companies was delayed to speed up the deployment of combat troops [14]. When planners were deciding to
delay trucks, the MLNPS could have been used to help them determine how many trucks could be cut without affecting logistical operations.

Determining how many trucks are needed to sustain logistical operations is done by first starting with how many trucks were present at the start of operations. Using available planning tools, planners must have determined that 200 trucks were sufficient since that is what was available at the start of OIF. 200 trucks are therefore entered into the model and the model is run. Figure 5.11 shows that, with 200 trucks, the number of requisitions in queue would reach around 15,000 by the middle of April before leveling out to more steady state.

The model clearly shows that 200 trucks are not sufficient to sustain logistical operation for OIF. The MLNPS is then used to incrementally increase the number of trucks until the queuing is at an acceptable level. The model is run with 300 trucks and queuing at the LTM trucks is observed. Figure 5.12 shows the queuing with 300 trucks. The graph values for 300 LTM trucks are offset by 1.5 days in order to observe both sets of data. When needed, this offset technique is used in subsequent graphs.
The queuing appears to near steady state at the beginning of the operations without ever having significant queuing, as was present with 200 trucks. This shows that the model suggests 300 trucks would be a sufficient number for the start of operations in Iraq. It is important to note that the number of trucks would also have to grow similar to how they actually grew for the operation; 300 trucks would not be enough for the duration of the operation. Knowing that 300 trucks was the minimum needed for the start of the operations, planners could have ensured the extra 100 trucks were not delayed in arriving to Kuwait. The MLNPS could be used to plan a phased increase in trucks, but was not in this case.

Having shown that the MLNPS can closely replicate an actual operation, using actual data, the next step is to show how the MLNPS could be used to plan a notional operation anywhere in the world. This is discussed in Chapter 6.
Chapter 6
Using the MLNPS to Plan a Notional Operation in Sudan

Once the MLNPS was validated as a credible tool for predicting the performance of the Army’s logistical system, the next step was to show how it could be used to help plan any contingency operation. With a list of forces required, a mission-based forecast can be generated. The movement of the requisitions from the mission-based forecast can then be simulated over a time horizon of interest; for example, the first 100 days of operations. The simulation results are then used to observe predicted network performance and determine the logistical requirements at each critical node.

6.1 The Notional Operation in Sudan

In order to use the MLNPS to plan the logistical network for an expeditionary operation, a notional operation had to be created. The background for the notional operation is that the Islamic State in Iraq and Syria (ISIS) has moved equipment and fighters from Libya into the bordering country of Sudan. The Sudanese government is harboring these fighters and facilitating the planning and execution of attacks on bordering countries. ISIS is using the safe haven in Sudan to stage attacks in other countries in Africa, mainly in South Sudan. The international community has condemned the actions of the Sudanese government in harboring ISIS. The United States sees the presence of ISIS in Sudan as a threat to African Allies and tremendous instability in the region. The United States has committed to helping protect South Sudan and other African Allies. The mission for the U.S is to destroy ISIS troops and equipment in Sudan, in order to prevent their ability to conduct attacks in Africa.

With the concentration of ISIS fighters in the capital of Khartoum and the impoverished Darfur region, the mission requires two U.S. Brigade Combat Teams (BCTs).
The plan calls for one Infantry Brigade Combat Team (IBCT) and one Stryker Brigade Combat Team (SBCT). The SBCT will conduct operations in the Darfur region and the IBCT will operate in Khartoum. The entire task organization (troops required) for the operation is presented in Table 6.1.

### Table 6.1: Sudan Mission Task Organization

<table>
<thead>
<tr>
<th>Task Organization</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 x Infantry Brigade Combat Team</td>
</tr>
<tr>
<td>1 x Stryker Brigade Combat Team</td>
</tr>
<tr>
<td>1 x Engineer Battalion (Construction Effects)</td>
</tr>
<tr>
<td>1 x Sustainment Brigade</td>
</tr>
<tr>
<td>1 x Aviation Battalion (Attack and Lift)</td>
</tr>
<tr>
<td>1 x Division Headquarters</td>
</tr>
<tr>
<td>3 x Battalion Miscellaneous Enablers</td>
</tr>
</tbody>
</table>

This task organization is mainly used to create the mission-based forecast, which will be discussed later in the chapter.

The path a requisition travels for the Sudan operation is similar to OIF except for the geographical differences once the supplies go overseas. The path of a requisition is shown in Figure 6.1.

![Figure 6.1: Requisition Path from CONUS to Sudan](image-url)
There are many ways to get forces into Sudan. One option would be to do a forced amphibious entry via the Red Sea; however, amphibious forced entries are extremely complex and risky operations. Another option would be to come through the friendly nations of Djibouti and Ethiopia. This option provides a port that is close to operations in Sudan, but the Ethiopian Highlands are a massive mountain range that splits Ethiopia and severely restricts any East to West movement across the country. Therefore, the seaport of debarkation (SPOD) selected for this notional operation is the port of Mombasa, Kenya. The Theater Distribution Center (TDC) is established in South Sudan, which borders the hostile nation of Sudan. It is assumed that the truck network in Africa is not sufficient to transport the shipping containers; therefore, military trucks must be used for all trucking operations. The distance between the port & TDC and the distance between the TDC & the units in Sudan are much greater than the distances during OIF. This will be discussed more, later in the chapter. The airport of debarkation (APOD) is located in South Sudan and in close proximity to the TDC.

6.2 Generating the Mission-Based Forecast

Due to the fact that there is no mission-based forecast for this notional operation, nor is there a dataset to act as a surrogate, a forecast had to be generated. The forecast was generated using numerous different properties of the OIF dataset. The following is a list of the characteristics that had to be generated for each requisition: Release date, demand node (ordering unit), mode of transportation, due date, supply node (distribution center), weight, and cube. For each characteristic a unique distribution was used. The distributions for each will be discussed in more detail later. The order of characteristic generation is important because some of the distributions used are conditioned on other characteristics of the requisition. Although some requisition characteristics are independent of the ordering unit,
requisition generation is done by unit and then concatenated to create one single forecast of requisitions.

Before any requisition generation can begin, a time horizon must be placed on the simulation. This establishes the time frame of the operation over which the logistical network will be analyzed and defines the period for which requisitions must be generated. For the notional operation in Sudan, the time horizon is the first 150 days of the operation or \([0, T = 150]\) days.

The first characteristic that had to be generated was the release date. A distribution had to be fit to the OIF data to begin this generation. The distribution for release date is conditioned on the type of unit (demand node) and the operational intensity level (OIL). Each unit in the task organization (see table 6.1) must be represented using a different distribution because each has a different order intensity. For example, the order intensity for a headquarters unit is much different than an IBCT conducting combat operations. The OIF dataset was parsed by unit type to represent the units supporting the notional operation in Sudan. The three levels of intensity correspond to different phases of combat operations. The three phases of combat operations are pre-combat (OIL 1), steady state FOB operations (OIL 2), and high intensity conflict (OIL 3). For each unit type, the OIF dataset was broken down into three different datasets, each having requisitions that were ordered during one of the three phases of combat operations. The different phases of combat operations during OIF were determined using historical evidence [50]. For each unit specific dataset, a distribution was fit to help generate datasets with similar intensity levels. Those distributions were then used to generate by-day requisition intensity.
For the operation in Sudan, 21 different distributions were used to generate the release dates; there are seven different unit types and three different operational intensities for each unit. All 21 distributions will not be discussed, instead the specifics will be discussed for one unit type; the aviation battalion. First, an operational intensity level schedule had to be established for the aviation battalion. For an actual operation, this would be pulled from paragraph 3 of the operation order. The operational intensity level schedule for the aviation battalion operations in Sudan is:

\[
\text{OIL schedule (AVN BN)} = \begin{bmatrix} 0 & 60 \\ 89 & 150 \\ 61 & 88 \end{bmatrix}
\]

This schedule is interpreted in the following manner: For the first 60 days of the simulation the unit is operating in OIL 1, from day 89 to 150 it is operating in OIL 2 and from day 61 to 88 it is operating in OIL 3. The schedule may be different for each unit depending upon the specific mission and progress of that mission.

Stat::Fit® was used to fit a distribution for each of the sub-datasets, using a significance level of 0.05 ($\alpha = 0.05$). Distributions were successfully fit for OIL 1 and OIL 3, but an empirical distribution had to be used for OIL 2 because it failed the chi-squared goodness-of-fit test. After data fitting, the following distributions were used:

**OIL 1:** \(N_{rel}^{1} \overset{\text{iid}}{\sim} \text{Weibull}(A = 172.22, B = 0.734928)\) (Requisitions)

- Chi-Squared: \(\chi^2_{3,05} = 7.81\) p-val = .651
- Kolmogorov-Smirnov: K-S\(_{22,05} = .281\) p-val = .903

**OIL 2:** \(N_{rel}^{2} \overset{\text{iid}}{\sim} EDF_{2}^{\text{AvnBN}}\) (Requisitions)

- Chi-Squared: \(\chi^2_{6,05} = 12.6\) p-val = .0306
- Kolmogorov-Smirnov: $K-S_{22,0.05} = .194$  \( p \)-val = .742

**OIL 3:** \( Nrel^3 \) \( \sim \) LogLogistic \((\mu = 1.56076, \sigma = 150.406)\) (Requisitions)

- Chi-Squared: \( \chi^2_{2,0.05} = 5.99 \)  \( p \)-val = .846
- Kolmogorov-Smirnov: $K-S_{18,0.05} = .309$  \( p \)-val = .91

Where \( Nrel^j \) is the set of the requisitions released each day the operation is in the \( j \)th OIL.

Using the aviation battalion as an example, \( Nrel^1 \) is a vector of length 61 where each number in the vector is the number of requisitions released on the corresponding day. Concatenating the vectors gives \( Nrel \), where

\[
Nrel \sim \begin{bmatrix} Nrel^1 \\ Nrel^3 \\ Nrel^2 \end{bmatrix}.
\]

The total number of jobs, \( Njobs \), becomes

\[
Njobs = \sum_i Nrel_i,
\]

where \( i \) represent the simulation day. For the Sudan operation, the number of jobs generated for the aviation battalion was \( Njobs = 63,674 \).

The next characteristic generated was the mode of transportation (\( Tmode \)). Mode of transportation is independent of any other characteristic as it was obtained from transportation mode frequency from OIF requisitions over the first 90 days. The mode of transportation is generated using the probability mass function presented in Table 6.2.
Table 6.2: Mode of Transportation pmf

<table>
<thead>
<tr>
<th>$T_{mode}$</th>
<th>$j$</th>
<th>$P(T_{mode}=j)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MilAir</td>
<td>1</td>
<td>0.7340</td>
</tr>
<tr>
<td>WWX</td>
<td>2</td>
<td>0.1292</td>
</tr>
<tr>
<td>Ocean</td>
<td>3</td>
<td>0.1368</td>
</tr>
</tbody>
</table>

It is important to note that this pmf is based off the high volume of MilAir used to transport sustainment supplies during OIF. The operation in Sudan may or may not have the same proportion of supplies moving via MilAir. If this were an actual mission, logistical planners would have a target percentage for each mode of transportation. The pmf vector could then be changed to reflect the transportation goals. Without such goals, it is reasonable to use OIF percentages.

Once the mode of transportation ($T_{mode}$) is determined, the due date can be generated. Due dates ($DD$) were generated as discussed in section 4.4.2.1.

$$DD_i = (SDT_i | T_{mode}) + RT_i \text{ (Days)}$$

Where the standard delivery times ($SDT$) are generated conditional upon the mode of transportation as such:

$$SDT_i | T_{mode} \sim Uniform(a(T_{mode}), b(T_{mode})) \text{ (Days)}.$$

The supply node is generated conditional upon the demand node. For each demand node, a pmf is generated using the percentage of time each of the 30 supply nodes fills a requisition for a demand node. The percentages are based off the historical OIF data. It is unique to each demand node because each different type of unit needs specific supplies. For example, a signal unit would have a higher than normal percentage of requisitions filled by the DLA distribution center in Tobyhanna, PA. That DC primarily supplies communications
and electronics equipment. An example supply node *pmf* for a demand node is presented in Table 6.3.

<table>
<thead>
<tr>
<th>Supply Node (SN)</th>
<th>j</th>
<th>P(SN=j)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDSP</td>
<td>1</td>
<td>0.64</td>
</tr>
<tr>
<td>Chrlst</td>
<td>2</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Rockls</td>
<td>30</td>
<td>0.09</td>
</tr>
</tbody>
</table>

The last characteristics to be generated are the weight and cube for each requisition. Analysis of the OIF dataset showed a correlation between weight and cube and each unit type had a different correlation. The correlation associated with each unit type is presented in Table 6.4.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Correlation WT &amp; CU</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBCT</td>
<td>0.7830</td>
<td>51,381</td>
</tr>
<tr>
<td>HBCT (SBCT)</td>
<td>0.7833</td>
<td>23,543</td>
</tr>
<tr>
<td>Aviation BN</td>
<td>0.6338</td>
<td>47,451</td>
</tr>
<tr>
<td>Engineer BN</td>
<td>0.3422</td>
<td>22,747</td>
</tr>
<tr>
<td>Truck Company</td>
<td>0.9813</td>
<td>9,901</td>
</tr>
<tr>
<td>Division HQs</td>
<td>0.7127</td>
<td>19,890</td>
</tr>
<tr>
<td>Sustainment BDE</td>
<td>0.7072</td>
<td>85,662</td>
</tr>
<tr>
<td>Misc Enabler BN</td>
<td>0.9865</td>
<td>1,466</td>
</tr>
</tbody>
</table>

In order to account for the correlation between weight and cube, the Gaussian Copula method is used. The Gaussian Copula method uses a multivariate normal probability distribution with the appropriate covariance matrix to achieve two separate sequences of random numbers that will have an expected correlation equal to some target correlation. This allowed for the
generation of a weight and cube for each requisition while maintaining the correlation between the two. Within the Gaussian Copula method, a lognormal is used for both weight and cube; each represented by a different lognormal.

Up to this point, everything modeled was or was assumed to be deterministic. Because of the deterministic nature of the models, single data points were used during analysis of the networks. Random generation of the mission-based forecast introduces a stochastic element to the model. Because single data points cannot necessarily be used with stochastic modeling, analysis had to be done to determine the number of data points needed to provide reliable results. Five forecasts were generated and simulated, and the variability in queuing at each of the critical nodes was analyzed. For each critical node, all five data points were compared. The results showed that across all critical nodes the maximum half-width for any day was 0.336 hours or just over 8 hours. Considering the smallest time unit of the simulation is days, a maximum half-width of eight hours is not significant. Thus, all further analysis was done using a single data point.

6.3 Using the MLNPS to Plan the Logistical Network

Due to the long distance between the SPOD and units in Sudan, network planning includes looking at two different locations to put the TDC. The first location for the TDC is in the capital of South Sudan, Juba. Placing the TDC in Juba decreases the distance between the SPOD and TDC, but increases the distance between the TDC and the units in Sudan. Placing the TDC in Juba will be referred to as Course of Action (COA) 1. The alternate location for the TDC is in the city of Wau. Wau is closer to the border with Sudan, thus decreases the distance between the TDC and the units in Sudan but increases the distance between the SPOD and TDC. Placing the TDC in Wau will be referred to as COA2. The geographic relationship between the two locations is shown in Figure 6.2.
Each course of action has distinctly different travel times for the trucks transporting supplies. Round trip times for convoys vary between six and ten days. The travel time was determined using the road distance from www.google.com, and a march rate of 30 kilometers per hour. A summary of the round trip times used for each COA is found in Table 6.5.

<table>
<thead>
<tr>
<th>Travel Leg</th>
<th>COA 1 (Juba)</th>
<th>COA 2 (Wau)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPOD to TDC</td>
<td>7 Days Round Trip</td>
<td>10 Days Round Trip</td>
</tr>
<tr>
<td>TDC to IBCT in Sudan</td>
<td>10 Days Round Trip</td>
<td>8 Days Round Trip</td>
</tr>
<tr>
<td>TDC to SBCT in Sudan</td>
<td>8 Days Round Trip</td>
<td>6 Days Round Trip</td>
</tr>
</tbody>
</table>

For each course of action, the MLNPS was used to determine the capacities needed for each of the critical nodes. The critical nodes analyzed for this operation are DDSP, APOE, A/SPOD trucks, TDC, and last tactical mile trucks. Once the MLNPS is used to determine the capacities needed at each critical node for each COA, the COAs are compared and a COA is recommended to the commander. Details of the two courses of action are discussed in the two subsequent sections.
6.3.1 Course of Action 1 (TDC located in Juba)

Course of Action 1 is to locate the TDC near the airport in Juba. The first node analyzed was DDSP. If doing the planning for an actual operation, a decision maker would determine what amount of queuing is acceptable at each node. In lieu of a decision maker, the steady state average of three days to pick & pack a requisition at DDSP was used as a benchmark. The capacity at DDSP was adjusted until the average pick & pack time was approximately three days, which resulted in a required capacity of 2,100 requisitions per day. The next node analyzed was wait time for pallets at the APOE. The same steady state average of three days wait was used as a benchmark. A capacity of 25 pallet positions per day resulted in an average queue time of approximately three days. The next node analyzed was the trucks that move containers from the SPOD to the TDC. Because this is a new operation without any data from which averages could be pulled, the MLNPS was used iteratively to find the required capacity. Capacity is in terms of number of truck companies. A truck company is assumed to be 60 medium trucks with 60 trailers. It is also assumed that security along the route is such that trucks must travel together in a convoy. The node was first tested with two truck companies. The queuing at the SPOD associated with a capacity of two truck companies is presented in Figure 6.3.
The y-axis is the time a container waited in queue to be loaded onto trucks headed for the TDC. The x-axis is the day of the operation, with D-day being the day the operation started. Figure 6.3 shows that the queuing grew linearly to a peak of approximately 90 days. This queuing is obviously unacceptable, so the model was run with three trucks companies. The queuing associated with a capacity of three truck companies is presented in Figure 6.4.
With three truck companies, the queuing dropped significantly, but still steadily increases after D+80 to over 30 days. The model was run with four truck companies and the resultant queuing is presented in Figure 6.5.
Again, the queuing drops significantly, but spikes to an unacceptable level after D+140. The model was run with five truck companies and the resultant queuing is presented in Figure 6.6.

![Figure 6.6: SPOD Queuing for COA 1 (5 Truck Companies)](image)

With five truck companies, the queuing is reduced to an average of approximately three days for the duration of the operation. It appears now that the queuing is due to the round trip time of the trucks, not due to insufficient capacity on the trucks when they depart. After using the MLNPS to analyze the queuing at the SPOD, the recommended number of truck companies to support the operation is five.

The next node analyzed was the theater distribution center. Unlike the DDSP and APOE nodes, the OIF dataset did not have a steady state average to use as a benchmark for operations is Sudan. It was therefore assumed that an acceptable level of queuing was the same as the DDSP and APOE nodes, three days. The TDC capacity was incrementally adjusted until the average queuing was approximately three days. The required capacity was
determined to be 500 pallet equivalents per day. Meaning the TDC needs to be able to break down and separate 500 pallet equivalents (a 40-foot container is equivalent to five pallets) per day.

The last node analyzed was the last tactical mile (LTM) trucks. Just like the SPOD trucks, no acceptable average queue time was available to use as a benchmark. Each time a convoy departs for either the SBCT or IBCT location, it must have enough days of supply (DOS) of food, water, and ammunition to sustain the unit until the next convoy arrives. Because the BCTs were different distances from the TDC, they each need a different number of days of supply of food, water, and ammunition. The SBCT requires eight DOS and the IBCT requires ten DOS. Due to the long roundtrip times associated with this operation, the number of trucks needed to haul just food, water, and ammunition creates a lower bound of approximately 6.5 truck companies. The model was therefore initially run with a capacity of 6.5 trucks, with the number of trucks dedicated to each BCT proportional to the number of DOS required. The resultant queuing for each of the two brigade combat teams is presented in Figure 6.7.
The average queue time for the IBCT, although between eight and ten days, appears to resemble near steady state; however, it is not for certain with this one data point. The average queue time for the SBCT is nowhere near acceptable, exceeding 40 days. The difference in queuing between the trucks supporting the SBCT and IBCT makes sense because the SBCT is farther from the TDC and has more (and much larger) vehicles than the IBCT (thus more and heavier required repair parts).

The number of truck companies was increased to seven and the queuing was observed. The resultant queuing is presented in Figure 6.8.
The average queue time for the IBCT did not change, confirming that the observed queuing is solely due to the time waiting for the trucks to return from a supply run. Because the trucks are sufficient for the IBCT, the number of trucks dedicated to the IBCT is held constant for all future runs of the model. The queuing for the SBCT trucks dropped to what looks like may be near a form of steady state, but the model needed to be run with additional capacity to confirm. The number of truck companies was increased to eight and queuing was observed. The resultant queuing for just the SBCT is presented in Figure 6.9.
The average queue time for eight truck companies did not differ from seven truck companies, confirming that the queuing with seven trucks was not due to a lack of capacity. The recommended number of truck companies to dedicate to last tactical mile operations is therefore seven.

A summary of the capacities required for COA 1, as determined using the MLNPS, are presented in Table 6.6.

<table>
<thead>
<tr>
<th>Critical Node</th>
<th>COA 1 Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDSP</td>
<td>2,100 Requisitions/day</td>
</tr>
<tr>
<td>APOE</td>
<td>25 Pallets/day</td>
</tr>
<tr>
<td>A/SPOD Trucks</td>
<td>5 Truck Companies</td>
</tr>
<tr>
<td>TDC</td>
<td>500 Pallet Equivalents/day</td>
</tr>
<tr>
<td>LTM Trucks</td>
<td>7 Truck Companies</td>
</tr>
</tbody>
</table>

6.3.2 Course of Action 2 (TDC Located in Wau)

The MLNPS was next used to determine the capacities needed at each critical node when the TDC is located in the city of Wau (COA 2). The MLNPS was used in the same manner as when determining the required capacities for COA 1; however, the capacities for the DDSP and APOE nodes were not modeled because the network does not differ from COA 1 until the SPOD trucks. Those values will be the same for both COAs. A summary of the capacities required for COA 2, as determined using the MLNPS, are presented in Table 6.7.
104

Table 6.7: COA 2 Required Capacities

<table>
<thead>
<tr>
<th>Critical Node</th>
<th>COA 2 Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDSP</td>
<td>2,100 Requisitions/day</td>
</tr>
<tr>
<td>APOE</td>
<td>25 Pallets/day</td>
</tr>
<tr>
<td>A/SPOD Trucks</td>
<td>7 Truck Companies</td>
</tr>
<tr>
<td>TDC</td>
<td>700 Pallet Equivalents/day</td>
</tr>
<tr>
<td>LTM Trucks</td>
<td>6 Truck Companies</td>
</tr>
</tbody>
</table>

As expected, the number of A/SPOD truck companies increased and the number of LTM truck companies decreased. This is logical because the only differences in the two networks are the locations of the TDC.

6.3.3 Course of Action Comparison and Recommendation to the Commander

With the combatant commander looking at two different courses of action, he/she has to receive a recommended course of action from each of the staff sections that represent the warfighting functions. For example, the staff section representing the protection warfighting function would probably recommend the COA that allows the forces to most easily secure the TDC and the convoys moving between it. For logistics, one has to look at the equipment and personnel needed to support a specific COA. A course of action comparison is conducted to determine which COA is better. Table 6.8 shows the COA comparison with only those criteria that differ between the COAs.

Table 6.8: Course of Action Comparison

<table>
<thead>
<tr>
<th>Comparison Criteria</th>
<th>COA 1 (Juba TDC)</th>
<th>COA 2 (Wau TDC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required Truck COs</td>
<td>12 Truck Companies</td>
<td>13 Truck Companies</td>
</tr>
<tr>
<td>TDC Capacity</td>
<td>500 Pallet Equivalents</td>
<td>700 Pallet Equivalents</td>
</tr>
<tr>
<td>Avg Total Queuing (in Theater)</td>
<td>10.4 days</td>
<td>14.6 days</td>
</tr>
</tbody>
</table>
Course of action 1 clearly is the recommended course of action, bettering COA 2 in each of the three distinguishing categories.

Although COA 1 is the recommended course of action, the required number of truck companies may lead to the commander requiring further analysis. Twelve truck companies appears to be a significant commitment of transportation assets to support two brigade combat teams. Other courses of action could be analyzed to include having more sustainment supplies flown directly in South Sudan and Sudan instead of going through the port of Mombasa. This obviously would require additional Air Force aircraft but the actual tradeoff is not known. By changing the logistical network to reflect such a change in the plan, the MLNPS could be used to plan the assets needed to support such a course of action. In fact, almost any course of action could be analyzed and compared. This research showed just two possible courses of action and how the MLNPS could be used to recommend and plan for a course of action.

6.4 Sensitivity Analysis of the Plan

Once a course of action is recommended and decided upon, the MLNPS can be used to see how robust or resilient the plan is to potential changes. These potential changes can be thought of as the “What Ifs.” As discussed in section 5.5, there are many “What Ifs” that can be analyzed. For this scenario, impacts of underestimated forecast and seven day disruption of supply lines were analyzed.

If the actual volume of requisitions created during the operation was actually 20% more than the mission-based forecast used during planning, how would that impact logistical operations? In order to answer this question, the volume of requisitions was increased by 20% and the resultant queuing at four critical nodes was compared to original queuing. The queuing comparison of the four nodes is presented in Figure 6.10.
The queuing at DDSP increases by a maximum of one day but then returns to the original queuing levels. The queuing at the APO increased by a maximum of nearly two days but no more than one day on average for the duration of the operation. The queuing for the SPOD and LTM trucks increased minimally. Although an actual decision maker may disagree, it appears that the network, as planned, is not sensitive up to a 20% increase in requisition volume.

Next, the SPOD and LTM trucks were analyzed to determine how sensitive they were to a seven day cut or disruption of the supply lines. Meaning the trucks are not able to move for a seven day period. This may be due to weather, a damaged bridge, enemy action, or many other potential reasons. The impacts of a seven day disruption on the SPOD trucks are shown in Figure 6.11.
The disruption causes an initial spike in queuing of approximately three days and then levels off to a near constant increase of one day. Because the queuing never returns to pre-disruption values, a reasonable conclusion is that the number of SPOD trucks does not make the network robust enough to handle a seven day disruption of the supply lines. If the decision maker agreed with this assessment, the number of SPOD truck companies would be increased and the sensitivity again tested for robustness.

The next node tested for robustness is the LTM trucks. The queuing of these trucks without a disruption of the supply lines is presented in Figure 6.12.
The queuing varies between the two BCTs, but is between five and eight days. A seven-day disruption of the supply lines is inserted into the model and the resultant queuing is presented in Figure 6.13.
The seven day disruption creates an initial spike in excess of 15 days for both BCTs before leveling off at queuing levels seen without a disruption. The fact that the queuing returns to levels seen prior to the disruption leads to a conclusion that the number of LTM trucks does make the network robust enough to handle a seven day disruption of the supply lines.

During this research, the MLPS was used only to plan the logistical requirements for an operation. It could also be used during an operation. It could be used to predict the impact of different operational scenarios on the logistical network. If for example a storm powerful enough to shut down air and ground logistical operations was nearing the area of operations, the MLNPS could be used to predict the impacts on the logistical network. The impacts could be presented to the commander, giving time to either adjust the logistical network or take other measures to limit the negative impacts.
Chapter 7
Future Research

The model presented in this research looks at the end-to-end movement of sustainment supplies needed for supporting expeditionary operations. This is just one potential use of this model. With additional adaptations to the model, it could be used to solve numerous other problems. Some potential extensions of the model are:

1) Include Reverse Logistics: Many of the repair parts that transit the Army supply system are recoverable items. These items must be shipped back to depots in the U.S. to be repaired or rebuilt. Once re-built, they are put back into the supply system. The assets used to transport these items back to the U.S. are the same assets that transported the items to the customer conducting combat operations. Just as is seen with the forward flow of supplies, there are other resources competing for the transportation assets used for reverse flow. Modeling the reverse logistics would require major adaptations to the current model, but if accomplished would better model the movement of sustainment supplies.

2) Fuel Logistics: Fuel is transported in different transportation assets than are sustainment supplies. Storage of fuel also uses different assets and has to be secured differently than sustainment supplies. The general model for fuel, however, is not much different that the model presented in this research. With minor adaptations, the MNLPS could model and help improve fuel network planning for expeditionary operations.

There are several areas where the model could be improved in order to make it more accurate and easier to use. The following are three areas where such improvements could be made:

1) The procedure for determining the required capacities at a node could be improved, making the model predictions more accurate and rapid. Currently, capacities are
determined, essentially, through trial and error. Capacities are increased or decreased until queuing reaches an acceptable level. The increments of change are also selected through trial and error. The trial and error approach works, but requires numerous runs of the model in order to get to a good solution. Depending upon the node and queuing level, this can increase the computation time significantly. Additionally, the accuracy of the solution is dependent upon the increment of change. If the increment of change is truck companies, the model will not find a better solution that is in a half-company increment. A form of regression might be able to provide a range of input values (node capacities) and the resultant queuing without having to run the model at each possible value. Fewer runs of the model may be able to provide enough data points to create a response surface suitable for this type of analysis. If possible, this would results in a more rapid and accurate planning process.

2) Just as the procedure for determining node capacities, the procedure for sensitivity analysis could be improved in a similar manner. Currently, node capacities are changed and the model is run to see if the change has a significant impact on queuing. This works well when the amount of possible change is known. The exact amount of change the network must be able to withstand is not always known. A similar response surface created using minimal data points could provide a commander with a range of changes to a node and the resultant impacts on the network.

3) A major extension of this research would be to look at the stochastic nature of the network. Currently the model uses deterministic numbers, usually mean-values, to represent operations that are not truly deterministic. For example, the time it takes to drive from a theater distribution center to forward operating base is not deterministic. Road congestion, weather, road conditions, enemy actions, and vehicle breakdowns, all have an
impact on the travel time and are stochastic in nature. Does the stochastic nature of these processes have a statistically significant impact on network performance? In order to answer this, the stochastic nature of the network must be addressed. Determining what questions can be efficiently and effectively answered using stochastic information should be researched. Accounting for the truly stochastic pieces of the model will greatly improve the predictive capabilities of the MLNPS.


