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The Added Value of UAVs in Last-Mile Humanitarian Logistics in South Sudan – A Simulation Study

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Dedication and Acknowledgement

This graduation project is dedicated to the people in South Sudan and everyone that has been involved in not only the Wings For Aid Project but also the noble work of humanitarian mission in general.

First and foremost, my eternal gratitude goes to my parents. Supporting their next generation to pursue a degree abroad is never easy. They somehow pull this off fantastically. During some trickiest times this world has ever experienced, their very existence is cherished more than ever. It has been a weird three-year period that I live thousands of miles away, but thanks to their unabashed love I never feel distant from them.
Same goes for my family members, who may not always understand my decision of going abroad or why my degree is taking so long to achieve but never hesitate to show their support any time.
My closest friends, who are now worthily my extended family, my brothers and sisters from different mothers, surely deserve a mention here. I feel truly blessed to have them around, despite texting is the only thing happening for the past few years. Because of them I can say without any hesitation that I am not alone on this road and I will never be so for the time to come. One of my best friends just got married. Congratulation to him and his wife for starting a brand new chapter in their lives. May every new day in their life be as bright as the sunshine I am enjoying while writing this.
I feel like a special thanks should go to the city of Enschede. I spent the darkest time in my life here in the Netherlands, during which it had been excruciating for me to even open my eyes and start a new day. But in this city, in this university, in their environments and their people did I learn that life goes on and help is within your reach.
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1. Project Plan

In this chapter, the research will be outlined. Section 1.1 will give the background information of the research, with the research context, the overarching project background, and the UAV featured in the project. In Section 1.2, the case description is given along with the motivation of this research. The core problem and objectives of the research are listed in Section 1.3. The course of the research, risk consideration, and milestone is explained in Section 1.4.

1.1 Problem Introduction

Subsection 1.1.1 introduces the context of project AIRLIFT, with the model of UAV used in the project covered in Subsection 1.1.2. Subsection 1.1.3 introduces the tool used for problem solving in this research while Subsection 1.1.4 introduces the background information of South Sudan, the country this research will look into.

1.1.1 Project Context

Last-mile Drone Logistics for Humanitarian Aid (AIRLIFT) is a research program at the University of Twente focusing on last-mile logistics for delivering relief aid goods under different humanitarian crisis situations using specifically Unmanned Aerial Vehicles (UAVs). This project is in collaboration with Wings for Aid, an organization founded in 2014 and since dedicated to developing a scalable and reliable delivery system using cargo drones. Currently, Wings For Aid is developing a remotely piloted aircraft system that delivers humanitarian goods to people isolated by natural disasters and crises caused by human activities (*Wings for Those in Need*). As a joint effort powered by knowledge and techniques from higher education, research institutions, government agencies, and even the military, Wings For Aid entered into a cooperation with the Department of Industrial Engineering and Business Information Systems at University of Twente for its expertise and knowledge in modelling, optimization, and analysis of the logistics processes and drone operations, including the development of a generic simulation model for UAV-aided humanitarian logistics (*WINGS FOR AID*). Within the scope of the mission, both sides expect to get a better understanding of the added value of UAVs within last-mile humanitarian logistics, develop algorithms to efficiently coordinate UAVs within their designated role and test and explore the feasibility and benefits of using UAVs for humanitarian logistics under different disasters scenarios.

1.1.2 Unmanned Aerial Vehicle

The UAV featured in AIRLIFT is specially designed by Wings For Aid. In terms of cargo shipment, it is not always practically feasible to land large fixed-wing aircraft safely. Parachute drops are prone to the influence of wind. Helicopters with both sufficient payload and range are rare and manned aircraft are expensive ("Dossier: Wings For Aid MiniFreighter," 2021). Hence the need for an automated system of UAVs that can carry substantial loads, safely and accurately drop packages and return for reloads rises. The latest drone from Wings For Aid, the MiniFreighter 8/500FW has the ability to carry eight self-landing delivery boxes and drop them with pinpoint accuracy (shown in Figure 1). It needs a 300-meter distance to take off. The cruise speed is 125km/h with a ferry range of 500 km and an operating radius of 250 km ("Dossier: Wings For Aid MiniFreighter," 2021). The delivery box is also specifically designed with the feature of automatically landing in an upright position from a height of 50-500 meters and absorbing the impact. The critical concept is for the box to get rid of the parachute. The drag force was planned to be created by a panel directly attached to the box but later replaced by a set of four air brakes out of practical concerns ("Dossier: Wings For Aid MiniFreighter," 2021). The rated capacity of each box is 20 kg (Wings for Aid). The total payload capacity is 160kg.

Figure 1: MiniFreighter and Cargo boxes

1.1.3 Simulation Framework

The toolkit of the research is a generic simulation framework developed in Plant Simulation. In order to insure the adaptability of this model framework, this framework is comprised of an implemented disaster case (for the possibility to quickly extend to other cases), a graphic user interface containing satellite images and control panels, geographical information including coordinates of sites, hubs and camps, a structured transportation network that is used to simulate the supply chain, statistical information including population, demand patterns and risks (level of uncertainty when it comes to modeling) and several basic routing algorithms that coordinate vehicles (van Steenbergen & Mes, 2020). Such a model is crucial for this research since it is a coordinated structure where testing system behavior, exploring alternative experiment configurations and logging experiment parameters are all possible. One of the unique features of the given model is its incorporation of multiple transportation methods, making it possible to study the behavior of multi-modality transportation coordination that would combine drones and trucks or helicopters. This research would require building a new case through context analysis, proposing core problems, solving the problem instance, and validating solutions. Nevertheless this simulation framework still serves as a first step to analytically deconstruct a real-life case.

1.1.4 Political Development and Humanitarian Background in South Sudan

The real-life case of humanitarian aid that is going to be examined here happened in South Sudan, arguably the youngest country in the world. By the time of its independence, South Sudan had 10 states (*South Sudan: administrative divisions and their centres*, 2011). During the time this research is based, there were 32 federal states following the presidential decree issued on January 14^{th}, 2017 (Wël, 2017) while in 2020 the 10-state system was reintroduced. The civil war broke out in late 2013. On July 9^{th}, 2021, South Sudan celebrated its first decade since independence. The attempts to quell the fighting were largely futile, countless ceasefires were broken and the first power-sharing agreement failed, while in 2018 the second peace deal has largely held (Mednick, 2021). Despite the war has ended, the progress to true peace is slow. The armed conflict continued in 2020 while in 2021 UN warned that the slow pace of implementing the peace accord would risk a relapse into “large scale conflict” ("South Sudan’s decade of independence: A timeline," 2021). The warfare has left 400,000 people dead and derailed the nascent state-building process. According to the UN, in 2021, 8.3m people are in need of humanitarian assistance in South Sudan. 1.4m children are expected to suffer from acute malnutrition with 60 percent of the population being “severely food insecure” (Schipani, 2021).

However, it is worth keeping in mind that a regional armed conflict is not the only factor causing a grave need for daily life supplies and adding uncertainty to transportation here. Recent research plotting the flood and drought occurrence in South Sudan revealed that the last 30 years have seen the highest number of floods compared to previous periods. Furthermore, floods have happened in South Sudan every year since 2005 (Tiitmamer, 2019). Although there seems to be a multi-fold reason for what could possibly cause the flood, with some arguing global warming has increased the frequency and magnitude of flood and drought (Tiitmamer, 2019) and others chose to focus on wetland dynamics and inundation patterns (Rebelo et al., 2012), the impact of the flood on livelihood is common: heavy rain destroys homes and crops leaving communities vulnerable with floods frequently destroys crops and livestock leading to food shortage (Malaak, 2020). In 2021, some parts of South Sudan have seen the worst flooding in 60 years. More than 700,000 people were affected, river bank burst and states usually spared from extreme flooding have been swamped ("‘Worst thing in lifetime’: South Sudan floods affecting 700,000," 2021). Hence the level of uncertainty for the delivery of humanitarian aid escalates quickly, highlighting the potential necessity for a transportation method that would touch the road as less as possible. The existence of an extensive rainy season is also the reason that during a certain period over a year barges are also used as a transportation method.

This research is inspired by the year of 2017 in South Sudan, a time with no peace deal but also a lot of extreme weather conditions. According to an assessment report issued by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), fighting broke out between government and opposition forces at Ketbek in Nasir County, Upper Nile, displacing an estimated 33,000 people, whose main needs to be food and/or livelihoods (particularly fishing gears), healthcare and water and sanitation and hygiene (WASH) (UN Office for the Coordination of Humanitarian Affairs, 2017a). This is only the tip of an iceberg as it is stated in a report from the World Food Program (WFP) detailing the findings of a rapid needs assessment (RNA) from 1-4 February 2017 in Ayod County, Jonglei that an estimated 85,000 people were in immediate need of food assistance and no market existence in any of the locations where the assessment took place (World Food Programme, 2017b). In the year 2017, it can be easily concluded that people in South Sudan were in a dearth of food and water. The number of settlements (located in hard-to-reach areas) with access to food has experienced an acute decrease from September 2016 to May and June 2017, with less than 25% of all settlements in many states reporting adequate access (REACH Initiative, 2017b, 2017c). REACH Initiative (2017a) has further indicated that by July only 35% of assessed settlements in hard-to-reach areas reported adequate access.

In April 2017, at least 200,000 people were forced to leave their homes due to conflict with the majority of the country in a state of stressed food supply and some areas in Unity state formally declaring famine (UN Office for the Coordination of Humanitarian Affairs, 2017b). In May the number of displaced people continued to rise. May also marks the beginning of the lean season in agriculture, seeing an estimated 5.5 million people across the country facing severe food insecurity, including 1.46 million on the brink of famine (UN Office for the Coordination of Humanitarian Affairs, 2017e). The following two months saw the food crisis escalate to an unprecedented level, with more counties in Unity state and nearby in “Catastrophic” food insecurity while crop-eating caterpillars might further damage farming and cholera and malaria worsening the situation (UN Office for the Coordination of Humanitarian Affairs, 2017c, 2017d).

The general accessibility to sites and shelters that decides the progress of humanitarian aid activities is constantly in question in South Sudan. South Sudan is one of the countries with the lowest road density in Africa, making delivering resources to people in need extra difficult. According to WFP, even with their considerable expertise in logistics coordination, the condition in Sudan was still challenging due to a limited road network that “deteriorates significantly during the rainy season and widespread insecurity” (World Food Programme, 2017l). It is truthfully reflected in their activity pattern as WFP relied upon land transportation to ship goods from neighboring countries but still needs airborne methods to send packages to wherever road conditions did not allow.

When in March, the majority of roads in the country were still open for trucks with a load of 40 tons (Logistics Cluster, 2017d). However, during July and August, half of the roads in the country were either only open for light vehicles or completely closed, leaving only a few established routes still available (Logistics Cluster, 2017k), presumably due to extreme weather conditions creating marshes on the roads and making heavy-weight lorry trucks susceptible of getting swamped.

The grave difficulty of land transportation forces a multiple-mode transportation approach in South Sudan. As previously mentioned, barges are used sometimes due to frequent flooding and South Sudan’s major river, White Nile. Both fixed wings aircraft and helicopters are involved, but the blockage of roads does not mean airborne shipment is always a guaranteed method. Organizations that frequently deploy aircrafts such as Logistics Cluster also reported the weather as a reason for incidents causing air rotations lost. In June and August 2017, 27 and 58 incidents happened respectively. Weather conditions would account for 79% and 65% of those incidents (Logistics Cluster, 2017c, 2017f).

1.2 Research Motivation

In the context of humanitarian aid missions in South Sudan, there exist an urgent need for a transportation method that would remain unaffected by road inaccessibility, ensure the in-time delivery of aid supply, and show a considerable degree of flexibility in dispatching and coordinating. UAVs have emerged as a promising candidate solution in relief aid delivery but needs to be examined in terms of added value not only in the humanitarian aid supply chain in South Sudan but also in humanitarian aid in general.

Hence in this research, we will start from a case study focusing on small-scale relief aid delivery in South Sudan to examine UAVs’ performance in a multi-modality transportation setting, its adaptability when facing risks and uncertainties, deduce to what degree it can be helpful in humanitarian aid missions in South Sudan and assess its potential in the field of life aid delivery in general.

1.3 Core Problems and Research Objectives

In the context of the humanitarian crisis in South Sudan, the research objective is three-fold.

First, build a new case on South Sudan and acquire case-specific parameters and information to truthfully reflect the dynamics in South Sudan in 2017. Second, apply a planning method in terms of a heuristic to optimize the route plan of vehicles (including UAVs) in humanitarian aid missions in South Sudan. Third, test and observe how dispatching and planning of vehicles involving UAVs can affect the performance of the humanitarian aid supply chain in South Sudan. The simulation study serves as a useful tool to implement algorithms, incorporate different risk scenario configurations and evaluate the solution performance.

There could at least be three different aspects in constructing the framework design: alternative routing heuristics, new objectives/priorities of route planning/optimization, and the trade-offs in choosing different modes of transportation. Hence here proposed main actions to be taken during the course of this research are: (1) extending or updating the framework by using alternative routing heuristics or optimization methods, (2) setting alternative objectives that would better reflect the priorities and purposes in humanitarian aid circumstances, (3) considering the trade-offs of different choices of vehicles (e.g., sending out truck only, drone only or mixed) while taking into account factors like road accessibility, payload, speed and cost and, (4) deliver findings on the synergy effect of using UAVs together with conventional vehicles while taking the disaster conditions in South Sudan in consideration. Among these, the crucial pair is adopting new routing heuristics aiming to improve the drone fleet performance and enabling mixed transportation method coordination, and setting new objectives/priorities in humanitarian logistics to better respond to the unique challenge of relief aid in South Sudan.

We defined the overarching research question as such: How can UAVs influence the situation of humanitarian logistics in South Sudan in 2017?

First, we need to conduct a context analysis of the humanitarian conditions in South Sudan in order to understand the problems and dilemmas South Sudanese were experiencing in 2017.

1. What is the general condition in South Sudan in the year 2017?
(a) What kind of disasters were there?
(b) What kind of damages have the disasters done?
(c) What kind of aid did South Sudanese receive?
(d) What will be the scope of this research (time frame, amount of goods, aimed population, type of transportation involved)?

Furthermore, the research is about humanitarian aid after all. Due to the special nature of humanitarian aid, the priorities could be different since the intuitive goal for humanitarian aid missions is to deliver relief goods to as many people as possible as soon as possible. Hence it is worthy to explore sets of new optimization objectives to reflect the urgency and scale of relief aid. For example, the new objective could be planning a route with the most population coverage or coordinating all the vehicles to cover all the sites in the shortest time. Hence the literature review will firstly dedicate to examining logistics in humanitarian aid.

The second part of the literature review will shift the focus to planning methodologies. Compared with conventional vehicles, UAVs show some unique traits such as their operation being undisturbed by road conditions, no unloading time due to their pinpoint airdrop, and cost, also they come in short in terms of their payload, cruise speed (when compared to helicopters and fixed-wing aircraft) and specific requirement of the runway. Thus while it is considered necessary to explore optimization methods in efficiently guiding UAVs, it should also be noticed that challenges remain in deploying UAVs and their integration with traditional modes of transportation should also be given a further look for their completely different characteristics and behaviors.

2. How is humanitarian logistics treated in the literature?
(a) What are objectives for logistics in the context of the humanitarian aid scenario?
(b) Will choosing new objectives affect transportation planning when delivering relief supplies?
(c) What are the trade-offs in selecting the most appropriate solutions?
(d) What are some known cases of UAVs in humanitarian missions?

3. How are routing heuristics solving a Vehicle Routing Problem (VRP) covered in literature?
(a) What are example heuristics in solving VRP? What are their advantages and disadvantages?
(b) How well can existing heuristics adapt to new optimization objectives?
(c) How do UAVs function in VRP settings?
(d) How is risk incorporated in decision making?

Next comes the design and implementation of heuristics, solving of the problem instance, and evaluating vehicle behavior.

4. How can we develop an optimization heuristic for this case study?
(a) What steps need to be taken?
(b) How can the chosen method fulfill the practical requirement?
(c) How can real-life settings be reflected in the method?
(d) How can collected data be implemented in the simulation model?

5. How well do vehicles perform in proposed scenarios?
(a) Does changing new optimization objectives greatly affect transportation performance?
(b) Among all the transportation configurations, which one achieves the best performance?
(c) How does the preference over a certain objective affect transportation decision-making?
(d) How do risk scenarios influence multi-modality transportation?

1.4 Problem Approach

The actual case study is going to be built around South Sudan in 2017, a time when armed conflicts were still active across the country and the rainy season worsened every problem the country was facing. The project will start with a context analysis going through available data, reports, infographics and updates from agencies, authorities, and organizations that conducted humanitarian response in South Sudan. By the end of the context analysis, it is expected that through extracting useful data and information, a feasible research scope can be constructed through data collection and filtering. The data collection needs to ensure the geographical data of regional warehousing facilities, airports, and all the human settlements marked as they are crucial for computing traveling distances. What is also important is to have population figures and demand patterns for all shelters or refugee camps that are needed to be visited. Demand patterns here could include the category and the number of resources needed for each location. Together with the technical specification of vehicles (payload, range, size of the fleet, etc.), they form the information required to generate constraints.

The literature study Section will be dedicated to the field of last-mile delivery and its variation in humanitarian aid logistics. It will start with popular heuristics/mathematical models for vehicle routing. The inter-modality approach to transportation should also be considered critical as it closely relates to practical deployment. The second phase of the literature study could shift the focus on humanitarian logistics itself regarding its priorities, objective, unique requirements of optimization, the process of decision support, and trade-offs among multiple goals. The literature review could also extend to existing case studies on last-mile logistics in relief aid to provide more inspiration and gain insights into the model design for the research. The effort will also be aiming at checking if there exist practices of UAV use in relief aid as a process of building knowledge and observing vehicle behavior.

The geodata, population numbers, and demand figures will be collected, arranged and implemented in the model. The main task is to design heuristics/algorithms that can conduct vehicle route optimization, enable multi-modality vehicle dispatch and take risk and uncertainty into consideration. A Simulation study is needed for analyzing and evaluating the quality of the planning method as it enables implementation of new disaster cases, incorporations of risk scenarios and documentation of performance measures. The software used here is Plant Simulation from Siemens.

It is necessary to specify that the risks indeed exist in the scope of this research. One foreseeable risk lies in the Section on data collection. As extensive as the currently available data is, it is still possible the data desired for this study does not exist in the exact form needed. Hence certain assumptions and deductions based on what is on hand have to be made to fill in the blanks. Another risk could be in the running of the simulation model as it could be very time-consuming to get to a result. This further highlights the importance of data collection and scope, as it is critical that the scope of the problem we are trying to solve here is both theoretically and practically feasible.

2. Context of Humanitarian Crises in South Sudan 2017

This chapter will dedicate to a more complete picture of the background information of this research project. The context analysis will be composed of several Sections answering questions including what kind of crisis were South Sudanese people experiencing in 2017, what kind of supply and how much supply were in need, the number of people affected, what is the location and distribution of relocation sites, what kind of activities have been conducted as part of relief support, how was transportation/logistical activities organized and what problems have occurred. Answers to the questions above will hopefully define a practical and manageable problem scale and scope and facilitate the following literature review and analytical model building, for instance constructing payload-related constraints for the route optimization problem, computing distances between relocation facilities, and sorting out the priorities of dispatching relief aid supplies as well as emphasizing the urgency and the level of complexity of South Sudan's situation.

Organizations, agencies and authorities have been churning out different initiatives and plans aiming to relieve the dearth of life supply in South Sudan. Due to the nature of this research project being humanitarian logistic-oriented, only logistical support carried out or anything related will be included in the discussion.

Section 2.1 introduces the humanitarian crises South Sudan faced in 2017. Section 2.2 raised several examples of several response schemes led by different humanitarian organizations. Section 2.3 elaborates on the steps taken to structure and shape the case study on South Sudan.

2.1 Humanitarian Crises in South Sudan 2017

The year 2017 is the year South Sudan has finally seen wisps of hope as there has been a largely effective peace treaty for the first time, marking a milestone for this newborn country. But there might be too many reasons that prevent local people from enjoying the change as the crisis was clear, present, and acute. By the year 2017, humanitarian crises, in which great numbers of people suffer as a result of extraordinary circumstances that are not the result of more or less direct actions of the government (Donnelly, 1993), were still looming in South Sudan. South Sudan in general was experiencing rapidly deteriorating food security, epidemics, crop failure, abnormal temperature fluctuation, and heavy rainfall (World Food Programme, 2017a). What is worth noticing is that not all humanitarian crises will be introduced here. Among what will be displayed below, apparently, not all crises are independent of each other. Hence different Sections will not be strictly separated. The idea is to highlight the emergency and necessity for international society to respond to the difficult position of South Sudan by presenting the accumulated effect of multiple crises on the life of South Sudanese.

Four different kinds of humanitarian crises are presented here. Subsection 2.1.1 is on internally displaced people. Subsection 2.1.2 focuses on the dire need for food. Subsection 2.1.3 explains hygiene and health-related issues and Subsection 2.1.4 covering South Sudan's troubled climate.

2.1.1 Internal Displaced People (IDP)

Internal displaced people and refugees construct the most direct representation of South Sudan's humanitarian crises. IDPs stay within their own country and remain under the protection of their government, even if that government is the reason for their displacement, while refugees are on the run at home (UNHCR). At the beginning of 2017, United Nations High Commissioner for Refugees (UNHCR) registered some whopping figures: the total number of IDPs had reached 1.853 million with the refugees in the country being 262,560 (United Nations High Commissioner for Refugees, 2017). By mid-August 2017, the total population of concern (South Sudanese refugees, South Sudanese IDPs and refugees in South Sudan) reached a staggering 4.28 million (UNHCR, 2017).

The context of internal displacement in South Sudan is multi-layered and hence complicated. The domesticate peace and security circumstances, first and foremost, is a major contributing factor. The long-sought declaration of independence in 2011 was expected to end the long conflict, instead, the stability was constantly undermined with the north and south relations making an inward turn, deriving problems such as internal armed conflict, intercommunal and ethnic violence, human rights abuses, and political instability. The situation was not alleviated even after the signing of the Agreement on the Resolution of Conflict as civilians having been attacked and homes having been destroyed (United Nations Office for the Coordination of Humanitarian Affairs, 2016). As a result, 1 out of 5 people has been forced to leave their homes. What further complicated the situation is the inflow of refugees from nearby countries including the Democratic Republic of Congo (DRC), Ethiopia, and the Central Africa Republic (CAR) due to their own domestic instabilities. In 2016 South Sudan was hosting more than 260,000 refugees while the number was expected to grow to more than 300,000 by the end of 2016. 90% of the refugees were located in the states where conflict had been particularly intense, and tensions over scarce resources between refugees and the local population had increased. Over the course of 2016, the protective environment of camps in South Sudan deteriorated since the camp was either closed due to insecurity or difficult to access, forcing refugees to seek safety in the wild or return to their home country (United Nations Office for the Coordination of Humanitarian Affairs, 2016, 2017b).

From a socioeconomic point of view, the state-building process for a newborn country requires national cohesion, reconciliation, and accountability which was lacking in South Sudan. Such insufficiency has given rise to tension and violence among ethnic groups, to which South Sudan is more susceptible due to its considerable ethnic diversity (Beyani, 2016). These could all serve as the cataclysm of aggressive conflict that leads to a volatile living environment and force people to live nomadic life.

Another recurring phenomenon is internal displacement owing to natural disasters. The wet season, which will lead to the flood situation, for example, has a significant impact on the resilience of people living in disaster-prone areas (Beyani, 2016).

2.1.2 Food Insecurity and Drinking Water Safety

The decline in socioeconomic status in South Sudan not only have given rise to domestic tensions and pushed people away from their homeland but also greatly undermined the living condition in South Sudan. The annual Consumer Price Index (CPI) skyrocketed from September 2014 to September 2015 (by 91.3%). The informal exchange rate of the South Sudan Pound (SSP) against the US dollar reached a historical low of 18 to 1, resulting in the price of staple food, including sorghum, maize, and beans reaching a record high. The purchasing power consequently greatly diminished, worsening the living condition of the urban poor (United Nations Office for the Coordination of Humanitarian Affairs, 2016). At the height of the lean season in July 2016, more than 1 in 3 people in South Sudan were estimated to be in severe food insecurity (United Nations

Office for the Coordination of Humanitarian Affairs, 2017b).

It is not hard to understand that there existed a causal link between general social instability and food insecurity as residents have very little access to food during conflicts, hence leaving for seeking it. In the latter half of 2016, the Greater Equatoria region, accounting for over half of the nation's net cereal production and the only surplus producing area, was severely impacted by ongoing violence, preventing many households from accessing farms for harvesting and second-season cultivation. A cereal deficit of more than 50% was reported in 2016 (United Nations Office for the Coordination of Humanitarian Affairs, 2017b). Over the course of 2016 and 2017, as a result of ongoing violence, the livelihoods of farmers were destroyed and shortages were frequently caused. Livestock was looted, killed and disease-prone with crops destroyed and planting delayed, while pest outbreaks and rain further worsened the prospect in the context where 78% percent of the household depends on crop farming or animal husbandry as the primary source of livelihood (United Nations Office for the Coordination of Humanitarian Affairs, 2016, 2017a).

It is no wonder that access to safe drinking water was also not guaranteed. The sanitation condition was extremely poor with only 41% having access to safe water by estimation for 2016 (United Nations Office for the Coordination of Humanitarian Affairs, 2017b). The portion of the income of an urban home used to purchase clean water had increased while water trucking had decreased due to the cost of fuel. The lacking of hand pumps also turned out to be a problem as people went to ponds, streams, and rivers for water, further exposing themselves to diseases. Repeated population displacement, insecurity, and damage to key infrastructure were proven to be problematic as access to clean water was not possible without tools, repairs and expertise (United Nations Office for the Coordination of Humanitarian Affairs, 2016, 2017a, 2017b).

2.1.3 Epidemics and Health Concerns

The lack of clean drinking water is also a public health concern as poor hygiene conditions could give rise to outbreaks of water-borne disease. Cholera, one typical water-borne disease, was of major concern. In fact, due to poor sanitation, lack of access to clean water, and crowded living conditions, communicable diseases remained a concern throughout the country (United Nations Office for the Coordination of Humanitarian Affairs, 2016).

In July 2016, South Sudan has experienced one severe Cholera outbreak. South Sudan Minister of Health advised partners to treat the recent rise in suspected cholera cases (14 suspected cases have been reported since week 15 of 2016 (World Health Organization, 2016)) as a cholera outbreak, and respond accordingly (UN Children's Fund, 2016). By 17 November, the outbreak has reached 3145 cases and 44 death. The capital Juba had the highest number of cases, accounting for 63% of the total (1990 cases) while Terekeka, a town in the north of Juba, had the highest case fatality rate (CFR) of 36.4 per cent compared to overall level of 1.4 per cent. A total of 2874 cases and all 44 death have been reported from counties straddling the river Nile (UN Office for the Coordination of Humanitarian Affairs, 2016).

Entering 2017, the Cholera outbreak was not yet to be contained with a cumulative of 4121 cases including 75 deaths reported (CFR 1.82%) (World Health Organization, 2017b). The weekly update kept reporting new cases of cholera, making this outbreak more protracted than ever. In early March, 5574 cases including 137 deaths were registered (CFR 2.46%) while there have been small outbursts of cases in some cities (World Health Organization, 2017c). By June 2017, cumulative cases have reached 5 digits (10832) including deaths of 248 with CFR 2.3% (UN Children's Fund, 2017a), officially marking the outbreak lasting for a year.

Cholera was far from being the only public health concern in 2017 for South Sudanese. Malaria was still looming as since week 1 of 2017 malaria is a leading cause of morbidity in non-conflict areas and IDPs (World Health Organization, 2017b, 2017c). Measles has been another threat with new or suspected cases kept being registered. By the end of April 2017, cholera, malaria and measle were all among the major public health morbidities/mortality in IDP locations and surrounding host communities (World Health Organization, 2017a).

One of the eventual outcomes of long-lasting food insecurity is widespread malnutrition among people. The February 2017 Integrated Food Security Phase Classification (IPC) estimated 4.9 million people (41.7% of the total population) to be food insecure between February and April with 100,000 people facing famine in Leer and Mayiendit counties. Acute malnutrition remained a major public health emergency with data showing 14 out of 23 counties have Global Acute Malnutrition (GAM) at or above 15% (United Nations Children's Fund, 2017b). The situation continued to deteriorate as further information estimated over 1.1 million children were estimated to be acutely malnourished in South Sudan. As hinted in the previous Section, armed conflict, economic crisis and below-average harvests that were exhausted well before the lean season were all reasons contributing to this complicated situation. The May estimation had people expected to be in severe food insecurity in June-July at 6.01 million, the greatest number ever (United Nations Children's Fund, 2017a). Among the food insecurity population, an estimated 21% were children under 5 years, 7% were the elderly and another 7% were pregnant and lactating women (United Nations Children's Fund, 2017c).

2.1.4 Climatic Abnormality and Flood

The climate in South Sudan shows a seasonal pattern throughout the year. Seasonal dry weather caused low water tables, heightening competing demands for water between humans and animals and scarce water sources being over-used (UN Children's Fund, 2017b). As a result, the population would have started to move in search of water and pasture. A second blow could come from a prolonged dry season (dry season normally lasts from November to March), which would have devastating consequences on already limited water and food security in the country and likely result in drought. Another possible outcome of extremely dry weather and drought is increased inter-communal conflict as populations migrate in search of water (UN Children's Fund, 2017c).

The rainy season, on the other hand, tends to cause surface water flooding. The rainy season in 2017 started around July and quickly escalated. It causes seasonal flooding that blocked the border points between South Sudan and Uganda, destroyed shelters of host community households, and rendered most roads to the refugee camp impassable, thus severely impacting the ability of South Sudanese to access asylum and the refugee response to asylum countries (UN High Commissioner for Refugees, 2017). In August, 12% of health facilities reported stockouts, due to inaccessibility caused by both insecurity and heavy rains (UN Children's Fund, 2017d). In September, the situation was rather alarming, with floods caused by rain having displaced more than 100000 people in South Sudan ("Floods displace hundreds in war-torn in South Sudan," 2017). A flood report has been issued by the Ministry of Humanitarian Affairs, warning the threat of floods continued to rise in South Sudan. The floods mainly affected Northern and Western Bahr el Ghazal, Terekeka, and

Maban regions, consequently uprooting people from their homes and destroying shelters and livelihoods (World Food Programme, 2017m). Due to poor road conditions that have been exacerbated by heavy rainfall, the road convoy scheduled to deliver supplies to Western Equatoria State was cancelled, and airlifting instead has been considered for the most urgent item (UN Children's Fund, 2017e).

Food and water insecurity, public health threats, and extreme weather conditions are far from the whole picture of all the calamities that happened in South Sudan. With armed conflict and inter-communal violence being persistent, different crises were intertwining and forging a mire that was too convoluted to get out of. It is only clear that the alarming situation in South Sudan called for external intervention and especially agile transportation to cope with all the uncertainties and volatilities.

2.2 Response Scheme

As indicated at the beginning of this chapter, only logistical support and supply chain-related activities will be discussed for their relevance. Due to the sheer number of international organizations and agencies carrying emergency aid in South Sudan, only a few representative ones will be included here for a compact scope of this research.

In terms of logistical support, multiple organizations have opted for an omni-channel approach in providing aid to South Sudan, with the road, water, and air transport all involved and regional stock-keeping facilities implemented.

The logistics operation in South Sudan must stick with the principle of flexibility as road accessibility is constantly being affected by various kinds of incidents. Hence a different coping mechanism needs to be in place to ensure the supply of resources will not be interrupted. Logistics gaps and bottlenecks always impede the ability of the humanitarian community to deliver the response. Major challenges included difficult advanced planning, airstrips subject to weather conditions, poor road infrastructure, fuel shortage, lack of available and well-maintained barges and all the apparent reasons such as insecurity, seasonal flooding and vast distance due to sparse distribution of population (Logistics Cluster, 2015). Hence prepositioning of resources needs to be done every year during dry season (when roads are open). The goal for WFP in 2017 is to preposition 115000mt of food to ensure uninterrupted food assistance once the road is cut-off during the rainy season. By June 2017, WFP has prepositioned 111,730mt (98%) of food commodities (World Food Programme, 2017l).

`WFP presented an exemplary case in terms of its multi-channel rapid response and joint effort with organizations including UN Humanitarian Air Service (UNHAS), UNICEF and Logistics Cluster. WFP (including Logistics Cluster and UNHAS) has a fleet comprising of 14 helicopters, 876 airdrop planes, 11 fixed wing passenger airplanes, 3 barge sets, 98 WFP-owned trucks and 1100 contracted trucks. The WFP average capacity has 40000mt per month (dry season) by road, 8000mt per month by air and 2000mt per month by river (World Food Programme, 2017l).

Some humanitarian aid effort from different organizations is presented in the remainder of this section.

The response provided by Logistics Clusters focuses on relieving the famine situation in the counties of Koch, Leer and Mayiendit, located in the central north of the country. The highlight of

Logistics Clusters' operation was its quick response time being 1 or 2 days. Depending on the different time periods and different sites it served, the number of resources carried over also differed (shown in Table 2). Helicopters turned out to be the primary vehicle in the famine response, with fixed wings aircraft being the auxiliary method (The amount of delivery carried by helicopters and fixed wings aircraft can be seen in Table 1). The choice of heavily relying on the helicopter is due to the population affected by famine being widely dispersed across all the counties with a large number fleeing to small islands in South swamp regions (Logistics Cluster, 2017b). The use of barges is an alternative to the costly airlift. Barge movement may not be as rapid as in the air, however, it does have much larger payloads, creating ideal conditions for moving bulky non-food items (NFI) (Logistics Cluster, 2017a). Nationwide, Logistics Clusters managed to reach more than 30 destinations while keeping an average response time to priority locations (which are solely determined by the national Inter-Cluster Working Group) between 1 and 2 days. Air deliveries remained to be the leading transportation method while road convoy was implemented as well.

The choice of transportation methods is truthfully reflected in Logistics Cluster's activities during the first 8 months of 2017. Mass cargo transportation was handled by helicopters and fixed-wing aircraft, with the truck convoy for further assistance. Starting from May, the KPI switched from average response time to priority locations to percentage of priority locations reached, with the number of destinations visited also rising. This is probably due to extreme weather that started in May and grew strong during summer, causing more people to be in trouble hence more sites to visit. Furthermore, the transportation infrastructure could be compromised due to bad weather and secondary disasters, greatly delaying the delivery of goods and thus making average response time less reliable in judging the efficacy of the work by Logistics Cluster.

Since July, barges were involved in cargo shipping. This could also be one of the countermeasures for the volatile summer weather since heavy rainfall would limit road access, making barges viable on this occasion. Another possible reason to deploy barges could be extreme weather conditions brought massive damage that would require vehicles with a much bigger payload.

From the tonnage delivered from February to August 2017 (Table 2), it is evident that food, drinking water, sanitation supplies, and shelters remained the most in need as the disaster had comprehensive damage to daily life.

	February	March	April	May	June	July	August
Average Response Time to Priority Locations (day)	2	1	1.5	NA	NA	NA	NA
Ratio of Priority Location covered	NA	NA	NA	8/8	14/14	10/10	7/7
Number of Destination Reached	31	30	31	30	41	39	39
Shipment facilitated by Helicopter (MT)	232	270	373	411	550	440	493
shipment facilitated by Fixed Wing (MT)	290	166	13	283	126	44	44
Shipment by Road (MT)	47	2	7	6	9	32	33
Shipment by Barge (MT)	NA	NA	NA	NA	NA	490	490

Table 1: Logistics Cluster South Sudan Monthly Figures
(Logistics Cluster, 2017c, 2017e, 2017f, 2017g, 2017h, 2017i, 2017j)

	February	March	April	May	June	July	August
Nutrition	27%	16%	9%	8%	6%	7%	29%
Operational Support	22%	1%	12%	12%	2%	4%	20%
Water, Sanitation & Hygiene (WASH)	20%	34%	17%	11%	11%	47%	19%
FSL/Agriculture	1%	1%	37%	47%	72%	22%	16%
Shelter	13%	21%	17%	12%	4%	14%	10%
Health	5%	5%	3%	6%	3%	1%	3%
Education	4%	8%	NA	NA	1%	3%	2%
Protection	3%	10%	1%	1%	NA	2%	1%
Logistics	5%	2%	2%	2%	1%	NA	NA
Early Recovery	1%	NA	2%	NA	NA	NA	NA

Table 2: Tonnage delivered by sector
(Logistics Cluster, 2017c, 2017e, 2017f, 2017g, 2017h, 2017i, 2017j)

United Nations Humanitarian Response Depot (UNHRD) utilized its network around the world that procures, stores, manages, and transports emergency items on behalf of the humanitarian community. Different from pinpoint delivering goods to sites, UNHRD mobilized its global resource to gather cargo in Juba, meaning it is usually not the end logistics carrier for shipments. From its regional facilities in Brindisi, Italy; Accra, Ghana; Dubai, UAE, supplies were shipped to cities in nearby countries (Addis Ababa, Kampala/Entebbe and Mombasa) by air, and then sent to Juba by road transport.

Table 3 below documented the percentage of each cargo category from 9 updates logged during April and August 2017. Support equipment, food, and shelter were the major supplies UNHRD transported.

	21 April	5 May	19 May	14 June	28 June	14 July	28 July	7 August	21 August
Support Equipment	36%	39%	38%	37%	36%	34%	34%	34%	34%
Food	44%	42%	40%	37%	37%	35%	35%	35%	35%
Medical	1%	1%	2%	2%	3%	3%	3%	3%	3%
Telecomms	1%	1%	1%	1%	1%	1%	1%	1%	1%
Shelter	15%	14%	16%	20%	20%	25%	25%	25%	25%
Water/Sanitation	3%	3%	3%	2%	2%	2%	2%	2%	2%

Table 3: Most Dispatched Cargo Types UNHRD
(World Food Programme, 2017c, 2017d, 2017e, 2017f, 2017g, 2017h, 2017i, 2017j, 2017k)

Combining what is displayed by three tables shown above, helicopters were the primary forces in making deliveries, while food and nutritional supplement were evidently the resource urgently needed.

2.3 Scoping and Structuring of the research project

It is unrealistic to aim for the entire country as vehicles all have limit in their capacities, ranges and operating times. Hence adjusting the scale and scope of the problem instance is necessary and important. It is crucial to define a scope that is suitable, typical, and practical enough to reflect the humanitarian aid in South Sudan, with a focus on a specific group of IDP settlements, during a certain time period and a specific sector of supply.

In this Section, the angle of extracting, filtering, and organizing of available information will shift from relatively long-term response schemes by organizations (for example, response action over a few months) to a limited practical range of a month or a few weeks. The aim is to assess the seriousness of disasters, the geographical distribution of locations served, demand patterns, and population information. At the same time, the effect of ongoing disasters on transportation accessibility will also be incorporated as key arguments for choosing modes of shipping methods.

Section 2.3.1 details the situation of several regions that suffer the most from incidents and natural disasters. Section 2.3.2 lists out necessary assumptions and decisions made in acquiring all the information needed. Sections 2.3.3 and 2.3.4 detail the process of selecting sites and the hub. The type of cargo package is introduced in Section 2.3.5.

2.3.1 Choice of Location

United States Agency for International Development (USAID) has released a series of maps containing universal information regarding the level of food security, the number of IDPs, and humanitarian assistance from worldwide organizations and agencies. Figure 2 is an overview of humanitarian circumstances in South Sudan in May 2017. May is a good point to start with as it normally marks the beginning of the summer rainy season in South Sudan and signals large-scale flooding that will deepen the suffering of IDPs and refugees.

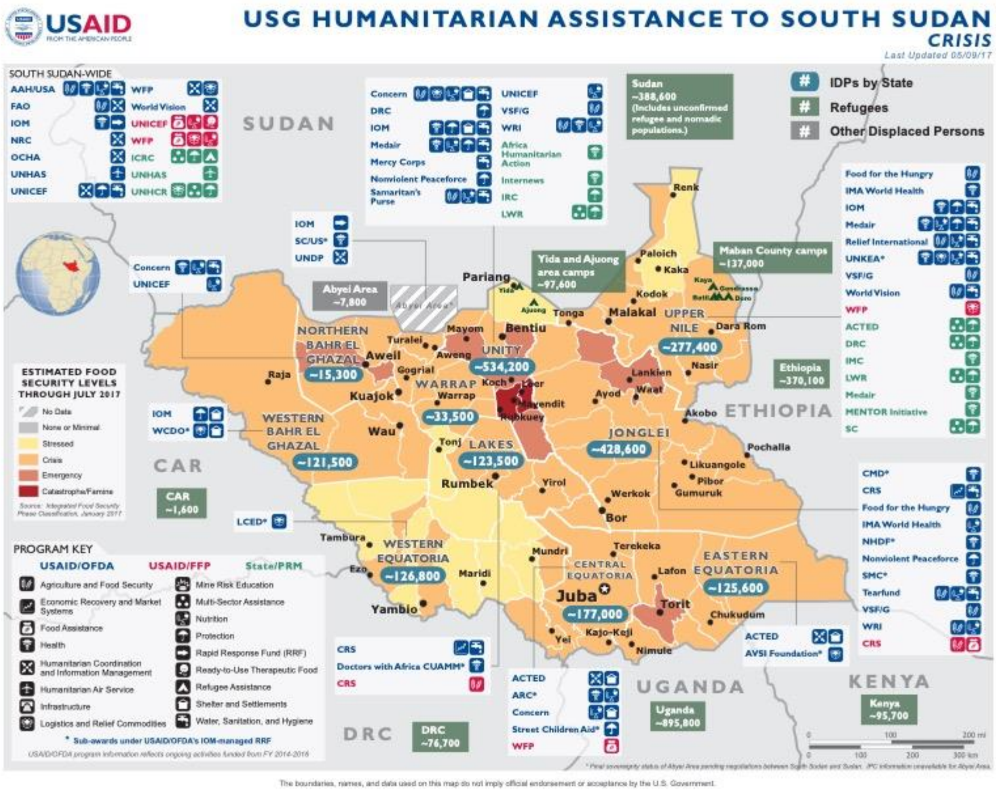

Figure 2: South Sudan Humanitarian Assistance Map - May
(*05.09.17 - USG Humanitarian Assistance to South Sudan - Crisis - Map*, 2017)

On the map, the number of IDPs and refugees are labeled for each region and neighboring country while the estimated level of food security is highlighted in different colors.

The state of Unity, Jonglei, and Upper Nile has the most IDPs. The counties of Koch, Leer, Mayiendit and Rubkuey show a catastrophic level of food insecurity, meaning them being in a state of famine, while most of Upper Nile and Jonglei have their food security level at "crisis". It is also Unity, Jonglei, and Upper Nile receiving the widest range of aid.

Table 4 below shows the general condition of humanitarian assistance received in the above-mentioned 3 states. It is not a surprise that each of the 3 states has received help in various forms considering the number of IDPs they were housing and the seriousness of the situation they were facing back then.

State	Number of Organizations involved	Categories of Aid received
Unity	14	Agriculture and Food Security, Logistics and Relief Commodities, Nutrition, Protection, Shelter and Settlements, Health, WASH, multi-sector assistance

Jonglei	11	Agriculture and Food Security, Protection, Health, WASH, Economic Recovery and Market Systems
Upper Nile	16	Agriculture and Food Security, Logistics and Relief Commodities, Nutrition, Protection, Shelter and Settlements, Health, WASH, multi-sector assistance

Table 4: Humanitarian Assistance in Unity, Jonglei and Upper Nile
(*05.09.17 - USG Humanitarian Assistance to South Sudan - Crisis - Map*, 2017)

Presented below in Figure 3 is the map depicting humanitarian conditions in July 2017, which is right in the middle of summer. The states of Unity, Jonglei and Upper Nile not surprisingly still had the most IDPs with more counties leveling up on food security levels and entering the emergency state. As the disaster situation escalated, multiple organizations ramped up their assistance to the designated region, especially with the states of Jonglei and Upper Nile seeing more of their counties with the situation worsening. Hence, it is decided that the first step of scoping the problem instance is to focus on groups of settlements located within one of these three states.

Figure 4 further shows that among Unity, Jonglei and Upper Nile, the state of Unity perhaps should be further examined in this research. UNHAS is shown to have an airfield for fixed-wing aircraft and several helipads for helicopters, indicating Unity had the conditions for active airborne activities. An airfield/airport would also enable the take-off and landing for drone fleets, meaning it has a practical value in simulating the drone behavior here under both solo mode and multi-modality mode.

More evidence can be seen in Figure 5, where the destination and routes of UNHAS after April 27 2017 are displayed. Unity featured multiple regular destinations of UNHAS. Furthermore, it was served from an operation base in Juba and maintained the connection with the base in Rumbek. A large area of Unity is labeled as “freshwater marsh”, probably hinting that the road condition was less than adequate and highlighting the necessity of aerial transportation.

Figure 3: Humanitarian Assistance in South Sudan - July 2017
(*07.10.17 - USG Humanitarian Assistance to South Sudan - Crisis - Map*
, 2017)

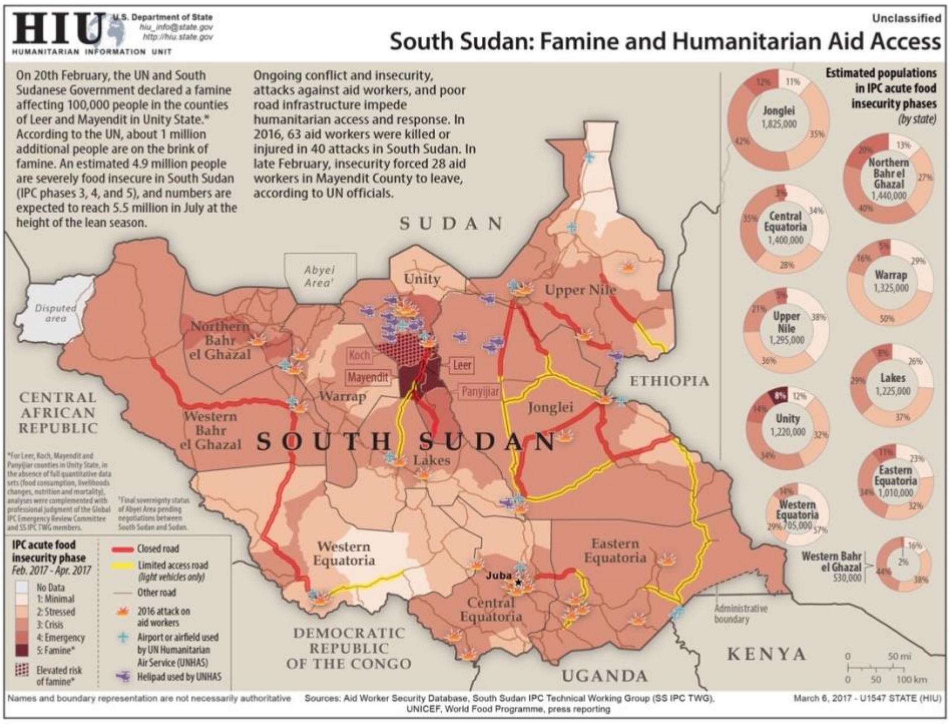

Figure 4: South Sudan Famine and Humanitarian Aid Access Map
(*South Sudan: Famine and Humanitarian Aid Access*, 2017)

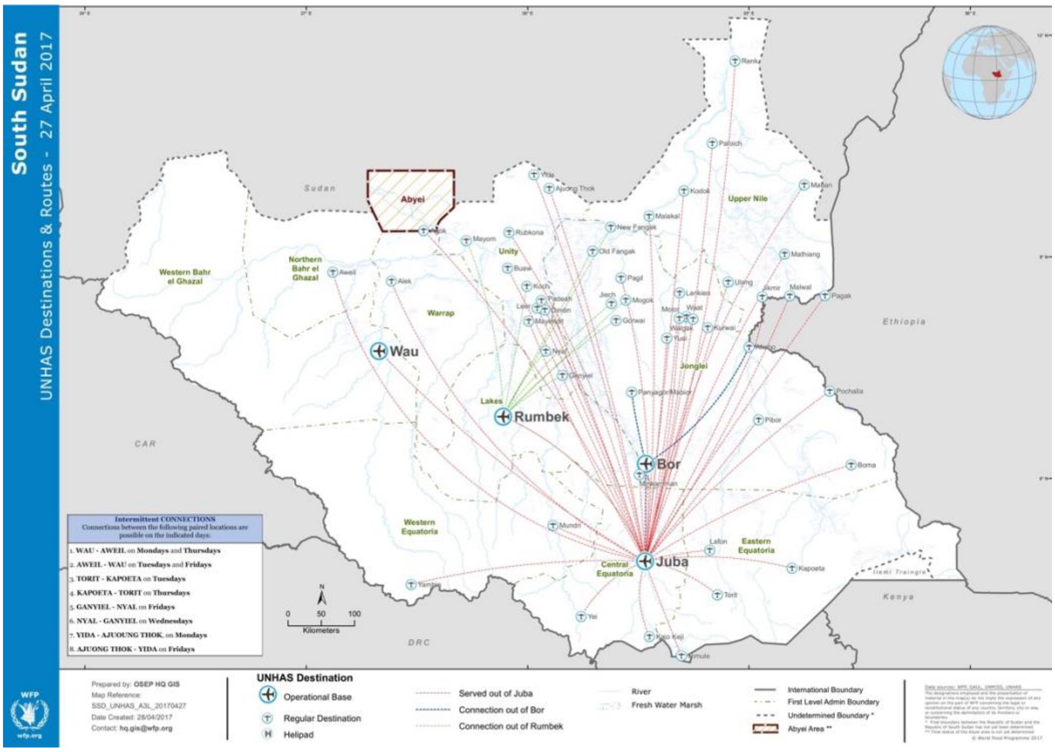

Figure 5: UNHAS Destinations and Routes in South Sudan
(*UNHAS Flight Destinations and Routes - effective 27 April 2017*, 2017)

2.3.2 Assumptions and further data exploration

An integrated look at the data and information presented till now will further support the provisional choice of Unity as the main location for the research. Information from Logistics Cluster has shown that during May and August, which is the identified disaster season, the majority of locations it served, including priority locations were located in Unity. It shows the value of studying the UAV operation in Unity as its frequent logistical activities display potential for UAVs' participation. Further looking at the tonnage of resources delivered to Unity, Jonglei and Upper Nile, it is revealed that food, nutrition, WASH, and shelter are among the frequently supplied resources, indicating in our research UAVs will be tasked to carry one or more kinds of supplies.

Critical information available till now includes population per state per county in South Sudan, geographical location data of settlements, and population figures of settlements including a set of village assessment data on South Sudan. Information that might be helpful in structuring the case study includes the general progress of humanitarian aid during the first half of 2017 in South Sudan and humanitarian response plans dedicated to South Sudan in 2017.

As mentioned earlier in Section 1.4, data collection is a task that faces uncertainty and unavailability. There simply may not be enough information around or the data existing does not come in the exact shape fit for the research. In the case of this research, in order to achieve a well-defined scope and scale, some critical information still needs to be established, namely, they are: (1) the information of aid resources dispatched, as in the amount of cargo sent in total, the number of supplies sent out by categories, the number of supplies received by villages/settlements and the number of supplies received per capita (2) the population that received aid by each settlement if not all people in all settlements were covered (3) the number and geographical location of settlements/camps/hospitals in Unity that are reached (4) the number and geographical location of airfield, airports, helipads and regional warehouses used by organizations and agencies.

Some key assumptions for filling the blanks in data include (1) further reducing the scope to only focus on the state of Unity in order to form a solvable case (2) using available information from humanitarian organizations to determine the content and size of delivery package (3) using map as a reference for the hub/airport's location information (4) using data and information from the same time in another year as a reference and a comparable source to fill the blanks of the missing data needed for the designated time period of the research.

2.3.3 Villages and Locations

In Section 2.3.1, it is established that the State of Unity should be given a higher priority to be focused on in this research. Within Unity, there are three especially "problematic" counties in terms of disaster emergency level which are Koch, Leer and Mayiendit.

A multi-sectoral village assessment survey conducted by the International Organization of Migration's Distance Tracking Matrix (IOM DTM), although conducted in 2019, can still be useful for the data collection on human settlement, their geodata and population figures. The map visualizations of all human settlements logged in IOM DTM dataset is presented below in Figure 6, Figure 7, and Figure 8.

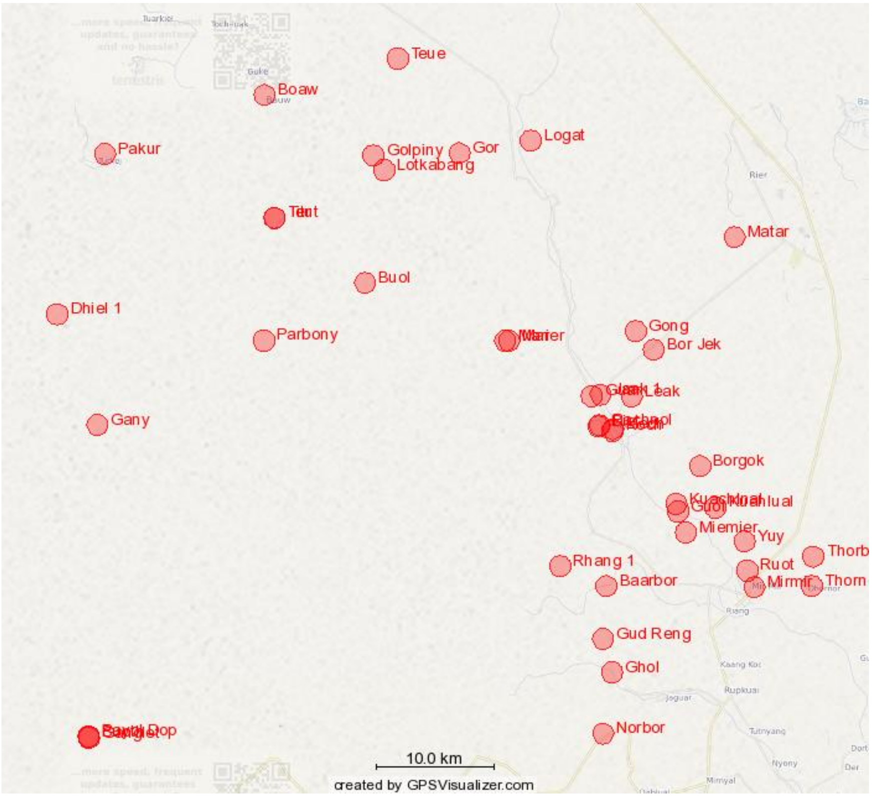

Figure 6: Koch human settlement map

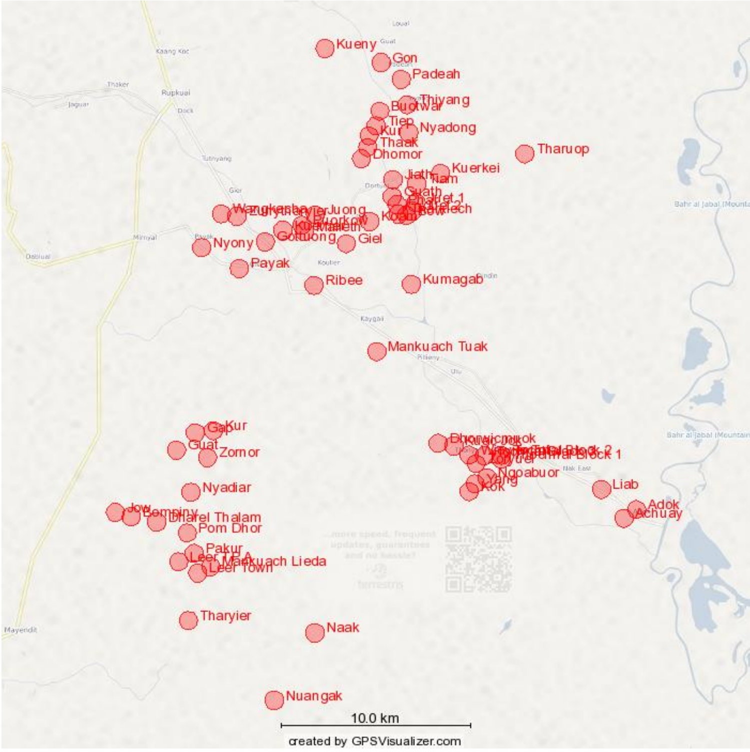

Figure 7: Leer human settlement map

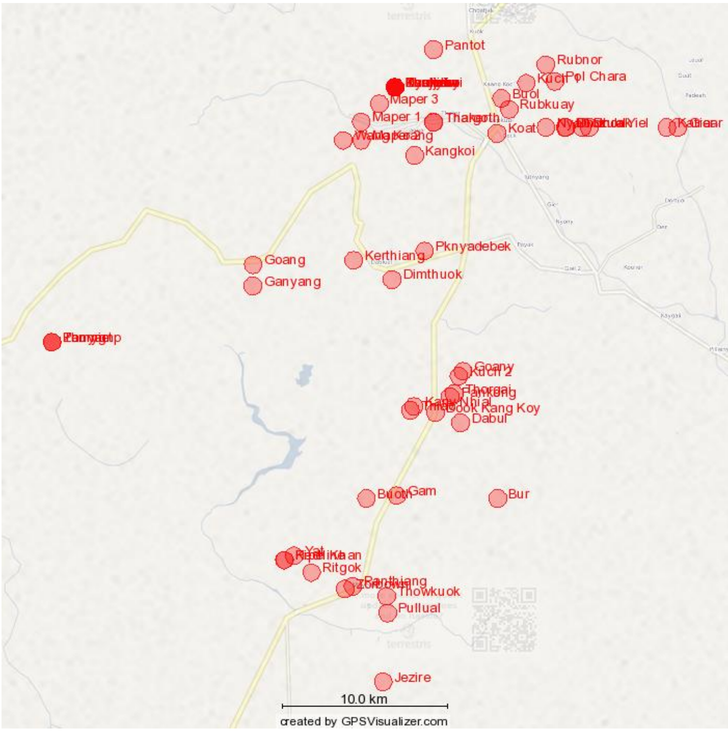

Figure 8: Mayiendit human settlement map

There are 43 villages/neighborhoods scattered in Koch, housing 5712 IDPs and 6344 returnees; 64 locations in Leer, containing 11513 IDPs and 8913 returnees and 58 locations in Mayiendit, housing 5350 IDPs and 9118 returnees. As shown in the maps above, all three counties shown similar pattern of geographical distribution of human settlements. All sites/villages are densely distributed across the map and often form clusters among several locations. See Figure 14, Figure 15 and Figure 16 in Appendix for a detailed population of IDPs and returnees and geographical information of all locations in Koch, Leer and Mayiendit. The population allocations of all sites in three counties are also in line with each other, having no sites being too crowded or having too little population. The research onward will pick one county as the representative of the general picture of humanitarian logistics in South Sudan.

2.3.4 Airports and Transportation Hubs

As indicated in Section 1.1.2, the drone deployed here requires a 300-meter runway to take off. Hence there must be such a location with conditions to enable drone operation. Such a location in the model will be considered the starting point and terminal for every drone route.

Below is presented the distribution of airports in Koch and Leer. The information is retrieved from South Sudan Humanitarian Integrated Humanitarian Data Package (IHDP). Koch is shown to have 3 small airports within its border while there are 2 in Leer. Mayiendit is shown to have no airport.

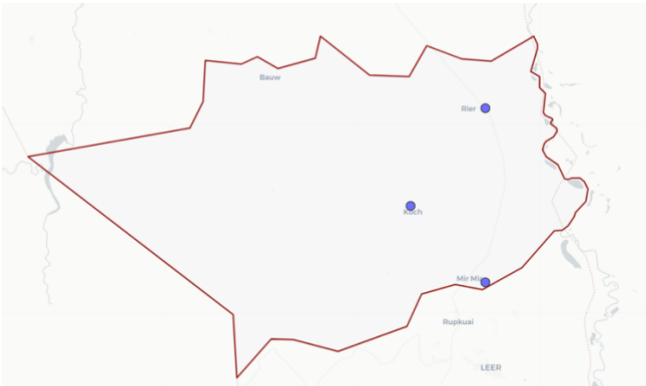

Figure 9: Airports in Koch

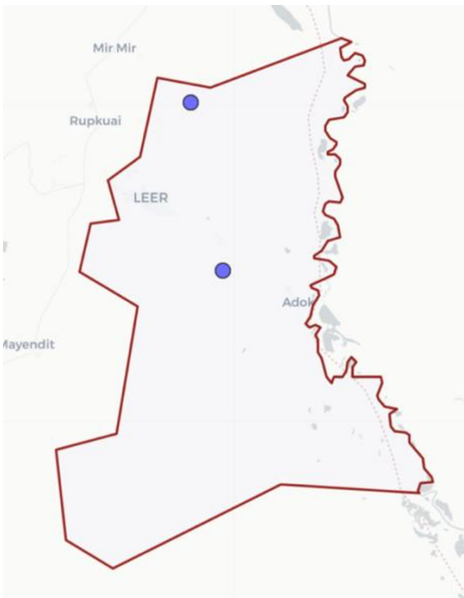

Figure 10: Airports in Leer

Although little is known about whether these airports/airstrips have the hanger and storage facility to enable local loading/unloading, it is important to assume that local facilities would suffice as the MiniFreighter is not strict on the runway conditions. Hence the drones and trucks will be considered as being able to load cargoes and depart from local airstrip and return for reload.

2.3.5 Amount, Unit, and Payload of Resources

Since it might be the case that the transportation of UAV may pose specific constraints, more information is needed for determining the content of cargo.

Shelter and support-related items need to be excluded first. The materials needed for constructing temporary or semi-permanent shelters and other living facilities often include timber, bricks and plastic sheets, which will be accompanied by professional equipment for cutting (Shelter Projects, 2019). All of these are supposed to be shipped by helicopters or trucks as they are too bulky to fit in drones and not compatible with the airdrop mode.

According to Red Cross, water-related materials, kits and resources are often valves, pumps, pipes and water tanks which may not always be compatible with UAV payload and airdrop mode. It is also impractical to assess individual demand on this equipment. Sanitation kits are mainly comprised of equipment for disinfecting, fumigating and water processing, which is always too heavy for air transport. The water pump or generator under this category often weighs more than 300 kg, making it too heavy for the drone (*ICRC Standard Products Catalogue - Sanitation*). Hence out of the purpose of practicality, resources fitting with UAV transportation will be hygiene or food package.

It is often the case that no numbers were given in the response plan or sitrep in terms of volume of the shipment or the size of a single ration/package. Thus information such as general guidelines for preparing emergency aid packages is the only source to refer to make assumptions for estimating the payload of UAVs and the demand of IDPs covered.

According to Table 2 and Table 3, nutritional supplies and food are among the most frequently needed and hence are dispatched most. Checking with available information, the amount of energy required for the emergency-affected population is 2080 kcal per capita per day (UNHCR; et al.). Among commonly-used food-aid commodities, there are canned corned beef, canned fish, canned ready meal and food ration bar which are suitable in terms of their payload and package size, with their calorie contained listed below.

Item	**Content Weight**	**Shipping Weight**	**Calories**
Corned Beef, Canned	200g	0.22kg	440 kcal
Fish, canned	150g	0.17kg	457.5 kcal
Emergency Food Ration	9*55g, box 500g	0.567kg	2178 kcal min.
Ready Meal, vegetarian, canned	200g	0.22kg	1200 kcal min.

Table 5: Weight and Calories contained

(*ICRC Standard Products Catalogue - Corned Beef, canned*; *ICRC Standard Products Catalogue - Emergency Food Ration Bar*; *ICRC Standard Products Catalogue - Fish, canned*; *ICRC Standard*

Products Catalogue - Ready meal, canned; UNHCR; et al.)

These four items in total weigh 1.17kg and count for 4272.5 kcal, with a box of food ration bars being adequate for a person's daily energy need. For the concern of food variety, it is decided here that one portion for a person should contain one can of corned beef, one can of fish and one can of ready meal, which in total weighs up to 0.61kg and provide 2097.5 kcal. Under this setting, one delivery box of 20kg will contain enough amount of food to cover 32 people for one day. A drone with a payload of 160kg will be able to cover 256 people for one day in one single trip.

2.4 Conclusion

To conclude, several assumptions and premises are made to ensure the data collection. Under these premises, counties of Koch, Leer and Mayiendit are identified as "troublesome" and hence will be looked into. Their respective airports are considered as transportation hubs for UAVs and trucks to start their trip. Food is selected as the major category of aid supply in this case and the MiniFreighter drone is able to cover the daily nutritional demand of 256 people in one delivery trip.

3. Literature Review

In this chapter, existing literature will be examined to answer our research questions presented in Section 1.3. Sections 3.1 and 3.2 will cover last-mile logistics and its evolution in humanitarian scenarios. Section 3.3 will look into the objectives and goals of humanitarian logistics. The rest will be dedicated to heuristics/algorithms designed to solve the Vehicle Routing Problem (VRP), with an emphasis on solving a VRP in humanitarian aid-related cases using these algorithms.
Since the transportation security and accessibility caused by the domestic unrest in South Sudan is a unique and significant trait that cannot simply be overlooked, Section 3.5 will look into variations of the VRP involving risk and danger and provide a theoretical ground for the algorithm that will be used in this model.
For the first part, the keywords/strings used for searching here include ("last-mile logistics" or "last-mile delivery", ("last-mile humanitarian logistics" and "humanitarian logistics"). The literature search is conducted on Scopus and ScienceDirect.

3.1 Last-mile Logistics

Last-mile logistics has shown a definition that is constantly being renewed and relates to various fields beyond the scope of logistics that is "right time, right place, right products, right condition, right user and reasonable cost" (Juhász & Bányai, 2018).

Normally the term last-mile logistics or last-mile delivery is frequently discussed in the settings of city logistics, e-commerce/retail, and crowdsourced backgrounds. While not strictly focusing on the literal "last mile" of the supply chain, figuratively the last mile of logistics is related to the freight transport over the last Section of the route using the last (in order) means of transport (Macioszek, 2018). When considering the impact of last-mile logistics on business, it is also regarded as one of the more expensive, least efficient, and most polluting Sections of the entire logistics chain. Hence Roel et al. (2011) proposed a set of fundamental aspects that determines the nature of the last mile under the requirement of the business environment, which is comprised of the customer service level, security and delivery type, the geographical area, the degree of market penetration and density, and subsequently identify meaningful last-mile subflows including low-value consumer goods, medium-value goods, and high-value durable goods.

In the extensive literature review by Olsson et al. (2019), last-mile logistics is described as "the process of planning, implementing, and controlling efficient and effective transportation and storage of goods, from the order penetration point to the final customer. The typology of Olsson et al. (2019) also brings out the concept of three central components of the core of the last-mile logistics system: last-mile fulfillment, last-mile transport and last-mile delivery. Such a concept puts an emphasis on the execution of an order, the movement of the goods in the last mile and the physical delivery to the final destination. Therefore the research regarding last-mile logistics can be directed to supply chain design, innovative vehicle solutions, and routing. Among themes addressed in last-mile logistics research, there are emerging trends and technologies, operation optimization, supply chain structures, performance measurement and policy (Olsson et al., 2019).

The review of Lim et al. (2018) agreed upon the notion that the definition of last-mile logistics should converge to a common understanding that refers to the last part of a delivery process. In the context of e-commerce, the definition from Lim et al. (2018) describes last-mile logistics as the last stretch of a business-to-consumer (B2C) parcel delivery service which takes place from the order penetration point to the final consignee's preferred destination point. Ranieri et al. (2018) highlight the disruptive force of innovative vehicles in last-mile logistics, stating UAVs have opened new opportunities in civil applications.

Some distinctions are also needed to be made when discussing last-mile logistics. A notable one is an intersection between last-mile logistics and sharing economy business models. Three foundational cores of sharing economy are identified as access economy (sharing underutilized assets to optimize their use), platform economy (intermediating decentralized exchanges among peers through digital platforms), and community-based economy (coordinating through non-contractual, non-hierarchical, or non-monetized forms of interaction) (Acquier et al., 2017). It means that crowd can indeed be an efficient means of making deliveries as drivers are independent contractors using their own vehicles to provide logistic service, hence offering explicit economic benefit for the courier and connecting platform (Moncef & Monnet Dupuy, 2021). City logistics is another concept needed to be distinguished. Last-mile logistics often emphasizes the perspective of private actors in supply chain networks, city logistics often conducts its research from the perspective of public actors (Olsson et al., 2019). City logistics aims to increase its effectiveness to reduce externalities and increase social sustainability, especially in terms of livability, while last-mile logistics increases efficiency to contribute to economic sustainability regarding reduced cost and increased profit (Olsson et al., 2019; Taniguchi, 2014).

3.2 Logistics in a Humanitarian Context

Lessons are always painfully learned in the field of post-disaster relief aid. Holguín-Veras and Jaller (2012) deducted from the experience of Hurricane Katrina that the lack of an efficient logistic system may have major negative consequences on the lives of the individuals impacted by an extreme event. Under such conditions, delivery of critical supplies is an extremely difficult task due to severe damage to the physical and virtual infrastructure and the limited or non-existent transportation capacity in the affected area (Holguín-Veras et al., 2007). Hence there rises a necessity of looking into logistics activities under the conditions of catastrophic events as emergency circumstances pose new challenges to the once direct concept of dispatch and delivery. The discrepancies between regular commercial logistics and humanitarian logistics responding to different levels of urgency will also be examined. Several traits that define humanitarian logistics are discussed in Section 3.2.1. The last-mile delivery in humanitarian aid context is covered in Section 3.2.2.

3.2.1 Purpose, Phases and Characteristics

The purpose of the humanitarian relief chain is to rapidly provide the appropriate emergency supply to people affected by disasters so as to minimize suffering and death (Balcik et al., 2008). The most significant problem in the last mile generally stems from the limitations related to transportation resources and emergency supplies (Balcik et al., 2008). While the prime consideration of operational efficiency is still akin to commercial logistics (Holguín-Veras et al., 2012), Holguín-Veras et al. (2014) concluded the characteristics that set post-disaster humanitarian logistics (PD-HL) apart from both commercial logistics and the various forms of longer term humanitarian logistics efforts: (1) the social networks that orchestrate the technical activities concerning logistics are severely disrupted or destroyed; (2) the infrastructure and communication systems supporting such process of logistics may have been impacted and unable to fully function; (3) uncertainty about infrastructure conditions; (4) large and dynamic volumes of critical supplies; (5) short timeframe to respond and prevent loss of lives and property; (6) huge amount of uncertainty about what is actually needed, where is needed and what is available at the site; (7) the ability of the local leaders, civil society, and private sector to organize an effective response may have been compromised by the event itself; (8) large proportions of local assets such as trucks and supplies may have been destroyed; and (9) huge flow of donations with large proportions of supplies that are not needed at the site. Combining the concluded traits with the real-life PD-HL process of the Tohoku earthquake, key lessons identified include the local distribution being the most challenging part and the availability of multi-modal transportation alternatives being successfully exploited to transport critical supplies to the disaster area (Holguín-Veras et al., 2014). The findings further reinforced the notion that logistics sectors involved in the distribution of food, water, medicines, and other supplies are likely to become critical after a disaster as well as possess unique features that require further exploring.

The central discussion regarding commercial logistics is that the main objective is to either minimize the cost of transportation or logistics. While taking a holistic view of how humanitarian logistics is defined, humanitarian logistics should cover a wide range of activities that occur at any one of the phases of emergency management, i.e., mitigation, preparedness, response and recovery (Holguín-Veras et al., 2012; National Governors' Association Center for Policy Research, 1979). The scope of vehicle dispatching mainly lies within the phase of the response and long-term recovery as the intention of using multiple modes of transportation is to conduct medical care support and mass feeding for a return to a normal or improved life.

Kovács and Spens (2007) summarized from the literature that phases of disaster relief operations comprise preparation, immediate response, and reconstruction. Logistical support is needed in prevention and evacuation-related measures before a disaster strikes (which might be foreseen like volcano eruptions); in instant medical and food relief procedures once a disaster strikes, and during reconstruction phases. Kovács and Spens (2009) proposed that specifically a modal shift from air to road transportation takes place between the emergency element and the recovery phase of disaster relief. Conclusively speaking, both the activation of organizations and the challenges of humanitarian logistics depend upon the phase of disaster relief.

Ludema and Roos (2000) on the other hand, argue that there are four phases, or rather four types of humanitarian relief to distinguish: emergency, rehabilitation, development and elementary (subsistence) while pointing out that rehabilitation and elementary relief operations have a long response time and are concerned with the supply of goods.

A significant trait of post-disaster context is the magnitude of a logistical challenge in terms of the volume of cargo to be transported. The needs are different because existing activities that consume freight disappear, while others that generate freight demand are created (Holguín-Veras et al., 2012). In plain words, the basic need of survivors of a disaster will need to be covered. In addition to supplies to survivors, humanitarian logistics in general also has to meet the needs of the response process, i.e., rations for responders and all kinds of equipment needed for medical treatment, rescue, security, and transportation.

Concurring with Balcik et al. (2008) in stating humanitarian relief supply chains should dedicate to minimizing suffering and death, Holguín-Veras et al. (2012) proposed that humanitarian logistics is mainly concerned with human suffering (well-being). Hence any mathematical models designed to support the decision-making in PD-HL should take into account minimizing "deprivation cost", which represents the suffering brought about by the lack of goods or services.

Another frequently overlooked difference between commercial and humanitarian logistics is how commodity flow reaching the impacted sites is generated. Typical but complicating to humanitarian relief aid, the occurrence of a disaster is accompanied by a process by which volunteers, the curious, emergency respondents, the press and material donations converge to the affected area (Destro & Holguín-Veras, 2011). The convergence of materials comprises a highly heterogeneous flow of goods, ranging from supplies of critical importance to the response process to large influxes of low-priority goods that clog the supply chains and entry points to the area (Destro & Holguín-Veras, 2011). The existence of low-priority goods is far from the only problem as their sheer volume was always much larger than the actual needs, distracting responders busy with other more important activities and hence disrupting operations (Holguín-Veras et al., 2012; Holguín-Veras et al., 2014). In other word, superfluous and unsolicited donations come in inappropriate sizes at inappropriate times and thus require the expenditure of considerable resources to manage or dispose of them (Holguín-Veras et al., 2007).

A distinction that is especially important for the premise of the South Sudan case is the level of uncertainty. While commercial logistics is designed to meet the demand for the portfolio of goods based on the forecast, there is a huge amount of uncertainty about what is needed and who needs what in the aftermath of a disaster. In an example of regular humanitarian logistics (R-HL), the transport of relief items to a crisis region can still face considerable amount of uncertainty such as conditions of roads and bridges being unsure due to rapidly changing conditions (Holguín-Veras et al., 2012). This exact troublesome feature of humanitarian logistics lays the groundwork for us to consider a transportation method that can operate regardless the volatility going on.

3.2.2 Humanitarian Supply Chain and its "Last-mile"

Humanitarian logistics includes traditional supply chain activities such as planning, forecasting, procurement, transportation, warehousing, and delivery and supplemental ones such as appeal and mobilization. In relief operations, logistics are required to organize and implement the efforts of organizations responding to a crisis. Russell (2005) offered a vision of the humanitarian supply chain by dividing into processes including preparedness, assessment appeals, resource mobilization, procurement, transportation execution, track & tracing, stock asset management, extended point of delivery, and relief to beneficiaries. Similar to a commercial supply chain, supplies flow through the relief chain via a series of long-haul and short-haul shipments. Supplies flowing through the relief chain primarily consist of pre-positioned stocks in warehouses, supplies procured from the suppliers, and in-kind donations. Supplies are shipped from various worldwide locations to a primary warehouse, which is usually located near a sea- or airport. Next supplies are shipped to a secondary hub (a large, permanent warehouse typically located in a larger city), where they are stored, sorted, and transferred to local distribution centers. Finally, local distribution centers deliver relief supplies to beneficiaries. Supplies acquired from local sources may also be stored at secondary and tertiary warehouses, or directly distributed to the beneficiaries (Beamon & Balcik, 2008).

Beamon and Balcik (2008) also outlines the basic process followed by a relief organization once a disaster occurs: performing an on-site assessment and translating the assessment into supply requirements, appealing for donations and mobilizing supplies (procuring and checking inventories), and shipping to the disaster site.

Last-mile distribution is the ultimate stage of the humanitarian supply chain. Before during and after a disaster, the necessity is to secure and moved the required materials (food, water, medicine, shelter, etc.) from one point to another in the most efficient and effective way (Roy et al., 2012). A working definition also provided by Roy et al. (2012) determines the last-mile relief distribution is associated with the delivery of relief supplies from the field warehouse to the disaster-affected people through the integration of facility location, inventory management, transportation management, and distribution decisions while taking into account the key factors affecting it.

The last-mile problem and in particular the logistic facility management, coupled with material distribution modalities is the objective of many studies. Transportation is frequently put under the spotlight for its role as a cornerstone of the last-mile distribution problem. Field vehicles are used to transport humanitarian staff, aid items, and materials in an environment where no vehicles mean no aid (Battini et al., 2014; Van Wassenhove & Pedraza Martinez, 2012). Balcik et al. (2008) concurred by pointing out that the main operational decisions related to last-mile distribution are relief supply allocation, vehicle delivery scheduling, and vehicle routing.

3.2.3 UAVs' application in humanitarian logistics

UAVs have been used as innovative solutions to overcome infrastructural and supply chain gaps, caused by lack of infrastructure, complicated terrain and extreme weather conditions (*Leveraging the power of drones to reach the last mile*). UNICEF set up the first ever humanitarian drone corridor in Africa. The corridor is designed to provide a controlled platform and will facilitate testing in three main areas including generating and analyzing aerial images for development and during humanitarian crises, exploring the possibility for UAVs to extend Wi-Fi or cellphone signals across difficult terrain, and delivering small low weight supplies such as emergency medical supplies, vaccines and samples for laboratory diagnosis (*Humanitarian drone corridor launched in Malawi*, 2017). In December 2018, a one month old baby became the world's first child to be given a vaccine delivered commercially by drone in a remote island in the South Pacific country of Vanuatu. The vaccine delivery covered almost 40 kilometers of rugged mountainous terrain, marking a big leap for global health (*Child given world's first drone-delivered vaccine in Vanuatu - UNICEF*, 2018).

The project Drones4Good from the German Aerospace Center (DLR) also commissions research of drones in similar fashions. The first aim is to use a camera installed on a drone to image a larger area than ground-based systems, enabling humanitarian workers on the ground to receive processed information about damage to buildings, supply routes and people in need. The second aim is to develop safe techniques for drones to drop supplies without endangering people and infrastructure below ("Humanitarian aid with uncrewed aircraft and artificial intelligence," 2021).

3.3 Objectives in Humanitarian Logistics

The many distinctions that set humanitarian logistics apart from conventional commercial logistics are exactly the reasons why humanitarian logistics always pursue different objectives. For humanitarian operations as a whole, objectives tend to differ among phases, sectors, departments, and organizations. The relief (aid for life-saving purposes) program in humanitarian logistics alleviates the suffering of affected people and hence has the time of response as its objective while the following development program (services to improve the quality of life) are implemented to support the rehabilitation of the affected community as well as improve community preparedness.

Hence the development program normally faces less uncertainty and has cost efficiency as the objective (Pedraza-Martinez & Van Wassenhove, 2012).

Deprivation cost, a term frequently brought up in humanitarian aid settings, is presented in Section 3.3.1. Multiple performance indicators of humanitarian supply chain are covered in Section 3.2.2.

3.3.1 Deprivation Cost

As what has already been made clear earlier in this review, humanitarian logistics concerns human suffering. May the objectives of different programs in humanitarian logistics be somewhat different, but their ultimate goal is to relieve human suffering. Now knowing the nature of humanitarian logistics, defining objectives is actually looking for proxy ways to represent human suffering. Holguín-Veras et al. (2013) argues that inter-temporal externalities, material convergence, and human suffering are essential to consider in the proper modeling of PD-HL operations. Inter-temporal externalities may be not always of concern because the time period is limited to a specific period while the effect of material convergence can sometimes be excluded as well due to the category of the shipment can be designated. Hence the factor of human suffering remains the most appropriate one to be considered. Among many objective functions reviewed, Holguín-Veras et al. (2013) recognizes their roots in commercial logistics and consequently identifies minimization of logistics costs, minimization of penalties/weighting factors, and minimization of unmet demands as some examples. Constraints identified include maximum headways between deliveries, minimum delivery amounts and maximum fill rates. But the focus on the cost of human suffering always brings the discussion back to the measuring of deprivation cost.

The objective function is fundamental to deciding how to harmonize conflicting goals and optimally allocate scarce resources. Maintaining high levels of service in the affected areas could require larger logistical expenditures than are possible. On the other hand, minimizing logistical costs without considering the impacts on the population could negatively affect their welfare. As a result, Holguín-Veras et al. (2013) made a point by attempting to incorporate a measure of the suffering experienced by the beneficiaries, from their lack of access to a good or service, which is defined as “deprivation cost”.

Deprivation cost can also be discussed by the anatomy of its characteristics: monotonicity (increases in the deprivation time are bound to lead to increases in deprivation costs across the entire range of values), convexity (deprivation costs are expected to grow increasingly faster as the deprivation time increases), non-linearity (a natural consequence of how human beings deal with shortages of life sustaining items), hysteretic effects and the non-additive nature of unmet demands (an individual who has been deprived of a good or service c that is consumed at a rate of u_c per unit time, for a deprivation time of δ_{it} time units, may not be able to consume the total of $u_c\delta_{it}$ when the needs are fulfilled) and inter-temporal externalities (a portion of the supplies from a large delivery is used to satisfy immediate needs, and rest could be save for later use, impacting deprivation cost in future time periods. The most common case in the initial stage of the response is that demand nodes not receiving aid at a given time period experience a concomitant increase in their deprivation costs, or the opportunity cost of the delivery strategy) (Holguín-Veras et al., 2013; Shao et al., 2020).

Despite a consensus being reached on considering human suffering in humanitarian logistics and Holguín-Veras et al. (2012) and Holguín-Veras et al. (2013) being widely considered milestones and pioneers in this field, researchers actually have not settled on a unified version of the conception of deprivation cost. The most notable divergences stem from different types of methodology to consider for humanitarian relief and different degrees of application in estimating deprivation cost. For example, Holguín-Veras et al. (2016) stresses consistency with real life when discussing critical supplies such as drinkable water, while Macea et al. (2018), similarly being loyal to consistency, adopts a different method to estimate the deprivation cost despite working on drinkable water as well. Cotes and Cantillo (2019) uses the global social cost (the sum of private costs, i.e., costs of transportation, inventory costs and fixed facility costs, and deprivation costs) as the goal of minimization. There are also researches going for a "maximalist" approach and opting for multiple objectives, such as Serrato-Garcia et al. (2016) taking deprivation cost as one of the many costs (all operating costs) to be optimized at the same time.

Quite evidently there is still much alignment needed to be done in spite of deprivation cost as the theme has gained much attention in recent years. As a newly born concept, it is natural for deprivation costs to incur various branches of research methodology, some of which are too ambitious, complex, and tedious for others to replicate or emulate. Different standards, scopes, methods, and formulations may apply to different types of goods or even different phases of the humanitarian aid operation. However, it is essential to keep in mind the overarching guideline of "reduce human suffering" to help customize specific objectives for research of different sizes.

3.3.2 Objectives as Performance Indicators

From another perspective, deriving objectives for humanitarian logistics can be in line with its performance measurement as we would like our model to represent the goal of humanitarian logistics. In a conjoint analysis conducted by Gralla et al. (2014), attributes for describing and assessing aid delivery include total cargo delivered, prioritization by item type and location, speed of delivery, and cost. The most important concern is shown to be increasing the total quantity delivered while cost is the least important one, reflecting that saving lives is much more important than saving money when emergency hits. The analysis is also a revelation on the conceptual trade-off between efficiency, effectiveness, and equity as effectiveness (delivering more cargo in a short time frame) is the most important of the three goals. Hence efficiency, in this case, is a secondary goal, having priority over cost.

Beamon and Balcik (2008) expanded the scope of performance metrics for the relief chain to resource, output, and flexibility metrics. Output metrics directly measure characteristics of supply and can be used to demonstrate supply effectiveness. Among them are response time and the number of items supplied/supply availability. A distinction for relief supply distribution is equity, meaning equitable and fair supply distribution is also an indicator of effectiveness for the relief chain. Therefore, the average amount of supplies delivered per recipient over the relief horizon can also be used as an output performance measurement (Beamon & Balcik, 2008). Typical output performance metric such as fill rate also applies to the situation where the relief chain is equipped with permanent warehouses. As one may realize, despite being crucial in the supply chain, fill rate is not the most appropriate objective for research related to vehicle routing and scheduling.

Turning to a real-life case for inspiration, The International Federation of Red Cross and Red Crescent Societies (IFRC) has a dedicated key performance indicator framework, which relies on four indicators, appeal coverage, donation-to-delivery time, financial efficiency, and assessment accuracy (Davidson, 2006). The scale of these KPIs used by IFRC is significantly large as a global organization will have to deal with mass donation and coordination. Compared to previously discussed KPIs and objectives, the set used by IFRC not only covers the initial stage of humanitarian operations but also measures the quality of the demand appeal and disaster assessment, making it too ambitious for conventional research to conduct.

Golden et al. (2014) concluded that the most common performance metric for evaluating commercial vehicle routing solutions is the total travel cost associated with the routes. It is asserted again that while acknowledging financial aspects play a role, the crucial question is how well the service alleviates human suffering. In the literature review, response time, demand satisfaction, service equity and transportation costs are all identified as well-researched performance metrics of humanitarian relief.

3.4 Optimization in Routing Problems

This Section will address the theoretical background in vehicle routing, dispatching, and coordinating combined with the practice in humanitarian logistics. The review here would include heuristics and algorithms used in VRP, logic used in vehicle dispatching and real-life applications.

Sections 3.4.1 and 3.4.2 provide the background of VRP and lay the ground for Section 3.4.3, where heuristics are discussed. Section 3.4.4 builds up on the previous Section and explores heuristics problem solving in real-life humanitarian aid scenarios.

3.4.1 Vehicle Routing Problem

Distribution in a humanitarian content involves decisions including replenishment of main depots, followed by directed shipments to satellite depots and then Less Than Truckload (LTL) deliveries from satellites to the population (Penna et al., 2018). In our case setting, the drone delivery is in charge of the part where small unit shipments reach the population in need from the depot (the airport hub in Rumbek). Replying to formulating the routing and dispatching of UAVs as a Vehicle Routing Problem, we hope to find the most fitting route with case-specific objectives incorporated.

The Vehicle Routing Problem (VRP) consists of designing optimal delivery or collection routes from a central depot to a set of geographically scattered locations/customers, subject to various constraints, such as vehicle capacity, route length, time windows, etc, (Laporte, 2007). VRP was first recorded in the literature studying a relatively large-scale Traveling Salesman Problem (TSP) in 1954 (Eksioglu et al., 2009). The generalization of this problem came later at 1964 and turn the problem into a linear optimization that is commonly encountered in the domain of logistics and transport: i.e., how to serve a set of customers, dispersed around the central depot, using a fleet of trucks with varying capacities (Braekers et al., 2016).

The standardized version is referred to as the classical VRP. The classical VRP is defined on an undirected graph where $V = \{0,1,\dots,n\}$ is the vertex set and $A = \{(i,j) : i,j \in V,\ i \neq j\}$ is the arc set. Vertex 0 is the depot at which are located at most m identical vehicles of capacity Q. Each customer $i \in V \setminus \{0\}$ is associated with a non-negative demand $q_i \leq Q$. A cost matrix is defined on A with elements c_{ij}, with $c_{ij} = c_{ji}$ for all i, j. It is also common to define the problem on an undirected graph $G = (V, E)$, where the edge set $E = \{[i,j] : i,j \in V, i < j\}$ (Laporte, 2007). Eksioglu et al. (2009) summarized that the VRP consists of finding a collection of k simple circuits, each corresponding to a vehicle route with minimum cost, defined as the sum of the costs of the circuits' arcs such that:

i. Each circuit visits the depot;
ii. Each vertex other than the depot is visited by exactly one circuit; and
iii. The sum of the vertices' demand visited by a circuit does not exceed the vehicle capacity.

In the problem, the vehicle routes will start and end at the depot and aim to minimize the total routing cost (Laporte, 2007). The classical VRP has been extended in many ways by introducing additional real-life aspects. The possibilities of extending this problem include Heterogeneous Fleet VRP (HFVRP)/Mixed Fleet VRP by varying the capacities; the VRP with Time Windows (VRPTW) by assuming deliveries to a given customer must occur in a certain time interval; the VRP with Pickup and Delivery (VRPPD) with goods to be picked up from a certain location and dropped off at their destination by the same vehicle; the VRP with backhauls (VRPB), where a vehicle does deliveries as well as pick-ups in one route; the Multi-Depot VRP assuming multiple depots are among customers, and the periodic VRP when planning is made over a certain period and deliveries can be done in different days (Braekers et al., 2016).

Other notable variants of VRP include Open VRP (OVRP) in which vehicles are not required to return to the central depot, Dynamic VRP (DVRP) where routes are adapted dynamically after inputs are updated continuously, and Time-dependent VRP (TDVRP) assuming travel times are deterministic but no longer constant (Braekers et al., 2016).

The VRP can be formulated as an integer program shown below:

Let x_{ij} be an integer variable which may take the value $\{0,1\}$, $\forall \{i,j\} \in E \ \backslash \{\{0,j\} : j \in V\}$ and value $\{0,1,2\}, \forall \{0,j\} \in E, j \in V$. $x_{0j} = 2$ when a route including the single customer j is selected in the solution.

(1) $Minimize \ \sum_{i \neq j} c_{ij} x_{ij}$

Subject to:

(2) $\sum_j x_{ij} = 1, \ \forall \, i \in V,$

(3) $\sum_i x_{ij} = 1, \forall \, i \in V,$

(4) $\sum_i x_{ij} \geq \ |S| - v(S), \{S: S \subseteq V \setminus \ \{1\}, |S| \geq 2\},$

(5) $x_{ij} \in \ \{0,1\}, \forall \, \{i,j\} \in E; i \neq j$

(1), (2), (3) and (5) formulate a modified assignment problem, i.e., assignments on the main diagonal are prohibited. (4) are for sub-tour elimination: $v(S)$ is an appropriate lower bound on the number of vehicles required to visit all vertices of S in the optimal solution (Laporte, 1992; Zirour, 2008).

Capacity-constrained VRPs will be referred to as CVRPs (Laporte, 1992). This describes our case as we expect drones to take off with a full load. In the CVRP all the customers correspond to the deliveries, the demands are deterministic, known in advance and may not be split, the vehicles are identical and are based at a single depot, only the capacity restrictions are imposed, and the objective is to minimize the total cost needed to serve all the customers (Toth & Vigo, 2002). CVRP shares the same set of key assumptions with VRP, as presented previously.

3.4.2 Exact Methods for solving the VRP

Exact methods for the VRP can be classified into 3 categories: direct tree search methods, dynamic programming and integer linear programming (Laporte & Nobert, 1987). Frequently-used and representative algorithms include branch-and-bound algorithm, set partitioning formulation and vehicle formulations (Laporte, 1992, 2007; Laporte & Nobert, 1987). However, the exact algorithms, for example, those based on brand-and-cut, have a performance limit as there is a certain threshold for the number of customers involved in solving. Hence it is concluded that exact methods are only for relatively small problems (Laporte, 2007; Laporte & Nobert, 1987). Thus the focus of this Section will be dedicated to heuristics, which look more suitable and applicable in our situation.

3.4.3 Heuristics for solving VRP

The VRP is deemed as NP-Hard, thus pushing researchers to use heuristics. A heuristic is a technique consisting of a rule or a set of rules which seeks (and hopefully finds) good solutions at a reasonable computational cost. A heuristic is approximate as it provides a good solution with relatively little effort, with no guarantee of optimality. A meta-heuristic is a top-level strategy guiding an underlying heuristics in solving a given problem (Voß, 2001). A fitting definition was given in Voß et al. (2012): "*A meta-heuristic is an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions. It may manipulate a complete (or incomplete) single solution or a collection of solutions at each iteration.* "

A *local search* heuristic starts from an initial solution s_0 (which may be infeasible) and moves at each iteration t from solution s_t of value $f(s_t)$ to another solution located in the neighborhood $N(s_t)$ of s_t. In most cases, s_t is the current solution but other multi-start mechanisms allow reinitiating of the search from a solution that differs from the current one. The neighborhood $N(s_t)$ consists of all solutions that can be reached from s_t by applying a given type of transformation, for instance relocating a vertex from its current route into another route. The search ends with the best known solution s^* after a stopping criterion has been satisfied, usually a preset number of iterations, or a given number of consecutive iterations without improvement in s^*(Laporte, 2007).

The exploration of neighborhoods leads to the occurrence of a series of metaheuristics. In Dueck (1993), a record is s^* and a solution s is randomly selected in $N(s_t)$. σ is a user-controlled parameter (deviation) generally slightly larger than 1 and it follows that $s_{t+1} \coloneqq s$ if $f(s) < \sigma f(s^*)$ (Laporte, 2007). In *variable neighborhood search*, a series of nested neighborhood structures are defined. When a local optimum is achieved, it proceeds to the next neighborhood in the nested structure; the search restarts from the first neighborhood whenever a new best solution is identified or all neighborhoods have been explored (Laporte, 2007; Mladenović & Hansen, 1997). Other neighborhood searches would for example involve neighborhoods of much larger size. Pisinger and Ropke (2007) introduced a version of *adaptive large neighborhood search* where a set of large neighborhoods corresponded to destroy and repair heuristics is predefined. The control process is realized by assigning a score to neighborhoods. The more a neighborhood has contributed to the solution process, the larger score it obtains, and hence it has a larger probability of being chosen.

Tabu search starts from an initial solution x_1 and moves at each iteration t from x_t to its best neighbor x_{t+1}, until a stopping criterion is satisfied. If $f(x)$ denotes the cost of x, then $f(x_{t+1})$ is not necessarily less than $f(x_t)$. To avoid cycling, solutions that were recently examined are forbidden, or *tabu*, for a number of iterations. To alleviate time and memory requirements, it is customary to record an attribute of tabu solutions rather than the solutions themselves (Laporte et al., 2000). In the version of tabu search introduced in Cordeau et al. (2001), each solution $s \in S$ is associated with an attribute set $B(s) = \{(i,k): customer\ i\ is\ visited\ by\ vehicle\ k\}$. The neighborhood $N(s)$ of a solution s is defined by removing an attribute (i,k) from $B(s)$ and replacing it with (i,k') where $k \neq k'$. The removed attribute (i,k) then is assigned with a tabu status for the next θ iterations. This is to prevent excessive bookkeeping due to the naïve way of forbidding the process of going back to previously encountered solutions (Cordeau & Laporte, 2005).

In tabu search, it is common to prohibit reverse moves for θ iterations to prevent cycling. Thus a customer moved from route r to route s at iteration t may be prohibited from being reinserted in route r until iteration $t+\theta$, or it may not leave route s until iteration $t+\theta$. Furthermore, the method of removing attributes introduced in the previous paragraph is to diversify the search by penalizing frequently used solution attributes or frequently performed moves. The penalizing can be done by adding to the routing cost $c(x_{t+1})$ of x_{t+1} a penalty term equal to the product of three factors: a factor measuring the past frequency of the move; a factor measuring instance size; a user-controlled scaling factor (Cordeau & Laporte, 2005).

The principles of *genetic algorithms* (GA) evolve a population of solutions. A population of solutions is maintained and a reproductive process allows parent solutions to be selected from the population. Offspring solutions are produced that exhibit some of the characteristics of each parent. The fitness of each solution can be related to the objective function value, in the case of VRP, the total distance travelled, and the level of any constraint violation. Offspring with relatively good fitness levels are more likely to survive and reproduce, with the expectation that fitness levels throughout the population will improve as it evolves (Baker & Ayechew, 2003; Laporte, 2007). The starting point for any GA is in the representation of each solution or population member. Typically this will be in the form of a string or chromosome. Individual positions within each chromosome are referred to as genes (Baker & Ayechew, 2003).
The steps of a GA can be sketched as follows:

Create an initial population of P solutions.
Evaluate each solution.
Repeat for a fixed number of generations:
- Repeat until P offspring solutions are created:
  - Select two parent solutions in the population (with replacement) using a randomized selection procedure based on the solution values.
  - Apply crossover to the two parent solutions to create two offspring solutions.
  - Apply mutation (with a small probability) to each offspring.
  - Include the two offspring in the new population.
- Evaluate each offspring in the new population.
- Replace the old population by the new one.

Return the best solution found.

Table 6: GA procedures (Potvin, 2009)

First, an initial population of solutions is created, either randomly or through heuristic means. Then, the value of each solution, "the fitness", is computed. The next population is then created from parent solutions chosen in the current population. In Katoch et al. (2021), the procedure of GA is explained as follows: "A population (Y) of n chromosomes are initialized randomly. The fitness of each chromosome in Y is computed. Two chromosomes $(C1\ and\ C2)$ are selected from the population Y according to the fitness value. The single-point crossover operator with crossover probability (C_p) is applied on $C1$ and $C2$ to produce an offspring (O). Thereafter, a uniform mutation operator O is applied with mutation probability (M_p) to generate O'. The new offspring O' is placed in the new population. The selection, crossover, and mutation operations will be repeated on the current population until the new population is complete."

A flowchart of the genetic algorithm used by Mohammed et al. (2017) is presented in the appendix.

The *simulated annealing* (SA) algorithm imposes different randomized search, acceptance, and stopping criteria on the local search method in order to escape poor local minima. It is named so because of its analogy to the process of physical annealing with solids, in which a crystalline is heated and then allowed to cool very slowly until it achieves its most regular possible crystal lattice configuration (i.e., its minimum lattice energy state), and thus is free of crystal defects. SA establishes the connection between this type of thermos-dynamic behavior and the search for global minima for a discrete optimization problem. Furthermore, it provides an algorithmic means for exploiting such a connection (Henderson et al., 2006).

Simulated annealing does accept non-improvement moves at some iterations with certain probabilities. The probabilities are determined by a control parameter, called temperature, which tends to zero according to a deterministic cooling schedule (Osman, 1993). The algorithm consists of two parts: an initial solution is generated using a set of constructive heuristics and then altered using another set of improvement heuristics (Haridass et al., 2014). The concept of the method is adopted from the annealing process used in the metallurgical industry. The optimization process of SA searches for a (near) global minimum mimicking the slow cooling procedure in the physical annealing process. It starts from a random initial solution. At each iteration, a new solution is taken from the predefined neighborhood of the current solution. The objective function value of this new solution is then compared with that of the current best to see if an improvement has been achieved. If the objective function value of the new solution is better, the new solution becomes the current solution with which the search continues with a new iteration. A new solution with a degraded objective function value may also be accepted as the new current solution, with a small probability determined by the Boltzmann function, $\exp\left(-\frac{\Delta}{kT}\right)$, where Δ is the difference of objective function values between the current solution and the new solution, k is a predetermined constant and T is the current temperature (Yu et al., 2010). The idea is not to restrict the search so that moves that increase the objective function (in a minimization problem) are also allowed in order to avoid being trapped (prematurely) in a local minimum.

The temperature here is a parameter. The initial temperature T_0 determines and limits the scope of the search in that dimension where the cooling process starts. One must select an initial temperature adequate to prevent the algorithm from being trapped in a local minimum and high enough to allow the system to have a high degree of freedom for changing neighboring solutions (Avila & Valdez, 2015).

The steps of SA are shown as follows (Alfa et al., 1991; Johnson et al., 1989):

Step 1. Get an initial solution S.
Step 2. Get an initial temperature $T_m \geq 0$.
Step 3. While not yet frozen do the following.

(Being Frozen means no further improvement can be done).
3.1 Perform the following loop L times.
3.1.1 Pick a random neighbor S' of S.
3.1.2 Let $\Delta = cost(S') - cost(S)$.
3.1.3 If $\Delta \leq 0$ (downhill move),
Set $S = S'$.
3.1.4 If $\Delta \geq 0$ (uphill move),
Set $S = S'$ with probability $e^{-\Delta/T_m}$.
3.2 Set $T = rT$ (reduce temperature). r is a cooling rate.
Step 4 Return S.

Table 7: SA Procedures

3.4.4 Heuristic-inspired Problem-solving in Humanitarian Relief

In the world of disaster management, the real-world VRPs are often more complex and challenging to be solved by any conventional means available. For such a problem, uncertainty and the dynamics of parameters are the main ingredients in addressing a complete and realistic model (Anuar et al., 2021).

Anuar et al. (2021) conducted an extensive literature review on the modelling method in routing optimization in humanitarian relief. The adoption of machine learning methods is shown to be very limited. Heuristic and metaheuristic approaches introduced before could be considered to be typical choices.

3.5 VRP Optimization involving risks

VRP problems are generally well-studied, but safety and security problems seem to be underrepresented in the literature possibly because the safety and security problems can take very different and seemingly unrelated forms (Fröhlich et al., 2022). Fröhlich et al. (2022) provided a set of useful definitions of risk and danger (risk is referred to when a mathematical term is used to measure risk and danger when the model is impacted by threats but does not explicitly formulate this), as well as a simple taxonomy of VRP-based problems focusing on safe and secure routing: cash-in-transit (CIT), patrol routing and hazardous material (hazmat) transportation.

For CIT problems, the danger can be seen as the probability of getting robbed, while specific points had to be visited to either pick up or drop off valuables. Patrol routing also focuses on visiting specific checking points. Hazardous material transportation typically involves visits to specific points but without accidents caused by malicious outside forces. These problems aim at minimizing expected harm to the population (Fröhlich et al., 2022).

Risk models have been developed in many hazmat transportation literature, in which a risk function is defined for each road Section and safe routes are selected looking at the minimization of the operating costs. The general basis for the risk functions is on the substance being transported, but also on the road characteristics (e.g., tunnels, road condition, light, traffic) (Talarico et al., 2015). However, in a CIT scenario, the goods being transported are not dangerous, but a robbery might generate two different types of unwanted consequences: the foreseeable ones linked to the loss of the cash/valuables being transported, and the unforeseeable ones related to the criminal activity itself and might resulting in personnel being harmed and incurring in some cases significant additional costs (Talarico et al., 2015).

Figure 11 shows the probability tree based on the notion that a route would end after a robbery (Fröhlich et al., 2022; Talarico et al., 2015).

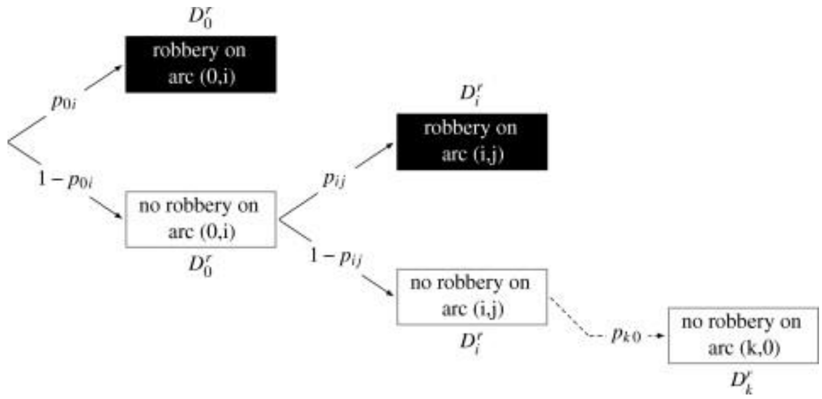

Figure 11: probability tree showing the risk along route (Talarico et al., 2015)

Hazmat transportation differs from the transportation of other materials by the risk associated with an accident release (incident) during the transportation (Tarantilis & Kiranoudis, 2001). Zografos and Androutsopoulos (2008) introduced a decision support system in hazmat transportation aiming at risk and cost optimization. The model contains two separate objective functions expressing the total travel time of the distribution routes and total transportation risk respectively. A bi-objective optimization was proposed by Androutsopoulos and Zografos (2012) in which the objective function is calculated by the sum of the travel time and risk of the arcs in any solution to the problem. The algorithm for solving the problem is based on the weighted sum method. The bi-objective vehicle routing and scheduling problem are decomposed into a series of single-objective instances of the problem (Androutsopoulos & Zografos, 2012). Since the objective function is the weighted sum of the total travel time and risk of the scheduled route paths, the corresponding cost function depends on the weights.

Zhao and Zhu (2016) introduced a bi-objective model minimizing total cost and total risk. The algorithm solves the sub-objectives separately to optimality and sets the weights (which in total sums up to 1) for each objective. The new model formulation with weight implemented will be solved. It is concluded that the solution is flexible to weights, which are usually set by decision-makers according to their personal preferences. Hence a model can be solved several times using different weights to obtain different representative efficient solutions.

Talarico et al. (2017) argues that in the context of multi-objective optimization problems, the concept of optimality needs to be abandoned in favor of the notion of domination. Effectively the goal of a multi-objective solution approach is to find a set of nondominated solutions that form as a whole the so-called Pareto frontier. From this Pareto frontier containing nondominated solutions, the decision maker is left to choose one according to his preferences. It is considered preferable that the decision maker chooses his/her favorite solution from a restricted set of high-quality alternatives, rather than from a huge amount of non-dominated solutions. It is believed that multi-objective optimization can be used as a decision support tool by CIT companies in order to select the most appropriate vehicle route plans depending on the relative importance of travel costs over the risk of exposure to robberies, expressed by the decision maker. Such a variant of the VRP where the total risk that each vehicle incurs during its route, is limited by a pre-specified risk threshold is called the Risk-constrained Cash-in-Transit Vehicle Routing Problem (RCTVRP). Using a specific risk index that is proportional both to the amount of cash being carried and the time or distance covered by the vehicle carrying the cash, it is possible to measure and limit the global risk faced by each vehicle along its route (Talarico et al., 2013).

3.6 Conclusion

In conclusions, humanitarian logistics have the purpose of rapidly provide emergency supplies to people in need and is hence limited by the lack of transportation resources and emergency supplies. Real-life post-disaster humanitarian logistics (PD-HL) is also characterized by the local distribution of food, water, medicine and other supplies.

Humanitarian logistics often pursues different objectives than commercial logistics. The deprivation cost is proposed as a representation of the reducing human suffering in post-disaster scenario. As a newborn concept, it has several branches in terms of estimating deprivation cost. Several researches opted for the method of considering the global cost as a representation of the deprivation cost and set minimization as the goal. Some other common performance metrics in humanitarian missions include total quantity of cargo delivered, financial efficiency (cost), fill rate (resource warehousing), coverage and delivery time.

In solving VRP, heuristics are generally regarded as more applicable methods than exact ones. Some well-researched heuristics include local search, tabu search, genetic algorithm and simulated annealing. Problem solving for VRP in humanitarian logistics scenario is very much in line with conventional VRP problem solving, relying on heuristics or meta-heuristics. Some VRP variants would incorporate the factor of danger or risk in them. Some research chose to use a probability tree to identify the risk along the route. The solving of such problems sometimes involves a bi-objective model combining cost and risk. Weight allocation is often applied to such models to reflect the preference of decision makers.

4. Model Design, Heuristic Design and Model Update

In this chapter, the medication of the simulation framework and the solving of the UAV/truck routing problem will commence. The chapter will be dedicated to documenting the reasoning behind the changes made, the steps of the change made, the incorporation of findings from the previous chapters, and the logic of heuristics.

Section 4.1 introduces the problem instances. Section 4.2 delineates the design of the heuristic. Sections 3 and 4 describes the parameters and performance logs in the simulation framework. Section 4.3 provide knowledge on incorporating risk and uncertainty in the model.

4.1 Problem Description

In this research, we aim to solve a capacitated Vehicle Routing Problem with a heterogeneous fleet. The fleet will be composed of trucks and UAVs (MiniFreighter introduced in Section 1.1.2) having their own range, capacity and speed. All vehicles will have a working window of 12 hours each day (6 am – 6 pm). The background of this research is Koch county in South Sudan. There are 1 airstrip and 43 sites to be visited, hosting in total 12056 people in need of humanitarian aid. The demand per person per day is made of a food package weighing 0.61kg. We will decide how many vehicle to dispatch to better serve all the locations. The fleet will be dispatched on a daily basis. For each vehicle dispatched, we will decide its route plan and the detailed amount of delivery assigned to each site visited. The optimization will dedicate to minimize total distance and cumulative risk for trucks and total distance for drones, as drones are not affected by road-bound risk. The risk is based on risk factors assigned to each arcs. The cumulative risk for a whole truck route is computed according to the formula presented in Section 4.3.2.

4.2 Design of Heuristics

The essential part of the problem-solving procedure is updating the heuristics to optimize the initial solution towards the direction of humanitarian logistics. The first step is altering the objective function in the optimization heuristics based on findings from the literature review. Although intuitively cost would be the goal, many authors in the field think otherwise. Hence objective function in the heuristics needs to be modified to enable route planning in the direction of e.g. maximum coverage or fastest response time. As introduced previously in Section 3.3.1, there is not a unified definition on deprivation cost or the measurement of alleviating human suffering. Many researches also settled for a definition they see fit. Hence here we would use a bi-objective model using total distance and risk for truck transportation and a single objective of distance for UAV transportation. Minimizing total distance and risk stands for our intention of delivering aid faster and with as little loss as possible. Thus this is our alternate definition of deprivation cost.

The realization of this step is through utilizing some appropriate meta-heuristic algorithm to further optimize the initial route plans for vehicles. The heuristic that is intended to be applied here is simulated annealing. The SA method offers a randomized search that would escape local minima. Furthermore, SA method provides a straightforward way to alter the initial route plan and adjust the objective function according to the decision maker’s preferences.

The idea is to explore the neighborhood solutions created by swapping the order of two locations and assess the performance between the original one and the altered one. Since the initial route plan is constructed by the constraints of time, cargo capacity, and range, the optimization could incorporate objectives such as shorter total distance travelled or cost. Following the principle of simulated annealing, worse solutions will still be accepted with some probability.

Some important features in simulated annealing are its starting temperature, cooling mechanism, stopping criteria and the probability to which we accept a worse result. While steps of simulated annealing are given in 3.4.3, a general simulated annealing algorithm for a maximization problem has been given by Rader (2010) as shown below:

$x \leftarrow generateInitialSolution$
Repeat
$x' \leftarrow RandomSolution(N(x))$
$\boldsymbol{if}\ f(x')\ is\ better\ than\ f(x)\ \boldsymbol{then}$
$x \leftarrow x'$
$\boldsymbol{else}$
$p \leftarrow generateRandomNumber()$
$\boldsymbol{if}\ p \leq e^{\frac{|f(x)-f(x')|}{T}}\ \boldsymbol{then}$
$x \leftarrow x'$
$\boldsymbol{end\ if}$
$T \leftarrow UpdateTemp(T)$
$\boldsymbol{until}\ termination\ conditions\ satisfied$

According to Rader (2010), a potential solution x' will be accepted as the new current solution if $f(x')$ is better than $f(x)$. However, a worse solution will still be accepted with a probability $e^{-|f(x)-f(x')|/T}$, which follows the Boltzmann distribution. For a fixed value T, the larger the difference between the function value of x and x', the smaller the probability of acceptance x'. Some possible termination conditions are the maximum number of iterations reached, the temperature T getting close to 0 and the current solution not changing after too many iterations.

The initial temperature T_0 should be chosen high enough so that the acceptance rate for "worse" solutions is high in the initial phase. It is known that many implementations typically try various values before settling on a specific value. The cooling schedule has the role of both allowing initial random fluctuations in the solutions early in the process and then preventing good solutions to be replaced by worse ones later. Common cooling schemes are a geometric approach $T_{k+1} = \alpha T_k$, where a is close to 1, and $T_{k+1} = \frac{T_k}{1+\beta T_k}$.

The principle of selecting parameters in this experiment is to ensure the algorithm can make an adequate number of updates in a manner that not many potential moves are missing and computation time is reasonable.

The pseudocode of the simulated annealing optimization method and its auxiliary methods is presented below. The simulated annealing operator used here is swapping. By randomly selecting a pair of sites and changing their sequence in the route plan, a new route plan is generated.

Algorithm: Simulated Annealing for UAV route optimization

Procedure **CopyOriginalRoute**
Begin

```
    Copy OriginalUAVRoutePlan to NewTable
End
```

```
Procedure OriginalRouteObjValue
Begin
    for i = 1 to NewTable.ColNum do //loop through all UAVs
    Begin
        for j = 1 to NewTable[Route, i].ColNum - 1 do
        //loop through all sites visited by every vehicle
        Begin
            TotalDistanceOld[i] += DistanceMatrixUAV[j, j+1]
            //adding up all distances
            TotalPopOld[i] += PopMatrixUAV[j, j+1]     //adding up population coverage
            if NewTable[Route, i][location, j] = = 1
            //count how many times a drone will visit the hub during the day
            Begin
                HubVisitCount += 1
            End
            TotalTimeOld[i] += TimeMatrix[j, j+1] + LoadingTime * HubVisitCount +
            UnLoadingTime * (SiteNum – HubVisitCount)
            //total time equals to the sum of traveling time between each pair of location
              and loading time multiplying total times the drone visits the hub and
              unloading time multiplying the number of total sites visited
        End
    End
End
```

```
Procedure SA_Drones
Begin
    Initialize StartingTemp
    Initialize MarkovLength
    Initialize TempLowerBound
    Initialize Alpha      //a cooling coefficient
    While StartingTemp > TempLowerBound
    Begin
        for n = 1 to MarkovLength do
        Begin
            for a = 1 to OriginalUAVRoutePlan do  //loop through all vehicles
            Begin
                status = True   //set a Boolean checker
                While status = = True
                Begin
                    x = RandRange(1, OriginalUAVRoutePlan[Route, a].ColNum)
                    //generate random location index
```

```
        y = RandRange(1, OriginalUAVRoutePlan[Route, a].ColNum)
        //generate another random location index
        if x \= y   //if two indices are not repetitive
        Begin
            Intermediatevalue = LocationSequence[x]
            LocationSequence[x] = LocationSequence[y]       //swap
            LocationSequence[y] = IntermediateValue    //swap again
            Also swap for associated demand value and demand type
            Status = False  //change status to stop generating and swap
        End
    End //End Swap

    Sub-Procedure FeasibilityCheck
    Begin
        for b = 1 to OriginalUAVRoutePlan.RouteSequence.ColNum do
        //loop through all vehicles
        Begin
            Compute total distance per vehicle per trip per day
            Compute total time used per vehicle per day
            Compute total payload per vehicle per trip per day
            if DistancePerTripNew[b] > 500 or TotalTimeNew[b] >
            12*3600 or PayloadPerTrip[b] > DroneCapacity
            //if range limit or time limit or capacity limit is exceeded
            Begin
                status = True   //set the status to True to swap again
            End
        End

        if the first location in the route plan being the depot or
            two locations appear consecutively or
            the last location in the route plan is not the depot
        //some practical constraint for the route plan
        begin
            Status = True //set the status back to swap again
        end
    End //End sub-procedure

if TotalDistanceNew[a] < TotalDistanceOld[a]
//if new objective value is better than the old one
Begin
    Continue        //swap succeeded, current solution is the new best solution
End
Else //if not better
Begin
```

```
            float = Rand   //generate a random float number
            if float < e^(-(TotalDistanceNew[a] –
        TotalDistanceOld[a])/StartingTemp)
            Begin
                Continue //accept the worse solution by a certain probability
            End
            Else
            Begin
                Change the route sequence to the original one
                //restore the original solution
                Change the objective function value to the old one
            End
        End
    End
  StartingTemp = Alpha * StartingTemp   //update the temperature
End //end procedure
```

Several auxiliary methods will also be needed to facilitate the implemented heuristics. Out of the purpose of comparing the route plan after optimization with the one before, the first step (procedure **CopyOriginalRoute**) is to replicate the original route plan table to enable the comparison between the objective values of the initial solution and the solution after swapping. Another one (procedure **OriginalRouteObjValue**) will compute the performance metrics/objective function values before the swap to enable the comparison for getting the current best solution.

The procedure **SA_Drones** initiates the simulated annealing. For every vehicle (UAV in this algorithm), two locations from its original route plan are randomly picked and swapped. The new route plan will be accepted and stored if the objective value function is better or some probability allows it. Else the route plan will have to be restored.

It is also important that the new solutions after every swap are still feasible i.e. the whole tour can still be completed within the or the total distance of the entire new trip is still within the vehicle's range. Thus it is necessary to include a series of checkers (procedure **FeasibilityCheck)** to ensure the feasibility of the new solution. In this procedure, the objective values of the new route plan will be computed and stored in a new table. The actual checking will see if the new route plan exceeds the range limit, if the vehicle can complete the journey during the time frame and if the vehicle exceeds the payload capacity. If the new solution is deemed infeasible, the swapping will be forced to happen again.

The same structure of the optimization algorithm also applies to truck routes. Since risk is also a factor in truck route optimization, there will be another procedure computing the risk level to reach the next destination and optimize in the direction of minimizing/averting risks. Details will be presented in Section 4.3.

The revised if-statement for excluding depots and any visit with a full load is shown in Table 8. Simply put, swapping these sites in the route plan would either generate a new infeasible trip immediately (a location assigned with a demand of full drone load should always form a trip of its own) or further complicate the solution space.

Generate a random first location x Generate a random second location y ***if*** x /= y ***and*** (location[x] /= depot ***and*** location[y] /= depot) ***and*** (demand[x] /= 160 ***and*** demand[y] /= 160)   ***proceed***

Table 8: if-statement revised

The next feature is enabling an inter-vehicle swap (swapping locations across vehicles). This is designed to enlarge the potential solution space and hopefully introduce more candidate solutions. An additional step of randomly picking two drones and checking they are not the same one is needed while the banning of swapping depots and locations with full load demand should also apply.

Generate the first vehicle a Generate the second vehicle b Generate the first location x Generate the second location y ***if*** a /= b ***and*** vehicle[a].location[x] /= depot ***and*** vehicle[b].location[y] /= depot **and** vehicle[a].demand[x] /= 160 ***and*** vehicle[b].demand[y] /= 160   ***proceed***

Table 9: if-statement for inter-vehicle swap

The third improvement is with regard to reverting the swap when conditions are not met. The original version of the algorithm does not revert the swap (restore the position of two randomly selected sites) if the status is true after the last feasibility checker, meaning the next iteration of randomly generating a pair of sites would start with an already altered yet still infeasible solution. This randomness may be too overwhelming such that the algorithm will spend an incredibly long time trying to reach feasibility. The new logic would force the site picking to start immediately after the new solution after swapping failed to pass any feasibility checker. Before a new iteration starts, the changed location will be swapped back. The flowchart is presented below.

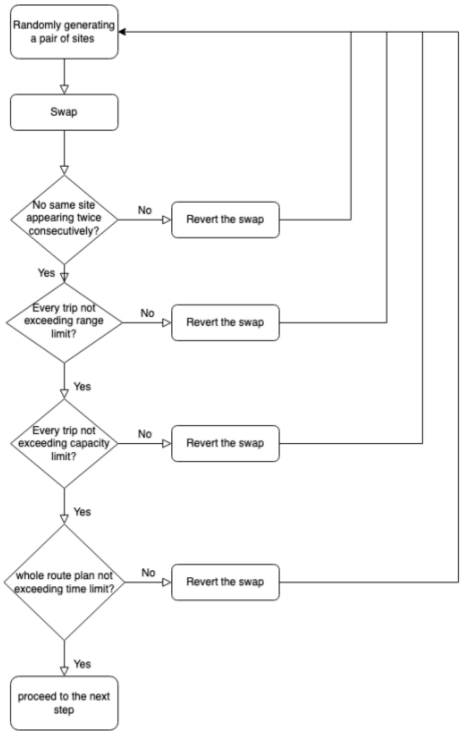

Figure 8: Flowchart for immediate abort and reverting the swap

4.3 Uncertainty and risks

As discussed earlier in Sections 1.1.4 and 2.1, South Sudan is plagued by armed conflict which poses a great threat to road transport. A destination could be unreachable for being in the conflict zone or even a truck fleet having the risk of being looted. Since the model also features a truck routing mechanism, it is reasonable to incorporate risk factors in the route planning phase. Random risk factor implementation is plausible in ways to make some grids/locations inaccessible to vehicles, but we would like to implement the uncertainty factor with certain prior knowledge i.e. having a general notion of the frequency and the distribution of disturbance and armed attacks.

Liberatore et al. (2013) have made an attempt to make definitions for both uncertainty and risk, stating that decision under risks refers to decision making where unknown states or consequences are represented through probabilities with the decision under uncertainty happening when other characterizations appear to deal with the not well known or definite information. Like Liberatore et al. (2013), we are not going to make a distinction here as a global perspective would benefit our situation of dealing with transportation insecurity more.

The five sets of parameters under uncertainty considered in the context of humanitarian logistics introduced in Liberatore et al. (2013) include demand (regarding the number of affected population and demand for required relief goods), supply (capacity, loss, quality availability), affected area, demand locations and transportation network (links capacity, availability, reliability and traversing time). The part regarding transportation network is clearly of our concern.

In the case of South Sudan, both danger and risk should be considered. The danger is concrete since the volatile situation in South Sudan has caused incidents and done harm while the risk is a factor that actually needs to be minimized as a part of optimization. Due to the lack of detailed information and data measurement, in the following Sections, a simple and straightforward

formulation of a risk formula will be introduced.
At the same time, it should also be made clear again that all the risk considerations and assumptions are made for road transport only, as this modality is the major, if not the only victim of a violent incident and the bandits targeting airborne vehicles is not much of a possibility.

4.3.1 The Risk Factor

The optimization toward lowering the risk requires the parameterization of risk. Ho et al. (2015) defines risk factors as various events and situations that drive a specific risk type. The factor includes war and terrorism, regional instability and political instability and lies in the macro risk factors (Ho et al., 2015). Under the umbrella of risk factors, there actually still are various ways of interpreting risk in the humanitarian relief supply chain and deriving a numerical representation.

Normally a risk-related value would be the probability of incidents happening. One possible mathematical formulation of such definition is shown below. In the formula, the risk probability is considered as the ratio between the number of incidents that happened in the region and the total number of delivery runs conducted in the region.

$$R = \frac{total\ number\ of\ incidents\ in\ the\ region}{total\ number\ of\ delivery\ runs\ in\ the\ region}$$

Alternative ways of defining this value could treat it as the percentage of resources actually delivered. This time the risk probability is the percentage of the amount of shipment that is lost compared to the total amount of the shipment.

$$R = \frac{total\ shipment\ amount - the\ amount\ of\ shipment\ successfully\ delivered}{total\ shipment\ amount}$$

On that aspect, some of the monthly feedback from on-site practice can offer us a general picture of cargo delivery affected by incidents (weather, security, partner issues, technical issues, etc.), which is presented in the table below.

Month	Percentage Lost
February	4%
March	4%
April	4%
May	12%
June	14%
July	2%
August	27%

Table 10: Percentage of cargo lost due to incidents by month
(Logistics Cluster, 2017c, 2017e, 2017f, 2017g, 2017h, 2017i, 2017j)

Understandably it is actually hard and not appropriate to directly translate the above shown percentage of cargo lost per month to the risk level desired. In the context of South Sudan, there may be too many factors other than security incidents such as extreme weather conditions and poor infrastructure that could impose risk.

Hence we take the liberty of generalizing and propose risk factor used here as the probability of the delivery job not completed on an arc between two locations A and B. Three different scenarios with different levels of risk are incorporated, namely the scenario with low risk, mid-level risk, and high risk. Every path between any pair of locations will be randomly assigned a risk level (decimal number) to indicate how probable it is for the vehicle to be attacked/affected. The risk level is scaled with the distance of the connection as we think the longer a vehicle is staying on the road, the more possible it is exposed in potential danger.

4.3.2 Optimization towards low risk

In the model, the distance and travel time between any two locations is stored in matrices. Likewise, there will be a new matrix added to store the risk coefficient between locations.

A procedure **RiskEval** (in fact a feasibility checker for the travel risk) will compute the risk level of getting to the next destination in the route plan. Within one round trip starting from the hub, the accumulated risk level will be computed.

Intuitively, the accumulated risk is computed as the product of all risk coefficients of individual road connections. Assuming the risk coefficient for the connection $B \rightarrow A$ is 0.5 with the coefficient for $A \rightarrow C$ is 0.4, the overall risk for a trip $B \rightarrow A \rightarrow C$ would be 0.2, lower than any individual connection within this trip. This is an unreasonable result as we would expect this value to be higher since both sectors should have their risk values accumulated instead of diminished. Figure 11 also provides important knowledge proof that a route would end after any incident during the trip. Hence, inspired by the probability tree presented in Figure 11, the computation of the overall risk level for a trip (starting and ending with the depot) should be defined as follows:

$$R_{overall} = 1 - \prod_{i} (1 - R_{i,i+1})$$

In such a manner, the total risk for the problem instance above would be $1 - (1 - 0.5) \times (1 - 0.4) = 1 - 0.5 \times 0.6 = 0.7$, a value higher than risks for both individual connections, fitting our intention.

From the definition above, the possibility of the vehicle successfully reaching the next destination $i + 1$ in the route plan from the current location i is just $1 - R_{i,i+1}$.

Introducing risk factors actually means introducing a new layer of decision-making: to what degree of risk is a route plan feasible to execute? Clearly, we would be hesitant in dispatching trucks if their routes have high risks of experiencing incidents as we would want to reach the planned destinations and deliver help. Hence it is natural to prevent the risk. Such risk aversion could be realized by assigning a high-risk route to drones as drone delivery is deemed risk-free.

Conventional optimization towards lower risk would consider a route plan with a risk level too high as infeasible. The SA algorithm will only terminate until swapping achieves a risk level that is below some designated risk threshold. Despite being a straightforward paradigm, swapping-till-not-risky would undoubtedly take a big amount of time before reaching feasibility and optimality.

However, the idea of a risk aversion mindset actually means instead of waiting for swapping to deliver an adequately low-risk solution, the “risky” route can be removed from the truck route plan table and added back to the open request table. Thanks to this project involving two modalities of transportation, drones can handle the transportation to “risky” locations are they are not affected. After all the “risky” locations are filtered out as unfulfilled orders, the routing constructing method will be called again to form routes to cover these remaining locations using drones.

4.4 Conclusion

This chapter provides the theoretical framework for this research. A description of the problem is given in Section 4.1, indicating we are going to solve a variant of the VRP using two types of vehicle and conduct a bi-objective optimization towards total distance and total risk for trucks. Section 4.2 introduced the improvement heuristic used in this research. The heuristic used here is a SA method equipped with additional features to ensure comparability between old and new solutions, solution feasibility and efficiency. The heuristic is also revealed to be able to facilitate site swapping across two vehicles. Section 4.3 introduces the motivation behind designing risk factors for this research and a new improvement method of re-assigning risky sites for truck transportation to drones.

5. Model Designs, Experiment Settings and Results

In this chapter, experiments will be conducted utilizing what-if conditions. The analysis will be about the results of multiple transportation methods planning, whether the total performance is improved, how the priorities affect the decision making in dispatching vehicles, and most interestingly how demand figures or risk factors would influence the transportation planning.

As illustrated, the objective function values for drone routing are total travel distance (which is equivalent to total travel time given the speed is assumed to be constant) and total cost. One extra objective function value for truck routing is a risk, with three different risk scenarios: full, partial and none.

Model settings and key model assumptions will be discussed in Section 5.1. The reasoning behind risk factors is introduced in Section 5.1.1 with Section 5.1.2 illustrating bi-objective optimization in this case. The experiment settings will be presented in Section 5.2. Section 5.3 will display the experiment results.

5.1 Model Settings and Key assumptions

The simulation study presents the planning and delivery process of the humanitarian aid mission in Koch County, South Sudan (one of the three counties introduced in Section 2.3.3). Trucks and UAVs are the two transportation methods used to make deliveries. All vehicles will depart from local airstrip and visit all 43 locations (shown in the Appendix) to deliver humanitarian aid supplies. The transportation planning process is modelled to generate route plans (the sequence of visiting locations) for all vehicles to follow. The optimization of the route plan is also modelled and incorporates objectives of total distances and risks (for truck only). The framework this study is based on is introduced in Section 1.1.3.

Basic settings and key assumptions of the models are listed below:

- A single truck runs at a speed of 20 km/h and bears the capacity of 5000kg.
- A single UAV flies at a speed of 125 km/h and bears the capacity of 160kg.
- The range of the truck is 999,999km (practically unlimited range in the model) while the range of the UAV is 500km.
- The working time for all vehicles is 6:00 – 18:00 every day.
- The number of trucks and drones is pre-set in the model before every model run.
- Not all locations are accessible by road, meaning that some locations will only be visited by UAVs.
- All vehicles will depart from and return to the local airstrip (designated as location 0).
- The local airstrip is considered to be equipped with necessary facilities to enable loading/unloading, charging and warehousing. The stock is ample.
- The route plans will be generated first and optimized later towards the designated objective(s).
- The constructive heuristic used here is the Cheapest Insertion.
- All vehicles will operate according to the final route plans.
- The distance matrices for trucks and drones are both diagonally symmetrical i.e., it is always the same distance back and forth.
- Every arc between two locations accessible by trucks will be assigned with a risk factor

scaled by distance. The risk factors for the scenarios of low, mid and high risk are 0.01, 0.02 and 0.03 respectively.

- In the objective function of truck route optimization, two objectives will be included: total distance and cumulative risk. Weight values will be assigned to both objectives to reflect the emphasis on each one.
- Each experiment will simulate the delivery mission for a day.
- Whether a site will be "risky" for truck to visit will be decided randomly in the model (due to the lack of real life reference).

5.1.1 Risk Factors

In order to observe the decision-making of the optimization algorithm under different levels of risk event distribution, there are three different scenarios designed: no risk, partial risk, and full risk, with all the locations to be visited categorized into two classes: risk regions and non-risk regions. Every arc between any two locations will be labeled with a risk level.

Fröhlich et al. (2022) argued that CIT operations also face the problem that it is difficult to measure whether any incidents have actually been prevented due to unpredictable routing. The difficult situation is further exacerbated by the sporadic nature of robberies, looting and armed conflict together with the lack of actual data collection from field work, making it challenging to create and validate models.

Due to the lack of actual data on the frequency of the humanitarian aid fleet being attacked, financial lost, and the number of casualties, the risk factors used in the model are generated intuitively and randomly. The sites that are going to be defined as "risky" hence are also determined randomly. The risk level of each arc will be scaled by its distance. The computation is shown as below:

$$R_{a,b} = riskFactor \times distance_{a,b}$$

5.1.2 Bi-objective optimization

Based on Sections 3.5 and 4.3, it is decided that the truck route optimization should be a bi-objective one as the security-related concern is too significant to omit in humanitarian aid in South Sudan. The objective function for truck routing will be the weighted sum of total risk level and total operating cost.

$$minimize\ Z = w_1 \cdot R_{total} + w_2 \cdot C_{total}$$

After a feasible solution is reached, a filter function is designed to pick out locations that are still too risky to reach. Those locations will be reassigned to drones afterwards as a part of the risk-averting process.

According to Section 3.5, the choice of weights in the bi-objective optimization reflects the decision maker's own preference. Under normal situations, the sum of weights usually is 1. In the case of South Sudan, we would like to see the impact of risk on route planning and trade-offs of dispatching vehicles. Hence in order to highlight the influence of risk on decision-making, the weight assigned to the total risk would be significantly larger than 1 as the risk itself is a relatively small value (less than 1). There must be a weight large enough to increase the impact of risk in the weighted sum.

Since the drone operation will not be affected by risk constraints, the objective function for drone routing will still feature cost as the sole objective.

5.2 Experiment Settings

The simulation experiment will be operated with the goal to explore the added value of UAVs in the last mile humanitarian logistics in South Sudan, e.g., how to involve UAVs in the transportation planning in humanitarian logistics in South Sudan and the impact of doing so. The experiment will be divided into two steps. The first step will be setting different numbers of vehicle available to see the best composition of the fleet. The fleet combination with the best performance in terms of demand coverage and cost will serve as the default setting for experiments in step two. The second step will optimize the route plan under different risk scenarios and risk significance.

The first set of experiments will set different combinations of vehicles available for dispatching to see how well the resulting fleet can cope with the humanitarian mission aid in this case. The experiment will use 1 truck and 1 drone to start with. Gradually we will increase the number of drones while keeping the number of trucks at 1 or increase the number of trucks while keeping the number of drones at 1 until all the demand and sites are covered. Since there are sites that are not directly accessible to road transportation, we need to have at least 1 vehicles for both types.

All remaining experiments will use the fleet combination from the first phase of the experiments. The second set of experiments of step two will include model runs for each of the three risk scenarios: low, mid, high. The intention is to see how the involvement of drones will improve the humanitarian mission under different risk circumstances. The third set of experiments will be about the significance of risk in decision-making. The objective function in truck route optimization involves distance and risk. Three different weight will be assigned to risk (namely 1, 3 and 5) to reflect different level of significance we would like to apply to risk level of road transportation.

5.3 Experiment Result Analysis

In this Section, the result and assessment regarding the added value of drones in different scenarios will be given under Sections 5.3.1, 5.3.2, and 5.3.3, respectively.

5.3.1 Fleet Combination

	cost	demand coverage	demand covered by trucks	demand covered by drones
1 truck 1 drone	4389.10959	73.58%	2387	3040
1 truck 2 drone	7896.90151	97.44%	2387	4800
1 truck 3 drone	8553.87763	100.00%	2387	4989

Table 11: Fleet Performance (increment only on drones)

	cost	demand coverage	demand covered by trucks	demand covered by drones
1 truck 1 drone	4389.10959	73.58%	2387	3040
2 truck 1 drone	5084.56145	85.91%	3617	2720
3 truck 1 drone	5961.52906	93.23%	4477	2400
4 truck 1 drone	6745.63302	98.43%	4860	2400

Table 12: Fleet Performance (increment only on trucks)

This set of experiments starts with the fleet of 1 truck and 1 drone only. Then we add 1 truck/drone to the fleet per time to observe how well it does. Table 11 and Table 12 shows the overview of different fleet performance under two categories: increasing the number of drones while keeping only 1 truck and increasing the number of trucks while keeping only 1 drone. The partial visualization of the two tables above are shown below.

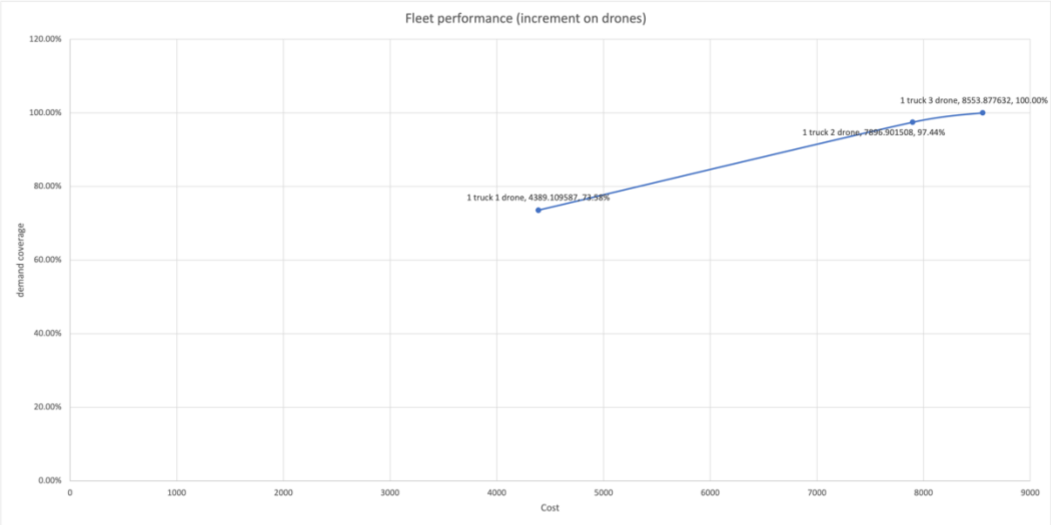

Figure 12: Partial Visualization (only increasing the number of drones)

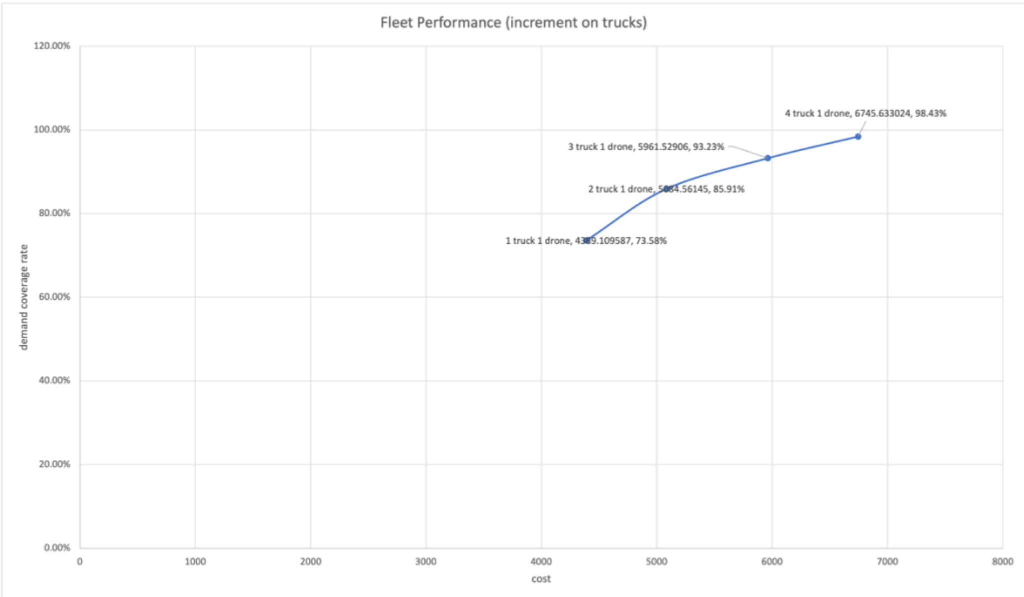

Figure 13: Partial Visualization (only increasing the number of trucks)

The fleet of 1 truck and 3 drones is able to cover the full daily demand of food packages in Koch County, with a cost of 8554 per day. The fleet of 1 truck and 2 drones already has a considerably well demand coverage rate of 97.33% but still needs additional vehicle to cover the remaining requests. The fleets with one drone eventually are not able to serve all sites, due to some of the sites are not accessible by roads. With more trucks added, the demand that is covered by trucks steadily increases but 4 trucks can only cover all sites that are accessible by roads. Drones will be needed to fill that final gap. Similar with the fleet of 1 truck and 2 drones, the fleet of 3 trucks and 1 drone also has a rather good cover rate of 93.23%.

In order to fully fulfill all requests in Koch County, additional fleet combinations were tested. Since 4 trucks can cover all road-accessibly sites, at least one additional drone is needed. For fleets of 1 truck and 2 drones and 3 trucks and 1 drone which have rather high demand cover rates, alternative increment of vehicles is considered. Hence additional fleet combination to be tested include 4 trucks and 2 drones, 2 trucks and 2 drones and 3 trucks and 2 drones. The result is shown below.

	cost	demand covered by trucks	demand covered by drones
1 truck 3 drones	8553.877632	2387	4989
2 trucks 2 drones	7526.453158	3617	3759
3 trucks 2 drones	7286.286219	4477	2899
4 trucks 2 drones	7074.045744	4860	2516

Table 13: All fleets that fulfill all requests

All additional experiments with new fleet combinations successfully fulfill all requests. From Table 11 and Table 13 we can see that keeping the number of drones at 2 generally yields good delivery performances. More trucks added would serve every site. What is worth noticing is that with more trucks available when keeping only 2 drones, the total cost actually decreases. The fleet of 4 trucks and 2 drones uses the trucks as much as possible and dispatches drones to cover the rest. It results in a lowest cost among all experiments of 7074.

The result should not come as much of a surprise as truck is a more cost-friendly option due to its large capacity and cheap operating cost. In the case of 1 truck and 3 drones, nearly 2/3 of the entire demand is carried by drones. 3 drones visited 30 locations and completed 32 trips in total, resulting in a much higher cost. The unique characteristics of drones (low capacity, high operating cost) would mean that other than visiting locations not accessible by road transportation (which is exactly the case of Koch), it may still be used as a supplement to regular transportation method instead of a replacement.

5.3.2 Risk Scenarios

The fleet configuration used here and onwards would be 4 trucks and 2 drones. Three model runs were done with each adopting one risk scenario (low, mid or high). The results are presented below. The risk threshold for truck transportation is 0.95, meaning that any location with a probability of reaching lower than 0.95 will be considered as "risky".

low risk	number of locations visited by truck 1	number of locations visited by truck 2	number of locations visited by truck 3	number of locations visited by truck 4	number of trips completed by drone 1	number of tripss completed by drone 2	total cost	demand covered by truck	demand covered by drones
before risk opt	14	10	4	2	15	1	7881.59075	3980	3396
after risk opt	14	10	2	0	15	7			

Table 14: Result - Low Risk

mid risk	number of locations visited by truck 1	number of locations visited by truck 2	number of locations visited by truck 3	number of locations visited by truck 4	number of trips completed by drone 1	number of tripss completed by drone 2	total cost	demand covered by truck	demand covered by drones
before risk opt	14	10	4	2	15	1	7813.93978	3896	3480
after risk opt	13	9	2	0	15	7			

Table 15: Result - Mid Risk

high risk	number of locations visited by truck 1	number of locations visited by truck 2	number of locations visited by truck 3	number of locations visited by truck 4	number of trips completed by drone 1	number of tripss completed by drone 2	total cost	demand covered by truck	demand covered by drones
before risk opt	14	10	4	2	15	1	8147.36784	3550	3826
after risk opt	13	9	1	0	15	9			

Table 16: Results - High Risk

The function of risk optimization for truck routes worked as expected. Sites deemed "too risky" will be re-assigned to drones, leading to drone 2 making more trips (as drone 1 is fully planned). It indicates that in a situation like South Sudan where risk of road transport cannot be ignored, drones can intervene and serve as a countermeasure. The number of sites re-assigned to drones would increase if the risk level got higher. The inevitable result of drones making more deliveries is the increased total cost. Despite the fact that after the filtering of risky sites, only 3 truck would actually be in use (truck 4 is now idle after all its locations re-assigned to drones), the increased use of drones will still lead to additional cost. We chose 4 trucks and 2 drones as the default setting of fleet as it is the most cost-friendly one, but the risk optimization will incur an extra cost of near 1000. The trade-off between increased total cost of transportation and more sites visited and delivered safely might be an important one for actual field operation for the cost spike it could cause.

On the other hand, recalling how the risk is computed in Section 4.3.1, if a trip of $A \rightarrow B \rightarrow C \rightarrow D$ have risk level of 0.5, 0.4 and 0.6 respectively for $A \rightarrow B$, $B \rightarrow C$ and $C \rightarrow D$, removing D from the trip would lead to the risk level changing from $1-(1-0.5)\times(1-0.4)\times(1-0.6)=0.88$ to $1-(1-0.5)\times(1-0.4)=0.7$. The probability of a truck going safely through the remainder of the journey actually increases. Hence this risk filtering function succeeded at minimizing total risks for trucks.

5.3.3 Weight allocation of risk

The fleet setting here is also 4 trucks and 2 drones. A weight for the cumulative risk in the objective function of the route plan of truck is applied. The result of experiments using the weights of 1, 3, and 5 respectively is presented below.

	cost
weight = 1	7074.04574
weight = 3	7074.04574
weight = 5	7074.04574

Table 17: Total cost for three experiments using different weights

In Table 17 there are cost figures for three experiments using different weights for risks in truck route optimization. All experiments have the identical total cost in the end. It means that the weight alteration and the SA method is not effective. It could mean that the constructive heuristic of Cheapest Insertion works fairly well that it leaves very little room for improvement. No better solutions can be found so nothing will change no matter the weight we put on the risks. Unfortunately due to the improvement heuristics failed to deliver, we are unable to see whether the significance level of risks will have an impact on the fleet operation.

5.4 Conclusion

In the first part of the experiment, several options of fleet combinations were found to be able to fulfill all demand requests. Among them we find the most cost-friendly one to be using 4 trucks and 2 drones. This fleet combination prioritizes the planning of trucks (using trucks as much as possible) and yields a cheaper result. On the other end of the spectrum, the fleet of 1 truck and 3 drones can also fulfill all the requests. However, at the price of having small capacity, drones will always make several small trips back and forth to fulfill the demand of one site leading to increasing. It can be concluded that drones will better be a supplement to trucks from the perspective of financial reasons.

The experiments using different risk scenarios and risk thresholds identified drones as a useful measure to relieve the impact of risk on road transportation. Drones are proven to be effective when risky sites for trucks are re-assigned. Inevitably letting drones taking up more trips will lead to increased cost, but it can be seen as a cost worth taking as it ensures delivery reliability to people in need.

The behavior of the SA algorithm needs some further investigation. It could be that the constructive heuristic can already produce a high quality result, thus leaving very limited space for improving. The behavior of the algorithm may also be caused by the geographical distribution of all sites. All sites picked are located in the village in a very compact way. There is a main straight road in the middle of the area with sites scattered alongside. Swapping locations will probably further disrupt the route plan and create new routes that are feasible but longer. For example when the locations to visit are aligned in a straight row, the route would be constructed by visiting these locations one by one. But swapping the sequence in this case would mean the vehicle will visit the farther site first and then going back to the closer one and therefore extend the whole journey. On the other hand, when all the sites are densely and closely distributed around the depot, switching them around has little chance of creating a shorter route. Another possible cause would be swapping is not really viable or meaningful if drones are for most of the time fully loaded.

6. Conclusion

This chapter will deliver the conclusion of this research, limitations on the research, recommendations for future improvement and outlook on humanitarian logistics and customized UAVs.

6.1 Conclusion

This research originates from the Wings for Aid project and is motivated by the condition of the humanitarian mission in South Sudan being disrupted by incidents like armed conflict and seasonal floods. UAVs emerge as an option that comes with decent mobility, pinpoint delivery accuracy and reliability. Thus the inclusion of UAVs in South Sudan's humanitarian logistics planning could have the potential to greatly improve the performance of delivery. In order to dig deeper in this direction, the main research objective is determined as looking into the performance of UAVs and their potential influence on humanitarian logistics in South Sudan. Research questions were formulated to cover areas including the humanitarian situation in South Sudan, priorities and objectives of humanitarian logistics, applications of optimization methods and added value of UAVs.

First, we analyzed the context of the humanitarian crisis in South Sudan with regards to the major problems affecting South Sudan, the main obstacles for humanitarian organizations and some examples of response schemes. Our first impression of this case was confirmed that South Sudan was deeply plagued by its volatile political situation and a series of problems caused by it. It is also revealed that seasonal floods and other extreme weather conditions could also hinder the operation of road transportation, hence highlighting the urgent need for flexible planning and risk optimization in humanitarian supply delivery.

The scoping and structuring part defined the case of focusing on a human settlement that contains a certain number of delivery sites that would not add too much burden for computation. The final case instance set the focus on a community of villages in the county of Koch, containing 44 locations including a local airstrip serving as the depot. The delivery volume of the mission is the food package for all residents in the community in one day.

The literature study introduced the concept of deprivation cost and concluded on reducing human suffering, which should be the priority and goal of humanitarian aid missions. It also cleared the common misunderstanding that humanitarian aid should put financial concerns aside as life weighs more than money, and stated that budget constraints do have an impact. With the recognition of the humanitarian aid vehicle planning in South Sudan as a VRP problem, simulated annealing is chosen as the method of optimizing the route for both trucks and drones, as traditional mathematical programming will not suffice for solving such a problem instance.

The operator used in the SA algorithm is swapping. Multiple feasibility checkers were added as a requirement out of vehicles' limit of capacity, range and operating hours. It was made sure the route would be restored after any infeasible swap and this iteration of the procedure terminated after too many attempts made. Risk evaluation is another function to filter out the sites that are too risky and leave them for drones. To incorporate the findings of the literature study, the objective function of truck routes includes both total distance and cumulative risk. In order to expand the potential solution space, the swapping procedure for drones included both swapping within one drone's route and swapping between routes of two drones.

Three sets of experiment settings were applied, covering aspects of possible fleet combinations, different risk scenarios and varying significance of risk to the total objective. When implementing the model, it is revealed that not all sites in the research are connected by roads. This makes the involvement of drones necessary and quickly proven the value of drones in going to places that cannot be covered by trucks. Another thing that is instantly proven effective is the risk circumvention function of drones. Since drones are not susceptible to incidents that happened on the ground, they are perfect alternatives to deliver to those sites that are too risky for trucks. Removing sites from the truck route will also lower the cumulative risk (i.e., the probability of truck delivery being not successful). The additional cost of drones making more runs is considered by us as the cost one should willing to pay. Through testing different fleet combinations, it is established that drones are better utilized as a supplement instead of a major force in aid transportation.

However, different levels of significance of risks did not lead to ideal results. The designed improvement heuristics cannot further optimize on the basis of initial results. The cause of such outcome could be multi-fold: the constructive heuristic working rather good, the distribution of all locations making it difficult to improve after altering routes or the capacity of drones posing limits.

6.2 Limitations, Recommendations and Outlook

The limitation of this research mainly stems from a lack of information. In general, there is a significant gap in data in several key factors in this research. The statistics on incidents causing supply loss, the category, amount and SKUs of delivery, demand volume and budget figures on humanitarian aid missions, have either rather ambiguous information or no information at all. Even the infrastructure information is incomplete so there is no certain information on which airstrip/transportation hub is actually actively in use in humanitarian missions. Hence assumptions and generalizations are widely applied during the phase of scoping and structuring to fill in blanks. The resulting model is an over-simplified representation that inevitably deviates from reality. Missing parameters such as the frequency of incidents and the budget of humanitarian activities greatly undermine the result of the model.

Furthermore, there has been an inconsistency in how the population census is depicted in South Sudan. Reports and surveys from different agencies tend to cover statistics of varying groups and on variable administrative levels. The resulting geodata used here (the acquired sites distribution and there geographical location) is an outcome of making compromises and is probably less than optimal because sites that are only accessible to airborne transportation are possibly noises. An interview conducted in the later phase of the project with a senior officer who is working on humanitarian missions in South Sudan confirmed this point as there indeed is little feedback from the fieldwork. We sincerely hope for future research there could be more feedback and data collected from on-site operations. We also recommend future researchers working on South Sudan-related cases would spare more time in conducting a more extensive and systematic data collection session in order to construct data sets that would bridge the gap of required information as much as possible.

Next, natural disasters and extreme weather are discussed as incidents that can affect humanitarian work. However, the risk incorporated is a generalized version and is inclined more to a representation of security incidents. It would be much welcomed if meteorological factors as well as alternative vehicles like barges can be taken into consideration for new risk scenarios. It is also worth noting that current risk calculation serves merely as a variable for evaluating the quality of a route but has no impact on a vehicle's movement. It will also be a valuable addition to see vehicles getting attacked and stopping on the road being realized in the model framework.

Last but not the least, the choice of the optimization method itself is also a limitation of this research. The selected optimization method is not a good fit with scoped locations and drones. Alternative heuristics ("destroy and repair", genetic algorithm, ant colony, etc.) can be studied to improve the result of optimization.

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Appendix

1. Population, Geodata for Villages/Other Locations

county name	sub-area name	location	latitude	longitude	IDPs	returnees	sum IDPs	sum returnees	location count
Koch	Norbor	Baarbor	8.47207951	29.989914	0	182	5712	6344	43
Koch	Boaw	Boaw	8.847426	29.726829	97	226			
Koch	Pakur	Buoth	8.35685	29.59142	149	275			
Koch	Pakur	Dhiel 1	8.679722	29.567324	161	280			
Koch	Boaw	Diet	8.59417	29.984	219	53			
Koch	Norbor	Ganglet	8.35611	29.59179	127	210			
Koch	Koch	Ghol	8.40612	29.994287	142	77			
Koch	Boaw	Golpiny	8.801261	29.810515	0	78			
Koch	Gany	Guar	8.61717	29.9786	132	90			
Koch	Norbor	Gud Reng	8.43170359	29.9872481	177	198			
Koch	Koch	Guol	8.52903594	30.0450218	109	38			
Koch	Jaak	Jaak 1	8.61838	29.985331	274	234			
Koch	Koch	Koch	8.5907	29.9946	202	528			
Koch	Koch	Kuahlual	8.532156	30.073704	37	37			
Koch	Gany	Leak	8.61688	30.0094	138	110			
Koch	Boaw	Liech	8.59198	29.9951	61	31			
Koch	Boaw	Lotkabang	8.790014	29.818943	112	38			
Koch	Boaw	Mar	8.659606	29.915002	41	35			
Koch	Boaw	Marier	8.659606	29.911919	134	32			
Koch	Koch	Miemier	8.51308622	30.0509961	123	83			
Koch	Norbor	Norbor	8.35926	29.9874	184	227			
Koch	Gany	Pachnol	8.59511	29.9846	162	116			
Koch	Pakur	Pakur	8.802283	29.604101	109	233			
Koch	Pakur	Payol Dop	8.35712	29.59137	140	185			
Koch	Gany	Rhang 1	8.48736	29.954387	138	120			
Koch	Boaw	Teue	8.875234	29.829506	221	63			
Koch	Boaw	Teut	8.75349	29.73454	97	97			
Koch	Boaw	Titr	8.753429	29.734583	213	40			
Koch	Boaw	Gor	8.80301	29.876889	49	50			
Koch	Boaw	Parbony	8.659666	29.7264	73	17			
Koch	Mirmir	Buol	8.70387379	29.8041956	89	38			
Koch	Mirmir	Thorbang	8.49463814	30.1489998	64	49			
Koch	Mirmir	Ruot	8.48395436	30.0983102	59	31			
Koch	Mirmir	Yuy	8.50645106	30.096252	105	85			
Koch	Mirmir	Thornor	8.4722379	30.1478967	57	42			
Koch	Mirmir	Mirmir	8.47120521	30.1037091	480	106			
Koch	Gany	Gany	8.59526	29.5983	203	142			
Koch	Jaak	Bor Jek	8.65276139	30.026306	101	212			
Koch	Jaak	Logat	8.8125443	29.9316781	244	296			
Koch	Jaak	Gong	8.66693383	30.0125786	0	203			
Koch	Jaak	Borgok	8.56369413	30.0621677	143	432			
Koch	Jaak	Matar	8.73881201	30.0885784	132	270			
Koch	Jaak	Kuachlnal	8.53484548	30.0437501	214	455			

Figure 14: Locations in Koch

county name	sub-area name	location	latitude	longitude	IDPs	returnees	sum IDPs	sum returnees	location count
Leer	Pilieny	Kuerkei	8.353016	30.21401	196	126	11408	8913	63
Leer	Pilieny	Mankuach Lied	8.16573	30.10389	30	18			
Leer	Pilieny	Mankuach Tual	8.268137	30.183442	49	37			
Leer	Pilieny	Nuangak	8.10207	30.13432	36	29			
Leer	Pilieny	Pakur	8.17208	30.09593	18	6			
Leer	Yang	Adok	8.192883	30.30785	244	119			
Leer	Yang	Liab	8.20249	30.29108	244	109			
Leer	Yang	Naak	8.13414	30.1538	251	93			
Leer	Thonyor	Ribee	8.299585	30.153294	181	80			
Leer	Thonyor	Tharyier	8.14005	30.093203	232	120			
Leer	Yang	Yang	8.2052	30.23055	259	98			
Leer	Yang	Zoryuel	8.21481	30.231	235	109			
Leer	Padeah	Gon	8.40568	30.18549	120	325			
Leer	Padeah	Padeah	8.39772	30.19516	268	319			
Leer	Padeah	Buotwar	8.38259	30.18492	280	361			
Leer	Padeah	Nyadong	8.37229	30.19879	120	360			
Leer	Padeah	Tiam	8.3478	30.20253	120	347			
Leer	Padeah	Tharuop	8.36225	30.25429	192	235			
Leer	Padeah	Thiyang	8.38562	30.19797	270	474			
Leer	Guat	Guat	8.2212	30.08742	70	58			
Leer	Guat	Gap	8.22939	30.09646	130	39			
Leer	Guat	Zornor	8.21757	30.10234	73	57			
Leer	Guat	Kur	8.23048	30.10517	44	70			
Leer	Guat	Kueny	8.4123955	30.1586413	35	70			
Leer	Bow	Bow	8.33302	30.19773	120	300			
Leer	Bow	Phar	8.33808831	30.193257	147	78			
Leer	Bow	Jiath	8.34993	30.1912	120	282			
Leer	Bow	Dhomor	8.3599	30.17605	175	210			
Leer	Bow	Thaak	8.3653	30.17905	48	102			
Leer	Bow	Guath	8.34183	30.19075	215	84			
Leer	Bow	Juet 1	8.33912	30.2023	280	324			
Leer	Bow	Juet 2	8.33517	30.20051	300	370			
Leer	Bow	Kumagab	8.300095	30.199987	144	180			
Leer	Bow	Tharkiech	8.33364	30.1938	162	244			
Leer	Bow	Koam	8.330057	30.17999	19	96			
Leer	Bow	Kur	8.37086	30.17969	168	240			
Leer	Bow	Tiep	8.37561	30.18308	132	180			
Leer	Juong	Juong	8.33315821	30.1539398	37	49			
Leer	Juong	Kuerrier	8.32581322	30.1385118	60	42			
Leer	Juong	Puorkow	8.32826251	30.1475592	26	58			
Leer	Juong	Zunytharyier	8.33253649	30.1164649	49	41			
Leer	Juong	Wangkecha	8.333655	30.1089668	35	49			
Leer	Juong	Malieth	8.32538304	30.1488352	26	58			
Leer	Juong	Gottuong	8.320318	30.1300074	14	70			
Leer	Juong	Giel	8.31952984	30.1687874	21	105			
Leer	Yang	Ngoabuor	8.20796	30.23629	244	98			
Leer	Yang	Wicyier Tot	8.21888353	30.2277075	251	126			
Leer	Yang	Kok	8.20149	30.22771	251	98			
Leer	Yang	Achuay	8.18875	30.30186	259	89			
Leer	Thonyor	Dhorwicmuok	8.22445	30.21276	224	96			
Leer	Thonyor	Kuac Jok	8.22323	30.22039	224	112			
Leer	Thonyor	Tochrial Block 3	8.2185	30.23504	232	128			
Leer	Thonyor	Tochrial Block 2	8.21872	30.24309	216	128			
Leer	Thonyor	Wanguiy	8.223001	30.23634	200	96			
Leer	Thonyor	hochrial Block	8.21701	30.24309	304	160			
Leer	Nyadiar	Leer T.P.A	8.16806072	30.0885349	2261	269			
Leer	Nyadiar	Nyadiar	8.20115415	30.0944227	145	120			
Leer	Nyadiar	Leer Town	8.16267304	30.0976681	336	121			
Leer	Nyadiar	Dharel Thalam	8.18696452	30.0779838		84			
Leer	Nyadiar	Pom Dhor	8.181799	30.092665	8	11			
Leer	Payak	Payak	8.30769662	30.1175604	105	140			
Leer	Payak	Bompiny	8.18953	30.06575	34	62			
Leer	Payak	Jow	8.19157	30.05818	70	70			
Leer	Payak	Nyony	8.31758792	30.0995381	49	84			

Figure 15: Locations in Leer

county name	sub-area name	location	latitude	longitude	IDPs	returnees	sum IDPs	sum returnees	location count
Mayiendit	Rubkuay	Buol	8.40325897	30.0875062	0	175	5350	9118	58
Mayiendit	Dablual	Bur	8.1832	30.08541	94	150			
Mayiendit	Luom	Dabul	8.224802	30.064911	48	145			
Mayiendit	Luom	Dhor Jak	8.387239	30.123257	70	135			
Mayiendit	Luom	Dhor Yiel	8.387239	30.132223	94	305			
Mayiendit	Dablual	Dimthuok	8.303606	30.026989	0	56			
Mayiendit	Luom	Gier	8.387239	30.185072	98	205			
Mayiendit	Babuong	Jezire	8.08241	30.02206	114	344			
Mayiendit	Rubkuay	Kangkoi	8.37184517	30.0394511	0	170			
Mayiendit	Luom	Katraar	8.387239	30.178956	0	200			
Mayiendit	Mal	Kech Khan	8.14933	29.96739	13	96			
Mayiendit	Rubkuay	Koat	8.3839888	30.0849544	0	238			
Mayiendit	Luom	Lual	8.387239	30.13603	42	156			
Mayiendit	Luom	Luom	8.387239	30.122647	0	77			
Mayiendit	Luom	Nyal	8.387239	30.112057	0	64			
Mayiendit	Mal	Pipeline	8.14936	29.96754	27	120			
Mayiendit	Bor	Pullual	8.12018	30.02453	60	216			
Mayiendit	Mal	Ritgok	8.14252	29.9825	43	90			
Mayiendit	Rubkuay	Rubkuay	8.39724897	30.0917262	0	210			
Mayiendit	Rubkuay	Rubnor	8.42171897	30.1120262	28	161			
Mayiendit	Bor	Thowkuok	8.12949	30.02397	184	270			
Mayiendit	Mal	Yat	8.15168	29.97289	25	90			
Mayiendit	Rubkuay	Dook Kang Koy	8.23046	30.05094	26	147			
Mayiendit	Rubkuay	Pankong	8.23905	30.05914	21	91			
Mayiendit	Rubkuay	Thiac	8.23167	30.03713	35	83			
Mayiendit	Rubkuay	Thorgai	8.24081	30.06127	196	175			
Mayiendit	Rubkuay	Kuch 1	8.41163125	30.1012322	17	28			
Mayiendit	Rubkuay	Kuch 2	8.25055	30.0639	0	14			
Mayiendit	Rubkuay	Pol Chara	8.41263249	30.1170172	0	63			
Mayiendit	Rubkuay	Goany	8.25324	30.06618	16	53			
Mayiendit	Rubkuay	Kany Nhial	8.23384	30.03902	35	49			
Mayiendit	Thaker	Pantot	8.430104	30.049994	203	133			
Mayiendit	Thaker	Zornori	8.40938	30.028563	175	140			
Mayiendit	Thaker	Kuok	8.40938	30.028563	140	210			
Mayiendit	Thaker	Panlolnoi	8.40938	30.028563	178	196			
Mayiendit	Thaker	Thokyier	8.40938	30.028563	121	238			
Mayiendit	Thaker	Tharjiew	8.40938	30.028563	126	224			
Mayiendit	Thaker	Thargoth	8.390154	30.050013	192	210			
Mayiendit	Thaker	Thaker	8.390021	30.049955	212	210			
Mayiendit	Thaker	Nyajiek	8.40938	30.028563	175	210			
Mayiendit	Thaker	Tharbika	8.40938	30.028563	77	189			
Mayiendit	Thaker	Kuorway	8.40938	30.028563	210	236			
Mayiendit	Tharjiath Bor	Ganyang	8.300085	29.949985	101	105			
Mayiendit	Tharjiath Bor	Maper 1	8.390227	30.009964	157	168			
Mayiendit	Tharjiath Bor	Maper 2	8.380105	30.010001	200	161			
Mayiendit	Tharjiath Bor	Maper 3	8.400322	30.02002	128	140			
Mayiendit	Tharjiath Bor	Goang	8.31171	29.950132	245	231			
Mayiendit	Tharjiath Bor	Wang Koang	8.380171	30.000032	280	175			
Mayiendit	Tharjiath Bor	Panyamp	8.269233	29.838927	147	259			
Mayiendit	Tharjiath Bor	Zornyiet	8.269233	29.838927	73	210			
Mayiendit	Tharjiath Bor	Thomg	8.269233	29.838927	184	217			
Mayiendit	Bor	Zorbowni	8.13349	30.00099	59	222			
Mayiendit	Bor	Kerthiang	8.31421	30.00572	90	132			
Mayiendit	Bor	Letwich	8.135	30.00533	231	72			
Mayiendit	Bor	Panthiang	8.13487	30.00534	60	120			
Mayiendit	Dablual	Buoth	8.183259	30.012857	0	89			
Mayiendit	Dablual	Gam	8.184857	30.02965	195	167			
Mayiendit	Dablual	Pknyadebek	8.31935601	30.0449897	105	78			

Figure 16: Locations in Mayiendit

2 The Genetic Algorithm procedures

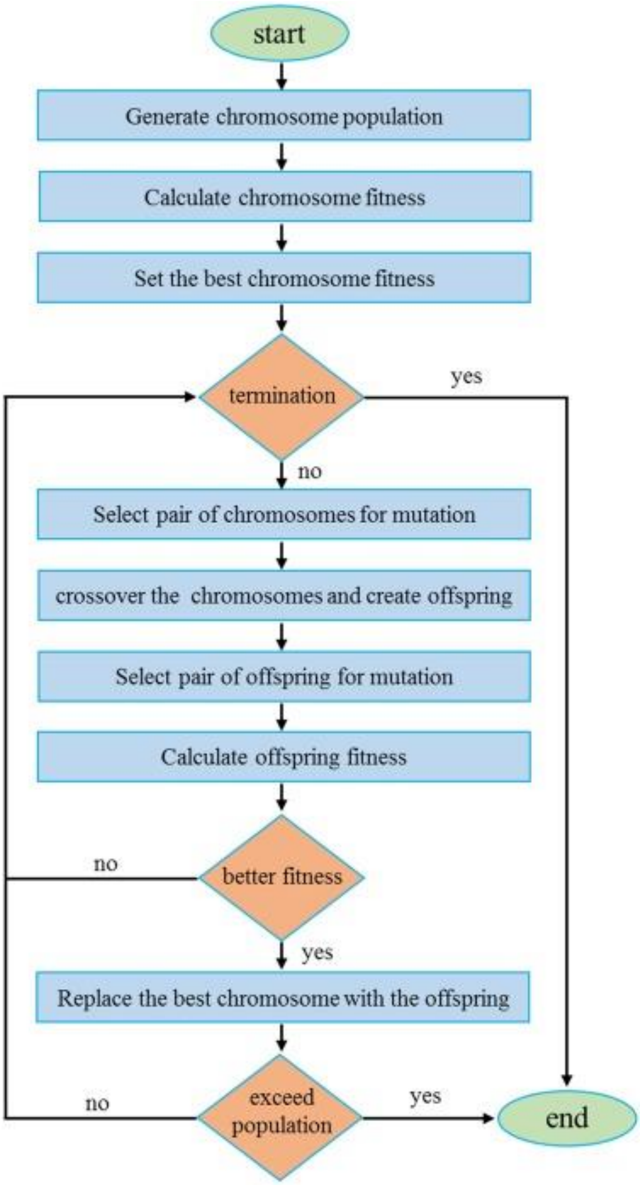

Figure 17: The Genetic Algorithm

3 The Parameters, tables and methods in Simulation framework

For the model to loyally reflect the South Sudan case defined in Chapter 1, data needs to be imported into the model as the basis of the entire problem-solving process. The first and foremost step is to import data of sites to be visited, which is presented in the appendix with reasoning provided in Section 2.3. The most crucial part includes the sites' geographical information (longitude and latitude) and the total number of people in need (refugees and IDPs).

The table storing information for all the sites and hubs can be found as .Models.GUI.PeopleDemand.SiteData. All the entries in the table need to be manually typed in other than all sites' relative locations in the model canvas. Columns of data include name, date, geographical location, accessibility, population, and demand. Extra attention should be given to demand categories in the table as there are two: unique demand and recurring demand. Unique demand represents the demand type that is sporadic, urgent, or one-time, meaning the demand pattern is volatile. For example, shelters are only needed for one time and thus require no further delivery. Recurring demand represents the demand type that is everlasting and essential to the people we aim to help. In this case, the food packages we aim to deliver undoubtedly belong to recurring demand as they are needed on a daily basis. The actual demand figure corresponds to the population (refugees and IDPs) in each village/site.

A screenshot of a partially filled SiteData table is presented below. The column "X" and "Y" in the table mark the relative position of each location in the model visualization canvas, which will be calculated and updated automatically upon model running.

	integer 1	string 2	datetime 3	real 4	real 5	real 6	integer 7	integer 8	integer 9	integer 10	integer 11	real 12	real 13
string	SiteNr	SiteName	DateTimeRevealed	Lon	Lat	Alt	Access	DaysToAccess	Population	UniqueDemandKG	RecurringDemandKG	X	Y
1	1	Koch Airport	2020/01/01 06:00:00.0000	29.98998000	8.60289000	0.00	1	0	0		0	10922.46985	-2076.78479
2	2	Baarbor	2020/01/01 06:00:00.0000	29.98991404	8.47207950	0.00	1	0	182	0	0	10922.46325	-2091.33025
3	3	Boaw	2020/01/01 06:00:00.0000	29.72682900	8.84742600	0.00	1	0	323		0	10896.17049	-2049.59363
4	4	Buoth	2020/01/01 06:00:00.0000	29.59142000	8.35685000	0.00	1	0	424		0	10882.63770	-2104.14319
5	5	Dhiel 1	2020/01/01 06:00:00.0000	29.56732400	8.67972200	0.00	1	0	441		0	10880.22954	-2068.24146
6	6	Diet	2020/01/01 06:00:00.0000	29.98400000	8.59417000	0.00	1	0	272		0	10921.87220	-2077.75441
7	7	Ganglet	2020/01/01 06:00:00.0000	29.59179000	8.35611000	0.00	1	0	337		0	10882.67468	-2104.22547
8	8	Ghol	2020/01/01 06:00:00.0000	29.99428700	8.40612000	0.00	1	0	219		0	10922.90029	-2098.66462
9	9	Golpiny	2020/01/01 06:00:00.0000	29.81051500	8.80126100	0.00	1	0	78		0	10904.53409	-2054.72694
10	10	Guar	2020/01/01 06:00:00.0000	29.97860000	8.61717000	0.00	1	0	222		0	10921.33253	-2075.19693
11	11	Gud Reng	2020/01/01 06:00:00.0000	29.98724810	8.43170358	0.00	1	0	375		0	10922.19682	-2095.81985
12	12	Guol	2020/01/01 06:00:00.0000	30.04502184	8.52903594	0.00	1	0	147		0	10927.97074	-2084.99699
13	13	Jaak 1	2020/01/01 06:00:00.0000	29.98533100	8.61838000	0.00	1	0	508		0	10922.00522	-2075.06238
14	14	Koch	2020/01/01 06:00:00.0000	29.99460000	8.59070000	0.00	1	0	730		0	10922.93157	-2078.14026
15	15	Kuahlual	2020/01/01 06:00:00.0000	30.07370400	8.53215600	0.00	1	0	74		0	10930.83724	-2084.65005
16	16	Leak	2020/01/01 06:00:00.0000	30.00940000	8.61688000	0.00	1	0	248		0	10924.41068	-2075.22917
17	17	Liech	2020/01/01 06:00:00.0000	29.99510000	8.59198000	0.00	1	0	92		0	10922.98154	-2077.99793
18	18	Lotkabang	2020/01/01 06:00:00.0000	29.81894300	8.79001400	0.00	1	0	150		0	10905.37638	-2055.97755
19	19	Mar	2020/01/01 06:00:00.0000	29.91500200	8.65960600	0.00	1	0	76		0	10914.97653	-2070.47826

Figure 9: SiteData (Partially Filled)

As the table shows, this case scenario has all the population numbers and demand figures per capita known beforehand, hence we will be performing a largely steady-state simulation here.

The parameters that need to be determined before each simulation run include the disaster date, start and end time per day, and total days to simulate. The counters to be set include the number of experiments, the number of days, and the scale factor for moving units (trucks or drones).

The scoping and structuring Section previously determined it would be a specific month set in the model to observe the fleet behavior. However, the previously known demand pattern makes the model essentially a steady-state one. Thus the decision is to run the model for one day but with different configurations to gain enough insight.

Another decision concerns with the selection of parameters for the simulated annealing, namely starting temperature, temperature lower bound, Markov length, and cooling coefficient. Like what

has been briefly mentioned at the end of **Error! Reference source not found.**, the selection of parameters has its emphasis but tuning and finding parameters for the best fit is not of importance in this research.
The Markov length is 20. The starting temperature is 20, with the cooling coefficient being 0.99 and the temperature lower bound being 0.05.

The algorithms that are used to construct the initial route plan for every vehicle (which can be found in the layer of LogisticsPlanningControl in the model) will store the trip in the table .Models.GUI.LogisticsPlanningControl.VehicleData.

4 Performance Log

The performance of vehicles is logged in a separate layer called “Performance”. The detailed log tables will be updated after every vehicle has gone to the next destination. The overview of vehicle performance will be recorded in a series of overview tables once every vehicle has finished its designated trips. Performance metrics recorded here include movement of vehicles, loading/unloading status, delivery status, and request fulfillment status. Overall performance per day, per trip, per vehicle, and per vehicle type will be updated by the end of the operation.