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Towards pre-emptive resilience in military supply chains: A compromise decision support model-based approach

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ABSTRACT

The complex and dynamic nature of military supply chains (MSC) requires constant vigilance to sense potential vulnerabilities. Several studies have employed decision support models for the optimization of their operations. These models are often limited to a best single-point solution unsuitable for complex MSC constellations. In this article, the authors present a novel approach based on decision support models to explore a range of satisficing solutions against disruptions in MSCs using a compromise Decision Support Problem (cDSP) construct and Decision Support in the Design of Engineered Systems (DSIDES). Two cases were evaluated: (1) a baseline scenario with no disruption and (2) with disruption to achieve target values of three goals: (1) minimizing lead time, (2) maximizing demand fulfilment and (3) maximizing vehicle utilization. The results obtained in Case 1 identified a more stable solution space with minimal deviations from the target value, while in Case 2 the solution space was unstable with deviations from the target values

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1. Introduction

Supply chain planning and operations is a difficult task for both the military and civilians alike, and any weaknesses may affect its ability to satisfy customers or meet combat needs (Ganapathy et al., 2003; Burns & Berkowitz, 2010, Bordetsky & Ascef, 2013). These weaknesses in the supply chain, maybe a result of numerous failures that have been noticed due to a few common disruptions, which include earthquakes, floods, storms, hurricanes, and so on (Hatefi et al., 2015). Supply chain managers are forced to adopt more resilient approaches to insulate the supply chain from disturbance (Han et al., 2020). Furthermore, disruptive events such as fires at distribution centers, natural disasters such as floods or earthquakes, or labour strikes at transportation companies can have a significant impact on the entire supply chain and must be identified in a timely manner in order to implement an appropriate mitigation strategy (Taghizadeh, 2021).

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A definition of supply chain disruption provided by Craighead et al. (2007) is the '*unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain*'. Gaonkar and Viswanadham (2003) defined supply chain resilience as the ability to maintain and recover after being disturbed. Hollnagel et al. (2006) defined the pre-emptive resilience capability of a system as the capability to recognise, anticipate and defend against the changing shape of risk before adverse consequences occur.

Although military and commercial supply chains operate on similar structures of three basic levels (producer, distributor, and retailer or end-user), they differ in a number of aspects, such as readiness for war at any time, great flexibility during times of war, a large diversity of items, and a long span with unstable demand; which demonstrate a divergence from standard civilian outcomes (Xiao et al., 2007). The major goal of the civilian supply chain is profit, while the major goal of the military supply chain is troop readiness (Burns et al., 2010). Another distinct aspect is that in commercial SC the flow of products is unidirectional between suppliers and retailers. In military SC, the flow between suppliers and end-users is bidirectional mostly because of preventive and corrective maintenance of equipment (Sokri, 2014). The complex and dynamic nature of the MSC has continuously increased the difficulty in improving its resilience and made it a more daunting task for military logistic planners since after the first world war (Sani et al., 2022). Therefore, the complexity of the MSC can be seen in the high rate of the consumption of military materials as a result of the development of military equipment and the widespread employment of sophisticated high-tech weapons in conflict (Xiong et al., 2020).

Since combat is reliant on logistics and with more than 70% of the bulk of combat supplies, such as ammunition, rations, water, and medical supplies, passing through this chain, the MSC logistical activities, equipment, and facilities have become priority attack targets for the opponent (Kova'cs et al., 2009, Özceylan and Paksoy, 2014, Pan & Nagi, 2010; Ross et al., 2008). An example would be an entity that is destroyed or disabled, which may impact other interconnected entities (Özdamar and Ertem, 2015). This affects the supply chain's normal operations and could lead to either delays in logistic flows or failures in wars (Zhou et al., 2016). According to the Global Terrorism Database (GTD) 2022 there has been a total of 79 attacks on military bases, logistic facilities, and supply lines in northeastern Nigeria between 2011 and 2021. This accounts for about 45% of combat causalities (loss of men and equipment) and significantly hindered the progress of combat operations in this region (Amao, 2020). Therefore, to boost the chances of success in warfare and to avoid undermining the overriding goal of the military's supply chain, which is to keep the war-fighter properly equipped and ready for combat, there is a need to develop a viable decision-support tool that highly supports predictive decision-making. Motivated by this, the research seeks to address the following gaps; first, several studies have focused on improving the level of preparedness for supply chain disruptions using traditional decision models like multicriteria decision models, deterministic decision-making models, and computational simulation/optimization models. These models are often limited to a single-point solution (optimization) usually optimal in nature and do not provide flexibility for designers/planners to reach a compromise. Designers and engineers need an approach for negotiating ***satisficing solutions*** for their problems rather than optimal solutions due to the increasing complexity and interactions of the system with its environment resulting in more and more uncertainty within the system (Nellippallil et al., 2020). Second, with growing interest in the realization of complex systems, there is a need for developing methods to explore the solution space that is defined by models that approximate reality and are typically incomplete.

The aim of this research is to develop a decision support model based on a compromise Decision Support Problem (cDSP) construct and Decision Support in the Design of Engineered Systems (DSIDES) to explore a range of satisficing solutions. The concept of '*satisficing*' first used by Simon (Brown, 2004) supposes that a decision maker will search for an alternative offering satisfactory performance on all criteria without necessarily attempting to maximize this performance. We model a case of MSC transportation of ration (water, food) from several base depots to combat units operating in a low-intensity conflict region of northeastern Nigeria, highly vulnerable to terrorist activity. The solution space was explored based on two cases: (1) a baseline scenario with no disruption and (2) disruption at one of the base depots in order to achieve target values of three goals: (1) minimizing lead time, (2) maximizing demand fulfilment and (3) maximizing vehicle utilization. We were able to identify a range of satisficing solutions that would help to mitigate disruptions along the MSC. Our work presents a novel approach to using decision support models to explore a range of satisficing solutions to manage disruptions in the MSC, using the cDSP construct and DSIDES. It would enable practitioners to have a good insight into the important variables as well as parameters required to establish a correlation among the various aspects of resilience in the supply chain. It also adds valuable insights to the theory and context of MSC resilience and recommends the most effective approach to achieve robust decisions in the management of disruption in MSC to satisfy daily combat demands.

The remainder of this paper is structured as follows. A review of related work is presented in Section 2 followed by an outline of the chosen research methodology in Section 3. A detailed elaboration on how the model is developed is presented in Section 4, followed by results and discussion in Section 5 and managerial insights in Section 6. Finally, conclusions are provided in Section 7.

2. Literature review

2.1. Supply chain disruptions and resilience

According to Barroso et al. (2008), a disruption is 'an unexpected incident that disrupts the normal operation and stability of an organization or a supply chain.' Supply chain disruptions can occur for a variety of reasons, including external factors such as natural disasters and internal factors such as a failure to integrate all supply chain operations (Ponomarov and Holcomb, 2009). Tang (2006) added that natural catastrophes include earthquakes, floods, and hurricanes, as well as man-made calamities, such as terrorist attacks, economic crises, and strikes, as a result, the impact of disruption on the supply chain is determined by proactive resilience measures as well as recovery contingency plans. There have already been numerous definitions of resilient supply chains. Christopher and Rutherford (2004), the most well-known authors in this field, underline two essential foundations in their broad definition: system flexibility and adaptation. Resilience, according to Fiksel (2006) economic definition, is "an enterprise's ability to survive, adapt, and flourish in the face of chaotic change. "Resilience is defined by Sheffi and Rice (2005) as 'the ability to bounce back from a disruption.' The basic goal of these standards is to construct a supply chain that is resistant to risk.

2.2. The concept of pre-emptive resilience

In the wake of widespread disruptions, supply chain managers need to be pre-emptive for event readiness and for reducing the susceptibility to disruptions (Pettit et al., 2010; Christopher & Peck, 2004; Jüttner and Maklan, 2011). Hollnagel et al. (2006) described the pre-emptive resilience capability of a system as the capability to recognise, anticipate, and defend against the changing shape of risk before adverse consequences occur. In a similar vein, a supply chain needs to forecast, identify risk, assess risk, and monitor deviation, sensing the early warning signal to prepare for mitigating disruptions (Pettit et al., 2011; Knemeyer et al., 2009). Further, preparation for recovery can be taken in advance if the disaster can be forecasted (Sheffi & Rice, 2005), which is also effective for organizations to identify risks in a timely fashion. Such type of risk identification initiative helps to know about the sources of risk (Christopher & Peck, 2004). As a result, one can take precautions against disruptions. Similarly, pre-emptive approaches such as early warning signal analysis are important in the sense that advanced information can be obtained about the likelihood of disruptions (Pettit et al., 2010). Organizations need pre-emptive capabilities to overcome uncertainties of business environments. Such capabilities can also be commensurate with the capability of supply chain readiness in the face of turbulence. Therefore, supply chain readiness is essential to overcome disruptive events and to develop resilience capability.

2.3. Strategies for building a resilient supply chain

According to Wicher et al. (2012), building resilient supply chains in practice can lead to a lot of issues and difficult decisions. The implementation of quality management decision-making and logistic approaches are significant components in getting them under control.Building reserves and developing inventory plans are two more ways mentioned for ensuring a continuous supply over a long period of time and being ready to withstand shock. This they said was demonstrated by the US Defense Department, which released around 5 million masks from its stockpiles in March 2020 to aid in the fight against the COVID-19 pandemic.

2.4. Disruptions in the military supply chain

Supply chain disruptions are a combination of the unanticipated triggering event and the subsequent effects that risk material flow and normal business operations significantly (Wagner & Bode, 2006, Ivanov et al., 2017). Tsiamas and Rahimifard (2021) categorised disruptions as '*anticipated*' which are those with some level of recorded historical data about their nature, range, and frequency, while '*unanticipated*' are those without reliable and dependable historical data. Since combat is reliant on logistics, enemy attacks on logistics activities, equipment, and infrastructure are inevitable. Hence, an MSC network is a priority target for disruptions (Özceylan and Paksoy, 2014, Pan & Nagi, 2010; Ross et al., 2008). As a priority target, MSCs often face disruptions since they operate in uncertain and risky environments. Disruptive triggers can be classified into 'Natural (earthquake, floods, fire, etc.) and man-made (terrorist attacks, accidents, etc.)' (Fahimnia et al., 2015) and could disrupt an MSC causing battle losses and casualties. Such disruption will thus affect the normal operations of the supply chain (Pettit et al., 2010). To live or win in combat, the armed force needs supplies (such as food, water, and fuels) which may be subject to natural calamities and terrorism with a high chance of jeopardizing the overall success of the operation. For example, in Afghanistan, the US military fuel supply chain to forward operating bases suffered frequent roadside bomb attacks by terrorists, which jeopardized the army's ability to complete its missions (Davids et al., 2013; Mihály, 2017).

In the wake of COVID-19, both military and commercial supply chains showed low resilience and slow recovery capabilities leading to unprecedented vulnerabilities to lead times (Ivanov, 2021,). Wincewicz-Bosy et al. (2022) identified and studied the impact of COVID-19 on the military food supply chain in Poland using process mapping. The conducted research led to the conclusion that the pandemic undoubtedly caused huge disruption and prompted the need to revise the existing solutions used in the supply chain in order to ensure the continuity of the feeding processes. In their research, Gaonkar and Viswanadham (2003), concluded that a wide variety of disruptive events including natural disasters and terrorist attacks pose a severe risk to the supply chain. The current Russian invasion of Ukraine had severely disrupted and negatively impacted the global food supply chain leading to shortages, increased lead times, and price increases (Jagtap et al., 2022). Loredo et al. (2015) for RAND Corporation (California, USA), identified disruptions in supplier, demand and process and suggested how they can be prevented to support Army Material Commands (AMC). Therefore, we identified natural disasters, terrorism and war as the reoccurring disruptions associated with the MSC.

2.5. Existing models for military supply chain resilience

Military logistic planners should be able to model and predict supply chain disruptions in a proactive rather than a reactive way for the purpose of solving disruptive event problems (Sani et al., 2022). For a military peacekeeping operation, Ryczynski and Tubis (2021) developed a risk analysis method that incorporates the Kaplan and Garrick approach as well as fuzzy theory to build the resilience of the fuel supply chain. The model supports decision-making and the proper functioning of supply systems in all high-risk conditions. However, the model may show insufficient measurement accuracy in complex systems. Xu et al. (2016) integrated a defender – attacker game with supply chain risk management, and the defender's optimal preparation strategy. Kaddoussi et al. (2011) proposed a general agent framework for disruption management optimization for the military with the goal of reducing the impact of disruptions and uncertainty in a 'highly distributed crisis management supply chain' using a disruption management agent (DMA). Similarly, for the purpose of military logistics deployment, Salmeron et al. (2009) developed a stochastic mixed integer programming model for deployment planning of U.S. sealift cargo delivery in wartime to proactively provide probabilistic information on the time and locations of potential enemy attacks on seaports of debarkations (SPODs). However, the results showed that with their model, the expected total disruption was reduced only by 8%, which shows low resilience against unexpected disruption.

Rogers et al. (2018), designed a military logistics network planning system (MLNPS) as an app on the Army's enterprise resource planning (ERP) system (Global Combat Support System-Army), to identify and mitigate logistical problems prior to and during the military's operations. They claimed that the impacts of an approaching storm on the logistical network can be predicted using the MLNPS to allow commanders time for the network adjustments to reduce the impacts. However, as a deterministic tool, the MLNPS does not adequately assess uncertainty or permit analysis of risk. Zhao et al. (2011) studied the resilience of complex supply network topologies against random and targeted disruptions using a military logistic network as a case study. They presented Degree and locality-based attachment (DLA), a hybrid and customizable network growth model in which new nodes create connections based on both degree and locality. They discovered that the DLA model's supply network design provides balanced resilience against both random and targeted disturbances. However, it is posited that their resilience against targeted disruptions is not adequate despite the fact that it has a high probability of occurrence.

Xiong et al. (2017) described the modelling of military supply chain networks using Arena Simulation, with a focus on evaluating their effectiveness, especially under conditions of disruption. They simulated a POL (petrol, oil and lubricant) network to solve the problem of supply chain network effectiveness evaluation from the perspective of dynamic and discrete networks. By applying the model and algorithms to a POL supply network in a theatre, they obtained the values of supply capability and efficiency metrics in a dynamic environment. Kim et al. (2017) designed a new 'Parallel Model' to replace the 'Substitute Model' in the Republic of Korea Military Supply system. Analysis of the two models' critical factors in warfare; the supply line's destruction ratio and the mean of demand using in-system dynamics simulation showed that the parallel supply model was a more resilient and effective method in the MSC. Sethi and Sharma (2018) dwelled upon the conceptual development of an ideal performance measurement framework for the MSC and discussed some of the principal performance measurement frameworks, like the Balanced Scorecard and Supply Chain Operations Reference model (SCORM). Rossetti and Bright (2018) described the conceptual modelling of bulk petroleum supply chains for the U.S. Defense Logistics Agency under contingency planning scenarios, such as increased surge demand and disruption events. Their methods, insights, and capabilities were developed to facilitate the analysis of the resilience of commercial bulk petroleum supply chains under conditions of disruption. Jenkins et al. (2020) developed an integer mathematical programming formulation to determine the location and allocation of MEDEVAC assets over the phases of a military deployment to support operations ranging from peacekeeping through combat to post-combat resolution. Although, these models contribute greatly to improving the resilience of the MSC, as the network is becoming increasingly complex and evolving, finding the optimal solution is computationally expensive, and difficult and does not provide the much-needed flexibility of selecting alternative solutions. Hence the need to develop a more efficient model.

2.6. Decision support models for supply chains

To effectively manage supply chain disruption, it is vital to employ appropriate decision support models that consider random event.). Raj (2014) concentrated on supply chain resilience measurement in terms of recovery time with a new metric based on a semiparametric model called the Cox-PH model. The model's ability to capture numerous origins of failure is significant. Taghizadeh and Taghizadeh (2021) evaluated the benefit and impact of using digital technology on supply chain resilience and presented a simulation model to explore three 'what-if' scenarios.

Carvalho et al. (2011) in their research provided a tangible model of an automobile supply chain. Their simulation study looked at how supply chains behave when they are disrupted using Arena simulation. A Supply Chain Disturbance Management Fuzzy Decision Support System was proposed by Nunes et al. (2011) to simulate the uncertainty associated with the disruptions and their impact on the supply chain. Teniwut and Hasyim (2020) stated that the most widely used approach in the application of the supply chain decision support system is a numerical simulation, which includes the use of linear programming, semantic, fuzzy logic, and multi-criteria and multi-objective decision making. Azaron et al. (2018) developed a stochastic programming approach for multi-period supply chain design problems under uncertainty. The supply chain design problem involved making location and allocation decisions to support the required flows in a supply chain. Dweiri et al. (2016) proposed a decision support model for supplier selection based on the analytic hierarchy process (AHP) using a case of the automotive industry in Pakistan. Although these models have greatly improved the performance of supply chains, they cannot be applied to complex problems like the MSC. Also, the vastness of data, decision variables, intricate interrelationships among variables and system constraints affects the performance of these models leading to poor decisions. Therefore, the cDSP presents a promising approach for developing decision support models due to its ability to incorporate several uncertainties. A detailed methodology used to achieve the objectives of this research is explained in Section 3.

3. Methodology

This study is carried out based on the methodology developed by Mistree (1995) using the cDSP for obtaining a range of satisficing solutions. The cDSP is employed in this research to develop the model as well as explore the solution space to obtain a range of satisficing solutions in order to achieve the goals of minimizing lead time, maximizing demand fulfillment and vehicle capacity utilization in the MSC. To understand the behaviour of the MSC, the whole network structure consisting of entities of that make up the MSC was modelled. Data regarding demand, locations, and transportation as well as the variables and parameters were used to formulate the model. While the cDSP was used to solve the model and obtain the solution points using DSIDES. The entire process is explained in Section 3.1 while Section 3.2 highlights the network structure of the MSC.

3.1. The compromise Decision Support Problem (cDSP) construct

The cDSP is a hybrid formulation in that it incorporates concepts from both traditional mathematical programming and goal programming and makes use of some new ones (Hughes, 1993; Mistree et al., 1993). According to Ahmed et al. (2014), the cDSP is a concept derived from both traditional mathematical programming and goal programming for solving multi-objective problems. It provides the opportunity for military logistic planners to explore various ranges of satisficing solutions rather than traditional models, which are often limited to a single-point solution usually optimal in nature and not suitable for complex problems like the MSC. A satisfactory or *satisficing* solution is the point of feasibility where system goals are achieved as close as possible (Nellippallil et al., 2020). In the cDSP, the formulation of the objectives is in form of system goals, deviation variables, and deviation functions. However, in traditional mathematical programming, the modelling of the objective function is only done in terms of the system variables. Using the cDSP construct, several solutions are identified by carrying out trade-offs among multiple conflicting goals. A set of design variables can be found using the cDSP to satisfy the problem's bounds and constraints and at the same time achieve as close as possible a number of conflicting objectives. The solution to this problem represents a trade-off between that which is desired (as modelled by the aspiration space) and that which can be achieved (as modelled by the design space) (Mistree et al., 1993). Therefore, it may be impossible to obtain a design that satisfies all the levels of aspiration. Hence, a compromise solution has to be accepted (Hernandez et al., 2001; Mistree et al., 1993).

The model was developed in six successive steps (Figure 1). The first step is formulating the supply chain problem. The problem considered in this research is that due to the complex and dynamic nature of the MSC, there is a need to develop a viable decision support tool that highly supports predictive decision-making to support and facilitate the flow of ratio thus improving its resilience by minimizing delivery time, maximizing distribution and vehicle utilization. The model is based on an existing military supply chain operating in a low-intensity conflict region, where combat units are deployed to several crisis-prone locations within northeastern Nigeria . Operating in this high-risk area, the ration supply chain is prone to a series of disruptions by terrorist attacks and also adverse weather effects like a sandstorm, there is a need for logistic planners to take proactive decisions against unexpected disruptions to ensure the continuity of supply.

The second step is framing the cDSP. After creating the design problem, the mathematical model was then formulated by identifying what is given, what needs to be found (design variables) and what needs to be satisfied (goals and constraints). After finding these, a relationship between them is satisfied. The third step is solving the mathematical model using DSIDES. The model is interfaced with the DSIDES to solve the model and obtain results. This involved using the DSIDES solver for exercising the cDSP and exploring the design space. The general strategy for using DSIDES includes discovering regions where feasible designs exist based on satisfying the system constraints and bounds or where feasible designs might exist by minimizing the violation of system constraints. From the neighbourhood of the better feasible or near feasible regions, refine the feasible design space extremities by adjusting the variable bounds and solve the cDSP using a pre-

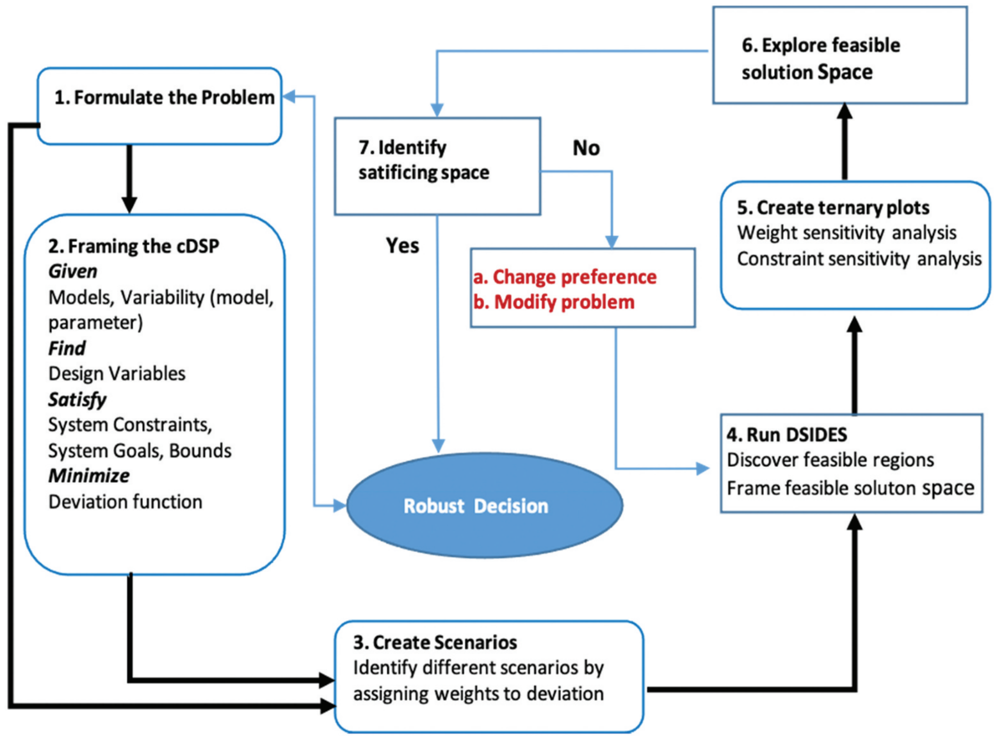

Figure 1. Research methodology.

emptive (lexicographic minimum) representation of the system goals and a higher-order search algorithm, for example, ALP – Adaptive Linear Programming (Sabeghi et al., 2015).

The fourth step is the exploration of the solution space. As we aim to obtain a range of satisficing solutions, the results obtained after solving the mathematical model using DSIDES are then used for the solution space exploration in order to identify a range of satisficing solutions that satisfy the overall requirements of the logistic planner, which are given in the mathematical formulation. To obtain the range of satisficing solutions, scenarios being generated are assigned different weights on the goals. Three goals are mandated in this method (to be able to use a ternary plot), and Scenarios 7 to 10 are recommended as a minimum to cover the aspiration space (Sabeghi et al., 2015). Total of 13 different scenarios have been run and the final solution value of the deviation variable for each goal is documented. The values of deviation variables are normalized between 0 and 1. Thereafter, ternary plots are generated for each goal using the MATLAB code. There are six separate files in the MATLAB code of ternary plots, which are *tersurf, terplot, ternaryc, termain, terlabel, tercontour* and *ter_main*. The solution space created in this plot represents the relation of one goal with respect to the other two.

3.2. Network structure

In this research, the MSC was modelled from the existing network structure, exclusively tailored towards the Nigerian Army Supply Chain in which the entities include various

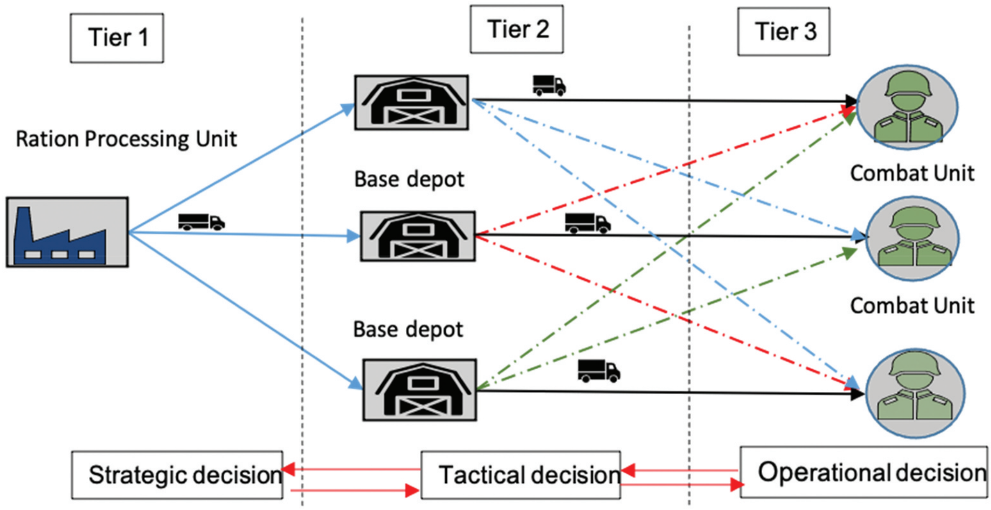

Figure 2. Military supply chain network.

facilities consisting of a three-tier supply chain, which consists of a ration processing unit (RPU) (Tier 1), base depots (Tier 2) and combat units (Tier 3) and three levels of decision planning (strategic, tactical, and operational) as shown in Figure 2. When compared to a regular supply chain, MSCs are one of the most discrete networks with more entities and an obvious dynamic element (Xiong et al., 2017). Entities, such as factories, depots, and end users, are mutually independent due to functional localization, geographical location, capacity, and so on.

The first tier is the production node which constitutes the ration processing unit that produces all the ration required to support the final consumer (combat units). The second tier of this supply chain is the storage/supply node also known as base depots (BD) which encompasses all facilities collecting and storing the ration supplied from the RPU for distribution to the combat units. The third tier of the supply chain is the combat units that are in need of ration supplies for the smooth conduct of their operation. The strategic decision phase covers the period from production to distribution and all decisions that have to do with allocation, selection of facilities, and security, while the tactical decision phase covers the flow of ration, level of inventory, etc. Lastly, the operational decisions phase is about the coordination of the logistics for the purpose of meeting the demands of the combat units, on-time delivery, and replenishment.

4. Model development

The model was built and designed the scenarios to test for no disruption and disruption at the base depots.

4.1. cDSP mathematical formulation (Initial solution for no disruption)

The model is formulated as a cDSP. There are seven system variables; quantity of ration transported from base depot 1,2,3 to combat unit 1,2,3 (x_1, x_2, x_3), number of expected vehicles to transport ration from base depot 1,2,3 to combat unit 1,2,3 (x_4, x_5, x_6), speed of vehicle(x_7)and three goals to be: (1) minimum delivery time and (2) maximum distribution, and 3) maximum vehicle utilization. The mathematical formulation is shown in Figure 3.

4.1.1. Assumptions

- The facilities in the entire supply chain have capacity restrictions, such as storage limits.
- Only ration flows through the supply chain.
- Ration flow is only in one direction (upstream to downstream).
- No disruption at the combat unit nodes.
- Rations are transported by limited-capacity vehicles.
- Combat demands can be fulfilled by other base depots during disruption.
- Delivery time is equal to or greater than the transportation time.
- The duration of the operation is a minimum of 6 months.

4.1.2. Given

System parameters

$$\text{Distance from base depot 1 to combat unit } 1(D_1) = 80.34 \text{ km}$$

$$\text{Distance from base depot 2 to combat unit } 2(D_2) = 109.55 \text{ km}$$

$$\text{Distance from base depot 3 to combat unit } 3(\mathrm{D}_3) = 51.62 \text{ km}$$

$$\text{Weekly demand of combat units} = 56.7 \text{ tons}$$

$$\text{Base depot supply capacity} = 65 \text{ tons}$$

$$\text{Vehicle capacity (C)} = 5 \text{ tons}$$

Target of goals

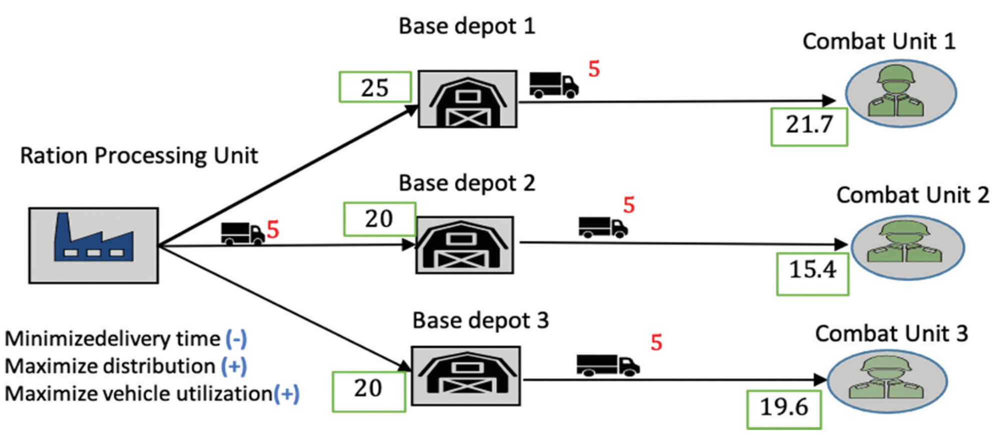

Figure 3. Baseline scenario (no disruption).

Delivery time target = 4 hrs

Delivery target = 65 tons

Number of vehicle target = 11

Function of goals

$$f_1(x) = (D_1 + D_2 + D_3)/x_7 \quad (1)$$

$$f_2(x) = (x_1 + x_2 + x_3) \quad (2)$$

$$f_3(x) = x_4 + x_5 + x_6 \quad (3)$$

4.1.3. Find

System variables

Quantity of ration transported from base depot 1,2,3 to combat unit 1,2,3 (x_1, x_2, x_3) Number of expected vehicles to transport ration from base depot 1,2,3 to combat unit 1,2,3 (x_4, x_5, x_6), speed of vehicle(x_7)

Deviation Variables

$$d_1^{\pm}, d_2^{\pm}, d_3^{\pm} \quad (4)$$

4.1.4. Satisfy

System constraints

$$C1 : (x_1 + x_2 + x_3)/11 \leq 65 \quad (5)$$

$$C2 : (x_1 + \; x_2 + x_3) \leq 65 \quad (6)$$

System goals

Delivery Time – Goal 1

$$\left[\frac{D_{t,Target}}{f_1(x)}\right] - d_1^- + d_1^+ = 1 \quad (7)$$

Distribution maximization – Goal 2

$$\frac{f_2(x)}{D_{F,Target}} + d_2^- - d_2^+ = 1 \quad (8)$$

Vehicle utilization – Goal 3

$$\frac{f_3(x)}{V_{,Target}} + d_2^- - d_2^+ = 1 \quad (9)$$

4.1.5. Bounds

$$0 \leq x_1 \leq 25 \qquad 0 \leq x_4 \leq 4$$
$$0 \leq x_2 \leq 20 \qquad 0 \leq x_5 \leq 3$$
$$0 \leq x_3 \leq 20 \qquad 0 \leq x_6 \leq 4$$
$$40 \leq x_7 \leq 60$$

4.1.6. Minimize

The deviation function

$$Z = \sum_{i=1}^{3} w_i \cdot (di^- + di^+) \sum_{i=1}^{3} w_i = 1 \tag{10}$$

We minimize the deviation function. The aim is to minimize the over or under achievement of a goal from the target specified value. The objective function is represented as a weighted sum of the deviation variable and is known as the deviation function (Z). The objective for us through the cDSP formulation is to minimize these deviation variables and achieve the target values of the goals as close as possible.

4.2. cDSP mathematical formulation (disruption at one base depot)

The disruption at one base depot is shown in Figure 4.

4.2.1. Given

System parameters

$$\text{Distance from base depot 1to combat unit 1}(D_1)$$

$$\text{Distance from base depot 2 to combat unit 2}(D_2)$$

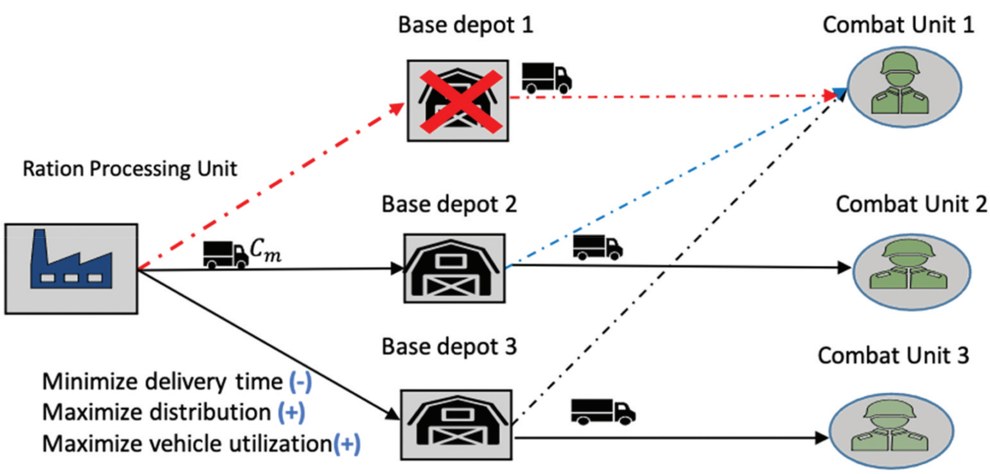

Figure 4. Disruption at one base depot.

$$\text{Distance from base depot 3to combat unit } 3(D_3)$$

$$\text{Weekly demand of combat units} = 56.7 \text{ tons}$$

$$\text{Base depot supply capacity} = 65 \text{ tons}$$

$$\text{Vehicle capacity (C)} = 5 \text{ tons}$$

Target of goals

$$\text{Delivery time target} = 4 \text{ hrs}$$

$$\text{Delivery target} = 65 \text{ tons}$$

$$\text{Number of vehicle target} = 11$$

Function of goals

$$f_1(x) = (D_2 + D_3)/x_7 \tag{11}$$

$$f_2(x) = (x_2 + x_3) \tag{12}$$

$$f_3(x) = x_5 + x_6 \tag{13}$$

4.2.2. *Find*

System variables

Quantity of ration transported from base depot 2,3 to combat unit 2,3 (x_2, x_3)
Number of expected vehicles to transport ration from base depot 1,2,3 to combat unit 1,2,3 (x_5, x_6), speed of vehicle(x_7)

Deviation Variables

$$d_1^{\pm}, d_2^{\pm}, d_3^{\pm} \tag{14}$$

4.2.3. *Satisfy*

System constraints

$$C1 : (x_2 + x_3)/11 \leq 65 \tag{15}$$

$$C2 : (x_2 + x_3) \leq 65 \tag{16}$$

System Goals

$$\text{Delivery Time – Goal 1}$$

$$\left[\frac{D_{t,\text{Target}}}{f_1(x)}\right] - d_1^- + d_1^+ = 1 \tag{17}$$

$$\text{Distribution maximization – Goal 2}$$

$$\frac{f_2(x)}{D_{F,Target}} + d_2^- - d_2^+ = 1 \quad (18)$$

Vehicle Utilization – Goal 3

$$\frac{f_3(x)}{V_{,Target}} + d_2^- - d_2^+ = 1 \quad (19)$$

Bounds

(1) $\leq x_2 \leq 20$ $\quad 0 \leq x_6 \leq 4$ $\quad 0 \leq x_5 \leq 3$
(2) $\leq x_3 \leq 20$ $\quad 40 \leq x_7 \leq 6$ $\quad 0$

Minimize

The deviation function

$$Z = \sum_{i=1}^{3} w_i \cdot (di^- + di^+) \sum_{i=1}^{3} w_i = 1 \quad (20)$$

4.3. *Solving the mathematical model using DSIDES*

The model is interfaced with the DSIDES to solve the problem. This involved using the DSIDES solver for exercising the cDSP and exploring the design space using a higher-order search algorithm, such as Adaptive Linear Programming (ALP). Details of the results are given in Section 5.

4.4. *Solution space exploration*

The results obtained after solving the mathematical model using DSIDES are used for the solution space exploration to identify robust solution space. The solution space in the cDSP comprises the design space (defined by the constraints and variable bounds) and the aspiration space (defined by the goals) (Triantaphyllou & Sánchez, 1997). We generated scenarios by assigning different weights to the goals. Three goals are mandated in this method (to be able to use a ternary plot), with a recommended minimum of 7 to 10 scenarios to cover the aspiration space (Sabeghi et al., 2015). We then ran scenarios and the final solution value of the deviation MATLAB code. Six separate files were prepared in the MATLAB code of ternary plots, which are *tersurf*, variable for each goal is documented. Ternary plots were then generated for each goal using the *terplot, ternaryc, termain, terlabel, tercontour*, and *ter_main*. The solution space in this plot represents the relation of one goal with respect to the other two.

5. Results and discussions

The results obtained from the solution are further used for the solution space exploration for the two cases; Case 1(no disruption) and Case 2 (disruption at one base depot).

Table 1. Scenarios with weights for goals.

Scenarios	W1	W2	W3	G1	G2	G3
1	1	0	0	4.02769835	56.70259	7.01671
2	0	1	0	4.83105507	64.9701	3.01415
3	0	0	1	5.83105507	49.7026	10.98269
4	0.6	0.2	0.2	4.02769835	58.9677	7.903421
5	0.2	0.6	0.2	4.02852454	61.9701	10.98269
6	0.2	0.2	0.6	4.026	60.3465	12.32292
7	0.5	0.35	0.15	4.02769835	62.9689	8.97926
8	0.15	0.5	0.35	4.02645633	64.9843	7.99449
9	0.35	0.15	0.5	4.06456332	54.9843	10.9945
10	0.7	0	0.3	4.02622144	57.7144	7.69309
11	0.3	0.7	0	4.0897333	63.9881	8.69467
12	0	0.3	0.7	4.06456332	56.7086	10.99449
13	0.34	0.33	0.33	4.02886721	60.9489	5.97869

5.1. Exploration of the solution space – Case 1 (No disruption)

In exploring the solution space, different weights were assigned for several scenarios. A total of 13 different scenarios were assigned for case 1 (no disruption). Details of the scenarios are provided in Table 1. These scenarios are selected based on judgment to effectively capture the design space for exploration in a ternary space with different combinations of weights on goals. While formulating the cDSP, all the goals are normalized, hence the solution for these goals lies between 0 and 1. If the objective is to reduce a certain goal, then the lower the value, i.e. closer to 0, the better the solution and, if it is to increase, any goal then the closer the value to 1, the better the solution.

On exercising the cDSP for these different scenarios, we are able to obtain setpoints and the achieved values of each of the goals. Ternary plots were then constructed. For Goal 1, we are interested in identifying regions to minimize the deviation function where the delivery time value is nearly 4 h. On analysing Figure 5, the region identified by the orange dashed line is a delivery time very close to the specified target value which is acceptable. The blue area which contains the minimum value of the deviation variable is desired. However, the red area is where less desirable solutions stand where the deviation values are large while the desirable stable solutions stand in the blue area. Here, we assume that a delivery time of a maximum of 4.02 h is acceptable.

For Goal 2, we are interested in maximizing distribution and the target value identified is 65 tons. In Figure 6, we see that the values in the region demarcated by the black dashed line are the region where the values of the deviation function are acceptable which is close to the target Value 1 on the ternary plot. The acceptable region lies between 0.7 and 1 which corresponds to any value between 60 and 65 tons. The red region indicates the stable and acceptable regions.

For Goal 3, the interest of the logistic planner is to achieve the maximum vehicle utilization within the defined limits. The target value for this goal is 11 vehicles. On analysing Figure 7, we see that the dark red contour within the blue dashed lines predicts the value of the goal close to the target. This indicates the acceptable region from 0.68 which corresponds to 9 vehicles as the acceptable value for Goal 3.

Since we are interested in identifying regions that satisfy all the three goals mentioned above, there is a need to visualize these spaces together in a single ternary plot. Therefore, the plots were superimposed. The superimposed plot of the regions of interest in

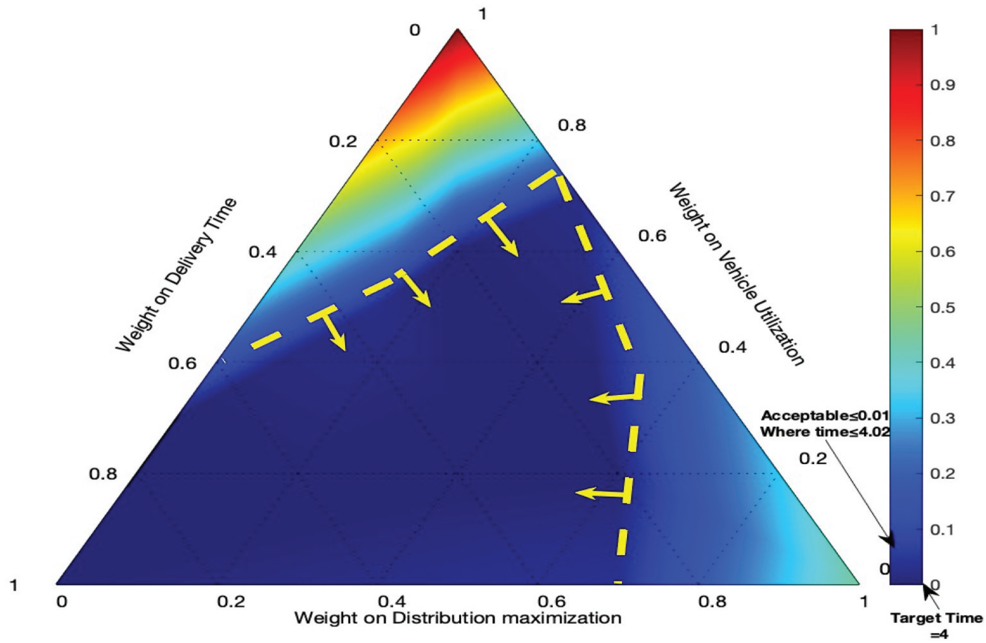

Figure 5. Ternary plot for Goal 1—Delivery time.

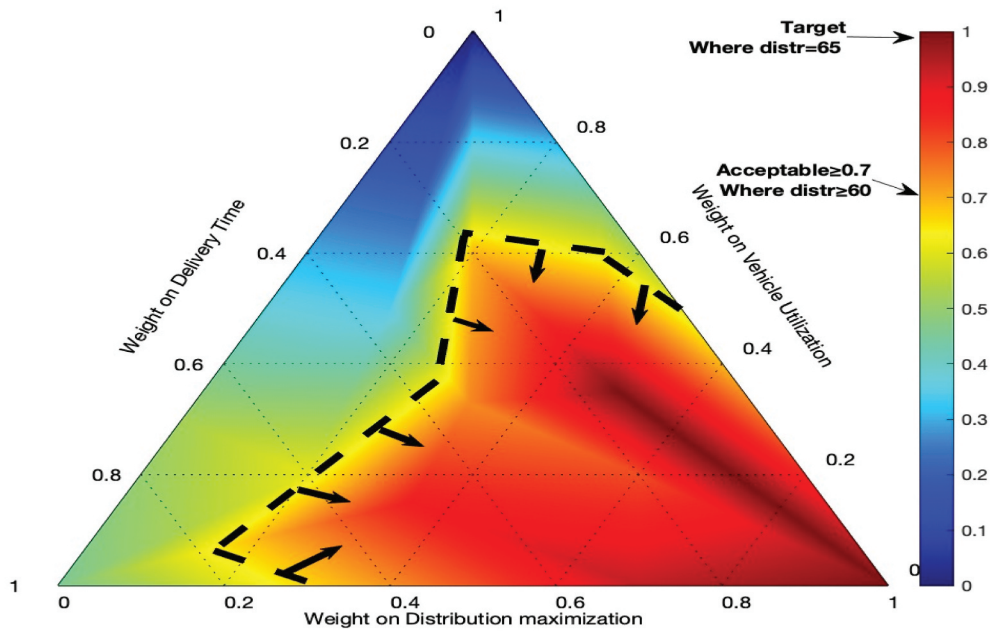

Figure 6. Ternary plot for Goal 2—Distribution.

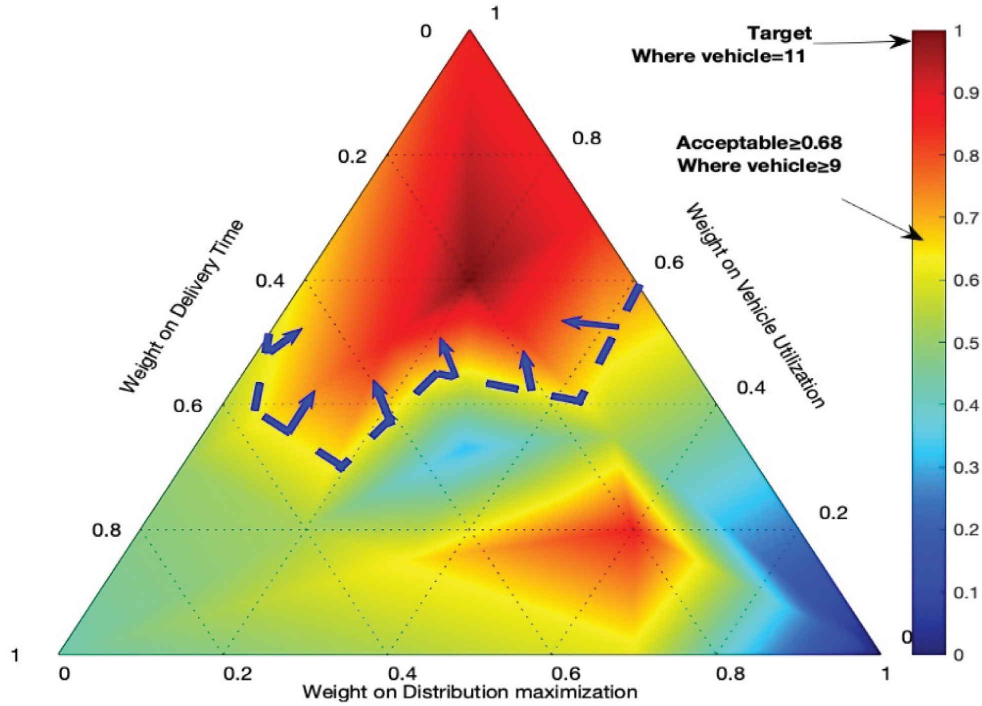

Figure 7. Ternary plot for Goal 3—Vehicle Utilization.

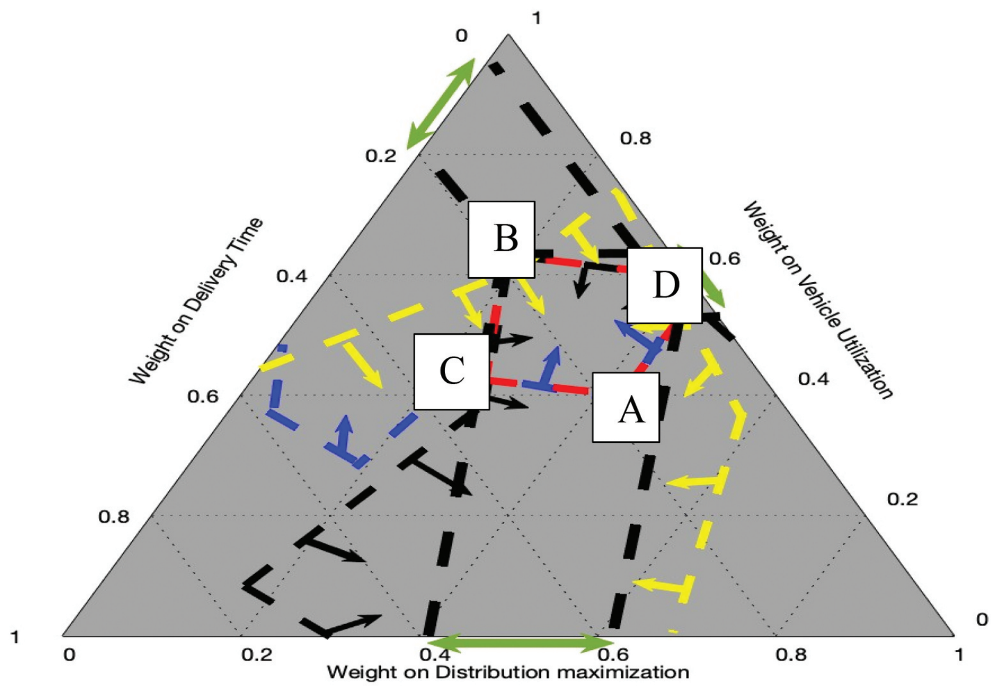

Figure 8. Superimposed ternary space for all goals.

Table 2. Identified boundary solution points after exploration.

	Supply chain Variables							Achieved Values of Goals		
Solution Points	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Delivery Time	Distribution	Vehicle utilization
A	24.99	19.99	17.98	2.99	2.99	2.99	59.97	4.02	58.96	8
B	29.99	19.99	19.99	3.99	1.99	1.99	59.99	4.02	64.98	8
C	22.99	14.99	16.99	3.99	2.99	3.99	59.99	4.02	54.98	11
D	24.58	18.32	17.44	4.55	2.87	4.89	60	4.79	60.35	12

Table 3. Scenarios with weights for goals.

Scenarios	W1	W2	W3	G1	G2	G3
1	1	0	0	6.03919627	2.90E + 01	2.02E + 00
2	0	1	0	6.35553755	4.00E + 01	2.02E + 00
3	0	0	1	6.35575494	2.90E + 01	7.00E + 00
4	0.6	0.2	0.2	6.03939256	4.00E + 01	6.99E + 00
5	0.2	0.6	0.2	6.03939256	4.00E + 01	6.99E + 00
6	0.2	0.2	0.6	6.03939256	4.00E + 01	6.99E + 00
7	0.5	0.35	0.15	6.04057055	3.99E + 01	6.97E + 00
8	0.15	0.5	0.35	6.03939256	4.00E + 01	6.99E + 00
9	0.35	0.15	0.5	6.03939256	4.00E + 01	6.99E + 00
10	0.7	0	0.3	6.1942591	2.90E + 01	6.99E + 00
11	0.3	0.7	0	6.35575494	4.00E + 01	7.00E + 00
12	0	0.3	0.7	6.35575494	4.00E + 01	7.00E + 00
13	0.34	0.33	0.33	6.03939256	4.00E + 01	6.99E + 00

a ternary space is shown in Figure 8. The region marked in red satisfies the requirements for all three goals. We can identify the common region which in our case is the area in the middle of the red hexagon bounded by the yellow and blue lines.

From the superimposed ternary plot, several solutions weights points (A, B, C, D) are identified and analysed. The results associated with these solution weight points are summarized in Table 3. On analysing Figure 8 and Table 2, it is seen that the red banded region satisfies all the requirements for robust decision, maximizing delivery time, maximizing distribution, and maximizing number of vehicles utilization in the best possible manner.

Next, we identify the system variable values for scenarios obtained by solving the cDSP. These system variable values are presented in Table 2. We use these system variable values to obtain the actual amount of ration to be transported to the combat units as well as the number of vehicles required.

5.2. Exploration of the solution space – Case 2 (disruption at one base depot)

In exploring the solution space, weight was assigned to several scenarios. We have also exercised 13 different scenarios for the baseline (no scenario). Different weights are assigned to each goal in these scenarios. Details of the scenarios are provided in Table 3. While formulating the cDSP, all the goals have been normalized hence the solution for these goals lies between 0 and 1. If the objective is to reduce a certain goal, then the lower the value, i.e. closer to 0, the better is the solution and, if it is to increase, any goal then the closer the value to 1, the better the solution.

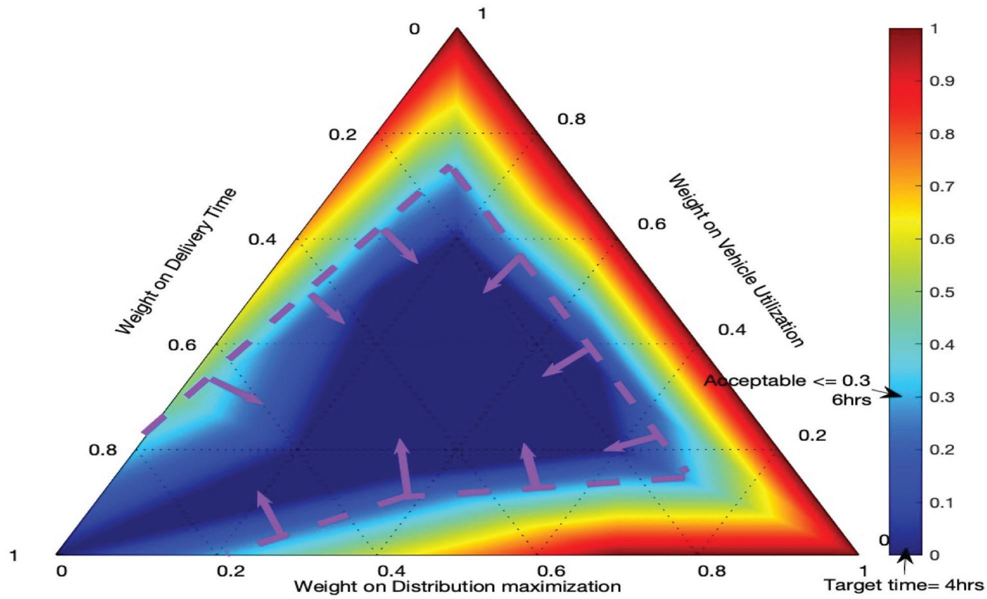

Figure 9. Ternary plot for Goal 1—Delivery time.

For Goal 1, the regions to minimize the deviation function where the delivery time value is nearly 4 h were identified. On analysing Figure 9, the region identified by the purple dashed line is a delivery time that is within the desirable stable solutions in the blue area. Here, we assume that a delivery time of a maximum to 6 h is acceptable but not desired.

For Goal 2, we are interested in maximizing distribution and the target value identified is 65 tons. In Figure 10, the acceptable region lies between 0.9 and 1 which corresponds to any value between 39 and 65 tons. The red region indicates the stable and acceptable regions.

For Goal 3, the interest of the logistic planner is to achieve the maximum vehicle utilization within the defined limits. The target value for this goal is 11 vehicles. On analysing Figure 11, the dark red contour within the yellow dashed lines predicts the value of the goal close to the target. This indicates the acceptable region from 0.8 which corresponds to 1 corresponding to 7 to 11 vehicles as the acceptable value for Goal 3.

From the superimposed ternary plot, several solution weight points (A, B, C) are identified and analysed. The results associated with these solution weight points are summarized in Table 4. On analysing Figure 12 and Table 3, it is seen that the black-banded region satisfies all the requirements for robust decision, maximizing delivery time, maximizing distribution, and maximizing number of vehicles utilization in the best possible manner. The values of the variables are also shown in Table 4.

6. Discussion

The results obtained indicate that the military logistic planners have a range of satisficing solutions to make robust decisions. Likewise, the ternary plots produced would assist the logistic planners understands the interactions of a particular goal

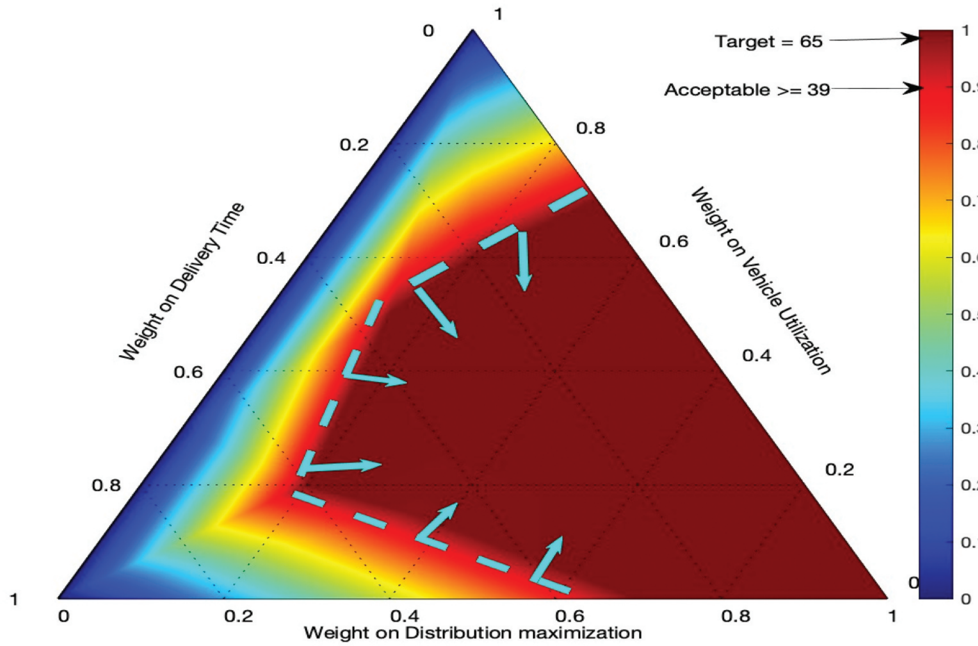

Figure 10. Ternary plot for Goal 2—Distribution.

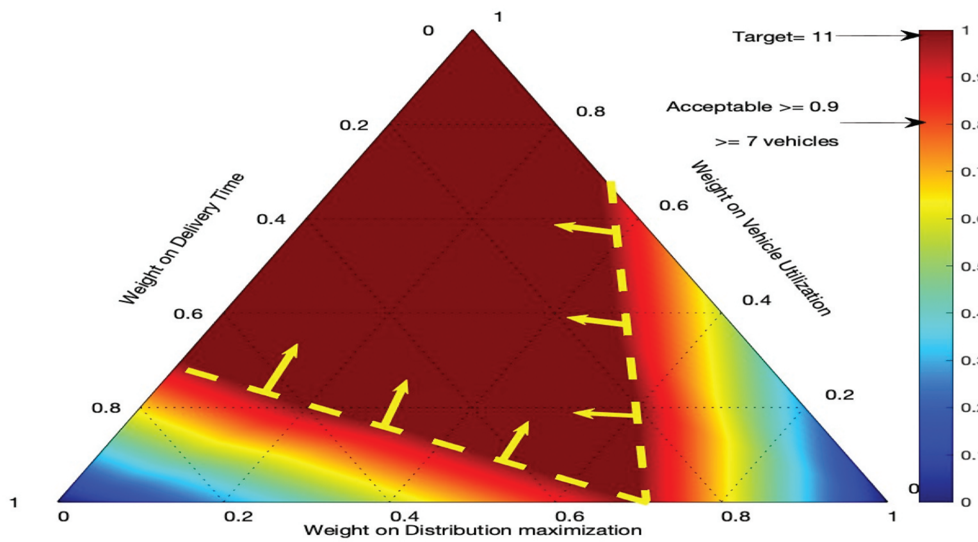

Figure 11. Ternary plot for Goal 3—Vehicle Utilization.

with other goals as different weights are put on them. In analysing the overall results, in Case 1, the identified robust solutions space tends to be much smaller when compared to Case 2 when there is disruption at one of the base depots, this is due to the fact that the state variables, which are quantity of ration transported from base depot 1,2,3 to combat unit 1,2,3 (x_1, x_2, x_3), number of expected vehicles to transport

Table 4. Identified solution points after exploration.

	Supply chain Variables					Achieved Values of Goals		
Solution Points	X_2	X_3	X_5	X_6	X_7	Delivery Time (hr)	Distribution (tons)	Vehicle utilization
A	19.98	19.99	3.99	3.99	39.99	6.04	40	7
B	19.98	19.99	3.99	3.99	39.99	6.04	40	7
C	19.98	19.99	3.99	3.99	39.99	6.04	40	7

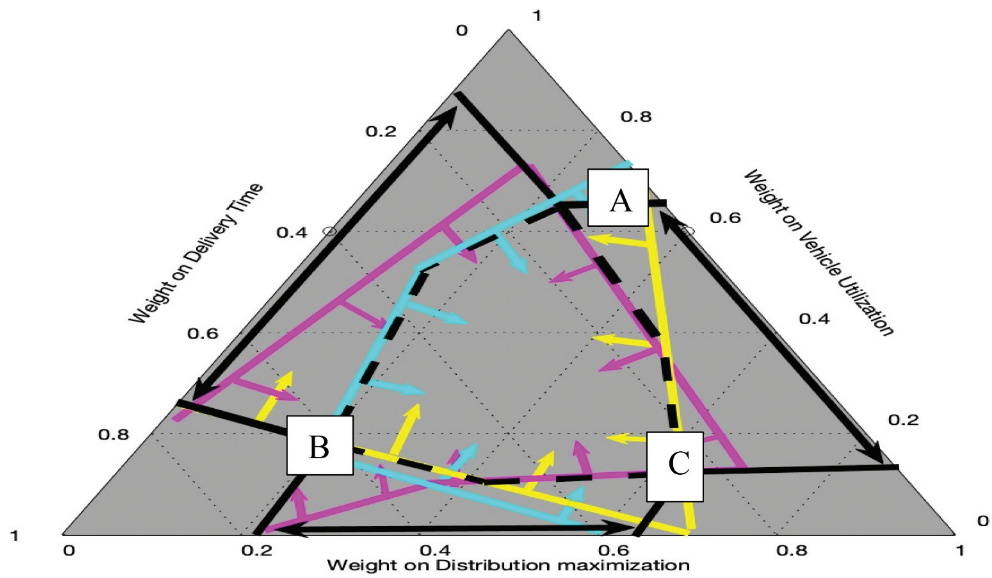

Figure 12. Superimposed ternary space for all goals.

ration from base depot 1,2,3 to combat unit 1,2,3 (x_4, x_5, x_6) and speed of vehicle$(x_7)$are not directly influenced by any disruptions hence achieving more stability with minimal deviations from the target values. For example, the target value for Goal 1 which is minimizing delivery time is 4 h, however, the value for Goal 1 obtained in Scenario 1 of Table 1 is 4.02 h. This indicates a minimal deviation from the target value, which is acceptable. Hence, the region bounded by A, B, C and D satisfies all the requirements for robust decision making where the goals of maximizing delivery time, maximizing distribution, and maximizing the number of vehicles utilization can be achieved in the best possible manner irrespective of the disruption. However, in Case 2 where there are disruptions, for example, at one base depot, the variable $x_1 and x_4$ which are directly associated with the base depot disrupted take the value of 0, while the other state variables, such as the quantity of ration transported from base depot 2, 3 to combat unit 2, 3 (x_2, x_3), number of expected vehicles to transport ration from base depot 1, 2, 3 to combat unit 1, 2, 3 (x_5, x_6) and speed of vehicle(x_7) tend to be more unstable. This instability indicates the presence of disruption and how the effects of the disruption propagate through the supply chain process. This means the achieved values for the goals have deviated further away from the target values. For example, the target value for Goal 1 is 4 h while the achieved value is 6.04 h. This indicates a huge deviation from the target value. However, the time is still acceptable, there will be little delays in the delivery of supplies. Hence, the region bounded by A, B and C satisfies all the requirements for robust decision making within an acceptable target for the set goals of maximizing delivery time, maximizing distribution, and maximizing number of vehicles utilization can be still achieved but with certain deviations from the target of the goals set. As for the limitations of this study, it should be noted that the DSIDES server is domiciled at the Systems Realization Laboratory, University of Oklahoma and permission has to be granted to enable usage, which may sometimes lead to delays in accessibility. Another limitation is that as the problem becomes more complex with disruptions occurring at two base depots and all the base depots (worst case) it became more difficult to achieve a convergence hence the solutions were not feasible. Therefore, the disruption scenarios had to be limited to just the baseline scenario and disruption at one base depot. In addition, the complexity of the MSC had to be because our analyses of the scenarios were confined to a limited number of variables and SC locations. Finally, it should be noted that research on MSC, unlike research conducted in the civilian sphere, is confronted with a lack of access to open data enabling more accurate mathematical modelling related to uncertainty and disruptions. Regardless of the limitations, the presented analyses and conclusions may be useful in practical, managerial, and scientific dimensions and constitute a starting point for broader, in-depth research.

7. Theoretical and managerial implications

The developed formulations contribute by representing real situations and proposing solutions of potential assistance to decision-makers. Therefore, from the scientific point of view, the contribution involves a novel approach to developing a decision support model that presents designers and engineers the opportunity for negotiating satisficing solutions for their problems rather than optimal solutions. Therefore, giving them the flexibility to make trade-offs among the goals, and the values of the design variables leading to robust decision-making not found in the reviewed literature. However, several practical contributions emerge from this research;

- It considers a large number of variables and parameters that give an in-depth analysis in distinguishing between desirable and stable and less desirable solutions against unexpected disruption.
- It gives the logistic planners and decision makers an insight of certain proactive decisions against unexpected disruptions, such as alternative routes, alternative modes of transportation, etc., required to improve the resilience of the supply chain.
- The approach facilitates the representation of several situations experienced by decision-makers due to the variations mainly in the parameters influenced by unexpected disruption.

8. Conclusion

The authors present research on a decision support model to identify and evaluate a range of satisficing solutions for improving the resilience of MSCs during disruption. They modelled a military supply chain for providing ration (food and water) to combat troops in conflict-prone areas. The supply chain enables the distribution of this ration from the base depot to the combat units and is thus prone to disruptions from weather or terrorist activity. The model is developed based on two cases: baseline without disruption and disruption at one of the base depots. The solution space has been explored with a range of satisficing solutions obtained based on the target value of the goals which are minimizing lead time, maximizing demand fulfilment, and vehicle utilization. The decision support would be instrumental in helping military logistics planners to obtain insight into the trade-offs among goals and the values of the design variables leading to robust decision making against disruption at various stages in the supply chain.

This research represents a novel approach to using decision support models to explore a range of satisficing solutions to manage disruptions in the MSC, using the Compromise Decision Support Problem (cDSP) construct and Decision Support in the Design of Engineered Systems (DSIDES) as a platform. Our work would therefore add valuable insights to the theory and context of MSC disruption and recommend the most effective approach to achieve robust decisions in the management of disruption in MSC by minimizing lead time to an acceptable time limit, maximizing demand fulfilment and vehicle utilization to satisfy daily combat unit demand. Nevertheless, our study suggests several directions for further research. One exciting research path would focus on a simulation model using Anylogistix to improve pre-emptive resilience in case of unexpected disruption. Another interesting future research avenue would create generic actions to prepare for unexpected disruption through digital technologies that enhance end-to-end visibility along the MSC. Finally, another promising research path would analyse how predictive analytics can help military logistic planners be prepared for unexpected disruption, adjusting their SC accordingly.

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Disclosure statement

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Data availability statement

The data that support the findings of this study are available from the corresponding author, [Jelena Milisavljevic-Syed], upon reasonable request.

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