Effective prepositioning of relief inventory for humanitarian operations in the Central African Region

by

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Abstract

Inventory management is a crucial aspect of humanitarian operations. Various inventory models and policies have been developed over the years to improve the efficiency of humanitarian inventory management. These models consider various elements, including sourcing, storage, prepositioning, distribution, and transportation. While the existence of literature and models supplied guidance and breakthroughs towards more informed decision-making, the complex setting of disasters has continued to preclude their application. Over-simplification, impracticality, and particularity of decision variables pose a challenge in using specific models in exceptionally distinct disasters owing to their complexity and ever-changing nature. This implies that the ability to manage inventory efficiently and its distribution depends on the preparedness and prevailing conditions in the post-disaster period.

This study focused on approaching these shortcomings by adopting an integrated approach which starts with the characterisation of inventory management challenges unique to disaster settings. Gaps within developed models are identified, and an inventory prepositioning and aid distribution model is developed and applied to bridge some gaps.

Therefore, this study presents two models (deterministic and stochastic programming with recourse) for prepositioning modelling. The models are implemented as multi-objective mixed-integer linear programming relief inventory prepositioning models for the Democratic Republic of Congo (DRC) and Central African Republic (CAR). The models minimise shortages and enhance equitability while minimising the total response time in areas with poor road network in a cross-border distribution setting. The model is solved using a pre-emptive optimisation approach, and a sensitivity analysis is conducted to evaluate the influence of the budget, priority items proportion, and capacity variation in the model input.

Results indicate that the models are sensitive to changing parameters. Of the two models, the stochastic model was determined to have higher reliability but required a higher budget to match the performance of the deterministic model. Results analyses confirm that the models can add value to humanitarian organisations when planning facility locations, inventory prepositioning, and conflict area-distribution centre assignments in the DRC and CAR. This study, therefore, contributes to the body of knowledge and humanitarian organisations in Africa.

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*Acronyms

CAR Central Africa Republic

CW Central Warehouse

DM Deterministic Model

DPM Deterministic Prepositioning Model

LDCs Local Distribution Centre(s)

IM Inventory Management

HL Humanitarian Logistics

HOs Humanitarian Organisation(s)

RI Multi-Objective Optimisation

OM Operations management

OR Operations Research

RI Relief Inventory

SLR Systematic Literature Review

SP Stochastic Programming

SPM Stochastic Prepositioning Model

Chapter 1

Introduction

1.1 Background

According to Bastos et al. (2014), aid worth billions of dollars is delivered by humanitarian organisations (HOs) to victims of disasters annually. These disasters are of all forms ranging from wars and conflicts artificial to natural disasters, such as earthquakes, famines, and floods. These disasters and their intensity are not expected to decline in the future (Balcik et al., 2016). Artificial disasters are continuously rising, threatening the livelihoods of several people. ECHO (2016) refers to one such disaster—the Syrian Conflict, a combination of terrorist attacks, nuclear accidents, and conflicts causing one of the world's largest crises in the humanitarian sector. The crisis has claimed lives over 200,000 while displacing millions of people.

In disasters, victims depend on relief lifesaving supplies. These supplies include aid, such as water, food, and shelter from HOs. HOs are tasked with coordinating the delivery of aid by sourcing, mobilising funds, and distributing aid to victims in the aftermath of disasters. Effective inventory management is critical to ensuring efficient logistical performance when responding to a disaster. The needs of victims differ significantly based on timing, location, disaster type, and intensity. These factors affect the scope and scale of disaster responses. The main objective of relief operations is ensuring timeous access and delivery of relief to the people in need (Balcik et al., 2016).

To achieve the crucial main objective, inventory management cannot be improved in isolation as it also depends on other humanitarian logistics (HL) operations. Areas conjoint with inventory management include procurement (sourcing), storage(warehousing), distribution, and transportation. Combined, these logistical considerations are among the costly aspects of humanitarian relief operations (Van Wassenhove, 2006). The unavailability of storage, poor infrastructure, precarious working conditions, and the environment increase these costs. Correspondingly, in recent years, there has been development in acknowledgement of the significance of managing humanitarian logistics effectively (Balcik et al., 2016; Kunz and Reiner, 2012). This importance has been acknowledged in equal measure by humanitarian missions and academic researchers. Specifically, the challenging and distinct nature of the humanitarian environment has been the main trigger of research in this field; therefore, there has been an increase in management science and operation research (OR) studies focusing on HL. There also exist several publications that examine HL from various perspectives (Altay and Green III, 2006; Kovács and Spens, 2009).

Similarities exist between humanitarian and enterprise supply chains regarding inventory management. They strive to approach decisions on order quantities, order timing, and inventory storage; however, there is a stark difference in that vast, well-established literature approaches the emphasised decisions for enterprise logistics, whereas the relevant literature in a humanitarian setting is scanty or simply not directly applicable in the management of humanitarian inventory. This can be explained by the complex and unique nature of humanitarian settings, which preclude the application of models and policies developed for enterprise supply chains (Whybark, 2007). The nature of humanitarian settings characterised by Bechtel et al. (2000) demonstrates that the only exception is in health services in the humanitarian sector. The extensive study in the health services sector can be applied in relief inventory management in areas, such as reservation of blood, medicine, and medical supplies.

To better support relief operations coupled with the pivotal need to save human lives, it is crucial to understand relief inventory (RI) concerns; therefore, operational cost and response time can be reduced while maximising the fulfilment of demand. Most of the existing literature reviews addresses concerns related to RI by implementing operation research (OR) and operation management (OM) models. The reviews conducted are exhaustive in classifying studies approaching RI issues and methodologies used. This is useful, though gaps exist in these reviews and implementation of the developed models. Some of these gaps exist because of practical difficulties in humanitarian settings because disasters are complex and erratic. Kovacs and Moshtari (2019) contend that most of the OR models developed in the humanitarian context have three major shortcomings—futile solutions, unrealistic assumptions, and oversimplified objectives. These shortcomings further undermine the practical use of these models.

Based on the consistent shortcomings, this study attempted to bridge certain consistent gaps with the objective to provide a model for efficient and effective RI management in the humanitarian sector. The study is unique because it integrates the characterisation of RI challenges and a review of existing models for RI to identify existing gaps to establish a mathematical model approaching some gaps. Preliminary research indicates a limited focus on slow onset regarding prepositioning planning and post-disaster distribution. This is because there is adequate time to plan and source the stock. Prepositioning is more related to sudden onset disasters. Limited studies approach the prediction of various scenarios in the aftermath using sensitivity analysis; therefore, the study also explored some plausible options where a sensitivity analysis can evaluate the outcomes of specific disaster parameters.

1.2 Problem statement

Inventory management has continuously proven to be a crucial aspect of humanitarian operations. Over the years, various models and policies have been developed to improve inventory management efficiency. These models observed the elements of inventory management, ranging from sourcing, storage, prepositioning, distribution, and transportation. Research approaching inventory management issues for most disasters lacks in-depth characterisation (Ye et al., 2020). It is yet to be profoundly discussed and understood.

While literature and models provided guidance and breakthroughs towards more informed decision-making, the complex setting of disasters continued to preclude their application. Over-simplification, impracticality, and particularity of decision variables pose a challenge in using specific models in exceptionally distinct disasters. The distinctiveness of disasters is premised on complexity and their ever-changing nature. This means that the ability to manage the inventory efficiently and distribution depends on the preparedness and prevailing conditions in the post-disaster period. This study attempted to focus on these shortcomings by adopting a comprehensive approach, starting with the characterisations of inventory management challenges unique to disaster settings. The study established gaps within developed models and finally developed a model to bridge some gaps. Sensitivity analysis and simulation were also conducted to evaluate the influence of certain outcomes based on various scenarios

1.3 Research questions

The primary research question this study attempted to direct is "*how can relief inventory be managed effectively in the Central African Region during humanitarian operations?*" To achieve this, the subsequent set of secondary research questions was formulated.

1. What are the possible inventory management challenges experienced post a disaster? How can they be predicted or simulated?

2. Which improvements should be made to existing inventory management models to bridge their practical implementation gap?

1.4 Research design

This research integrated an inventory management model incorporating pre-disaster and post-disaster phases. The integration adds to existing prepositioning and facility location decision models to determine the optimal placement of distribution centres (DCs) and post-disaster strategies to maximise effectiveness. The model adds to existing models, aiming to reduce cost by ensuring strategies are adopted to minimise undesired outcomes. The model presents the balance between the cost burden on relief missions and efficiency for better and timeous inventory management to reduce the suffering of disaster victims.

The research deviates from existing models and studies by adopting a holistic approach leading to practical solutions. Earlier studies provide context concerning literature and systematic reviews while suggesting solutions as future research areas. This study deviated from such approaches by adopting an integrated approach of problem characterisation and systematic review followed by solution development in some gaps. Particularly, the study developed a model based on characterising specific challenges. The adoption of strategic decisions in the CAR, and improving efficiency, is supported.

1.5 Research methodology

1.5.1 Existing challenges and gaps

As the main aim of this research is to bridge gaps in the existing models for inventory management—focusing on pre-disaster and post-disaster phases, a profound understanding of challenges concomitant to them needs to be characterised; therefore, an extensive literature review on perpetual challenges in disaster inventory management was conducted. Improvements in RI modelling were notable as modelling included the CAR, a region not studied adequately in the past. In addition to modelling in the CAR context, a unique problem involving two countries experiencing armed conflict was the case study. The conflicts in the CAR emerged in the form of slow-onset disasters, but they have since escalated into a complex emergency. The consistent ambushes on innocent civilians have rendered the insurgencies sudden onset, with their uncertainty complicating the humanitarian response logistics. For HOs in this region to respond rapidly to the attacks efficiently and effectively, they must be proactive in their pre-disaster planning phase. This necessitates pre-establishing their relief inventory stocking points and the conflict area-distribution centre assignment. A prepositioning relief inventory model was considered of great contribution.

It is remarked that it would be complex to develop a model that approaches all the aspects required. This study focused on developing a solution that would consider an armed conflict setting. The model is based in the central Africa region (CAR), a region that has been plagued by multiple artificial disasters and conflicts. It is remarked that studies were conducted in the DRC context; however, studies attempting to model a humanitarian response involving two countries from this region are lacking. This study resolved to extend the DRC context to include an additional country—the Central Africa Republic (CAF).

For gaps identification, the systematic literature review (SLR) method was applied in the review of previous models and studies. A concise review of issues approached by various models and studies was reviewed. The general considerations approached by IM models and studies for disaster were reviewed, and narrowed down to a few. Problem aspects considered in the review were broadly categorised into disaster types, stakeholders, facilities, planning horizons, and performance measures. As the study approached the issues in the pre-disaster and post-disaster phases, the problem aspects were also categorised into two aspects. Post-disaster in this study refers to when a disaster has occurred or when (post) warning of an imminent is given. Several models and studies concern issues related to decision-making for prepositioning.

The standard SLR method was applied, involving all the steps of planning, searching, filtering, and extracting. The planning stage considered the already framed main research question of how can RI management in the CAR be improved? In the searching stage, key terms were developed and used to collect research publications in humanitarian IM. Key words such as "disaster relief", "disaster inventory management models", and "humanitarian aid operations" were used. The key terms were then implemented to search various publication databases. The search was set between 2000 and 2021. This period was used to understand the previous work before the time of this study.

In the last two stages, screening was conducted to define the inclusion and exclusion criteria. In the review of gaps, only studies applying mathematical models were included. This was to ensure that the reviewed studies applied the same solution approach as the one for this study. Mathematical modelling in health care and commercial logistics were excluded as they do not contribute to the scope of this study. Last, extraction was conducted to select a few studies crucial to this study with the possibility of extending their work to bridge the gaps.

1.5.2 Applicable data

Statistical data required to evaluate the relevant influence on RI management were obtained from the disaster database of the region under consideration. The data used for this study were from 2010 and 2018. This period represents the duration where reliable data could be obtained. The databases contain reliable armed conflict data from 1989 to 2018. Data for 2019 and 2020 exist, but since some of the data has not been updated, the data included was up to 2018. As disasters are more in the public domain, the data were obtained from various public domain agencies. This included the World Food Programme,WFP (2021), EM-DAT (2021), ACLED (2021),Humdata (2021), United Nations-affiliated databases such as UNHCR (2021), and several emergency agencies for the two countries under consideration in the CAR. The relevant data include the frequency of conflicts, the number of victims, populations, road conditions, and general infrastructure. Previous humanitarian publications in CAR and the Democratic republic of Congo (DRC) were also included as data sources to supplement the data from the mentioned databases.

The model developed is based on a review of existing models and relevant data collated for disasters under consideration. Sourced supply, disaster type, population served, and general use of relief inventory guided the model development. The development of the solution model was based on the approaches by Lee et al. (2014), and Mpita et al. (2016) studies. In their approaches, demand requirements are estimated and then translated into supply requirements, followed by an evaluation of various scenarios. The results from these inputs are then used to estimate the outcomes of varying inventory and distribution scenarios regarding distribution means and transportation. Estimating such outcomes is crucial in corroborating proactive actions to respond to humanitarian needs.

1.5.3 Model method, solution, and outputs

To solve the OR mathematical model developed, the existing standard options for solving it were explored. The options were two, either solving by optimisation software or heuristics. The difference between the two is that the software provides an exact solution based on decision variables, whereas the heuristic method uses an algorithm to estimate a solution acceptable. The solution from a heuristic method is not always optimal, but it is helpful where the software cannot find an optimal solution in a reasonable time owing to the complexity of the models. In this study, as the model developed, a mixed-integer problem required a software approach.

A sensitivity analysis was conducted based on the model solution to understand the influence of the variations of the optimal solution. These can then evaluate the sensitivity of the strategy employed to determine the effectiveness of inventory management during a disaster. This is significant because most models focus on inventory prepositioning; therefore, results from the sensitivity analysis are important in achieving the objective by providing guidelines to ensure inventory is positioned at various facilities. This must be effectively managed by extension to distribution and transportation.

1.6 Research contribution

As the world is continuously being affected by disasters, it is increasingly becoming important to produce more innovative yet practical methods of optimising inventory management. Though a significant corpus of literature and models have been developed in this regard, most perennial disaster challenges distinct from inventory management remain unresolved. Unique to this study is the disaster setting of conflicts. Most studies approached prepositioning for disaster response planning in major sudden-onset disasters, such as earthquakes and hurricanes, as illustrated in the literature review section. Conflicts are unique artificial disasters classified under slow-onset disasters, therefore, precluding the need for prepositioning planning as the tension flare-up time allows for adequate response; however, sometimes, conflicts result from ambushes or unforeseen invasions. Planning for these conflicts can be achieved through preposition planning as it is in sudden-onset disasters, and this study contributes.

This study acknowledges the progress of previous studies and contributes to bridging the existing research divergence. The main contribution concerns pre- and post-disaster planning. In the pre-disaster phase, the study contributes by identifying proactive ways of improving inventory prepositioning. In the post-disaster phase, the study provides proactive strategic decisions based on scenario outcomes. The scenario outcomes are specific to inventory performance on distribution and transportation based on prepositioned locations. It, therefore, makes a significance contribution by enabling HO to respond to armed conflicts within a shorter time. With preposition for armed conflicts, it provides guidelines on the crucial phases of disaster response, such as need assessment, aid deployment, sustainment, and reconfiguration conducted in shorter lead times, with the largest potential improvement being in the deployment phase. This can potentially reduce the impoverishment and suffering of victims by increasing timely access to basic services when desperately needed; therefore, this study contributes to humanitarian operation efforts by improving efficiency in the distribution of relief to victims of historical conflicts.

1.7 Document structure

The background to the problem being attended to by the research is articulated in this document. The objectives, design, contribution, and framework of how the study was conducted are provided. The second chapter—the literature review, provides a critical and detailed review of inventory management (IM) for disaster. The review focuses on IM performance based on adopted strategies, pre-planning, and post-disaster management based on models and frameworks. IM gaps are also identified in this chapter. Chapter 3 approaches the preliminary design of the proposed model to yield a solution that remedies the gaps in IM based on the findings. Chapter 4 discusses the implications of the ideal deterministic model. Chapter 5 presents a stochastic model adopted from the deterministic model to accommodate uncertainty in various humanitarian phases. Comparison and decision support from the two models are also conducted in Chapter 5. Chapter 6 provides a conclusion based on the model solution and suggestions for future studies.

Chapter 2

Literature review

2.1 SLR review summary

This chapter conducts a comprehensive review of existing literature. An SLR characterises RI management problem settings to identify the gaps. SLR examined the findings and data of the existing IM articles relative to the research questions. SLR in research is more precise and comprehensive because it attempts to answer specific research questions. The SLR literature review, including the process and key words, were implemented as discussed in subsection 1.5.1. A summary is tabulated for the studies used in the SLR. Primarily, the characterisation of the inventory management challenges supplies more details to the background of inventory modelling in this study.

2.2 Characterisation of inventory management challenges in humanitarian setting

Adiguzel (2019) opine that inventory managers in disaster settings are confronted by certain distinct challenges that preclude using knowledge for commercial logistics. According to Roh et al. (2013) and Whybark (2007), the uniqueness of these challenges is attributed to the varying magnitude and frequency of natural disasters. This is relevant as it complicates implementing OR models developed for improving IM during disasters. In this part, the consistent IM challenges during disasters are illustrated by contrasting them with commercial settings in the applicable areas. The applicable areas categorised as sourcing, storage, and distribution are discussed. Characterising these inventory management challenges is crucial because it sets the foundation for understanding existing challenges and developing model solutions to some gaps identified.

2.2.1 Sourcing

This section encompasses two major considerations, the first one being acquisition and storage to prepare for an imminent disaster. The other consideration is identifying or establishing sources of aid required for humanitarian relief operations. Often, managers strive to secure sources near places earmarked as potential disaster sites. This contributes to the challenge of identifying sources with adequate capacity and capability. Safeer et al. (2014) further remarks that the capability of sources in some countries to respond to disasters adequately may be curtailed by underlying political interests or situations.

Lambert et al. (2008) posit that commercial logistics managers supervise the movement, distribution, and storage of goods. They determine to reorder times and inventory amounts to order or make based on the estimation of future demands; however, for disaster inventory managers, this is not necessarily the case owing to the uncertainty of disasters and their influence. Disaster inventory managers cannot accurately determine how much to produce or order a little earlier, resulting in an inability to create buffer aid supplies. Seshadri and Subrahmanyam (2005) attribute the ineptitude to the impossibility of predicting the occurrence of a disaster based on enterprise setting, the uncertainty of demand and the timing and location of the catastrophe.

Another unique challenge in the management of disaster RI is ownership. Relief is solicited or owned by non-governmental organisations (NGOs), governments and private organisations. It is difficult to determine the gross RI available. Relief organisations are resolving this challenge by creating a centralised source of disaster information. Information centres maintain relief aid data and enhance coordination among humanitarian collaborators. One such information centre is the United Nations (UN) coordination office (OCHA). According to the UN (2004), this office also boosts information sharing between disaster partners resulting in better management of diffused ownership. The creation of platforms has also revolutionised information sharing among partners through the Internet. Coordinating agencies should always know the availability of relief inventory in one country to serve another, a concern not experienced in commercial inventory management (Whybark, 2007). Since the study intended to model for a cross-border setting, this understanding becomes necessary concerning the derived humanitarian decision insights.

2.2.2 Warehousing

Roh et al. (2013) cites ownership, political considerations, disaster sites, and transportation cost as the main aspects affecting warehouse decision-making. A challenge exists in achieving an optimal trade-off among supply sources, donors, and accessibility for shipping or monitoring when a disaster strikes (Balcik et al., 2016); (Roh et al., 2013). Unlike commercial inventories, disaster inventories have other crucial considerations influencing the trade-off, such as corruption, security, the possibility of damage during disasters and cooperation (Balcik et al., 2016).

Balcik et al. (2016) postulate that another parameter is the form and type of supplies required. Some relief supplies include medicine, medical supplies, and food, subject to expiry dates. Continuous monitoring of perishable and other expiry-subject items must ensure usability when a disaster occurs (Balcik et al., 2016). This calls for supplies nearing expiry to be used first; otherwise, they translate to waste. When this is impossible, these supplies are replenished with fresh supplies resulting in the need to dispose of expired supplies. This discarding must be conducted safely, which requires secure areas and minimal corruption to prevent such goods from sale in the contraband markets (Whybark, 2007).

The last challenge in storage is the technological obsolescence of equipment, especially in medical and communication aspects. This gets even more complicated because, in disaster response, the criticality lies in having a technology suitable for use with the available infrastructure and not necessarily the latest technology. To circumvent this challenge, disaster IM requires monitoring to ensure items due for replacement are identified and replaced on time. Whybark (2007) remarks that technology is not always a challenge and can be used in providing inherent solutions, such as extending the storage life of certain items by altering their storage forms. Even though commercial logistics rarely store items for extended periods, equipment obsolescence also plagues commercial logistics.

2.2.3 Distribution and transportation

Disaster inventory managers encounter challenges in distribution by not having enough information to estimate inventory usage, location, and amount. Whybark (2007) contends that such information is crucial when determining parameters, such as the holding of relief inventory in certain locations and quantifying its benefits. Inventory managers in the commercial sector usually have a relevant theory to guide their decisions. Besides cost saving, disaster aid has other benefits that are difficult to quantify, such as social contribution among various groups. The easier quantification includes recovery of opportunities, infrastructure restoration, and saving lives. Another challenge that affects disaster IM is the political relationship between an aid-receiving country and the origin country. Disaster IM are confronted when countries needing aid refuse inventory from certain countries. According to Çankaya et al. (2019), this challenge is usually overcome by having multiple sources, but this increases relief costs.

With demand estimation, Ye and Yan (2020) remark that disaster inventory managers encounter the challenge of using a pull system to deliver the required aid. Before a disaster strikes, relief agencies attempt to estimate the demand and push the supply to various locations; however, needs are estimated more accurately as an actual condition in the disaster site is determined. The boundary of the push-pull system is not easily determined. Relief agencies must delegate such control to local managers and use efficient information flow systems to enhance information sharing.

The study reviewed IM management challenges from sourcing to distribution. These challenges cause certain model complexities. Models developed to approach a particular challenge ends up with certain limitations and omissions; therefore, a need exists to review systematically existing models and their shortcomings; therefore, more details on the need and contribution of this study become apparent. The review of existing studies and solution methods are discussed in the subsequent section.

2.3 Systematic Review of Gaps in the Existing Models

Characterising inventory management challenges in a humanitarian setting demonstrates evidence of the existing gaps in the HI models. In this section, a concise analysis of the issues approached by various models and studies is reviewed. First, the general considerations approached by IM models and studies for disaster are reviewed, and narrowed down to a few. Problem aspects considered in this review are broadly categorised into disaster types, stakeholders, facilities, planning horizons, and performance measures. As the study aimed to approach the issues in the pre-disaster and post-disaster phases, the problem aspects are also categorised into two. Post-disaster in this study refers to either when a disaster has occurred or when (post) warning of an imminent is given. Several models and studies focus on issues related to decision-making for prepositioning. Main decisions in prepositioning include the selection of strategic locations for emergency aid storage in anticipation of a disaster to achieve an improved response. Effective prepositioning is vital to solicit and distribute aid timeously, provided the uncertainty of demand, location, and timing of disasters.

2.3.1 Stakeholders

There are various stakeholders in a disaster playing various roles in humanitarian logistics. They include aid suppliers, governments, donors, local and global humanitarian organisations, and affected populations

Pre-disaster IM phase

Balcik et al. (2016) remark that a single HO is the sole decision-maker in most studies, forecasting the quantity of RI to preposition before a disaster. The HO decision-maker owns and is in charge of relief operations and distribution to the victims. Other studies, such as Davis et al. (2013), Campbell and Jones (2011) and Duran et al. (2011) considered two-tier relief supply networks with options of having emergency aid stored at facilities distributed to beneficiaries and procurement of emergency aid from suppliers. The procurement option is twofold and allows suppliers to send emergencies directly to the locations in need or other facilities. Noteworthy, whether the emergency aid is stored at facilities awaiting distribution or procured from suppliers, the amount delivered is determined by the HO, hence, retaining the decision-making status.

Post-disaster IM phase

Like in the studies approaching the pre-disaster phase, SLR demonstrates that most studies consider one HO as the sole decision-maker. These studies allow for interaction between HO and various stakeholders, while some consider replenishing local facilities from central facilities a process managed by the principal HO. Das and Hanaoka (2014) considered a HO that owns and manages central and local warehouses and uses them to serve various victims. This concept directly applies to this study, where a central warehouse is established and used to replenish the local distribution centres in a cross-border setting. Ozguven and Ozbay (2013) and Beamon and Kotleba (2006b) considered facilities replenishment involving an external supplier. These two studies allow demand from single warehouses to be satisfied by multiple suppliers. Beamon and Kotleba (2006b) further differentiated external suppliers according to lead times, allowing the replenishment of urgent demand by short lead time suppliers despite being expensive. As evidenced in the studies, the HO is still the principal decision-maker and determines the amounts of humanitarian aid from the suppliers.

Even though most studies regard one HO as the sole decision-maker, Knox Clarke and Campbell (2020) remarked that this is not always the case. In a real-world setting, multiple organisations stock relief items in the same warehouse and use the stocked items to serve various beneficiaries. Umbrella organisations can also coordinate the delivery of such aid. From the extracted studies, only Davis et al. (2013) incorporates a scenario involving a collaborative effort by multiple HO managing individual inventory in local warehouses. The study considered a post-warning scenario where a reallocation of stored inventory occurs after more information regarding the intensity of a disaster is provided. Due to this collaboration, inventory can be shifted among various local warehouses preventing them from destruction, which boosts the timeous delivery to the affected victims. Since post-warnings provide information, such as the route of the disaster and predicted damage to delivery infrastructure, such as roads, alternatives can be evaluated. Other studies, including Beamon and Kotleba (2006b) and Ozguven and Ozbay (2013), were motivated by a multiple HO setting, although the proposed model focused on a single HO, contrary to the model proposed by Davis et al. (2013) that boosts prompt delivery of aid. As evidenced, timely delivery of relief aid to several beneficiaries is anchored on the collaborative nature of IM among various local warehouses.

A few studies consider relief IM decision-making involving stakeholders from private companies for aspects, such as manufacturing and distribution. Studies consider private company stakeholders in anticipation of a surge in demand from victims during a disaster. This is important, especially for locally sourced relief inventory, because certain disasters may cause a strain on the manufacturing or retailing private facilities. By considering the possibility of demand surge, proactive and reactive approaches can be evaluated. For example, Taskin and Lodree Jr (2010) acknowledged the possibility of increased risk and cost due to the delayed ordering of relief supplies. They recommended using more accurate information provided as a hurricane occurs. Models may also allow private manufacturers to produce certain items in advance and preposition them at various retailers in anticipation of a spike in demand. This strategy is known as vendor-managed inventory (VMI) (Lodree Jr et al., 2012). Lodree Jr et al. (2012) posit that VMI allows post-disaster decisions to be made by the manufacturers regarding the transhipment of stock prepositioned among the retailers as considered by Lodree Jr et al. (2012). Whereas VMI is important for prepositioning sourced relief inventory locally, Lodree Jr et al. (2012) did not incorporate a scenario where inventory is not locally sourced. Lodree Jr et al. (2012) failed to consider a scenario where multiple HOs source relief aid from an umbrella local warehouse, which might be limited to the diverse needs of various beneficiaries. Although the primary focus of this study is not the sourcing aspects of relief inventory, the stakeholder discussion provides introductory insights used in the decision-making process in IM. This discussion, hence, expounds on the existing gaps of IM resultant of stakeholders' decision-making.

2.3.2 Disaster type

Pre-disaster

Disasters may occur in the same or various locations. A plethora of research studies investigate disaster types, such as artificial, slow-onset, and sudden-onset disasters (Kunz and Reiner, 2012). The further review indicates that studies focus on sudden-disaster types usually characterised by high uncertainty levels. Examples of sudden onset disasters include hurricanes, floods, and earthquakes

SLR of the extracted articles indicates short-term post-disaster (warning) modelling for the disaster characteristics and types similar to those approached in the pre-disaster phase; however, post-disaster studies differentiate these unique characteristics, unlike pre-disaster IM studies that do not distinguish those presenting a warning before they happen and disasters that do not. Studies, such as Lodree Jr and Taskin (2009), used a Bayesian framework to present warnings before they happen on hurricanes, storms, and those that do not include earthquakes. The distinction among these disaster types is necessary as some disasters—such as hurricanes, affect certain areas, are cyclic through seasons and present prior warning. The intensity of these disasters, despite the warning, remains uncertain; therefore, the need for the incorporation of dynamic information during planning and response. For instance, Ozguven and Ozbay (2013) suggested using dynamic hurricane strength for more reliable safety stock determination using an online control methodology. Other considerations, such as using short-term forecasting in affected areas to determine post-warning relief inventory prepositioning, were made by Davis et al. (2013). Interestingly, studies observing disaster response for complex emergencies are few. Since most complex emergencies are artificial, long-term relief plans are required. Beamon and Kotleba (2006b) are among the studies that aimed to develop long-term IM plans for complex emergencies in Africa. Fluctuation in demands for multiple periods is a significant aspect that should be included in complex emergencies in addition to disaster types.

Although the warning characteristics have largely been approached in natural disasters; some similarity exists with armed conflict situations. For instance, the study could consider the tension among the warring groups and use it to determine the possibility of a conflict. Conversely, the ambush of innocent victims would present no warnings. A differentiation of artificial disasters is necessary to distinguish those that present a warning prior and those that do not. This is vital as it would enhance prepositioning of relief supplies despite the uncertainty of disaster intensity.

2.3.3 Demand characteristics

Pre-disaster-disaster

Humanitarian relief supplies are usually prepositioned in anticipation of a disaster to ensure timely response when a disaster occurs. The amount prepositioned at various facilities is usually based on the projected demand of disaster victims' needs. Existing models consider single item prepositioning and multiple-item prepositioning (Campbell and Jones, 2011); (Chakravarty, 2014); (Garrido et al., 2015); and (Rabbani et al., 2015). Various items prepositioned for disasters include food supplies, blankets, tents, hygiene kits, and other shelter-related commodities. Some studies, such as Hong et al. (2015), bundle certain relief items (such as kitchen sets, blankets, and tents) and consider them as single bundled commodities when developing the model. From Table 2.1, it is observed that the focus on prepositioning multiple items is higher than on single items. One study focusing on single-item prepositioning is Chakravarty (2014), which focused on optimising emergency inventory levels and the subsequent delivery using analytics. Campbell and Jones (2011) suggested a single-item model without bundling. Studies, such as Rawls and Turnquist (2010), Garrido et al. (2015) and Balcik and Beamon (2008) focused on prepositioning multiple commodities while differentiating them. Commodities are differentiated according to various parameters, including cost per unit, demand, and capacity. The demand parameter also includes coverage requirements, such as urgency. The related costs include shortage penalties, inventory, procurement, and transportation costs. By differentiating commodities, supplies can be stocked in the most suitable locations based on the ease of distribution during an emergency.

Prepositioning studies focus on generic emergency and specialised supply; however, because of the rare occurrence of disasters requiring specialised relief, only a few studies, such as Mete and Zabinsky (2010) and Rabbani et al. (2015) conducted studies to this regard. Special supplies include medical supplies and perishable supplies. Mete and Zabinsky (2010) and Rabbani et al. (2015) developed models and policies that consider close-to-expiry replacement. Further SLR indicates that emergency supplies demand considered stochastic by studies, such as Mete and Zabinsky (2010) and Noyan (2012). This is because the number of victims during a disaster is usually uncertain at the response time and changes with time. Studies by Mete and Zabinsky (2010) and Noyan (2012) characterise emergency demand uncertainty by simulating discrete scenarios. Demand distribution scenarios can be generated using Monte-Carlo or assuming certain probabilistic distribution approaches as applied by Chakravarty (2014) and Garrido et al. (2015). For certain disaster locations, studies, such as Galindo and Batta (2013) use historical data to estimate the demand and later incorporate it as a parameter when solving the model.

Post-disaster

Evidence-based pre-disaster studies demonstrate that demand in the post-disaster phase can also be depicted stochastically following various forms of distribution. Beamon and Kotleba (2006b) modelled the demand distribution during a conflict emergency IM as normal. The normal distribution is used when a numerical analysis is used to predict the demand, whereas some disasters, such as hurricanes, modelled by Taskin and Lodree Jr (2010), have no assumed distribution. A significant gap noted in some cyclic disaster studies is that demand is assumed to be uncertain, although periodic. Decisions regarding distribution and transhipment are made based on updates obtained from response operations. Economic order quantity (EOQ) models are used where the demand is considered deterministic as used by Shen et al. (2011). Studies can also have distributions for regular demand and the spike realised during disasters. To bridge the demand uncertainty gap, this study adopted deterministic demand, where average demand is considered and stochastic demand, where the assumption of a certain distribution of affected people is based on historical data. A comparison of the two models was then conducted to understand their performance.

Another significant gap observed in post-disaster practices is the penalisation of unsatisfied demand. This is important because it helps in evaluating the effectiveness of post-disaster IM, as the lost demand equates to a loss of human life. Some studies, such as the one by Salas et al. (2012), allow unsatisfied demand to be met through back-ordering; however, according to Beamon and Kotleba (2006b), unlike in the commercial supply chains where backorders have implications of lost profit, in HL they should be attributed to human suffering and even death.

last, it is observed that most studies considering post-disaster scenarios focus on durable products. Most studies do not even specify the product category under consideration (durable or perishable), a significant gap in the IM models. Subsequently, models developed from these studies are more suited for durable relief items, such as technological items, shelter stock, and other relief equipment. Additional aspects need to be included in the demand for perishable products, such as disposal cost and Salas et al. (2012) is among the few studies that incorporated this aspect in their models.

Supported by findings from the demand review, this study adopted some approaches, estimating the demand based on historical data and using it as an input to the models. For example, in the stochastic model, deriving the demand from a uniform distribution of victims. Several items were grouped based on priority and the needs they approach. Next, facility considerations when developing prepositioning inventory models were reviewed. Facilities usually hold the prepositioned humanitarian relief supplies for disaster preparedness (Tian et al., 2018).

2.3.4 Facilities considerations

Pre-Disaster

During a disaster, various levels of facilities are managed by coordinating organisations and or humanitarian organisations. Tofighi et al. (2016) opine that these facilities are usually large warehouses or other forms of permanent infrastructures used to hold prepositioned humanitarian relief. Because of disasters and distribution required, these facilities are usually two-tier (Tofighi et al., 2016). The first tier is near disaster sites, serving the region directly while receiving replenishment from the second tier as indicated by Tofighi et al. (2016). Limited studies, such as Galindo and Batta (2013), assume a third-tier facility network where the corresponding third-tier facility locations and capacities are known. Suppliers and central warehouses are examples of facilities corresponding to third-tier facilities in these studies. Some studies, such as Tofighi et al. (2016), aim to determine optimal inventory levels and the location of local distribution centres and central warehouses. Models ensure that critical relief items, such as medical kits and food, are stored in both levels of facility tiers, whereas less critical and durable items, such as tents and shelter-related items, are retained at central warehouses; however, some studies may consider developing models using prepositioning on central facilities whereas local facility location is predetermined but only used in the post-disaster phase as modelled by Döyen et al. (2012).

Another crucial facility consideration approached in studies is capacities and possible destruction during disasters. Studies, such as Rawls and Turnquist (2010) and Paul and MacDonald (2016) consider capacitated facilities, but the aforementioned also differentiate facilities according to size and classify them under the same tier. Destruction is incorporated in some models to evaluate alternatives in case of damage of the facilities and the prepositioned stocks. Studies, such as Galindo and Batta (2013), incorporated the potential effects of destruction on facilities during disasters by applying a scenario-based approach. This is crucial because it increases the reliability of a certain distribution centre. This study accommodated this requirement by ensuring that distribution centres are only established in areas with lower possibilities of risk.

In addition and guided by the facilities review, there was a potential of incorporating some permanent infrastructure as distribution centres for the study model; however, this option was not explored. Limited infrastructure would be because undeveloped areas were selected as potential LDC locations. It was best to model with new facilities in this study owing to the limited and unreliable infrastructure in the CAR. The expected influence of this was a strained budget owing to increased LDCs establishment costs.

Post-disaster

A huge difference exists in the studies approaching post-disaster facility decisions compared to the pre-disaster studies. Limited studies consider decisions on the location and capacity of warehouses. These studies consider facilities without capacity limitation with replenishment policies. Only Ozguven and Ozbay (2013) and Rabbani et al. (2015) considered warehouses with capacity limitation, whereas Yadavalli et al. (2015) considered the capacity of warehouses for two products separately. These two products are perishable and substitutable, such as medicine and blood-sachets. To set the foundation for the decision-making insights section of this study based on proposed models, the planning and decision considering for humanitarian inventory modelling are systematically reviewed in the section below.

2.3.5 Planning period and decision-making

Pre-disaster

Studies by Paul and MacDonald (2016),Mete and Zabinsky (2010) and Garrido et al. (2015) indicate an extensive focus on sudden onset disasters with the long-term prepositioning approach. They also approach various future-based disaster scenarios and attempt to determine relief inventory prepositioning at various facilities. Decision type during the studies is categorised into pre-disaster and post-disaster. In pre-disaster decisions, location and the amount to be positioned at each warehouse are evaluated, whereas post-disaster decisions involve deciding on relief delivery means to the victims, among other operational decisions (Balcik et al., 2016). Other decision-influencing factors in the post-disaster phase, such as the possibility of damage to stock and facilities, are considered by Paul and MacDonald (2016). Likewise, Mete and Zabinsky (2010) approached vehicle routing and modelled transshipping among various prepositioning facilities. This approach is applied to the study model to allow various distribution centres to receive supplies from other distribution centres. This is because the approach fosters cost-effectiveness and efficiency in the processing and distribution of humanitarian relief supplies in an emergency. This includes cost-effectiveness and efficiency; the approach mitigates delays that might result during procurement.

Post-disaster

Studies in the pre-disaster phase of humanitarian IM focused on the long-term decisions, but here it was observed that post-disaster studies, such as Mete and Zabinsky (2010) and Paul and MacDonald (2016) mainly approach short-term decisions. Short-term decisions are centred on factors affecting stock build-up either after a disaster or after a warning about an upcoming disaster has been identified. Two main decision variables are used in the models, reorder points and order quantities. Additional variables, such as emergency reorder points, and emergency order quantities, enhancing the practicality of models, are also included by some models as used by Beamon and Kotleba (2006b) and Das and Hanaoka (2014). Emergency orders are considered special and have a shorter lead time than normal ones. The downside of emergency orders is that they are more expensive than normal orders, which increases the inventory cost for the HO. Other decision variables may also be included for additional stock to achieve the required safety stock level after a disaster has occurred. Ozguven and Ozbay (2013) are among the studies that include transhipment between facilities, additional safety stock levels, and the capacity to hold diverse products in various facilities. Increased inventory cost for the HO owing to the expensive nature of emergency orders, the safety of stock levels post-disaster, and the capacity to hold assorted products in various facilities are some gaps identified in the existing models in the reviewed studies.

Notably, post- disaster approach replenishment decisions as opposed to pre-disaster one that model for stockpiling of relief inventory decisions. This creates a gap in the models because there is an unequal mix of replenishment decision-making between multi-period and single-period replenishment approaches. Multi-period replenishment is the majority and includes Das and Hanaoka (2014) whereas the few single-period replenishment include Beamon and Kotleba (2006b). In both approaches, information updates, such as the intensity of the disaster, must be considered for more accurate decisions. This ensures that replenishment times are accurately determined to ensure the satisfaction of the demand and to mitigate large operational costs resultant from frequent replenishment. Aspects such as cost, response time, demand satisfaction, and equity, are performance parameters in relief IM. As evidenced in the next section, these aspects aid in rating performance effectiveness in various IM models.

2.3.6 Measures of performance

Pre-disaster

Measuring performance is a crucial attribute as it helps in rating the effectiveness of performance if the proposed models by various studies were to be implemented (Balcik et al., 2016). Incorporating these metrics is included in the pre-disaster stage of IM in two ways, either as constraints or objectives in the models. Balcik et al. (2016) remark that the metrics considered in various models are coverage, cost, and response time. When approaching the coverage metric in prepositioning, studies focus on the proportion of demand or beneficiaries served with relief items from the prepositioned stock (Balcik et al., 2016). This metric is also incorporated in some studies as shortage (unsatisfied demand) combined with response time limitations. From the SLR, this metric is evaluated in various ways. Hong et al. (2015) and Rawls and Turnquist (2011) focused on covering a certain demand proportion in a specified response time. Other studies, such as Balcik and Beamon (2008), focused on minimising penalty costs owing to unachieved coverage while maximising coverage.

The other metric used in studies is cost, perhaps a primary concern, although not always applicable when rescuing the victims of a disaster. The excessive costs can curtail HO performance owing to the daunting task of funds solicitation. Most studies, therefore, aim to minimise total costs either by applying budget constraints to the models or in the objective function. Balcik and Beamon (2008) indicated that the most incorporated cost attributes are unsatisfied demand penalties, inventory holding, supplies transportation, procurement of supplies, and establishment of facilities in various locations. Shortage and transport costs are second-stage costs, whereas inventory holding and purchasing and facility establishment are first-stage costs in various two-stage stochastic models (Balcik and Beamon, 2008).

Response time is considered in prepositioning models to rate the time to deliver relief inventory to victims. Some models, such as the one by Döyen et al. (2012), aimed at minimising the response time in the objective function. This can also be achieved by constraining the maximum response time when formulating the models. As evidenced, various parameters considered pre-disaster IM. The proposed models in the systematically reviewed articles incorporate these measures through objectives or constraints. These pre-disaster IM measures are similar to the post-disaster IM measures.

Post-disaster

Performance measures in the post-disaster studies are the same as those for pre-disaster studies. Likewise, they are also included as constraints and objective functions. In addition to the metrics used in the pre-disaster studies, post-disaster IM includes equitable response as a significant concern. A specified proportion of demand satisfaction in every affected area is introduced in constraints to achieve equity in response, as modelled by Davis et al. (2013) and Noyan (2012). Providing equitable services regarding response time to the affected locations is also considered important by Tofighi et al. (2016). Hong et al. (2015) in their models aimed at ensuring equitable service regarding the fraction of demand satisfied.

This study implemented priority item proportions as indicators of equity. From the discussed measures of performance, the proposed models aim to reduce the total response time while minimising shortages as measures of performance. Equitable service provision to demand locations is anchored on response time and demand satisfaction.

Table 2.1 summarises the studies considered with the aspects approached in each. In the subsequent Section, 2.3, gaps are then summarised. As evidenced by the summary, despite propositioning inventory models, several areas have not been approached. This study aimed at approaching some lacking areas to bridge some gaps.

Table 2.1: Various aspects considered in pre- and post-disaster phases by various studies used for SLR

Article	Disaster Type	Continent	Number of items	Decision-maker	Metric
Davis et al. (2013)	Hurricane	North America	single	Collaborative	Total costs, equity, and response
Campbell & Jones (2011)	General	Global	single	HO	Risk, total costs
Duran et all (2011)	General sudden onset	Global	multiple	HO	Response time
Das & Hanoka (2014)	Earthquake	Asia	multiple	HO	Response time and total costs
Ozguven & Ozbay (2013)	Hurricane	North America	multiple	HO	Demand satisfaction, total costs
Beamon &Kotleba(2006)	Complex emergency	Africa	single	HO	Costs for back-ordering, ordering and holding
Lodree and Taskin (2010)	Hurricane	North America	single	multiple	Costs for shortage,ordering and holding
Lodree et al. (2012)	Hurricane	North America	single	multiple	Costs for production, shortage,transportation
Balcik & Beamon (2008)	Earthquake	Globla	multiple	HO	Cost for aid transport, facility, satisfaction
Manopiaiwes et al. (2014)	Flood	Asia	multiple	HO	Cost for facility, transportation, holding
Hong et al (2015)	Hurricane	Global	single	HO	Equity, total demand satisfaction

Continued on next page

Table 2.1 – continued from previous page

Article	**Disaster Type**	**Continent**	**Number of items**	**Decision-maker**	**Metric**
Chakravarty (2014)	General	Global	single	HO	Response time,cost for ordering, and holding
Rawls et al (2010)	Hurricane	North America	multiple	HO	Cost for facility,transportation and shortage
Garrido et al. (2015)	Flood	South America	multiple	HO	Transportation and holding cost
Mete & Zabinsky (2010)	Earthquake	North America	multiple	HO	Cost for facility, shortage, and transportation
Noyan (2012)	Earthquake	Europe	single	HO	Accessibility, Response time, and equity
Rabani et al. (2015)	Earthquake	Asia (Iran)	multiple	HO	Costs for shortage, back-ordering, ordering
Galindo &Bata (2013)	Hurricane	North America	single	HO	Damaged supply, transportation, and facility
Shen et al. (2013)	Epidemic	North America	single	Government	Salvage, ordering, and holding cost
Salas et al. (2012)	Hurricane	Global	single	HO	Costs for disposal, shortage ordering
Paul& Mac-Donalds (2016)	Earthquake	North America	multiple	HO	Cost of facilities and ordering
Yadavalli (2015)	General	Global	multiple	HO	Average of substituted demand, inventory

2.4 Summary of existing gaps as identified from SLR

From the SLR and the studies summarised in Table 2.1, it was observed that diverse models approach various aspects, but certain parameters and considerations remain unexplored or not adequately approached. In addition to the background provided in Chapter 1, these gaps further emphasise the main motivation of this study and uncover additional gaps that future studies could address.

1. The investigation of how relief inventory can be effectively managed during armed conflicts in the affected area by using an integrated approach. The integrated approach would incorporate the prepositioning planning and the post-disaster phase of aid delivery while accounting for various forms of destructions, such as routes, facilities, and inventory in Africa.

2. Incorporation of equity objectives in models to investigate its effect on stocked inventory and facility location. Even though Davis et al. (2013) and Noyan (2012) included equitability in their constraints, it was not through an integrated approach.

3. The modelling of disaster IM while considering multi-agency coordination regarding decision-making. Most studies in the SLR recognise the reality of disaster response, but they model a single HO as an independent decision-maker for disaster inventory planning and ordering in Table 2.1. The benefits of collaboration with other stakeholders, such as manufacturers and suppliers, vendor-managed inventory, and pre- and post-disaster inventory contracts, could be examined further.

4. In-depth post-disasters models for multiple items are limited. Most studies in SLR focused on decision-making for a single item against the reality of disasters where victims need several relief items.

5. Post-disaster studies approaching the deprivation cost and general suffering of victims are limited, and only a few studies, such as Loree and Aros-Vera (2018), consider it. As identified in the literature, unmet demand is modelled as lost sales or penalised, with some studies allowing back-ordering. Implementation of the lost sales approach is more suited for commercial logistics, and therefore, the inclusion of deprivation cost would improve the reality of disaster IM modelling.

6. The modelling of disaster IM for conflicts and or approaching the logistical challenges regarding danger, displaced victims in camps or population on the move. The characteristics of conflicts worsen the already complicated modelling of disaster IM; therefore, modelling efficient aid delivery in this setting would benefit the humanitarian actors and researchers.

7. The inclusion of essential aspects in prepositioning with standard problems for diverse disasters is lacking, and including the same would be beneficial. Most models focus on two disaster types, earthquakes, and hurricanes, which complicates extending some standard aspects to other disasters, such as drought, famine, and conflicts. Developing models in these settings and subsequent comparison of solutions from the former (earthquakes and hurricanes) would help identify standard problems in various disaster settings.

8. A need exists to develop novel models that prioritise relief distribution based on the level of damage and people more affected by a disaster. This model can further focus on minimising the risk of victims by mapping and allocating victims to health facilities during rescue missions. The prioritisation here would be based on the severity of injuries.

9. last, a need exists to develop RI management and distribution models that consider integrated approaches that accommodate more effects of uncertainty and dynamic situations. Dynamic situations include barriers from other organisations and governments, political barriers, and environmental changes during relief operations. Uncertainty could incorporate the availability of resources (such as trained workers, vehicles, and relief items) and variations in demand and supply.

From the gaps identified it would be complex to develop models that approach all the aspects required. This study focused on developing a solution that would approach Gap 1 and incorporate elements to approach Gap 2 with a special focus on the central Africa region (CAR). Multiple artificial disasters, such as conflicts have plagued CAR. It is also remarked that studies were conducted in the DRC context; however, studies attempting to model a humanitarian response involving two countries from this region are lacking. The study, therefore, resolved to extend the DRC context to include an additional country, the Central Africa Republic (CAF). The subsequent section reviews existing solution approaches in similar settings that use prepositioning planning.

2.5 Review of applicable solutions methodologies for armed conflict invasions

2.5.1 Introduction

In addition to the findings of SLR sections revealing a limited focus on armed conflict preposition modelling, this discusses some applicable solutions in modelling for the pinpointed gaps. Evidence from SLR revealed that most studies apply a methodological approach where identified performance measures are optimised either in single or two-stage programming, with the latter one as the most common approach. For instance, a certain proportion of demand satisfaction is enforced by introducing probabilistic constraints by Renkli and Duran (2015) and Rawls and Turnquist (2011). Based on various performance measures, these models may have single or multiple competing objectives. Similarly, including some measures of performance may introduce a certain level of uncertainty in the modelling process. Models where all attributes are devoid of uncertainty are called deterministic models (Higle, 2005); however, this is rarely the case in real-world situations, causing the need for stochastic programming. Multiple objectives result in multiple objective functions that can be resolved using various interventions (Rardin, 1998). Concepts related to stochastic programming and multi-objective optimisation are discussed in the subsequent sections.

2.5.2 Multi-objective optimisation (MOO)

As most humanitarian operations need to satisfy various objectives during the response stage, it is necessary to review the techniques employed to solve multi-objective models. In such cases, Rardin (1998) remarks that an obvious way of comparison lacks all the feasible solutions. For instance, a HO may want to maximise demand satisfaction to victims while minimising the inventory level at various prepositioning facilities. Neither of these performance measures can be discounted, leading to the need for MOO where all perspectives are considered simultaneously (Rardin, 1998). Rardin (1998) further remarks that some interventions used in MOO include pre-emptive optimisation, goal programming, and the weighted sums method.

First, the application of pre-emptive optimisation is discussed.Rardin (1998) stipulates that pre-emptive optimisation involves the reduction of a multi-objective model to a single objective model in a sequential manner based on the order of priority for the objective criteria. Rardin (1998) remarks that in real-life scenarios, objectives rarely have the same importance. Pre-emptive optimisation, therefore, considers these objectives one at a time. The others first optimise the most important objective on the priority list. During the solution process, subsequent objectives are optimised so they do not violate the optimal value of the preceding objective. The final result of the pre-emptive technique is an efficient point where one objective cannot be optimised further without degrading the rest of the objectives (Gutjahr and Nolz, 2016; Rardin, 1998). Whereas not degrading the optimal values of the higher priority objective is one of the greatest advantages of the pre-emptive technique, Gutjahr and Nolz (2016) indicate that it has a drawback of placing too much emphasis on the first objective. Zhang et al. (2013), Wang et al. (2014), and Rath et al. (2016) are some studies that applied pre-emptive optimisation as interventions of MOO during their studies. Wang et al. (2014), implemented their model in a deterministic setting whereas Rath et al. (2016) was in a stochastic setting. Interestingly, Zhang et al. (2013) were interested in deterministic and stochastic settings, as is the case with this study; however, they minimised cost while maximising coverage. This study used a modified version of this approach where the pre-emptive technique was applied in both orders. If this study's objectives were to minimise shortages and total response time, it needed first to minimise shortages followed by total response time. In the reverse order, the total response time was minimised, followed by the shortages and compared the results.

The second technique, the weighted sums method, involves the combination of various objective functions into one composite objective function. This method is used when decision-makers can prioritise their objectives by assigning weights to each objective according to preferences(Günay et al., 2019; Rardin, 1998). The general form of weighted sum method is $max\ \sum_{i\epsilon \mathbf{I}} w_i f_i$ where w_i represents the weight of the ith objective with f_i being the function of the objective. Günay et al. (2019) used this method in HO operations to integrate two objective functions. The two objective functions were the maximisation of demand coverage and the minimisation of total transportation distance. This approach was not applied in this study to avoid the bias of weighting,

The third approach is goal programming (GP), one of the most used approaches for solving multi-objective models. In GP, the decision-maker evaluates solutions by specifying target levels(goals) for all the criteria involved. In optimisation, the decision-maker considers the specified values for the objective functions to be sufficient (Rardin, 1998). Understand three main terminologies used in GP, such as soft constraints, hard constraints, and deficiency variables. Soft constraints specify the requirements that the decision-maker considers desirable to satisfy (the goals); however, in feasible solutions, soft constraints may still be violated because hard constraints determine the feasible solutions (Rardin, 1998). Deficiency variables are introduced in GP to control the violation of the soft constraints or the goal concerning underachievement or overachievement. Humanitarian optimisation studies that considered GP include Chong et al. (2019), where they had four goals. The four goals that had to be met by objectively totalled cost, safety stock fulfilment, and the number of open warehouses. Other variations of GP exist, such as pre-emptive GP, where goals are considered one at a time. The implementation principle is similar to normal pre-emptive optimisation. In pre-emptive GP, the deficiency of the most important goal is minimised first, followed by the second on the priority list on condition that the first achieves its minimum (Rardin, 1998). Vitoriano et al. (2011) and Barzinpour and Esmaeili (2014) are some studies that used GP in the humanitarian supply chain. Having determined the multi-objective and uncertainty nature of the data, the need to evaluate stochastic programming became apparent. The subsequent section discusses the basis of stochastic programming and the subsequent application of the same to the study model.

2.5.3 Stochastic programming

Stochastic programming (SP) is the application of mathematical modelling in decision-making under uncertainty, also called stochastic optimisation, by several researchers (Li and Grossmann, 2021). SP considers several aspects of uncertainty in the modelling process from various parameters, such as prices, demand, and risk. Most of these uncertainties are disregarded by assumptions used in deterministic modelling (DM). Higle (2005) identifies various reasons SP can be observed as the ultimate model in OR. Higle (2005) further cites the blending of deterministic (traditional) mathematical models with stochastic models as the main reason. Stochastic linear programmes (SLP) arise from linear programmes (LP) with some variable elements best described by random variables.

Higle (2005) opine that the inclusion of various uncertainty aspects renders the formulation and solution of SP more difficult than DM. There are interventions used to improve the acceptability of DM models, including using post-optimality analysis, such as sensitivity analysis (Higle, 2005). Sensitivity analysis improves the applicability of DM by allowing modellers to investigate uncertainty (Higle, 2005). With sensitivity analysis, the influence of changing a single data element on the optimal solution can be investigated-mainly because the primary structure of the model stays the same. This helps the modeller to understand the robustness of the model by studying the solutions from variations of the parameters used in the model (Higle, 2005); however, there are several drawbacks to using sensitivity analysis as a device for uncertainty investigation. The sense of assurance obtained from a sensitivity analysis in several cases are false-largely because uncertain data elements are not included in the model leading to an unchanged optimal solution not always true (Higle, 2005).

For sensitivity and scenario analysis in a DM, it is assumed that the quantity of all the data elements is known-therefore all scenarios can be evaluated one by one, and the best outcome can be selected (Higle, 2005). It can be presumptuous to model an armed conflict situation while expecting all the data elements to be known. It is more reasonable to model data elements with some uncertainty-especially the ones beyond the control of a HO. For instance, HOs may have control of resources, facilities, and labour requirements to distribute aid to various demand points, but the demand remains unknown until a conflict; therefore, the demand for items will be unknown when the HO commences the planning process. There are various demand scenarios, such as expected (mean value), high, medium, and low scenarios and a balanced solution can be achieved only by explicitly considering these scenarios. SP provides a latitude where a balanced solution and interplay between uncertainty and decisions can be captured accurately by considering various scenarios collectively and not individually (Higle, 2005). Recourse and chance-constrained models are some SP techniques that can achieve a balanced solution while capturing the required interplay (Higle, 2005). The subsequent section discusses recourse models in more detail to understand their implementation as an intervention to uncertainty in the modelling data.

Recourse SP models

Modelling uncertainty using SP means decisions can be made in stages, with decisions from one stage influencing the subsequent ones. Decision timings must be specified concerning the uncertainty's resolution before an SP model can be developed. The modeller, therefore, controls which decisions are made first and which ones are made later after the uncertain information becomes available. A recourse model is an adaptation where decisions in SP are delayed and only made after the uncertain data information becomes available. The resultant decision variables associated with recourse models are called recourse variables. These variables may change depending on the scenario (Higle, 2005). In modelling, some decisions can be delayed while some cannot, and this is usually beyond the control of the modeller. Where possible, delaying decisions until more information becomes available adds value to the modelling process (Higle, 2005). Recourse models create a setting where decisions are delayed while some must be fixed first, even before the availability of uncertain data information.

In a humanitarian setting, some decisions, such as the availability of resources, must be determined relatively early, whereas distribution quantities can be determined later after obtaining demand information. Distribution quantities are adaptive, whereas resource availability decision is not. Distribution quantities can be modelled depending on demand scenarios (Liberatore et al., 2013). For example, resource quantities that include labour and trucks, distribution quantities comprising water, food and clothing, and demand scenario of a low, medium, and high maybe be modelled as $\{(y_w, \omega, y_f, \omega, y_c, \omega)\}\omega \ \epsilon\{l, m, h\}$. Here the variable $y_{w,m}$ represents the water in the units distributed if the demand is "medium" for the other variables. The resource variables x_l and x_t for labour and trucks, respectively, would stay the same regardless of the scenario Higle (2005). The result would enable a humanitarian organisation to circumvent the risk of distributing items not needed because the distribution quantities are only determined after establishing the demand scenario. Some of the humanitarian inventory studies that included recourse include Shehadeh and Tucker (2022).

According Elçi et al. (2018), chance constraint (CC) models are also called probabilistic programming. The guiding principle of recourse SP models is the latitude of second-stage model uncertainty at a specified penalty. Recourse activities have a cost assigned to them to ensure feasibility in the second stage of the model. Unlike recourse-based SP models, CC models focus on the model's reliability where data elements are uncertain; therefore, reliability is a minimum requirement on the constraint's satisfaction probability Sahinidis (2004). CCs can be of two types, either separate (Individual) or joint constraints. Joint constraints require a set of requirements to hold together for the probability, whereas individual constraints impose that a goal constraint must hold to the required probability (Elçi et al., 2018; Ruszczyński and Shapiro, 2003). According to Elçi et al. (2018), separate CCs should be imposed when individual requirements are described differently. Otherwise, joint CCs are more suitable when one goal is described collectively by a set of individual requirements. The general form of individual CC can be described as $min\ z = C^T X$ subject to $P(T_k >= \xi) >= 1 - \epsilon_k\ \ \forall\ k = 1...n$ where $x\ \epsilon\ \chi$ and ϵ_k is the risk tolerance.

2.5.4 Model solution and applicable studies

Regarding solving the models, for two-stage stochastic models, two main techniques are employed. SP solution techniques depend mostly on numerical approximation and statistical estimation methods (Higle, 2005). This is because of uncertainty in data (not determinate) which triggers the need to use several operations research techniques to achieve better estimates. These techniques use heuristic algorithms and optimisation solver software, such as Lingo, CPLEX, and Gurobi. Döyen et al. (2012) used a lagrangian heuristic, Mete and Zabinsky (2010) used CPLEX solver and Mpita et al. (2016) used Lingo to solve their optimisation model. A limitation exists in using model solver software when the problem has large data sets. In large problems, solvers mostly fail to find a good solution at practicable times. As an alternative, distinct types of heuristics are applied to find good solutions within a reasonable time; however, as some heuristics use various relaxations to achieve the desired output, the result is not always an optimal solution (Jozefowiez et al., 2008). At the time of this research, two studies attempted to model prepositioning planning in some countries in the CAR. Studies by Mpita et al. (2016) and Munyaka and Yadavalli (2021) focused on approaching HO disaster response by prepositioning planning for armed conflict regions in the DRC. The solution methods applied in these two studies apply to this study because the solutions can be extended to cover a larger geographical region allowing the inclusion of CAF.

The study by Mpita et al. (2016) aimed to improve the response to armed conflicts in DRC by increasing response preparedness for HOs.They contended that exiting prepositioned stock was not in strategic locations based on a World Health Organization (WHO) report from 2012. Another major concern was that warehouses holding these RI had inadequate capacities. Their study was also cognisant of other underlying difficulties hampering RI distribution, such as insecurity, poor transport infrastructure, and capacity limitations. Their study resolved to develop a prepositioning plan as a scientific decision support device for HOs operating in DRC regions of South and North Kivu. They reviewed existing conflict data from the relevant databases, formulated a facility location and capacity model and then evaluated its sensitivity to various situations. The disaster statistics review timeline for their study was between 2012 and 2014.

To estimate the demand for various disaster instances, Mpita et al. (2016) examined reports published weekly by RDC Humanitaire in 2014. They then grouped people into categories according to their needs and calculated the average demand per conflict instance in each area. They also investigated various transport options based on the stock prepositioned from their model and the subsequent distribution to the affected areas. Their formulated model was solved using Lingo 14.0 and considered conflict probability, expected demand, potential locations, and response times as their performance measures. The response time was calculated based on average speed. Even though the average speed consideration partially catered for the dynamism of road conditions, the dynamism could be improved using actual speeds for each route in the model; therefore, the influence of varying road conditions between a DC and the conflict areas would become apparent.

Munyaka and Yadavalli (2021) employed a solution methodology similar to Mpita et al. (2016) in their solution approach for DRC disaster response transportation planning but extended their coverage to include an extra region, Ituri. Their formulated model aimed to identify the potential locations of prepositioned RI by minimising the cost and transportation time for HSC in the selected regions. They used historical data and estimated the time, distances, and cost per tonne for transportation based on various modes of transport. Because their model was approaching a typical transportation problem, they evaluated two decision scenarios. Scenario one involved the computation of transportation time and cost using air links and connecting roads. Decision scenario two involved the computation of transportation cost and time on a province-by-province basis depending on security, health, administrative offices, and road conditions. This evaluation was then used to determine the mode of transportation for each area while considering the security of goods and personnel. This study used a similar approach to estimate cost, time, and risk while expanding to accommodate a cross-border setting involving CAR and DRC.

Attributable to the expensive nature of air transport, although it is faster, Munyaka and Yadavalli (2021) used the evaluation of road conditions to improve its feasibility by prioritising delivery by road except in cases of poor or unsafe road conditions. This prioritisation was affected in their model by ensuring a certain proportion was met in the model constraints. They also made further assumptions of RI inventory donations being available at each of their DCs and personnel, trucks, helicopters, and cargo planes being ready for deployment whenever needed. This study applied similar assumptions to allow for the last-mile distribution of aid. For instance, instead of using air transport, military trucks were used where roads were inaccessible.

2.6 Concluding remarks

Inventory management and disaster planning have been explored extensively in developed countries and in countries where there is strong interest from developed countries; however, limited research has been conducted in the African context and, more so, not in an integrated manner. Various optimisation models were explored as a potential solution, and their respective performance measures were reviewed. Their solutions methodologies were also reviewed, culminating in a summarisation of the identified gaps. The CAR was identified as the ideal location for the study focus.

To improve on the identified gaps, applicable solutions were reviewed and summarised. Using deterministic and stochastic models were chosen as preferred options for prepositioning modelling. Because of competing objectives and uncertainty of data inputs, multi-objective programming and recourse stochastic models were discussed as potential solutions for the case study region. The study then employed recourse intervention owing to the nature of the affected people and the resultant uncertain demand. The subsequent chapter, therefore, discuses the full deterministic model formulation as a foundation for the stochastic model in Chapter 5.

Chapter 3

Model formulation and solution framework

This chapter describes the conflict background, model background, and other steps leading to the deterministic prepositioning model formulation as a solution to the selected focus gaps identified in the previous chapter.

3.1 Conflict background in the Democratic Republic of Congo (DRC) and Central African Republic (CAR)

Both DRC and CAR continue to experience artificial disasters as conflicts. Conflicts in the DRC have mostly affected the eastern part of the country, which comprises three provinces, North Kivu, South Kivu, and Ituri. According to the Counsel of African Affairs (CFR) (2021), these conflicts originated from the refugee crisis spillover caused by Rwanda's genocide in 1994. Rwanda's Hutus fled into Eastern DRC and reorganised into armed groups to combat the Tutsi, which led to opportunistic armed rebel groups. DRC's government engaged the rebels but could not defeat them, and the rebels eventually took control of this region. The population in the eastern region was left to combat the militias on their own, leading to a war. CFR (2021) and Akamo (2021) further remark that this war led to the proliferation of militia groups, which controlled local economies, some even taking control of various mines in Eastern DRC. Munyaka and Yadavalli (2021) emphasise ADF-NALU, APCLS, FDLR, FRPI, M23, Rai Mutomboki, Sheka, UPCP, and Mai Mai groups as the major rebel groups operating in Eastern DRC.

Like the DRC, CFR (2021) remarks that CAR has experienced decades of deadly conflicts since its independence in 1960. Major similarities exist between conflicts and instability insurgency encountering these two neighbouring countries, that of the government losing control to armed rebel groups. CAR's government efforts to regain control in the western and eastern regions have been futile. The government only has adequate control of the country's capital, Bangui. The western and eastern regions are under the control of Islamic groups, which identify mainly as a coalition of the Seleka alliance. The emergence of Seleka forces, mostly Islamic, helped to form Christian fighters that conducted reprisal attacks. This has exacerbated the instability, fuelling animosity as ethnic and religious violence. This has been followed by numerous counterattacks, which have plunged CAR into a humanitarian crisis. Thousands have been killed, and over 575,000 displaced, with the majority fleeing into neighbouring countries of DRC and Cameroon (CFR, 2021; IDMC, 2020).

According to a string of reports by the UN's Office for the Coordination of Humanitarian Affairs (OCHA) (2014) and various human rights groups, the violence by rebel groups in the DRC, anti-balaka, and ex-seleka groups in CAR amount to a crime against humanity. The UN 2014 established a peacekeeping force in the CAR to reduce the scale of the crisis. The forces were drawn from the French and African Union forces. The main mandate of these forces was to disarm the militant groups in the region while protecting civilians. Karlsrud (2015) and CFR (2021) report over 15000 peacekeeping forces in CAR's territory alone. Major challenges experienced by these forces in their mission of preventing sectarian violence include hesitation to use military force, lack of infrastructure, and attack on the peacekeepers.

The conflicts in the CAR emerged in the form of slow-onset disasters, but they have since escalated into a complex emergency. The consistent ambushes on innocent civilians have rendered the insurgencies sudden onset, with their uncertainty complicating the humanitarian response logistics CFR (2021). According to UNOCHA (2021), for HOs in this region to respond rapidly to the attacks efficiently and effectively, they must be proactive in their pre-disaster planning phase. This necessitates pre-establishing their relief inventory stocking point and the conflict area-distribution centre assignment. A prepositioning relief inventory model was formulated to achieve this.

3.2 Model background

The model sought to develop a solution by employing an integrated approach to manage RI in the pre-disaster and post-disaster phases effectively. The proposed model was generic in that it can be adopted for testing in other individual countries with a similar disaster setting. For this study, the model was tested in the conflict-plagued Central African Region (CAR) with a specific focus on DRC and CAR, emphasised in Figure 3.1. The study discusses the problem background regarding the relief inventory flow from humanitarian organisations (HOs) until it reaches the victims.

Figure 3.1: Countries considered in CAR

Based on the applicable studies summarised at the end of chapter two, the study models a typical standard relief aid flow involving a HO, central warehouse (CW), local distribution centres (LDCs) and the victims (affected area) as depicted in Figure 3.2. For instance, the risk was reduced based on the work by Mpita et al. (2016) while incorporating the budget limitation approach from Lee et al. (2014). The study derived applicable items, data sources, and implementation strategies from Van Wyk et al. (2011). Because the model aimed to approach response time and shortage reduction, it does not approach sourcing aspects in the RI flow. It assumes a setting where a HO has its RI inventory already stocked in a CW; however, prepositioning is considered to ensure short lead times when victims require aid in various regions. To accommodate for disruptions, the prepositioned LDCs are categorised into reliable and unreliable. Reliable LDCs are prone to a high risk of disruption or even damage, whereas reliable ones have a low risk of disruption. As echoed by Ransikarbum and Mason (2016), unreliable LDCs can either be damaged or inaccessible during a disaster (conflicts). It is expensive to establish reliable LDCs as they are not necessarily in ideal locations to reduce establishment costs. Ideal locations include areas with pre-existing infrastructure, but when such areas are not in ideal locations, the infrastructure must be established first.

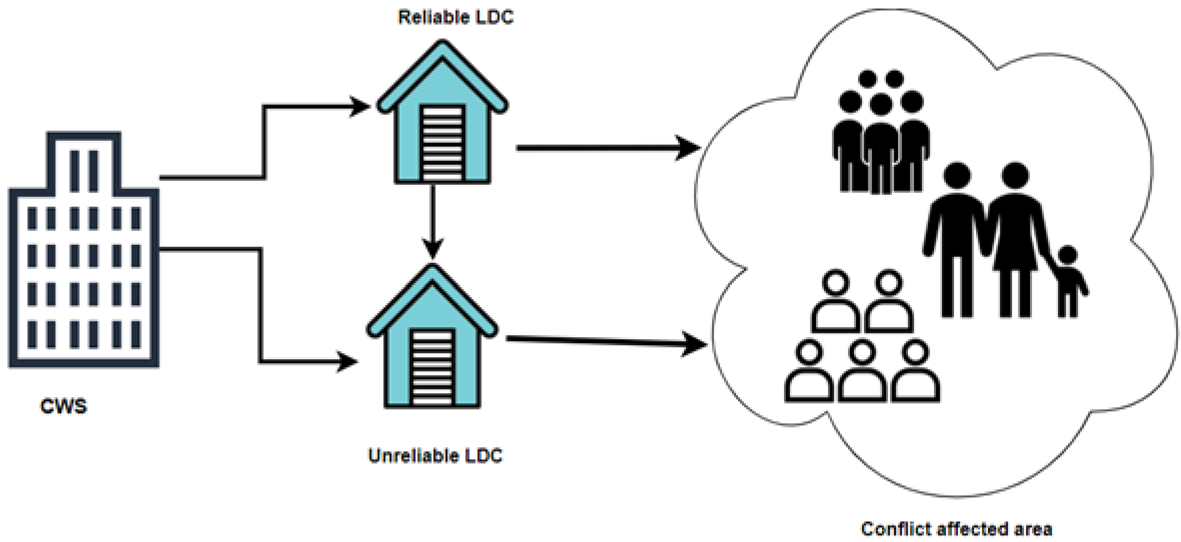


Figure 3.2: Relief flow from the central warehouse to victims

According to Noyan et al. (2016), CW is a strategic facility with a large enough capacity for storing the relief aid and is set up in a safe location. For a quick response, the model aimed to locate LDCs close to potential demand points to reduce the total response time. Using a CW with several LDCs is critical to reducing the response time, and presenting the geographical size of the focus area as being wide. Poor road networks and potential attacks or inaccessibility of distribution centres necessitate the stocking of relief inventory in various locations. By doing do, long-term inventory planning can be achieved as demonstrated by Noyan et al. (2016) and Das and Hanaoka (2014) in their modelling.

The study model is further motivated by the possibility of security availability to ensure the reliability of the CW that replenishes the distribution points according to the cited risk index. During modelling, an additional assumption was made that the CW stores the initial inventory before the conflict areas are captured, after which the LDCs are used in the post-disaster phase to distribute RI consistent with assumptions from Döyen et al. (2012). For modelling purposes in the prepositioning stage, the model is developed such that the preliminary inventory level for LDCs is determined to reduce the risk of scarcity which might cause unmet demand. The demand is estimated from the combined displaced population of the region under consideration up to 2018. This is achieved with the need assessment supplemental reports contained or referenced in the databases under review. Additional details on the demand estimation are in Chapter 4 under the data collected section, with the main sources being ACLED (2021), IDMC (2020) and LogisticsCluster (2021). The model also allows for transhipment among various LDCs to ensure that one LDC can serve more than one demand point. The unmet demand of victims from unreliable LDCs can be met using stock from reliable LDCs. Besides enhanced responsiveness, allowing lateral transhipment reduces the unmet demand proportion of relief aid remarkably, as revealed in models from Bozorgi-Amiri et al. (2013). Since the conflict areas in this study region are widely spread out, lateral distribution enhances some element of fairness during humanitarian relief response.

3.3 Mapping out conflict areas and prepositioning modelling

To accurately determine the locations of the LDCs, the potential and existing conflict areas in the CAR were represented with a special focus on DRC and CAF. These conflict areas are identified by extracting regions with recurring conflicts as captured in the ACLED (2021)and IDMC (2020) databases. The conflict areas into regions were then categorised while noting their total population and the likelihood of risk. The risk probability is estimated from the data obtained from the databases identified in Chapter 1. The applicable databases were World Food Programme (WFP), EM-DAT, ACLED (2021), Humdata, United nations affiliated databases and several emergency agencies for the two countries under consideration. The probability of risk in a conflict area is calculated as the number of conflict incidences in an area divided by the total of conflict occurrences in DRC and CAF. This information is presented in Table 3.1 to determine the position of the CW and various LDCs. The geographical depiction of the conflict areas and potential LDCs locations are revealed in Figure 4.1. In this transformation, any conflict area with a conflict probability of over 0.01 would be eliminated as a potential location for LDC because motivated by benchmark studies, such as Lee et al. (2014) and Mpita et al. (2016). The detailed data collection and corresponding analysis are discussed in section 3.6.

A single CW was considered; therefore, a combination of the stability index of the two countries and the probability of risk to determine the most suitable location for the CW were used. Cognisant of the two countries considered to be experiencing violence, and political instability, the stability used here is relative. Relative stability was, therefore, based on perception measures of the likelihood that the government and prevailing communities would be destabilised or disrupted by violent means owing to the violence between rebels and the government. The study further associated the more populous regions with better administrative facilities and infrastructure, such as security institutions; therefore, more reliable locations for LDCs are considered by Munyaka and Yadavalli (2021). The primary focus of the CW and LDC positioning is to ensure the location of these facilities in more reliable locations. The model also determines the prepositioned RI stock in the LDCs based on historical data collected. The cross-border regulations allow free movement of RI between DRC and CAF LogisticsCluster (2021). The summary indicates the subsequent data as input to the first stage of the model.

Table 3.1: Conflict probability based on extracted data

Province/Country	Conflict area	Instances	Conflict probability	Population
CAF				
Bangui	Bangui	169	0,086	889000
Basse-Kotto	Alindao	39	0,020	14000
	Kembe	7	0,004	12000
	Mobaye	10	0,005	10000
	Zangba	7	0,004	9000
Haute-Kotto	Bria	80	0,041	30000
	Ouadda	12	0,006	6000
	Yalinga	12	0,006	2700
Haut-Mbomou	Obo	20	0,010	13000
	Zemio	30	0,015	14500
Mbomou	Bakouma	19	0,010	20000
	Bangassou	22	0,011	37000
	Gambo	5	0,003	3000
	Ouango	2	0,001	5000
	Rafai	22	0,011	14500
Nana-Grebizi	Kaga-Bandoro	52	0,026	30500
	Mbrès	19	0,010	7500
Ouaka	Bakala	15	0,008	2700
	Bambari	110	0,056	52000
	Grimari	5	0,003	20500
	Ippy	22	0,011	22000
	Kouango	50	0,025	10500
Ouham	Batangafo	51	0,026	16000
	Bouca	19	0,010	14000
	Markounda	15	0,008	1500
Ouhum-Pende	Bocaranga	21	0,011	65200
	Koui	8	0,004	14200
	Ngaoundaye	16	0,008	109000
	Paoua	29	0,015	21500
DRC				
Ituri	Djugu	115	0,058	28100
	Irumu	14	0,007	366200
	Mambasa	3	0,002	249100
North Kivu	Beni	306	0,155	232000
	Lubero	59	0,030	57400
	Masisi	85	0,043	6600
	Rutshuru	227	0,115	250000
	Walikale	61	0,031	201000
South Kivu	Fizi	75	0,038	1000000
	Kabare	11	0,006	780100
	Kalehe	38	0,019	500000
	Mwenga	9	0,005	800000
	Shabunda	18	0,009	926000
	Uvira	16	0,008	1200000
	Walungu	7	0,004	721000

- Mapped location of conflict areas in various countries and their stability index. The stability index is the measure of the perceptions of the likelihood that the government and prevailing communities would be destabilised or disrupted by violent means owing to the violence between rebels and the government in DRC and CAR.

- Population of affected and potential regions and historical conflicts leading to the eventual calculation of the probability of risk

- The existing support systems (such as security and administrative facilities) and condition of existing infrastructure.

Minimising risk in an armed conflict response situation is crucial as it is more desirable to have LDCs in safer areas than closer to the affected areas. To minimise risk, from Table 3.1, any conflict area was further eliminated with a predetermined conflict probability as discussed in section 4.1, and then the final candidate LDC location areas were selected to be used in the model. This part of the model involved solving a mixed-integer linear programme (MILP) where an LDC is in a certain region. Using MILP in this study is easily discernible because some relief items in the model had to be distributed as a whole. For instance, a tent, as a relief item providing shelter, cannot be distributed as a fragment, alike a toilet. Likewise, when establishing a distribution centre, it must be recognised fully and cannot be partial. The place holder for the decision value for the LDCs can only be zero or one-binary integers. This results where some variables in the model are integers whereas others are not- then rendering the problem to be a MILP challenge. A second objective function was introduced to minimise the total travel time between the LDC and the conflict area to ensure that the travel time between the LDC location and the potential conflict area is not undesirably high. It was ensured that stock in established LDCs can serve a certain proportion of the total demand, especially for the priority items. This had to specify the desired parameter for distribution—without which, for instance, aspects, such as weight, would influence which items are distributed from the LDCs to various conflict areas. This would be the case where the objective is to reduce cost provided that the heavier the item, the higher the cost of its transportation because the total cost is a factor of tonnages; therefore, the shortages would increase from the lightest to the heaviest item. Ultimately, the model focused on minimising the risk, maximising demand satisfaction (by minimising shortages) and minimising the total response times within a budget. The summary flow diagram of the solution development is disclosed in Figure 3.3.

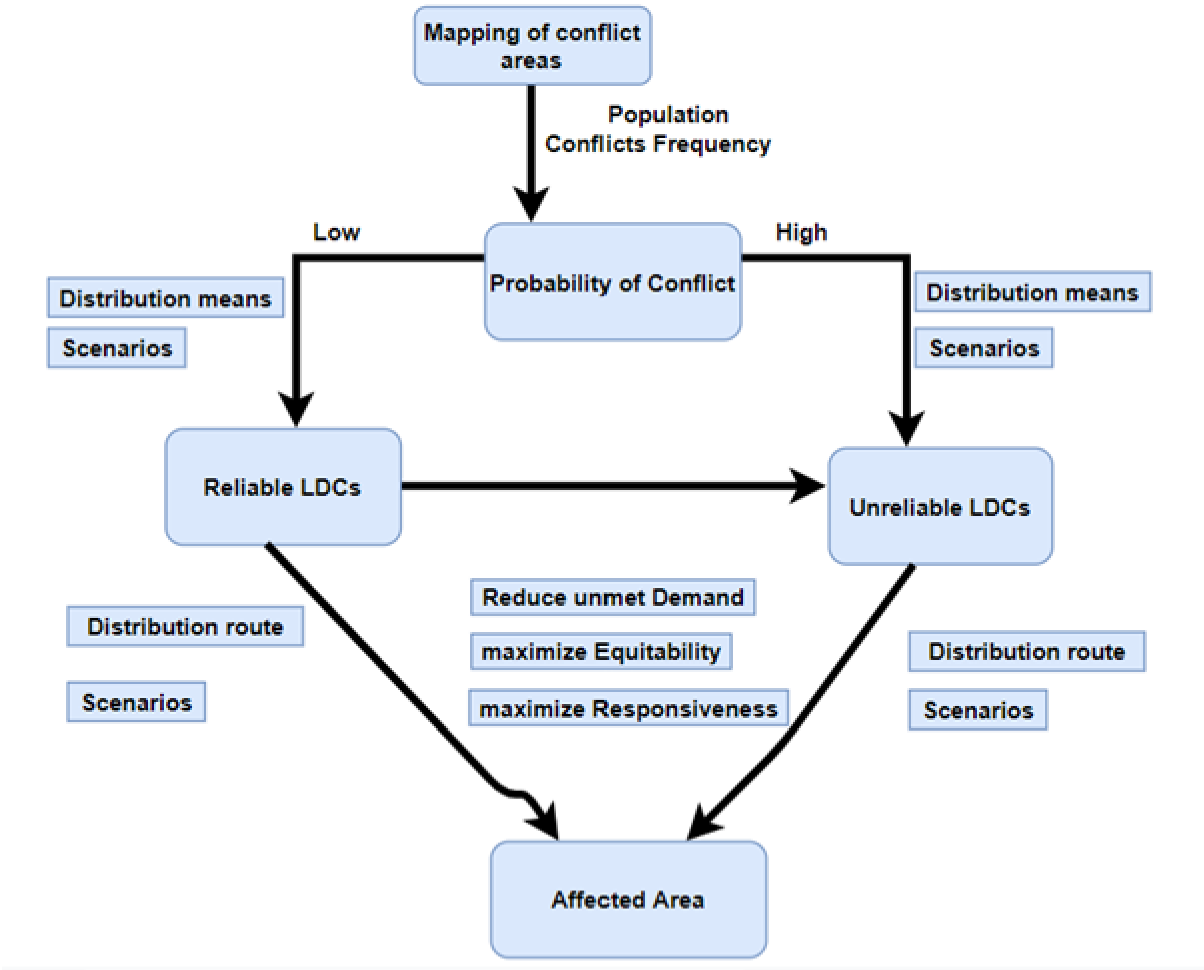


Figure 3.3: Preposition and post-disaster distribution model flow

The flow in Figure 3.3 ends with distribution options and competing objectives to be minimised or maximised, such as demand, equitability and responsiveness. These objectives are competing for two main reasons. First, if they do not responding on time, victims would suffer more. There is a deprivation cost associated with the suffering of victims, as discussed by Loree and Aros-Vera (2018). Second, and in this study, there was poor and limited infrastructure and a limited budget- which affected the distribution of aid to meet victims' demands. Competition here becomes apparent because the model can not necessarily deploy all the resources to minimise the response time without compromising parameters, such as equitability. If the model distributes aid to the nearest victims to minimise the response time, the furthest victims remain subserviced, causing inequitably. Minimising shortages and total travel times are the only explicit objective functions. This study used proportions of demand satisfied and response time as indicators of equity. In the humanitarian context, competing objectives can be supported through a trade-off analysis as discussed by Serrato-Garcia et al. (2016) and incorporated based on priorities as discussed by Günay et al. (2019). The model formulation and considerations leading to a balanced solution are discussed based on these competing objectives in the subsequent sections. As identified in the literature review, various performance measures can be optimised in humanitarian response; however, the performance measures cannot be optimised in a single model owing to complexity. The model, therefore, aimed to combine demand satisfaction, response time, and equitability to reduce the suffering of victims. Response time is important as the main motivation for prepositioning modelling is to ensure expeditious aid delivery after a disaster. Response time in this study is the time taken by prepositioned aid to reach beneficiaries in the conflict zones. This was affected by minimising the total travel response time.

This study derives the need to combine the three performance measures from studies, such as Hong et al. (2015), Mohammadi et al. (2016) and Noyan et al. (2016) where proportions of demand satisfaction are used as indicators of equitable service; however, including equitable service in this study is achieved implicitly through minimum priority items constraint. Minimising shortages and total travel times are the only explicit objective functions. This study employed the proportion of demand satisfied and response time as equity indicators.

3.4 Distribution in pre-disaster and post-disaster

After mapping and locating CW and LDCs from section 3.2, we model the distribution of prepositioned stock to these facilities by assessing existing policies regarding cross-border humanitarian operations in the CAR region as discussed by LogisticsCluster (2021) and infrastructure and road network for various modes of transports as reviewed by Munyaka and Yadavalli (2021). The study further reviewed the cooperation between the government and HOs in these two countries regarding distribution centres' location and support for various modes of transporting relief aid from LogisticsCluster (2021). According to WFP(2021), these collaborations help attenuate challenges associated with poor infrastructure, long distances, insecurity and the absence of commercial airlines. For instance, communication, logistics, and humanitarian access are improved by WFP in the region through Logistics Cluster, ETC (Emergency Telecommunications Cluster) and UNHAS(UN Humanitarian Air Service). For instance, if there is a collaboration between the HO, instead of establishing a new LDC, existing government infrastructure can be an LDC, therefore, reallocating the funds for distribution. Similarly, collaboration has the potential to improve the security of established LDCs, which could turn, improve the reliability of those LDCs. The key driver of running these utilities, according to WFP(2021), is to achieve efficient, reliable, and safe access to aid victims.

Various Memorandums of Understanding (MOUs)exist between DRC, CAF and the HOs regarding transit, distribution, and customs clearance of relief goods. These MOUs enable UN agencies and other HOs to obtain tax exemptions, expedited customs clearance, and transit permits. The Ministry of Foreign Affairs validates other expeditions upon submitting the documentation known as "Note Verbale" (LogisticsCluster, 2021). Existing collaborations can be leveraged to allow the HOs to use various government and regional government facilities as LDCs and other administrative purposes as expressed in LogisticsCluster (2021). This consideration is important for prepositioning in section 3.2 as it would greatly reduce the establishment cost of the required LDCs. This collaboration allows the establishment of more reliable LDCs owing to safety provisions during storage and aid delivery to affected victims.

Preliminary data from ACLED (2021) and LogisticsCluster (2021) review indicates UN missions in these countries through the branch of the World Food Programme (WFP). The presence of WFP and its utilities, such as ETC, Logistics Cluster, and ETC, expands the modes of transport that can be considered for optimal distribution to enhance responsiveness and equitability. For instance, owing to WFP presence, there is a possibility of using military trucks or air transport to distribute aid to interior areas characterised by impassable road networks. The model makes these assumptions for distribution:

1. The CW in a particular country, as determined from Section 3.2, has enough RI to service the LDCs in various countries requiring replenishment. Also, it was assumed that an LDC in one country could serve an affected area in various countries depending on its location (based on existing collaboration agreements discussed under the cross-border aid distribution section). A limitation to this assumption would be the influence of regulations changing and affecting distribution in the two countries.

2. The availability of trucks, labour, and operation stock, such as fuel for the various modes of transport, is unlimited. According to LogisticsCluster (2021), trucks and labour are available owing to regional humanitarian missions. Fuel is also available in the stocking reserves unless there are external factors affecting the replenishment of stock.

3. For regions where the roads are nearly inexistent, it was assumed that military trucks could be used for last-mile aid delivery and considered for the specific area. Munyaka and Yadavalli (2021) modelled similarly, but also included air transport as an alternative to impassable routes. A variation to their implementation in this model would have been incorporating other modes of transport, such as motorbikes and animals; however, provided that the number of victims involved is high and the availability of the suggested means is unknown, using military trucks was the better option.

3.5 Prepositioning Mathematical model

Guided by the literature review findings about the diverse needs and competing objectives for disasters, a multi-objective model was developed for this study. Pre-emptive intervention techniques for MOO were then applied. The model was solved using the pre-emptive technique, and then compared the results by reversing the order of the priorities as a way of counteracting the disadvantages associated with some of these interventions. This technique is important as it helps set priorities and goals(e.g. within budget) during a real disaster response operation. Goals and priorities are intertwined in disaster prepositioning modelling because goals are targets to be achieved, whereas priority determines the order of execution. Examples of goals include limiting the total cost to a specific value, limiting shortages or demand satisfaction to a certain proportion, achieving the desired response time and achieving a specific number of distribution centres.

From the tabulated data, the model indicates the main objectives resulting in two objective functions. These objective functions ensure that shortages and response times are minimised. The option of incorporating an additional objective function aimed at minimising the cost; however, guided by the understanding that most HOs operate on a limited budget, the study modelled the cost aspect as a constraint. Limited budget is predominantly apparent when responding to disasters where HOs fail to raise adequate needs to meet the needs of victims, as illustrated in Figure 3.4. Despite the funding coverage increasing over the years, there is a huge deficit to meet the required coverage.

HRP	People in need	People targeted	Requirements (US$)	Funding coverage
2022	3.1 M	2.0 M	461.3 M	
2021	2.8 M	1.8 M	444.8 M	82%
2020	2.6 M	1.6 M	387.8 M	68%
2019	2.9 M	1.7 M	430.7 M	70%
2018	2.9 M	1.9 M	515.6 M	54%
2017	2.2 M	1.6 M	497.3 M	46%
2016	2.4 M	1.9 M	531.5 M	38%

Table: Global Humanitarian Overview 2022 • Source: Financial Tracking Service

Figure 3.4: Humanitarian resources requirement in CAR and corresponding coverage(Financial Tracking Service,2022)

Other constraints of the objective functions include LDCs capacity limitation and various goals that each objective function must meet. All these constraints are executed based on Figures calculated from the collected data before running the model. For instance, delivery time for each mode of transport to a certain conflict area is calculated using the distance from the servicing LDC and the chosen mode of transport. This is conducted consistent with literature from Holguín-Veras et al. (2013) and Loree and Aros-Vera (2018) where a need exists to reduce cost while increasing the survival chances of victims by reducing the deprivation time. The cost parameter includes operational costs, such as the cost of transporting aid in dollars per tonne per kilometre. Cognisant of the prohibitive cost attributed to other modes of transport, distribution, as determined from data analysis, is associated with road transport. These data sets and variables are defined and used in the model. The study denotes:

$\mathbf{I} = \{1, 2, 3...44\}$ the set of armed conflict locations i

$\mathbf{J} = \{1, 2, 3...24\}$ the set of potential locations for LDCs j

$\mathbf{K} = \{1, 2, 3...6\}$ the set of victim's needs k

The parameters for the model are then defined as follows:

$s_i \triangleq$ the expected number of affected persons in in conflict area $i \epsilon \mathbf{I}$

$l_k \triangleq$ the expected requirement of item $k \epsilon \mathbf{K}$ per affected person

$D_{ik} \triangleq$ the expected demand in unit item $k \in \mathbf{K}$ in conflict area $i \in \mathbf{I}$

$T_{ij} \triangleq$ the estimated travel time in hours from LDC $j \in \mathbf{J}$ to conflict area $i \in \mathbf{I}$

$R_{ij} \triangleq$ the estimated distance in kilometres from LDC $j \in \mathbf{J}$ to conflict area $i \in \mathbf{I}$

$C_{ij} \triangleq$ the cost in \$ per tonne-kilometre to transport items from LDC $j \in \mathbf{J}$ to conflict area $i \in \mathbf{I}$

$C^v \triangleq$ the fixed cost of establishing an LDC in \$ per m^3

$V_j \triangleq$ the capacity of LDC $j \in \mathbf{J}$ in m^3

$U_k \triangleq$ volume of one unit of item $k \in \mathbf{K}$ in m^3

$W_k \triangleq$ Weight of one unit of item $k \in \mathbf{K}$ in tonnes

$x_k \triangleq$ the the specified percentage of item $k \in \mathbf{K}$ that can be supplied for priority items

Last, the binary and decision variables for the model are defined as follows:

$$Y_{ij} \triangleq \begin{cases} 1 & \text{if LDC } j \in \mathbf{J} \text{ is used to service conflict area } i \in \mathbf{I} \\ 0 & \text{otherwise} \end{cases}$$

$Q_{ijk} \triangleq$ number of unit items $k \in \mathbf{K}$ sent from LDC $j \in \mathbf{J}$ to conflict area $i \in \mathbf{I}$

$O_{ik} \triangleq$ shortage amount of item $k \in \mathbf{K}$ in conflict area $i \in \mathbf{I}$

$$Z_j \triangleq \begin{cases} 1 & \text{if LDC } j \in \mathbf{J} \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

The objective functions of the model to minimise shortages and total response time are included in constraints 3.1 and 3.2, respectively.

$$minimise\ z = \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{J}} O_{ik} \tag{3.1}$$

$$minimise\ z = \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{J}} Y_{ij} T_{ij} \tag{3.2}$$

Subject to these conditions:

$$O_{ik} \geq 0 \text{ and } \quad \text{integer,,} \quad \forall \ i \epsilon I, \ k \epsilon K \tag{3.3}$$

$$\sum_{j \in \mathbf{J}} Z_j (C^v * V_j) + \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{J}} (\sum_{k \in \mathbf{K}} W_k Q_{ijk} * C_{ij} R_{ij}) <= B \quad for\ \forall \ i \epsilon I, \ j \epsilon J, \ k \epsilon K \tag{3.4}$$

$$Q_{ijk} \geq 0 \text{ and } \quad \text{integer,} \quad \forall \ i \epsilon I, \ j \epsilon J \ k \epsilon K \tag{3.5}$$

$$D_{ik} = l_k s_i, \quad \forall \ i \epsilon I \ k \epsilon K \tag{3.6}$$

$$O_{ik} = D_{ik} - \sum_{j\epsilon \mathbf{J}} Q_{ijk}, \quad \forall \; i\epsilon I \; k\epsilon K \tag{3.7}$$

$$\sum_{k\epsilon \mathbf{K}} \sum_{i\epsilon \mathbf{I}} U_k Q_{ijk} \leq V_j Z_j, \quad \forall \; j\epsilon J, \tag{3.8}$$

$$\sum_{k\epsilon \mathbf{K}} Q_{ijk} \leq MY_{ij}, \; \forall \; i\epsilon I, \; j\epsilon J, \tag{3.9}$$

$$\sum_{i\epsilon \mathbf{I}} Y_{ij} \leq MZ_j, \quad \forall \quad j\epsilon J, \tag{3.10}$$

$$Y_{ij} \; \epsilon \; (0,1), \qquad \forall \; i\epsilon I, \; j\epsilon J, \tag{3.11}$$

$$Z_j \; \epsilon \; (0,1), \qquad \forall \; j\epsilon J, \tag{3.12}$$

$$\sum_{j\epsilon \mathbf{J}} Q_{ijk} \geq xD_{ik}, \quad \forall \; i\epsilon I, \; K\{1..4\} \tag{3.13}$$

From the stipulated constraints, constrain (3.3) enforces the non-negativity and integer requirement for item shortages in the conflict areas. Constraint (3.4) ensures that the model operates within the allowed budget for the fixed costs and the distribution costs. Constraint (3.5) enforces the non-negativity and integer requirement for the items supplied. The calculation of shortages for items required in the conflict areas is achieved through constraint (3.7). Constraint (3.8) ensures that the total volume of items stored in a distribution centre does not exceed the capacity of that distribution centre. Constraints (3.9) and (3.10) are fixed charge constraints ensuring the linking of variables. (3.9) ensures that aid supplied to a conflict area only exists when designated LDC services that conflict area while (3.10) ensures that the two binary variables are linked. Last, constraints (3.11) and (3.12) guarantee the binary requirement for the servicing of an area by an LDC and the establishment of a distribution centre, respectively.

3.6 Data collection, clean-up and Processing

This study relied on open-access humanitarian databases, online reports and other publications by HOs operating in the CAR. This section outlines the procedure followed to gather, clean-up, and process the data required for modelling. The three main databases where data were collected are ACLED(Armed Conflict Location and Event Data), HDX (Humanitarian Data Exchange) and

EM-DAT (Emergency Events data). All these databases are inter-referenced or cross-referenced from the same sources, such as UNOCHA and ReliefWeb, and were reviewed as of 2021. Data examinations determined that ACLED contains reliable armed conflict data from 1989 to 2018 concerning completeness. Data for 2019 and 2020 exist, but since some data have not been updated, it was up to 2018.

ACLED and HDX contain almost the same data sets, with HDX allowing access to data from 1989 to 2018, whereas ACLED allows free access for the past three years up to the most recent update (ACLED, 2021; HDX, 2021). The two databases were considered complementary. The two databases also contain similar predefined data extraction procedures followed. The procedure discussed is for ACLED's database, also in their step-by-step guide available on their data portal. A user account was created on the data portal using an institutional email approach to access the data. The database system then sent an access key to the registered email approach. This access key was used to access and navigate the data portal where conflict data for the regions under consideration was reviewed. Upon navigating to the data portal, data were downloaded by using a data filtering process. This process involved navigating to the CAR region and then selecting the country and regions of interest. The database also allows an Application Programming Interface (API) to extract data through query filters; however, the API procedure was not used because it was much easier to select the column types and download the data in CSV file format.

After downloading the data in CSV format, the downloaded files were pre-processed in R. Pre-processing included removal and filtering of irrelevant inputs for the rows and columns in the files and then saving the pre-processed file in excel format. Removed entries were optional for the study and included refugee data, cumulative numbers of returnees, and geographical coordinates. Entries to be removed were identified using column names and entry codes in the metadata instructions. Saving the data in excel and CSV formats were preferred because the Lingo solver would import and export data into the same files during the model solution process. The key column types from the HDX and ACLED data files downloaded were the number of displaced people column, year of occurrence, the corresponding province, and the specific town/village where attacks occurred. Most column entry headings were named using some coded format; for instance, "adm-1" and "adm-2" corresponded to province and region, respectively. These entries were essential in determining the number of people per region and their corresponding distributions. Interpreting codes used in the data entry are in the code guides for the respective databases. The subsequent section discusses the sensitivity analysis in the context of the prepositioning model, discussing the data collection process.

3.7 Analysis of models sensitivity distribution network

The last part of the solution evaluates the changes in the model solution by varying parameters in the model. The subsequent scenarios are evaluated:

- The influence of altering the budget on shortages and location-allocation. This is because, as discussed, often, most of the HOs operate under a limited budget. The optimal location of LDCs would greatly improve their performance.

- The influence of altering the capacity of LDCs on shortages and location-allocation. The capacity of a distribution centre is one of the most aspects as it dictates the ability to store the relief inventory. Varying the capacity based on demand becomes a crucial aspect of determining the ideal capacities of LDCs based on location.

- The influence of varying the specified proportion of priority items requirement. Different items have various priorities, which influence which item gets distributed first. When HO desires to reduce bias, controlling the proportion of items to be distributed by providing a p-value becomes necessary.

3.8 Model validation and verification

Validation and verification stage form the last stage of conceptual model development and aim to ensure that the model is sufficiently accurate. For the prepositioning model, this was achieved by intermixing three main tasks, such as debugging, verification, and validation. These tasks are complex and iterative, used in the subsequent definitions as denoted by Carson (2002). *Debugging* is a process that uses various techniques to identify a bug and its causes and then fix them. *Verification* refers to the techniques and processes of ensuring that the model is correct and is congruent with the set assumptions and predetermined specifications. In this process, the modeller runs and applies the conceptual model for the intended purposes while identifying and fixing modelling flaws (Sargent, 2013). Furthermore,Sargent (2013) remarks that *Validation* concerns the techniques and processes taken by the modeller, clients or decision-maker to guarantee that the model depicts the real situation within the desired accuracy level. The model development process was revisited while illustrating the link between the validation and verification processes with the model development process to validate and verify the model. This can be observed in two main ways—complex and simple, with figure 3.5 indicating the simplified paradigm by Sargent (2013).

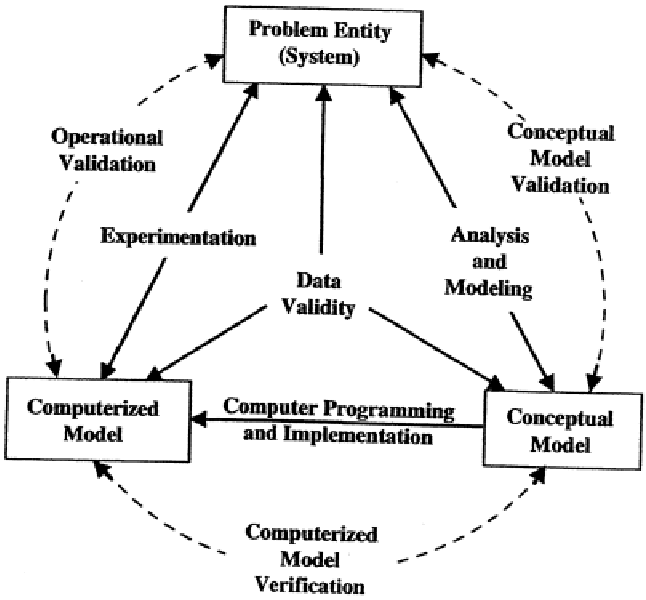


Figure 3.5: Simplified model development process(Sargent,2013)

Noting that *Problem entity* and *conceptual models* have been covered in section 3.2 and 3.5 respectively, the validation, and verification efforts focused on the linking processes between the *conceptual model* and *computerised model*. *Computerised model verification* was conducted to ensure that the Lingo code representation of the mathematical model was correct. In contrast, *operational validation* was conducted to ensure that the outputs from the execution of the Lingo code behaved satisfactorily and yielded within-range accuracy in application. As illustrated by Lindo (2022) documentation, Lingo has inbuilt functionalities known as "generate model" and "debug" that allow basic debugging and verification of the computerised model. The "debug" function was used to review the coded version of the model line by line until all the syntax errors were eliminated. Afterwards, the computerised model was generated and compared to the expanded manual form of the conceptual model to validate the accuracy. Logical errors are some key errors eliminated by the computerised model validation process. Carson (2002) defines *logical errors* as modelling errors in execution or specification in solver or simulation languages. These errors depend on the language and syntax of the solver software and can easily be resolved through debugging.

The last validation involving the two-way linkage between *computerised model* and *problem entity* followed a systematic procedure derived from a recommendation of validation and verification techniques by Carson (2002) and Sargent (2013). First, using sample data, experimentation through test runs was conducted while exporting the outputs to an excel spreadsheet. These outputs were compared manually with the live file results output from the solver software (lingo). Model variables (mainly the binary and the Q_{ijk} variable) were used to validate the outputs. For instance, by using the Y_{ij} binary variable, it was easy to determine if an LDC was established and if so, items are expected to have been shipped from that specific LDC and captured in the corresponding index in the Q_{ijk} variable. Extreme and rare cases were also used to evaluate the model's behaviour in these cases (for example, having zero budget; therefore, the model would be expected to disprove any LDC). During these validations, considerable runs were made while noting any modelling errors indications from internal system conditions.

Many runs using extensive input parameter settings are necessary before commencing the formal experimentation captured in paradigm 3.5. These runs are helpful because they assist in trend analysis or observation that indicates whether the outputs follow the expected direction (increase or decrease) after varying some input parameters. For instance, by specifying the minimum supply *p value* for priority items to be 0.5, it is expected that all supplies to be above this limit and increase or decrease with the variation in the *p value*. This was coupled with model iterations while comparing the coded model and output data. To enhance accuracy and reliability in the system's behaviour, several sets and experimental conditions were used. Last, to validate the results of the model in the case study area, a simulation using the assumed uniform distributions was conducted in Chapter 5. Uniform distribution is among the most suitable distribution for conflicts as motivated by Beamon and Kotleba (2006c) and Beamon and Kotleba (2006a) because of the unpredictability of conflict occurrences and the resulting number of victims. This was achieved by simulating 100 instances while noting the success and failures based on the shortages obtained from the model solution as discussed in section 5.4.

3.9 Conclusion on the model framework and implementation

This chapter provides a preliminary solution formulation for the model implementation in the subsequent chapters. The model and conflict environment are discussed and motivated, then mapping out the conflict areas. The measures of performance and drivers of LDCs reliability by using probabilities of risk were discussed. Shortages, total time travelled, and equitability was selected as the performance metrics for the model. The mathematical model, data processing, and the verification and validation criteria of the model were also stipulated. This was aimed at answering the main research question,*what is the strategic way to manage RI inventory when more than one country needs aid in the CAR?* To answer this, the following approach was required.

1. The strategic location of various LDCs and relief items. This was achieved by executing the equations for both stages of the model, followed by data input.

2. Tabulate the data in the two countries to input into the model to determine strategic locations by solving the model in Lingo.

3. Based on the collected data and determined LDCs locations, perform a sensitivity analysis based on scenarios identified in section 3.7. The influence of these variations on the parameters is then interpreted.

4. Improve the deterministic model to incorporate the uncertainty in conflict data

5. Fit distributions from the collected data and simulate the conflict occurrences to generate realisations for the stochastic model followed by a reliability test to determine the performance of the two models.

Although the model formulation in this chapter is from a deterministic perspective, it sets the foundation for implementing the stochastic version in Chapter 5. Including the stochastic model improves the model's practicality by acknowledging that the number of affected people in conflict situations is usually uncertain.

Chapter 4

Prepositioning model application and implementation

This chapter presents applying the model formulated in Chapter 3 and evaluates the key strategic objectives of the research. The demand, among other parameters, is estimated and used to determine the locations of LDCs by running the model in the CAR region.

4.1 Data gathered

As described in Chapter 3, the various data were collected from the identified databases and studies under review. The conflict areas identified in Table 3.1 are transformed into potential facility locations and summarised in Table 4.1. The geographical depiction of the conflict areas and potential LDCs locations is displayed in Figure 4.1. In this transformation, any conflict area with a conflict probability of over 0.01 was eliminated as a potential location for LDC because motivated by benchmark studies, such as Lee et al. (2014) and Mpita et al. (2016). The studies suggest that risk higher than 0.01 is considered high, therefore, reducing the reliability of the distribution centres. This is a lower risk than the studies, such as Mpita et al. (2016) who used a probability of 0.02 for elimination. The uncertainty and frequency informed this decision of armed conflict in the study region; however, an exception was made for conflict regions with a population of over 500,000 people, provided the probability of conflict was less than 0.09. This is because the absence of LDCs in such populous regions would defeat the purpose of the model, that of providing aid to several victims while minimising the total time travelled. For example, the high population in Bangui and the high conflict probability were remarked, but security agencies in the capital guided the study. An exception was made, while not eliminating it based on its high conflict probability. This exemption was also applied to North Kivu to ensure a regional facility location. The difference in this exemption is that North Kivu has various sub-regions as opposed to Bangui, where Lubero was selected as it had the lowest probability of conflict.

The selected potential LDCs locations were tabulated against the conflict regions, and the corresponding distances were determined. Google maps achieved this by allowing the evaluation of road conditions and more accurate estimation of the actual distances. Missing attributes of geographical coordinates captured in the databases under review eliminated the possibility of using other techniques for distance estimation. Distances between potential LDCs location and the conflict zones are summarised in Tables 6.1 and 6.2 in the appendices section of this study. Similarly, the corresponding travel times based on the road conditions are captured because they are crucial in determining response times based on speed. These travel times are presented in Tables 6.3 and 6.4 attached in the appendix section.

Table 4.1: Candidate LDCs Locations

Country	**Regions**	**Index**	**Potential LDC Location**
CAF	Bangui	1	Bangui
	Basse-Kotto	2	Kembe
		3	Mobaye
		4	Zangba
	Haute-Kotto	5	Ouadda
		6	Yalinga
	Mbomou	7	Bakouma
		8	Gambo
		9	Ouango
	Nana-Grebizi	10	Mbrès
	Ouaka	11	Bakala
		12	Grimari
	Ouham	13	Bouca
		14	Markounda
	Ouhum-Pende	15	Koui
		16	Ngaoundaye
DRC	Ituri	17	Irumu
		18	Mambasa
	North Kivu	19	Lubero
	South Kivu	20	Kabare
		21	Mwenga
		22	Shabunda
		23	Uvira
		24	Walungu

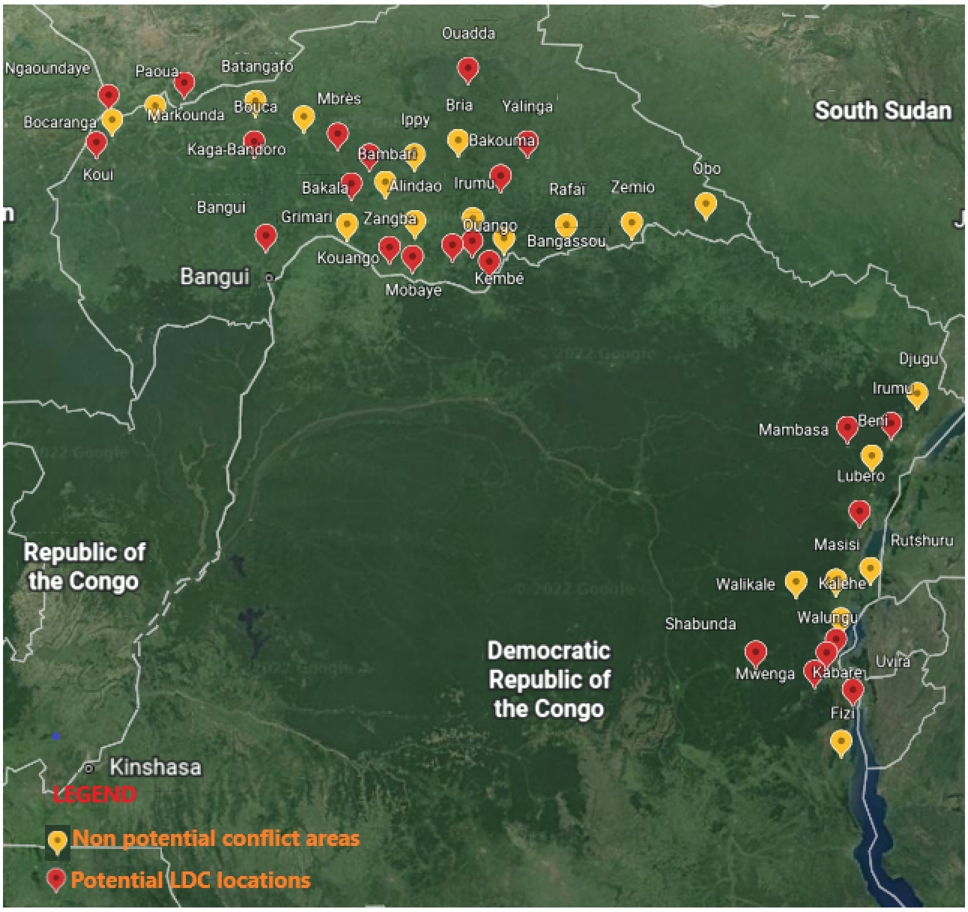


Figure 4.1: Geographical illustration potential LDCs locations and conflict areas

4.1.1 Supply and demand of items by victims

The supply requirements for armed-conflict victims were estimated from the displaced information data obtained from ACLED (2021), HDX (2021) and IDMC (2020) databases for the period under review. In this study, the victim's needs (demands) were determined based on the number of affected people per conflict instance. This was achieved by multiplying the number of affected people with the need factor, and the results are in Table 4.3. These needs in Table 4.3 were classified into six main categories, such as displaced people shelter, food, water, general relief, sanitation, and non-food relief because they are the essential relief items (UNHCR, 2021). These needs were then converted into supply items requirements and then used to determine the LDCs where they should be prepositioned in. In this conversion, UNOCHA relief reports and previous studies were used to determine standard relief items and packaging. For instance, water-packs of 50 litres per victim, one tent for ten people, and a blanket per victim (UNHCR, 2021).

Table 4.2: Volumes of various relief supply items

Item category	Displaced(Tent)	Foodpack	Water	Sanitation pack	Non-Food	General relief
Volume (m^3)	0,2	0,056	0,052	3,132	0,009	0,01209
Weight (tonnes)	0,062	0,06	0,05	0.07	0,01	0,05
Need factor (units)	0,1	1	1	0.05	1	0,1

For modelling, the volume and weight of each supply item were also estimated from previous studies and adopted for the six categories of items under consideration in this model. The volume, weight and need factor of the supply items based on category is captured in table 4.2. The displaced shelter need was provided for by the supply of tents, food packages (Instant food and a 50kg bag of rice), and a water package of 50 litres. The sanitation pack contained a portable toilet, while the non-food relief included blankets and clothes. Last, the general relief pack included items, such as lamps and a general medication box.

4.2 Model Results and Discussion

The model was solved using LINGO 19.0 solver software installed in an 8GB RAM and Intel Core i7 1.50 GHz SSD personal laptop. The computation time varied during the various test run scenarios, but it was under five hours in the first step of the pre-emptive programming run. The model's initial budget was set to $20,200,000 to evaluate the scenarios. This minimum budget is significant in many ways during humanitarian operations because it represents the minimum amount at which the model can supply 50% of the demand items. HOs work with a limited budget and thus the minimum budget helps to evaluate and compare diverse options to achieve their main goals in CAR. As such, if a HO wants to establish more LDCs and supply more items, the budget would have to be set higher than the determined benchmark. These goals may include working with a limited budget, several LDCs, a certain level of acceptance of risk, desired response time, desired level of satisfaction for certain items and minimisation of shortages in general. This was the minimum budget at which the model would yield a feasible solution without compromising the critical requirements. Adjustments were made to the budget by incrementing the initial budget with 10%, 20%, 30%, 40%, 50%,60% and 70%

Table 4.3: Supply requirements for various regions

Province	**Conflict-Area**	**Tents**	**Food packs**	**Water pack**	**Sanitasion pack**	**Non-Food relief**	**General relief**
CAF/Bangui	Bangui	7540	75400	75400	3770	75400	7540
Basse-Kotto	Alindao	676	6757	6757	338	6757	676
	Kembe	528	5277	5277	264	5277	528
	Mobaye	490	4900	4900	245	4900	490
	Zangba	325	3250	3250	163	3250	325
Haute-Kotto	Bria	3300	33000	33000	1650	33000	3300
	Ouadda	724	7239	7239	362	7239	724
	Yalinga	227	2269	2269	114	2269	227
Haut-Mbomou	Obo	1314	13132	13132	657	13132	1314
	Zemio	892	8918	8918	446	8918	892
Mbomou	Bakouma	994	9933	9933	497	9933	994
	Bangassou	2502	25017	25017	1251	25017	2502
	Gambo	796	7958	7958	398	7958	796
	Ouango	1690	16898	16898	845	16898	1690
	Rafai	710	7095	7095	355	7095	710
Nana-Grebizi	Kaga-Bandoro	2528	25274	25274	1264	25274	2528
	Mbrès	543	5426	5426	272	5426	543
Ouaka	Bakala	185	1847	1847	93	1847	185
	Bambari	2480	24800	24800	1240	24800	2480
	Grimari	792	7915	7915	396	7915	792
	Ippy	897	8970	8970	449	8970	897
	Kouango	1531	15303	15303	766	15303	1531
Ouham	Batangafo	1792	17917	17917	896	17917	1792
	Bouca	1586	15856	15856	793	15856	1586
	Markounda	500	5000	5000	250	5000	500
Ouhum-Pende	Bocaranga	1077	10767	10767	539	10767	1077
	Koui	362	3617	3617	181	3617	362
	Ngaoundaye	1800	18000	18000	900	18000	1800
	Paoua	1992	19916	19916	996	19916	1992
DRC/Ituri	Djugu	34239	342385	342385	17120	342385	34239
	Irumu	5020	50200	50200	2510	50200	5020
	Mambasa	519	5188	5188	260	5188	519
North Kivu	Beni	5104	51040	51040	2552	51040	5104
	Lubero	2248	22476	22476	1124	22476	2248
	Masisi	1311	13105	13105	656	13105	1311
	Rutshuru	5312	53114	53114	2656	53114	5312
	Walikale	4500	45000	45000	2250	45000	4500
South Kivu	Fizi	7914	79137	79137	3957	79137	7914
	Kabare	1244	12435	12435	622	12435	1244
	Kalehe	6808	68077	68077	3404	68077	6808
	Mwenga	2846	28455	28455	1423	28455	2846
	Shabunda	5209	52089	52089	2605	52089	5209
	Uvira	4117	41167	41167	2059	41167	4117
	Walungu	1598	15979	15979	799	15979	1598

to test the other scenarios. The model was then executed in two sequences; the first with the main priority being to minimise the shortage, followed by minimisation of the total time travelled. The second sequence was the reverse order where the second priority (minimising total time travelled) was implemented first, followed by minimising total shortages.

4.2.1 Pre-emptive solution process for the model

The pre-emptive solution process followed for the first order is discussed. The dominant objective function 3.1, $minimise\ z = \sum_{i\epsilon\mathbf{I}} \sum_{k\epsilon\mathbf{K}} O_{ik}$ (shortages) was solved (subject to all the constraints) while ignoring the second objective function (total time travelled). For the initial budget scenario discussed in 4.2.2, the shortage objective value (Z_1) was 2,473,131 unit items. This optimal Z_1-value was then included as a constraint, and the second objective was solved. That is, $minimise\ z = \sum_{i\epsilon\mathbf{I}} \sum_{j\epsilon\mathbf{J}} Y_{ij} T_{ij}$ subject to $\sum_{i\epsilon\mathbf{I}} \sum_{k\epsilon\mathbf{K}} O_{ik} \leq 2473131$ with constraints 3.3 - 3.13 having to hold. The model was then run to yield the resulting Z_2-optimal values of total hours travelled. This process was repeated for all the budget adjustments and the other scenarios.

The next step was to test for the scenarios with the model results guided by the goal of understanding the changes in conflict areas-LDC assignments and the resulting shortages. This was achieved by varying the budget and the allowed capacity of the LDCs. Running the model using the first sequence and reverse order yielded identical results for scenarios that returned a solution within practicable times. The idea of assessing the model using goal programming was explored implicitly but eliminated; however, it would have been insightful for comparison purposes with the results from the pre-emptive technique. The main reason for eliminating goal programming was the lack of a tenable process for setting the goal for the total time travelled. The results from evaluating various scenarios are discussed in the subsequent section starting with the initial budget change.

4.2.2 Initial budget case scenario

The conflict areas-distribution centre allocations for the initial run at \$20,200,000 and 12000 m^3 are presented in table 4.4. From the results, eight of the 24 potential LDCs locations were not selected as distribution centres. These are Alindao, Kembe, Zangba, Bria, Obo, Bangassou, Ouango, and Rafai all in CAR. The model chooses cross-border allocation for only three conflict areas such as Djugu, Mambasa, and Irumu. This is expected as cross-border allocations would involve longer distances resulting in higher costs that would violate the budget constraint requirements. This is identical to in-country allocations as the model does not allocate LDCs to conflict regions far apart. This points to the model being sensitive to the transportation cost instead of the LDC establishment cost. The model prefers to locate LDCs more centrally owing to this sensitivity; therefore, few LDCs are

Table 4.4: Conflict area LDCs allocations

Index	Potential LDC	Assigned Conflict areas
1	Bangui	Bangui
4	Zangba	Djugu,Kouango,Gambo,Zemio,Zangba,Mobaye,Alindao
7	Bakouma	Djugu,Bangassou,Bakouma
8	Gambo	Mambasa,Djugu,Rafai,Ouango,Gambo,Bangassou,Zemio,Obo,Kembe
10	Mbrès	Irumu,Bambari,Mbrès,Kaga-Bandoro,Ouango,Zemio,Obo,Kembe,Alindao
11	Bakala	Djugu,Ippy,Grimari,Bakala,Yalinga,Ouadda,Bria
13	Bouca	Bouca,Djugu,Batangafo,Grimari,Kaga-Bandoro,Kouango
16	Ngaoundaye	Ngaoundaye,Bocaranga,Koui
17	Irumu	Djugu and Irumu
18	Mambasa	Mambasa,Djugu and Irumu
19	Lubero	Rutshuru,Lubero,Beni,Djugu
20	Kabare	Kalehe,Kabare,Walikale,Masisi,Lubero
21	Mwenga	Mwenga,Kalehe,Masisi,Lubero,Beni
22	Shabunda	Shabunda,Fizi
23	Uvira	Uvira,Fizi
24	Walungu	Walungu, Fizi,Walikale,Rutshuru,Masisi

chosen without compromising the servicing of the respective conflict areas.

The model allocated several conflict areas to the same LDC, and the reverse also holds. The model allocated some conflict areas to multiple distribution centres. There is partial and total demand satisfaction for the item types or the conflict area. For some conflict areas, some required relief items were supplied in full, and for partial, only a proportion of the total demand was met. During initial test runs, some remarked that the model was sensitive to the weight of the items, mainly because it influences the transportation cost. The lighter items were being prioritised, resulting in higher shortages for the heavier items. Conflict areas with low servicing of heavier items are located relatively far from the areas selected as LDC centres. This points to the significance of the transport cost factor with allocation. The total shortage concerning items was 780,846 against a demand of 4,184,369 items. This represents a shortage of 18.66% which could be a misleading statistic as it implies a low shortage for an armed conflict response situation; however, item-by-item shortage comparison evinces the disparities in item distribution. For instance, the non-food items had the lowest shortage percentage at 0%, whereas the sanitation pack had the highest shortages at 86% owing to it having the highest weight. Shortages of all the other items followed a similar trend.

To control the item weight influence, the allowed supply of the affected items was limited through the addition of constraint 3.13. The x value for the initial run was set to 50%. This resulted in a more reflective shortage of 2,473,131 (59%). During this run, every conflict area was serviced, but no area had total demand satisfaction. Notable in the demand satisfaction trend is that conflict areas with higher demand satisfaction serviced are those selected as LDCs or had lower demand for items. With the weight influence control, the general relief item package had the highest shortage with 85% followed by general relief items at 80%. All shortages were calculated as percentages of unfulfilled items per item type divided by the total across all the conflict areas of that specific item type. For priority items, the shortages were 48.7%, 48.5%, 47.7% and 49.2% for tents, foodpacks, water, and sanitation packs, respectively. The preferred location of items is tabulated in 4.5.

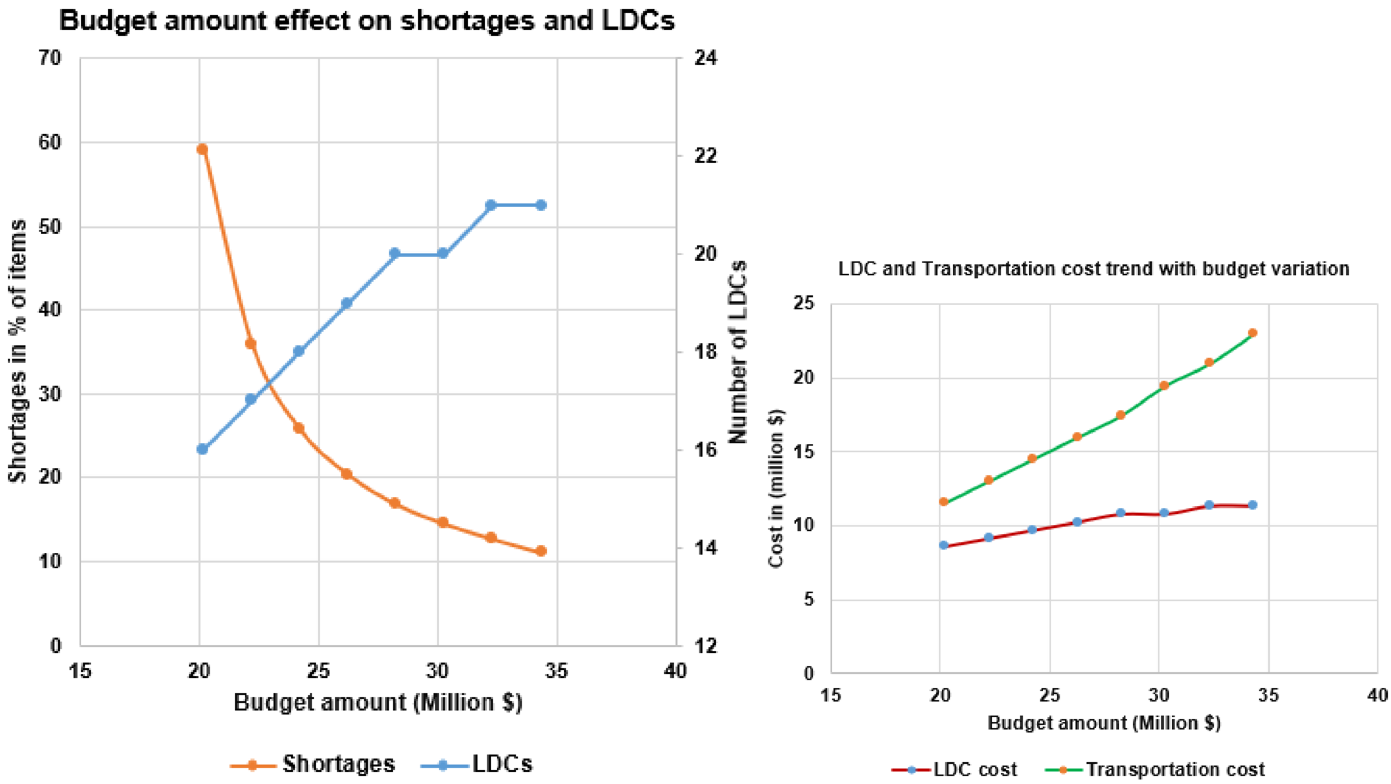
Table 4.5: Item quantity storage in the selected LDCs

LDC/item	**Tents**	**Food packs**	**Water pack**	**Sanitation pack**	**Non-Food relief**	**General relief**
Bangui	3770	37700	47332	1885	75400	7540
Zangba	1511	15105	15105	3204	3250	325
Bakouma	497	4967	4967	3597	9933	994
Gambo	4215	42148	42148	2083	7958	796
Mbrès	1535	18063	18063	3093	5426	543
Bakala	4302	43020	43020	2068	1847	185
Bouca	2732	27315	27315	2664	15856	1586
Ngaoundaye	3515	35150	35150	1758	18000	1800
Irumu	0	196293	19378	0	0	0
Mambasa	12602	2594	179510	0	0	0
Lubero	13619	63315	63315	779	0	0
Kabare	6931	69309	69309	964	12435	0
Mwenga	1423	14228	14228	3169	28455	0
Shabunda	2605	26045	26045	2598	52089	5209
Uvira	6016	60152	60152	1343	10497	0
Walungu	799	7990	7990	3459	15979	0

4.2.3 Effect of increased budget

Provided the considerably high shortages at the initial budget limit of $20,200,000; the effect of increasing the budget on shortages and the conflict area-LDC allocation was tested. With a 10% budget increase, the model increased the number of LDCs to 17 and reallocated some conflict areas. Similarly, the LDC additions were achieved by dropping some LDC assignments and adding new preferences for the LDC locations. The preferred additions were Mobaye, Ouadda, and Grimari, whereas Zangba and Bakala were dropped. With the newly preferred LDCs, Mobaye assumes the servicing of Djugu, Ouango, Mobaye, Gambo, Zangba, Kembe, and Alindao. Ouadda was distributed to Djugu, Ippy, Yalinga, Ouadda, and Bria while Grimari serviced Grimari, Bakala, Bambari, Djugu, Kouango, and Ippy. Interestingly, the model maintained the number of LDCs servicing Djugu at seven even after these reallocations. The model also maintained the cross-border LDC-conflict area allocation by assigning Djugu and Mambasa in DRC to LDCs in CAR.

The number of LDCs opened increased linearly as the budget was increased by 10% ,20%,30% and 40%. As expected, there were significant reductions in shortages and LDC-conflict area reallocations in Figure 4.2. The resulting shortages for items were 35.9%,25.7% 20.4% and 16.8% for 10% ,20%,30% and 40 % increments respectively. When comparing the 20% increase to the initial budget, five major reallocations led to a 33.3% reduction in shortages.



(a) Budget change influence on shortages and LDCs

(b) costs trend

Figure 4.2: Budget influence and costs trend for the deterministic model

Figure 4.3: Geographical illustration of assignments at 30%

First, was the addition of four new LDCs at Grimari, Ouango, Ouadda, and Mobaye. Second, was the dropping of Zangba as an LDC location. The model still chose Bangui's demand deficit to be met by Bouca. Last, the model added Rutshuru to conflict areas being serviced by Kabare, bringing the total areas serviced by Kabare to five. This was mainly because Kabare is located centrally in this region, as depicted in Figure 4.3 with relatively low demand; therefore, its unused items were used to service other conflict areas.

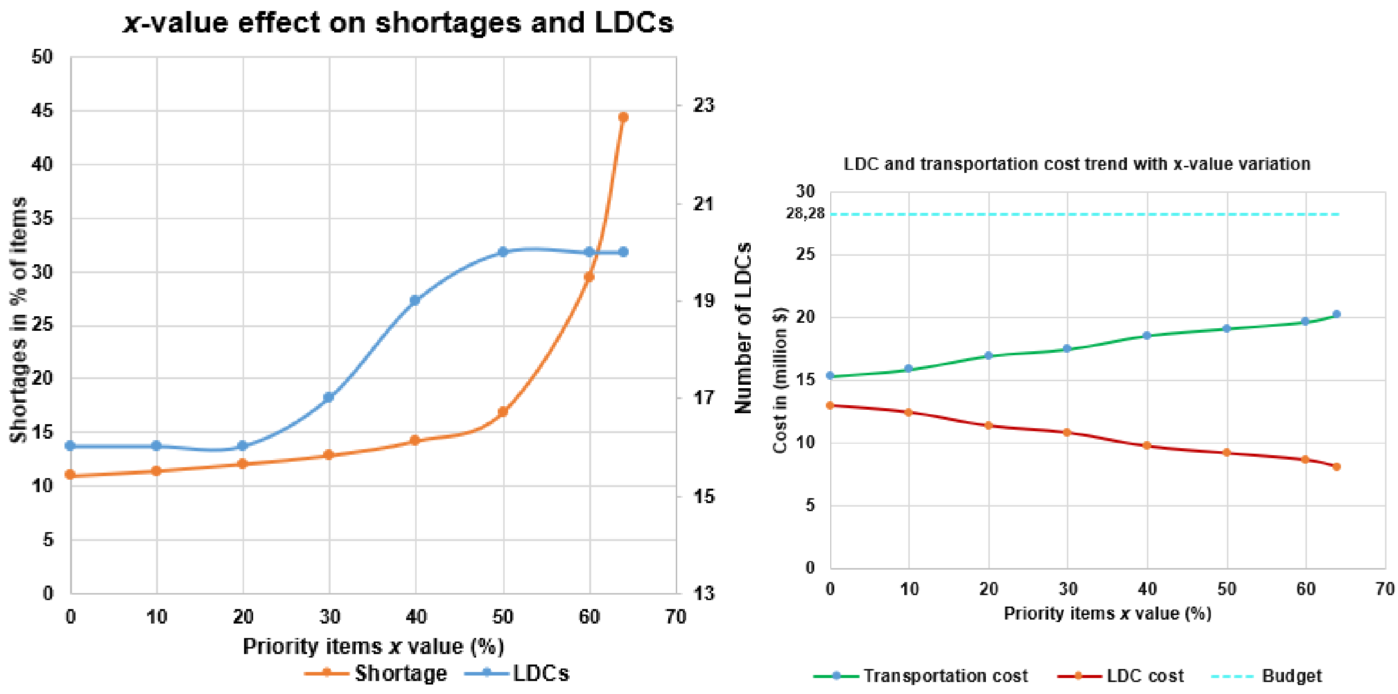
Table 4.6: LDCs-conflict areas reallocations after 30% budget increment

Index	**Potential LDC**	**Conflict areas Allocation**
1	Bangui	Bangui
3	Mobaye	Mobaye,Masisi,Rutshuru,Djugu,Zemio, Zangba,Kembe, Alindao
5	Ouadda	Oudda,Djugu, Ippy,Yalinga,Bria
7	Bakouma	Bakouma,Djugu
8	Gambo	Gambo,Obo,Zemio,Rafai, Bangassou,Kembe,Irumu, Mambasa
9	Ouango	Kalehe,Walikale,Ouango,Gambo
10	Mbrès	Mbrès , Kaga-Bandoro,Beni, Lubero,Bakala, Alindao
11	Bakala	Bakala,Ippy ,Bambari,Bangassou,Gambo, Yalinga, Bria,Obo
12	Grimari	Grimari,Djugu, Kouango,Bambari,Zangba
13	Bouca	Bouca, Batangafo ,Bangui,Markounda,Kaga-bandoro
16	Ngaoundaye	Ngaoundaye,Kaga-bandoro,Paoua,Koui,Bocaranga,Markounda
17	Irumu	Djugu ,Irumu
18	Mambasa	Mambasa,Djugu, Irumu
19	Lubero	Lubero, Djugu, Beni, Rutshuru,Mambasa,Irumu
20	Kabare	Kabare, Kalehe,Walikale ,Rutshuru,Masisi
21	Mwenga	Mwenga ,Walungu,Kalehe, Fizi
22	Shabunda	Shabunda,Fizi
23	Uvira	Uvira, Fizi
24	Walungu	Walungu,Uvira,Kalhe,Kabare,Walikale,Rutshuru,Masisi

When increasing the initial budget by 30%, shortages were realised through major reallocations, mainly through adding and dropping several LDCs preferences. The additions were Mobaye, Ouadda, Ouango, and Grimari, whereas the dropped LDC was Zangba in Table 4.6. Like it was with the initial budget, despite Gambo being selected as an LDC, the model preferred to receive items from Ouango and Bakala as it used its relief items to service the other seven regions. Here, the model preferred reducing the items shortages at Bangui by supplementing its supplies from Bouca. The shortages of five item types were eliminated. The only item with shortages was the sanitation pack. The reallocation was random, while the model reallocated to reduce the shortages in other areas. The number of LDCs opened for 40%, and 50% increments (to the initial budget) were the same (20), with Kembe, Zangba, Markounda, and Koui being the unpreferred options; however, for the 50% increase, significant shortages reduction and LDC-conflict area reallocations were notable. Last, for 60% and 70% increments, the number of LDCs increased to 21, with the model adding Kembe, Mobaye, Ouadda, Yalinga, Ouango, and Grimari, as LDCs in this scenario.

4.2.4 Effect of varying the LDCs's capacity and x value

To better understand the dynamics of the model, some additional scenario runs were conducted. To understand the influence of changing the x value on the main variables (shortages and number of LDCs opened), the model was run with various proportions for the priority items. This was conducted while keeping all the other parameters constant, where the budget was fixed at an optimistic value of \$ 28,280,000. The fixed budget value was a 40% increment of the initial value. This value was premised on the model only feasibly solving the initial x value of 0.5 at \$20,200,000; therefore, if a higher x value were used, the budget needed to be higher; otherwise, the model would be infeasible. The relationship between the x value, shortages, and the number of LDCs opened is presented in Figure 4.4.

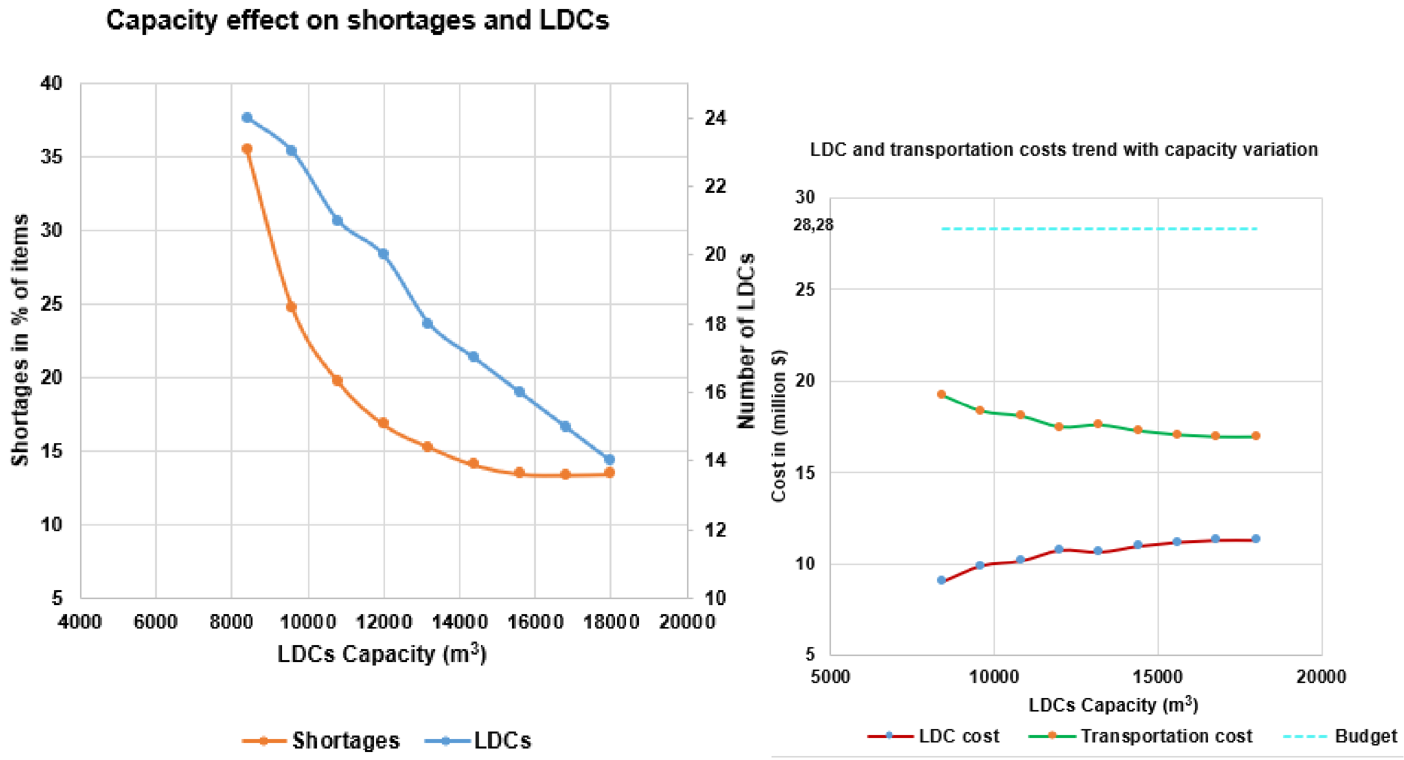


(a) x-value change influence on shortages and LDCs (b) LDC and transportation costs trend

Figure 4.4: x-value influence and costs trend for the deterministic model

From Figure 4.4a, shortages increased with an increase in x value, whereas the number of LDCs stayed constant and then decreased with an increase in the x value. It is interesting for shortages to increase with an increase in x value instead of decreasing. This is because a higher x value would be expected to force the model to supply more items as specified. This can be interpreted analogously as discussed in Section 4.2.5. Subsequently, the inverse proportion relationship can be associated with the item weight influence. This emphasises one of the main drawbacks of using total items supplied to calculate shortages, especially if the weight influence on item distribution is not controlled. Where items are distributed based on unit counts, and the model aimed to minimise shortages, the heavier items are least preferred owing to their transportation cost factor. Using the x value helped to reflect the true shortages with some uniformity in distribution. Otherwise, within a budget, the model would prioritise distributing lighter items to increase the count of distributed items which eventually causes a smaller proportion of shortages.

Specifying or increasing the x value causes an increase in shortages in two main ways. First, the x value is associated with priority items which coincidentally are heavier than the non-priority items for items considered in this model. A higher x value means more priority items (heavier) have to be distributed, which uses a substantial proportion of the available budget in Figure 4.4b. This leaves a smaller portion of the budget available to distribute the lighter items, resulting in an increased shortage. Second, from the relationship between the x value and the number of LDCs illustrated in Figure 4.4a, with a low x value (or without specifying the x value), the model increases the number of LDCs with an increase in x value; therefore, it can be inferred that the model establishes several LDCs in areas with high demand for lighter items. This may result in no service for some conflict areas; however, when the x value is increased (or introduced), the model is forced to open fewer LDCs as it must distribute the items evenly as required without the influence of weight.



(a) Capacity change influence on shortages and LDCs

(b) costs trend

Figure 4.5: Capacity influence and costs trend for the deterministic model

Figure 4.5 illustrates the influence of varying LDCs capacities while keeping the other parameters constant. As shown, the number of LDCs and shortages decrease with increased LDCs capacity. This was expected because, with increased capacity, more items can be stored and distributed to meet the requirements without establishing additional LDCs. Similarly, shortages reduce with an increase in LDC capacity because the budget proportion saving by not needing to establish additional LDCs for storage is used to distribute items. The increase in cost associated with an increase in capacity is smaller; therefore, the greatest influence lies in using the resultant savings in the distribution of more items. Evident from Figure 4.5 is the almost linear decrease in the number of LDCs with several increments in capacity. The model opts to drop some LDCs preferences until no more conflict areas are within range to be serviced by the number of lDCs . This is achieved by performing reassignments to conflicts areas with a higher demand to better use the increased capacity.

4.2.5 LDC-conflict area allocation and shortages results interpretation

In the initial budget of $20,200,000 scenario and without the item weight control, the model opted to reduce the shortages by supplying the lightest items first, followed by the heavier ones. Some conflict areas were left subserviced, and for those partially serviced, it was only for the lighter items.

This was expected because other factors being constant (budget, time, and distance), the weight influences which item gets distributed from the LDCs to various conflict areas. The heavier the item, the higher the cost of transportation because the total cost is a factor of tonnages; therefore, the shortages increase from the lightest to the heaviest item.

After the control using the x value, the difference in shortages of the various items reduced significantly, resulting in a more even distribution which can be interpreted in two main ways. First, the x value forces the model to, at a minimum, supply the specified percentage of items to all areas; therefore, more LDCs are established. Second, having established more LDCs and having met the minimum supply for the priority items, the model uses the remaining amount to supply the other items, mainly lighter in weight. Because of the increased LDCs established, these lighter items are transported through shorter distances enabling more lighter items to be distributed, which subsequently causes some parity in all the items.

With the model's initial budget and x value of 0.5 for the priority items, the model selected 16 out of 24 areas as actual LDCs. This is a substantial number, and notwithstanding, the shortages were still high at 59%. This can be explained by the budget being exhausted; therefore, the model splits the available budget into optimal LDCs establishment and transportation cost proportions to satisfy the specified x value. These shortages are reduced with an increase in the budget as it allows more LDCs to be opened and more items to be transported. The relationship between shortages, budget, and number of LDCs is summarised in Figure 4.2.

The adjusted LDC capacity run at 18,000 m^3 yielded a significant change in the number of LDCs opened and the resultant shortages in Figure 4.5. The solution to a large number of LDCs opened would be to increase the acceptable risk during the screening stage captured in Table 3.1. This would ensure the availability of more options concerning locations within range, then allowing one LDC to service more conflict areas; however, increasing the risk would reduce the reliability of that LDC as the chances of it being inaccessible because of armed conflict outbreak would be higher. Some LDCs are already assigned to multiple conflict areas, which means the demand could surpass their storage capacity. Subsequently, and as an alternative, increasing the LDC capacity by 50 % was investigated as a potential solution. The shortage reduced significantly from 59% to 13.5% for \$ 28,280,000 with the 50% increase in storage space. The number of LDCs also reduced by six, emphasising the effect of insufficient capacity in the initial number of LDCs to store all the required items. From the parameters evaluated in the budget, x value and capacity scenarios, several concluding remarks were derived, discussed in the subsequent section.

4.3 Concluding remarks

This chapter provides a detailed step-by-step implementation of the deterministic model formulated in the previous chapter. The data collection from the selected databases was discussed, followed by the calculation of demand and translation of demand items into supply items. The explicit calculation of demand items in this chapter was unnecessary, provided that the translation is inherent in the coded mathematical Lingo model; however, the explicit discussion and calculation were necessary to enhance lucidity from a reader's perspective. The resulting LDC-conflict area assignments were analysed while discussing notable changes and preferred RI stocking locations where necessary. The influence of budget, capacity, and x value variation was considered and documented to prepare for comparison with the stochastic model. The cost trends were also graphed to aid in interpreting shortages and LDCs numbers for the parameters under consideration.

Chapter 5

Stochastic prepositioning model (SPM)

The previous chapter focused on prepositioning modelling for DRC and CAR from a deterministic demand perspective; however, in reality, HOs cannot always be certain of the expected number of affected people; therefore, this chapter incorporates uncertainty into the deterministic model from Chapter 3, which results in a stochastic prepositioning model (SPM). Because of uncertainty in a stochastic model, probabilistic distributions are used to describe the randomness of variable states. This is achieved by estimating the distributions of the number of affected people for all the conflict areas. These distributions are then used in the model to enhance randomness and the subsequent estimation of demand arising from these realisations. As the problem here involves uncertain data, a recourse stochastic model was adopted. For instance, because the number of affected people is uncertain, resultant shortages were modelled as the recourse variable in this model. A recourse model is an adaptation where decisions in SP are delayed and only made after the uncertain data information becomes available. The resultant decision variables associated with recourse, models are called recourse variables. These variables may change depending on the scenario (Higle, 2005). The stochastic sets and variables were then adopted from the deterministic model and redefined for the stochastic recourse problem.

5.1 Adopted stochastic model

We denote:

$\mathbf{I} = \{1, 2, 3...44\}$ the set of armed conflict locations i

$\mathbf{J} = \{1, 2, 3...24\}$ the set of potential locations for LDCs j

$\mathbf{K} = \{1, 2, 3...6\}$ the set of victim's needs k

$\mathbf{M} = \{1...5\}$ the set of m realisations

The parameters for the model are then defined as follows

$\tilde{s}_i \triangleq$ the random number of affected persons in conflict area $i \, \epsilon \, \mathbf{I}$

$l_k \triangleq$ the expected requirement of item $k \, \epsilon \, \mathbf{K}$ per affected person

$D_{ik} \triangleq$ the expected demand in unit item $k \, \epsilon \, \mathbf{K}$ in conflict area $i \, \epsilon \, \mathbf{I}$

$T_{ij} \triangleq$ the estimated travel time in hours from LDC $j \, \epsilon \, \mathbf{J}$ to conflict area $i \, \epsilon \, \mathbf{I}$

$R_{ij} \triangleq$ the estimated distance in kilometres from LDC $j \, \epsilon \, \mathbf{J}$ to conflict area $i \, \epsilon \, \mathbf{I}$

$C_{ij} \triangleq$ the cost in \$ per tonne-kilometre to transport items from LDC $j \, \epsilon \, \mathbf{J}$ to conflict area $i \, \epsilon \, \mathbf{I}$

$C^v \triangleq$ the fixed cost of establishing an LDC in \$ per m^3

$B \triangleq$ the expected budget of the HO in dollars

$V_j \triangleq$ the capacity of LDC $j \, \epsilon \, \mathbf{J}$ in m^3

$U_k \triangleq$ volume of one unit of item $k \, \epsilon \, \mathbf{K}$ in m^3

$W_k \triangleq$ Weight of one unit of item $k \, \epsilon \, \mathbf{K}$ in tonnes

$x_k \triangleq$ the the specified percentage of item $k \, \epsilon \, \mathbf{K}$ that should be supplied for priority items

Last, the binary and decision variables for the model are defined as follows:

$$Y_{ij} \triangleq \begin{cases} 1 & \text{if LDC J is used to service conflict area i} \\ 0 & \text{otherwise} \end{cases}$$

$Q_{ijk} \triangleq$ number of unit items k sent from LDC j to conflict area i

$O_{ik} \triangleq$ random shortage amount of item k in conflict area i

$$Z_j \triangleq \begin{cases} 1 & \text{if LDC j is opened} \\ 0 & \text{otherwise} \end{cases}$$

The stochastic objective function variation from 3.1 of the deterministic model to minimise shortages and total response time becomes 5.1 whereas the second objective of minimising the total time travelled stays the same.

$$minimise\ z = \sum_{i \epsilon \mathbf{I}} \sum_{k \epsilon \mathbf{K}} E_{\tilde{s}_i}[O_{ik}(\tilde{s}_i)] \tag{5.1}$$

$$minimise\ z = \sum_{i \epsilon \mathbf{I}} \sum_{j \epsilon \mathbf{J}} Y_{ij} T_{ij} \tag{5.2}$$

Subject to these conditions:

$$O_{ik}(\tilde{s}_i) \geq 0 \text{ and } \quad \text{integer,,} \quad for\ \forall\ i \epsilon I,\ k \epsilon K \tag{5.3}$$

$$\sum_{j\epsilon\mathbf{J}} Z_j F_j + \sum_{i\epsilon\mathbf{I}} \sum_{j\epsilon\mathbf{J}} (\sum_{k\epsilon\mathbf{K}} W_k Q_{ijk} * C_{ij} R_{ij}) <= B \quad for\,\forall\;\, i\epsilon I,\; j\epsilon J,\; k\epsilon K \tag{5.4}$$

$$Q_{ijk} \geq 0 \text{ and } \quad \text{integer}, \quad \forall\;\, i\epsilon I,\; j\epsilon J\; k\epsilon K \tag{5.5}$$

$$\sum_{j\epsilon\mathbf{J}} Q_{ijk} + O_{ik}(\tilde{s}_i) = D_{ik}(\tilde{s}_i), \quad for\,\forall\;\, i\epsilon I\; k\epsilon K \tag{5.6}$$

$$D_{ik}(\tilde{s}_i) = \tilde{s}_i l_k \tag{5.7}$$

$$\sum_{k\epsilon\mathbf{K}} \sum_{i\epsilon\mathbf{I}} U_k Q_{ijk} \leq V_j Z_j, \quad \forall\;\, j\epsilon J, \tag{5.8}$$

$$\sum_{k\epsilon\mathbf{K}} Q_{ijk} \leq MY_{ij}, \qquad\qquad ;\forall\;\, i\epsilon I,\; j\epsilon J, \tag{5.9}$$

$$\sum_{k\epsilon\mathbf{I}} Y_{ij} \leq MZ_j, \quad \forall\;\, j\epsilon J, \tag{5.10}$$

$$Y_{ij}\;\epsilon\;(0,1), \qquad \forall\;\, i\epsilon I,\; j\epsilon J, \tag{5.11}$$

$$Z_j\;\epsilon\;(0,1), \qquad \forall\;\, j\epsilon J, \tag{5.12}$$

$$\sum_{j\epsilon\mathbf{J}} Q_{ijk} \geq x D_{ik}(\tilde{s}_i), \quad for\,\forall\;\, i\epsilon I,\; K\{1..4\} \tag{5.13}$$

5.1.1 Stochastic model realisations

An intervention of discretising the data into five bins was applied to the stochastic model to transform it to the deterministic equivalent through dual decomposition structure (Beamon and Kotleba, 2006a,c).To derive the dual decomposition, a new set, $\mathbf{M} = \{1...5\}$ the set of realisations $m\;\epsilon\;\mathbf{M}$ was introduced. Subsequently, it becomes necessary to modify the parameters O_{ik}, D_{ik} and $\tilde{s}_i$ defined to O_{ik}^m, D_{ik}^m and S_i^m respectively where $\tilde{s}_i \;\; \sim \{(p_i^m, s_i^m)\}_{m\epsilon M}$. O_{ik}^m and D_{ik}^m correspond to the shortage and demand for items $k\;\epsilon\;\mathbf{K}$ in conflict area $i\;\epsilon\;\mathbf{I}$ in realisations $m\;\epsilon\;\mathbf{M}$ respectively. Similarly, S_i^m is the number of affected people for conflict area $i\;\epsilon\;\mathbf{I}$ in in realisations $m\;\epsilon\;\mathbf{M}$. The stochastic objective function 5.1 after incorporating the five realisations becomes 5.14 while the stochastic constraints

(5.3), (5.6), (5.7) and (5.13) are adjusted to (5.15), (5.16),(5.17)and (5.18) respectively as follows.

$$minimise\ z = \sum_{m\epsilon\mathbf{M}} \sum_{i\epsilon\mathbf{I}} \sum_{k\epsilon\mathbf{K}} p_i^m O_{ik}^m \tag{5.14}$$

subject to:

$$O_{ik}^m \geq 0 \text{ and } \quad \text{integer,,} \quad \forall\ m\epsilon M, \forall\ i\epsilon I,\ k\epsilon K \tag{5.15}$$

$$\sum_{j\epsilon\mathbf{J}} Q_{ijk} + O_{ik}^m = D_{ik}^m, \quad \forall \quad i\epsilon I,\ k\epsilon K, m\epsilon M \tag{5.16}$$

$$D_{ik}^m = l_k S_i^m \quad \forall\ i\epsilon I,\ k\epsilon K\ \ m\epsilon M, \tag{5.17}$$

$$\sum_{j\epsilon\mathbf{J}} Q_{ijk} \geq x \sum_{m\epsilon\mathbf{M}} p_i^m D_{ik}^m, \quad \forall\ i\epsilon I,\ K\{1..4\},\ \ m\epsilon M \tag{5.18}$$

5.2 Stochastic model data inputs and Execution

The data used as inputs in the stochastic model were obtained in a procedure similar to that of the deterministic model. The only difference is the assumption of the most suitable distribution for the number of affected people data and the subsequent simulation of instances in R. The distribution assumed for this model's data was uniform. This was inspired by findings from the systematic literature review where uniform distribution is preferred for complex emergencies, especially during conflicts, as considered by Beamon and Kotleba (2006c) and Beamon and Kotleba (2006a). The discretisation of the data into the five realisations was executed in R using a seed value of 10,000. The resulting values and probabilities were then exported into a CSV file and used as input into Lingo during the model solution process.

It is impossible to determine the number of people affected and their needs after a conflict attack. Subsequently, using the average number of affected people was improved by incorporating a distribution for the number of people affected after every conflict occurrence. As already stated, this was achieved using five realisations for each conflict area. This was conducted by discretising the data into five bins and running the R simulation to obtain the number of affected people from each bin and the corresponding probability of occurrence. The reliability of the R simulations increased with the increase in the number of bins used; however, increasing the number of bins eventually increased the complexity of the SPM. An extract of the first five conflict areas R simulation output data used as input into the model is presented in Table 5.1. As revealed in the table, the resultant

Table 5.1: Realisations data extract

Conflict area	**Realisation**	**Number of affected people**	**Probability**
	1	31239	0,2039
	2	72369	0,1983
	3	113500	0,1975
1	4	154631	0,1998
	5	195761	0,2005
	1	2798	0,2085
	2	6484	0,2014
	3	10169	0,2006
2	4	13855	0,196
	5	17540	0,1935
	1	2185	0,2021
	2	5064	0,2035
	3	7943	0,1966
3	4	10822	0,2014
	5	13701	0,1964
	1	2029	0,2028
	2	4702	0,2001
	3	7375	0,2002
4	4	10048	0,1981
	5	12721	0,1988
	1	1346	0,1997
	2	3119	0,2011
	3	4891	0,1994
5	4	6664	0,2009
	5	8437	0,1989

number of victims in each conflict area is the aggregation of the number of affected people per realised multiplied by the probability of occurrence. Every other parameter was the same as used in the deterministic model.

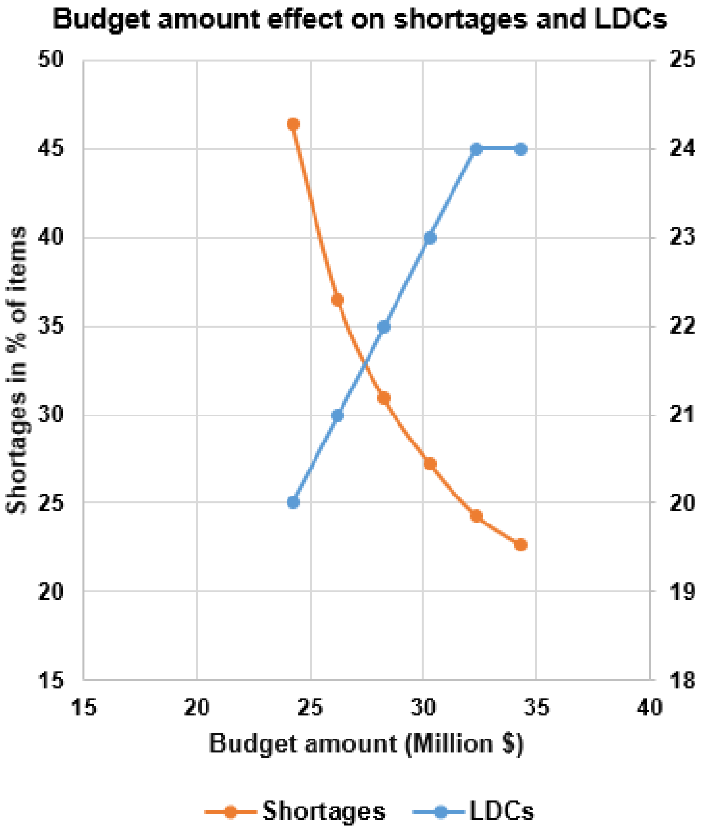
Since it is nearly impossible to predict a conflict and the resulting number of affected people, using influence and probability in the SPM enhances reliability by ensuring that the possibility of various conflict situations is accounted for. Each realisation resulted in demand and shortages as calculated in equations (5.17) and (5.16), respectively. The summation of those shortages multiplied by the probability occurring was then minimised as revealed in equation (5.14).

5.3 Stochastic model solution and comparison with the deterministic model results

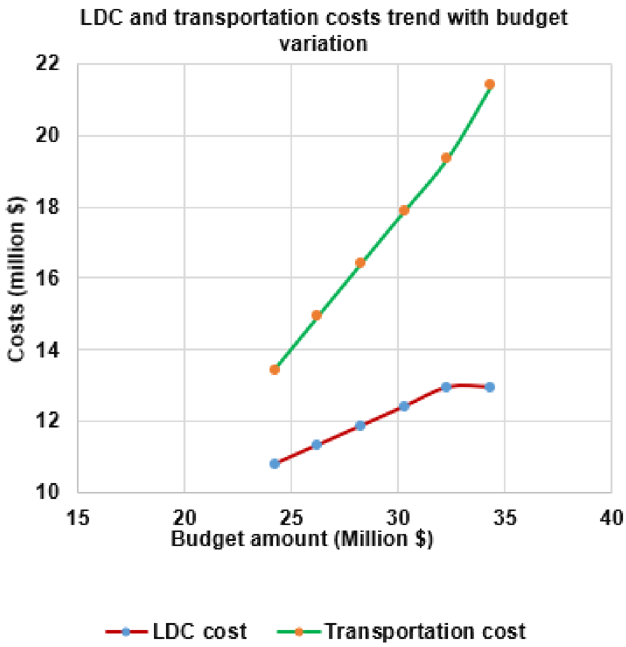
As the main motivation for developing the stochastic model was to investigate and compare the performance of uncertain data in the same environment, the model was evaluated and executed using a procedure similar to that of the deterministic model on the same parameters. To test the other scenarios, adjustments were made to the budget by incrementing the initial budget with 10%, 20%, 30%, 40%, 50%,60% and 70%. The model was then executed in two sequences, the priority being to minimise the shortage, followed by minimisation of the total time travelled. The second sequence was the reverse order where the second priority (minimising the total time travelled) was implemented first, followed by minimisation of total shortages. The pre-emptive MOO approach was implemented the same way outlined in Section 4.2.1. The influence of varying the budget, ability and x-value on the number of LDCs and shortages are discussed in this section. This is followed by a summary conclusion on the comparison findings from the performance of the two models.

5.3.1 Impact of budget variation

The budget under which reasonable feasibility could be achieved for the SPM was $ 24,240,000, a 20% increment on the base budget used in the deterministic model. This is attributed to the additional items arising from the overcompensation of the number of affected by the stochastic model. Overcompensation for the number of affected people directly affects the resultant demand. For instance, the total demand from five realisations of the recourse model amounts to 4,923,369 items, while deterministic models result in 4,184,405 items. The stochastic demand is, therefore, 17.6% higher than the deterministic model's value which explains the higher budget requirement to meet the same supply requirement of priority items. The $24,240,000 budget is 20% higher than the deterministic model's. Reasonable feasibility in this study is where the model attains at least 50% of priority items demand satisfaction. To examine SPM's model budget variation influence on the number of LDCs and shortages, the model was run with budget increments of 10%, and the results are presented in 5.1.



(a) Budget change influence on shortages and LDCs



(b) costs trend

Figure 5.1: Budget influence and costs trend for stochastic model

From Figure 5.1a, the number of LDCs increases linearly with the increase in the budget until the maximum number of LDCs is reached. The shortages decrease with budget increments. These trends are expected, and figure 5.1b illustrates the split in LDC establishment and transportation costs as the budget varies. As the budget increases, there are more funds available to both establish new LDCs, and to transport more items to the conflict areas, causing reduced shortages. From Figure 5.1b, transportation cost has the higher share in any budget. Also, it has a higher upsurge rate compared to the establishment cost. The higher share and upsurge of transportation costs can be attributed to the sparsely spaced LDCs, which cause items to be transported over longer distances. The highest possible number of LDCs is reached at a budget of $ 32,320,000, which explains the sharp rise in transportation costs beyond this amount.

For comparison purposes, the LDC-conflict areas assignment was remarked as documented in Table 5.2 and the corresponding geographical depiction in Figure 5.2. Referring to table 5.2, at a budget of $26,260,000, there are several interesting cross-border LDC-conflict area assignments. Djugu in DRC is assigned to several LDCs, such as Mobaye, Ouadda, Yalinga, and Grimari in CAR. Because these LDCs have insufficient relief inventory, provided they are already servicing other conflict areas within CAR, additional LDCs also service Djugu in DRC, such as Irumu, Mambasa, and Lubero. The other cross-border allocations involve the assignment of Beni in DRC to Gambo and Mbrès in CAR. The last cross-border assignment involves the servicing of Irumu in DRC by Gambo in CAR. Servicing of Irumu by other LDCs, despite being an LDC location, can be explained in two main ways. First, Irumu has high demand that cannot be met owing to capacity limitation and second, some RI items stored at Irumu are used to service Djugu, therefore, resulting in the shortfall. Since all cross-border assignments are also assigned to local LDCs, it can be inferred that the model attempts to use LDCs whose inventory has not been depleted, regardless of their locations. This result can be explained in two main ways. First, the model has established LDCs in the most optimal locations resulting in spare funds to transport relief items. Second, maybe the remaining budget cannot establish a new LDC and, therefore, be used to transport aid to conflict areas with unmet demand.

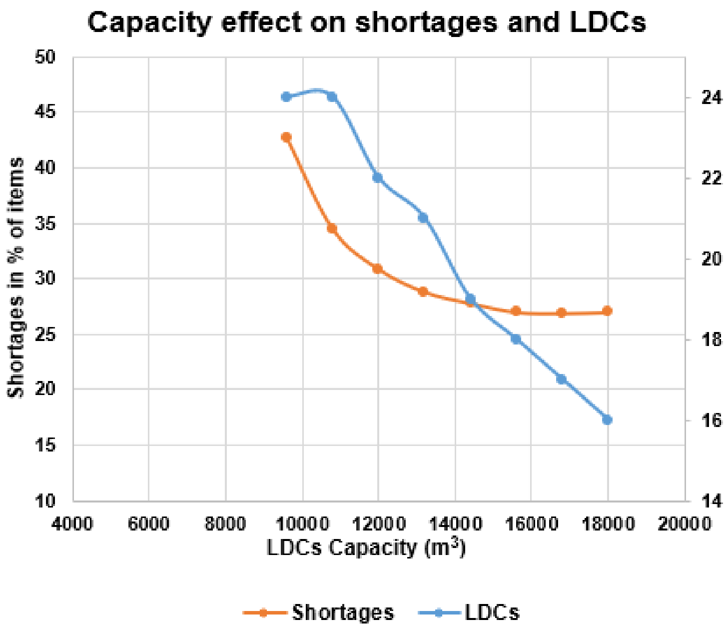
Figure 5.2: Geographical illustration of stochastic model assignments at 30%

Table 5.2: LDC-Conflict area assignment at 30% increase for the stochastic model

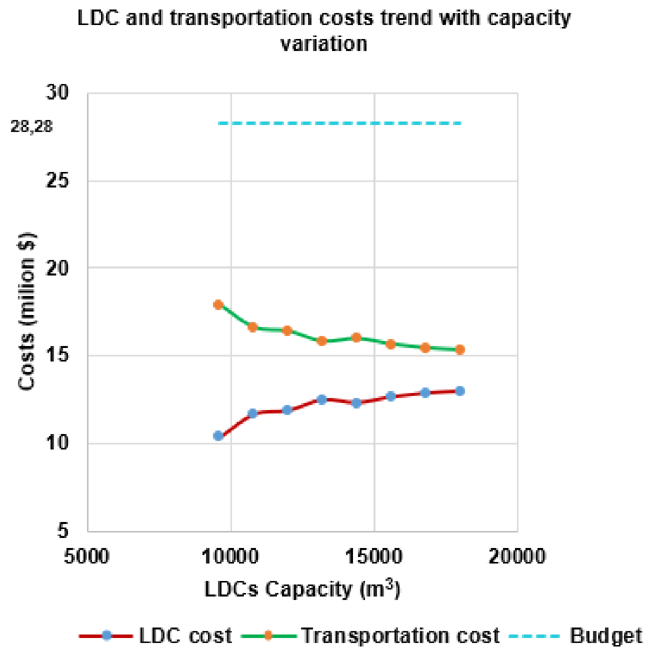
Index	Potential LDC	Conflict areas Allocation
1	Bangui	Bangui
3	Mobaye	Mobaye, Alindao,Kembe,Zangba,Obo,Djugu,Masisi ,Rutshuru
5	Ouadda	Oudda,Bria,Ippy,Djugu
6	Yalinga	Yalinga , Bria,Djugu
7	Bakouma	Bakouma,Djugu,Lubero,
8	Gambo	Gambo,Kembe, Obo,Zemio,Bangassou,Rafai,Irumu,Mambasa ,Beni
9	Ouango	Ouango,Zemio,Bangassou,Gambo,Rafai,Irumu
10	Mbrès	Mbrès ,Kaga-Bandoro,Beni
11	Bakala	Bakala, Alindao,Ippy , Bambari ,Walikale
12	Grimari	Grimari,Bambari, Zangba, Kouango,Djugu
13	Bouca	Bouca,Bangui, Batangafo,
14	Markounda	Markounda,Bangui,Kaga-Bandoro,Batangafo,Bocaranga,Paoua
16	Ngaoundaye	Ngaoundaye,Koui,Bocaranga,Paoua
17	Irumu	Djugu and Irumu
18	Mambasa	Mambasa,Djugu, Irumu
19	Lubero	Lubero, Djugu,Irumu,Beni, Rutshuru
20	Kabare	Kabare,Kalehe, Masisi, Walikale, Rutshuru
21	Mwenga	Mwenga,Kalehe , Walungu
22	Shabunda	Shabunda,Fizi
23	Uvira	Uvira, Fizi
24	Walungu	Walungu, Rutshuru,Fizi,Kabare, Uvira

5.3.2 Impact of capacity adjustment

As already identified, capacity is among the most influential parameters with facilities location and conflict areas-LDC assignment. The capacities of the LDCs varied between 0.8 and 1.5 times the base capacity while noting the effect of shortages and the number of LDCs to understand SPM's behaviour. The model achieved a 50% demand satisfaction for the priority items at a capacity of 9,600 m^3, corresponding to 0.8 times the base capacity.



(a) Capacity change influence on shortages and LDCs



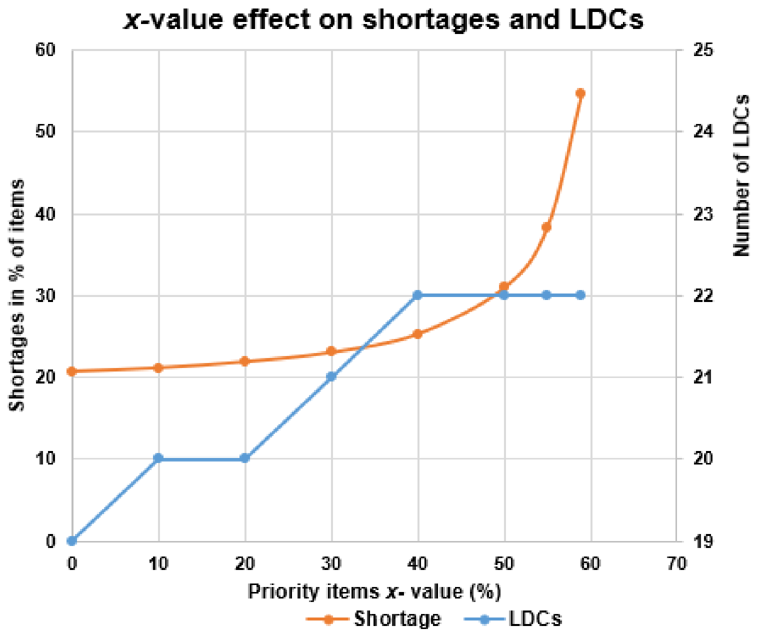
(b) costs trend

Figure 5.3: Capacity influence and costs trend for stochastic model

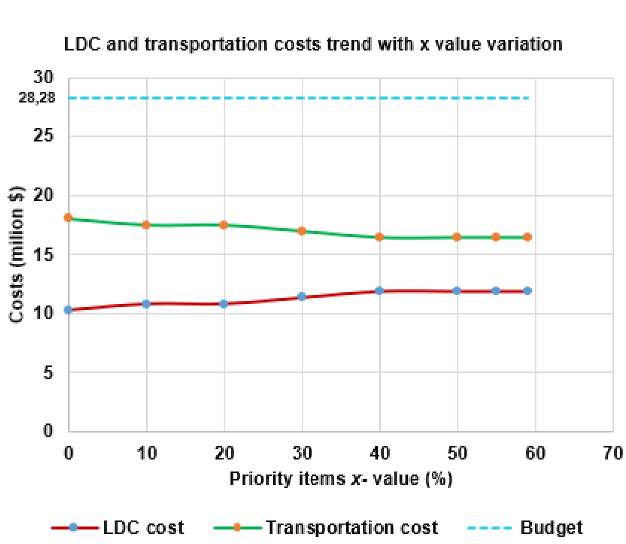
As presented in Figure 5.3a, as the capacity was increased, the number of LDCs and shortages decreased as expected. With increased capacity, more items can be stored and distributed to meet the requirements without establishing additional LDCs. Similarly, shortages reduce with the increase in LDC capacity because the budget proportion saving by not needing to establish additional LDCs for storage are used to distribute items. The increase in cost associated with increase in capacity is smaller; therefore, the greatest influence is in using the resultant savings in the distribution of more items. As the capacity increases, the model locates LDCs in a more central position resulting in more conflict areas being serviced, eventually reducing the shortages. This explanation is further supported by the cost trend in Figure 5.3b where the transportation cost proportion is decreasing whereas the LDCs cost proportion is increasing. The increase in LDC costs is owing to the additional LDC capacity that comes at a cost.

5.3.3 Impact of x-value variation

To investigate the influence of specifying the minimum priority items to be supplied, the SPM was executed at a budget of $28,280,000 and capacity value of 12,000 m^3. Both the shortages and number of LDC increase with an increase in the x value for the SPM in Figure 5.4a. The shortage increase is small for x value less than 0.4, after which the increase is steep. This can be attributed to the model being forced to prioritise certain items that are coincidentally heavier, preceding the supply of several lighter items. From a cost perspective, the model opts to meet the priority items requirement by increasing the number of LDCs, which cause items to be transported over short distances. This is demonstrated by the marginally declining transportation cost matched by the marginally rising LDCs cost in Figure 5.4b



(a) x-value change influence on shortages and LDCs



(b) costs trend

Figure 5.4: x-value influence and costs trend for stochastic model

Referring to Figure 5.4a, it can be observed that the number of LDCs increases almost in phases marked by the horizontal steps. The model prefers to establish additional LDC only when the capacity of the existing ones has been exhausted. It would have been interesting to observe the trend beyond an x value of 0.7, but the model was not feasible owing to the fixed budget.

5.3.4 Stochastic model results comparison with deterministic model solution

Having executed the deterministic and stochastic models under the same conditions, the similarities and differences in the model results are summarised in this section. The budget variation is presented first, then capacity variation, and lastly, the x value variation. The reliability of the two models is compared in the subsequent section.

Budget variation comparison

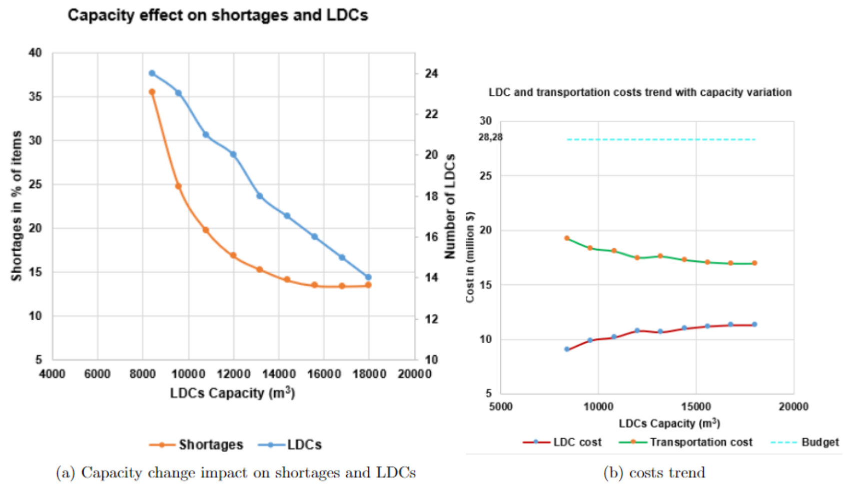
For the budget variation, the deterministic model met the minimum supply ($x = 0.5$) of priority items at a budget of \$20,200,000, whereas the stochastic model could only achieve this at a budget of \$24,240,000. This is attributed to the additional items arising from the overcompensation of the number of affected by the stochastic model. Overcompensation for the number of affected people directly affects the resultant demand. For instance, the total demand from five realisations of the recourse model amounts to 4,923,369 items, whereas deterministic models result in 4,184,405 items. The stochastic demand is, therefore, 17.6% higher than the deterministic model's value which explains the higher budget requirement to meet the same supply requirement of priority items. The $24,240,000 budget is 20% higher than that of the deterministic model.

When comparing Figure 4.2 and Figure 5.1, at a budget of $24,240,000, the stochastic model realised shortages of 46% whereas the deterministic model had 26%. When comparing the number of LDCs at the same budget, SPM preferred 20 facilities, whereas the deterministic model had 18. This can be attributed to the additional items from the stochastic model. The average demand in the deterministic model (lower than the stochastic model) allows the DM to easily meet the supply requirements despite having fewer LDCs. The increase in shortages and decrease in shortages and the LDC and transportation costs splits are identical in both models; however, there is a slight difference, with the SPM having steeper curves than the DM. This can be attributed to the difference in the relief quantities estimation, where the SPM has higher quantities resulting in higher proportions for transportation and LDCs establishment costs.

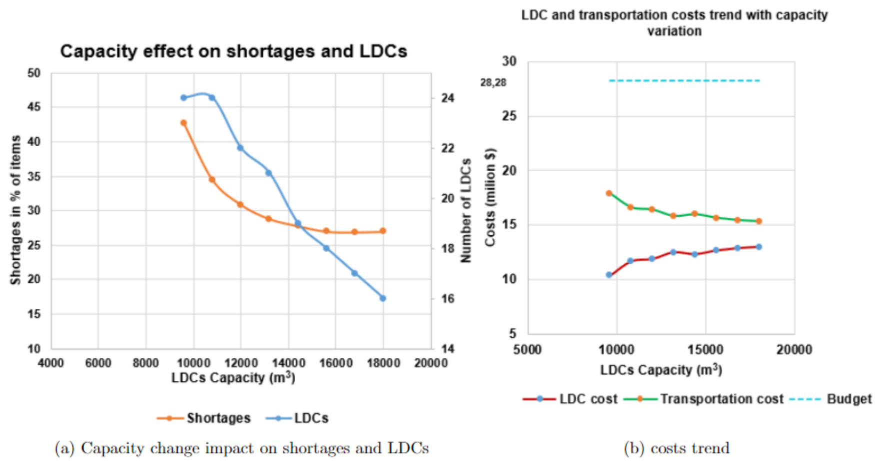
Reviewing the LDC-conflict area assignment at a budget of $26,260,000, as captured in Table 4.6 and 5.2 for deterministic and stochastic models respectively, there are several notable differences. First, the SPM designates Yalinga and Markounda as LDC locations, options not preferred by the DM. Delving into the other assignments, both models allocate the LDCs such as Mobaye, Grimari, Irumu, Mambasa, Kabare, Shabunda, and Uvira identical assignments. In the other 14 LDCs, there are marginal and significant differences in LDC-conflict area assignment. The marginal differences involve either adding or removing a conflict area from being serviced by a specific LDC. When using the stochastic model as the reference point, the marginal additions are Bakouma to Lubero and Beni to Gambo. The removals are Yalinga from Ouadda, Markounda, Kaga-Bandoro from Ngaoundanye, Mambasa from Lubero and Fizi from Mwenga. Significant changes in the assignments involve assignments to Yalinga, Ouango, Mbrès, Bakala, Bouca, Markounda and Walungu. Significant changes to the initial results from the deterministic model involve adding and removing over two conflict areas from being serviced by a particular LDC. The main cause of the differences is the number of LDCs opened by the diverse models. The selection of more LDCs by the stochastic model results in conflict areas being closer or central to most LDCs, triggering several changes. The capacity comparison is conducted in the subsequent section having compared the two models' trends with budget variations.

Capacity variation comparison

When varying the capacity, the minimum capacity under which the stochastic model could provide reasonable feasibility (x value of 0.5) was 9600 m^3. Meanwhile, the deterministic model achieved the same at 8,400 m^3. This was at the comparison budget of \$ 28,280,000. Like the other parameters, this can be inferred to be occasioned by the stochastic demand being at least 17.6 % higher than the average demand used in the deterministic model. Comparing the graphs in figures 5.5, the decrease in shortages and number of LDCs for the deterministic model is steeper than that of the stochastic model. The difference in the budget splits for transportation and LDC costs is higher for the deterministic model, as depicted by comparing the figures in 5.5.



(a) Deterministic



(b) Stochastic

Figure 5.5: Comparative capacity change influence for deterministic and stochastic models

There is a relationship between the steeper curves and the considerable difference in the cost elements of the deterministic model. As the LDC capacity is increased, the deterministic model establishes more LDCs in favourable central positions, which reduces the transportation distance of items and, ultimately, the need for several LDCs; however, since the stochastic model has a higher demand estimation, while LDCs are established centrally, more items still must be stored and transported. This causes fewer dipping curves of shortages and LDCs curves and a smaller difference in the cost elements for the stochastic model.

5.4 Reliability testing of the stochastic model and deterministic model

In modelling, reliability is defined as the probability of a model to function and yield the desired results according to the predetermined conditions in the test environment. According to Mohajan (2017) and Lillis (2006), by evaluating the reliability of a model, the modeller is interested in establishing how often the results achieved using a solver software or a model algorithm can be reproduced. There are various methods of testing the reliability of an optimisation model. One of the main approaches is implementing a solution over time while recording the number of successes and failures. The second method is a simulation of the model environment using computer software. Several challenges inhibit the first method, including the risk of model failure and time limitations for the implementation. If where the model fails and an organisation must respond to reality, the real price attributed to this reality can be enormous. Since simulation offers the ability to understand complex systems, simulation is a powerful device used to circumvent these challenges (Fu et al., 2013). According to Brito et al. (2012), simulation should not be used to accurately predict the system's performance but rather as a device for understanding the system variables and subsequently enabling the modeller to respond to variable behaviours in the model.

Reliability testing of a model through simulation of instances also provides model validation. For instance, in this study, reliability defines the chance of obtaining the same results in the actual case study environment when models are implemented. Although the reliability of this study was calculated based on simulated data, it provided an indication expected accuracy of the models provided the uncertainty of data. The alternative reliability calculation would involve implementing the proposed models in CAR and monitoring their performance. Conflict instances occurrences take a long time to document, and actual reliability testing is based on actual data, therefore, beyond the scope of this study. In this study, a simulation approach for reliability testing as stipulated by Brito et al. (2012) was used to achieve the main functions. First, the mathematical model must be analysed before practical implementation in the conflict area. Second, the reliability of the hypothetical deterministic and stochastic models developed needed to be compared for this study. In the humanitarian settings for the study models, the repeatability of the model settings was evaluated, based on the results obtained. To achieve this, the two measures of performance, shortages and total time travelled, were considered.

In this study, the model's reliability was defined as the ability of the selected distribution centres to satisfy the demand of victims whenever a conflict occurs. Humanitarian conflict area-distribution centre assignments must use the items prepositioned at various stocking points to realise the lowest possible shortages according to the model results. This was tested by simulating the number of affected people in the conflict area based on the assumed distributions. The test was simulated in R and run for N number of instances while noting the objective values (total shortages) after every run. By simulating to determine the reliability of the models, users can investigate the reliability of humanitarian distribution chains without waiting for actual conflicts to occur. This is helpful because limitations of the proposed prepositioning models can be identified and approached before the actual implementation. A sample of this algorithm is displayed in algorithm 5.4. Descriptive comments for the logical working of the code have also been added for explanation purposes.

$N = 100$

$z.base = 704429$ `/* z value from deterministic model */`

$z.base_{stoch} = 1520779$ `/* z value from stochastic recourse model */`

`/* empty data frame for capturing deterministic instances */`

$r = data.frame(matrix(nrow = N, ncol = 3))$

`/* assigning column names for det df empty df for capturing stochastic instances */`

$r = setNames(r, c("zbase", "z", "r.instance"))$ `/* empty df for capturing stochastic instances */`

$r_{stochastic} = data.frame(matrix(nrow = N, ncol = 3))$ `/* assigning column names stochastic data frame(df) */`

$r_{stochastic} = setNames(r_{stoch}, c("zbase", "z", "r.instance"))$ `/* looping through N sampled observations */`

for m in 1:N **do**

`/* reading the totals unit items supplied per item type, stochastic and deterministic */` $q_{stochastic} = read.csv(file = "quantstoch.txt", header = F)$ $q_{det} = read.csv(file = "quant.txt", header = F)$ `/* loading minimum and maximum data for uniform distribution */`

`/* min values of the distribution */`

$mn = read.csv(file = "mn.csv")$

```
/* max values of my distribution */
mx = read.csv(file = "mx.csv")
/* empty df for no of affected people in 44 conflict areas */
s = data.frame(rep(0, nrow(mn)))/* empty df for demand calculation */
/* empty df for demand calculation ,need factor for calculating demand from stochastic
data frame) */
demand = data.frame(matrix(nrow = nrow(mn), ncol = length(l)))
/* renaming the columns for demand df) */
demand= data.frame(mapply('*',s, l))
/* empty df for demand calculation */
/* renaming the columns for demand df */
demand = setNames(demand, c("it1","it2","it3","it4","it5","it6"))

l = c(0.1, 1, 1, 0.05, 1, 0.1) /* need factor */
for (i in 1:nrow(mn)) do /* generating random number of people */
s[i, ] = runif(n = 1, min = mn[i, ], max = mx[i, ]
end for
for i in 1:nrow(mn) do
for k in 1:length(l)) do
/* demand calculation using need factor, such as 44 by 6 items */
demand[i, k] = s[i, ]l[k]
end for
end for
end for
/* Calculate recourse,where it is item */
z = sum(demand$it1)+sum(demand$it2)+sum(demand$it3)+sum(demand$it4)+sum(demand$it5)+
sum(demand$it6) − sum(q)
r$z[m] = sum(demand) − sum(q)
r_stochastic$z[m] = sum(demand) − sum(q_stochastic)
sum(demand$it1)+sum(demand$it2)+sum(demand$it3)+sum(demand$it4)+sum(demand$it5)+
sum(demand$it6)
r$zbase[m] = z.base
r_stochastic$zbase[m] = z.base_stochastic
if r$z[m] ≥ z.base) then
```

$r\$r.instance[m] = 0$

else

$r\$r.instance[m] = 1$

if $r_{stochastic}\$z[m] = z.base_{stochastic}$ **then**

$r_{stochastic}\$r.instance[m] = 0$

else

$r_{stochastic}\$r.instance[m] = 1$

end for

```
/* Calculate reliability                                                              */
```

$r\$r.instance$

$reliability = sum(r\$r.instance)/N100$

$z.det = 704429$

$z.rc = 1520779$

$min(r\$z)$ =0

The humanitarian supply chain prepositioning models simulation determines the number of affected people per conflict instance and, subsequently, the demand for every item type. The number of affected people is based on the random uniform distribution discussed in the stochastic model section. Using uniform distribution incorporates the uncertainty associated with the number of affected people. As discussed during the fitting distribution process, the number of affected people during a conflict is usually unpredictable; therefore, assuming a uniform distribution depicts equal chances of the affected people's number being in the range between minimum and maximum values of the distribution during the simulation process. As discussed in the stochastic demand distribution section, uniform distribution is among the most suitable distribution for conflicts as motivated by Beamon and Kotleba (2006c) and Beamon and Kotleba (2006a) because of the unpredictability of conflict occurrences and the resulting number of victims. The probability of victims being between the observed minimum and maximum is equal.

To ensure consistency with the conditions used in the two models, the resultant demand per simulated instance (m) was calculated using the need factor and the realised number of victims for the item types. Consistency here means that the models were compared on the same conditions for all the parameters of interest (budget, capacity, and x value). This was achieved by using the relationship $D_{ik}^m = l_k S_i^m$, such as the stochastic demand calculation. Last, a condition was introduced in the simulation model to ensure that the demand for the diverse item types from the various conflict areas could only be met using the prepositioned stock of the corresponding item type. For every m instance, reliability was calculated using a binary requirement where $instance = 1$ if the shortages realised from that instance were less than ones from the model results, and $instance = 0$ otherwise. $\sum_{I\epsilon\mathbf{i}} O_{ik} \leq z\ model$ then $instance = 1$, else $\sum_{I\epsilon\mathbf{i}} O_{ik} > z\ model\ instance = 0$ as illustrated in algorithm 5.4. The simulation was then run for the stochastic and deterministic models, and the results of the reliability tests involving N=100 instances are disclosed in Figure 5.6.

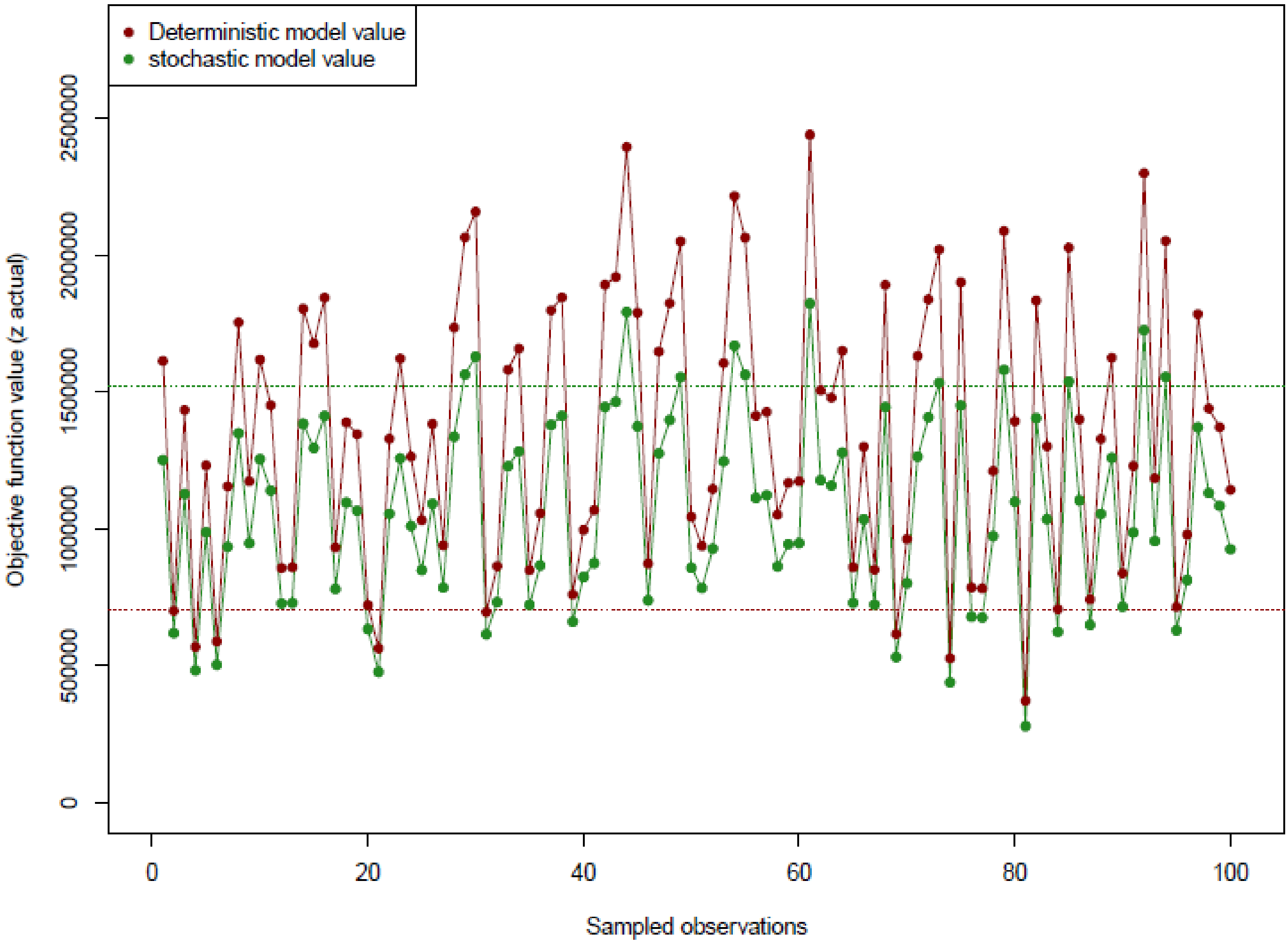


Figure 5.6: Reliability comparison of stochastic and deterministic models

From 100 instances, the reliability of the stochastic model was 88%, whereas that of the deterministic model was only 8%, a massive difference of 80%. From Figure 5.6, the difference in the reliability of the two models is obvious. As depicted, out of the 100 instances, only eight have shortage amounts less than the z base value for the deterministic model. This means that the deterministic model would be less reliable when the underlying level of uncertainty is high. Using the average demand to represent the expected demand when a conflict occurs is not ideal. Contrastingly, only 12 instances have shortage amounts greater than the z base value for the stochastic model-resulting in its higher reliability of 88%. It was expected that the stochastic model would have a higher reliability; however, the magnitude of the difference is interesting. It can be inferred that the vastness of the difference in the reliability of the two models is proportional to the wide range between the minimum and maximum values of affected people. This results in a huge variance which attenuates the repeatability of outcomes when using the average values in the deterministic model. The higher reliability of the stochastic model can be attributed to incorporating discretised data in the model solution. Referring to figure 5.6 again, most of the *z actual* values, which are shortage values for the simulation, are well below the value obtained from the model solution. This is because using the five bins in the recourse programme allows the model to overcompensate to reduce the penalty in this case, the shortage values.

5.5 Decision-making support based on the two models

Results from these models provide essential insights to decision-makers in the humanitarian supply chain. These insights include armed conflict response planning, risk, and cost attributes. The models enable decision-makers to gain crucial managerial insights to respond promptly to armed conflict disaster needs. They can evaluate and compare diverse options to achieve their main goals in CAR. These goals may include working with a limited budget, several LDCs, a certain level of acceptance of risk, desired response time, desired level of satisfaction for certain items and minimisation of shortages in general.

If humanitarian decision-makers are risk averse, there are costs associated with low levels of risk. In the CAR setting and because of the high frequency of conflicts, the risk is higher. The minimising risk would involve eliminating several potential LDC locations and causing widely spaced LDCs. The HOs would have to establish a higher number of LDCs to satisfy a certain demand of various conflict areas as desired unless there are exceptions. For instance, in this study, an exception was made for conflict regions with a population of over 500,000 people, provided the probability of conflict was less than 0.09. This is because the absence of LDCs in such populous regions would defeat the purpose of the model, that of providing aid to several victims while minimising the total time travelled. This resulted in Bangui being selected as a distribution centre. Because of the widely spaced LDCs, HOs can expect a huge proportion of the budget to be used for relief items distribution. It is, therefore, the onus of the decision-makers to determine their acceptable risk level as it influences all the other outputs of the prepositioning models. This way ensures a balance between the available budget and acceptable response time

The models would enable decision-makers to predetermine LDCs capacity, locations and LDC-conflict areas assignment based on their organisation's risk tolerance, budget limitation, and priority items proportions. As evidenced in the results of this study, shortages changed significantly by increasing the budget from $20,200,000 to $2,828,000. Similarly, resulting travel times and shortages changed depending on the available capacity and the specified p-value of the priority items. Because LDC-conflict area assignment also changed based on the prevailing change in variables, decision-makers can use these parameters to choose the desired locations depending on the prevailing circumstances. The models provide a dynamic and systematic approach by evaluating deterministic and nondeterministic settings using a combination of key decision-influencing factors. This systematic approach would allow various humanitarian practitioners to determine which level of risk, locations, assignments, and inventory stocking locations would suit their specific goals. It, therefore, enables efficient network design and planning while assessing the resulting performance.

Incorporating facility locations with inventory stocking provides relief practitioners with an avenue for tactical and strategic decisions. Establishing LDCs, especially for conflict areas with close to non-existent infrastructure, involves a long-term and, therefore, a strategic decision. To finalise such decisions, relief practitioners must evaluate various scenarios and perform sensitivity analyses on their most dynamic factors. Inventory stocking locations are determined after establishing LDCs; therefore, they can be updated and re-optimised afterwards when making tactical decisions. By determining the optimal location of relief items, the model can also indirectly help humanitarian practitioners with other humanitarian relief supply chain decisions. These decisions include attributes disregarded in this model, such as procurement and sourcing of relief inventory. For instance, because the model considers multiple items, managers can decide where to source certain items based on proximity, transportation, and capacity. This is helpful for HOs because they can prepare by establishing a long-term relationship with suppliers, mostly by establishing agreements.

Last, from the model results and test runs, budget limitation affects most objectives associated with disaster response significantly. For instance, it was infeasible to supply certain proportions of priority items when the budget was below a certain amount, even before total response time minimisation could occur. This implies not only that HOs must plan but also must include post-disaster planning when allocating funds for any disaster response in the initial planning. For any expeditious, effective, and efficient disaster response, HOs must not plan for the post-disaster in isolation or at later stages. Preparedness is key for the pre-disaster and post-disaster phases and can be achieved by performing various sensitivity and scenario analyses supported by the models.

5.6 Concluding remarks

The full modification of the deterministic model to incorporate uncertain elements in prepositioning modelling for conflict areas is conducted in this chapter. This was achieved by following the steps for the deterministic model as stipulated in Chapter 3 while adjusting certain elements as required. The adjusting involved the introduction of stochastic elements brought about by uncertain data inputs-which was attributed to the unpredictable number of affected people. After introducing the stochastic elements, a recourse problem was developed and solved. The stochastic model was executed in the same base conditions while investigating the influence of budget, capacity, and x value variation to ensure the comparison was even. Performing the SPM was compared to the DPM while documenting the major similarities and differences. The drivers of the similarities and differences were then interpreted. It was determined that even though the SPM resulted in a better demand estimation, the associated budget was higher. This was attributed to the additional items arising from the overcompensation of the number of affected by the stochastic model, which had a direct influence on increasing the resultant demand.

The last part of this chapter involves the reliability testing of the two models. It was determined that the stochastic model has a higher reliability of 88% compared to 8% for the deterministic model. It was also deduced that this is owing to the stochastic demand being 17.6% higher than the deterministic demand. The use of the two models as a device for decision-making by HO organisations was narrowed down to two main elements such as risk aversion and model preference. The buffer RI realised by the SPM would involve more cost than the deterministic model, as discussed in the decision-making support section. The subsequent chapter presents the conclusions based on the results from Chapters 4 and 5 while elaborating on the realisation of objectives set in the preceding chapters.

Chapter 6

Conclusion

This study aimed to approach the primary research question,*how can relief inventory be managed effectively in the CAR during humanitarian operations?* To answer this, three secondary research questions were formulated. The first secondary question sought to approach the characterisation of inventory management problems in a disaster setting. This was conducted by categorising these challenges into supply chain phases sourcing, warehousing, distribution, and transportation. A comparison with commercial logistics illustrated the uniqueness of humanitarian logistics challenges. It is revealed that the main challenges of humanitarian logistics are tied to the complex and uncertain nature of disaster settings, which precludes using existing knowledge from the commercial logistics counterparts.

The second secondary research question sought to identify the inventory management challenges approached by OR models in the pre-disaster and post-disaster phases. To answer this, problem aspects considered by various models were broadly categorised into stakeholders, disaster type, demand characteristics, facility considerations, measures of performance, planning period, and decision-making. For each of these problematic aspects, a systematic literature review of numerous studies was conducted approaching each problem aspect in the pre-disaster and post-disaster phases. Gaps in these OR models regarding aspects considered in their formulation and regional areas of implementation were then identified. It is observed that most of these studies are focused on North America modelling for hurricanes and earthquakes. Limited studies are approaching conflicts and, concernedly, only a meagre in the African context. A lack of an integrated approach considering the pre- and post-disaster phases coupled with simulation and sensitivity of various disaster scenarios is missing. This is crucial in the CAR region plagued by conflicts where infrastructure, such as roads leading to conflict areas, is nearly non-existent. This led to the last secondary research question, which improvements can be made to improve the practicality gap? To answer this, Gap

1 was approached while including certain aspects from Gap 2 by OR modelling for RI management modelling with CAR as the case study environment. Gap 1 entailed investigating how relief inventory can be effectively managed during armed conflicts in the affected area by using an integrated approach. The integrated approach incorporated the prepositioning planning and the post-disaster phase of aid delivery while accounting for various forms of destruction, such as routes, facilities, and inventory in Africa. Conversely, Gap 2 is concerned with incorporating equity objectives in the model to investigate its effect on stocked inventory and facility location. The study model relied on three main aspects of the integrated approach, such as a critical review to understand the gaps and shortcomings of existing models, followed by the subsequent development and simulation of instances to improve on the shortcomings. This was because even though Davis et al. (2013) and Noyan (2012) included equitability in their constraints, it was not through an integrated approach.

To formulate the model for the CAR setting, the model background and the RI flow from the CW to the affected area are described while identifying the data required for each stage. Identifying the conflict assisted in determining the potential location for the CW and various LDCs required for disaster response. The CW is based in the country with the highest stability ranking, whereas the LDCs locations were confirmed by model runs aimed at minimising shortages and total time travelled, ensuring equitability of the selected priority items. For efficient distribution, applicable modes of transport were considered to ensure aid reaches the victims and modelled for the same. Last, the parameters of interest were evaluated and varied, such as budget, capacity, and the x value of priority items for the deterministic and stochastic models under the same conditions. They were then analysed to determine the influence of changes in these parameters on the performance measures, including costs, reliability, risk, and decision-making. The reliability of the SPM was determined at 88%, whereas that of the DPM was only 8%—a difference attributed to overcompensation of uncertainty by the SPM model.

Results indicate that both models were sensitive to changing parameters. Results analyses confirm that the models can add value to humanitarian organisations when planning facility locations, inventory prepositioning and conflict area-distribution centre assignments in DRC and CAR. This study, therefore, contributes to the body of knowledge and humanitarian organisations in Africa. By extension, fundamental insights for decision-makers in the humanitarian setting were deduced. The primary managerial insights deductions would provide the guidelines required to respond promptly to armed conflict disaster needs by allowing managers to evaluate and compare various options to achieve their main goals in CAR and similar conflict settings. These goals may include working with a limited budget, several LDCs, a certain level of acceptance of risk, desired response time, desired level of satisfaction for certain items and minimisation of shortages

Last, this study has notable scientific contributions. First, it incorporates using an integrated approach when approaching problems in a humanitarian setting, as demonstrated by reviewing previous scientific works while identifying several models and their limitations. The integrated approach incorporated the prepositioning planning and the post-disaster phase of aid delivery while accounting for various forms of destruction. These forms include routes, facilities, and inventory in Africa. Based on the limitations, it was possible to devise a solution approach to approach some limitations in an integrated manner. The model provides an important foundation for future multi-objective programming stochastic inventory management challenges that can be approached depending on the situation and case study environment; however, implementing the mathematical models and stochastic interventions were only applied to a certain extent. For instance, the model reliability calculation was based on simulated situations. Scientific works can adopt these models and implement them to evaluate all the parameters to determine the actual performance.

6.1 Future work research

This study considered prepositioning inventory modelling in a poor road network setting. Despite the approach using the actual road network to enhance the model's practicality, some aspects were simplified through some assumptions. The assumption of military trucks where roads are inaccessible can be removed to incorporate the option of multi-modal last-mile distribution. This would entail splitting the distribution routes into sections based on the road conditions and subsequently matching the sections with the best mode of transport. The means that can be included are animals, motorbikes, and air transport. This approach would improve the reliability of the models by ensuring uninterrupted aid distribution even when certain sections are blocked owing to ongoing conflicts or ambushes.

Adequate accommodations were made to incorporate the cost-influencing parameters for the transportation and distribution centres' establishment costs. Future modelling can explore quantifying the specific cost influence of existing collaborations between the government and HOs.

Last, there is an opportunity to use the proposed models as a foundation to improve the solution process in armed conflict settings. Goal programming, among other multi-objective intervention approaches, should be investigated for comparison purposes. To achieve this, the modellers must devise a standard procedure for quantifying the total time travelled goal by HOs. After devising the quantification procedure, chance-constrained intervention for stochastic modelling should incorporate the confidence expectations of certain parameters as desired by HOs. This study considered a case study location involving 44 conflict areas and 24 potential distribution centre locations. It was possible to solve the models using the academic version of the solver software; however, if more demand points were involved, it would become impractical and computationally expensive to solve using the solver software; therefore, the solution process for large-scale settings can be improved by developing an efficient algorithm. This study approached the set-out objectives.

6.2 Contribution of the study to literature

This study developed and assessed deterministic and stochastic prepositioning models for relief inventory while deriving insights for HO strategic decision-making process as a solution to some gaps inadequately investigated in the African context. No previous studies attempted to implement risk and demand uncertainty while modelling for a cross-border conflict setting. This study contributes to humanitarian operations towards a more efficient relief distribution to victims of historical conflicts. The study attempted to build on this work to improve application and implementation of humanitarian inventory propositioning models.

In summary, it provided the necessary information required to explore innovative and practical methods of optimising inventory management, and planning for conflicts through prepositioning. The existing research divergence has been bridged by this study, with the main contribution being in pre- and post-disaster planning. In the pre-disaster phase, proactive ways of improving inventory prepositioning have been identified, while in the post-disaster phase, proactive strategic decisions based on scenario outcomes have been provided. The significance of this contribution lies in enabling HOs to respond to armed conflicts within a shorter time by providing guidelines on crucial phases of disaster response, including need assessment, aid deployment, sustainment, and reconfiguration, conducted in shorter lead times, with the largest potential improvement being in the deployment phase. By improving efficiency in the distribution of relief to victims of historical conflicts, this study contributes to humanitarian operation efforts and has the potential to reduce the impoverishment and suffering of victims by increasing timely access to basic services when desperately needed.

Bibliography

ACLED (2021). https://acleddata.com/dashboard/#/dashboard/Middle-Africa [Accessed: 20th June 2021].

Adiguzel, S. (2019). Logistics management in disaster. *Journal of Management Marketing and Logistics*, 6(4):212–224.

Akamo, J. O. (2021). The democratic republic of congo (drc) conflict insights.

Altay, N. and Green III, W. G. (2006). Or/ms research in disaster operations management. *European journal of operational research*, 175(1):475–493.

Balcik, B. and Beamon, B. M. (2008). Facility location in humanitarian relief. *International Journal of logistics*, 11(2):101–121.

Balcik, B., Bozkir, C. D. C., and Kundakcioglu, O. E. (2016). A literature review on inventory management in humanitarian supply chains. *Surveys in Operations Research and Management Science*, 21(2):101–116.

Barzinpour, F. and Esmaeili, V. (2014). A multi-objective relief chain location distribution model for urban disaster management. *The International Journal of Advanced Manufacturing Technology*, 70(5):1291–1302.

Bastos, M. A. G., Campos, V. B. G., and de Mello Bandeira, R. A. (2014). Logistic processes in a post-disaster relief operation. *Procedia-Social and Behavioral Sciences*, 111:1175–1184.

Beamon, B. M. and Kotleba, S. A. (2006a). Inventory management support systems for emergency humanitarian relief operations in south sudan. *The International Journal of Logistics Management*.

Beamon, B. M. and Kotleba, S. A. (2006b). Inventory modelling for complex emergencies in humanitarian relief operations. *International Journal of Logistics: research and applications*, 9(1):1–18.

Beamon, B. M. and Kotleba, S. A. (2006c). Inventory modelling for complex emergencies in humanitarian relief operations. *International Journal of Logistics: research and applications*, 9(1):1–18.

Bechtel, G. A., Hansberry, A. H., and Gray-Brown, D. (2000). Disaster planning and resource allocation in health services. *Hospital Materiel Management Quarterly*, 22(2):9–17.

Bozorgi-Amiri, A., Jabalameli, M. S., and Mirzapour Al-e Hashem, S. (2013). A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty. *OR spectrum*, 35(4):905–933.

Brito, T. B., dos Santos Silva, R. C., Trevisan, E. F. C., and Botter, R. C. (2012). Discrete event simulation combined with multiple criteria decision analysis as a decision support methodology in complex logistics systems. In *Discrete event simulations-development and applications*. IntechOpen.

Campbell, A. M. and Jones, P. C. (2011). Prepositioning supplies in preparation for disasters. *European Journal of Operational Research*, 209(2):156–165.

Çankaya, E., Ekici, A., and Özener, O. Ö. (2019). Humanitarian relief supplies distribution: An application of inventory routing problem. *Annals of Operations Research*, 283(1):119–141.

Carson, J. S. (2002). Model verification and validation. In *Proceedings of the winter simulation conference*, volume 1, pages 52–58. IEEE.

CFR (2021). https://www.cfr.org/global-conflict-tracker/conflict/violence-central-african-republic [Accessed: 20th August 2021].

Chakravarty, A. K. (2014). Humanitarian relief chain: Rapid response under uncertainty. *International Journal of Production Economics*, 151:146–157.

Chong, M., Lazo, J. G. L., Pereda, M. C., and De Pina, J. M. M. (2019). Goal programming optimization model under uncertainty and the critical areas characterization in humanitarian logistics management. *Journal of humanitarian logistics and supply chain management*.

Das, R. and Hanaoka, S. (2014). Relief inventory modelling with stochastic lead-time and demand. *European Journal of Operational Research*, 235(3):616–623.

Davis, L. B., Samanlioglu, F., Qu, X., and Root, S. (2013). Inventory planning and coordination in disaster relief efforts. *International Journal of Production Economics*, 141(2):561–573.

Döyen, A., Aras, N., and Barbarosoğlu, G. (2012). A two-echelon stochastic facility location model for humanitarian relief logistics. *Optimization Letters*, 6(6):1123–1145.

Duran, S., Gutierrez, M. A., and Keskinocak, P. (2011). Pre-positioning of emergency items for care international. *Interfaces*, 41(3):223–237.

ECHO (2016). Syrian crisis. *European Commission's Humanitarian Aid and CivilProtection*.

Elçi, Ö., Noyan, N., and Bülbül, K. (2018). Chance-constrained stochastic programming under variable reliability levels with an application to humanitarian relief network design. *Computers & Operations Research*, 96:91–107.

EM-DAT (2021). https://www.emdat.be/ [Accessed: 10th July 2021].

Fu, M., Gross, D., Wu, J., and Wei, R. (2013). Simulation of stochastic discrete-event systems. *Encyclopedia of Operations Research and Management Science*, pages 1410–1418.

Galindo, G. and Batta, R. (2013). Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies. *Socio-Economic Planning Sciences*, 47(1):20–37.

Garrido, R. A., Lamas, P., and Pino, F. J. (2015). A stochastic programming approach for floods emergency logistics. *Transportation research part E: logistics and transportation review*, 75:18–31.

Günay, E. E., Park, K., Kandukuri, S., and Kremer, G. E. O. (2019). Facility location selection for the humanitarian needs of refugees. In *IIE Annual Conference. Proceedings*, pages 952–957. Institute of Industrial and Systems Engineers (IISE).

Gutjahr, W. J. and Nolz, P. C. (2016). Multicriteria optimization in humanitarian aid. *European Journal of Operational Research*, 252(2):351–366.

HDX (2021). *Central African Republic: Displacement Data - Baseline Assessment* . https://data.humdata.org/dataset/car-baseline-assessment-data-iom-dtm [Accessed: 15th July 2021].

Higle, J. L. (2005). Stochastic programming: optimization when uncertainty matters. In *Emerging theory, methods, and applications*, pages 30–53. Informs.

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L. N., and Aros-Vera, F. (2013). On the appropriate objective function for post-disaster humanitarian logistics models. *Journal of Operations Management*, 31(5):262–280.

Hong, X., Lejeune, M. A., and Noyan, N. (2015). Stochastic network design for disaster preparedness. *IIE Transactions*, 47(4):329–357.

Humdata (2021). https://data.humdata.org/dataset/ucdp-data-for-democratic-republic-of-the-cong [Accessed: 17th August 2021].

IDMC (2020). *Global Internal Displacement Database* . https://www.internal-displacement.org/database/displacement-data [Accessed: 20th Jan 2022].

Jozefowiez, N., Semet, F., and Talbi, E.-G. (2008). Multi-objective vehicle routing problems. *European journal of operational research*, 189(2):293–309.

Karlsrud, J. (2015). United nations mission in the central african republic and chad i and ii (minurcat i and ii). In *The Oxford Handbook of United Nations Peacekeeping Operations*.

Knox Clarke, P. and Campbell, L. (2020). Decision-making at the sharp end: a survey of literature related to decision-making in humanitarian contexts. *Journal of International Humanitarian Action*, 5(1):1–14.

Kovacs, G. and Moshtari, M. (2019). A roadmap for higher research quality in humanitarian operations: A methodological perspective. *European Journal of Operational Research*, 276(2):395–408.

Kovács, G. and Spens, K. (2009). Identifying challenges in humanitarian logistics. *International Journal of Physical Distribution & Logistics Management*.

Kunz, N. and Reiner, G. (2012). A meta-analysis of humanitarian logistics research. *Journal of Humanitarian Logistics and Supply Chain Management*.

Lambert, D. M., García-Dastugue, S. J., and Croxton, K. L. (2008). The role of logistics managers in the cross-functional implementation of supply chain management. *Journal of business logistics*, 29(1):113–132.

Lee, W.-S., Kim, B. S., and Opit, P. F. (2014). A stock pre-positioning model to maximize the total expected relief demand of disaster areas. *Industrial Engineering and Management Systems*, 13(3):297–303.

Li, C. and Grossmann, I. E. (2021). A review of stochastic programming methods for optimization of process systems under uncertainty. *Frontiers in Chemical Engineering*, page 34.

Liberatore, F., Pizarro, C., Blas, C., Ortuño, M., and Vitoriano, B. (2013). Uncertainty in humanitarian logistics for disaster management. a review. In *Decision aid models for disaster management and emergencies*, pages 45–74. Springer.

Lillis, A. (2006). Reliability and validity in field study research. *Methodological issues in accounting research: Theories and methods*, pages 461–475.

Lindo (2022). https://www.lindo.com/doc/online_help/lingo15_0/model_generation.htm [Accessed: 20th June 2021].

Lodree Jr, E. J., Ballard, K. N., and Song, C. H. (2012). Pre-positioning hurricane supplies in a commercial supply chain. *Socio-Economic Planning Sciences*, 46(4):291–305.

Lodree Jr, E. J. and Taskin, S. (2009). Supply chain planning for hurricane response with wind speed information updates. *Computers & Operations Research*, 36(1):2–15.

LogisticsCluster (2021). https://logcluster.org/ops/caf13a [Accessed: 20th June 2021].

Loree, N. and Aros-Vera, F. (2018). Points of distribution location and inventory management model for post-disaster humanitarian logistics. *Transportation Research Part E: Logistics and Transportation Review*, 116:1–24.

Mete, H. O. and Zabinsky, Z. B. (2010). Stochastic optimization of medical supply location and distribution in disaster management. *International Journal of Production Economics*, 126(1):76–84.

Mohajan, H. (2017). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University Economics Series*, (4).

Mohammadi, R., Ghomi, S. F., and Jolai, F. (2016). Prepositioning emergency earthquake response supplies: A new multi-objective particle swarm optimization algorithm. *Applied Mathematical Modelling*, 40(9-10):5183–5199.

Mpita, S. N., Yadavalli, V. S., and Bean, W. L. (2016). Integrated facility location planning and demand assessment for humanitarian logistics: a case study in the democratic republic of the congo. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, 25(1):34–50.

Munyaka, J.-C. B. and Yadavalli, V. S. S. (2021). Using transportation problem in humanitarian supply chain to prepositioned facility locations: a case study in the democratic republic of the congo. *International Journal of System Assurance Engineering and Management*, 12(1):199–216.

Noyan, N. (2012). Risk-averse two-stage stochastic programming with an application to disaster management. *Computers & Operations Research*, 39(3):541–559.

Noyan, N., Balcik, B., and Atakan, S. (2016). A stochastic optimization model for designing last mile relief networks. *Transportation Science*, 50(3):1092–1113.

Ozguven, E. E. and Ozbay, K. (2013). A secure and efficient inventory management system for disasters. *Transportation research part C: emerging technologies*, 29:171–196.

Paul, J. A. and MacDonald, L. (2016). Location and capacity allocations decisions to mitigate the impacts of unexpected disasters. *European Journal of Operational Research*, 251(1):252–263.

Rabbani, M., Manavizadeh, N., Samavati, M., and Jalali, M. (2015). Proactive and reactive inventory policies in humanitarian operations. *Uncertain Supply Chain Management*, 3(3):253–272.

Ransikarbum, K. and Mason, S. J. (2016). Goal programming-based post-disaster decision making for integrated relief distribution and early-stage network restoration. *International Journal of Production Economics*, 182:324–341.

Rardin, R. L. (1998). *Optimization in operations research*, volume 166. Prentice Hall Upper Saddle River, NJ.

Rath, S., Gendreau, M., and Gutjahr, W. J. (2016). Bi-objective stochastic programming models for determining depot locations in disaster relief operations. *International Transactions in Operational Research*, 23(6):997–1023.

Rawls, C. G. and Turnquist, M. A. (2010). Pre-positioning of emergency supplies for disaster response. *Transportation research part B: Methodological*, 44(4):521–534.

Rawls, C. G. and Turnquist, M. A. (2011). Pre-positioning planning for emergency response with service quality constraints. *OR spectrum*, 33(3):481–498.

Renkli, Ç. and Duran, S. (2015). Pre-positioning disaster response facilities and relief items. *Human and Ecological Risk Assessment: An International Journal*, 21(5):1169–1185.

Roh, S.-y., Jang, H.-m., and Han, C.-h. (2013). Warehouse location decision factors in humanitarian relief logistics. *The Asian Journal of Shipping and Logistics*, 29(1):103–120.

Ruszczyński, A. and Shapiro, A. (2003). Stochastic programming models. *Handbooks in operations research and management science*, 10:1–64.

Safeer, M., Anbuudayasankar, S., Balkumar, K., and Ganesh, K. (2014). Analyzing transportation and distribution in emergency humanitarian logistics. *Procedia Engineering*, 97:2248–2258.

Sahinidis, N. V. (2004). Optimization under uncertainty: state-of-the-art and opportunities. *Computers & Chemical Engineering*, 28(6-7):971–983.

Salas, L. C., Cárdenas, M. R., and Zhang, M. (2012). Inventory policies for humanitarian aid during hurricanes. *Socio-Economic Planning Sciences*, 46(4):272–280.

Sargent, R. G. (2013). An introduction to verification and validation of simulation models. In *2013 Winter Simulations Conference (WSC)*, pages 321–327. IEEE.

Serrato-Garcia, M. A., Mora-Vargas, J., and Murillo, R. T. (2016). Multi objective optimization for humanitarian logistics operations through the use of mobile technologies. *Journal of Humanitarian Logistics and Supply Chain Management*.

Seshadri, S. and Subrahmanyam, M. (2005). Introduction to the special issue on risk management in operations “. *Production and Operations Management*, 14(1):1–4.

Shehadeh, K. S. and Tucker, E. L. (2022). Stochastic optimization models for location and inventory prepositioning of disaster relief supplies. *Transportation Research Part C: Emerging Technologies*, 144:103871.

Shen, Z., Dessouky, M., and Ordóñez, F. (2011). Perishable inventory management system with a minimum volume constraint. *Journal of the Operational Research Society*, 62(12):2063–2082.

Taskin, S. and Lodree Jr, E. J. (2010). Inventory decisions for emergency supplies based on hurricane count predictions. *International Journal of Production Economics*, 126(1):66–75.

Tian, X., Liao, H., and Pcng, X. (2018). A bio-objective location-inventory model for pre-disaster humanitarian logistics. In *2018 37th Chinese Control Conference (CCC)*, pages 2156–2160. IEEE.

Tofighi, S., Torabi, S. A., and Mansouri, S. A. (2016). Humanitarian logistics network design under mixed uncertainty. *European Journal of Operational Research*, 250(1):239–250.

UNHCR (2021). https://emergency.unhcr.org/REST-portlet/downloadEntries/format/pdf?id=32948 [Accessed: 25th August 2021].

UNOCHA (2021). Central africa situation report. Technical report, UN.

Van Wassenhove, L. N. (2006). Humanitarian aid logistics: supply chain management in high gear. *Journal of the Operational research Society*, 57(5):475–489.

Van Wyk, E., Yadavalli, V., and Bean, W. (2011). Strategic inventory management for disaster relief. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, 20(1):32–41.

Vitoriano, B., Ortuño, M. T., Tirado, G., and Montero, J. (2011). A multi-criteria optimization model for humanitarian aid distribution. *Journal of Global optimization*, 51(2):189–208.

Wang, H., Du, L., and Ma, S. (2014). Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake. *Transportation Research Part E: Logistics and Transportation Review*, 69:160–179.

WFP (2021). https://www.wfp.org/countries/democratic-republic-congo [Accessed: 14th July 2021].

Whybark, D. C. (2007). Issues in managing disaster relief inventories. *International journal of production economics*, 108(1-2):228–235.

Yadavalli, V. S., Sundar, D. K., and Udayabaskaran, S. (2015). Two substitutable perishable product disaster inventory systems. *Annals of Operations Research*, 233(1):517–534.

Ye, Y., Jiao, W., and Yan, H. (2020). Managing relief inventories responding to natural disasters: Gaps between practice and literature. *Production and Operations Management*, 29(4):807–832.

Ye, Y. and Yan, H. (2020). Disaster relief supply management. In *Natural Hazards-Impacts, Adjustments and Resilience*, page 13. IntechOpen.

Zhang, J., Dong, M., and Chen, F. F. (2013). A bottleneck steiner tree based multi-objective location model and intelligent optimization of emergency logistics systems. *Robotics and Computer-Integrated Manufacturing*, 29(3):48–55.

Appendix A

Table 6.1: Distances between potential LDC locations and Conflict areas in kilometres

	LDC candidate											
Conflict Area	1	2	3	4	5	6	7	8	9	10	11	12
	Bangui	Kembe	Mobaye	Zangba	Ouadda	Yalinga	Bakouma	Gambo	Ouango	Mbres	Bakala	Grimari
Bangui	0	601	600	572	788	745	855	651	710	403	376	298
Alindao	494	107	106	122	469	426	362	157	216	281	185	197
Kembe	601	0	135	175	576	533	254	50,8	109	388	291	304
Mobaye	600	135	0	79	636	532	390	186	244	387	291	303
Zangba	532	175	79	0	592	548	430	225	284	374	307	235
Bria	584	371	370	386	205	164	626	421	480	294	195	287
Ouadda	788	576	575	592	0	369	831	627	685	498	400	491
Yalinga	747	533	532	548	369	0	788	583	642	457	359	450
Obo	1223	623	758	798	1199	1156	625	572	631	1011	914	927
Zemio	1020	419	554	593	995	951	421	368	426	807	710	723
Bakouma	856	255	390	430	831	788	0	204	262	643	546	559
Bangassou	728	127	262	301	703	659	128	76	134	515	418	431
Gambo	652	51	186	225	627	583	204	0	58	439	342	355
Ouango	710	109	244	284	685	642	262	58,3	0	497	401	413
Rafai	870	269	405	444	845	802	271	219	277	658	561	573
Kaga-Bandoro	332	524	480	455	591	550	736	532	590	92,8	192	221
Mbres	403	388	387	374	498	457	643	439	497	0	99	140

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Table 6.1 – continued from previous page

	LDC candidate											
Bakala	376	291	291	307	400	359	546	342	401	98,8	0	80
Bambari	377	225	224	241	412	370	480	276	334	164	67	80
Grimari	298	304	303	235	491	450	559	355	413	140	80	0
Ippy	487	336	335	351	301	260	591	387	445	198	99	190
Kouango	403	303	207	129	547	506	558	354	412	246	185	106
Batangafo	488	593	592	567	703	662	848	644	702	205	304	333
Bouca	284	642	543	475	731	690	799	595	653	254	319	241
Markounda	445	788	787	719	975	934	1043	839	897	389	488	485
Bocaranga	500	939	938	869	1126	1085	1193	989	1048	610	714	635
Koui	562	1149	1013	944	1201	1159	1268	1064	1122	723	789	710
Ngaoundaye	602	973	975	876	1133	1092	1200	996	1055	655	921	642
Paoua	479	823	822	753	1010	969	1078	874	932	532	598	519
Djugu	2212	1612	1747	1786	2187	2144	1613	1561	1619	2000	1903	1915
Irumu	2058	1457	1593	1632	2033	1990	1459	1406	1465	1845	1749	1761
Mambasa	1948	1347	1482	1522	1923	1880	1349	1246	1355	1735	1639	1651
Beni	2084	1483	1619	1658	2059	2016	1485	1433	1491	1871	1775	1787
Lubero	2178	1577	1713	1752	2153	2110	1579	1527	1585	1965	1869	
Masisi	2053	1452	1587	1627	2028	1985	1454	1401	1460	1840	1744	1756
Rutshuru	2202	1601	1736	1776	2177	2134	1603	1550	1609	1989	1892	1905

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Table 6.1 – continued from previous page

	LDC candidate											
Walikale	1902	45	1436	1475	1877	1833	1303	1250	1308	1689	1592	1605
Fizi	2370	1769	1904	1944	2345	2301	1771	1718	1776	2157	2060	2073
Kabare	2118	1517	1652	1691	2092	2049	1518	1466	1524	1905	1808	1821
Kalehe	2134	1533	1668	1708	2109	2065	1535	1482	1540	1921	1824	1837
Mwenga	2240	1639	1775	1814	2215	2172	1641	1589	1647	2028	1931	1943
Shabunda	2284	1683	1818	1858	2259	2216	1685	1632	1691	2071	1974	1987
Uvira	2244	1643	1778	1818	2219	2196	1645	1592	1650	2031	1934	1947
Walungu	2163	1562	1697	1737	2138	2095	1564	1511	1570	1950	1853	1866

Table 6.2: Distances between potential LDC locations and Conflict areas in Kilometres

	LDC cand											
Conflict Area	13	14	15	16	17	18	19	20	21	22	23	24
	Bouca	Markounda	Koui	Ngaoun	Irumu	Mambasa	Lubero	Kabare	Mwenga	Shabunda	Uvira	Walungu
Bangui	284	445	562	602	2058	1948	2178	2118	2241	2283	2244	2163
Alindao	437	681	856	839	1564	1454	1684	1623	1746	1790	1750	1669
Kembe	642	788	1149	973	1458	1347	1578	1517	1640	1683	1643	1562
Mobaye	543	787	1013	945	1593	1483	1713	1652	1775	1818	1778	1697
Zangba	475	719	944	876	1632	1522	1752	1691	1814	1858	1818	1737
Bria	527	771	996	928	1828	1718	1948	1887	2010	2054	1238	1933
Ouadda	731	975	1201	1133	2033	1923	2153	2093	2215	2259	2219	2138
Yalinga	690	934	1159	1091	1990	1880	2110	2049	2172	2216	2175	2095
Obo	1167	1411	1636	1569	1124	1014	1244	1878	2009	2635	2012	1931
Zemio	963	1207	1432	1364	1329	1219	1449	1682	1805	1848	1808	1727
Bakouma	799	1043	1268	1200	1381	1349	1579	1519	1641	1685	1645	1564
Bangassou	671	915	1140	1072	1331	1221	1451	1390	1513	1557	1517	1436
Gambo	595	839	1064	996	1407	1297	1527	1466	1589	1632	1592	1511
Ouango	653	897	1123	1055	1465	1355	1585	1524	1647	1691	1650	1570
Rafai	814	1057	1283	1215	1473	1363	1593	1533	1921	1699	1659	1578
Kaga-Bandoro	207	296	560	493	1938	1828	2058	1998	2120	2164	2124	2043
Mbrès	254	389	723	655	1846	1735	1966	1905	2028	2071	2031	1950

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Table 6.2 – continued from previous page

	LDC cand											
Bakala	319	488	789	721	1749	1639	1869	1808	1931	1975	1934	1854
Bambari	320	564	789	721	1683	1572	1803	1742	1865	1908	1868	1787
Grimari	241	485	710	642	1761	1651	1881	1821	1943	1987	1947	1866
Ippy	430	674	900	832	1793	1683	1913	1852	1975	2019	1979	1898
Kouango	346	590	815	748	1761	1651	1881	1820	1943	1986	1946	1865
Batangafo	95	185	450	382	2051	1940	2171	210	2233	2276	2236	2155
Bouca	0	244	469	401	2002	1891	2122	2061	2184	2227	2187	2106
Markounda	244	0	396	328	2245	2135	2366	2305	2427	2471	2431	2350
Bocaranga	394	322	75	70	2396	2286	2516	2455	2578	2622	2581	2501
Koui	469	396	0	144	2471	2361	2591	2530	2653	2697	2656	2575
Ngaoundaye	401	328	144	0	2403	2293	2523	2462	2585	2629	2588	2508
Paoua	279	206	195	127	2280	2459	2400	2339	2462	2506	2466	2385
Djugu	2156	2399	2625	2557	136	248	373	1396	1519	1563	1013	1442
Irumu	2001	2245	2471	2403	0	112	238	1261	1383	1427	877	1306
Mambasa	1891	2135	2361	2293	112	0	231	1149	1272	1316	1275	1194
Beni	2027	2271	2497	2429	140	137	99	545	668	1453	774	591
Lubero	2121	2365	2591	2523	237	231	0	493	571	1547	574	494
Masisi	1996	2240	2466	2398	577	571	341	224	347	936	350	270
Rutshuru	2145	2389	2614	2546	427	421	192	256	379	726	382	301

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Table 6.2 – continued from previous page

	LDC cand											
Walikale	1845	2089	2314	2246	1045	933	492	216	339	784	342	261
Fizi	2313	2557	2782	2714	1030	1401	700	257	359	656	126	281
Kabare	2061	2305	2530	2462	1261	1149	448	0	128	475	131	50
Kalehe	2077	2321	2546	2478	622	616	386	63	185	532	189	108
Mwenga	2184	2427	2653	2585	1383	1272	571	128	0	347	233	78
Shabund	2227	2471	2696	2629	1427	1316	1547	475	346	0	580	424
Uvira	2187	2431	2656	2588	877	1275	574	131	233	580	0	155
Walungu	2106	2350	2575	2508	1306	1194	493	50	78	424	155	0

Table 6.3: Estimated travel times between potential LDC locations and Conflict areas in hours

	LDC candidate											
Conflict Area	1	2	3	4	5	6	7	8	9	10	11	12
	Bangui	Kembe	Mobaye	Zangba	Ouadda	Yalinga	Bakouma	Gambo	Ouango	Mbres	Bakala	Grimari
Bangui	0	8	8,5	7,8	11,5	11,8	12,3	8,7	9,8	5,4	5,4	4,1
Alindao	6,9	1,3	1,6	1,8	6,9	7	5,5	1,9	2,9	4,3	2,8	2,8
Kembe	8	0	1,9	2,5	8,2	8,3	4,2	0,5	1,5	5,5	4	4,1
Mobaye	8,5	1,9	0	1,3	8,5	8,4	6	2,5	3,5	6	4,3	4,4
Zangba	7,8	2,5	1,3	0	8,8	8,9	6,6	3	4	6,1	4,5	3,8
Bria	8,5	5,2	5,5	5,8	3	3,3	9,3	5,8	6,8	4,9	3,2	4,5
Ouadda	11,5	8,2	8,5	8,8	0	6,3	12,3	8,8	9,8	7,9	6,2	7,5
Yalinga	11,8	8,3	8,4	8,9	6,3	0	12,5	8,9	9,9	8,1	6,3	7,7
Obo	15,8	7,7	9,6	10,1	15,9	16	9	7,1	8,1	13,3	11,7	11,9
Zemio	13,6	5,5	7,3	7,9	13,6	13,8	6,7	4,9	5,9	11,1	9,5	9,5
Bakouma	12,3	4,2	6,4	6,6	12,3	12,5	0	3,6	4,6	9,8	8,2	8,3
Bangassou	9,6	1,5	3,3	3,8	9,6	9,8	2,8	0,9	1,9	7,1	5,5	5,5
Gambo	8,7	0,5	2,5	3	8,8	8,9	3,6	0	1	6,2	4,5	4,7
Ouango	9,8	1,6	3,5	4	9,8	10	4,6	1	0	7,3	5,6	5,7
Rafai	11,6	3,3	5,3	5,8	11,5	11,7	4,7	2,9	3,9	9	7,4	7,5
Kaga-Bandoro	4,3	7	7,3	6,8	9,2	9,5	11,1	7,5	8,5	1,3	3	3
Mbres	5,5	5,6	5,9	6,1	7,8	8,1	9,8	6,2	7,2	0	1,7	2,3

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Table 6.3 – continued from previous page

	LDC candidate											
Bakala	5,5	4	4,3	4,5	6,2	6,3	8,2	4,6	5,6	1,7	0	1,3
Bambari	5,4	2,8	3,1	3,3	6,1	6,3	7	3,3	4,3	2,9	1,3	1,3
Grimari	4,1	4,1	4,3	3,8	7,5	7,7	8,3	4,7	5,7	2,3	1,3	0
Ippy	7,1	4,4	4,7	5	4,5	4,7	8,6	5	6	3,3	1,7	3
Kouango	5,8	4,5	3,4	2,1	8,2	8,5	8,7	5,1	6,1	4	3	1,7
Batangafo	5,8	9	9,3	8,8	11,2	11,5	13,2	9,6	10,6	3,4	5,1	5,1
Bouca	4,1	7,8	8,1	7,5	11,2	11,4	12	8,3	9,3	3,7	5,1	3,8
Markounda	6,6	11,6	11,8	11,2	14,9	15,2	15,7	12,1	13,1	6,8	8,5	7,5
Bocaranga	8,1	13,6	13,9	13,8	17	17,2	17,8	14,2	15,2	9,5	10,9	9,5
Koui	10,1	16	16,2	15,6	19,3	19,5	20,1	16,5	17,5	11,8	13,2	11,9
Ngaoundaye	8,5	13,5	13,8	14,7	16,8	17,1	17,7	14,1	15,1	9,3	14,8	9,5
Paoua	6,8	11,8	12,1	11,5	15,1	15,8	15,9	12,3	13,3	7,7	9	7,7
Djugu	31	23,3	25	26	31	32	25	22,8	23,8	29	27	27
Irumu	31	22,3	24	25	31	31	23,7	21,8	22,8	28	26	26
Mambasa	28	20	21,9	22,4	28	28	21,3	19,5	20,5	26	24	24
Beni	31	23,3	25	26	31	32	25	22,8	23,8	29	27	27
Lubero	34	26	28	28	34	34	27	25	26	32	30	30
Masisi	32	24	26	27	32	33	26	23,6	25	30	28	28
Rutshuru	38	30	32	32	38	38	31	29	31	36	34	34

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Table 6.3 – continued from previous page

	LDC candidate											
Walikale	28	19,6	21,6	22,1	28	28	21	19,1	20,1	25	23,6	23,8
Fizi	40	31	33	34	40	40	33	31	32	37	35	36
Kabare	33	24	26	27	33	33	26	23,8	25	30	28	28
Kalehe	33	25	27	28	33	34	27	25	26	31	29	29
Mwenga	37	28	30	31	37	37	30	28	29	34	32	33
Shabunda	35	27	28	29	35	35	28	26	27	32	31	
Uvira	36	28	30	31	36	36	29	28	29	34	32	32
Walungu	34	26	28	28	34	34	27	25	26	31	30	30

Table 6.4: Estimated travel times between potential LDC locations and Conflict areas in hours

	LDC cand											
Conflict Area	13	14	15	16	17	18	19	20	21	22	23	24
	Bouca	Markounda	Koui	Ngaoun	Irumu	Mambasa	Lubero	Kabare	Mwenga	Shabunda	Uvira	Walungu
Bangui	4,1	6,5	8,1	8,5	31	28	34	32	37	35	36	34
Alindao	6,5	10,3	14,7	12,3	23,8	21,3	27	26	30	28	29	27
Kembe	7,8	11,5	15,9	13,5	22,3	20	26	24	28	27	28	26
Mobaye	8,1	11,9	16,3	13,8	24	22,9	28	26	30	28	30	28
Zangba	7,5	11,2	15,6	13,2	25	22,4	28	27	31	29	31	28
Bria	8,2	11,9	16,3	14,3	28	25	31	29	34	32	33	31
Ouadda	11,2	14,9	19,3	16,9	31	28	34	33	37	35	36	34
Yalinga	11,4	15,1	19,5	17,1	31	28	34	33	37	35	36	34
Obo	15,5	19,2	23,6	21,2	18,9	16,5	22,2	29	33	31	33	31
Zemio	13,2	17	21,3	18,9	21,1	18,7	25	27	31	29	31	28
Bakouma	12	15,7	20,1	17,7	23,7	21,3	27	26	30	28	29	27
Bangassou	9,2	13	17,3	15	21	18,6	24	23	27	25	27	24
Gambo	8,3	12,1	16,5	14	21,8	19,5	25	23,8	28	26	28	25
Ouango	9,3	13,1	17,5	15	22,8	20,5	26	25	29	27	29	26
Rafai	11,2	15	19,3	16,9	22,9	20,5	26	25	29	27	29	26
Kaga-Bandoro	2,7	5,5	10,5	8	29	27	33	31	35	34	35	33
Mbrès	3,7	6,8	11,8	9,3	28	26	31	30	34	32	34	31

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Table 6.4 – continued from previous page

	LDC cand											
Bakala	5,1	8,5	13,2	10,8	26	24	30	28	32	31	32	30
Bambari	5	8,8	13,2	10,7	25	22,8	29	27	31	29	31	29
Grimari	3,8	7,5	11,9	10	26	24	30	28	33	31	32	30
Ippy	6,3	6,7	14,8	12,3	27	24	30	29	33	31	33	30
Kouango	5,3	9,1	13,5	11,1	27	25	30	29	33	31	33	30
Batangafo	1,7	3,5	9,8	6,1	31	29	35	33	37	36	37	35
Bouca	0	3,8	8,2	5,7	30	28	34	32	36	34	36	34
Markounda	3,8	0	7,3	4,8	34	32	37	36	40	38	40	37
Bocaranga	5,8	4,9	2,3	1,1	36	34	39	38	42	40	42	39
Koui	8,1	7,2	0	3,5	38	36	42	40	44	43	44	42
Ngaoundaye	5,7	4,8	3,5	0	36	33	39	38	42	40	42	39
Paoua	4	3,1	4,3	1,9	34	32	38	36	40	38	40	38
Djugu	31	35	39	37	4	6,5	10,3	24	28	26	28	26
Irumu	30	34	38	36	0	2,5	6,3	20,1	24	22,3	23,9	21,6
Mambasa	28	32	36	34	2,5	0	5,9	17,8	21,9	20	21,5	19,2
Beni	31	35	39	37	3,5	3,3	2,8	17,7	21,8	23,3	14,3	19,1
Lubero	34	37	42	39	6,2	5,9	0	15,1	19,1	26	18,8	16,5
Masisi	32	36	40	38	17,5	17,2	11,4	9,7	13,8	16,5	13,5	11,2
Rutshuru	38	42	46	44	11,6	11	5,6	9,5	13,6	21,2	13,3	11

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Table 6.4 – continued from previous page

	LDC cand											
Walikale	27	31	36	33	15,5	13	16	4,7	8,8	12	8,5	6,1
Fizi	39	43	47	45	27	25	22,2	7,3	10,6	12,8	3,3	8
Kabare	32	36	40	38	20,1	17,7	15	0	4,3	12	4	1,7
Kalehe	33	37	41	39	19	18,8	13	2,1	6,2	13,8	5,9	3,6
Mwenga	36	40	44	42	24	21,8	19,3	4,3	0	7,6	7,3	2,6
Shabund	34	38	43	40	22,3	20	26	12	7,6	0	14,9	10,3
Uvira	36	40	44	42	17,5	21,5	18,9	4	7,3	14,9	0	4,7
Walungu	34	37	42	39	21,6	19,2	16,5	1,7	2,6	10,3	4,7	0