A framework for optimizing sustainment logistics for a US Army infantry brigade combat team

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Abstract

Purpose – The purpose of this paper is to help optimize sustainment logistics for US Army brigade combat teams, which may face challenges in transporting their assigned assets.

Design/methodology/approach – This paper develops a simulation framework with an integrated integer programming optimization model. The integer-programming model optimizes sustainment outcomes of supported battalions on a daily basis, whereas the simulation framework analyzes risk associated with shortfalls that may arise over the entire duration of a conflict.

Findings – This work presents a scenario reflecting the steady resupply of an infantry brigade combat team during combat operations and presents an in-depth risk analysis for possible fleet compositions.

Originality/value – The risk curves obtained allow decision-makers and commanders to optimize vehicle fleet design in advance of a conflict.

Keywords US Army, Infantry brigade combat team, Sustainment logistics, Integer programming, Simulation

Paper type Research paper

1. Introduction

The US Army's primary warfighting unit is the brigade combat team (BCT). Before 2004, the Army's organizational structure was built around divisions of 15,000 soldiers.

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At the time, divisions were the smallest type of unit capable of deploying and sustaining themselves without outside support. General Peter Schoomaker, the Chief of Staff of the Army from 2003 to 2007, led the transformation to create BCTs, which are self-sufficient formations of approximately 3,000 soldiers. This change was designed to allow the Army to deploy smaller groups of personnel and equipment based on needs (Garamone, 2004).

BCTs are standardized across the army based on function. The current types of BCT formations are infantry, armored and Stryker. The army has directed the manning and equipping of a brigade support battalion to meet the sustainment needs of the BCT (Field Manual 3–96, 2015).

Commanders are responsible for ensuring that adequate transportation vehicles, also termed *assets*, are available to move supplies and equipment forward in the operational area (Field Manual 4–0, 2019, p. 7–5). Truck convoys in both the army and Marine Corps are subject to attack, disrupting sustainment (Giordano, 2012; Lynch, 2019). Recently, the army identified a shortfall in truck transportation capacity within BCTs, so commanders must exercise careful judgment in allocating these scarce resources (Bobzin *et al.*, 2019; Bobzin *et al.*, 2020; Van Howe, 2019).

Mixed integer programming (MIP) has been used to analyze theater-level distribution of supplies (Hill and Pohl, 2010; Longhorn and Muckensturm, 2019; Muckensturm and Longhorn, 2019). In addition, MIP can support analytical modeling of the force design of army logistics units (Connors and Ewing, 2017; Salgado, 2016), which is particularly important as the army transitions to a greater focus on large-scale combat operations (Sweeney, 2019).

The convoy movement problem associated with military vehicles is also an established area of application for MIP models (Bovet *et al.*, 1991; Giordano, 2012; Lam *et al.*, 2020; Mokhtar *et al.*, 2020). Heuristics and simple algorithms have been found to be effective in resolving the convoy movement problem (Tuson and Harrison, 2005; Xiong *et al.*, 2017). MIP approaches are also used for optimizing the use of commercial vehicle fleets (Coelho *et al.*, 2014; Gorman *et al.*, 2014).

In this paper, we develop a simulation framework with an integrated integer programming optimization model for the sustainment of an infantry BCT (IBCT). In Section 2, we provide background information on IBCTs and their resupply process. In Section 3, we describe the components of our framework. In Section 4, we introduce a realistic IBCT combat scenario and present our computational results. We conclude in Section 5 with a summary of our contributions and future research opportunities.

2. Background

An IBCT consists of seven battalions: three infantry battalions, one cavalry (reconnaissance) battalion, one field artillery battalion, one engineer battalion and one brigade support battalion. The brigade support battalion is relied upon to support the mobility and endurance of the six other units engaged in combat operations by conducting regular resupply of needed supplies.

2.1 Supplies

The US Armed Forces divide all military supplies into ten classes (Army Regulation 710–2, 2008; Field Manual 4–0, 2019), shown in Table 1. Estimating daily consumption is often a tactical focus of logistics planners and is essential to the conduct of battle. Supplies such as repair parts and construction materials can also be critical to force sustainment.

Class	Description
Class I	Subsistence, including free health and welfare items
Class II	Clothing, individual equipment, tentage, tool sets and tool kits, handtools, administrative and housekeeping supplies and equipment (including maps). This includes items of equipment, other than major items, prescribed in authorization/allowance tables and items of supply (not including repair parts)
Class III	POL, petroleum and solid fuels, including bulk and packaged fuels, lubricating oils and lubricants, petroleum specialty products; solid fuels, coal and related products
Class IV	Construction materials, to include installed equipment, and all fortification/ barrier materials
Class V	Ammunition, of all types (including chemical, radiological and special weapons), bombs, explosives, mines, fuses, detonators, pyrotechnics, missiles, rockets, propellants and other associated items
Class VI	Personal demand items (nonmilitary sales items)
Class VII	Major items: a final combination of end products which is ready for its intended use: (principal item) for example, launchers, tanks, mobile machine shops, vehicles
Class VIII	Medical material, including medical peculiar repair parts
Class IX	Repair parts and components, including kits, assemblies and subassemblies, reparable and nonreparable, required for maintenance support of all equipment
Class X	Material to support nonmilitary programs, such as agricultural and economic development, not included in Class I through Class IX

Source: Army Regulation 710–2 (2008)

Table 1.
Ten classes of supply

For our analysis, we group these ten supply classes into four modified categories: I (water), III (fuel), V (ammunition) and All Other, a catch-all category that includes Classes I (food), II, III (prepackaged lubricants), IV, VI, VII, VIII, IX and X.

Our primary method for measuring supported unit supply inventories is days of supply (DOS), the number of days that a given quantity of supplies will sustain a supported unit under specific conditions. A DOS is a function of unit size, type and mission. For example, one DOS of food for a 500-soldier infantry battalion will be more food than one DOS of food needed to sustain a 300-soldier engineer battalion. One DOS of fuel will be much higher for the engineers. DOS gives the commander a common unit to understand the supply readiness of subordinate units. It allows one to quickly grasp the current status of a given unit, without requiring in-depth knowledge of actual quantities of goods needed for readiness in one battalion vs another. Unless specified for a mission, units deploy with three DOS on hand and expect to be resupplied with one DOS every subsequent day. This provides a cushion for variability of consumption, as well as for the times when resupply is infeasible for one or two days.

2.2 Transportation assets for supplies

The load handling system in Figure 1 is a primary logistics resupply vehicle. The M1076 Palletized Load System Trailer in Figure 2 would be transported by the load handling system in Figure 1. A trailer can transport the equivalent of eight single stacked pallets. The Compatible Water Tank Rack (also known as "Hippo") shown in Figure 3 attaches to the trailer shown in Figure 2. The Hippo has a capacity of 2,000 gallons of water and requires the complete volume capacity of the transportation platform. The M978 HEMTT Fueler in Figure 4 is the army's prime mover for Class III (fuel). It has a capacity of 2,500 gallons and is also able to tow a trailer with additional fuel capacity provided by a modular fuel system.

Figure 1.
Photo of HEMTT Load Handling System downloaded from https://en.wikipedia.org/wiki/M1120_HEMTT_Load_Handling_System#/media/File:HEMTT_M1120A2.jpg

Note: The appearance of U.S. Department of Defense (DoD) visual information does not imply or constitute DoD endorsement

3. Mathematical modeling framework

We introduce a mathematical modeling framework for optimizing resupply that includes several components:

- a quantitative method for prioritizing distribution decisions (subsection 3.1);
- an integer programming model for optimizing daily distribution (subsection 3.2);
- a simulation-based heuristic algorithm for measuring risk associated with a fixed fleet of trucks (subsection 3.3); and
- a simulation-based heuristic algorithm for generating risk curves to optimize a fleet's composition of trucks (subsection 3.4).

We have used optimization and simulation by designing a series of algorithms that are run in sequence, and for which, we directly adjust parameters through an iterative search. One upside of an iterative search is its ability to produce a complete spectrum of strategies with their associated risks, which can then be considered and acted upon by a leadership team.

3.1 Prioritizing distribution

The central aspect of optimizing distribution is the decision the brigade support battalion must make on how best to use its distribution assets to resupply supported units. When allocating a limited number of transportation assets across competing shortages, a supporting logistics unit would prioritize resupply efforts according to three main *criticality factors* that describe the urgency of the need:

Figure 2.
Photo of M1076 Palletized Load System Trailer downloaded from https://commons.wikimedia.org/wiki/File:=M1076_PLS_trailer.jpg

Note: The appearance of U.S. Department of Defense (DoD) visual information does not imply or constitute DoD endorsement

Figure 3.
Photo of Water Tank Rack downloaded from https://asc.army.mil/web/portfolio-item/cs-css-load-handling-system-compatible-water-tank-rack-hippo/

Note: The appearance of U.S. Department of Defense (DoD) visual information does not imply or constitute DoD endorsement

Figure 4.
Photo of M978 HEMTT Fueler downloaded from https://commons.wikimedia.org/wiki/File:M978_tank_truck_in_Beatty,_Nevada.jpg

Note: The appearance of U.S. Department of Defense (DoD) visual information does not imply or constitute DoD endorsement

- Ending inventory level or shortage: when a unit's current inventory stores fall below a certain threshold of supply, maneuver options become increasingly constrained. Any ending inventory level under the target DOS is considered a *shortage*.
- The relative importance of a supply class: supply class importance is determined by the maneuver commander. For example, in the army's response to COVID-19, Class VIII (medical) may be the top priority for support in certain areas.
- The relative importance of the unit: any mission order will designate one unit as the *main effort* in a particular phase of an operation, indicating that the actions of this unit among all others are essential to accomplishing the mission.

We assign these quantitative scores to the replenishment of specific supplies for specific units and use them to optimize resupply. Typically, avoiding low inventory levels is the highest priority, supply classes are next and prioritization based on unit ranks lower. However, relative priorities may differ by mission.

3.2 Optimizing distribution

We develop an integer programming model to allocate shipping capacity for classes of supplies to units, to best meet operational priorities. The model is framed in terms of truckloads because the decision of interest is shipping trucks, so shortages tracked in DOS must be converted to truckloads. Trucks may be shipped at partial capacity when fully resupplying a unit to max capacity.

Indices and sets:

- $t \in T$ – truck type;
- $i \in I$ – class of supply;
- $t_i \in T$ – truck type of supply class $i \in I$;
- $I_t \subseteq I$ – supply classes using truck type $t \in T$; and
- $j \in J$ – supported unit.

Parameters:

- c_t – distribution capacity measured in number of trucks of type $t \in T$;
- d_i – distribution capacity measured in number of trucks of type t_i for class $i \in I$;
- s_{ij} – shortage of class $i \in I$ at unit $j \in J$ (measured in trucks); and
- p_{ij} – prioritization weight for supply level of class $i \in I$ for unit $j \in J$.

Decision variables:

- x_{ij} – integer number of trucks of supply $i \in I$ shipped to unit $j \in J$; and
- y_{ij} – binary decision to ship a partial truckload of supply $i \in I$ to unit $j \in J$.

Integer programming model:

$$\text{Maximize} \quad \sum_{i \in I} \sum_{j \in I} \left(x_{ij} - y_{ij}\left(\lceil s_{ij} \rceil - s_{ij}\right)\right)p_{ij} \tag{1}$$

$$\text{subject to} \sum_{i \in I_t} \sum_{j \in J} x_{ij} \leq c_t \qquad \forall t \in T \tag{2}$$

$$\sum_{j \in J} x_{ij} \leq d_i \qquad \forall i \in I \tag{3}$$

$$x_{ij} \leq \lceil s_{ij} \rceil \qquad \forall i \in I, j \in J \tag{4}$$

$$x_{ij} - y_{ij} \leq \lfloor s_{ij} \rfloor \qquad \forall i \in I, j \in J \tag{5}$$

$$x_{ij} \in \mathbb{Z}^+ \qquad \forall i \in I, j \in J \tag{6}$$

$$y_{ij} \in \{0, 1\} \qquad \forall i \in I, j \in J \tag{7}$$

Our objective function (1) prioritizes shipments based on the current level of supply, by class of supply and unit, seeking to maximize aggregate value. The model allocates transportation capacity subject to four main constraint types. Constraint (2) ensures distribution of all supplies using a truck type does not exceed capacity for that truck type. Constraint (3) ensures that each supply class transported does not exceed its available transportation capacity. To differentiate between constraints (2) and (3), consider water, which is limited both by the number of water racks and by the number of load handling systems. Constraint (4) ensures that no more than the amount of trucks required to meet demand may be shipped, which is necessary because our objective maximizes prioritization points. To ensure the binary variables enforced in constraint (7) are activated when partial-truck demand uses full-trucks for shipments, constraint (5) acts as a linking constraint, by rounding down the shortage amount measured in vehicles to less the actual shortage amount allowed in constraint (4), and when the shortage is already an integer value, constraints (4) and (5) become redundant. Constraint (6) ensures that our decision variables are integers, as distribution assets cannot be divided owing to the specialized shipping requirements of each class of goods.

3.3 Assessing risk for a given number of trucks

Our integer programming model (1)–(7) optimizes distribution plans for a single day. To use the model for upfront planning in advance of a conflict, it is important to understand the relationship between the number of trucks in a BCT's fleet and the BCT's ability to sustain distribution over the duration of a conflict. To do so, we need to introduce a measure for risk, which tracks supply levels falling below certain thresholds.

In our computational results, we use six thresholds measured in DOS to assess risk. These DOS thresholds (3.0, 2.5, 2.0, 1.5, 1.0 and 0.5) are tracked for each supply class, unit and day. For example, if the cavalry unit starts Day 7 with 2.3 DOS of fuel, some level of Day 7 risk would be associated with the 3.0 and 2.5 DOS categories, but not with the 2.0, 1.5, 1.0 and 0.5 categories. It is useful to distinguish between the risk categories for decision-making purposes. A commander may be willing to accept risk of units occasionally having between 2.0 and 2.5 DOS of fuel over the course of a conflict. However, that commander will take stronger measures to avoid risk of units starting a day with less than 0.5 DOS of some types of supplies, because that corresponds to running out of those supplies completely.

Although one could introduce any number of risk functions, we simply sum the number of units experiencing a supply class shortage on a given day and divide by the total number of units to obtain an average risk for a supply class on that day. We then average the risk over the number of days in the conflict. To ensure the risk measure is robust, it should not be a function of a single sample, so we again compute its average value over a sufficient number of simulation runs. Note: these averages are by DOS threshold, so information on the severity of shortages is retained in the risk measure.

Our method for assessing risk for a given number of trucks is summarized in Algorithm 1.

Algorithm 1. This function computes risk of supply shortages, for a given fleet of trucks. The call to the *runOptimization* function solves an instance of our integer programming model (1)-(7) for each day in the specified time horizon. Risk is averaged.

```
risk = 0
for k = 1 to numRuns do
  initialize starting inventory to target days of supply
  for 1 to numDays do
    measure risk r of starting inventory
    risk = risk + r/numDays
    generate distribution capacity scenarios c⃗ and d⃗ for truck availability
    compute shortages s⃗ by generating scenarios for consumption
    compute prioritization points p⃗
    runOptimization(c⃗, d⃗, s⃗, p⃗)
    compute starting inventory for the next day
  end for
end for
risk = risk/numRuns
return risk
```

3.4 Optimizing truck capacity

Intuitively, with an infinite number of trucks, we would always have shipping capacity to fully sustain all units, with all supplies, on all days. Similarly, with very few trucks, we would certainly not be able to sufficiently sustain all units. However, determining the optimal number of trucks that provides sustainment coverage is a more challenging problem to solve.

We introduce a method for computing risk curves for each number of trucks, which allows the decision-maker to focus on the region of interest, in which risk is small and falls to zero. Owing to interdependencies between supply classes and truck types, when analyzing one truck type we assume infinite capacity of other truck types. For example, water requires its own unique set of tank racks (shown in Figure 3) but also uses load handling systems (shown in Figure 1). So, to compute risk curves for water, we assume an infinite number of load handling systems, which transforms our interdependent problem into a computationally simpler independent one.

For each truck type, we can iteratively increase from having zero to one to two trucks, etc., and compute a risk assessment using Algorithm 1, until we reach a point where the risk level decreases to 0 or below some user-specified cutoff value, at which point we have identified the maximum capacity a decision-maker would consider. Recall though that our risk measure is indexed by supply classes, not by truck types, so the stopping condition must ensure the risk level is sufficiently low for all supply classes that use the given truck type.

Our method for computing risk curves, so a decision-maker can optimize truck capacity, is summarized in Algorithm 2.

Algorithm 2. This function computes risk versus number of trucks required to sustain supplies for a given truck type, for risk levels less than some input cutoff. Additional inputs include number of days and number of runs for the simulation performed in *runRiskAssessment* (*Algorithm 1*).

```
riskCurve = {}
c⃗ = ∞⃗
c_t = 0
flag = true
while flag do
   flag = false
   risk = runRiskAssessment(c⃗, numDays, numRuns)
   if risk > riskCutoff then
      flag = true
   end if
   riskCurve[c_t] = risk
   if flag then
      c_t = c_t + 1
   end if
end while
return riskCurve
```

4. Scenario and computational results

We developed a detailed scenario with input from subject matter experts in army IBCT operations. First we discuss the scenario parameters followed by computational results.

4.1 Prioritizing distributions

Recall the three aspects of prioritizing distribution discussed in subsection 3.1:

(1) Ending inventory level or shortage: we use a piecewise-linear prioritization function $p_1(z)$ in equation (8) to obtain a prioritization coefficient for a given supply level z measured in DOS:

$$p_1(z) = \begin{cases} 1 - 0.5z & 0 \leq z \leq 1 \\ 0.5 - 0.3(z-1) & 1 \leq z \leq 2 \\ 0.2 - 0.2(z-2) & 2 \leq z \leq 3 \end{cases} \quad (8)$$

Notice that $p_1(3) = 0$, $p_1(2) = 0.2$, $p_1(1) = 0.5$ and $p_1(0) = 1$, so that low supply is prioritized in an increasingly strong manner.

(2) The relative importance of a supply class: we analyze four categories: Class I (water), Class III (fuel), Class V (ammunition) and All Other, a catch-all category that includes Classes I (food), II, III (prepackaged lubricants), IV, VI, VII, VIII, IX and X. The prioritization coefficient $p_2(i)$ of supply class $i \in I$ is provided in Table 2.

Class I (water) provides basic life support that supersedes all other supply priorities in our scenario. Class III (fuel) is essential to unit mobility but is less important than Class V (ammunition), which provides for self-defense. Although certain parts or materials might be deemed critical, taken together, the All Other class will not be more important than I (water), III (fuel) or V (ammunition).

(3) The relative importance of the unit: the prioritization coefficient $p_3(j)$ of supported unit $j \in J$ is provided in Table 3.

Our *main effort* is the first infantry unit, whose actions are only slightly more important than the other two infantry battalions. Next, the field artillery and cavalry units are more likely to provide essential support to the infantry battalions and, therefore, the combat mission overall. Of the six units, we consider the engineer battalion the lowest priority during large scale combat operations. Although the importance of a unit to the overall mission varies greatly with circumstance and might change over the course of an entire operation, we hold these relative priorities constant in our scenario. Note: the relative priorities provided are estimates informed by subject matter experts but are not defined in any military doctrinal reference.

4.1.1 Overall prioritization. The overall prioritization function $p(z, i, j) = p_1(z)p_2(i)p_3(j)$ is used to compute the parameter P for our integer programming model. Low supply will have the greatest impact, followed by relative importance of the supply class and then supporting unit.

4.2 Optimizing truck capacity

The integer programming model produces plans to distribute supplies and, in particular, decides on the number of each type of truck sent to each supported unit. The simplest unit of measure for describing and analyzing most aspects of our framework is DOS. So, to optimize and enforce the integrality constraint for the number of trucks, we need a unit measure conversion table that is specific to our scenario. For example, a conversion factor from DOS to number of trucks would be higher for units with more people because they need a larger volume of supplies than the same type of unit with fewer people. The DOS to truck conversion factors are provided in Table 4, along with additional information regarding personnel and DOS quantity requirements.

Supply class	Relative importance
I (water)	1.0
III (fuel)	0.5
V (ammunition)	0.7
All Other	0.3

Table 2. Relative priority of supply classes

Supported unit	Relative importance
Infantry 1	1.0
Infantry 2	0.95
Infantry 3	0.95
Field artillery	0.9
Cavalry	0.85
Engineer	0.75

Table 3. Relative priority of supported units

4.3 Assessing risk through simulation

We incorporate two main aspects of uncertainty in our simulation:

(1) uncertainty in the number of trucks available, owing to maintenance and personnel availability; and

(2) uncertainty in consumption, owing to climate and mission needs.

Historical data are unavailable, so we rely on subject matter expertise and use triangular distributions for both these sources of uncertainty. The algorithms we present incorporate uncertainty through sampling and are agnostic to distribution assumptions. Therefore, if data were to become available to support more precise distribution assumptions, it could be easily incorporated.

4.3.1 Uncertainty in truck availability. Uncertainty in truck availability is owing to both maintenance and driver availability. The distribution for trucks is provided in Table 5. Water racks are assumed to always be available; however, they are attached to load handling systems, which are not always available. If an insufficient number of load handling systems are available, the optimization model will account for it and prioritize distribution accordingly.

4.3.2 Uncertainty in consumption. The distribution for consumption is provided in Table 6. Given the small volume of Class V (ammunition) required for all supported units except the field artillery battalion, as seen in Table 4, their distribution is likely to be handled separately, e.g. in other types of armored vehicles. We set Class V (ammunition) simulation parameters accordingly and assume no consumption, when consumption volume is negligible, so resupply will not be handled by load handling systems.

Supported unit	# Personnel	Supply class	DOS quantity	# Trucks per DOS
Infantry 1 through 3	459	I (food)	2,066 gallons	1.0328
Infantry 1 through 3	459	III (fuel)	1,486 gallons	0.2972
Infantry 1 through 3	459	V (ammunition)	145 pounds	0.0625
Infantry 1 through 3	459	All Other	17 pallets	1.0625
Field artillery	556	I (food)	2,502 gallons	1.2510
Field artillery	556	III (fuel)	3,126 gallons	0.6252
Field artillery	556	V (ammunition)	22,509 pounds	1.1255
Field artillery	556	All Other	17 pallets	1.0625
Cavalry	343	I (food)	1,544 gallons	0.7718
Cavalry	343	III (fuel)	1,833 gallons	0.3666
Cavalry	343	V (ammunition)	80 pounds	0.0625
Cavalry	343	All Other	14 pallets	0.8750
Engineer	533	I (food)	2,399 gallons	1.1993
Engineer	533	III (fuel)	5,156 gallons	1.0312
Engineer	533	V (ammunition)	68 pounds	0.0625
Engineer	533	All Other	20 pallets	1.2500

Table 4. Unit measure conversion factors from DOS to number of trucks, by supply class and supported unit

Truck type	Min (%)	Mode (%)	Max (%)
Water	100	100	100
Fuel	60	80	100
Load handling system	60	80	100

Table 5. Triangular distribution for percentage of trucks available

Supported unit	Supply class	Min	Mode	Max
Infantry 1 through 3	I (food)	0.75	1.00	1.25
Infantry 1 through 3	III (fuel)	0.75	1.00	1.25
Infantry 1 through 3	V (ammunition)	0.00	0.00	0.00
Infantry 1 through 3	All Other	0.85	1.00	1.15
Field artillery	I (food)	0.75	1.00	1.25
Field artillery	III (fuel)	0.85	1.00	1.15
Field artillery	V (ammunition)	0.90	1.00	1.10
Field artillery	All Other	0.85	1.00	1.15
Cavalry	I (food)	0.75	1.00	1.25
Cavalry	III (fuel)	0.40	1.00	1.60
Cavalry	V (ammunition)	0.00	0.00	0.00
Cavalry	All Other	0.70	1.00	1.30
Engineer	I (food)	0.75	1.00	1.25
Engineer	III (fuel)	0.90	1.00	1.10
Engineer	V (ammunition)	0.00	0.00	0.00
Engineer	All Other	0.70	1.00	1.30

Table 6. Triangular distribution for consumption in DOS, by supply class and supported unit

4.3.3 Simulation dynamics. The simulation tracks daily inventory levels, measured in DOS, by supply class and supported unit. We assume that each unit can only hold three DOS on-hand owing to limited storage and holding space. If the optimization model sends two trucks when only one and a half trucks are needed to reach 3.0 DOS, then the inventory level will be set to 3.0 DOS, which is both the target amount of supplies and the maximum allowed. Any amount of inventory below 3.0 DOS reflects a shortage of a particular supply, for a given unit. We assume that resupply occurs early enough in the day for supplies to be available for consumption that day.

4.4 Results and discussion

We developed our framework in Python 3.7, using CPLEX V12.10.0 to solve the integer programming subproblems. We ran the scenario for a conflict duration of 63 days and simulated 100 runs to produce robust risk curves. We also ran the scenario as an expected value problem, where supply of trucks and consumption remained constant (i.e. the average values in Tables 5 and 6), for comparison.

4.4.1 Simulation with 100 runs. First, we review the risk curves for optimizing Class III (fuel) truck capacity over a 63-day conflict simulation, which are provided in Figure 5. To ensure no risk of always maintaining 3.0 DOS, the fleet would need eleven fuel trucks. With minimal risk, nine or ten fuel trucks would suffice. By reducing the buffer from 3.0 DOS to 2.5 DOS, fuel supplies can robustly be maintained with eight trucks. Having less than seven fuel trucks would introduce risk for maintaining even 2.0 DOS consistently. The status quo for this scenario is five fuel trucks, which maintains only 1.5 DOS with almost no risk.

Figure A1 in the Appendix provides risk curves for all supply classes.

4.4.2 Expected value problem. Next, we repeat this analysis using the risk curves obtained by solving the expected value problem for optimizing Class III (fuel) truck capacity over 63 days of conflict, which are provided in Figure 6. Using expected value, no more than nine fuel trucks would be needed to robustly maintain 3.0 DOS. Only five fuel trucks, the status quo for this scenario, would be required to maintain 2.0 DOS with almost no risk.

Figure A2 in the Appendix provides risk curves for all supply classes.

4.4.3 Randomly generated truck availability vs expected truck availability. Intuitively, we can understand the relationship between the tails of the simulation using randomly generated truck availability versus the expected value problem. In the expected value problem, 80% of the fuel trucks are available, so with nine trucks that would leave seven trucks available. When simulating a day with 60% truck availability, with eleven trucks then seven would also be available. So, the tails in both Figures 5 and 6 are owing to the same need for seven trucks to be always operational to experience no risk of maintaining 3.0 DOS.

When faced with limited resources, a decision-maker might be tempted to equip the fleet with only five fuel trucks, based off the expected value risk curves in Figure 6, with mistaken confidence about the risk involved. Figure 5 shows that the risk is actually not insignificant: about 20% of the time, units would fall short of 2.0 DOS in fuel. This

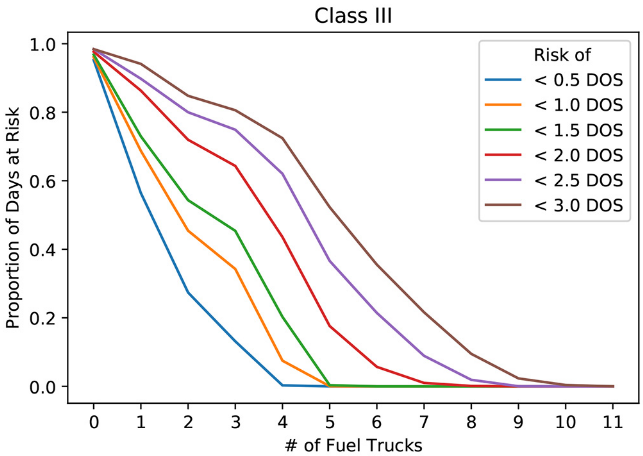

Figure 5.
Simulation with 100 Runs: risk of Class III (fuel) shortage as a function of fuel truck capacity for a 63-day conflict, using triangular distributions to generate random samples for truck availability and consumption

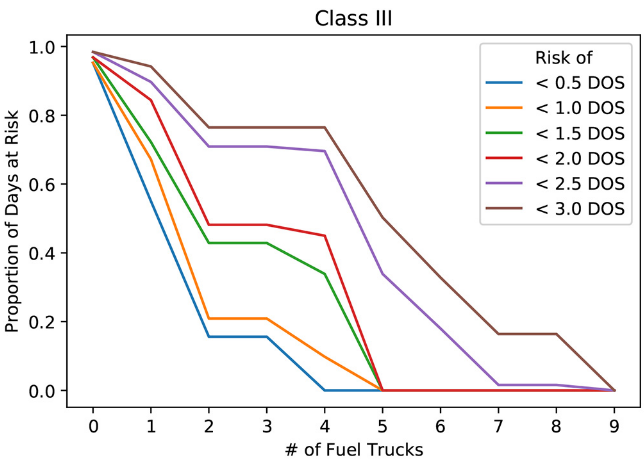

Figure 6.
Expected value problem: risk of Class III (fuel) shortage as a function of fuel truck capacity for a 63-day conflict, using expected values for truck availability and consumption

highlights the usefulness of simulating the entire range of uncertainty vs simplifying the dynamics with expected values.

5. Conclusions

Our framework for optimizing IBCT sustainment logistics informs strategic decisions for fleet design in advance of a conflict. It can be directly applied to analyze risk and pinpoint opportunities for mitigation. Realistically, not all equipment a unit has will be available for operational use. Both planned and unplanned maintenance limit the number of vehicles available at a given time. Similarly, consumption of goods is not constant from day to day but depends on required tasks, weather conditions and a host of other factors.

In the absence of modeling frameworks that can capture these sources of uncertainty, decision-makers may rely on averages and expectations. As we show in subsection 4.4, introducing such simplifications can hide potential risks and lead to less effective decisions. We incorporate this variability in our model through simulation. We thereby provide a more robust method for measuring risk and informing decisions that effectively mitigate it. Our method proved effective both in terms of the quality of results produced and in terms of computational tractability.

The risk curves our framework produces are designed to be easily interpreted by decision-makers who are faced with challenging resource decisions. One can easily prioritize certain supply classes over others and understand the associated fleet requirements. Commanders can also quickly generate what-if scenarios to test how changes in vehicle availability or consumption would affect the risk of supply shortages, for example, if new vehicle technology is introduced and worst-case downtime increases from 40% to 50%.

5.1 Future work

While our framework is designed for logistics planning in advance of a conflict, the optimization model we introduce in subsection 3.2 can also be used to assist in daily planning during a conflict. Such plans can provide a starting point that commanders adapt while taking into account additional details that are informed by in-depth knowledge of actions on the ground. One aspect that can be incorporated into future modeling efforts is risk owing to attack and interception of vehicles (Hudson *et al.*, 2017; Sweeney, 2019).

The US Army is currently piloting Autonomous Ground Resupply technology through the ongoing Expedient Leader-Follower program. Autonomous vehicles will reduce personnel requirements and thereby increase available road time. However, uncertainty will also increase because of unknowable maintenance requirements. Designing fleet requirements in the absence of historical experience and data will rely heavily on the development of analytical models. The framework presented in this paper can be readily adapted to meet such needs. Other mathematical frameworks for optimizing decisions under uncertainty, such as a combined simulation-optimization approach, stochastic programming or chance-constrained programming, may provide opportunities for complementary analyses and for future methodological research.

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Appendix

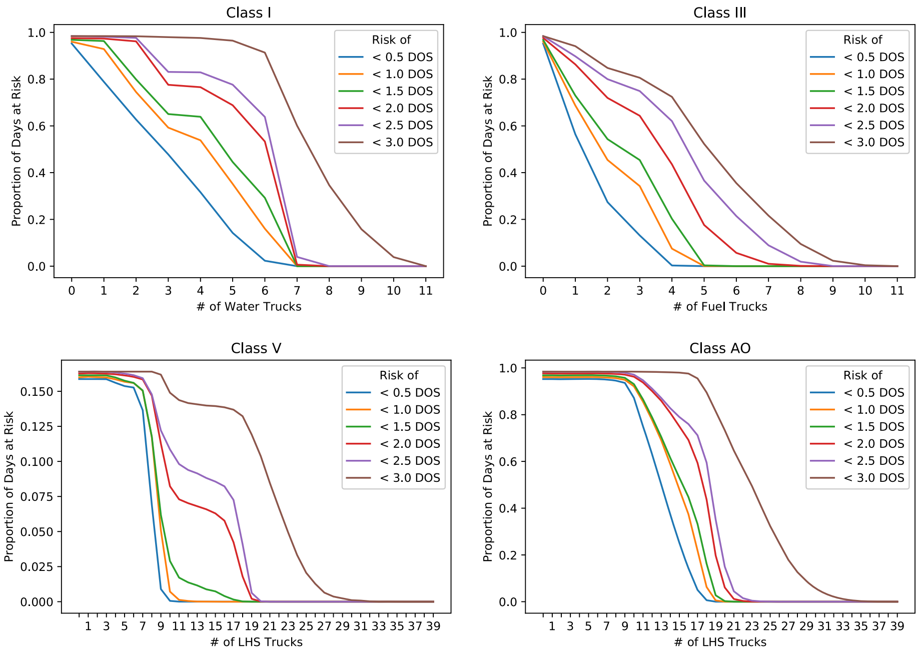
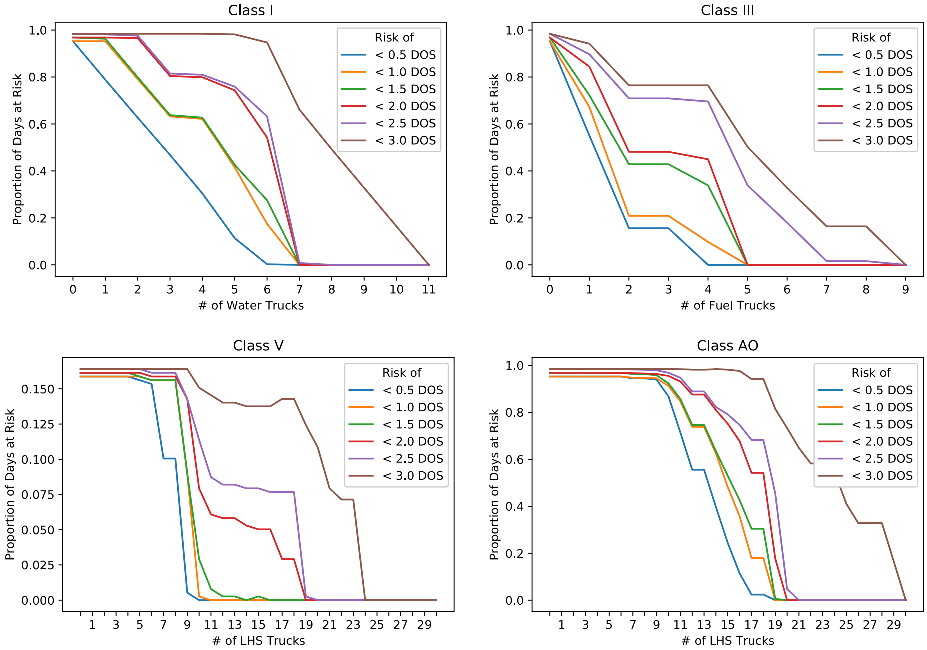


Figure A1.
Simulation with 100 Runs: risk of supply shortage as a function of truck capacity for a 63-day conflict, using triangular distributions to generate random samples for truck availability and consumption

Notes: Each subfigure corresponds to a unique supply class. The demand for load handling systems is driven by the All Other supply class, as opposed to Class V (ammunition)



Notes: Each subfigure corresponds to a unique supply class. The demand for load handling systems is driven by the all other supply class, as opposed to Class V (ammunition)

Figure A2.
Expected value problem: risk of supply shortage as a function of truck capacity for a 63-day conflict, using expected values for truck availability and consumption

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