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7. PERFORMING ORGANIZATION NAMES AND ADDRESSES
North Carolina State University
2701 Sullivan Drive
Admin Srvcs III, Box 7514
Raleigh, NC 27695 -7514

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RPPR Final Report
as of 04-Nov-2019

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INVESTIGATOR(S):

Name: Ph.D. Brandon McConnell
Email: bmmcconn@ncsu.edu
Phone Number: 9195152362
Principal: N

Name: Russell King
Email: king@ncsu.edu
Phone Number: 9195155186
Principal: Y

Organization: **North Carolina State University**
Address: 2701 Sullivan Drive, Raleigh, NC 276957514
Country: USA
DUNS Number: 042092122
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Final Report for Period Beginning 07-Jan-2019 and Ending 06-Oct-2019
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Submitted By: Ph.D. Brandon McConnell
Email: bmmcconn@ncsu.edu
Phone: (919) 515-2362
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STEM Degrees: 1
STEM Participants: 4

Major Goals: The research objectives are to investigate and design integrated mathematical models---collectively known as the Military Logistics Network Planning System (MLNPS)---capable of supporting relevant logistical planning and decision-making in near-real time using data that would exist on the US Army ERP system (GCSS-Army). This includes a ``test drive'' or ``what if'' capability to estimate the performance of a given logistics plan. The other related but different aspect is to mathematically identify feasible logistics plans given desired sustainment network performance (capacity planning). Of particular interest is these must be performed under uncertainty and the application requires quantifying associated risks and uncertainties.

Additional detail provided in enclosed PDF (Final Report).

Accomplishments: The research accomplished:
(1) Improved Methods to Measure Sustainment Network & Plan Performance that capture network adjustments that would occur upon disruptive events or required changes;
(2) Created novel framework for measuring network robustness that includes the potential changes in response to disruptions;
(3) Began foundational work to support a prescriptive model to identify required capacities for logistics network.

Additional details are in the enclosed PDF report.

Training Opportunities: Nothing to Report

Results Dissemination: Further details in uploaded report.

25 October 2019. Invited by Defense Logistics Agency|Aviation (DLA-A) to present our research during a leaders' professional development (LPD). Richmond, VA.

8 October 2019. Short presentation on our research to SES Executive Director for the Joint Special Operations Command (JSOC) during her visit to NC State. Raleigh, NC.

27 August 2019. US Army Special Operations Command (USASOC) Combat Development Division (CDD). Two active duty officers and one civilian visited NC State to receive a briefing on the MLNPS capabilities and learn more about the model. Raleigh, NC.

22 August 2019. Workshop by Co-PI to DoD & US Army logistics professionals in professional broadening offerings by the Institute for Defense & Business (IDB) [18]. How Could GCSS-Army Data Drive Expeditionary Military Logistics Planning? Chapel Hill, NC.

9 April 2019. Workshop by Co-PI to DoD & US Army logistics professionals in professional broadening offerings by IDB. GCSS-Army and Global Operations. Chapel Hill, NC.

16 October 2018. Leveraging Real-Time Data for Operational Sustainment Optimization. Presentation by MAJ B. Schwartz at the 2018 Army Operations Research Symposium (AORS), Aberdeen Proving Ground, MD. Selected as Best in Working Group (Operations).

Honors and Awards: 2018 Army Operations Research Symposium Best Paper award (presented at 2019 AORS) (Department of the Army-level award)

2019 Richard H. Barchi Prize from the Military Operations Research Society

More details in uploaded PDF.

Protocol Activity Status:

Technology Transfer: Additional details in enclosed report.

PARTICIPANTS:

Participant Type: PD/PI
Participant: Russell E King
Person Months Worked: 9.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Co PD/PI
Participant: Brandon M McConnell
Person Months Worked: 9.00 **Funding Support:**
Project Contribution:
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International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Research Experience for Undergraduates (REU) Participant

Participant: Jack Werner
Person Months Worked: 4.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Faculty
Participant: Thom J Hodgson
Person Months Worked: 9.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: Y
Other Collaborators:

Participant Type: Graduate Student (research assistant)
Participant: Blake E Schwartz
Person Months Worked: 9.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Graduate Student (research assistant)
Participant: Caleb Sheffield
Person Months Worked: 9.00 **Funding Support:**
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Article Title: A Military Logistics Network Planning System
Authors: Matthew Rogers, Brandon McConnell, Thom Hodgson, Michael Kay, Russell King, Greg Parlier, Kristin
Keywords: military logistics
Abstract: This paper presents a proof of concept for a Military Logistics Network Planning System (MLNPS) to be used during mission planning to quickly identify a robust logistical footprint that can adequately sustain units deployed in an expeditionary environment. The logistical network is modeled using an efficient form of goal-seeking deterministic discrete event simulation to process supply requisitions through the logistical network. The queuing information obtained from the simulation informs capacity adjustments to the network to maximize efficiency. This process of simulation and network tuning continues interactively until an adequate and robust logistical footprint is found. During the planning stages, the MLNPS can be used to identify and mitigate logistical problems instead of waiting to react to backlogs when the military's operations would have already been affected. Contingency operation scenarios are used to demonstrate the MLNPS' capabilities.
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Authors: Matt Shipman
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Volume: Issue: First Page #:
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Publication Location:
Article Title: Improving Chemotherapy Infusion Operations through the Simulation of Scheduling Heuristics: a case study
Authors: Ryan Slocum, Herbert Jones, Brandon McConnell, Thom Hodgson, Javad Taheri, James Wilson
Keywords: discrete event simulation (DES), scheduling, healthcare, chemotherapy
Abstract: Over the last decade, the healthcare industry has experienced a substantial shift from inpatient care to outpatient services as the ability to provide timely, safe out- patient care has increased. There has been a dramatic movement away from inpatient chemotherapy treatments, such that nearly 90% of all infusions are now administered outpatient. This shift has challenged oncology clinics to make chemotherapy treat- ment as widely available as possible, while attempting to treat all patients within a ♀xed period of time. Historical data from a Veterans A♂airs (VA) chemotherapy clinic in the United States supplemented with sta♂ input informed the development of a discrete event simulation model of the clinic. The simulation study simulation examines the impact of altering the current schedule, where all patients arrive at 8:00 AM, to a schedule that assigned patients to two or three di♂erent appointment times based on the expected length of their chemotherapy infusion. The results iden-
Distribution Statement: 1-Approved for public release; distribution is unlimited.
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RPPR Final Report
as of 04-Nov-2019

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Volume: Issue: First Page #:
Date Submitted: 11/4/19 12:00AM Date Published:
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Article Title: Automatic Feature Based Inspection and Quali♀cation for Additively Manufactured Parts with Critical Tolerances
Authors: Christopher Kelly, Richard Wysk, Ola Harrysson, Russell King, Brandon McConnell
Keywords: additive manufacturing, CNC machining, hybrid manufacturing, inspection
Abstract: This work focuses on expanding the capabilities of the Digital Additive and Subtractive Hybrid (DASH) system by extending the functionality to include some geometric qualification of mechanical products. Specifically, the developments for this research incorporate the extended Additive Manufacturing Format ♀(AMF-TOL) which include American Society of Mechanical Engineers (ASME) Y14.5 specifications for planes, cylinders and other features so that \in-process" inspection can be completed automatically as part of the hybrid process. A Renishaw touch probe is used to perform On Machine Measurements (OMM), collecting sample radii to create con♀fidence bounds on the accuracy of size and position of ♀finished cylindrical features. Measurements are imported to a spreadsheet where a nonlinear least squares regression algorithm creates statistical bounds on the true size and position of the cylindrical feature. These statistical bounds can then be compared to the specifi♀ed tolerance callouts.
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ARO STIR Final Report: #W911NF1910055
Expeditionary Logistics Analysis for Decision Support: The Military Logistics Network Planning System (MLNPS)

Russell E. King (PI)

Brandon M. McConnell (Co-PI)

6 October 2019

1 Background

In March 2003 during Operation Iraqi Freedom (OIF), within a week of the fall of Baghdad, the 3rd Infantry Division experienced a drop in equipment readiness for key ground combat systems from 90% to under 70% due to distribution problems for relatively cheap repair parts (US Armed Forces Class of Supply Nine, or CL IX). A 2005 RAND study [1] examining the issue concluded that the distribution problems stemmed from a lack of automated logistics decision-support tools capable of supporting the rapid pace of operations enabled by long and complex sustainment networks. This research centers on the investigation and design of mathematical models to support military logistics associated with sustaining an expeditionary force in response to the capability gap identified by the 2005 RAND study [1]. One major catalyst for innovation has been the emergence of the US Army enterprise resource planning (ERP) systems, powered by the commercial SAP software [2], which provide a web-based end-to-end system that allows the Army to see and share supply chain information in real time. Of particular relevance is the tactical ERP known as the Global Combat Support System-Army (GCSS-Army) [3–5].

US Army senior leaders, logistics professionals, and academics have consistently called for enhanced logistics planning and decision-support tools. GCSS-Army makes this possible in new ways that were simply not feasible before. There are several key themes to these calls for innovation:

- Enable decision-making, [6–9],
- Incorporate GCSS-Army data (& other ERP data) [8, 10, 11],
- Serve both combat arms & sustainment leaders [8],
- Execute rapidly enough to support operational pace [1],
- Enable logistical analysis with an "end-to-end" perspective [6],

In 2018, the Defense Science Board Task Force on Survivable Logistics concluded that "[l]ogistics data is neither as accessible nor used as efficiently as it should be" and provided recommendations that included increasing the ability to wargame logistics with sufficient "fidelity to identify logistics constraints to operations" [12]. This research aims to address these gaps by creating a mathematical modeling framework that leverages sustainment data to predict and evaluate sustainment performance.

2 Military Logistics Network Planning System (MLNPS)

2.1 Research Objectives

The research objectives are to investigate and design integrated mathematical models—collectively known as the Military Logistics Network Planning System (MLNPS)—capable of supporting relevant logistical planning and decision-making in near-real time using data that would exist on the US Army ERP system (GCSS-Army). As illustrated in Figure 1, this includes a "test drive" or "what if" capability to estimate the performance of a given logistics plan. The other related but different aspect is to mathematically identify feasible logistics plans given desired sustainment network performance (capacity planning). Of particular interest is these must be performed under uncertainty and the application requires quantifying associated risks and uncertainties.

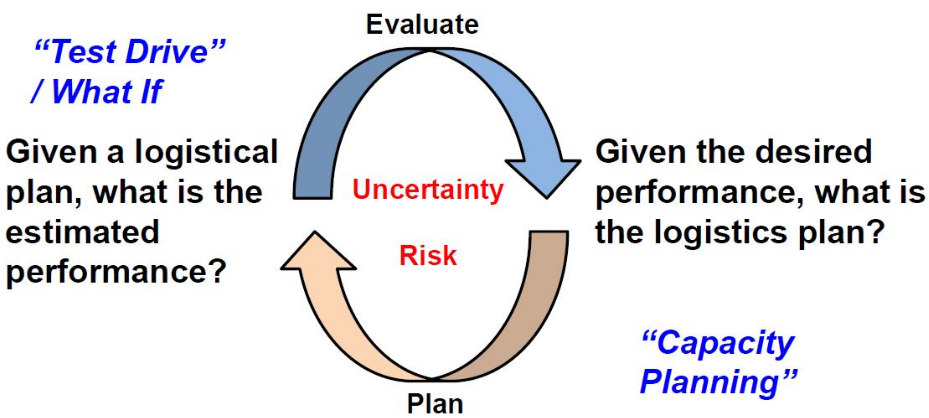


Figure 1: Conceptional operations required of the mathematical model.

2.2 Participants

This research has largely focused on using active-duty US Army students which has magnified the impact of the STIR grant supporting the researcher salary.

Researcher	Months Funded
Russell E. King (PI)	0
Brandon M. McConnell (Co-PI)	9
MAJ(P) Blake Schwartz (PhD student)	0
MAJ Caleb Sheffield (Masters student)	0

2.3 Technical Reports & Articles

Reporting Period: January–September 2019

- B.M. McConnell, T.J. Hodgson, M.G. Kay, R.E. King, Y. Liu, G.H. Parlier, K.A. Thoney-Barletta, & J.R. Wilson. 2019. Assessing Uncertainty and Risk in an Expeditionary Military Logistics Network. *Journal of Defense Modeling and Simulation*, Published online, 10 July 2019, 1–22. http://www.lib.ncsu.edu/resolver/1840.20/36775. [13]

  This paper won the 2019 Richard H. Barchi Prize from the Military Operations Research Society.

- B. Schwartz. 2018. Leveraging Real-Time Data for Operational Sustainment Optimization. Technical Report. Invited paper presented for the "Best of the 2018 Army Operations Research Symposium (AORS)" competition after being selected "Best in Working Group (Operations)."

  This paper won the 2018 Army Operations Research Symposium Best Paper award (presented at 2019 AORS).

- B. Schwartz, B.M. McConnell, & G.H. Parlier. 2019. How Data Analytics will Improve Logistics Planning, *Army Sustainment*, Vol 51, No 3, 54–57. [14]

Pre-existing Research
PhD Dissertations:

- M.B. Rogers. A Logistic Planning System for Contingency Missions to Identify a Feasible and Efficient Logistical Footprint, 2016. PhD Dissertation, Department of Industrial & Systems Engineering, North Carolina State University, http://www.lib.ncsu.edu/resolver/1840.16/10968. [15]

- B.M. McConnell. Assessing Uncertainty & Risk in an Expeditionary Military Logistics Network, 2018. PhD Dissertation, Operations Research Graduate Program, North Carolina State University, http://www.lib.ncsu.edu/resolver/1840.20/35098. [16]

Journal Articles:

- M.B. Rogers, B.M. McConnell, T.J. Hodgson, M.G. Kay, R.E. King, G.H. Parlier, & K.A. Thoney-Barletta. 2018. A Military Logistics Network Planning System (MLNPS). *Military Operations Research*, Vol 23, No 4, 5–24, http://www.lib.ncsu.edu/resolver/1840.20/36268. [17]

2.4 STEM Student/Supported Personnel Metrics

The graduate student researchers consisted of two active-duty military officers (one masters & one PhD student) who were funded through the US Army Advanced Civil Schooling (ACS) program. The undergraduate researchers were funded through an internal program within NC State.

Student Type	Number	Support Source
Undergraduate STEM	2	NC State Research Experience for Undergraduates
Graduate STEM	2	US Army Advanced Civil Schooling (ACS) Program

One active duty student graduated with a masters in Industrial & Systems Engineering.

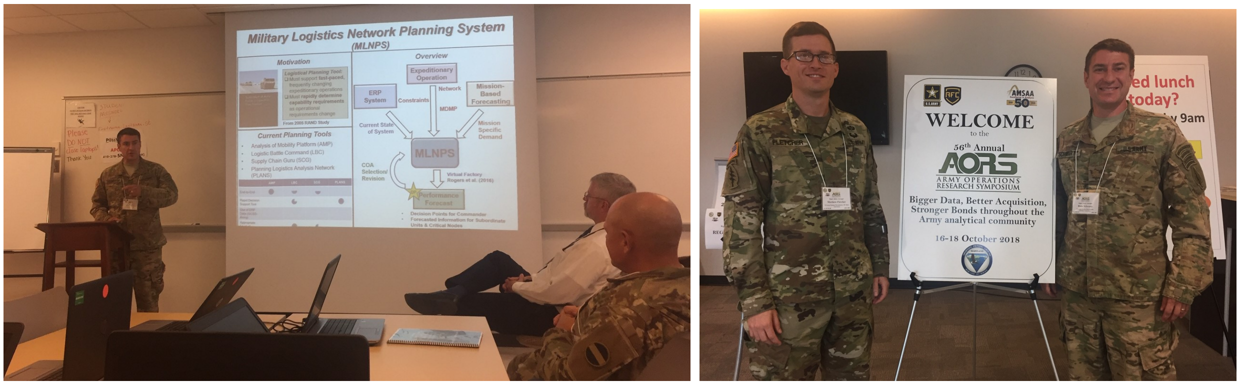
Number of students that received a STEM degree	1 (masters)

2.5 Technology Transfer

Interactions:

- 25 October 2019. Invited by Defense Logistics Agency—Aviation (DLA-A) to present our research during a leaders' professional development (LPD). Richmond, VA.

- 8 October 2019. Short presentation on our research to SES Executive Director for the Joint Special Operations Command (JSOC) during her visit to NC State. Raleigh, NC.



(a) (b)

Figure 2: (a) NC State OR PhD student MAJ Blake Schwartz presenting research at the 2018 Army Operations Research Symposium (AORS). MAJ Schwartz won "Best Presentation in Working Group (Operations)" and subsequently won the "Best Paper" award. (b) NC State OR PhD students MAJ Matt Fletcher and MAJ Blake Schwartz at the 2018 AORS in Aberdeen Proving Ground, MD.

- 27 August 2019. US Army Special Operations Command (USASOC) Combat Development Division (CDD). Two active duty officers and one civilian visited NC State to receive a briefing on the MLNPS capabilities and learn more about the model. Raleigh, NC.
- 22 August 2019. Workshop by Co-PI to DoD & US Army logistics professionals in professional broadening offerings by the Institute for Defense & Business (IDB) [18]. *How Could GCSS-Army Data Drive Expeditionary Military Logistics Planning?* Chapel Hill, NC.
- 9 April 2019. Workshop by Co-PI to DoD & US Army logistics professionals in professional broadening offerings by IDB. *GCSS-Army and Global Operations.* Chapel Hill, NC.
- 16 October 2018. Leveraging Real-Time Data for Operational Sustainment Optimization. Presentation by MAJ B. Schwartz at the 2018 Army Operations Research Symposium (AORS), Aberdeen Proving Ground, MD. Selected as Best in Working Group (Operations).

Previous Interactions:

- 31 May – 1 June 2018. Co-PI & MAJ Schwartz visit US Army Combined Arms Support Command (CASCOM) and GCSS-Army headquarters to discuss research and learn about their ongoing efforts. Fort Lee, VA.
- 27 April 2017. Co-PI invited to give departmental seminar to faculty of the Department of Mathematical Sciences, United States Military Academy, West Point, NY.
- 6 February 2016. Co-PI & LTC Rogers visit TRAC-MTRY to provide briefing on research and learn more about current models. Monterey, CA.
- 10 December 2015. Co-PI & LTC Rogers visit TRAC-LEE to provide briefing on research and receive briefing on Logistics Battle Command (LBC). Fort Lee, VA.
- 1 December 2015. Co-PI & LTC Rogers visit US Army Corps of Engineers (USACE) Engineer Research & Development Center (ERDC) to provide briefing on research and receiving briefing on Planning Logistics Analysis Network System (PLANS). Vicksburg, MS.

2.6 Scientific Progress & Accomplishments

This section is organized as follows: Section 2.6.1 provides a brief overview of pre-existing research that directly relates to the efforts completed under this STIR that are described in greater detail in Rogers [15] and Rogers et al. [17]; Section 2.6.2 summarizes the mathematical model for assessing uncertainty and risk from [16], the publication [13] of which was supported by this STIR; Section 2.6.3 presents the automation and visualization work supported by the STIR which has enabled both a faster research pace as well as improved engagement with the US Army; and Section 2.6.4 describes the research completed under this STIR.

2.6.1 Foundational Work (Pre-STIR)

This line of research investigated, designed, and created the Military Logistics Network Planning System (MLNPS) [15, 17]. The resulting decision-support tool enhances an existing scheduling methodology—the Virtual Factory—as a framework to construct an end-to-end model of the military logistics network. The key idea is to model supply requisitions traversing logistics nodes in the network as jobs to be processed in a large job-shop. The Virtual Factory is an efficient form of a goal-seeking deterministic discrete event simulation [19, 20].

Lieutenant Colonel Rogers [15] presents a proof of concept for the MLNPS by constructing an end-to-end model of the military logistics network for the 2003 US invasion of Iraq known as Operation Iraqi Freedom (OIF). Rogers validates the model using data from the 2005 RAND study on OIF sustainment [1] then demonstrates how to use the MLNPS to forecast significant backlogs and delays throughout the logistics network and identify mitigating or preventative actions using an iterative procedure. Finally, Rogers introduces a notional contingency operation set in Africa and then uses the MLNPS to identify the logistical assets required throughout the network to meet performance requirements and to perform what-if analysis to assess potential disruptions [15, 17].

Rather than focusing on the sequencing, Rogers et al. [17] demonstrate the tool provides a forecast of when, where, and how much queuing will occur at various nodes across the logistics network. Validating their model against real performance data from the 2003 invasion of Iraq during OIF demonstrates the MLNPS can accurately approximate real logistics network performance. Using this model and mean value parameters, they develop a trial-and-error method to test drive a logistics plan and assess how well it will support a planned expeditionary operation using deterministic outputs from the VF. Their model assesses the logistics network both for the invasion of Iraq and for a notional intervention scenario set in Africa. With two analysts, model setup took 1–2 days from scratch (hours if already created) with run times taking minutes to hours depending on time horizon and the size of the network studied; to our knowledge, this is faster than contemporary models.

2.6.2 Risk Enhancements (publication funded by STIR)

Nonstationary Network Queueing Model. McConnell [16] models the military logistics network—stretching from US depots to the expeditionary theater of operation—as a queueing network where logistical nodes (or processes) are queues and the requisitions are arriving as orders via GCSS-Army. The simplified model in Figure 3 illustrates how orders are sourced, picked and packed, then shipped to the ordering unit. The model is a feed-forward queuing network as supply requisitions move from the sourcing depot across the network to the ordering unit and do not require rework or depart the network through a lateral exit. There are multiple classes of arrivals based on the mode of transportation to be used whether military air, a contracted point-to-point service denoted world-wide express (WWX), or surface shipment (ocean freight). Within each arrival class

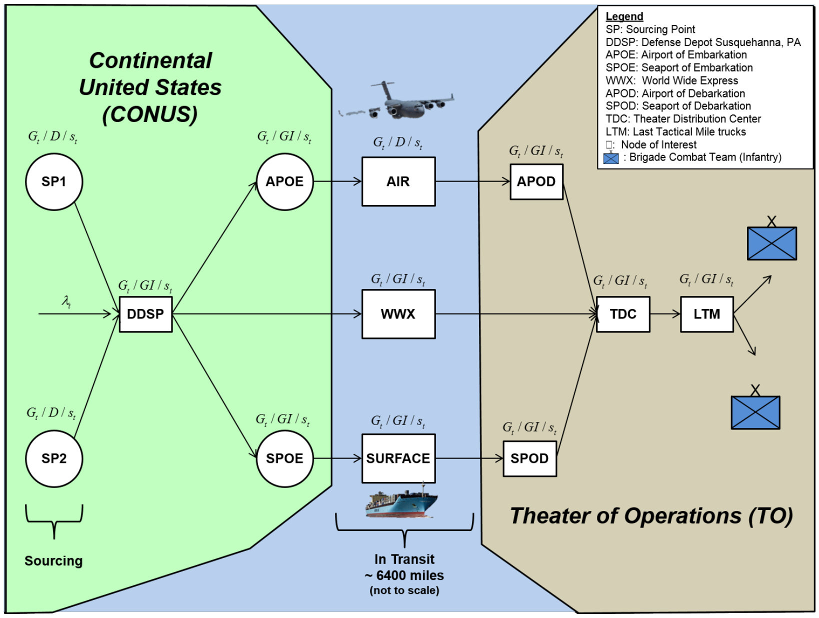


Figure 3: Military logistics network as a queueing network (simplified for illustration).

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

The feed-forward structure implies that by estimating the performance or capacity required at an upstream location, if the departure process is obtainable it also provides the arrival process to the downstream nodes so the analysis can be repeated for downstream locations. Consider the simplified military logistics network depicted as a feed-forward queuing network in Figure 3; supply requisitions arrive at either Defense Depot Susquehanna, Pennsylvania (DDSP), or to an alternative depot acting as a sourcing point (SP1 or SP2). The requisitions from alternative depots still move to DDSP as it is the primary consolidation and containerization point (CCP) for palletizing and containerizing shipments. As Rogers [15] discusses, most requisitions travel via military aircraft, world-wide express, or surface shipment. Shipments traveling on military aircraft (ocean freight) are palletized (containerized) at DDSP then loaded onto military aircraft (container ships) at the airport (seaport) of embarkation, or APOE (SPOE) for movement into theater where they are offloaded at the airport (seaport) of debarkation, or APOD (SPOD). These shipments are then transported to the theater distribution center (TDC). Requisitions being shipped via WWX travel directly to the TDC. At the TDC, pallets and containers are broken down and moved forward via military transportation to the ordering units. This final process is often referred to as the last tactical mile (LTM) due to the transportation occurring through a designated combat zone.

Using mission-based forecasting (MBF) and the data from GCSS-Army, it is possible to estimate the arrival processes to the network shown in Figure 3. As opposed to using historical average usage rates for repair parts, MBF provides a tailored forecast using stratified sampling [21] that considers force composition, environmental conditions, operation duration, and planned mission profiles [14, 22–26]. MBF incorporates regression methods using these explanatory factors, a new technique to improve forecast accuracy for intermittent demand referred to as the "Markov-Bootstrap Method" [27–29], and both predictive and prognostic methods using sensor-derived data associated with Condition-Based Maintenance (CBM) [11, 22, 30, 31]. Since MBF is not available for all unit types, we construct a data-driven approach to forecasting requisitions for a given scenario. This forecast provides an estimated nominal time-varying arrival rate to the upstream sourcing nodes.

VF-DIS Network Model. We construct a tandem Virtual Factory Delayed Infinite Server (VF-DIS) offered load approximation for each location; the model alternates between using the VF and the DIS approximations for each location moving across the network from upstream to downstream. The appeal lies in leveraging each submodel's strengths. The Virtual Factory is efficient and can handle nested batch processing (e.g., a multipack inside a pallet on a truck) as well as a number of realistic constraints, and with small refinements, the DIS model [32] provides a computationally efficient method to evaluate performance and predict capacity requirements while communicating a sense of the uncertainty in the predictions. This tandem approach uses each model to the maximum potential while avoiding each model's weaknesses.

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

Figure 4 offers a visualization of the VF-DIS process with a small portion of the network. It depicts the network as two complementary models, the DIS and the VF approaches, with the bold (blue) line representing the VF-DIS hybrid solution approach for an analyst conducting risk analysis and military logistics planning. The dashed line represents the model workflow if only using a single model in isolation from the other. Taking the logistics network, processing logic, and requisition forecast, the $\lambda(t)$, as inputs, VF-DIS first uses the VF at the upstream nodes to assess the arrival process and the resulting departure process given the default time-dependent capacity plan, the s_t, which can be initialized via a simple constant capacity. With the average delay targets for the upstream nodes, the DIS model calculates the time dependent capacity required to meet the targets by providing both a time dependent average (the s_t) and the stochastic variability around that average. These capacity plans (functions over time) are inputs to the VF which accounts for location-specific policies, logic, and schedules; the VF then returns the time dependent departure process represented as $\sigma(t)$. Since the network is feed-forward, the departure process is the downstream arrival process so the model advances downstream once the upstream planning is complete and repeats the process until it reaches the most downstream nodes.

The VF can model location-specific policies via its processor logic. These are important because some locations do not work weekends, and resources vary according to specific schedules driven by real-world considerations. Another example stems from a working policy used by a container packing location (one of several batch processes): a container is considered full when it reaches its effective capacity, reaches the minimum capacity to send and there are no orders left to pack, or when it has been sitting open (and partially filled) for at least three days. The VF's processor logic conveniently incorporates these nuances [17].

VF-DIS Node Approximation Model. Consider an arbitrary node in the logistics network. Let w be the average delay taken as the performance target for this node and denote the average arrival rate on day t as $\lambda(t)$; the VF provides this nonstationary arrival rate using the data-driven requisition forecast. The logistics node is represented as a $G_t/GI/s_t$ queueing model where the processing time, S, at this location is independent and identically distributed (i.i.d.) according to the general distribution F_S. Figure 6 labels this Model 1. Define $\sigma(t)$ as the average departure

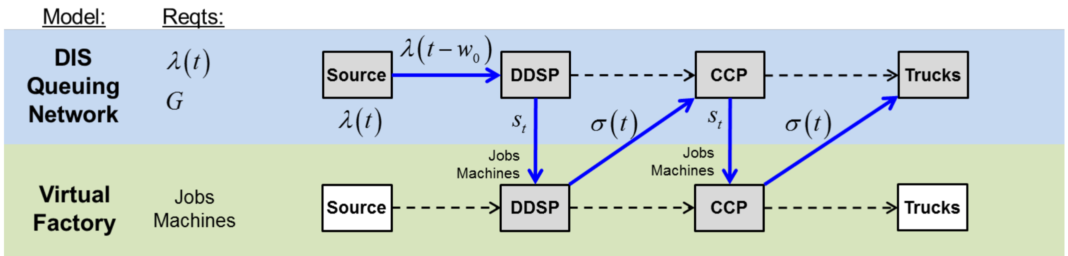


Figure 4: Visualization of the Virtual Factory Delayed Infinite Server (VF-DIS) offered load network model. The models complement each other — our unified approach denoted in bold (blue). The dashed lines represents using the two single model approaches. Note: w_0 represents the average elapsed time from a requisition establishment to the release to the source depot.

rate on day t for the associated departure process. Denote $Q(t)$ as the queue length at time t. Let $B(t)$ be the number of busy servers at time t with mean $m(t) = \mathrm{E}[B(t)]$ and variance $v(t)$; $B(t)$ is approximately

$$B(t) \sim \mathrm{Normal}(m(t) + 1/2, z(t)\, m(t)), \tag{1}$$

with

$$\mathrm{E}[B(t)] = \int_0^{(t-w)^+} \lambda(t - w - x)\bar{F}_S(x)dx, \tag{2}$$

where the notation $(x)^+ = \max\{x, 0\}$, and the service time complementary cumulative distribution function, $\bar{F}_S(x) = 1 - F_S(x)$. Equation 2 calculates the average capacity over time required to maintain the performance target $w > 0$.

Define $\{A(t),\, t \geq 0\}$ as the counting process that tracks the number of arrivals (events) by time t, then the arrival process *index of dispersion* (for counts), $I(t)$, is the variance-to-mean ratio of the cumulative number of arrivals (events) as given by Equation (3). If the node sees M_t arrivals according to a nonhomogeneous Poisson process (NHPP) [33], $I(t) = 1,\, t > 0$.

$$I(t) = \frac{\mathrm{Var}(A(t))}{\mathrm{E}[A(t)]},\, t > 0 \tag{3}$$

The arrival process is *overdispersed* if $I(t) > 1$ and *underdispersed* if $I(t) < 1$. If the arrival process to Model 1 is significantly overdispersed then a naïve implementation of the DIS offered load approximation will underestimate risk to the decision-maker because while the predicted average will be true, the model will underestimate the variance. Using the Sudan scenario from Rogers et al. [17], Figure 5 provides an estimated dispersion for the LTM trucks revealing the LTM arrivals are over five times more variable than a NHPP. In other applications, healthcare clinics often see underdispersion (≈0.4–0.6) in appointment-based systems but overdispersion (≈1.5–2.5) in emergency departments or at call centers [34–37].

If arrivals occur according to a NHPP, then $I(t) = 1$, $\forall t$, and for a fixed t, $B(t)$ is a Poisson random variable with mean $\mathrm{E}[B(t)]$ (2). [32, 38] This implies $m(t) = v(t)$. If the arrival process is not a NHPP, then $m(t) \neq v(t)$ and the heuristic risk correction factor (RCF), $\tilde{z}(t)$, enables the approximation

$$v(t) \approx \tilde{z}(t)m(t), \tag{4}$$

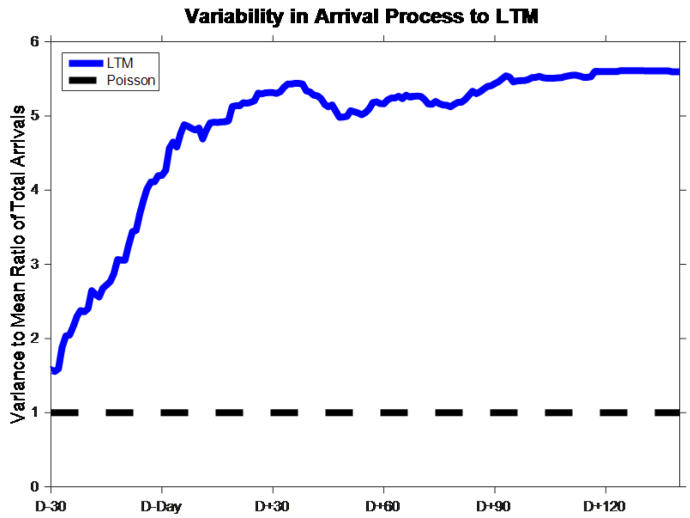


Figure 5: LTM arrival dispersion for the Sudan scenario is over 5 times more variable as a NHPP (dashed line). Graph shows arrival dispersion in 463L pallet equivalent units (PEU) from Equation 9.

with the correction factor

$$\tilde{z}(t) = \max\{z(t), 1\}, \tag{5}$$

$$z(t) = 1 + \frac{(c_a^2(t) - 1)}{E[S]} \int_0^\infty [1 - F_S(x)]^2 dx, \tag{6}$$

where

$$c_a^2(t) \approx \frac{\mathrm{Var}(A(t-w) - A(t-w-\eta))}{\int_{t-\eta}^t \lambda(u-w)du}, \tag{7}$$

for a chosen $\eta > 0$.

The capacity recommendation follows the square root staffing (SRS) rule

$$s_\gamma(t) = \left\lceil \mathrm{E}[B(t)] + \delta_\gamma \sqrt{\mathrm{Var}(B(t))} \right\rceil, \tag{8}$$

establishing a buffer to hedge against stochastic variability by establishing a probability γ and associated quality of service parameter δ_γ such that $P(\mathrm{N}(0,1) > \delta_\gamma) = \gamma$, which exploits the Normal approximation to the Poisson.

Model Discussion. Figure 6 graphically depicts the node specific approximation. Model 2 ($M_t/GI/s_t$ queue) can approximate Model 1 (see Figure 6) as it captures the time-dependent fluctuations in the arrival process with the same deterministic mean function while retaining Model 1's non-exponential service time distribution and time-varying capacity. The only difference is in the arrival process variability. Convenience motivates the transition to Model 2 and requires a correction to account for the arrival variability. There is no reliable method to obtain analytical approximations for the capacity required over time to meet performance targets for Model 1 and use of simulation will not permit the analysis to be performed in near-real time. From the network perspective, Model 2 enables Poisson superposition at a downstream node that receives requisitions from multiple upstream nodes; the aggregate arrival process is then a nonhomogeneous Poisson process (NHPP).

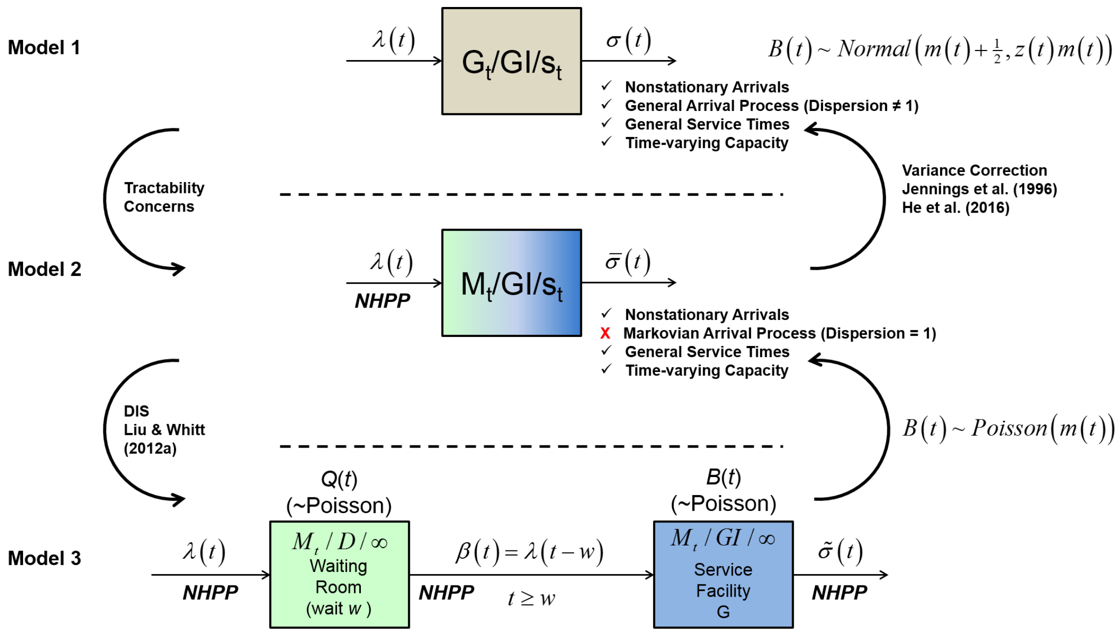


Figure 6: Queueing models for a location. Model 2 approximates Model 1 by focusing on the time-dependent behavior. Model 3 is the Delayed Infinite Server (DIS) offered load approximation for the $M_t/GI/s_t$; Liu & Whitt[32] show Model 3 approximates Model 1. Within Model 3, the contents of the first two queues, $Q(t)$ and $B(t)$ respectively, are independent Poisson random variables for a fixed t. See Table 1 for departure rate, $\tilde{\sigma}(t)$.

To identify the capacity to achieve the average delay target $w > 0$ for Model 2, Liu and Whitt [32] show that the Delayed Infinite Server (DIS) offered load approximation works well for systems such as the military logistics system where requisitions may be expected to wait for some (even small) amount of time before processing. The DIS model, depicted as Model 3 in Figure 6, approximates Model 2 by using two infinite capacity queues in series. This presentation of the DIS model omits the abandonment process implying the assumption that there is no lost, misrouted, or frustrated cargo. The first queue represents the waiting space in Model 2; the second queue represents the service facility of Model 2.

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

At the second queue, requisitions immediately begin processing according to the general service time distribution $G = F_S$. The objective is to determine the number in the second queue at time t, $B(t)$, which serves as the first order approximation of the number of busy servers in Model 2 while maintaining an average delay of w. In simpler terms, Model 3 approximates Model 2 by having all requisitions wait the desired average delay then simply observes how many busy servers would be in the second queue over time. Based on the mathematics of the infinite server queue, this is obtained via direct calculation using Equations 1– 2 applying known results for the $M_t/GI/\infty$ queue (see Theorem 1, Eick et al.[38]) [32].

While Equation 2 calculates the average capacity over time required to maintain the performance target, the mathematics of Model 3 fully specify the approximate distribution of this predicted capacity requirement. This implies Monte Carlo methods may also be used to estimate what is not available analytically. Table 1 summarizes the remaining analytical formulas for the DIS offered load approximation.

Table 1: Model 3 DIS approximations for Model 2 (assumes M_t arrivals).

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

Notes: **System* refers to a specific node; $t \wedge w = \min\{t, w\}$; $(t-w)^+ = \max\{t-w, 0\}$.

The DIS approximation prediction for Model 2 with M_t arrivals implies $B(t) \sim \text{Poisson}(\mathrm{E}[B(t)])$. Correcting for the variability of the G_t arrival process requires application of a result from the stationary $G/G/\infty$ queueing model as a heuristic which is consistent with Jennings et al. [39](see Sec. 6) and He et al. [40](see Sec. 3). This research is the first to use a time-shifted variance correction to integrate the DIS approach.

The function $\tilde{z}(t)$ (5) does not allow a reduction in variance (an optional modeling assumption due to lack of dispersion data — this avoids a false sense of certainty) and can increase the variance for $B(t)$ using the time-dependent generalization of the heavy-traffic peakedness (6) taken from Whitt's [41] treatment of the stationary $G/G/\infty$ model which characterizes the variance-to-mean ratio of the steady-state number of busy servers. Since Model 1 is nonstationary, (6) is a heuristic. Equation (6) assumes a stationary service time distribution but this can be relaxed. Equation (7) is a time-dependent generalization of the asymptotic variability parameter and is similar in form to (3); this paper time-shifts the asymptotic variability parameter by w to account for the DIS approximation. The parameter η determines the dispersion estimate in the local interval $[t-\eta, t]$; this paper uses a timestep of one day and numerical evaluations confirmed $\eta = 1$ is a good choice for this application. The intuition is that both the arrival variability (7) and the service time variability (6) affect the variance of the capacity prediction (number of busy servers). Specifically, the tail of the service time distribution drives the impact on the variance with the term $\int_0^\infty [1 - F_{S_t}(x)]^2 dx$ in (6).

Since we estimate the arrival variability parameter (7) empirically, it can be undefined when $\int_{t-\eta}^t \beta(u)du = 0$ which occurs during lulls in arrivals on η consecutive days. When this occurs, we define $c_a^2(t) = 0$ for this special case such that the RCF $z(t) = 1$ which aligns with engineering intuition.

This RCF (5) corrects the variance in the approximation for Model 2 so the final results may serve as an approximation for Model 1. The Normal approximation to the Poisson implies that instead of $B(t) \sim \text{Poisson}(m(t))$ which underestimates risk, the required capacity is actually approximated by $B(t) \sim \text{Normal}(m(t) + 1/2, z(t)m(t))$. Adding a half to the mean function corrects for the conversion between a discrete distribution to a continuous one but may be omitted in practice if desired. This continuity correction may lead to a positive bias in the capacity forecast when the nominal requirements are relatively low and the continuity correction has a larger relative impact on the mean. In the case study which demonstrates this technique, $B(t)$ is a Normal distribution truncated on the interval $[0, +\infty)$ to prevent the sampled $z(t)$ from pushing probability below zero; this is equivalent to $(B(t)|B(t) > 0)$. Figure 6 displays an overview of the entire process to predict capacity requirements for a single location. The VF is responsible for both the arrival rate to each node, $\lambda(t)$, and determining the departure rate $\sigma(t)$ as it is designed to handle location specific packing policies, work schedules, and other realism constraints.

Much of the queueing literature cited is motivated by staffing requirements for call centers and often employs (8) over a discretized time horizon. In the case of expeditionary military logistics such continuous control is not likely to be possible, even over long subintervals. Our case study addresses this concern and also demonstrates a technique to use the VF-DIS model structure to generate possible capacity plans for a location given the time-varying risk information.

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

While the feed-forward structure imparts computational efficiency and suggests a simple sequential approach, the time-varying (nonstationary) property and presence of non-Markovian (non-exponential) arrival and service processes greatly complicate the analysis. The reader will notice the fundamental modeling unit traversing the network is changing as well and there is no common unit for capacity (number of servers); Rogers [15] uses number of requisitions per day for DDSP, 463L pallets per day for the APOE, and forty foot container equivalents (FEU) per day for surface freight, and even the number of medium truck companies as a capacity unit. Queueing theory has no easy way of accounting for these unit changes.

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

Establishing the PEU unit also provides an opportunity to account for the tare weight. One can calculate the number of PEUs arriving (or departing) location m on day t by taking the total weight and volume for that day and location and dividing by the effective maximum capacity of the 463L pallet given by Equation 9 below. The larger of the two determines the 463L pallet equivalent capacity required; note for resources the smaller of the two is the offered resource capacity. Table 2 lists the 463L maximum and effective capacity. The use of cubic inches preserves integrality in the model for computational efficiency and adequately models the many requisitions with less than a unit cubic foot volume.

$$P_{mt} = \max\left\{\frac{TotalWT_{mt}}{\text{95\% PEU WT}}, \frac{TotalCU_{mt}}{\text{85\% PEU CU}}\right\} \tag{9}$$

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

Table 2: Maximum and effective capacity of the 463L pallet.

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

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

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

An author from the 2005 RAND study [1] provided OIF repair part requisitions and U.S. Transportation Command (TRANSCOM) provided data on all requisitions DDSP processed in 2003. Together these datasets provide the weight, volume, sourcing depot, requisition date, requesting unit and location, and other factors for all repair part orders processed by DDSP and those destined for units in Kuwait and Iraq. For specific operational characteristics, the process relies on data from the first 87 days of OIF which consists of 647,189 individual requisitions (11.6 million parts) spanning the two weeks prior to crossing the line of departure through the end of May 2003. The DDSP-specific data contains the 7.7 million requisitions from 2003. Both datasets have a time precision of days which aligns with the chosen time step for this work. Due to similar terrain and environmental factors the OIF dataset is sufficient for the analysis which considers a notional operation in Sudan.

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

The timeline is essential to breaking down the time horizon of interest into distinct missions for the units. The forecast must account for the fact that repair part demand is different by both unit type (think infantry versus aviation units) and type of operation (preparing for combat versus combat). This is accomplished by defining three operational intensity levels (OIL) then using the OIF invasion data to characterize each type of unit's demand under those operational descriptions to describe pre-combat (OIL 1), steady-state operations out of an established base (OIL 2), and direct (major) combat operations or high intensity conflict (OIL 3). Since these levels are qualitative in nature, Table 3 provides recommended guidelines for identifying these levels using historical data.

Figure 7 graphically shows the forecasting process which begins by generating requisitions for the food, water, and ammunition supplies that must sustain the units in the model. Then a specific

Table 3: Guidelines to Identify Operational Intensity Levels.

Operational Intensity	Distinguishing Features
Level 1	☐ Prior to crossing line of departure ☐ Not conducting combat operations ☐ Preparation for combat operations
Level 2	☐ Operations conducted from established and secured base or fixed location ☐ Operations take on a steady-state, routine nature during this period
Level 3	☐ Conducting invasion ☐ Major combat operations / high intensity conflict

workflow addresses repair part demand for every unit for every OIL. This workflow determines the number and timing of requisitions, how those requisitions are routed to the ordering unit, the required delivery date, order weight and volume, and the sourcing depot. Once this has occurred for every unit for every operational intensity level, the concatenation of these requisitions constitutes the forecast. Due to how the forecast employs probability distributions, the resulting forecast is a projected sample path for that time horizon.

Unit size plays an obvious role in estimating CL I requirements. Since bottled water was the primary source of potable water during OIF and this research focuses on initial expeditionary operations, we generate pallets of bottled water to supply the units originating at the TDC [1, 15]. This assumption may vary across the time horizon as are the starting locations of those pallets depending on the logistics plan. Army Tactics, Techniques, and Procedures (ATTP) 4-41, "Army Field Feeding and Class I Operations" recommends ration cycles and feeding plan guidelines (see Sec. 5.3 of Rogers [15]) to identify the capacity required to haul CL I to the units so the remaining capacity may be allocated to other classes of supply.

Assuming an average Brigade Combat Team (BCT) strength of 4,500 Soldiers with attached enablers that increase the troop count by 10% yields approximately 4,950 personnel per BCT. Consistent with doctrinal water planning guides, assume 7.27 gallons of water per person per day is required in an arid environment to account for hydration, hygiene, and feeding purposes. The standard planning factor estimates a pallet may hold up to 228 gallons of bottled water [42]. Using a 10% breakage planning factor, this yields a daily water requirement of 173 pallets of water per day for a BCT [15]. A pallet holds 576 Meals-Ready-to-Eat (MREs) and assuming initial rations are three MREs per day, the daily food requirement is approximately 26 pallets per day. These rations are nonperishable. Based on planning factors provided by the Army's Training & Doctrine Command Analysis Center–Fort Lee (TRAC-LEE, a logistical analysis center), ammunition requirements would be approximately 60% of the water weight and 40% of the water volume [15].

The irregular shaded (blue) box in Figure 7 contains the workflow that must occur for each unit and OIL. This process occurs for each unit with generated requisitions being collected into a large list along with the CL I and CL V requisitions. Depending on multiple factors such as time horizon, task organization, and mission, this process generates a significant number of requisitions. For reference, the Sudan scenario in the case study generates requisitions for 61 days prior to LD and 90 days of operations after. In addition to the almost 2.3 million requisitions that competed for DDSP resources during the OIF invasion used as a surrogate for global, non-Sudan demand, the random requisitions generated for just the Sudan operation is on the order of 294,149 requisitions

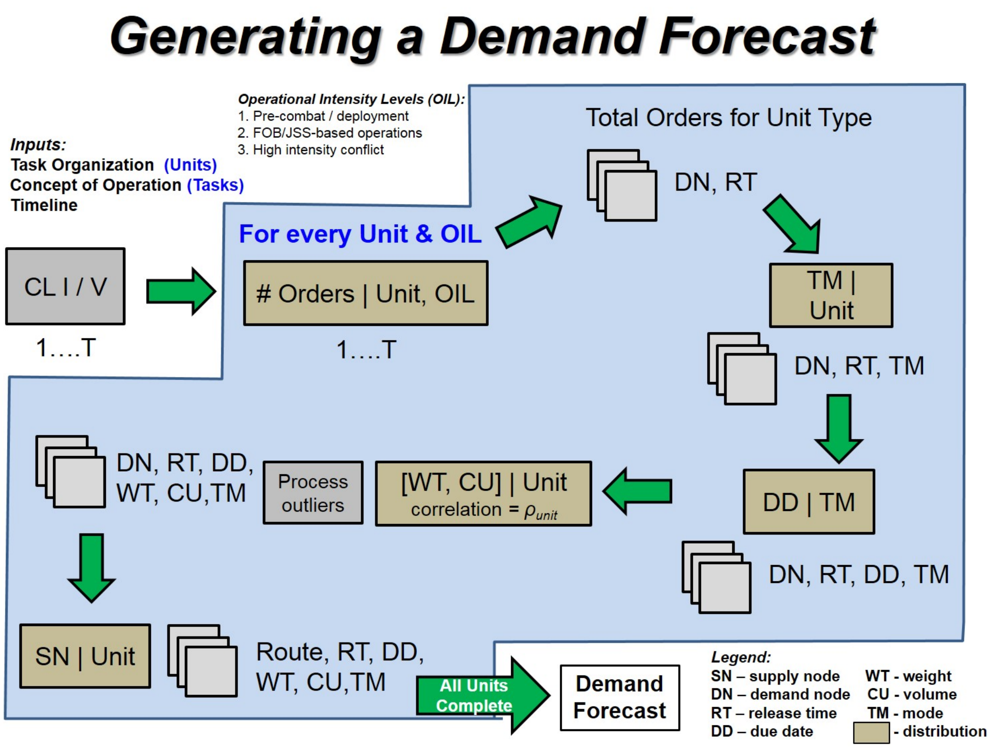


Figure 7: Process overview to generate a demand forecast. More details available in McConnell [16]. The irregularly shaped (blue) box indicates the steps required for every unit type and OIL.

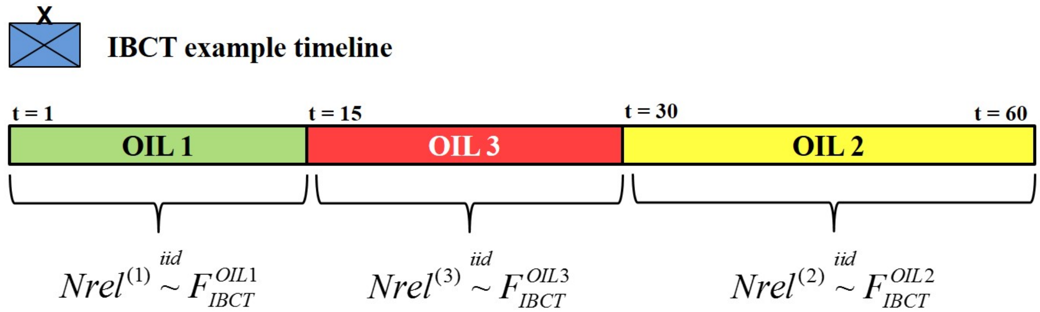


Figure 8: Example for generating number of requisitions by day for IBCT. Note: $F_{unit\ type}^{OIL\ level}$ is the estimated probability distribution for the number of requisitions required by day for a particular unit type at a specific OIL.

Table 4: Unit types supported by model. Relies on historical data taken from OIF invasion 6 March – 31 May 2003.

Unit	Operational Intensity Level (OIL)
IBCT	1, 2, 3
HBCT†	1, 2, 3
AVN BN	1, 2, 3
EN BN	single level only
DIV HQ	single level only
Sustainment BDE	single level only
Misc Enabler BN	single level only
3x Truck CO	single level only

Notes: † now called ABCT, also used as surrogate for SBCT.

on average (20 samples with sample standard deviation 11,538).

Analysis of the OIF invasion data clearly identified that the number of daily requisitions varies both with the type of unit and based on that unit's OIL. For a given unit, the model assumes each day as independent and identically distributed within an OIL as the data showed weak auto-correlations. This assumption is not limiting and can be relaxed. The OIF invasion data permits modeling the 8 unit types listed in Table 4. For each unit, the sub-timeline of each OIL determines the number of requisitions per day. If an IBCT has an OIL schedule as depicted in Figure 8, the number of requisitions released on days 1 through 14 requires the appropriate estimated probability distribution for OIL 1. In Figure 8, $Nrel^{(j)}$, $j = 1, 2, 3$, is the daily number of requisitions ordered (released by GCSS-A) for OIL level j. Table 4 lists unit types the model can support using the OIF data taken from 6 March–31 May 2003; interested readers may refer to McConnell [16] (p. 92–94) for distribution and sample size details.

After generating a unit's requisition volume across the timeline of interest, the process randomly selects each requisition's mode of transportation according to a specified distribution which identifies the route. The Sudan operation in the case study employs the distribution from Table 5 taken from the OIF invasion data.

The allotted time to deliver the requisition in days, known as the standard delivery time (SDT), is generated based on a requisition's transportation mode ($TransM$). This time is added to the release time (RT) to calculate the due date (DD) according to Equation (10) where i indexes each requisition. In Equation (11), each standard delivery time (conditional on transportation

Table 5: Transportation mode distribution taken from OIF data.

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

Table 6: Bounds for Standard Delivery Times (SDT) in days modeled by the discrete uniform (DU) distribution in Equation 11. Transportation mode distribution taken from OIF invasion data.

Transportation Mode	(a_{TransM}, b_{TransM})	Probability
Military Air	(12, 18)	0.734
World Wide Express (WWX)	(10, 14)	0.129
Surface (Ocean)	(52, 75)	0.137

mode) is modeled with a discrete uniform distribution (denoted DU). Since standard delivery times vary by requisition priority and service-specific processes, assuming the actual standard delivery times found in Table 6 from the Department of the Army Pamphlet (DA PAM) 710-2-1 (Using Unit Supply System) are the upper bounds (b_{TransM}) and allowing up to an approximate 70% reduction (a_{TransM}) to account for varying priority designations helps to account for individual prioritization [43]. For more details on requisition priorities see Rogers [15] (p. 31) and DA PAM 710-2-1 [43] (Ch. 2 and Table 2.2).

$$DD_i = (SDT_i|TransM_i) + RT_i \tag{10}$$

$$(SDT_i|TransM_i) \overset{\text{iid}}{\sim} \text{DU}(a_{TransM}, b_{TransM}) \tag{11}$$

The VF requires orders to have both a weight and volume to properly capture the details of processes such as movement by truck, packing a 463L pallet, and breaking down and sorting packages in a forty foot container. The OIF invasion data provides an estimate of these marginal distributions. Reality requires them to be correlated. Using a Gaussian copula (see Ross [21]) allows using a different target correlation based on the unit type from Table 4 while respecting the correct marginal distributions for weight and volume (see p 94–95 of McConnell [16]). Sampled weights or volumes that exceed that requisition's transportation mode get reassigned to the maximum capacity for the offending weight or volume; this is reasonable as this only occurs less than one-fifth of one percent of the time in the data.

Each requisition is assigned to a sourcing depot conditional on the requesting unit according to the empirical probability mass function found for each unit type's source depot location. These empirical distributions can vary based on order content; since the model does not specify individual types of repair parts, this approach permits capturing the unit type variation of supply depots while keeping the level of detail at overall requisition attributes. As explained by Rogers [15], certain Defense Logistics Agency (DLA) distribution centers have specialized stock—such as communications equipment at Tobyhanna, Pennsylvania—and these specializations affect these sourcing distributions.

After specifying the unit (demand node), transportation mode, and sourcing depot (supply node), it is a simple lookup from the appropriate route matrix that stores the route for a requisition going from that depot to that unit with that transportation mode. Collectively these route matrices comprise the route library which is an output of the logistical network modeling process. After identifying each requisitions route, the entire requisition forecast is completed by aggregating the

Table 7: Task Organization for Sudan mission [15].

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

CL I / CL V requisitions, each unit's forecast, and the forecast for global requisitions that will compete for DDSP resources. A comparable set of requisitions that routed through DDSP in OIF provides a start point for the non-expeditionary requisitions that share continental US (CONUS) resources upstream [15].

This procedure (Figure 7) provides a data-driven approach to generating requisition forecasts since MBF is not yet available for all Army units and platforms. The result is a sample path approach which requires replication to assess the uncertainty in the forecast itself which is the arrival process to the queueing network previously described.

Risk-based Expeditionary Logistics Planning for a Notional Operation: A Case Study. The case study uses the same fictional scenario used by Rogers[15] where an Infantry Brigade Combat Team (IBCT) and a Stryker Brigade Combat Team (SBCT) are conducting operations from South Sudan into Sudan against the self-styled Islamic State in Iraq and Syria (ISIS). The SBCT will operate in the outlying Darfur region while the IBCT operates in the capital of Khartoum. [15] A Division Headquarters conducts command and control for the operation and the units are provided with enablers that include engineer and aviation units; Table 7 presents the Task Organization used to generate the forecast for supply requisitions using the procedure previously described. In his analysis, Rogers [15] evaluates different courses of action (COAs) based on potential locations for the TDC. While the techniques from this section could assist with evaluating the COAs presented by Rogers, this section focuses on Rogers' selected option, Sudan COA 1, locating the TDC in Juba, the capital of South Sudan.

Applying the model to the final plan recommended by Rogers [15] illustrates the contribution of this methodology. The LTM trucks—the ground units that transport supplies from the TDC to the BCT Supply Support Activities (SSAs)—are the ideal candidate for this demonstration for several reasons. The LTM trucks are the logistical link to the units which implies this may be a location where a theater commander has the most control as they are not necessarily constrained by ties to airports, seaports, or other infrastructure or process restrictions, including CONUS effects. Practically, their geographical proximity to the units also incurs more risk. Given the feed-forward structure of the network, the LTM trucks are the final node to analyze and identify the required capacity for operations; the process to analyze other nodes is almost identical except that no other node is the furthest downstream resource. This property creates a few technical challenges that are readily overcome but not present at any other place in the feed-forward network. In simpler terms, if analysis of LTM trucks is possible, it is possible to do this for any node upstream.

The operational details and timeline are identical to Rogers' [15] scenario; Figure 9 provides a visual summary. The SPOD is located in the port of Mombasa, Kenya. The TDC is located in Juba, South Sudan, with the APOD nearby. Though not depicted in Figure 9, the CONUS network is also identical to Rogers' scenario.

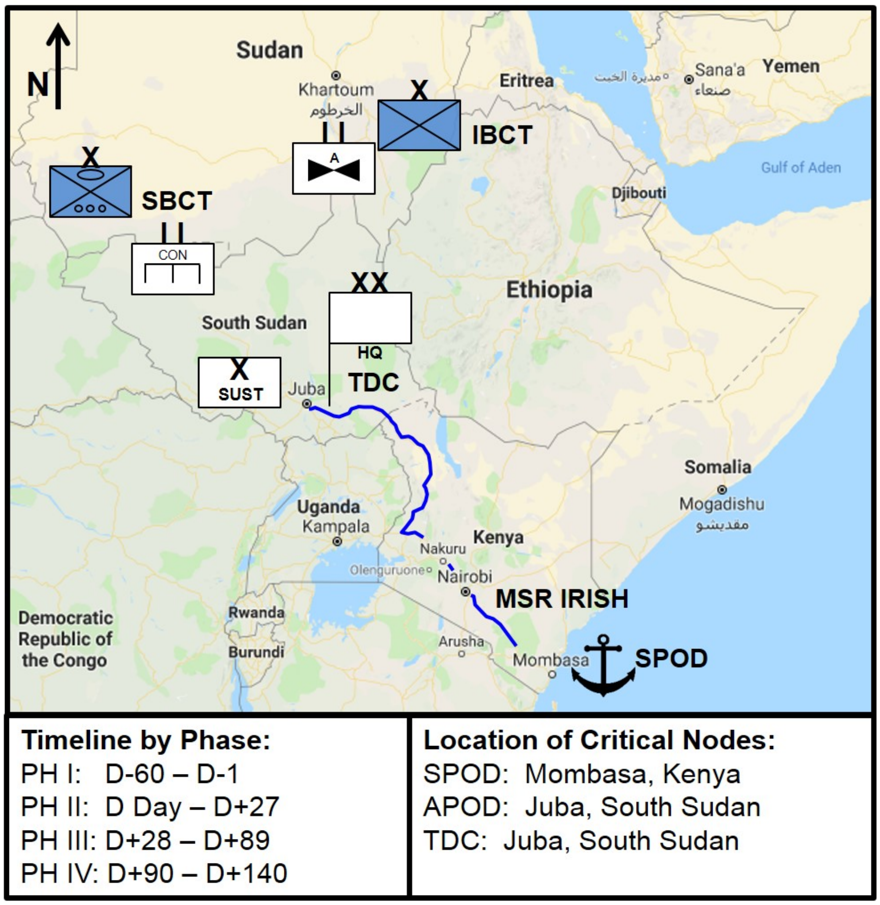


Figure 9: Sudan COA 1 Overview with Main Supply Route (MSR) IRISH annotated [44]. Note: PH: phase.

The logistics network in Figure 9 is identical to the one used by Rogers to enable direct comparison with key details summarized here. For more details on the logistics network, the reader is encouraged to see Ch. 3, of Rogers [15]. To model the logistics network, we make the following assumptions:

1. CONUS dedicated truck routes depart six days a week (Monday through Saturday). Trucks travel seven days a week but may not deliver on a Saturday or Sunday.

2. CONUS dedicated trucks have unlimited capacity as DLA can quickly acquire additional trucks. Similarly, there are always enough trucks to move requisitions from source depots to CCPs or from a CCP to the APODs/SPODs.

3. Restocking the sourcing depots does not require the same resources used by the distribution system.

4. A CONUS depot sources all orders then ships them to their destination.

5. Once a multipack, pallet, or container has started loading, it remains at the location until full or the maximum waiting period has been met (whichever is soonest). Pallets wait up to three days with containers waiting up to fifteen. Multipacks, pallets and containers are considered full when they reach 95% of maximum weight capacity or 85% maximum volume capacity. If at least one of these criteria are met, prior to sending, any requisitions that could fit in the remaining space are pulled from the queue and packed (on a revised slack basis) to ship forward to the next location.

6. All pallets and containers contain repair parts for different units unless the route to a unit does not support break bulk operations. This ensures the model does not ship near empty containers.

7. If a requisition can fill an entire multipack, pallet, or container, the logistics node builds it unit-pure (no other unit orders included). Unit pure multipacks, pallets, and containers do not require breakdown and sorting operations at the TDC and advance directly to the LTM trucks.

8. All air shipments use 463L pallets and all ocean freight employ 40 foot containers. These pallets and containers are comprised of multipack boxes and individual parts that are too large to fit in the multipacks.

9. All surface (ocean) freight travels on commercial ships. This is not a limiting assumption but fits the Sudan scenario.

10. Orders for the Sudan scenario follow the same distribution of transportation modes as occurred in OIF. This is not a limiting assumption as this is an input to the forecasting procedure.

Unlike Rogers [15], times to process requisitions are stochastic and are akin to service time distributions. The mean roundtrip times from Rogers [15] are kept fixed (10 days for IBCT, 8 for SBCT) but this research assumes LTM convoys may sometimes return up to one day early if there are good conditions but may be delayed significantly if adversely impacted by weather or mechanical failures. Without data to estimate these deviations, we assume the LTM roundtrip time is distributed via a generalized Beta distribution having the form $a + (b - a)\text{Beta}(\alpha_1, \alpha_2)$ with first shape parameter $\alpha_1 = 1.2$, and second shape parameters $\alpha_2 = 12$ [45]. The generalized lower and upper bounds result from the assumption that roundtrips to support the maneuver units take a minimum of 90% of the mean roundtrip time from Rogers [15] and no more than twice the mean time.

With the network capacities determined by Rogers et al. [17] for this scenario, the VF readily provides the sample average arrival rate in PEU to the LTM trucks using 55 sample paths. The reader is reminded multiple sample paths are necessary due to our method of forecasting repair part demand; with a different and perhaps more direct forecasting method——such as consumption data-driven MBF——the average scenario demand over time might be more accessible which would require only one run of the VF instead of the multiple runs required in this work. The analysis presented used 55 sample forecasts.

The DIS model requires a performance target for this node. Based on Rogers' [15] findings, this section uses a performance target that requires the capacity needed to achieve a requisition average (not time average) delay of seven days. The sample dispersion at the LTM is both time-varying and greater than 1 (≈ 5) which requires the RCF to adjust the forecasted variance. Without this correction, the model would underestimate risk.

The forecasted requirements presented in Figure 10 include the risk correction for LTM required capacity given in PEU. The solid bold (blue) line marks the average with shaded regions denoting the probability the required capacity is in that range on any given day. The graph is not smooth for good reasons. The LTM node is located furthest downstream and is subject to the accumulated effects of every node's schedule nuances (e.g. some logistics nodes in CONUS do not operate on Saturdays and Sundays). With the timeline fixed, ship schedules, dedicated trucking routes, and long convoy round trip times create a very jagged forecast.

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

The queueing theory that permits construction of the forecast depicted in Figure 10 implies a continuous or near-continuous control of that logistics node but that is hardly possible in the military logistics context, especially under expeditionary conditions. It may be possible to plan for significant capacity changes once per phase. Perhaps a commander can adjust resources once in the planning horizon or maybe not at all. The forecast generated with the VF-DIS model is useful for generating some default capacity options for a specific location.

Developing multiple options is attractive as the computational efficiency of these models permits rapid detailed analysis of each option and permits comparing them over time. One approach is to simply look at the requirements forecasted by Figure 10 and visually set the capacities with intuition or external knowledge about the plan; this technique might develop a plan to ensure the LTM trucks have 70 PEU for Phase I and II then only 20 PEU for Phase III and IV (presumably freeing up some capacity for other missions including a reserve). A more detached technique would be to simply use Figure 10's forecast to calculate the daily value-at-risk ($\mathrm{VaR}_{0.95}$), also known as the 95th quantile, and plan each phase to receive the capacity set to the phase's time-averaged $\mathrm{VaR}_{0.95}$. Alternatively, a constant capacity throughout the planning horizon may be appropriate. The analysis proceeds with these three plans, though one can evaluate any given plan.

Figure 11 provides a visualization of these competing options over time with the constant option set to 78 PEU consistent with Rogers' [15] final recommended plan for the LTM trucks. The chart overlays the three LTM options against the backdrop of average required capacity, the 75th quantile for required capacity, and the 95th quantile for required capacity to convey a sense of the stochastic variation that exists about the average. These options serve to demonstrate the flexibility of this approach and the capability to evaluate any given logistical capacity plan.

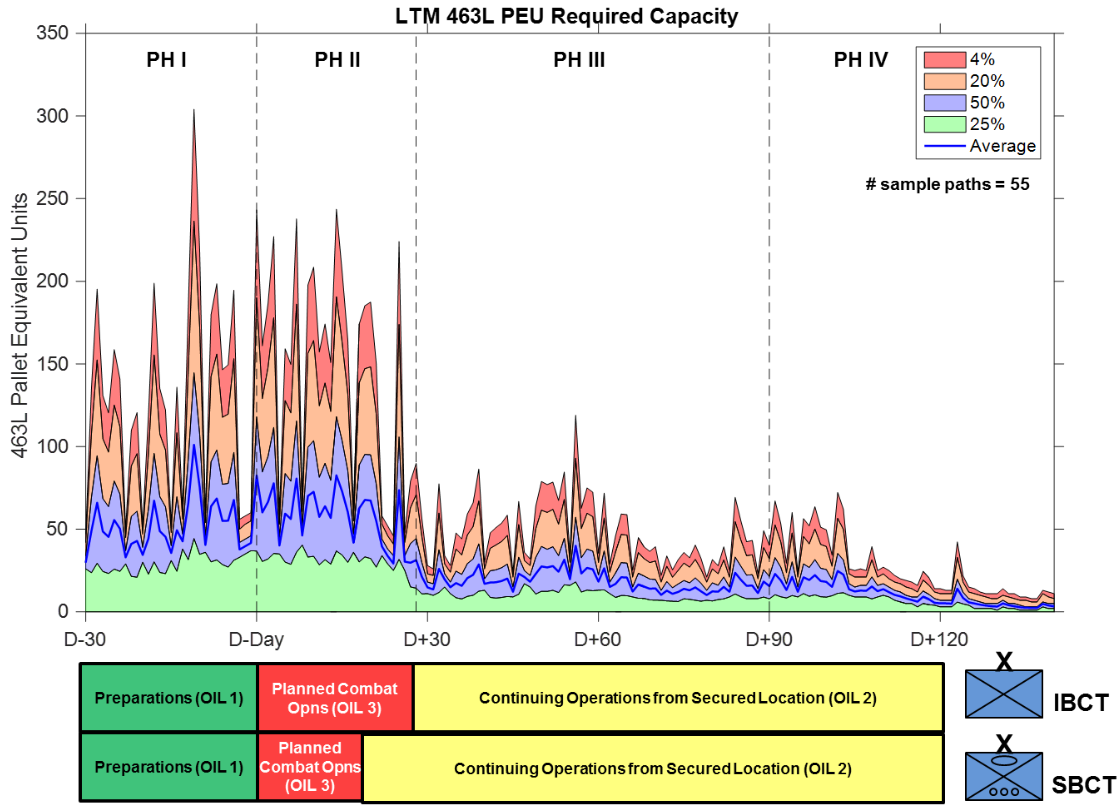


Figure 10: Forecasted Capacity Required at LTM in 463L PEU to Achieve Target Performance of 7 day Average Delay (55 sample paths). Dashed vertical lines denote phases of the operation. BCT operational intensity level timelines displayed below graph for reference.

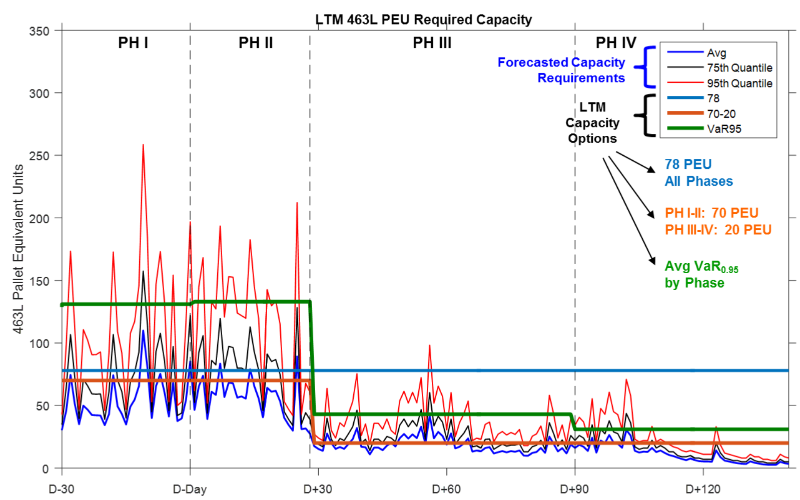


Figure 11: Generating Options for the LTM trucks in the Sudan scenario.

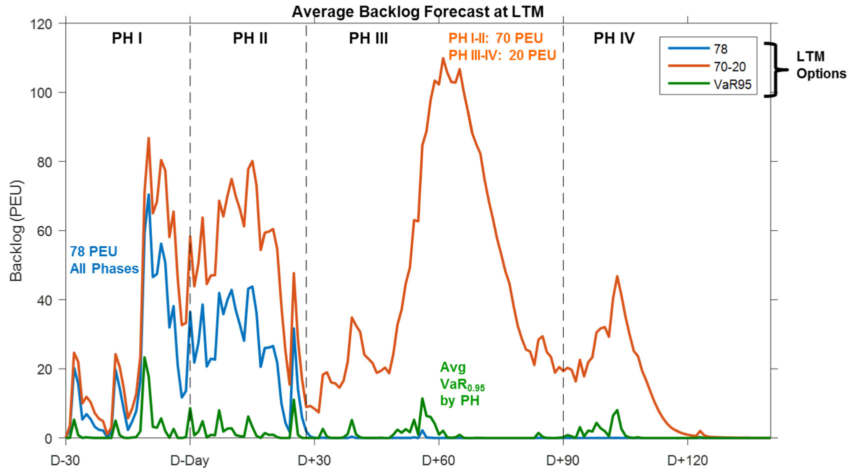


Figure 12: Average Backlog in PEU at LTM trucks for the LTM capacity plans from Figure 11.

Regardless of the complexity or the number of the capacity plans, the visualization provided by Figure 11 is not enough. Commanders want to understand the impacts of these plans in meaningful terms that include both expected performance and an understanding of the uncertainty involved. With the VF and the DIS models, an analyst can evaluate backlogs, delay, lateness, utilization, and other measures by location, by day, by requesting unit, transportation mode, or any combination of these. The model equips the analyst to dig for insights. We present some examples of initial insights that may be constructed by default to inform the decision-maker. Figure 12 shows average backlog over time for the three options as an example.

This approach extends Rogers et al. [17] by not only evaluating average delay across the time horizon but also by making stochastic information available either directly calculated analytically using the distributions (by day) or via Monte Carlo methods [46, 47] which are both quick and accessible with modern computers. Though Figure 12 currently shows average backlog only, it is just as easy to present confidence intervals, quantile bands, or another stochastic visualizations for a chosen metric of interest. Presenting risk-based information that depicts the uncertainty coupled with delay predictions provides a more complete understanding of the tradeoffs between multiple courses of action. Senior leaders seek to understand the risks faced and how to mitigate them — to that end it is critical to estimate how bad things can actually get both by location and over time.

After evaluating a set of plans over time, we arbitrarily select the constant capacity plan taken from Rogers et al. [17] for further analysis. With the outputs of the VF and DIS models, an analyst can evaluate backlog, delay, lateness, and other constructed metrics over time for a specific plan and under multiple what-if scenarios. Motivated by the massive sandstorm that resulted in a seven day disruption to CL IX part resupply early in the invasion of Iraq in 2003, Rogers [15] evaluates the impact of a complete disruption of the resupply vehicles for this Sudan scenario. It is possible to perform a risk-based analysis of the constant 78 PEU capacity plan for LTM trucks from Rogers [15] under a complete disruption of the resupply vehicles.

Rogers [15] shows the value of performing what-if analysis on a given plan to assess how it performs under different potential outcomes. This VF-DIS model permits the same analysis but also shows information beyond the average by connecting potential outcomes with their likelihoods. Figure 13 illustrates this by showing the average backlog at the LTM trucks with and without a

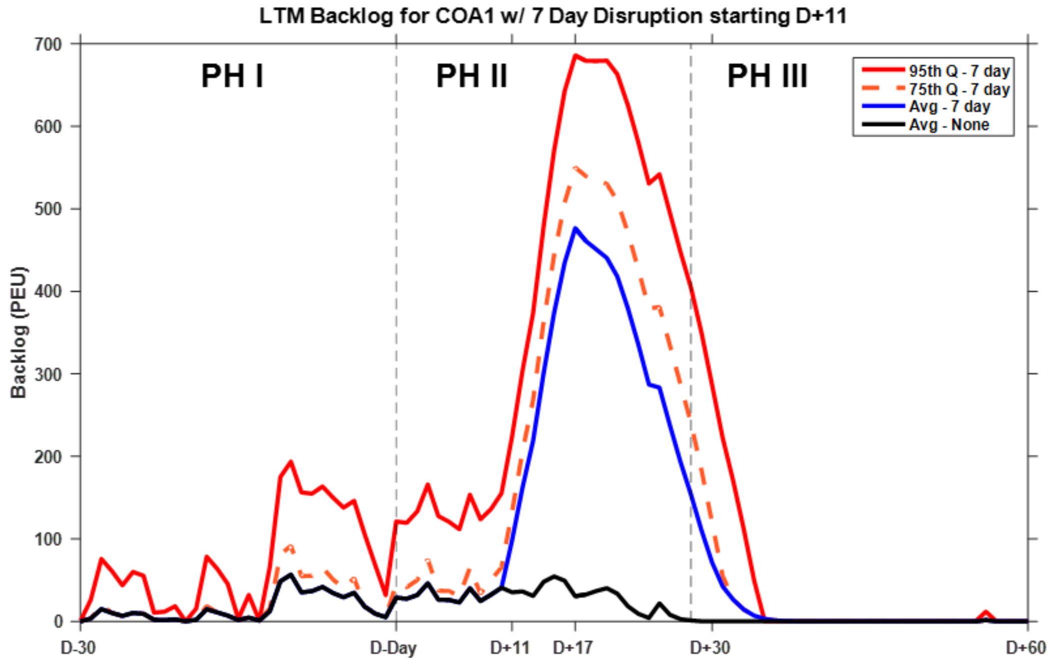


Figure 13: Daily LTM backlog with & without a 7 day disruption (starting D+11) for Sudan COA 1 scenario in Rogers [15] for the 78 PEU LTM plan.

seven day disruption starting at D+11; the figure also depicts how bad the backlog can get by showing the 75th and 95th quantiles. The peak backlog with a 7 day disruption will be almost 480 PEU (7.4 times the no disruption peak). By taking into account the variation around the average, an analyst can forecast there is a 75% chance the peak backlog with this 7 day disruption would be less than 550 PEU (8.7 times the no disruption peak) if the LTM trucks have 78 PEU capacity. Similarly, there is a 95% chance the peak backlog would be no more than 685 PEU (11 times the peak when there is no disruption peak). The recovery times are also available from Figure 13.

Because of the underlying distribution forecast by day, Monte Carlo methods are readily available to assess not only average behavior over time for a specified logistics plan but the full distribution of worst-case behavior. Traditional average worst case metrics used in finance such as conditional value at risk can be readily computed but the computational speeds enable looking at more than the conditional expectation of the worst case scenarios (e.g. worst 5%). Further, the worse case distribution of a particular metric is available [16].

The utility of risk-based measures for what-if analysis cannot be overstated. These tools enhance the MLNPS and extend the possible depth of analysis. Using multiple demand forecasts (sample paths) required multiple runs of the VF to estimate the sample arrival rate as well as the sample dispersion. If the U.S. Army continues to develop MBF beyond aviation units, this analysis would require only one run with the VF if GCSS-Army data provided the sample dispersion for the variance correction. Multiple sample paths are currently required to obtain the required capacity forecast (Figure 10) but with an approach such as MBF that does not rely on sample paths, this is obtainable with a single run of the VF.

By exploiting the strengths of both the DIS model and the VF as well as the feed-forward network structure, this approach maximizes its computational advantages. After obtaining the forecasted requirements to meet a logistics target (Figure 10), the subsequent analysis is computationally efficient using either analytical results, VF output, or simple Monte Carlo methods which are extraordinarily fast in our experience just working with MATLAB [48].

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

These enhancements to the MLNPS center on two fundamental tasks: (1) given a plan, estimate the plan's performance, and (2) given a target performance, find the required plan. This research provides a data-to-decision support process that yields a framework for assessing risk as both the severity and likelihood of possible outcomes become available via analytical calculation or Monte Carlo methods. Our intent is to highlight the utility GCSS-Army data can provide by enabling decision support and planning models in ways not previously possible.

The methods in this research apply to other contexts that employ an underlying stochastic queueing network model that exhibits nonstationary and/or non-Markovian (non-exponential) arrival processes. These applications include disaster relief, humanitarian operations, and understanding international commercial global chain chain disruptions.

2.6.3 Automation & Visualization (advising funded by STIR)

US Army Major Caleb Sheffield, a graduate student at NC State during the STIR, created an app in R (using R Shiny) to automate visualization of VF outputs [49, 50]. His source code has supported current PhD and active duty Army officer Major Blake Schwartz rapidly analyze model outputs.

Outreach to the US Army. Both the PI and the Co-PI teach workshops as part of the Institute for Defense & Business [18] which holds multi-week industry and academic broadening programs for DoD logistical professionals with most attendees coming from the US Army. The Co-PI teaches a workshop focused on how GCSS-Army data can support expeditionary logistics planning. The Co-PI and Major Sheffield modified the source code to create a practical exercise designed to provide an intuitive look at how GCSS-Army data might be useful for logistics planning.

The exercise presents teams of participants with the concept of the operation for the Sudan scenario as depicted in the screenshot in Figure 14. They have a set of tasks to perform which drive team discussion.

The team has access to two basic courses of action (COAs) with varying levels of resource allocations for total of 18 total options. To enable their analysis, the app has a COA Analysis tab as shown Figure 15's screenshot. In this tab, the teams can pick any two of the potential plans to analyze. They must choose a metric to plot, such as backlog or delay, and specify the time horizon

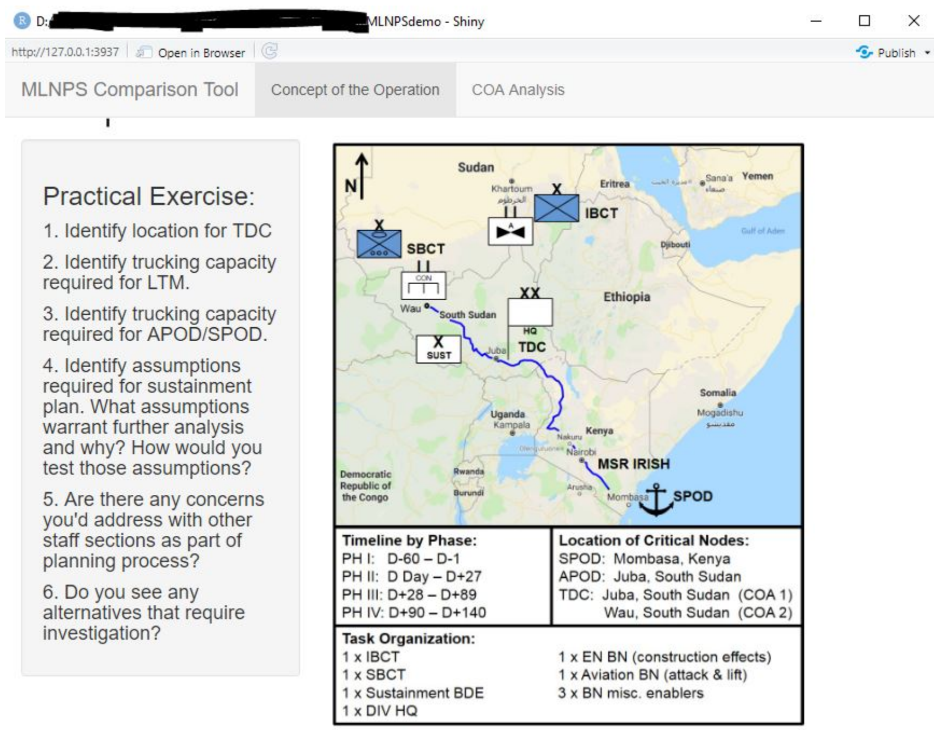


Figure 14: Screenshot of a practical exercise designed to illustrate how automated logistical planning and decision-support tools could impact the US Army using the Sudan scenario.

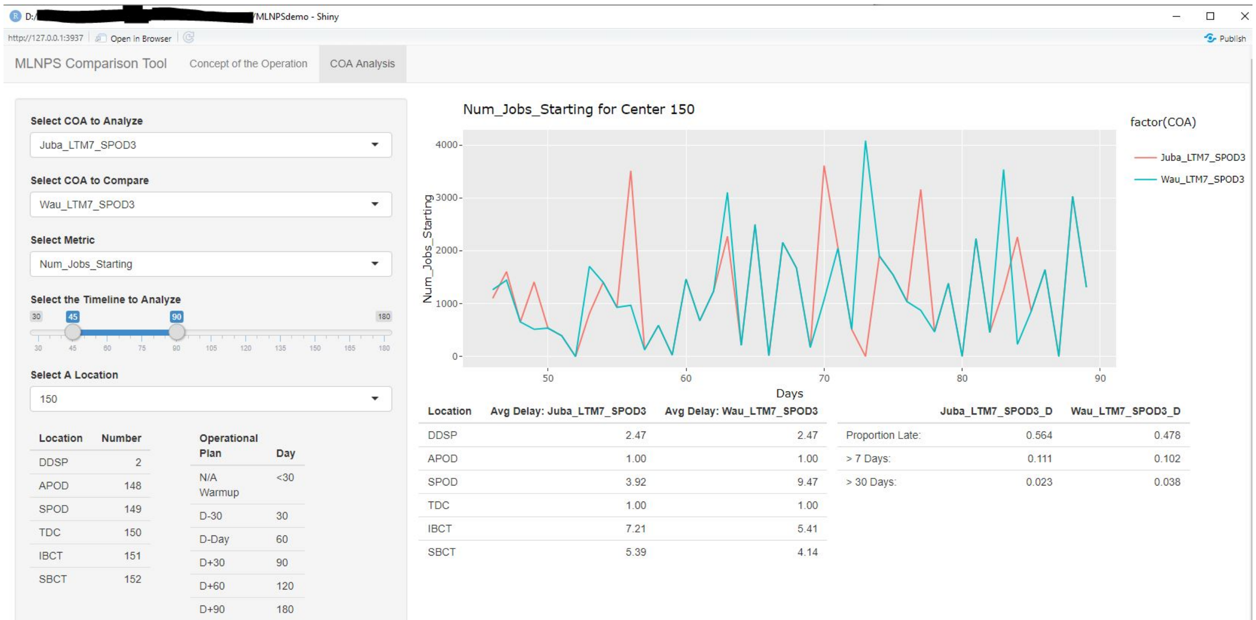


Figure 15: Screenshot of automated dashboard to compare multiple COAs across a user-specified operational timeline for the Sudan scenario.

and location. The plot on the right automatically and immediately updates in real-time. Beneath the plot, summary statistics for the entire network and various locations also update for the chosen COAs.

This app is not running the VF. Instead it is referencing a library of outputs from scenarios already run. The purpose is to demonstrate the utility of having an automated logistical planning and decision-support tool to these logistical professionals using a graphical interface with a web-based feel.

2.6.4 Completed Efforts (funded by STIR)

Active duty US Army officer and current PhD student, Major Blake Schwartz is extending the MLNPS. His focus has been on measuring sustainment network and plan performance, designing a performance measure to properly assess robustness, accounting for uncertainty, and modeling the problem to enable and automate prescriptive solutions.

Measuring Sustainment Network & Plan Performance MAJ Schwartz has focused on how to measure sustainment network performance. This is accomplished by continuing the network modeling approach but incorporating the idea of *plan robustness* because military planners will adjust the plan to changing conditions on the ground. The MLNPS must account for some of the various options and contingency (branch) plans available inside the model. Figure 16 illustrates the utility of assessing the impact of disruptions with this framework; notice that while the baseline is the best option without disruption, disruptions lead to decision points where switching to an alternate would improve performance.

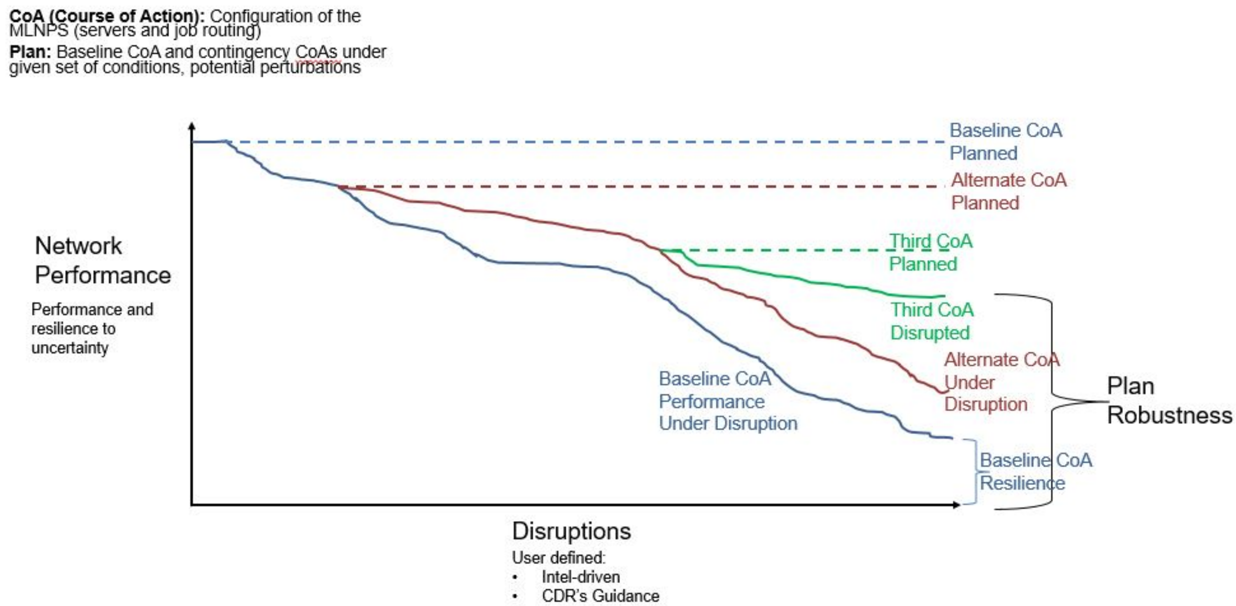


Figure 16: Capturing the robustness of an entire plan that includes multiple contingencies and branch options.

To enable modeling these challenges, MAJ Schwartz has designed new additions to the Sudan scenario to include additional and more complex disruptions, additional realism, and new alternate courses of action. Tables 8–9 summarize these additional disruptions and alternate courses of action to test the model.

Table 8: Potential Disruptions to A/SPOD in Sudan scenario.

Disruptions	Impacts
APOD	0 capacity for 11 days D+50 – D+60
SPOD	D+10 90% capacity D+25 70% capacity D+40 50% capacity
Both	All of the above

Table 9: Alternate plans for A/SPOD and impact on ground transit from those locations to the TDC.

Alternate Plans	Impacts
APOD (alt)	Assume 3 days to establish D+50 0 capacity for ground transit D+53 100% capacity with alternate transit time D+60 100% capacity with primary transit time (runway repaired) alternate transit time = 3×primary transit time
SPOD (alt)	D+10 Transport capacity to TDC reduced to 90% D+20 100% with alternate transit time alternate transit time = 1.57×primary transit time
Both alternates	All of the above

Measuring Robustness. Since military units deploy with a safety stock across classes of supply, operational readiness becomes degraded when that safety stock is depleted. MAJ Schwartz has capitalized on this to design a sustainment network performance measure that identifies sustainment shortcomings to the supported units in terms of the unit's aggregated safety stocks. Unlike performance measures from Rogers and McConnell [15, 16], this accounts for requisitions previously delivered by the sustainment network which should be considered on hand. If $N_E(t)$ is the expected number of requisitions delivered on day t and $N_A(t)$ is the actual sustainment delivered on day t, then the *sustainment lateness* on day t (in number of requisitions), $SL(t)$, is

$$SL(t) = N_E(t) - N_A(t). \tag{12}$$

We use the scheduled completions from MLNPS due dates as a proxy for expected sustainment flow for each day t, and actual completions from MLNPS runs to represent actual sustainment flow. Equation (12) provides a measure of the sustainment deficit on day t.

This daily metric is of limited use as it fails to account for previously delivered sustainment. We define *accrued lateness*, $AL(t)$, to measure the cumulative sustainment performance by day t using

$$AL(t) = \int_0^t SL(s)ds = \int_0^t N_E(s) - N_A(s)ds, \tag{13}$$

where the time period of 0 assumes a start time after the system warm-up which coincides with the operational preparation prior to D-Day. In the MLNPS, time is discretized to increments of 1 day due to the data-fidelity provided, so Equation (13) can be rewritten

$$AL(t) = \sum_{s=0}^{t} \text{Requisitions Due}(s) - \text{Requisitions Complete}(s). \tag{14}$$

If $AL(t) < 0$, the sustainment flow by day t has exceeded the anticipated requirements. Conversely, if $AL(t) > 0$, the sustainment flow has failed to keep up with the cumulative anticipated demand as defined by the forecast.

To find the level at which accrued lateness impacts operational units, we account for the safety stock κ that units deploy with and keep on hand. When accrued lateness exceeds this critical level, we call the amount by which the threshold is exceeded the *accrued critical lateness* (ACL), which is the performance measure we introduce for sustainment networks. If the ACL is positive, the deficit in sustainment flow is sufficient that we expect to see negative impacts on the mission.

If our timeframe of interest is $t \in \{0, 1, 2, \ldots, T\}$ then the ACL is

$$ACL(T) = \int_0^T AL(s)\, \mathbf{1}_{\{AL(s)>\kappa\}} ds, \tag{15}$$

where $\mathbf{1}_{\{\text{condition}\}}$ is an indicator that returns 1 if the condition is true and 0 otherwise.

This method accounts for materiel stocks on hand. In addition, because lateness is calculated at the end of the network, this measure may reflect impacts on tactical units better than the last node queuing backlog proxy method.

Recall that κ is determined by military planners for each mission, and is the expected safety stock level upon deployment (it may also be the expected demand during the anticipated worst-case resupply interval). By comparing the accrued lateness to κ for ACL, we assess whether a logistics network or plan is expected to exhaust the safety stock during the operation. If not, then the sustainment plan is adequate to prevent negative impacts from any anticipated disruptions.

The safety stock may come from planned levels of deploying safety stocks, or may be estimated by

$$\kappa = \text{Estimated Daily Demand} \times \text{Resupply Interval}, \tag{16}$$

where the Estimated Daily Demand comes from the demand forecast. The resupply interval is determined by planners and commanders for the mission. Efforts are ongoing to accurately describe, model, or approximate the uncertainty or variability in the ACL measurement in Equation (15).

A Prescriptive Model. Ongoing efforts seek to provide a mathematical model capable of providing automated assistance to design a robust logistical plan. This involves modeling the tradeoffs inherent between having various network designs. We envision these ongoing efforts resulting in a risk mitigation design matrix to provide insights on how to "optimize" various resilient, robust, adaptive, or flexible logistics network mitigation strategies against potentially disruptive conditions or catastrophic events within an operational risk landscape (defined by event probability and consequence).

This mathematical framework will set the foundation to model the complex decisions involved with alternate routing, contingency plans to address new disruptions, and other realistic challenges.

Some preliminary work in this area is promising, though the mathematics require further development. Table 10 provides results from a pilot study that link decisions to divert flow from a primary to an alternate A/SPOD to the probability of a disruptive event. In this example, the model does not recommend standing up alternate A/SPODs unless the probability of disruption rises above 0.1. Notice that even if the odds of a disruption are a coin toss, only 28–30% should be diverted to the alternates.

Table 10: Results from pilot study showing the fraction of requisition flow to continue sending to the primary APOD and SPOD given the corresponding probability of disruption. The model minimizes total lateness. The fraction to divert to the alternate is available from the complement.

Probability of Disruption	Fraction of Airborne Flow to Primary APOD	Fraction of Seaborne Flow to Primary SPOD
0	100%	100%
0.1	100%	100%
0.3	95%	90%
0.5	72%	70%
0.7	50%	49%
0.9	27%	28%
1	16%	18%

In addition to providing what-if analysis of sustainment COAs, the MLNPS may be used to determine the best allocation of given limited resources across the nodes in the network. By allowing the MLNPS to determine how much capacity is needed to reach a user-defined threshold of sustainment flow, we determine whether it is feasible for the network to achieve the performance measures desired. For a logistics planner who would use the system, automatic allocation of resources to find the best solution could significantly streamline the COA development and analysis process. Combined with the flexible network approach presented in this research, which provides a prescriptive method of designing and selecting a sustainment plan, automatic resource allocation could create a holistically prescriptive model.

3 Contribution Summary

This STIR (#W911NF1910055) has supported:

1. Publication of new variance corrections and approximations to support performance analysis and capacity planning for nonstationary non-Markovian queueing networks and the subsequent use in risk analysis as applied to expeditionary logistics planning. This work resulted in one PhD dissertation and one journal paper which won the 2019 Richard H. Barchi prize from the Military Operations Research Society.
2. Designing new performance measures for sustainment networks to better capture sustainment's impact on readiness, and account for contingency plans.
3. Creating a mathematical model that can use existing predictive models and new representations to provide a prescriptive framework, laying the foundation for a decision-support system.

The last two bullets occurred as part of doctoral research from US Army officer MAJ Blake Schwartz who won the 2018 Best Army Operations Research Symposium Paper which was drafted and submitted in early 2019 under this STIR.

4 Conclusion & Future Work

Efforts to capture readiness-based performance metrics and model a logistical plan while including the collection of contingency (branch) plans are already underway. Current efforts are also working towards modeling alternative routing and decision points into the modeling framework.

Future efforts must expand this emphasis on readiness and provide prescriptive decision-support capability rather than the predictive outputs currently produced by research. Outputs should include identification or visualization of the readiness-versus-cost tradeoffs.

These future steps should

- include a mathematical model to account for allocating shared resources in near-real time with nonstationary capacity and demand. This would support higher-fidelity modeling of the complexities that occur in expeditionary logistics networks, especially at the last tactical mile. This would result in a new processor and given the complexities of the network and the speed of the Virtual Factory, this is a nontrivial requirement.
- expand the risk analysis capabilities by discovering an improved required capacity approximation in nonstationary non-Markovian queueing networks. Rather than using the expected delay as a single parameter, this approximation should incorporate senior leader guidance in the form of the percentage of requisitions that must be processed at a location within x days. This provides a two-parameter risk framework to manage the tail probability of delay and would be more useful in both the Army and non-military applications.
- design an end-to-end prescriptive model that provides recommendations in near-real time using these other models.

Disclaimer

The views expressed in this report are those of the authors and do not reflect the official policy or position of the Army Research Office, the United States Army, the Department of Defense, or the United States Government.

ORCID iD

Russell E. King (PI) https://orcid.org/0000-0003-4576-6600
Brandon M. McConnell (Co-PI) https://orcid.org/0000-0003-0091-215X

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List of Acronyms

Readers seeking definitions of military acronyms will find Joint Publication (JP) 1-02 *Department of Defense Dictionary of Military and Associated Terms* a valuable resource [51].

ABCT	Armored Brigade Combat Team
APOE	Airport of Embarkation
APOD	Airport of Debarkation
AVN BN	Aviation Battalion
BCT	Brigade Combat Team
BDE	Brigade
BN	Battalion
CL	US Class of Supply
CO	Company
CONUS	Continental United States
CPP	Consolidation and Containerization Point
DD	Due Date
DDSP	Defense Depot Susquehanna, Pennsylvania
DIS	Delayed Infinite Server
DIV HQ	Division Headquarters
DLA	Defense Logistics Agency
EN BN	Engineer Battalion
ERP	Enterprise Resource Planning
FEU	Forty foot container Equivalent Unit
GCSS-A	Global Combat Support System-Army
HBCT	Heavy Brigade Combat Team
IBCT	Infantry Brigade Combat Team
LD	Line of Departure
LTM	Last Tactical Mile
MBF	Mission-based Forecasting
MLNPS	Military Logistics Network Planning System
MRE	Meals Ready-to-Eat
MTOE	Modified Table of Organization and Equipment
NHPP	Nonhomogeneous Poisson Process
OIF	Operation Iraqi Freedom
OIL	Operational Intensity Level
PEU	463L Pallet Equivalent Unit
RCF	Risk Correction Factor
RT	Release Time
SBCT	Stryker Brigade Combat Team
SDT	Standard Delivery Time
SP	Sourcing Point
SPOE	Seaport of Embarkation
SPOD	Seaport of Debarkation
SSA	Supply Support Activity
TDC	Theater Distribution Center
TEU	Twenty foot container Equivalent Unit
TPFDD	Time Phased Force Deployment Data
TRANSCOM	US Transportation Command
VF	Virtual Factory
WWX	World Wide Express