UAVs for humanitarian aid - simulation study for Dhanding and Nuwakot (Nepal 2015)

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1 MANAGEMENT SUMMARY

WingsForAid (WFA) is a dutch start-up whose mission is the creation and delivery of cargo drones for humanitarian aid relief good distribution. As Unmanned Aerial Vehicles (UAVs) popularize, there is a general lack of insight on how they can be applied and to what extent they can add value to relief operations. Humanitarian aid is characterized by *short response times with minimal operational costs, through covering the full demand received within a time frame*. After the problem analysis, through expert interviews and literature consultation, we define the action problem as the lack of efficiency in humanitarian aid missions. To find a solution for this main issue, we look into the core problem of a lack of insights into UAV implementation and added value to humanitarian aid logistics. With this, we hope to provide further insights to WingsForAid on how cargo drones can be utilized in different scenarios.

We deliver a simulation model, further updated from v. Steenbergen and Mes (2020), modified to the logistics after the Nepalese 2015 earthquake. The Nepal earthquake relief mission is characterized by mountain roads and altitudes too high for helicopters. We choose two regions to model, Dhading, and Nuwakot, characterized by scattered population density, high altitudes, and prioritization based on the accessibility of sites only after 2 weeks of the original disaster. In this case study, we study separately the logistics of Dhading and Nuwakot, and a combined single-depot case of the two regions. The research environment is Discrete Event Simulation (DES) experiments, focusing on the development of an algorithm and measuring deprivation. In the results, we provide general insights for UAV applications based on the Nepal case and recommendations for WFA regarding situations similar to Nepal.

After experiments, in the single-depot cases of Dhading and Nuwakot, there is a strong correlation between the number of UAVs and deprivation costs. Deprivation costs are the costs of an inhabitant's suffering since the start of the disaster. However, this results in high operational costs due to the increased fleet size. We attempt to find an optimal heterogeneous fleet based on cost change, the impact on deprivation costs, and demand coverage. As a result, with 3 deployed UAVs, the delivery of recurring demand in Nepal is increased by around 80% from the trucks-only case. Regarding unique demand, when UAVs are introduced, *unique demand is able to reach 80% delivery* within the first week. With 3 UAVs, unique demand uncovered reduces by 40%.

Regarding the heuristic study, we recommend future research on heterogeneous fleet multi-depot VRP. The heuristic chosen has limitations on efficiently using UAVs and optimizing the selected sites across vehicles. Additionally, utilizing deprivation cost and multi-criteria objective, is important to understand UAV application and their societal impact. Regarding UAV application, we emphasize the need for research focused on dynamic road failure and constraints, and on new types of scenarios/ disasters where UAVs can be utilized.

After the case study, we see benefits in UAV deployment. These benefits are in accessing high altitudes and demand that is inaccessible via road. We also recommend strategic early deployment from the start of the relief mission, with a multi-depot approach, for regions like Nepal: mountainous, poor infrastructure, high altitude, and road network only. On the heuristic, we conclude that more optimization is needed to better reflect UAV applications.

2 INTRODUCTION

Demand for efficient and effective disaster management policies at different stages has increased, as most populated cities are located in disaster-prone areas. Recently, disaster management research has taken an interest in the application of the emerging technology of Unmanned Aerial Vehicles (UAVs). The use of such types of vehicles can provide additional information to support decision-making by government or rescue teams (Hup et al, 2020). UAV usage can already be found in taking pictures of disaster areas for information updating, as well as for delivering necessities in isolated areas. The main advantage is the lack of constraint of using established road infrastructure, facing fewer obstacles such as destroyed infrastructure and inaccessible areas.

WingsForAid (WFA) is a Dutch start-up aiming to develop and deliver a scalable and reliable delivery system based on cargo-drone technology. The main attention for the company in the past years has been the development of this technology. Currently, WFA is planning its strategic movements by cooperating with the United Nations with a focus on disaster-prone areas, such as Nepal. They would like to conduct extensive research on the application of UAVs, testing the following: predictability of tasks post-disaster, scalability of the UAV usage in relief missions, and usage of drones in last-mile operations to avoid crowding and long lead times for relief goods.

In this graduation project, real data from Nepal's 2015 earthquake is used to evaluate UAV contribution to humanitarian logistics. The assignment attempts to analyze the value UAVs could bring to delivery efficiency for the first phase of the operation organized by the World Food Programme (WFP) and Red Cross, following the Nepalese earthquake of 7.8 Mw. From this analysis, a discussion on the prospects of UAV application can be drawn. Hence, we pose the question: ***In what way and to what degree can UAVs contribute to humanitarian aid logistics, considering minimum operational costs and response time?*** Consequently, WFA gains insights to further develop their UAVs for efficient humanitarian logistics.

Following the Managerial Problem-Solving Method, we analyze the problem in the following subsections. We include a summary of the action problem and the core problem. There is a distinction between the general need for UAV applications in humanitarian aid, and the needs of WFA, regarding the optimal deployment of their drones and researching their added value.

2.1 The Action Problem

An efficient humanitarian mission aims for the optimal distribution of relief goods, considering response time and costs. The Nepal earthquake relief mission is characterized by difficult-to-reach mountain roads, and altitudes too high for helicopters. With the main earthquake of 7.8 Mw and a major aftershock 17 days later of 7.3 Mw, the case received international attention.

WFA is a cargo drone producing company and so they aim to find systematic usage of their drones in these missions. Talking to the company and experts' consultations led to identifying a series of correlated problems that can influence UAV application in relief missions. One utilization considers the number of drones to be dispatched for a mission, which depends on the combinations with the different modalities (vehicles), their capacities, and the situational factors with specific needs (infrastructure, terrain, etc.). As WFA aims for cooperation in different countries, scenario-based studies in disaster-prone areas are valuable. These studies offer a perspective on the impact of UAVs in historical cases and general takeaways for future missions with similar settings.

The benefits of UAV usage can be found in different stages of relief missions. In literature, we distinguish between stages pre- and post-disaster. There are multiple frameworks, models, and procedures for disaster management, but the most common and generalized is the cycle with mitigation/prevention, preparation, response, and recovery. In post-disaster, United Nations Development Programme (UNDP), acknowledges four phases: relief, early recovery, recovery, and development. However, there seems to be a blurred line between time frame and tasks per phase, hence we focus on the generalized model. These phases also represent different levels of decision-making regarding UAV usage, with more strategic decisions made pre-disaster, and operational ones post-disaster.

First, pre-disaster decisions include an outline of possible humanitarian missions in case of a disaster. Decisions regarding UAVs can be related to area vulnerability, disaster-prone areas, depots and warehouse placements, and budget constraints. Hence, contingency planning includes decisions on evacuation plans, emergency operations centers, and disaster recovery plans, which impact the choice of UAV usage (Castillo, 2005). Figure 1 shows decisions that can be taken in this strategic phase, including the usage of UAVs as an information-gathering tool, for distribution and their utilization duration.

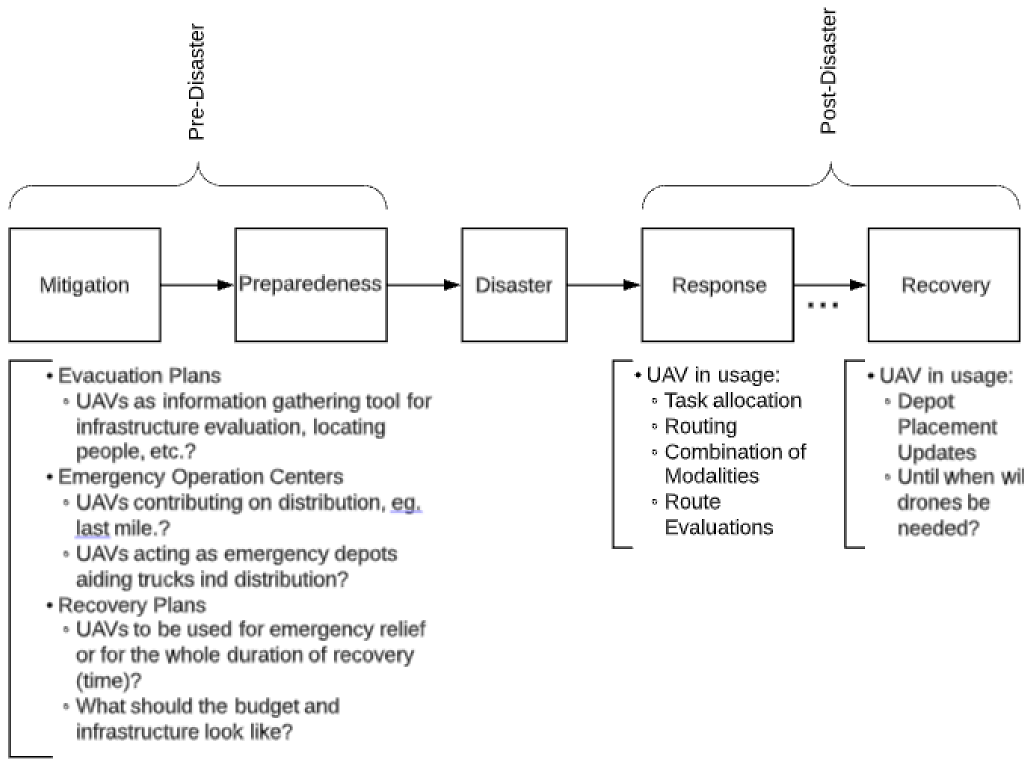


Figure 1. Disaster Management and Decisions on UAVs

Second, post-disaster implies short time-frame decisions. These decisions can be operational (daily) or tactical (weekly). The immediate response deals with operational-level decisions, which include route and task allocation of UAVs. In recovery, we deal with the slightly more tactical placement of depots and UAVs. In other words, drone utilization impacts the daily operations of a relief mission, hence they are part of operational decision-making.

The aim is to have efficient missions. Hence, for successful UAV implementation in humanitarian aid, *there needs to be better preparation for UAV utilization*. In addition, we need to further understand the abilities and impacts of UAVs during the response phase, as we lack insight into the implementation of UAVs. The overarching question is: *How do we increase efficiency in humanitarian aid through the use of UAVs?*

2.2 The Core Problem

As UAVs become more popular, a general lack of insight on how they can be applied to different situations prevents their direct implementation. In humanitarian aid, the main goal is to have *short response times with minimal operational costs, by covering the full demand received within a time frame*. These Key Performance Indicators will be further explained in the next chapter, and they define an efficient mission. A simplified cluster of topics is found in Figure 2 as an introduction to the Problem Analysis.

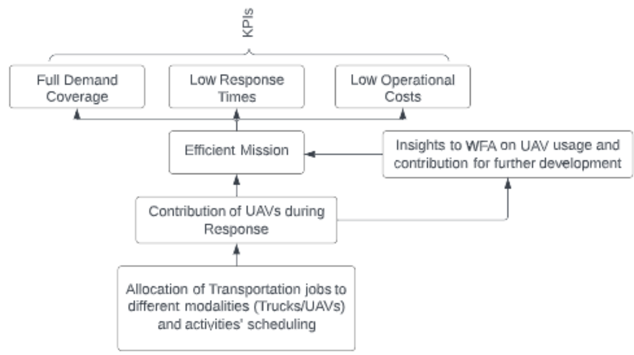


Figure 2. Simplified Topic Cluster

In Figure 2 we underline the contribution of UAVs during Response as a topic directly related to the efficiency of the mission. From the action problem, we understand that UAVs can have an impact in increasing efficiency if their application is well constructed on the phases pre- and post-disaster. With UAVs being the new vehicle technology, insights into their potential can aid companies and governments in creating efficient missions based on well-defined protocols. For WFA, this implies further insight for business development, particularly on further usage and scalability of their cargo UAVs, such as logistics, information gathering, etc.

The first step in achieving last-mile distribution logistics protocols is the allocation of transportation jobs to different modalities (type of transport) and different activity scheduling. Heterogeneous fleets are difficult to study and so they form a cluster of not thoroughly explored possibilities for mixed vehicle fleets, such as those including UAVs. Vehicle Routing Problem (VRP) is a class of optimization problems, consisting of a fleet of vehicles delivering a fixed amount of goods while minimizing costs. VRPs are common studies in disaster management; however, few consider heterogeneous fleets, with even fewer ones considering drones. Hence, we choose to tackle this core issue of understanding UAV contribution through the study of *single depot heterogeneous fleet vehicle routing problems*. Figure 3 shows how exploring heterogeneous fleets composed of new technologies, such as UAVs, can contribute to an efficient mission and simultaneously aid WFA's business development in humanitarian aid and logistic deployments.

The exploration of such routing problems is only one of the ways to investigate UAV possibilities. Facility location and inventory management can also be discussed on an operational level. UAVs can contribute to expanding the location range of the facilities, providing information in real-time through scouting, but this is beyond the scope of this thesis. The implementation of new developments depends on budget constraints and scenario adaptation. Hence, Figure 3 is a simplified representation of the societal level problem analysis.

As discussed in the previous section, to influence the efficiency of the mission, governments should prepare their protocols beforehand and adapt during the response phase. During the response, a major cause of inefficiency is the poor infrastructure with inefficient information gathering and chaotic documentation. The poor infrastructure can come as a result of various constraints such as ongoing disasters (war/ earthquake aftershocks/ etc.), weather conditions, and the physical terrain. This is beyond WFA's control. However, within their control is the understanding of the routing complexity and allocation of jobs for mixed fleets. Right now, there is a lack of insight on how these UAVs can be utilized and add value to mixed fleets, leading to complex and ill-defined routing, uncertain activity scheduling, and sub-optimal delivery allocation.

Figure 3 links the vehicle constraints and terrain to the timing and the scope of the mission. This implies that if the mission is well prepared in timing and scope it will enable different modalities to perform efficiently. In discussion with WFA, cargo drones' *flying range, altitude, deployment, and fleet*

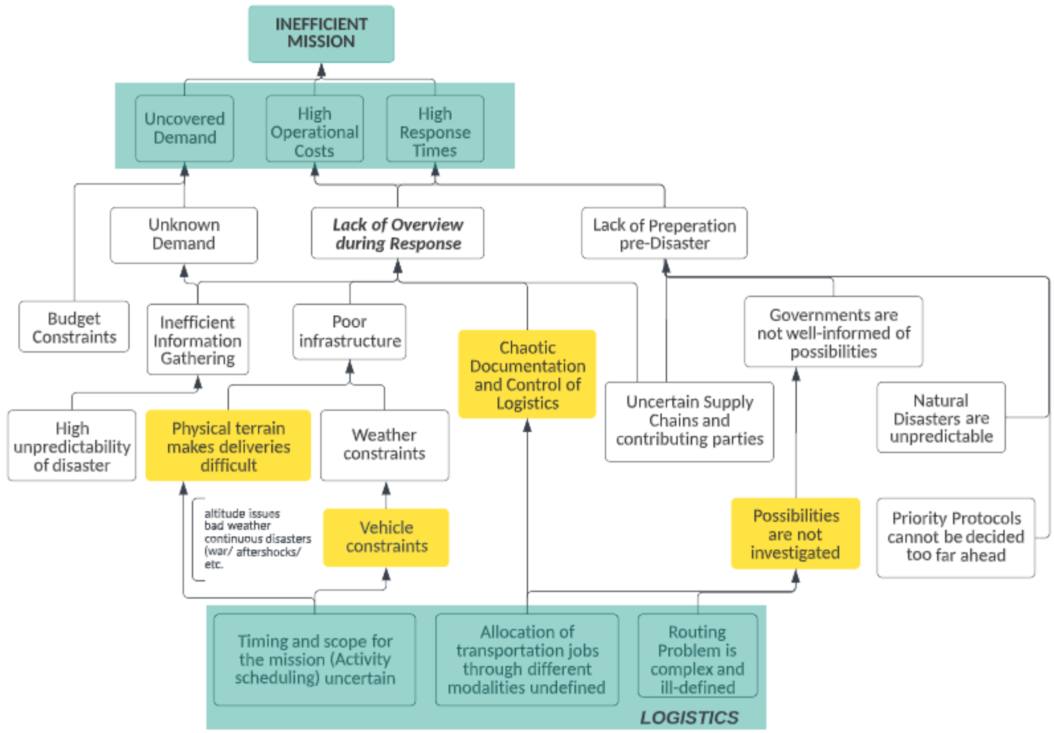


Figure 3. Simplified Problem Cluster

size were identified as areas of investigation to further develop UAV technology. Insights on these areas would provide benchmarks for the company on to what extent to develop their technology. Additionally, these insights should provide an overview of UAV possibilities in implementation after a disaster occurs.

Furthermore, meeting demand highly affects the overall time frame of the mission, as budgetary constraints do not allow for demand to be present at all moments in time. However, demand is dependent on timely information gathering, priority distribution, and budget constraints. The World Food Programme (WFP) and Red Cross often lobby for months to gather the necessary funds to increase their budgets as missions continue. These budgets and other time constraints (such as weather) also impact the direct implementation of UAVs, but the most tangible factor to increase efficiency is studying the impact UAVs have on these missions. For this reason, we conclude that a study of heterogeneous fleets with UAVs would contribute to new knowledge for more efficient missions, leading to proper utilization of vehicle capacity and constraints and the designing of a well-informed network.

2.3 Operationalization of Norm and Reality

In conclusion to the problem analysis, we define the action problem as the lack of efficiency in missions. We tackle this problem by analyzing the implementation of UAVs and studying their potential, as a solution to the core problem of a lack of insights into UAV contribution. To further define and operationalize efficiency, we have chosen the three KPIs: *demand coverage, response time, operational costs*. The norm and reality are situational to the disaster scenario. Overall, conclusions can be drawn on the standard of humanitarian missions with UAV applications.

To find a logistical solution to unexplored possibilities, physical terrain, and vehicle constraints, we ask the following research question: ***In what way and to what degree can UAVs contribute to humanitarian aid logistics, considering minimum operational costs and response time?*** As the norm and reality depend on disaster scenarios, in order to study UAV applications, we choose to focus on a specific case study, namely Nepal's 2015 earthquake. The Nepalese mission is of international attention and encompasses a range of difficulties when dealing with earthquakes. In the next chapter, we aim to find the best approach to analyze the application of UAVs in the Nepalese case.

2.4 Problem Solving Approach

Overall, we choose to apply the main research question to a historical case and extrapolate results. Firstly, to investigate UAV contribution, there should be a thorough investigation of what happened in the 2015 relief operation in Nepal, such as the amount and type of goods needed, time frame, regions, etc. Secondly, we create a simplified model and consider input and output data, creating thus the conceptual model for a simulation framework. The third step involves heuristic literature investigation for similar problems, in order to create a well-informed solution, which is the fourth step. Lastly, we define and run the experiments, and compare the results.

2.5 Design and Deliverable

The research environment used is experimented by means of simulation, with a focus on heuristics and improvement algorithms to solve the problem at hand. The study has a quantitative approach to the main problem, with qualitative scanning in some sub-questions. Literature review, consultation with experts, field researchers, and the company are the main means of data gathering. Additionally, a lot of data gathering is based on open sources and in cooperation with Red Cross. Data modification is done quantitatively by normalization.

The main deliverable is *a simulation model update, tailored to a chosen region of the Nepal case and an analysis in the Nepal response mission of UAV application*. We build further upon the existing model of v. Steenbergen and Mes (2020) and modify it for the Nepal case. With this, we aim to provide insights to improve decision-making on future similar cases. We choose an area to model for the logistics operation, on the bases of the available historical data gathered.

Currently, there is no concrete literature overview on general heuristics and algorithms relevant to response after earthquakes or that are based on simulation. We define the case as a **Single Depot Heterogeneous Fleet Vehicle Routing Problem**. There is no concrete study on this particular definition within humanitarian aid logistics. Additionally, the complexity of the VRP relevant for humanitarian aid missions has challenges in generalization. For this reason, for future research, we document the analysis and choices made for the modeling and studying of heuristics and the algorithms used. Lastly, what-if scenarios in Nepal would solidify the answer to the value added by UAVs. This includes a comparison of different capacity settings and ranges, under a base heuristic and priority rule.

2.6 Research Questions and Design

In this subsection, we break down the research into sub-questions for investigation and outline their research design. The process starts with understanding the case and relevant research in the field and follows with the creation of a simulation and solution design. Conclusions will be drawn via simulation experiments and analysis. Question 2 is answered through a systematic literature review, and utilized in the theory chapter, Section 3. Conclusions drawn from literature are used in Section 5.

1. **How was the Nepal 2015 mission conducted?** This question and its sub-questions will be thoroughly answered and discussed in Section 4.
    (a) What were the events of the historical disaster and what does the time frame look like?
    (b) Which area in Nepal should be the focus and what is the model definition?
    (c) How was the mission conducted in practice?
    (d) What are the modeling objectives?

According to Robinson (2004), understanding the model is necessary for the conceptual model. To define the events and the timeline, it is important to gather qualitative data in terms of how the mission was conducted in reality. This will be done through interviews with municipalities and Red Cross documentation and performance reports.

The second sub-question aims to break down the project into areas of most interest. Due to data availability, to make the project reliable and model reality, choosing to model one region within Nepal might be of great interest. In the conceptual model, the data from sub-question one and two will be simplified and operationalized in events, tasks, and methods.

The third sub-question focuses on events that happened during the mission, which make the case unique from previously simulated ones. An example would be the major aftershock 17 days after the initial earthquake, changing infrastructure and availability.

Finally, the last question is based on Robinson (2004). We define modeling objectives related to the KPIs. Additionally, we related these modeling objectives to situational aspects of the Nepal 2015's case.

2. **What are common solutions and the influential variables?** This question and its sub-questions will be thoroughly answered and discussed in Section 3.

    (a) How is the defined task allocation problem usually solved in the literature of humanitarian aid?

    (b) What is considered effective prioritization in humanitarian aid?

    (c) What are some best practices for the defined task allocation problem?

    The first question will be answered through a systematic literature review and focuses on the problem-solving approach. While the other phases depend heavily on the quantitative environment, we start the research in a non-linear manner, as insights of this first question aid the output of question 4. Due to the broad nature of the solution-finding phase, we divide this phase into literature research within humanitarian aid, then in other areas. Later we specify the implementation and design for the Nepal situation. Notably at this stage, we define the problem as a VRP, in order to not remove literature that can be utilized. However, the overall nature of this VRP is a **Single Depot Heterogeneous Fleet Vehicle Routing Problem.**

    In heuristics and vehicle routing problems, deciding on priority is a main influence on the logistic operations. In humanitarian logistics, priority policies are a difficult matter ethically and have a great influence on KPI performance. This graduation thesis does not focus on this variable but considers the influence, particularly on modeling objectives. For this reason, we ask question 2c. Concluding on priority policies that could have been used or were used in Nepal will affect the experiment results, and hence will be properly documented.

3. **What does the conceptual model look like for the Nepalese 2015 earthquake?** This question and its sub-questions will be thoroughly answered and discussed in Section 6.

    (a) What simplifications and assumptions are necessary?

    (b) How should the simulation framework used be adapted to the specific case?

    (c) What are the detailed inputs, outputs, and content of the model?

    (d) What are the general modeling objectives?

    (e) To what extent does the model reflect reality?

    Reality is difficult to model, and the framework allows leeway to include most of the important aspects in the simulation. Simplifying the defined model and outlining assumptions is needed for the simulation verification and will influence the data gathered. Expert confirmation and literature examples will be consulted.

    In terms of data for the simulation itself, this must be gathered according to the guidelines of the ethical committee, through public databases, and in cooperation with the Red Cross and WFA. It is assumed that most data are scattered and need normalization and operationalization. Some of the data needs scanning for relevance and being familiar with the simulation framework is important in the data processing.

Regarding the simulation framework itself, question 3b addresses modification and updates needed on the simulation framework created by v. Steenbergen and Mes (2020), due to the unique attributes of the Nepal case. Lastly, verification of the model should be done in cooperation with experts, and if needed sensitivity analysis might be used.

4. **What solution can be designed for heterogeneous fleets transportation in the Nepal case?**

   This question and its sub-questions will be thoroughly answered and discussed in Section 5.

   (a) To what extent can we translate the general modeling objectives into a solution?
   (b) How can the conclusions from literature be used for the specific case?
   (c) What is the final solution used and its limitations?

   Question 4a considers the general modeling objectives for the simulation, given the historical context and the outline from question 3d. It is important to be able to outline the specific needs of a solution and the simplifications and limitations of the general modeling objectives.

   Question 4b relates to the insight from question 2 and the theoretical background. With this question, we aim to take the conclusions on heuristics and prioritization from literature and apply them to a solution that can provide insights into the Nepalese case.

   The last sub-question finalizes this solution, designed specifically for the Nepal Case. Does it also consider limitations,

5. **What conclusions can be drawn on the solution and variables used?** This question and its sub-questions will be thoroughly answered and discussed in section 7 and section 8.

   (a) What should the experiments look like?
   (b) What are the experimental outcomes?
   (c) To what degree do variables influence the outcomes?
   (d) What is the role and contribution of UAVs in humanitarian aid, based on these outcomes?
   (e) What conclusions are there on the solution and the characteristics of the Nepal case?
   (f) What discussion points can be raised based on these outcomes?

   Results can be drawn through an experimental design and outcome interpretation, of the solution and influential variables. Hence question 5a and 5b focus specifically in the experiments on the research environment. Question 5c takes a look at the influence of the variables and the reliability of the outcomes.

   Afterwards, question 5d and 5e draw conclusions on our main research question. Here we provide advice based on the Nepalese case to any stakeholder involved, given the reliability mentioned. Particularly we look into UAV contribution to the case studied, and the role of the solution. Lastly, we should provide further discussion and research points given the outcomes of this thesis.

2.7 Key Constructs, Variables, and Concepts

In this section, we define and contextualize the most relevant concepts for this thesis. Additionally, the section provides an overview of the relation of the key constructs explored and on which the research design depends.

Simulation “Simulation is the imitation of the operation of a real-world process or system over time” (Banks, 2000).

Discrete Event Simulation (DES) "A simulation model in which the state variables change only at those discrete points in time at which events occur. Events occur as a consequence of activity times and delays. A discrete-event simulation model is conducted over time ("run") by a mechanism that moves simulated time forward"(Banks, 2003).

Vehicle Routing Problem (VRP) This is a class of optimization problems that originates from the Travelling Salesman Problem (TSP), and is extended to include multiple capacitated vehicles. (Moshref-Javadi et al., 2019). The basic VRP consists of a fleet of identical vehicles delivering fixed amounts of goods through computed trips of minimal total costs (Prins, 2000).

Covering Tour Problem (CTP) was firstly introduced by Gendreau, Laporte, and Semet (1997). In this problem "it is assumed that when a customer vertex is within a pre-specified distance of a visited facility vertex, it is covered" (Karaoglan et al, 2018).

Deprivation Cost "Economic Value estimated of the human suffering caused by the lack of access to a good or service" (Shao et al, 2021)

Social Costs "and benefits are the summation of all private and external costs, and benefits, respectively" (Holguin-Veras et al, 2013). In the context of humanitarian aid, social costs are the summation of logistics (operational) costs and deprivation costs.

Local Search takes a potential solution and checks for an improved one in the potential solution's neighborhood, leading to similar solutions with minor changes.

Global Search takes a potential solution and checks for an improved one in the larger search space, leading to a global optimum.

GRASP (Greedy Randomized Adaptive Search Procedures) "is an iterative randomized sampling technique in which each iteration provides a solution to the problem at hand" (Feo and Resende, 1994). Firstly a solution is constructed via an adaptive randomized greedy function, and then local search procedures are applied to find improvements. The final result is the incumbent solution over all GRASP iterations.

Simulated Annealing is a global search probabilistic technique to approximate the global optimum of a search space. The technique prioritizes an approximate global optimum over precise local optimums.

Nearest Neighbour Algorithm is a greedy algorithm that on each iteration finds the shortest route to the next connection and adds it to the route.

Cheapest Insertion Algorithm is a greedy algorithm that on each iteration calculates the cheapest possible connection and adds it to the route.

Tabu Search Created in 1989 by Fred W. Glover, Tabu Search improves the performance of local search, which has a tendency to look into sub-optimal neighborhoods and reach a plateau. Tabu Search accepts "worsening" solutions in the neighborhood if improvements cannot be found, and it introduces "prohibitions" to discourage searches in previously visited solutions.

Genetic Algorithm was developed in 1975 and is inspired by the evolution theory. This algorithm starts with a population of strings, consisting of different variables. These stings crossover and create offsprings in the new population, given a solution fitness score. The solution is then generated once no distinct "offsprings" can be reproduced.

Figure 4 is a simplified visualization of the dependent and independent constructs for the research design. The focus is on the implementation and effects of a suiTable heuristic. This heuristic is constructed by a basic prioritization and goods allocation rule and an improvement of these rules by looking for solutions locally and globally in the solution set. There are two factors to be experimented upon, in order to see the effects of UAV application in humanitarian aid, based on the selected KPIs. The suitability of

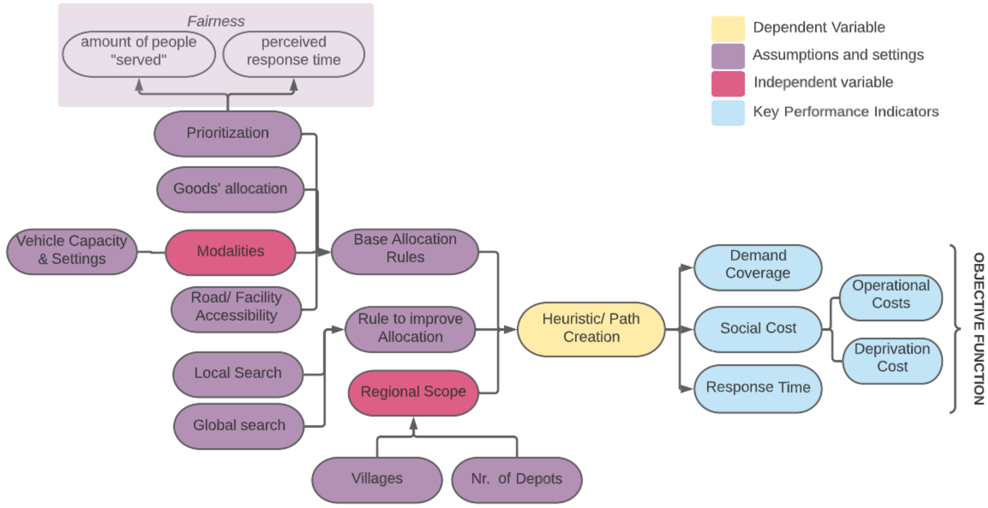


Figure 4. Relation of constructs for the Experiments

the heuristic will be further investigated in the theoretical part of the thesis. This figure is a relationship visualization, that is further elaborated upon in the input data and framework relationship in Section 5.

The first factor is the modalities, differently referred to as the heterogeneous fleet for air and land road network. Vehicle capacity (and other settings) influence the path network creation. On a complex heuristic algorithm, these settings provide an overview of the UAV influence on the KPIs.The second factor is the regional scope. This thesis considers the Nuwakot and Dhadhing regions. The amount of nodes (customers/ benefactors/ sites) depends on the area scope to be studied. The scope experiments should provide insights into the suitability of a single-depot VRP approach.

2.8 Design Limitations

Scope

This thesis studies the Nepal earthquake of 2015 and creates a simulation model for two of the affected regions. This design choice limits the applicability of the research. However, every humanitarian aid mission is categorized by specific challenges, and a case-by-case study provides insights on best practices. For this reason, the research should draw conclusions on UAV usage as the main characteristic of the Nepalese humanitarian aid mission. This implies difficult mountainous terrain, inaccessible road infrastructure, short time response due to weather conditions, and a large affected population.

Research environment

The chosen research environment, a Discrete Event Simulation (DES), provides insights and bridges reality with the theoretical approach. This simulation environment comes with a set of assumptions and simplifications, which have an effect on the real-world application of the heuristic and UAV applications. Taking this into consideration, given a set of simplifications and assumptions, simulation results can come quite close to reality. Experimenting with the scope and the heterogeneity of the fleet should provide close to real insights into the regions studied. Additionally, we investigate the validity of the simulation by the characteristics of the original mission: primarily truck usage, and one-depot with no communication among municipalities.

3 THEORETICAL OVERVIEW

This section looks into the relevant literature on the topic of humanitarian aid and disaster management. The background literature discusses the general need for simulation in disaster management and relevant applications, that include UAV implementation. We proceed by defining all theoretical concepts, and we advise the reader to consult Section 2.7 for all definitions throughout this thesis. After defining the concepts, we look into humanitarian aid and equity as defined in recent literature. Lastly, through a literature review, we define the task allocation problem and relevant solutions previously researched in disaster management (Appendix A).

3.1 Background

In this section, we will discuss disaster management, humanitarian aid, and relevant methods of study. For the methods, we look into the methodology of studying disaster management and the application of innovative methods in humanitarian aid.

Disaster management is a field of study that requires modeling complex networks in different areas of research, such as relief goods distribution, facility and inventory management, evacuation plans, etc. Most populated cities are located in risky faults, hence discussing and planning for disaster management is necessary for companies as well as governments.

One method of study is Discrete Event Simulation (DES), a powerful tool for an intuitive and flexible representation of complex systems. Mishra et al. argue that simulation modeling in the field of disaster management is still at an early stage, yet evolving rapidly (2019). More importantly from 2000 to 2016, there were about 16 relevant papers on DES application, and only two of them considered the distribution of goods to provide optimal logistics for emergency humanitarian aid (Mishra et al., 2019). As there is no consensus on best practices for the distribution of goods during the emergency phase, we can establish that there is still a lot to be investigated.

In February 2015, The Production and Operations Management journal created a research category of "Disaster Management" to encourage research in the field. Of the 268 relevant papers evaluated by Gupta et al. (2016), supply distribution, heuristics, and simulation-oriented research are relatively new when it comes to last-mile humanitarian logistics. Furthermore, few papers consider in detail the use of the emerging technologies of Unmanned Aerial Vehicles (UAVs), which could provide solutions to associated distribution problems. Research on UAV applications has become popular in recent years. UAVs are not limited by established infrastructure and face fewer complex obstacle avoidance scenarios, hence researchers concord on their suitability for post-natural disaster missions (Hou et al., 2020)

Chang et al. argue that major objectives for humanitarian missions are the distribution of resources and crew, the location of relief centers, and the optimization of transportation routes (2014). V. Steenbergen and Mes (2020) propose a simulation framework for UAV-aided humanitarian logistics, emphasizing the need to bridge the gap between theory and practice. While UAVs have mostly been used for civil applications, there is a huge market potential for "substantial cost savings in monitoring difficult to access infrastructure, as well as deliveries of packages" (Otto et al., 2018).

Building upon the extensive literature, we focus on the holistic literature on emergency aid, UAV application, and simulation. We conclude that all these factors lead to more comprehensive research in the field. Moreover, we identify some important areas to be discussed and researched, such as equiTable distribution of relief goods and transportation route optimization. The latter includes heuristic applications and prioritization of demand and goods. The following subsections dive into the literature on these subtopics.

3.2 Humanitarian Aid and Equity

Equity and fairness are major issues not only in economics. Fair and equiTable distribution of relief commodities has become a discussion in humanitarian logistics literature, particularly due to the philosophical correlation and difficulties in specifying equiTable distributions. Fundamentally, the philosophical discussions between utilitarianism, maximizing utility for the greatest number of people, and other diverse theories on justice and choices, date back quite some time [1].

Gutjahr and Fischer argue that aid organizations should take into account the total degree of demand satisfaction and equal distribution among the affected population (2018). Equity objectives have been pursued by several authors in different manners. Holguin-Veras et al. suggest the use of *social cost* - definition above - as the base parameter for humanitarian aid objective functions (2013). Until this date, Holguin-Veras et al. note that only two models in literature fully use the idea of social costs. Others minimize logistic costs, penalties or weighting factors, or unmet demand, often not multi-objectively (Holguin-Veras et al., 2013).

Researchers either use an *equity constraint*, meeting a certain level of equity, or a *multicriteria optimization model* that includes equity as criteria. After the breakthrough of social costs in humanitarian aid, and therefore deprivation costs, Shao et al (2021) investigate thoroughly the application of this methodology in objective functions in recent years. Noteworthy is that only six of these relevant papers are specifically for earthquake scenarios. There is no defined consensus on the best deprivation cost form and where it is applied. The application varies from the use of social costs in the objective function to a performance measure and evaluation tool. Meanwhile, the form of deprivation costs has transformed from a proxy model - penalty, constraints - to a more complex and situational deprivation cost function and intensity.

To conclude this section on equity and fairness, we emphasize the need for continuous use and adaptation of deprivation cost theory in humanitarian aid. Assumptions that consider inequity (either in the objective or as a constraint) deserve future investigation and have the potential for other breakthroughs in the field, particularly with the usage of new technologies, such as UAVs. In fact, few papers combine investigations of deprivation cost functions, and UAV usage, and little research has been conducted in this area.

3.3 Heuristics and Priority

This section focuses on the question: "*How is the defined problem usually solved in the literature of humanitarian aid?*" We define the problem as a VRP with a heterogeneous fleet and focus on UAV application in complex situations. Moreover, we have earlier introduced it as a single-depot study of VRP. In this literature review, we are interested in all heuristics related to heterogeneous fleets. It is challenging in humanitarian missions to schedule tasks efficiently and equitably, as seen in the previous section. As humanitarian aid studies have started to popularize, the application of innovation has increased. Hence, we expect research in the body of knowledge of the field to lead to a conclusion on best practices for transportation in VRP with heterogeneous fleets. *To answer the question, we conduct a systematic literature review.*

For this systematic literature review, we had three primary objectives. Firstly, we find solutions to task allocation and activity scheduling with at least a heterogeneous fleet of two modalities. Secondly, these solutions should be applicable to humanitarian relief missions, particularly earthquakes. And thirdly, these solutions are based on simulations and/or transportation logistics. For this reason, we limited our search to Industrial Engineering, Operation Research, and Transportation databases and journals. Additionally, we focused on case studies, simulation design, and algorithms, without looking into systematic review papers. These papers do not give the overview required for detailed solutions to be applied in a simulation environment. For more details on the systematic literature review, please refer to Appendix A.

[1] Classical Utilitarism by Bentham (1879) and Mill (1966) versus justice as separate criterion argued in the 20th century by eg. Rawls (1971), Nozick (1974), or Nagel (1995)

Figure 5 and Figure 6 show the screening process of the literature review. We studied 13 unique citations, listed in Table 8. Regarding research application, we look into the type of research conducted and its purpose. For the type of solution, we evaluate the priority and the heuristic used. We look into the number of vehicles and the number of different modalities used. And lastly, we evaluate the problem definition and objective function used in the selected papers. Following are the conclusions of these subtopics.

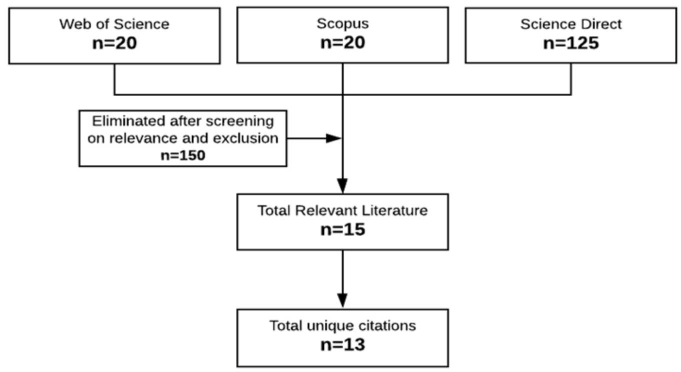


Figure 5. Selection from Literature Review

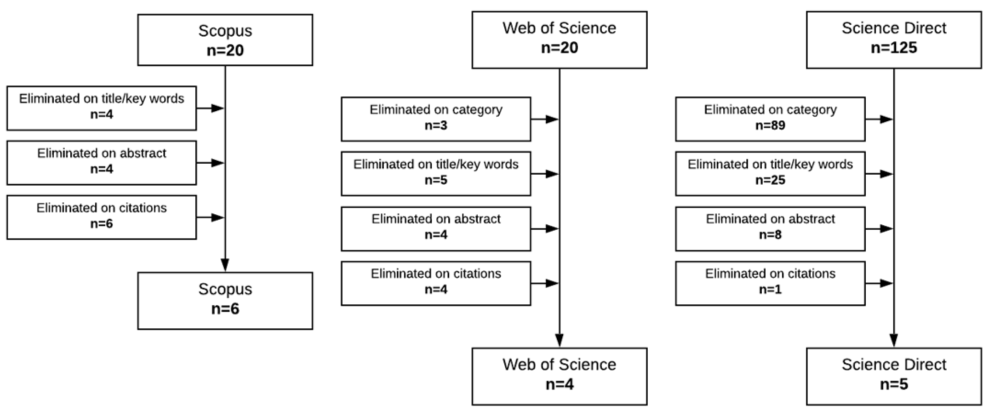


Figure 6. Databases Selection from Literature Review

Area of Research Application

Even though the initial search was constrained to humanitarian aid, after screening on abstract and keywords, only 9 are completely conducted for disaster management. The papers not fitting in this category provide useful solutions to the task definition, but the research has not been applied in the field of humanitarian aid. Additionally, we pay attention to the fact that 11 papers had a heuristic or meta-heuristic approach, to mathematical modeling. Noteworthy is the fact that despite the heuristic research, no relevant paper creates a simulation environment, particularly DES.

Type of Solution

Despite the lack of simulation usage, we can still use the result of heuristics used and researched in the field. The most studied algorithms are genetic algorithms with a classical local search, greedy algorithms, and simulated annealing. Tabu search is very typically used in Capacitated VRP and Cumulative Tour Problem (CTP). From these papers, we conclude that the Nearest Neighbor Heuristic, a simple algorithm, is not the most efficient. Some papers even consider hybrid models and at least 3 algorithm phases. Additionally, some papers address equability by providing a priority system, either through demand or location.

Vehicle Types and count There is a limited number of papers that link heuristics with UAV applications (3 in total). Some papers address the efficiency of using the aerial, road, and marine networks, relating to route accessibility in case of disruption. To solve the different variations of VRP, authors take different limitations, including capacitated or incapacitated vehicles. Additionally, most authors using heterogeneous fleets conclude on unlimited vehicles and multi-trip VRPs.

Type of Problem definition The VRP is one of the most popular optimization problems, whose objective is finding a fleet of vehicles with a set of tours, to visit all customers as efficiently as possible (Anh, T. et al, 2017). The 13 selected papers solve different variations of the VRP. Noteworthy are the multi-depot covering tour VRP, multi-vehicle CTP, VRP with soft time windows, and a combination of them. These variations result because, as mentioned in Section 3.2, the objective of humanitarian aid differs from the regular VRP, leaving room for creative problem definitions.

The deprivation Cost theory is considered a breakthrough in humanitarian aid evaluations. Some papers look upon multi-objective weighting to single-objective problems so that they can consider different KPIs. Recent publications, however, suggest that minimizing the duration of VRP may not properly reflect the need for quick service which includes a fast response, including equality and fairness, a characteristic of humanitarian aid missions (Flores et al, 2017).

3.4 GRASP: Scientific Background

In their literature review, Moshref-Javadi et al. outline research on VRP and UAV usage (2020). Among different approaches, they emphasize a Greedy Randomized Adaptive Search (GRASP) procedure developed to solve a traveling salesman problem with drones, with up to 100 customer instances, considering cost minimization. Meanwhile, Allahyari et al. attempt to solve the Multi-Depot Covering Tour Vehicle Routing Problem (MDCTVRP) using a hybrid heuristic of iterated local searches, GRASP, and simulated annealing (2015). Essentially the algorithm performed quite well in different variations of a covering tour VRP problem. As the GRASP algorithm becomes popular in mathematical modeling and meta-heuristics, with this thesis we attempt to bridge the gap between this literature and practice, attempting a simplified version of hybrid-heuristics to test in a **Single Depot Heterogeneous Fleet Vehicle Routing Problem.**

3.5 Conclusions

In conclusion in this section, we highlight the most important heuristics that provide an efficient and flexible solution for the VRP. Table 8 gives an overview of all 13 papers that were analyzed for these conclusions. Primarily, a heuristic in humanitarian aid should be *multi-objective.* As concluded in the previous section, including deprivation costs and penalties, without limits on cost minimization objectives, is very important in this field of study.

Secondly, *hybrid algorithms* give very good results. The most noteworthy is the hybrid combination of random iterated local searches with a Greedy Algorithm and finalized with Simulated Annealing, from Gharib, Z et al. (2018), and similarly from Allahyari et al. (2015). However, Simulated Annealing, Tabu Search, and Genetic Algorithms are common solutions to regular VRPs in literature. In fact, the Genetic Algorithm has been more frequently studied in recent research compared to Tabu Search (Hesam Sadati, M.E. et al., 2020).

Therefore, there is a need to combine previous best practices in heuristics as solutions to VRPs. Case studies and simulation in practice can bridge the gap to better understand improvement and prioritization

Table 1. Selected Literature

Author(s)	Title	Year
Gharib, Z.;Bozorgi-Amiri,A. et al.	A cluster-based emergency vehicle routing problem in disaster with reliability	2018
Santos, Andréa Cynthia	New trends and opportunities in post-disaster relief optimization problems	2019
Lin, Y.-H.; Batta, R. et al.	A logistics model for emergency supply of critical items in the aftermath of a disaster	2011
Flores-Garza, D.A.; Salazar-Aguilar, M.A et a;.	The multi-vehicle cumulative covering tour problem	2017
Cannioto, M.; D'Alessandro, A. et al.	Brief communication: Vehicle routing problem and UAV application in the post-earthquake scenario	2017
Bruni, M.E.; Beraldi, P. ; Khodaparasti, S.	A fast heuristic for routing in post-disaster humanitarian relief logistics	2018
Burcu Balcik, Benita M. Beamon; Karen Smilowitz	Last Mile Distribution in Humanitarian Relief	2008
Huo, L.; Zhu, J.; Wu, G.; Li, Z.	A novel simulated annealing based strategy for balanced uav task assignment and path planning	2020
Pham, Tuan Anh; Hoàng Hà, Minh et al.	Solving the multi-vehicle multi-covering tour problem	2017
Ke, Liangjun; Feng, Zuren	A two-phase metaheuristic for the cumulative capacitated vehicle routing problem	2013
Allahyari, Somayeh; Salari, Majid et al.	A hybrid metaheuristic algorithm for the multi-depot covering tour vehicle routing problem	2015
Hesam Sadati, Mir Ehsan; Çatay, Bülent et al.	An efficient variable neighborhood search with tabu shaking for a class of multi-depot vehicle routing problems	2021
Karaoğlan, İsmail; Erdoğan, Güneş et al.	The Multi-Vehicle Probabilistic Covering Tour Problem	2018

in humanitarian aid. Hence, facilitating an environment to use some of these most frequently used heuristics is the next step for research.

4 HISTORICAL OVERVIEW OF THE NEPALESE MISSION 2015

This chapter attempts to answer the first research question regarding the humanitarian aid mission after Nepal's earthquake in 2015. It includes a historical overview describing the main operational events during the first six months, and a focus and scope based on an analysis of a collected data set. We conclude with assumptions and decisions regarding timeline, priority, categories, distribution hierarchies, and capacities. These choices play a vital role in the following chapters and build a case for UAV application in the mission.

The historical overview has been made through a collection of data and scenarios from Red Cross operational reports and data sets. Part of the data used is open data, while the rest is primary data collected through collaboration in Nepal for this project.

4.1 Overview

On the 25th of April 2015, a 7.8 magnitude earthquake struck Nepal, followed by a 7.3 magnitude aftershock on the 12th of May and resulting in a devastating number of 8891 causalities. Areas around Kathmandu, the capital, were completely damaged, causing the country to be in a state of reconstruction and humanitarian aid for more than a year. There were different international parties involved in the humanitarian aid mission, including United Nations, World Food Programme (WFP), World Health Organization (WHO), and the (International) Red Cross.

As seen in Figure 7, most of the regions near the epicenters of the earthquakes are characterized by highlands. This characteristic had an influence on the approach of humanitarian aid and depot placements.

Figure 7. Earthquake Overview

Due to the large scale of the problem, there were major operational gaps that left room for improvement in the way decisions were made. Importantly, emergency warehouses and propositioning of relief materials with proper inventory were lacking. Additionally, there was a gap between people affected and delivery services, caused by the absence of modern technology, a weak database, and a lack of communication between municipalities (Government Report, 2015). Recreating the original mission through simulation is constrained by these gaps in information.

Within the initial response phase, after the major aftershock, World Food Programme (WFP) engaged new solutions to the latitude problem of the mountainous areas and remote villages, including climbers, local porters, and pack animals, as well as two MI8 helicopters and one AS350 helicopter. Due to the monsoon season of June to August, the delivery response had to be quick in the first months, before the extreme change in weather, which would induce landslides and even more challenging road infrastructure. The six most heavily affected districts were *Gorkha, Dhading, Nuwakot, Rasuwa, Sindhupalchok, and Kabhre*.

September marked the end of some funding issues in logistics during summer and the start of utilizing cargo helicopters for the transportation of humans and goods, ending as a service at the end of December. The districts of Dhading and Nuwakot were part of the major districts that were prioritized for road transportation and had free-of-charge delivery (RedCross, 15 September 2015). October was the official start of the recovery phase, immediately after the structured relief operation ended in September (RedCross, 10 October 2015).

4.2 Focus and Scope

Dhanding and Nuwakot were some of the most severely damaged areas. These two districts highlight the challenges of the 2015 Nepalese Earthquake first response, including the inaccessibility of villages by trucks, and the usage of climbers in high-altitude areas. Some of the villages are located above the 4000-meter altitude. For this representation, this graduation thesis will be studying in-depth these two regions.

Table 1 provides an overview of the relevant regional hubs in Nepal. The two districts had a warehouse in the central areas, mainly for last-mile distributions to the nearby sites. Note that the hubs in Nuwakot and Dhading opened after the 11th of May. Additionally, the two regions' truck deliveries were coordinated by two different hubs.

Table 2. Logistics Hubs - Capacity and Purpose: in blue, Nuwakot and Dhading hubs, respectively

Location	Storage Capacity (m^2)	Purpose
Kathmandu International Airport	2320	Staging Hub
Deurali	1440	Gorkha hub; To western regions; Local air operations
Chautara	1120	Sindhupalchok hub; To western regions; Local air operations
Dhulikhel	1280	Kavrepalanchok hub
Bharatpur	880	Chitwan hub; Inbound Cargo from India; Additional storage space
Charikot	480	Dolakha hub; For last mile operations
Bidur	320	Nuwakot satellite hub; For last mile operations
Dhading Besi	320	Dhading satellite hub; For last mile operations

Regarding the logistic hubs for these two districts, Dhading Besi had access to helicopters and road infrastructure, while Nuwakot more relied on less innovative solutions of transportation from the Bidur hub, such as hikers and animals. About 97,9% of Nuwakot's population was affected by the earthquake, and this figure is only at 59% for Dhanding.

The overall operation starts in the days after the earthquake, and proceeds in three phases, according to the Red Cross operational Report. This project aims to model UAV usage in the first week of the earthquake, focusing on the immediate response. Data is limited, but, a network of 108 cities will be investigated, which were the sites that received aid in the original mission.

We have chosen the district of Dhading and Nuwakot as a representation of the severity of the damage, early responses with some data availability, and to be able to compare solution cross-municipalities. It is interesting to study UAV application on the region regarding high altitudes and the scope range.

4.3 Data Evaluation

This analysis considers public data from different sources and records from the municipalities. We evaluate the cities and items distributed in Nuwakot and Dhading separately. First, we compare the villages distribution per number of inhabitants. Second, we study the distribution of goods from April to December, for an overall picture of good distribution. Last, we compare the frequency of delivery (amount of truck trips) per type of good versus sites' population density.

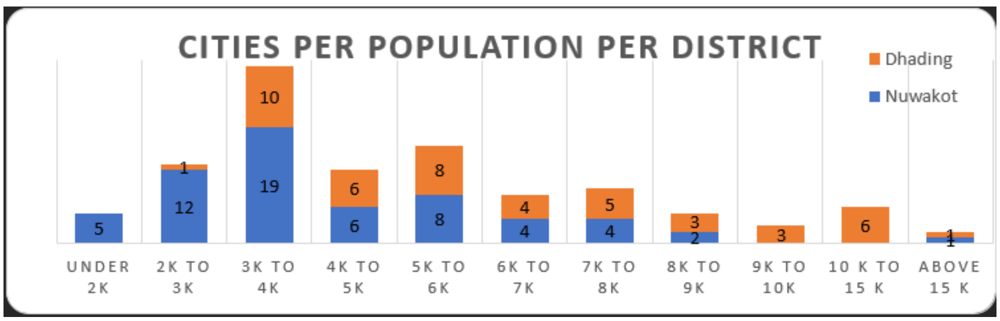


Figure 8. Villages in each District per Inhabitants

Figure 8 indicates the nature of the districts on villages to serve. Dhading has a more balanced distribution of inhabitants compared to Nuwakot, although most villages are still under 6,000 inhabitants. Noteworthy is the amount of smaller villages in Nuwakot and the fact that this is a more mountainous region. As mentioned in the previous section, Nuwakot had about 97,9% of the area influenced by the natural disaster, hence the region considers more destinations to deliver goods to and more damaged infrastructure.

With this overview of the villages per district, we need an item and historical delivery overview to better understand how the sites were prioritized and the nature of the mission. Firstly, we analyze the frequency of items distributed, given the limitations of the datasets. Figure 9 shows the frequency of categorized items as a function of time (in months). For simplification and to generalize the data set while allowing comparisons, we have constructed the following initial categories: Blankets and Mats; CGI Bundles; Food; Kitchen Sets; Lighting; Medical and Psychological; Other Shelter; Tarp; Tool Kits.

Firstly, as indicated in Figure 9, most of the emergency relief happens in May, focusing on tarp distribution and blankets/mats. Secondly, there were frequent deliveries, measured in the number of truck trips in the region, for medical items, food, and other shelter supplies. Noteworthy in the time progression is the predicted weather changes of the monsoon season (July-September). This has two impacts on the mission: the priority of particular items in the emergency response to meet the need of preparing for the weather change and the lack of difficulty of delivery in July-September.

Hence, *The Nepal mission in 2015 is characterized by a fast initial response of urgent shelter items. So, in April-June, tarps and blankets/mats are considered high-priority items to meet all the demands per household. Food, medical kits, and other shelter items are considered recurring goods to be fully distributed as soon as possible.* These are the priority resources for the first stage of the relief mission. Tarp later has a complete decline in delivery as it is substituted with tool kits and CGI bundles for more

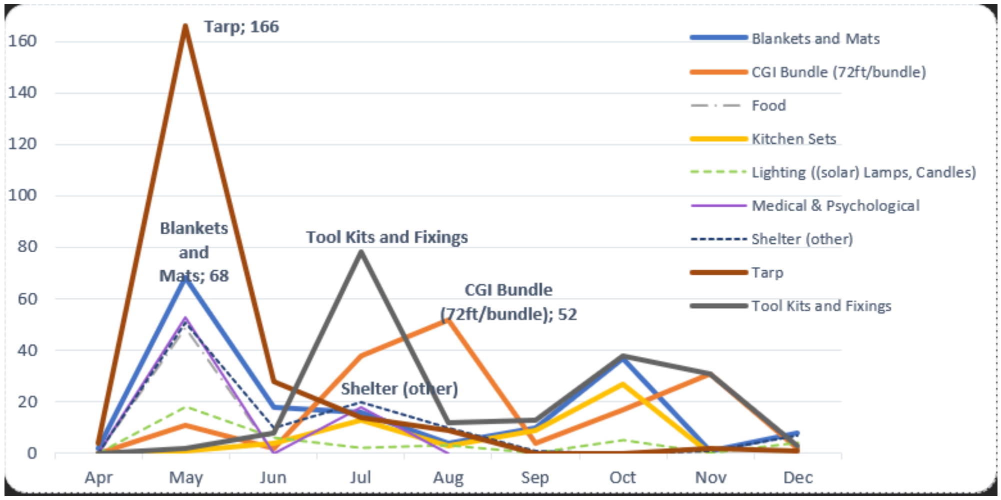


Figure 9. Time progression: frequency of item delivery

secure and guaranteed shelter.

Lastly, per district, we analyze the demand of different villages in these main categories. As seen in Figure 10, there were frequent trips to distribute tarps in villages with populations of 7,000 to 8000 and to medium size villages with populations of 3,000 to 4,000. Based on this data, Dhading had significantly more deliveries than Nuwakot.

Based on the 2011 census, Dhading had slightly more than 316,000 inhabitants, and this number is slightly above 273,000 for Nuwakot. Despite the population size being similar, we see a discrepancy in the village size distribution and deliveries made. We acknowledge the limitation of the dataset, as well as the discrepancy in prioritization of goods in these two districts, perhaps due to difficulty to reach certain regions in Nuwakot. Noteworthy is the number of cities delivered in May. For Dhading this stands at 37 out of 47 recorded until December, and for Nuwakot 31 out of 61 recorded visits.

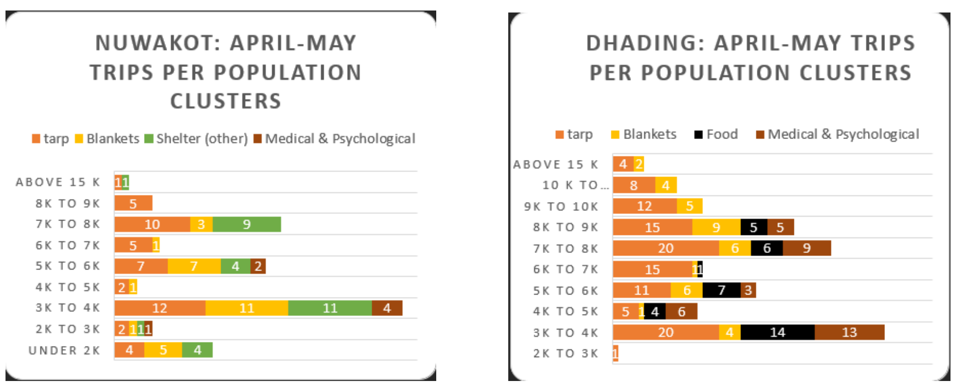


Figure 10. Deliveries per Population Cluster

4.4 Prioritization

In this subsection, we evaluate the least visited sites in Nuwakot and Dhading. Through this, we aim to understand the prioritization made in the historical event. We attempt to evaluate based on timing, altitude, and population density.

Firstly, we evaluate and study the sites least visited. In this, we are limited by the gathered data as the only source of records for evaluating fulfilled demand. For both Nuwakot and Dhading, we gather

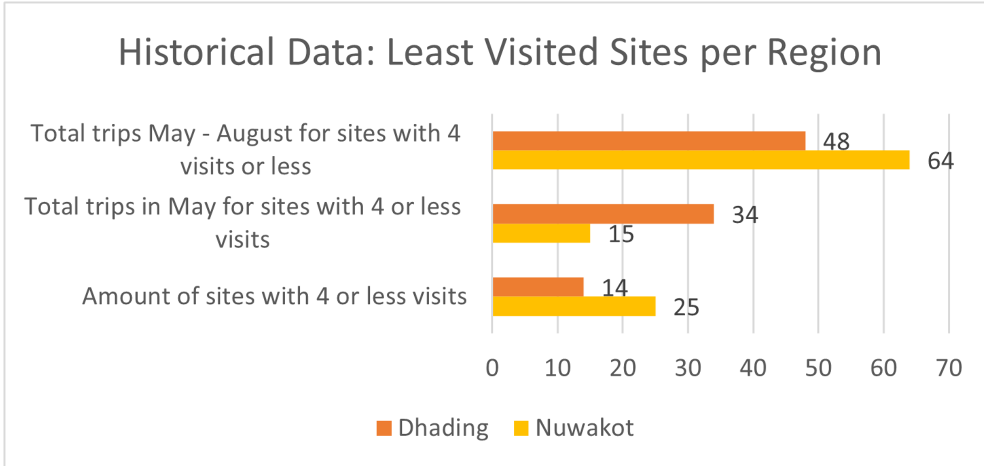


Figure 11. Historical Overview of Least Visited Sites

information on sites visited 4 or fewer times in the period May to August, and we refer to these as the least visited sites.

In Figure 11, we notice that the least visited sites in Nuwakot constitute about 40,9% of the total sites studied (61). For Dhading, the 14 least visited sites make up about 29,8% of the sites evaluated (47). Moreover, all trips on these sites for both regions were shelter deliveries with nonunique demand (tarp or blanket). So, for these sites, there is no record of food deliveries during the first phase of the relief mission. Additionally, visitation in May of these sites, particularly for Nuwakot is very low. As Nuwakot is characterized by more mountains and lower population density, we investigate the relation between the altitude of the site, population density, and trip frequency.

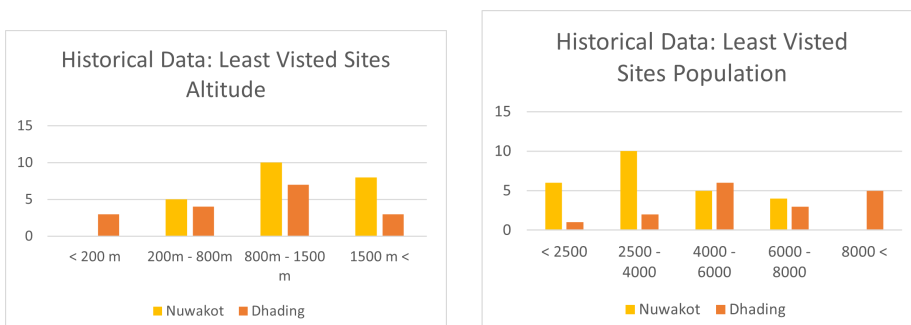


Figure 12. Population and Altitude versus least visited sites

Figure 12 shows the number of sites distributed in different altitude bins and population ones. The altitude of 800m to 1500m for the least visited sites is the mean for both regions. However, in terms of population, most of the sites that are least visited in Nuwakot, have a density lower than 4000 inhabitants. Based on these graphs, we calculated the correlation coefficient of altitude and population in relation to total trips to these least visited sites and trips in May. The results are presented in Table 3.

As indicated in Table 3, the delivery amount to Nuwakot was impacted by the altitude of the overall region. With more than 95% of the total region's population affected, the correlation coefficient shows that sites with a higher density were served earlier. The amount of least visited sites indicates some difficulty within the region. For Dhading, the altitude did not affect decision-making and deliveries. However, there is a strong positive correlation between population density and early deliveries in this region.

Table 3. Correlation Results on Altitude and Population with least visited sites

Variable	Coefficient for Nuwakot	Nuwakot Result	Coefficient for Dhading	Dhading Result
Altitude and Total Trips in Least Visited Sites	-0.27	negative correlation: altitude decreases, total trips increase	-0,06	almost 0: not correlated
Altitude and Trips in May in Least Visited Sites	0.02	almost 0: not correlated	0.07	almost 0: not correlated
Population and Total Trips in Least Visited Sites	0.15	slight positive correlation: population increases, total trips increase	0.12	slight positive correlation: population increases, total trips increase
Population and Trips in May in Least Visited Sites	0.34	positive correlation: population increases, trips in May increase	0.56	positive correlation: population increases, trips in May increase

4.5 Conclusion

To conclude the analysis and findings in this chapter, some general modeling goals are created. These modeling goals aid in the creation of assumptions and simplification in Section 6. Here, we address the priority of villages, items, categories, timeline, and distribution capacity.

In the theoretical section and this historical overview, we conclude that the original mission was categorized by unfair distributions. Prioritization was made on population density only, and sites in high altitudes were not served as early as possible. There is a discrepancy in the distribution process in Dhading compared to Nuwakot. A goal of the simulation modeling is to tackle this prioritization in order to consider altitudes and population density.

For priority items, we recognize *tarp, blankets/mats* to be unique demand to be delivered as soon as possible. Additionally, we identify *other shelter items, food, and medical items* to be recurring deliveries. Once tarp and blankets have been delivered, these do not need to be re-delivered for the same population. While food, shelter, and medicine need a frequency of delivery to the same inhabitants. These demand needs to be implemented and considered in prioritization. Regarding the timeline, all deliveries need to happen by May, as the first phase of the relief mission.

On distribution capacity, we recognize demand coverage and operational costs as immediate trade-offs. *Demand covered through equiTable distribution is an important consideration for the objective function and UAV reliability and implementation.*

5 HEURISTIC DESIGN

This section elaborates on the developed heuristic and motivates choices and assumptions made. Firstly we explain the chosen objective function as a conclusion of the research and the relevance to the historical case. Secondly, we motivate the decision of the cheapest insertion construction, followed by the theoretical relevance and choice of a Grasp algorithm and simulated annealing. Importantly, this section aims to provide insides into the limitations of the heuristic design.

5.1 Objective Function

Determining a fitting objective function is an important step to understand UAV application in humanitarian aid. As per the literature section, the objective function is based on social costs and is addressed per village so that we can address the overall equity. Gutjahr and Fischer provide a framework of deprivation costs and penalties (2018). The simulation framework runs on aspects of the utilitarian objectives they set in their paper, but on a day-to-day basis.

Table 4. Overview of Deprivation Costs adaptation

Notation	Gutjahr and Fischer (2018)	Simulation
w_k	number of beneficiaries to be supplies	Site population
k	demand point or node	Site to be visited
N	$\sum w_k$	Overall people demand
τ_k	The day that delivery takes place	Last Delivery Date
g(t)	Deprivation Intensity Function (Assumption)	Food: g(x)= $1.1x^2$ Shelter/Medicine: g(x)= $2x^0.7$ Tarp/Blankets: g(x)= $0.011x^2$
t	Deprivation Time	Day Since Last Delivery

Table 4 provides an overview of the notation regarding deprivation costs, as adapted in the heuristics design. We consider the accumulated value of a good's deprivation intensity for the period since a request was entered until it is delivered (0 to t). Hence, we define the average deprivation cost for an inhabitant of demand node k per time unit as $\delta_k = \frac{1}{\tau_k}\int_0^{\tau_k} g(t)dt$

Taking this formula, through Matlab we created a Table of the average inhabitant deprivation intensity for each good, on a scale from 1 to 10. Then for each delivery that is inserted in the route, we consider the deprivation cost of the unsatisfied demand on that city for that good. So the deprivation cost at simulation time t for site k if we deliver, or partially deliver is[2]:

$$DeprivationCost_t = (w_k - PopulationSatisfied) * \delta_k$$

This formula implies that deprivation costs as time t of the simulation is a function of the unsatisfied (undelivered/ remaining) population that requested the delivery, and the average intensity as previously defined.

In the context of the simulation, the above formula is used for the Unique demand. For the recurring demand, we take an average of food, medicine, and shelter deprivation intensity, while giving a higher value to the deprivation from lack of food (hunger). hence the following assumption is made in calculating deprivation costs:

[2] Overall uncovered demand will be calculated as a KPI. Population Satisfied and Unsatisfied Population are an assumption, as capacity and goods are measured in KG. Please refer to the assumptions section for further explanation

$$DeprivationCost_t^{Recurring} = 0.5(w_k - PopulationSatisfied) * \delta_{k(FOOD)} + 0.4(w_k - PopulationSatisfied) * \delta_{k_{(}SHELTER/MEDICINE)}$$

Objectively, early in the construction heuristic, we attempt to minimize deprivation costs. However, humanitarian aid is bounded by operational costs (fixed and variable). For this reason, the following objective function is defined to be minimized in-vehicle deployment and task allocation:

$$SocialCost := 0.7 * DeprivationCosts + 0.3 * OperationalCosts$$

The reason why we prioritize the minimization of deprivation costs is particularly the importance of fulfilling the 80% of the required delivery of the week as soon as possible, while funding can be acquired later. As per the previous section, we aim for this due to expert opinion in the literature on humanitarian aid logistics.

To improve the construction heuristic, we implement an improvement objective solely on operational costs, with some potential impact on deprivation costs. Social costs are still an integral part of accepting the improvement heuristic. The improvement heuristic, as will be later elaborated in the following subsections, only focuses on route optimization after construction. No cross-route improvement is implemented. This choice is done to keep the heuristic simple, yet fulfilling all the required historical needs of Section 4.

In the general objectives of Section 4.5 we define the importance of a fair distribution of goods with high demand coverage. We believe that the usage of Deprivation costs and these assumptions made to simulate the recurring and unique demand create a viable environment to test the contribution of UAVs in fast and fair response to humanitarian aid.

5.2 Cheapest Insertion

figure 13 outlines the cheapest insertion construction, which is used in the method VehicleSeqCI. This construction considers the objective function, with the aforementioned calculations of deprivation and operational costs.

As mentioned before, this function is a choice made to prioritize deprivation cost minimization early on in construction. However, the influence of the weights is not thoroughly studied and it is an assumption. We assume a 70% to 30% ratio of deprivation costs to social costs. This is solely based on the attempt of a strong weight factor on deprivation costs to account for equity in not delivering on small villages for a long period of time. Further research on this type of cost function in simulation-based research should be encouraged, as multi-objective optimization can be complicated and its scope is beyond this thesis.

5.3 Developed Heuristics and Algorithms

1. Motivation

Allahyari et al. elaborate on the challenges of high-quality results in accepTable CPU time, in their study of the Nepal case (2015). Despite the problem at hand not being the same definition as that of Allahyari et al., we have chosen to implement partially their meta-heuristic. It is important to note that the main aim of this thesis is to provide a heuristic on which heterogeneous fleets can be studied in a simulation design. Hence, we choose to scale down the heuristic to incrementally study the improvements of the trip in relation to UAV usage. Above all, we are uncertain how the presented GRASPxILS heuristic of Figure 14 would react to last-mile logistics, as the studied case considers all 14 affected regions in Nepal (Allahyary et al., 2015). Additionally, the original objective function does not consider deprivation costs. Hence, to reduce the amount of uncertainty regarding the effect of the different improvement heuristic elements, we scale down the literature-based heuristic and keep the simulated annealing as an important approach based on the systematic literature review.

With this motivation, the first adjustment is *the lack of iterative local searches.* In fact, apart from

```
while there are Requests Opened
VehicleNr += 1
        if the VehicleNr> Vehicle Limit then exit the loop
        end if
BestSiteSC = max
TripNr = 0
TimeRemaining(Vehicle) = Vehicle.Settings.EndTime - Vehicle.Settings.StartTime
        while there is Time Remaining in the Vehicle
                TripNr += 1çq
                Calculate Vehicle Capacity (Vehicle.Settings)
                Calculate Vehicle Time (Vehicle.Settings)
                Calculate Vehicle Range (Vehicle.Settings)
                BestCalculation = 0

                loop over all Opened Requests to find furthest site possible
                        Hub = 1
                        Site = Site of Opened Request
                        Calculate Time, Range, Distance, Costs, Deprivation and Access
                                if Calculations are better than best calculation & site fits in time, range and access
                                        choose site
                                end if
                next for loop

                if the furthest site is found
                        Calculate insertion in route and all remaining values
                        Update Trip (Social Costs, Operational Costs, and Deprivational Costs)
                otherwise exit loop
                end if

                while there is time, capacity and range in the current trip.
                        BestCalculation(Cost, Deprivation, SiteSC) = maximum
                        loop over Opened Requests for a site to enter on route
                                loop over all route positions for the Opened Request
                                        if SiteSC < BestSiteSC (cheapest is selected)
                                                insert site on route
                                                update vehicle and trip stats
                                        otherwise exitloop
                                        end if
                                end loop
                        end loop

                Plan Route to hub and record all data in Route Table draft
                Simulated Annealing (Shaking)
                        update iteration data
        end while loop
end while loop

Record iteration Data
```

Figure 13. Algorithm for Cheapest Insertion in VehicleSeqCI

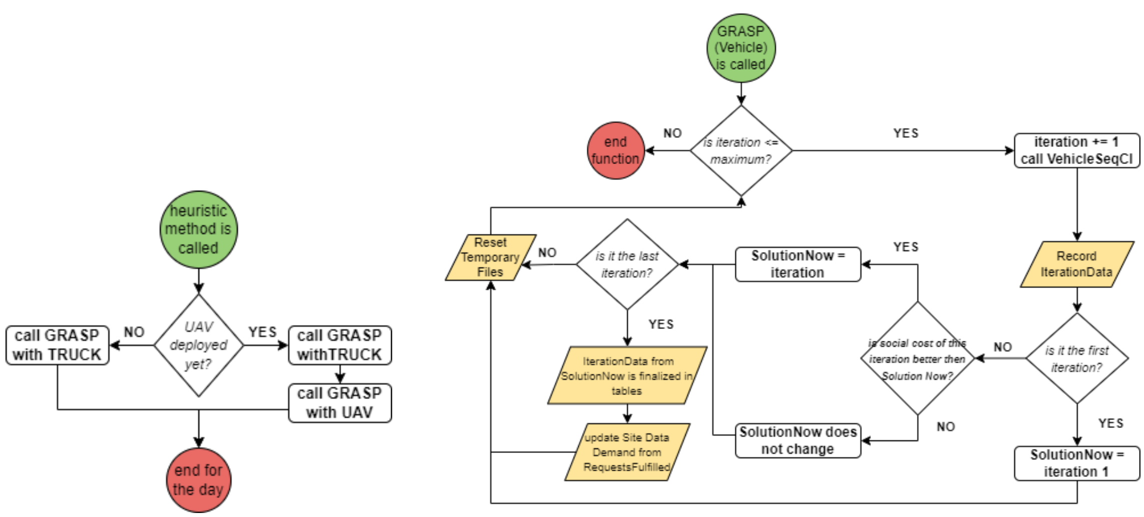
the shaking procedure, there are no local searches in the heuristic. GRASP is rarely studied in relation to deprivation costs or social costs. Hence, local searches that consistently optimize the deprivation or operational costs, can lead to over-complication of variables. Understanding the influence of the local searches with different experiments on UAVs was beyond the scope of this thesis.

To counter the uncertainty of applying GRASP in an objective function that accounts for deprivation, - new for the GRASP algorithm, - *we vary the objective of the decision-making when choosing the sites.* After the cheapest insertion based on social costs, the Shaking Procedure optimizes on operational costs only, while the acceptance of the Simulated Annealing considers the overall Social Costs. This adaptation is the second most prominent one from the original meta-heuristic, attempting to utilize the GRASPxILC to look for optimal social costs and counter any effects of high operational costs within a trip.

```
Algorithm 1: The framework of the GRASP×ILS.
Input:
φ: number of GRASP iterations;
T_ini: initial temperature;
T_fin: final temperature;
γ: cooling rate;
Output: S_best;
S_best := ∅;
Cost(S_best) := +∞;
GRASP_iter := 0;
while (GRASP_iter ≤ φ) do
    GRASP_iter := GRASP_iter + 1;
    S := construction();
    S_imp := local search (S);
    T_cur := T_ini;
    ILP_iter := 0;
    S_cur := S_imp;
    while (T_cur ≥ T_fin) do
        ILP_iter := ILP_iter + 1;
        S_temp := shaking (S_cur);
        S_temp := local search (S_temp);
        if (ILP_iter = ξ) then
            S_temp := ILP_based procedure (S_temp);
            ILP_iter := 0;
        end
        if (Cost(S_temp) < Cost(S_imp)) then
            S_imp := S_temp;
        end
        if (Cost(S_temp) < Cost(S_cur)) then
            S_cur := S_temp;
        end
        else
            ΔS := 100·((Cost(S_temp) - Cost(S_imp))/Cost(S_imp));
            if (U(0, 1) ≤ exp(−ΔS/T_cur) then
                S_cur := S_temp;
            end
            else
                S_cur := S_imp;
            end
        end
        T_cur := γ · T_cur;
        if (Cost(S_imp) < Cost(S_best)) then
            S_best := S_imp;
        end
    end
end
Return S_best.
```

Figure 14. GRASPxILS framework by Allahyari et. al. (2015)

GRASPxILS shows great results in MDCTVRP, but, with our problem definition, a full implementation might not have provided the same results. This simplified approach to the original meta-heuristic leaves room for more complex iterations in further research. In the next subsection, we elaborate on the implemented algorithm, considering the highlighted adaptations.



1. Heuristic is called 2. GRASP Construction is called

Figure 15. Implemented GRASP

2. The Implemented Algorithm

As previously mentioned, Figure 14 outlines the originally proposed algorithm. Figure **??** presents the two functions being called and the adapted algorithm as described in the motivation. As mentioned, we have taken out the iterative local searches and introduced multiple objective functions in the construction and improvement.

At the start of the day, the heuristic is called, and we evaluate if UAVs are being deployed that day. If they are, the planning of the vehicles happens sequentially. We firstly allocate tasks to a limited fleet of trucks and utilize UAVs for requests that were not able to be allocated to them (Figure 15.1.

After this, for every vehicle allocation, we call an iterated GRASP (refer to the next section for concrete values). In every GRASP we first construct utilizing the cheapest insertion with simulated annealing. This process will be described in the next section.

In the first GRASP iteration, we record the data. In all other iterations, we compare if the social costs of the new iteration, as defined in the objective function section, are better or worse than the previous iteration, to determine the current overall solution of the heuristic. A solution is defined as a list of requests allocated to routes of multiple-trip vehicles. The current solution of the last GRASP iteration is the one implemented for the day.

5.4 Simulated Annealing

As a follow-up to Figure 13, which details the construction heuristic and touches upon the simulated annealing, we present Figure 16. In this figure, we outline in detail the simulated annealing and the shaking procedure, adapted from Allahyari et al.(2015). This section elaborates upon the design choices of this part of the algorithm.

1. The Implemented Algorithm

The algorithm can be found in Figure 16. The Simulated Annealing algorithm starts with the initial temperature as defined in Table 5. These parameters are taken from the literature on which the shaking procedure was based. Conducting a sensitivity analysis on these parameters is beyond the scope of this thesis. Moreover, with this choice, we attempt to stay as close as possible to the scientific literature on which the algorithm was based.

In the simulated annealing, a shaking procedure that randomly removed a percentage of the sites is executed. The main assumption of this algorithm is that, if a site cannot be re-entered in the route, then we count for a deprivation cost of lost opportunity. Hence we increase a route's deprivation cost by the deprivation of a lost opportunity to deliver, based on the cheapest insertion. The shaking attempts re-insertion based on optimizing operational costs. Then the simulated annealing accepts the improvement results based on social costs.

The main motivation of this diversification for the objective function is that logistically, we want to improve operational costs, hence the algorithm would want to fully minimize them, to the cost of high deprivation costs. Hence, we do not allow acceptance of results that are worse than the cheapest insertion regarding social costs. If the simulated annealing acceptance only considered operational costs, then we completely disregard improvements on deprivation cost minimization. This way, the simulated annealing has layered multi-objective decision-making.

2. The Shaking Procedure

This procedure is based on the GRASPxILS proposed by Allehyari et al (2015), in order to escape from local optima. From the initial solution that the Cheapest Insertion finds, we remove an h percentage of sites, randomly generated in the interval defined in Table 5. This only happens if there is more than 1 customer in the route and if the randomly generated h percentage of to-be-removed sites does not exceed the number of customers.

After this removal, we attempt to re-insert the removed deliveries in their operationally cheapest possible position, on first-come, first-served bases. In the scenario that a site cannot re-enter the route due

```
Algorithm for Simulated Annealing
 Tcur := Tini
while Tcur > Tfin
        TripDCimp, TripOCimp, TripSCimp := 0
        TimeRemainingimp:= Vehicle.EndTime - Vehicle.StartTime - Vehicle.LoadingFix
        CapacityRemainingimp := Vehicle.Capacity
        RangeRemainingimp := Vehicle.Range
        if Route is empty
                exitloop
        else:
                ShakingProcedure
                        generate h = percentage of sites to remove
                        Copy current trip to currenttrip table
                        T := h * SitesinCurrentTrip (amount of lines to remove)
                        if T <=1 (only one site to be removed)
                                Tcur := CoolingRate *Tcur
                                update Iteration data
                                exit loop
                        end
                        randomly select T Sites from CurrentTrip
                        InsertSites to be removed in ShakingTable
                        CurrentTripTemp := CurrentTrip - ShakingTable sites
                        CurrentTrip := CurrentTripTemp
                for all sites in CurrentTrip calculate Trip Data after shaking
                        if Site calculation is not possible due to access or time
                                do not include ininsertion
                        else
                        TripDCimp, TripOCimp, TripSCimp += Calculation
                        TimeRemainingimp -= Calculation
                        RangeRemainingImp -= Calculation
                        Capacity remaining -= Delivery
                end
                for all Sites in ShakingTable (sites removed) find best positions
                        for all positions in CurrentTrip
                                if position is feasible in time, range and capacity
                                        BestPos := CurrentPos
                                        BestSiteOC, SiteDC, SiteSC := Calculation
                                        PosRange, PosTime := Calculation
                                next
                        if BestPos is not found
                                Check category of good
                                        SiteDC := PopulationDissatisfied *1,5
                                        SiteSC := 0,7*SiteDC + 0 (no operational costs)
                                        TripDCimp, TripSCimp += Calculation
                        if BestPos is found
                                if position doesn't fit in time or capacity (error debug)
                                        SiteDC := PopulationDissatisfied *1,1
                                        SiteSC := 0,7*SiteDC + 0 (no operational costs)
                                        TripDCimp, TripSCimp += Calculation
                                otherwise
                                        TripDCimp, TripOCimp, TripSCimp += Calculation
                                        TimeRemainingimp -= PosTime
                                        RangeRemainingImp -= PosRange
                                        Capacity remaining -= Delivery
                                        Reinsert Site in CurrentTrip
                                end
                        end
                next
                Accepting the SImulated ANnealing Results
                        if TripSCimp <= TripSC
                                improved solution parameters are made current parameters
                                Iteration data += Trip parameters
                                insert currenttrip in vehicleData. Route
                        else
                                SolutionDifference := 100* (TripSC - TripSCimp)/TripSCimp
                                if z_uniform(2,0,1) < emp (- SolutionDifference/Tcur)
                                improved solution parameters are made current parameters
                                Iteration data += Trip parameters
                                insert currenttrip in vehicleData. Route
                                else
                                Iteration data += Trip parameters
                                end
                        end
                end
        end
        Tcur := CoolingRate*Tcur
        Reset Tables
        Update Requests Fulfilled based on Current Trip
end
```

Figure 16. Detailed algorithm - Simulated Annealing and Shaking Procedure

to changes in distance, capacity, or time, from re-arrangement, we calculate the site's deprivation cost. This deprivation cost is an opportunity cost: the promise of delivering a number of goods to a customer

Table 5. Parameter Symbols

Symbol	Meaning	Allahyari et al. (2015)
φ	maximum number of GRASP iterations	5
τ_{ini}	initial Temperature for Simulated Annealing	650
τ_{fin}	final Temperature for Simulated Annealing	0.0001
γ	cooling rate for Simulated Annealing	0.999
ξ	number of iterations for local search (not used)	10
δ_1	lower bound for percentage generation on Shaking Procedure	15
δ_2	upper bound for percentage generation on Shaking Procedure	45

and by how much we have deprived these customers.

After the shaking, the trip's social cost is recalculated, and the Simulated Annealing makes a decision based on the previously defined social cost function. Importantly, the simulated annealing is sequentially applied to different types of vehicles, and not cross-modalities. The main motivation for this is to the

5.5 Heuristic Validation

In this section, we compare and validate the final constructed heuristic. This final heuristic includes GRASP iterations, construction with cheapest insertion on social costs, and simulated annealing that shakes a vehicle's route to optimize operational costs, but consider the overall societal impact. We demonstrate how and to what degree the heuristic impacts costs and deprivation index (please refer to the experiment chapter for a full definition of the deprivation index). We choose to validate only for the Dhadhing case and assume similar behavior in all other cases.

As indicated in Table 6, we compare the truck-only case on three dimensions: a simple vehicle sequence with nearest neighbor heuristic, GRASP iterations with a greedy cheapest insertion on social costs, and then with the introduction of the simulated annealing optimizing on operational costs. The results indicate that cheapest insertion with social costs works better than the nearest neighbor algorithm. Additionally, the introduction of simulated annealing improves the costs of the truck-only case by around 68%. Hence, there is quite some efficacy in the introduction of the improvement algorithm, despite the slight increase in deprivation.

Secondly, we validate with UAV implementation. The heuristic first allocates and optimizes on trucks, then it calls UAVs for all remaining opened requests. The main reason why we choose not to validate with the nearest neighbor heuristic is that, from the truck-only validation, we can see that for trucks this heuristic is not beneficial. Hence we look into the improvement the simulated annealing does when UAVs are introduced.

In both cases, with one and two UAVs, we notice that the deprivation index remains the same. From this, we conclude that the simulated annealing does not improve on allocating sites to minimize deprivation costs. On the other hand, there is an improvement of 34% in costs for the one UAV case, and 29% for the two UAVs case, once the simulated annealing is introduced. From this, we can conclude that the simulated annealing takes the optimized cheapest insertion and truly attempts to minimize the operational costs, with little impact on increasing the social costs.

However, we suspect that the heuristic does not truly optimize the routes of the UAVs. This is mostly due to the time constraints UAVs have, which lead to routes of one to two sites. Hence UAVs do not benefit from the implemented simulated annealing.

Therefore, we have shown that the GRASP construction with cheapest insertion works better to

Table 6. Results from Comparing heuristic

MODE	HEURISTIC	COSTS	DEPRIVATION INDEX
Truck only	Vehicle Sequence Nearest Neighbour	∼29 K	18,3
Elevation up to 1000m	GRASP with cheapest insertion on social costs	∼24 K	12,88
	GRASP with cheapest insertion and simulated annealing	∼7.5 K	13
1 UAV	GRASP with cheapest insertion on social costs	∼50 K	9,66
Truck elevation up to 1000m	GRASP with cheapest insertion and simulated annealing	∼33 K	9,66
UAVs visit higher than 1000m			
2 UAV	GRASP with cheapest insertion on social costs	∼73K	6,61
Truck elevation up to 1000m	GRASP with cheapest insertion and simulated annealing	∼57 K	6,61
UAVs visit higher than 1000m			

optimize task allocation on trucks, compared to simple greedy heuristics. Particularly, more sites are timely visited, resulting in minimal deprivation. So, the usage of the previously defined social cost function effectively prioritizes sites. However, despite being truly effective with trucks, UAV routes do not benefit from the current improvement heuristic.

5.6 Limitations

1. After the Shaking Procedure, there are sites that are not reinserted in the newly constructed trip. Ideally, recalculation of the trip should happen at the end, after the current trip is shaken and new sites are re-inserted. The motivation behind the current procedure is to calculate the deprivation of each individual entry and accumulate it to make decisions.

2. The current requests fulfilled recording is done after the acceptance testing of the simulated annealing. Ideally, there should be a more efficient way to manage the requests fulfilled information flow.

3. In the case that the best position for re-insertion is not found, there is an assumption on opportunity-cost-based deprivation. This assumption strongly influences the acceptance of the simulated annealing, hence it is important to reconsider what not re-inserting means for deprivation costs and to study the effects of opportunity cost assumptions.

4. Currently, the Simulated Annealing does not improve cross-modalities, and truck trips to UAVs. This relates to the fundamental approach of UAVs utilized sequentially, as a support to the truck logistics. Introducing and experimenting with local searches, cross-route, and cross-trips might produce different results. This thesis purposely omits this to provide incremental testing of the heuristic in the case of UAV deployment.

5. The variation of the objective function in the improvement heuristic requires further sensitivity research. The choice to vary the objective function in site insertion and improvement acceptance limits the understanding of the impact of the simulated annealing on the deprivation costs.

6. The parameters taken from the literature might not have been optimal in this scenario. Further research is needed.

Overall, as identified in the heuristic validation and the contribution of the different elements, the chosen heuristic provides a platform for utilizing UAVs and optimizes deprivation costs as well as operational costs. Limitations within the design choices and scalability are important for further research. The most important contextual limitation is the cross-modality and cross-route optimization that the heuristic provides. In the context of UAV usage as a primary transportation modality, and not sequential, the current heuristic does not provide insights and may limit optimization. Hence, further enrichment is needed.

6 SIMULATION PROCESS

This section discusses the simulation framework and the unique updates made to fit with the Nepalese case, connecting to the research question 3. The original simulation design (framework), as designed by Van Steenbergen and Mes (2020), provides a methodology to conveniently study different cases. The required inputs and output of the original methodology are shown in Figure 17. We normalize the site data for chosen scope, including population, demand, and geographical information. Origin destination matrices are created per vehicle, and site accessibility is based on the terrain.

In this section, we cover an explanation of the framework, and the various data required and elaborate on the objective function as a follow-up to Section 4.5. Lastly, we highlight the most important assumptions made to make the case viable.

6.1 The Framework

In this section, we elaborate on the simulation design framework. Importantly we further explain the frames that the simulation considers and elaborate on the used functions that relate these frames with the algorithms explained in the previous section. The flow shown in Figure 17 is complemented by Figure 18, which provides an overview of the adapted information flow for the heuristic.

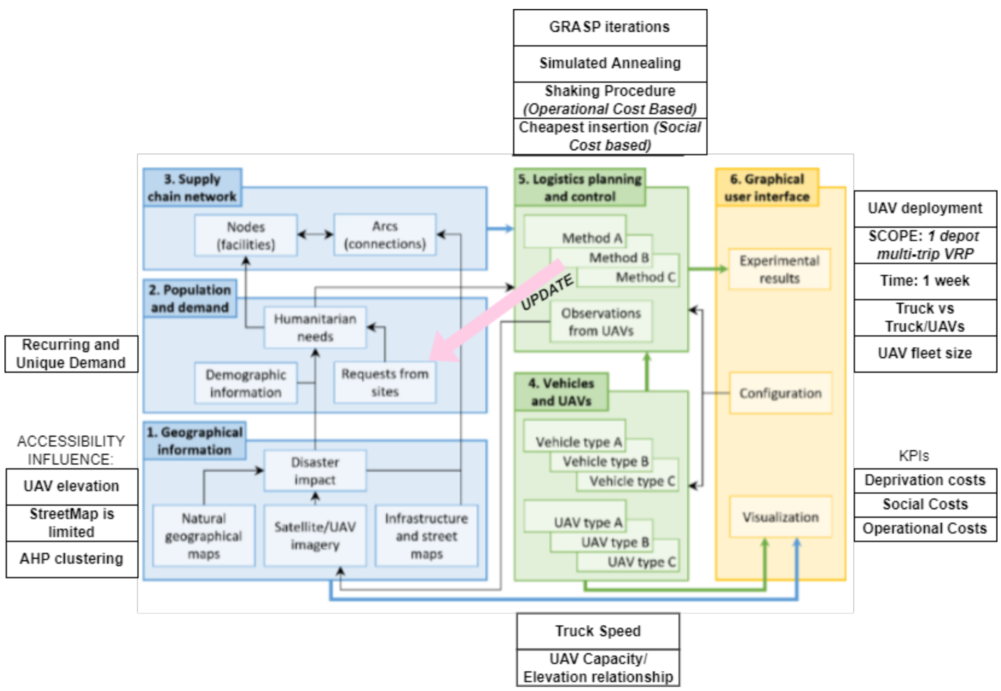


Figure 17. Simulation Framework with notes

Most of the adaptations made from the original simulation design regard Logistics Planning Control and People Demand. Specifically, most changes are in relation to demand assumptions and daily heuristic planning. Every day, demand is filled and requests are loaded. Then the heuristic is called. This heuristic is iterated multiple times under a GRASP with a greedy construction on social costs. Then a shaking procedure is executed based on Allahyari et al.(2015), under simulated annealing.

1. *Geographical Information*

   The natural geographical maps and infrastructure of Nepal provide a challenging environment for vehicles. The final developed site network includes slow routes (maximum 50 km per hour), multiple types of roads, such as residential and tertiary, and sites fundamentally inaccessible by

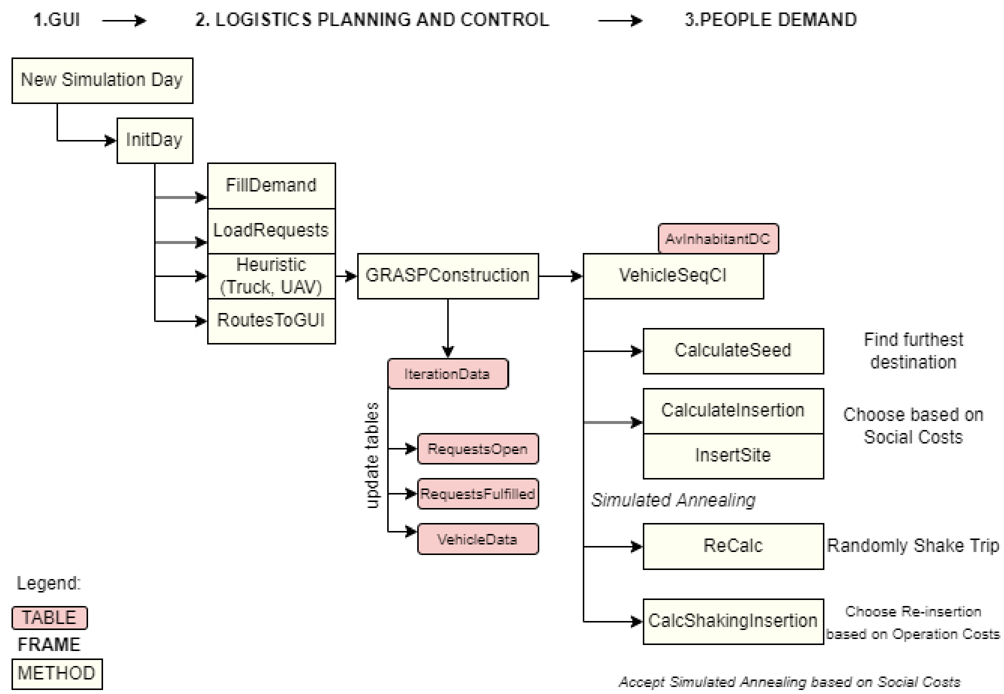


Figure 18. Solution Overview

trucks. This inaccessibility comes as a result of the high altitude of the terrain as well as the poor infrastructure with unavailable StreetMap data. Through multiple testing, we have created the most detailed and accurate road network to support arc-creation and realistic vehicle trips.

2. *Population and Demand*

   Section 4 describes various necessary goods that needed emergency delivery in Nepal. Based on this section and the theoretical study of deprivation costs in Section 3.2, the simplification was made to consider recurring and unique demand.

   Unique demand consists solely of tarps and blankets, and it is a direct reflection of the population. Recurring Demand is daily evaluated for requests, based on the time of the simulation and the type of good (general shelter, food, medicine). The general assumption is that the population requires food more frequently than other goods, the amount of which is an increasing function against time. The demand for the recurring goods additionally gets updated at the end of each day and directly influences the deprivation costs as a form of perceived waiting time.

3. *Supply Chain Network*

   The Supply Chain Network connects the Sites and Geographical Network for the simulation. It is important to note the creation of Origin Destination matrices. For Air Vehicles this is the euclidean distance between sites, while road vehicles take into account the mapped geographical terrains and the uploaded road network within the simulation. No major adaptations were made to this frame. The results of the network creation were partially dependent on the StreetMap data for Nepal, which was limited.

4. *Vehicles and UAVs*

   Here we define the UAV and vehicle settings. No major changes have been applied to this part of the original simulation design. The chosen utilized vehicles are trucks and UAVs. Despite the use of helicopters in the original mission, their deployment starts after the aftershock on the 12th of May, and they were not regularly used in daily logistics. Hence, we do not consider them in last-mile logistic operations. The main addition to the vehicle settings is the introduction of UAV elevation. In experiments, the UAVs' capacity reduces given an increase in altitude to be reached (elevation). Additionally, the speed of trucks has been reduced to a constant of 30 km/h, in order to reflect the road infrastructure and reflect realistic delivery times.

5. *Logistics Planning and Control*

   This part of the framework constructs the trips and routes for all vehicles. The main adjustment made is the construction of a new heuristic as will be defined in the next section, and will be our main focus for the solution. Essentially, the heuristic constructed considers the UAV deployment, UAV elevation, and accessibility of the sites due to elevation and road network.

6. *Graphical User interface*

   This part of the original framework has almost no changes, apart from the definition of the new experiments. The visualization component is still an important aspect of the simulation and the configuration of vehicles and Logistics Planning and Control is further explained in the next subsection, with the main inputs Table.

6.2 Relevant Implemented Functions

In relation to Figure 18, we highlight the most relevant implemented functions for the adapted simulation design [3].

a. **Init Day:** This method is called every new simulation day. It adjusts the visualization, fills demand, load requests, and calls the heuristic.

b. **Fill Demand:** In this method we fill demand in site data in accordance to assumptions of Section 6.4. It is called by Init Day, and calculates the simulation time to fill demand accordingly.

c. **Load Requests:** After the site data demand is filled, requests are loaded in as individual entries in the Request Open Table. This Table registers the type of demand, the amount needed, and the request time.

d. **Calculate Insertion and similar functions:** When a site allocation decision needs to be made, the method is called to calculate the remaining vehicle time, range and distance, along with the access, deprivation costs, and operational costs for inserting this site on a route. This is done according to the objective function specifications and calculates other costs and remaining time, range, and distance in relation to the vehicle settings. Similar methods are created to recalculate after the shaking procedure, or for calculating the first site.

e. **Insert Site:** After the calculation, and if the site is considered the best option, we insert the site in the route of the vehicle. Then, the data is recorded on requests fulfilled, and it is removed as an opened request.

f. **Requests Fulfilled Table:** This Table consists of a list of the last delivery and the amount delivered per site. Importantly, the list is only finalized after all GRASP iterations, once a solution is found. Then, site data demand is adjusted accordingly.

g. **Heuristic Tables:** Until the end of the GRASP procedure, all heuristic data is recorded in draft Tables. So, adjustments in opened and fulfilled requests, routes and iteration data are all recorded in temporary files, until the end of the procedure.

h. **Heuristic / GRASPConstruction/ VehicleSeqCI:** These are the main three methods that describe the solution. The first sees if UAVs are deployed or not and calls the GRASP iteration. The second constructs routes per iteration of GRASP, and looks upon the most efficient solution. In the end, it finalizes the Tables. Lastly, the VehicleSeqCI is called on each GRASP iteration to construct the routes and optimize them with simulated annealing with a shaking procedure. *The rest of this section explains these algorithms in more detail.*

[3] In SimTalk 2.0, the language of the simulation design, these functions are referred to as methods.

6.3 Data

As a follow-up to Section 2.4 and Figure 4 in this thesis, we have listed the most impacted variables and input data needed in the simulation framework. Table 7 provides an overview of the inputs that will be experimented upon, the heuristic components, and some of the most influential settings.

1. **Settings**

   In this category, as defined in Figure 4 we define vehicle capacities and specifications, and loading/unloading times as the main settings for the input data. The studied fleet is a truck and UAV combination, and we account for a simulation time of 7 days.

   The regions of Dhadhing and Nuwakot, based on the historical case, only received aid on May 11th, with an aftershock immediately disrupting the operation on May 12th. Hence, we simplify the study by looking into the immediate response after the disaster on the 24th of April 2015. We define this operation within the first week to see how much demand will be able to be covered. According to Gralla et. al, experts in humanitarian logistics aim for and prefer delivering at least 80% of the total cargo requested in the first week and this 80% should be completed within the first 1-3 days (2013). Hence measuring for the first week of the disaster can be a good indicator in understanding last mile humanitarian logistics as a first response. We assume that, if there is effectiveness within 7 days, this week can be replicated in results for the duration of the humanitarian aid operation.

   The set inputs account for a heuristic that follows a base allocation of cheapest insertion based on a social costs function, and a shaking procedure inside simulated annealing.

2. **Input**

   This is the needed input to facilitate decisions and prepare the experiments. Table 7 color codes four experimental variables that will be further elaborated in later chapters.

   Importantly, we have a fixed truck vehicle fleet limited to 100, to reflect infinity. The number of UAVs, on the other hand, is a variable to be experimented upon. In the original mission, records show around 10 available trucks each day for the Dhading municipality.

   Vehicle capacity is treated as a specification. In the case of UAV capacity, it is dependent upon their flying altitude (UAV elevation). This attribute is used in two ways, depending on the experiment. Firstly, it indicates truck priority, as trucks do not visit sites that are deemed as difficult, or that can be easily allocated to UAVs. Secondly, in order to test UAV flying capacity, UAV elevation is used as an indicator of maximum flying range for UAVs. If a site is higher than the elevation, UAVs do not have access, hence it is allocated to trucks.

   For a UAV to reach a higher elevation, it needs to carry less, hence a reduction in capacity. UAV deployment and Scope are considered independent variables, and each experiment would have to be dependent on these inputs on the framework. Overall these inputs influence the heuristic's outcomes and its efficiency.

3. **Output**

   The KPIs as mentioned in the problem definition stage are the outputs of the simulation. Response time is the simulation time. Operational costs are a measure of vehicle expenses. The Deprivation Index, as defined in the upcoming Section 7, provides insights into an inhabitant's average deprivation. Uncovered demand is a measure of inhabitant number for recurring and unique goods.

Please refer to Table 7 to further understand the upcoming sections on solution design and experiments.[4]

[4] Yellow: experiment on how many UAVs are needed
Green: experiment on capacity and altitude, if one increases, the other decreases too
Blues: experiment on the early or late deployment of UAVs: what is the effect of a UAV's timing
Orange: experiment on the regional scope to compare between large regions, small ones

Table 7. Classification of Variables

Variables	Type	Options / Notes
Loading Time UAVs/ Trucks	SETTING	-
Unloading Time UAVs/ Trucks	SETTING	-
Number UAVs	INPUT	LIMITED FLEET: 0 - 100
Number Trucks	INPUT	FLEET: 100
UAV Capacity	INPUT	Correlated to Flying Altitude
Flying Altitude	INPUT	Correlated to UAV Capacity
UAV availability Date	INPUT	0 - 5 days after disaster (deployment)
Heterogeneous Fleet	SETTING	TRUCK— UAV
Heuristic Construction	SETTING	CHEAPEST SOCIAL COST INSERTION in a GRASP
Local Search	SETTING	Shaking Procedure in Simulated Annealing
Global Search	SETTING	SIMULATED ANNEALING
Number of iterations	INPUT	for GRASP for SIMULATED ANNEALING
Scope	INPUT	DHADING, NUWAKOT, COMBINED
Simulation Time	SETTING	7 DAYS
Deprivation Cost Index	OUTPUT	measure of deprivation during simulation time and population
Operational Costs	OUTPUT	variable and fixed vehicle costs
Demand Uncovered	OUTPUT	recurring and unique demand

6.4 Assumptions and Simplifications

1. *Geographical Information*

   1. The aftershock on the 12th of May is not considered in the research. However, the simulation can support the study of an aftershock through road failure and accessibility disruption. This choice was the result of wishing to first investigate deployment within the first few weeks and understand UAV application without the influence of an aftershock variable.

   2. Sites that do not have a road from the StreetMap arc creation. connect to a road within 10 km. The main reason is that the coordinates taken are the coordinates of the center of the site, rather than the distribution center utilized in the original case. Hence, we attempt to always connect the sites to a recognized road.

2. *Population and Demand*

   1. The simulation measures good capacity in kilograms

   2. Population is based on the 2011 Population census of Nepal.

   3. The following formulas are used to determine the population needs in KG:

$$\begin{bmatrix} UniqueDemandKG = 0.2 * w_k & \text{CALCULATE ONCE} \\ RecurringDemandKG_{food} = 0.1 * w_k & \text{CALCULATE EVERY 3 DAYS} \\ RecurringDemandKG_{medicine+shelter} = 0.04 * w_k + 0.03 * w_k & \text{CALCULATE EVERY 5 DAYS} \end{bmatrix}$$

   4. For all formulas in 3, we use the inverse function to determine the number of people satisfied with delivery in KG.

5. Based on the data, the original mission delivered 4 blankets per household. For the simulation, this converts to 2 kg of unique goods per household.

3. *Supply Chain Network*

   1. The studied case is classified as a **single depot, multi-trip VRP**. Despite the scope, the hub remains Dhading Besi, as Bidur did not have access to an airport to handle UAVs, as per Section 4.

   2. The chosen nodes for Nuwakot and Dhading are based on the served sites during the Nepal 2015 humanitarian aid mission, as investigated in section 4.

   3. Firstly, the accessibility of a site is determined by the results of the StreetMap data. If no roads to the site were generated, and connection within 10 km is not possible, then the site is inaccessible by truck.

   4. Secondly, accessibility depends upon the original site network and a clustering per site on a 3-point category (easy, medium, difficult). We cluster based on an Analytical Hierarchical Process (AHP), explained in Appendix B. If a site is categorized as easy, despite the terrain elevation, it will be accessible by truck. If a site is categorized as difficult, it is only reachable via UAVs. If a site is medium, then it won't be reachable by trucks if it is above the set UAV elevation. This way we encourage truck accessibility even on high-altitude sites.

4. *Logistics Planning and Control*

   1. Section 5 covers the heuristic algorithm and main methods that were added to the simulation

   2. Main simplifications include the objective function and decision-making on the shaking procedure as outlined in Section 5.1.

5. *Vehicle Data*

   1. As aforementioned, the capacity of UAVs reduces flying altitude. For more information please refer to Section 7.

   2. StreetMap Data was calculated with an average of 30 km/h truck speed.

   3. As aforementioned, the usage of helicopters was omitted, and the only two vehicles to be included in heterogeneous fleets are UAVs and trucks.

6. *GUI*

   1. Section 7 covers the experimental results and Table 7 provides an overview of the main experiments

   2. Total Costs are generated by the Performance Data.

   3. Deprivation Costs are calculated after each route insertion only for calculating the objective function. Instead, the main KPIs are the deprivation Cost Index and Village Deprivation, as defined will be defined in section 7.

   4. Demand Uncovered is calculated at the end based on the remaining kilograms in site data. This is calculated separately for the uncovered recurring goods and uncovered unique goods.

7 EXPERIMENTS

This section outlines the experimental settings and results. We have conducted similar experiments in 2 different regions in Nepal, with their characteristics mentioned in Section 4. Importantly, we classify Dhadhing as a large region, Nepal, as a small to medium-sized region, and the combined case, as a single-depot large region. In accordance with the questions posed by WFA, and to provide optimal insights from the Nepal case on UAV usage, we have chosen to conduct experiments and answer the following questions:

a. Validation of Heuristic on Truck only, per region

b. Introducing UAV fleets, per region: *How many UAVs were needed and what would their impact be?*

c. Introducing UAV fleets with late deployment per region: *How would the conclusion on UAV numbers change if UAV deployment was done 5 days after the initial disaster?*

d. Dhading: *What is the relationship between UAV elevation and their capacity? Does UAV elevation and capacity impact their contribution?*

e. Combined Case: *In the event of a bigger region and single-depot, what would UAV contribution look like?*

7.1 Comparison Criteria

1 **Deprivation Index:** A measure of overall remaining deprivation after a week. It is calculated as follows, in a total Deprivation for the region, and for each village:

$$TotalVillageDeprivation = \sum_1^k (UncoveredDemand_{unique_k} * \delta_{unique_k} + UncoveredDemand_{recurring_k} * \delta_{recurring_k})$$

$$TotalDeprivationIndex = \frac{TotalVillageDeprivation}{RegionPopulation}$$

2 **Operational Costs:** Consists solely of vehicle fixed and variable costs. Due to detailed costs confidentiality, we will compare costs as graph progressions, and as a ratio of the increase in cost to deprivation index reduction:

$$\frac{\Delta DeprivationCostIndex}{\Delta TotalCosts} \quad \frac{decrease\Downarrow}{increase\Uparrow} \quad \text{defined in } [1\ ,\ \text{-}1]$$

3 **Uncovered Demand**: For both recurring and unique demand we will measure uncovered demand in the number of people still to receive goods. This number is a direct reflection of the population for unique demand. For recurring demand, in 7 days, there are 3 food requests placed per person, and 2 shelter/medicine requests placed per person. So, the number of unsatisfied recurring demands is not a percentage of the population, but an accumulation. Based on Section 6, we look into demand coverage for the week compared to the population.

In this thesis, the social cost has been used as an objective function in order to facilitate multi-criteria decision-making. However, cross-case comparisons and experimental results cannot be evaluated on this assumption. For this reason, we evaluate experiments by the aforementioned KPIs, which encompass the idea of social costs, as a function of operational and deprivation costs.

7.2 Report on truck Usage

We start the comparison with a report on vehicle utilization.

Compared to the only truck scenario per region, truck usage only changes in the Dhading case, once UAVs are introduced. In this scenario, UAVs substitute trucks. In the other two cases, UAVs complement the initial allocation to trucks. In fact, once the UAVs are introduced, increasing their fleet size, does not reduce the truck fleet size. This might be the result of a well-optimized truck route.

On the other hand, compared to the combined case, dealing with the Nuwakot and Dhading regions separately, in a multi-depot setting, mobilizes fewer trucks and fewer UAVs in total. In a heterogeneous fleet, the combined case mobilizes 12 trucks, while in total, Dhading and Nuwakot separately mobile 10 trucks. From further insights, we notice that this choice also produces better deprivation and cost minimization results.

FLEET	*DHADING*	*NUWAKOT*	*COMBINED*
TRUCKS ONLY	10 trucks	4 trucks	12 trucks
HETEROGENOUS FLEET	6 trucks	4 trucks	12 trucks

7.3 Case 1: Dhading in 7 days

Settings

1. Settings for UAV deployment and vehicle numbers

   TRUCK SPEED: 30 KM/HR

   INACCESSIBLE SITES FROM STREETMAP: 13 IN DHADING AND 10 IN NUWAKOT

   PRIORITY: TRUCKS DO NOT GO TO DIFFICULT SITES OR SITES IN ALTITUDES OF 1000+ DURING THE FIRST WEEK

   UAVS CAN REACH ALL SITES.

   UAV CAPACITY: 160 KG

2. Settings for UAV altitude experiments

   TRUCK SPEED: 30 KM/HR

   INACCESSIBLE SITES FROM STREETMAP: 13 DHADING

   PRIORITY: TRUCKS DO NOT GO TO DIFFICULT SITES OR SITES IN ALTITUDES OF 2000+ DURING THE FIRST WEEK

   PRIORITY FOR LAST CASE: TRUCKS DO NOT GO TO DIFFICULT SITES OR SITES IN ALTITUDES OF 1000+

   UAVS CAN REACH SITES WITH ALTITUDE UP TO UAV ELEVATION.

   UAV CAPACITY: ~ 31 METERS OF ALTITUDE, UAV CAPACITY GETS REDUCED BY 1 KG.

Experiments on UAV deployment

For Dhading, there is a strong correlation between UAV number and deprivation index (Figure 19). This is particularly linked to the UAVs ability to reach difficult sites and villages that do not have a road connection, based on StreetData. For early immediate deployment of UAVs, at a fleet of 3 UAVs there is a significant improvement in access and total deprivation index. This seems to improve in an exponentially decreasing function in relation to UAV numbers introduced.

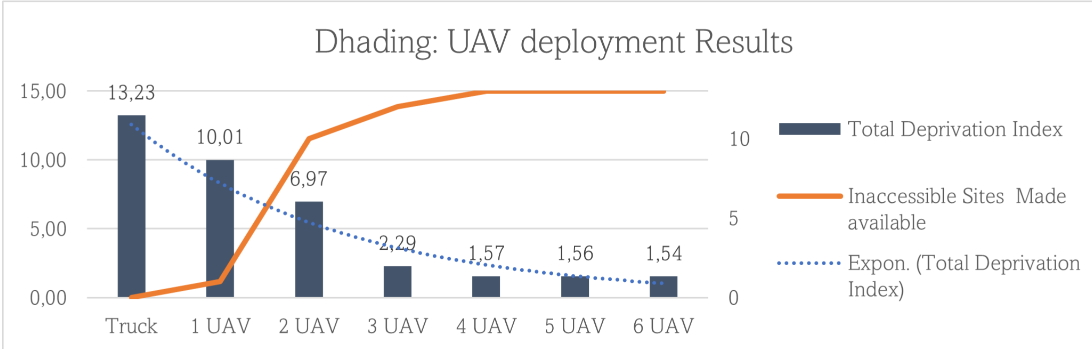


Figure 19. Dhading: Results on UAV Deployment

In terms of costs, Figure 20 indicates the relationship between deprivation costs and operational cost difference from the truck-only scenario. The lower the ratio, the better the investment in terms of deprivation costs, compared to the truck-only case. The best ratio turnover is on the case with 3 UAVs.

At 3 UAVs, based on Figure 21, recurring demand is strongly prioritized, and uncovered demand strongly decreases from other scenarios. However, 80% demand coverage for unique demand in the first week is not met until 6 UAVs are introduced.

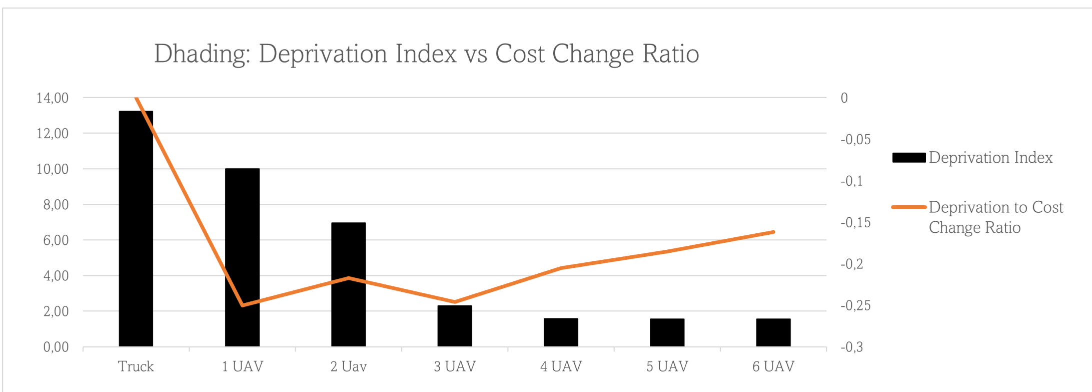


Figure 20. Dhading: Deprivation Costs to Total Costs Ratio

Experiment on UAV late deployment

When UAVs are introduced after 5 days, there seems to be a linear improvement in the Deprivation Cost Index. Additionally, within the first week, not all inaccessible sites are reached. In the case of late deployment, cost-benefit comes in fleets bigger than 5 UAVs.

Experiment on altitude

Based on the previous experiments, we conducted the altitude experiments on the 3 UAV setting. We compare this case to the truck-only setting that results in the best deprivation index. In this setting, trucks can reach all villages, apart from the ones inaccessible through street data. Additionally, in this setting trucks can travel 50 km/hr. These settings are big assumptions for Nepal due to the poor and destroyed road infrastructure, but it is important to contrast the altitude scenario with the best possibilities.

Figure 23 shows that there is a significant improvement in any UAV usage case. Importantly, it can be concluded that for Nepal, drones that fly higher but with lower capacity are favored.

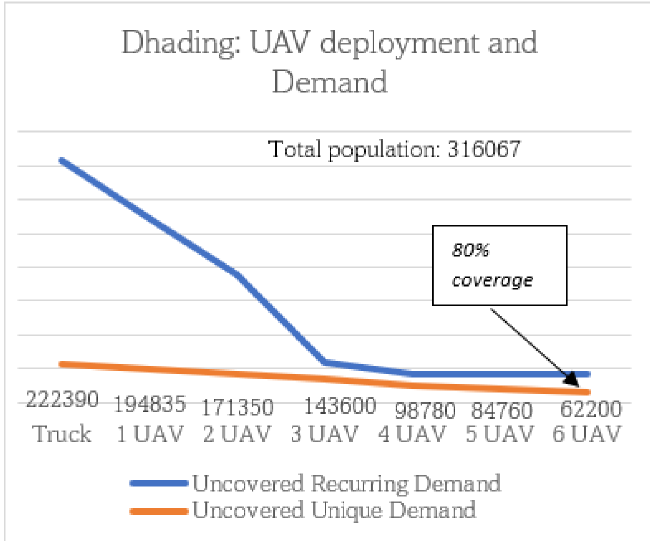


Figure 21. Dhading: Demand Results for UAV Deployment

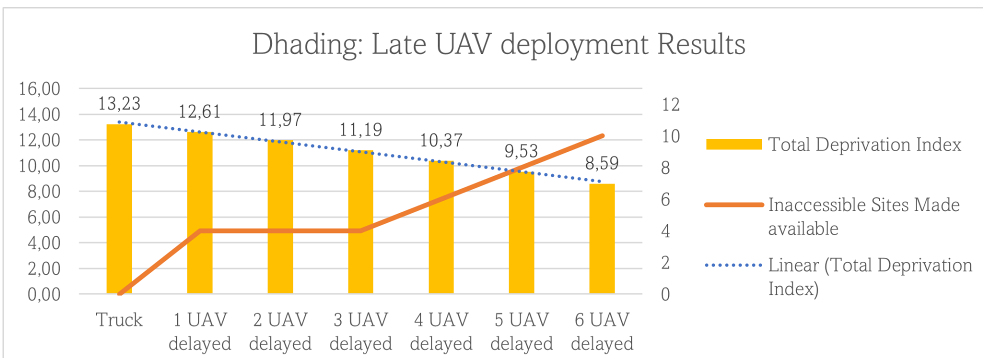


Figure 22. Dhading: Late UAV Deployment Result

MODE	*INACCESSIBLE SITES MADE ACCESSIBLE*	**TOTAL DEPRIVATION INDEX**
TRUCKS	0	8,18
3 UAV/ 650 M/ 160 KG	6	4,52
3 UAV/ 1000 M/144 KG	11	2,73
3 UAV/ 2000 M/120 KG	11	1,83
3 UAV/ 1000 M/144 KG/TRUCKS DO NOT PRIORITIZE SITES THAT ARE HIGHER THAN UAV ELEVATION.	11	8,46

Figure 23. Dhading: Altitude Experiment Results

7.4 Case 2: Nuwakot in 7 days

Settings

1. Settings for UAV deployment and vehicle numbers

TRUCK SPEED: 30 KM/HR

INACCESSIBLE SITES FROM STREETMAP: 13 IN DHADING AND 10 IN NUWAKOT

PRIORITY: TRUCKS DO NOT GO TO DIFFICULT SITES OR SITES IN ALTITUDES OF 1000+ DURING THE FIRST WEEK

UAVS CAN REACH ALL SITES.

UAV CAPACITY: 160 KG

Experiment on UAV deployment

For Nuwakot, just like the other case, there is a strong correlation between UAV number and deprivation index (Figure 24). Similarly, the reachability of inaccessible sites really influences the deprivation cost. For early immediate deployment of UAVs, at a fleet of 2 UAVs there is a significant improvement in access and total deprivation index. This seems to improve in an exponentially decreasing function and seems to diminish in higher fleet numbers.

In terms of costs, Figure 25 indicates the relationship between deprivation costs and operational cost difference from the truck-only scenario. Compared to the Dhading case (Figure 20), this cost-benefit ratio is not as improved. For Nuwakot, a heterogeneous fleet of 2 UAVs is seen as the best cost-benefit solution.

Figure 26, recurring demand is strongly prioritized at 2 UAVs and 3 UAV fleets. Uncovered unique demand decreases linearly and 80% demand coverage for unique demand in the first week is not met until 4 UAVs are introduced.

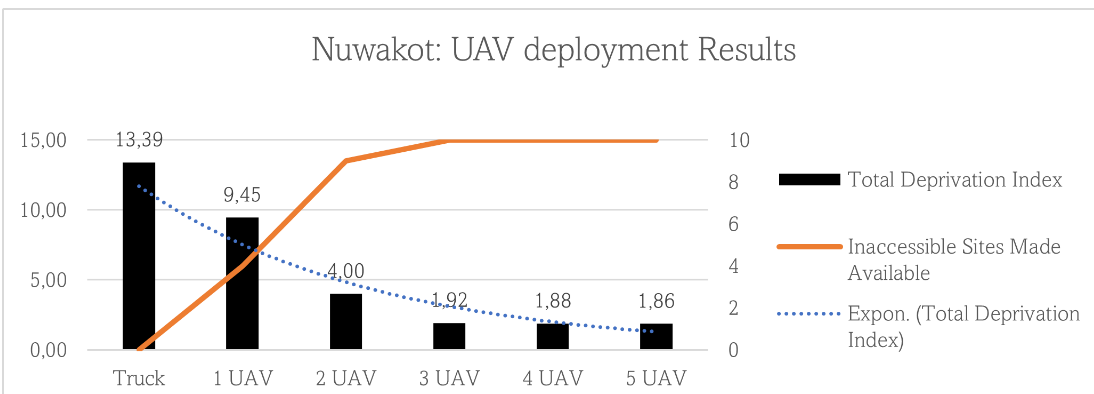


Figure 24. Nuwakot: Results on UAV Deployment

Experiment on UAV late deployment

Figure 27 shows that Nuwakot has the same linear correlation as Dhading to late UAV deployment and deprivation cost index. Similarly to Dhading, UAVs in late deployment need a bigger fleet to show improved results in site accessibility and deprivation cost index. The most effective results based on a cost-to-deprivation index reduction seem to be around 4 UAVs.

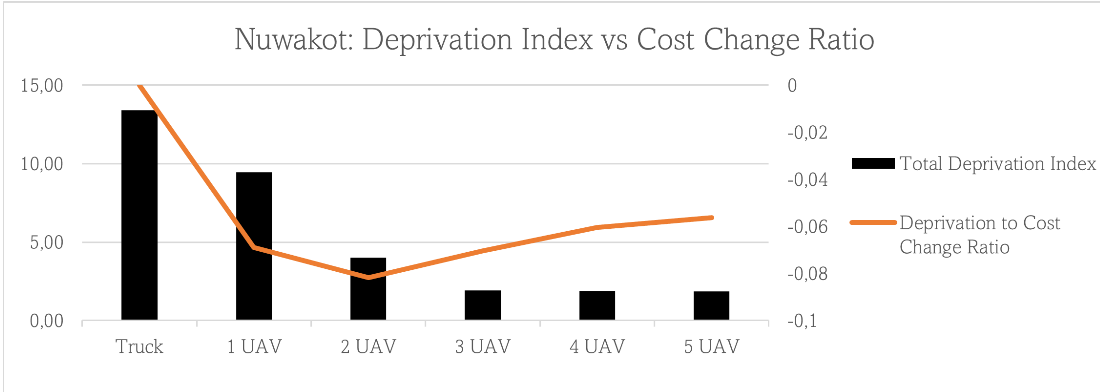


Figure 25. Nuwakot: Deprivation Costs to Total Costs Ratio

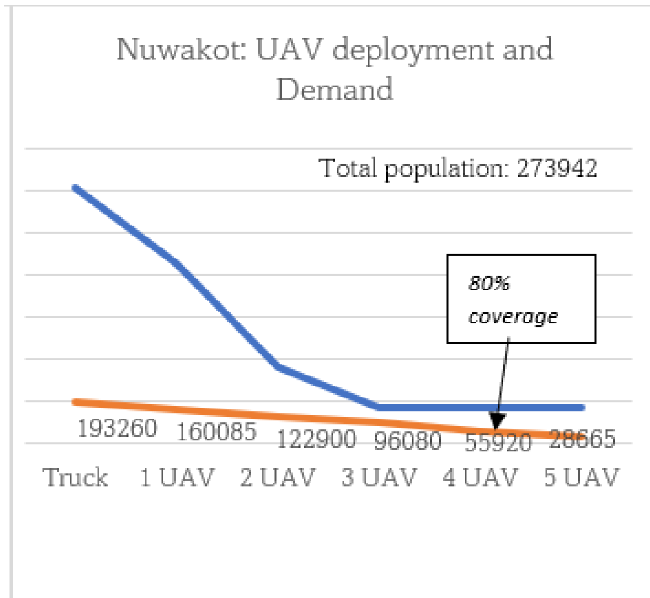


Figure 26. Nuwakot: Demand Results for UAV Deployment

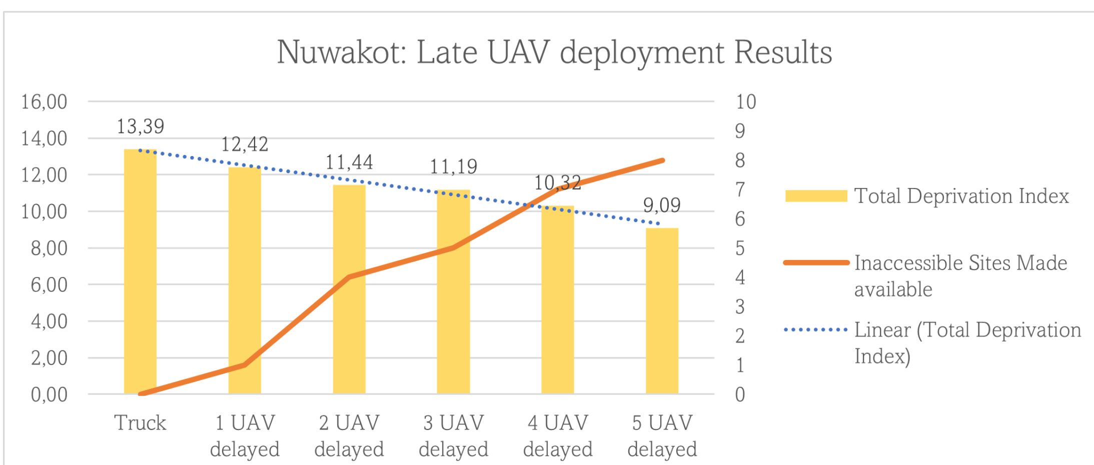


Figure 27. Nuwakot: Demand Results for UAV Late Deployment

7.5 Costs Comparisons for Case 1 and 2

For effective, but confidential, cost comparisons, Figure 28 and Figure 29 present the increase in costs for UAV introduction. The trend line indicates an exponential fit of cost increase for early deployment in both Nuwakot and Dhading. On the other hand, in late UAV deployment, the more UAVs are used the higher the cost, which is linearly increased. These patterns indicate a diminishing cost increase, with an optimal point for the UAV fleets, where minimal costs and high usefulness in terms of demand coverage and deprivation minimization are both possible. In late deployment, these higher costs are less diminishing due to the large unfulfilled requests from early simulated days.

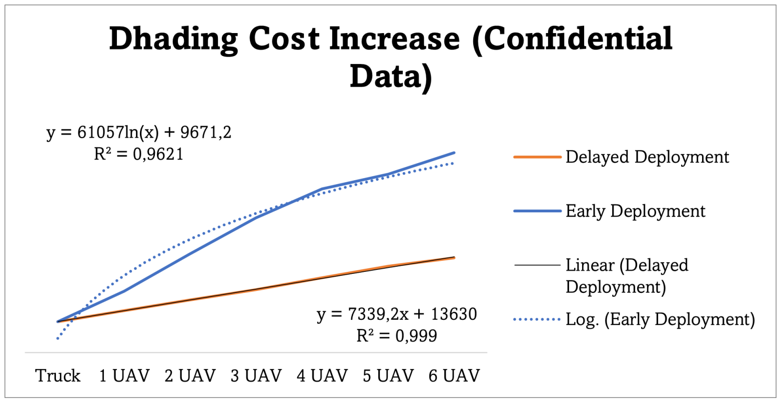


Figure 28. Dhading: Cost increase pattern with UAV introduction

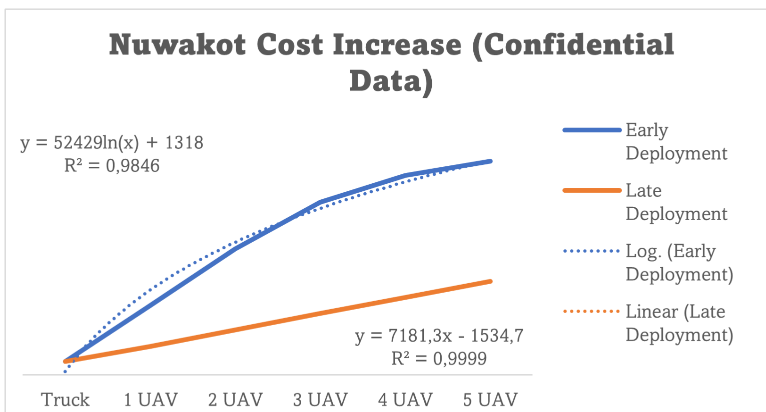


Figure 29. Nuwakot: Cost increase pattern with UAV introduction

7.6 Case 3: Combined Municipalities in 7 days

In this case, we only evaluate site accessibility for heterogeneous fleets. Originally, the two municipalities were treated as multi-depot, and with this thesis, we aim to study a single-depot case for the larger region.

In Figure 30, we see a negative linear trend of the Deprivation Cost Index in relation to the amount of UAVs introduced. With this experiment, we notice that covering a bigger range requires a bigger amount of UAVs. However, although the deprivation cost index reduces, even with 8 UAVs, inaccessible sites are not all visited.

Compared to the case of separate decision-making for the two regions, where we identify that Dhading and Nuwakot independently need 3 UAVs, in the combined case, 5 UAVs do not entail full site accessibility or a huge reduction in deprivation costs. Hence, UAVs seem to be more efficient in smaller regions for last-mile delivery.

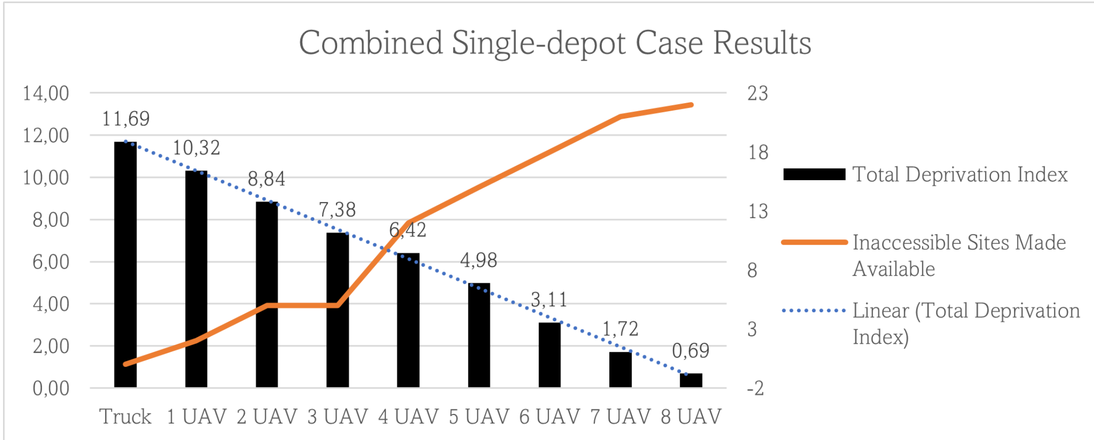


Figure 30. Combined Municipality: Results for UAV Deployment

Importantly, in terms of demand coverage (Figure 31), the pattern changes drastically compared to that of UAV deployment in Dhading and Nuwakot separately. Uncovered recurring demand and unique demand follow a linear pattern, and only 60% of unique demand is covered with 7 UAVs. These results lead to the conclusion that UAV application leads to better results in smaller regions.

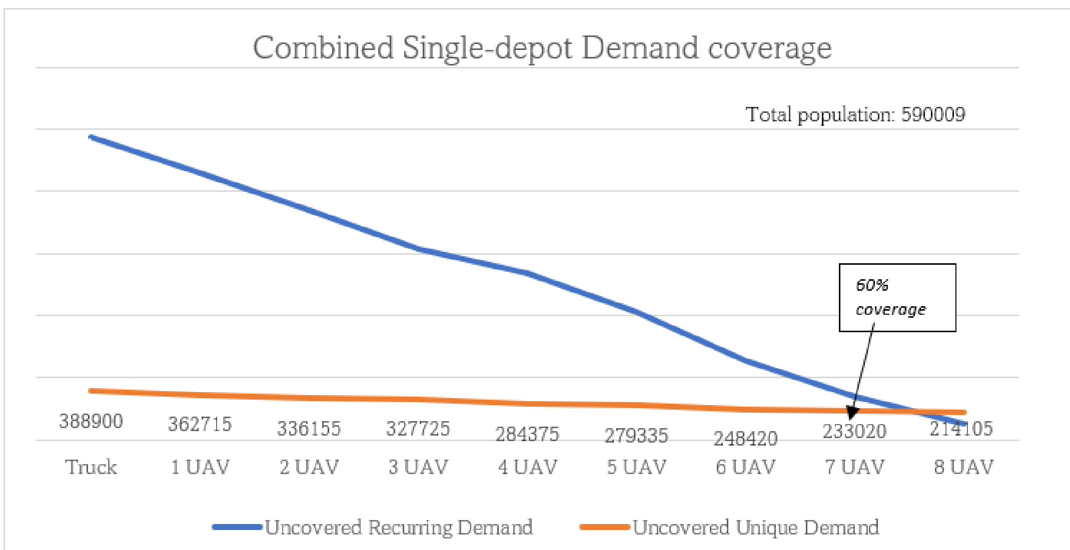


Figure 31. Combined Municipality: Demand Results for UAV Deployment

8 MAIN CONCLUSIONS

Through the experiments outlined in Section 7, here we draw conclusions on the research question: ***In what way and to what degree can UAVs contribute to humanitarian aid logistics, considering minimum operational costs and response time?*** These conclusions are summarized for general UAV performance, Nepal-based performance, and advice for WFA regarding UAV fleet specifications. Lastly, we outline identified possibilities for future research.

8.1 UAV Performance

Deprivation Costs: For the single-depot case in Dhading and Nuwakot, there is a decreasing exponential trend in the relation between Deprivation Costs and UAV introduction, deployed early or not. UAV utilization *improves demand coverage and response time, reaching almost 80% coverage of unique goods in the first week*. In terms of, operational costs, the trends indicate *an efficient point per region for heterogeneous fleet numbers* in respect to deprivation cost minimization and cost increase benefit.

Scale of the Region: Based on the single-depot case of a larger region in Nepal, UAVs are able to distribute last-mile in larger regions, leading to good delivery performance. However, *their performance is significantly better in smaller regions, with a multi-depot scenario*. The best use for UAVs in humanitarian aid is medium-scale regions, with small fleets.

8.2 Benefits of UAVs in Nepal

Accessing Inaccessible sites: In all scenarios in Nepal, inaccessible sites are only able to be served through UAVs. In the original mission, these sites were not prioritized and deliveries happened quite late. Hence, *UAVs can highly contribute to complementing trucks in poor or failed infrastructure or where there is no road network present*.

Demand Priority: UAVs significantly *improve the delivery of recurring demand* in Nepal, particularly due to accessing inaccessible sites. If UAVs are introduced, *unique demand is able to reach 80% delivery* within the first week, almost impossible in the first mission in Nepal. Due to the weather uncertainty in Nepal, this delivery percentage implies *timely delivery of necessary goods*.

Heterogeneous fleets: In most scenarios, UAV fleets are *an addition to the already needed truck fleet*. For Nepal, this implies that UAVs mostly served inaccessible sites or ones that are difficult to prioritize or reach for trucks.

8.3 Advice for WFA Limited to the Nepal Case

UAV Numbers: Based on the Nepalese case, it is recommended to look into utilizing UAVs in multiple depots and not through centralization. The number of UAVs needed depends on the region and time of deployment. *In small scale regions, with early deployment*, we recommend testing fleet sizes of **2-4 UAVs**. If there is a *centralized depot*, the fleet size is recommended to be **higher than 6 UAVs.**

UAV Deployment: *The earlier the deployment, the better.* Having strategically placed hubs in countries prone to disaster, is better than deploying UAVs one week later. The impact of UAV fleets diminishes the longer they are deployed after the disaster. In the case of late deployment, we recommend **fleets of at least 4 UAVs per region.**

UAV Flying Altitude: Based on the Nepal case, flying altitude is more significant to an operation than capacity. Being able to fly on an **altitude of 1000m**, with a capacity of around 140 kg, will be beneficial for regions in mountainous terrain.

8.4 Discussion

Heuristic Limitations and Possibilities

To conclude regarding the heuristic study, it is important to conduct more multi-depot VRP research with UAVs. This thesis concludes that UAVs are beneficial for last-mile operations, and further research should focus on non-isolated cases of last-mile delivery. Additionally, the GRASP heuristic with Simulated Annealing in a Shaking Procedure has limitations in efficiently utilizing and optimizing UAVs. A heuristic that improves cross routes and among modalities might provide more interesting results in heterogeneous fleet sizes. More importantly, the shaking procedure and complex heuristics should be better adjusted to a DES research environment.

From the validation, we conclude that the heuristic fully optimizes truck routes in a sequential vehicle utilization procedure. The question remains if this heuristic has the same results if UAVs and trucks are deployed equally, rather than UAVs supporting remaining open requests.

The used heuristic highly considers calculated deprivation costs, as it attempts to minimize social costs. Future research should have a higher focus on deprivation cost and multi-criteria objective, in order to truly understand UAV application. In addition, a heuristic that better optimizes the social costs needs to be found. Utilizing the village deprivation cost index of uncovered demand during daily decision-making might be an area for future research.

Lastly, truck prioritization and village clustering, as done by the AHP in this thesis, is a good next step to understanding what type of sites UAVs should prioritize. This can also be linked to research on recurring and unique demands, to prioritize delivering particular goods from different vehicles. Future studies should take prioritization further into consideration.

UAV application

This thesis draws conclusions on UAV fleets and altitude. However, further research on UAV logistics should focus on road failure from aftershocks. Additionally, gathering information through sensors is an important possible contribution for UAVs. This can be incorporated with delivery and analyzing road failure for the next day. Lastly, as this thesis concludes in the early deployment of UAVs, we recommend further studies in strategic deployment to answer more complex questions about on-demand distribution through UAVs and prioritization.

9 APPENDIX A: SYSTEMATIC LITERATURE REVIEW PROTOCOL

9.1 Definition of Research Question

Research question: *How is the defined task allocation problem usually solved in the literature on humanitarian aid?*

Definition: The defined problem is the allocation of transportation jobs to multiple modalities (vehicles, in particular trucks and UAVs) and the scheduling of these tasks/activities. So, we are looking for solutions to this type of problem, with at least two different types of vehicles in use. We restrict the search on research in humanitarian aid logistics. The main areas/ fields of knowledge are heuristics and simulation, on which a qualitative scan of abstracts would be conducted.

Objectives:

- Find solutions to task allocation and activity schedule with at least a heterogeneous fleet of two modalities.
- Focus on humanitarian aid, particularly earthquakes.
- Prefer literature where the solution is based on simulation and/or logistics.

9.2 Inclusion and Exclusion Criteria

Table 8. Selected Literature

Category	Inclusion Criteria	Exclusion Criteria
Publication Type	Conference Journals Peer Reviewed Open Access Sources	Any not subject to peer review
Study Type	Case Studies Simulation trials Algorithm based	Systematic Reviews Book Chapters
Publication year	20 years (2000-2021)	Anything older than 20 years
Indications	At least 2 different modalities Heterogeneous fleet Drone — UAV usage Industrial Engineering Transportation Operation Research	Based on simple vehicle routing problems Facility management problems Mathematical Programming solutions Areas nonrelevant to production and operation management Environmental considerations Single trip Other irrelevant fields
Language	English	Non-English
Citations	More than 3 citations	Less than 3 citations

Motivation: *Choices of particular interest are to include open access sources, to not include systematic reviews, to exclude papers earlier than 2000, and to only include papers of more than 3 citations.* Open access sources are important due to the nature of the humanitarian aid discipline, with non-governmental institutions playing a big role, and generally, it makes sense for this type of literature to be open access. Systematic reviews, although good, do not give a complete overview of the detailed solution that is being searched. The past 20 years have been quite productive when it comes to humanitarian aid. In the previous century, we did not have the technology or the high interest in the topic as it has increased with the introduction of new technologies. Lastly, the application of the knowledge in other papers is important for good quality and reliable research. Due to a possible lack of detailed research, we have chosen the border of 3 citations. The “answer” to this knowledge problem will be applied on a trial-and-error basis in the simulation, hence it is easier if the literature is highly regarded.

9.3 Databases and Motivation

1) Scopus Large database, containing a huge amount of literature. It particularly covers sciences and technology. Emergent technologies such as UAVs and vehicle routing problems seem to be stored in this database. 2) Web of Science Contains data from high-impact research journals and conferences. I am particularly interested in simulation conferences and high rated research that should not be missed. 3) ScienceDirect Like Scopus, the database covers a lot of disciplines, including science and technology. It is not enough however as most of the sources come from Elsevier, and variety is necessary for a literature review. 4) Directory of Open Access Journals This database covers journals and articles that are easily accessible. The topic of humanitarian aid is mostly within non-governmental institutions; hence it can be that this database, due to its funding model, includes disciplines of humanitarian aid. However, on second look, I have very little experience with searching this database, hence due to the large search results on the other databases, I decided to not conduct the literature review here as well. 5) arXiv.org This database was recommended by the UT library for my IEM discipline. It is interesting as it specializes in Mathematics, Computer Science, and Statistics, which are relevant fields to my topic. However, due to this nature, it might be hard to find exactly what I need in this Database as mathematical programming papers are in my exclusion criteria. However, after careful exploration of the database search options, the problem seems to not be available in the disciplines set. Hence, I decided not to include this database in the literature review (systematically).

9.4 Used Search terms and Overall strategy

Strategy: Synonyms are found for the following main concepts: application area, type of solution, type of vehicles and number, and type of problem to be solved. There should be at least 2 search strings documented, with a recorded number of results on Scopus (for testing). The motivation for each search string can be found below. Then we filter according to date, and categories of the exclusion criteria. The filtering steps for each database are title, keyword filter ¿abstract filter¿ and citation number filter. Afterward, we check for duplicates.

9.5 Search Results — Duplicates — Final set of Articles

We excluded two initial databases for searching. As mentioned in the strategy, the removal was done on irrelevant fields such as facility location, environmental issues, mathematical-oriented algorithms, and military drone usage. This was qualitatively done during abstract reading.

It should be noted that there were results outside of humanitarian aid logistics that ended up in the final review, as the problem that these papers treated was very closely related to the area of this thesis. For a brief reflection, Science Directory had very limited operator usage, hence there was a lot of filtering to be done on title/keywords, leaving room for a lot of missing papers. The overview of the articles and selection procedure can be found in section 3.

9.6 Conceptual Matrix

This section evaluates the articles on the different important concepts, individually. The concepts are related to the search terms, as well as more problem specific on my thesis, to make answering the question easier. Additionally, the last column summarizes my main takeaway from each individual article and any other core topics of distinction that might need further exploring. This conceptual Matrix was also used in section 3.

Year	Authors	Concepts	TOTAL relevant concepts per source	humanitarian aid oriented	demand/location priority	vehicle routing problem (VRP) and variants	Covering tour problem (CTP) and variants	heuristic | meta-heuristic algorithms	drones | UAV	multi-vehicle	genetic algorithm	simulated annealing	simulation	local search | swap algorithm	heterogeneous fleet	homogeneous fleet	demand coverage KPI	response time KPI	Core concepts and take a ways
		TOTAL sources per concept		9	5	8	5	11	3	5	5	3	0	7	1	1	5	4	
2018	Gharib, Z.; Bozorgi-Amiri, A.; Tavakkoli-Moghaddam, R.; Najafi, E.	A cluster-based emergency vehicle routing problem in disaster with reliability	8	x	x	x		x		x	x				x			x	usage of non-dominated sorting genetic algorithm and multi-objective firefly algorithm;clustering of affected areas; maximizing travel reliability - hard to implement in a simulation framework. Mathematical programming that can be easily translated to a solution.
2019	Santos, Andréa Cynthia	New trends and opportunities in post-disaster relief optimization problems	3	x					x								x		good evaluation of drone usage in humanitarian aid; takes a huge focus on facility location; helpful with Nepal data and schematics to study in the simulation; talks about network accessibility and changes in people location This is quite hard to implement yet, however good reference point
2011	Lin, Y.-H.; Batta, R.; Rogerson, P.A.; Blatt, A.; Flanigan, M.	A logistics model for emergency supply of critical items in the aftermath of a disaster	6	x		x		x		x	x						x		priority of items; takes into account schedulingmulti-objective integre linear programming; 2 heuristic approaches - genetic algorithm and decomposition of the problem. VRP with soft time windows. Multi-period routing and split delivery strategy Aggregation of multi objectives to one through weighted sum method. HAZUS-MH to simulate natural disasters, interesting to use for my case. Similarly for Decomposition of Assignment heuristic
2017	Flores-Garza, D.A.; Salazar-Aguilar, M.A.; Ngueveu, S.U.; Laporte, G.	The multi-vehicle cumulative covering tour problem	6	x	x		x	x						x				x	Core concepts: mixed integer linear formulation; greedy randomized adaptive search; comulative VRP; minimizing sum of arrival time They use an iterated local search, first eliminating redundant locations, then swaping within the tour and then between tours
2017	Cannioto, M.; D'Alessandro, A.; Lo Bosco, G.; Scudero, S.; Vitale, G.	Brief communication: Vehicle routing problem and UAV application in the post-earthquake scenario	5	x		x		x	x			x							focus on short computing time; VRP; drone focus; simulated annealing tested priorly to genetic algorithm and was chosen. Genetic annealing was inferior; simmulated annealing explanation; focuses on UAV information provision

2018	Bruni, M.E.; Beraldi, P. ; Khodaparasti, S.	A fast heuristic for routing in post-disaster humanitarian relief logistics	7	x	x		x	x		x				x				x	emphasizes the arrival time issue that is overtaken by cost minimization; stochastic travel times; multi-vehicle; cumulative routing problem - travelling repairment problem with profits; prioritization according to utility level Greedy heuristic; usage of a warm up period; adaptive local search procedure used
2008	Burcu Balcik, Benita M. Beamon; Karen Smilowitz	Last Mile Distribution in Humanitarian Relief	4	x	x					x							x		the only paper addressing inventory routing problem and scheduling correletation. Great literature review; categorizing emergency relief items; limited number of vehicles and different types; a modeling approach with two phases, very interesting the modelling is inspirational on scheduling a route, with equal allocation principle of demand coverage.
2020	Huo, L.; Zhu, J.; Wu, G.; Li, Z.	A novel simulated annealing based strategy for balanced uav task assignment and path planning	5			x		x	x		x	x							task assignment and path planning;swap and judge simulated annealing variant; combinatorial discrete optimization problems; maximum flying distance of UAVs;
2017	Pham, Tuan Anh; Hoàng Hà, Minh; Nguyen, Xuan Hoai	Solving the multi-vehicle multi-covering tour problem	6	x			x	x			x			x			x		multi trip options, where vehicles can return to the same location during or after a tour; order crossover; classic local search is applied; mindful of demand changes; greedy heuristic variant number of vehicles is a variable which is good for simulation experiments.
2013	Ke, Liangjun; Feng, Zuren	A two-phase metaheuristic for the cumulative capacitated vehicle routing problem	4			x		x			x			x					tabu neighborhood search; meta-heuristic to VRP, as exact algorithms are not time efficient; multi-depot open VRP; literature review on problem and solution algorithm: tabu search most popular for this type of problem, followed by genetic algorithm
2015	Allahyari, Somayeh; Salari, Majid; Vigo, Daniele	A hybrid metaheuristic algorithm for the multi-depot covering tour vehicle routing problem	6		x	x	x	x				x		x					capacitated VRP; CTVRP: cover demand or pass by it; Greedy randomized adaptive search; local search and simmulated annealing - three step hybrid not comparison.
2021	Hesam Sadati, Mir Ehsan; Çatay, Bülent; Aksen, Deniz	An efficient variable neighborhood search with tabu shaking for a class of multi-depot vehicle routing problems	5	x		x		x						x				x	cumulative capacitated VRP; min total arrival time; starts from a solution: two interdependent phases to solution improvement in each iteration; promising, but lacks further research to implement; comparison with memetic algorithm
2018	Karaoğlan, İsmail; Erdoğan, Güneş; Koç, Çağrı	The Multi-Vehicle Probabilistic Covering Tour Problem	7			x	x	x		x				x		x	x		integer non-linear programming problem and linearization; probabilistic based; they use a branch and cut algorithm and a local search based on variable neighborhood search: obtain minimum number of vehicles, then branch and cut and lasts variable neighbourhood search CTP is an interesting idea is interesting when it comes to centering facilities and accumulating demand based on data proivision.

Figure 32. Conceptual Matrix

10 APPENDIX B: ANALYTICAL HIERARCHICAL PROCESS

The Analytical Hierarchical Process (AHP) is a method to organize and analyze complex decisions, developed by Thomas L. Saaty in the 1970s. Following multiple kinds of literature in humanitarian aid that uses clustering and site prioritization, it was important to make a decision in terms of the accessibility of the sites and how they classify.

The classification for Nuwakot and Dhading was conducted separately and the results were also used for the combined case. The files will not be presented in this document, but are available upon request. This appendix aims to explain the unconventional use of AHP as a decision tool to make assumptions about accessibility.

First we define the criteria upon which we will evaluate each site. The top 3 criteria chosen were Road Slope (altitude), access by truck index from the matrix, and population density. Then we set preference levels to rate the different criteria among each other.

Criteria List	Remarks
Road Slope	<650 altitude = easy 650-2000 altitude = medium >2000 = difficult
Access by truck	Access hindered if road slope too high
Individuals	Population
Distance by Truck	from Depot
Distance by UAV	from Depot

Preference Level	*Numeric Value*
Equally preferred	1
Equally to moderately preferred	2
Moderately preferred	3
Moderately to strongly preferred	4
Strongly preferred	5
Strongly to very strongly preferred	6
Very strongly preferred	7
Very strongly to extremely preferred	8
Extremely preferred	9

Figure 33. Step 1: AHP Criteria and Rating

Secondly, we compare the importance of each criterion against each other, as defined by the preference level. Importantly, the normalization stage provides us with weights from the row averages. These weights are later used in the preference matrix, or result matrix to determine the index importance.

Criteria	Road Slope	Access by Truck	Individuals
Road Slope	1,000	0,333	5,000
Access by Truck	3,000	1,000	6,000
Population Density level	0,200	0,167	1,000
SUM	4,200	1,500	12,000

Normalization	Road Slope	Access by Truck	Individuals	Row Average/ ***WEIGHTS***
Road Slope	0,238	0,222	0,417	**0,292**
Access by Truck	0,714	0,667	0,500	**0,627**
Population Density level	0,048	0,111	0,083	**0,081**
				1,000

Figure 34. Step 2: Criteria Weight and Importance

Then all sites were compared with each other on each individual criterion. It is important to note that the comparison was made on scale bases. For example: for Road Slope, each site gets assigned a level as remarked in figure **??**. Then each site is assigned a comparison index from 1 to 3: 1 means an equal scale/ 2 means the site is 1 scale higher, which means the other site is rated 1/2 as it is 1 scale lower, and so on.

The matrix in figure 35 is a simplified representation of this rating. Normalization of this Table provides the column scores in the preference matrix, figure 36.

$$\begin{bmatrix} & \textsc{Value for site} & DhadingBesi & Aginchok & \cdots & Semjong \\ \textsc{Value for site} & (a..b) & (a..b) & (a..b) & (a..b) & (a..b) \\ DhadingBesi & (a..b) & 1 & compare & \cdots & compare \\ Aginchok & (a..b) & \frac{1}{compare} & 1 & & \\ \vdots & (a..b) & \cdots & \cdots & \ddots & \vdots \\ Semjong & (a..b) & \frac{1}{compare} & \frac{1}{compare} & & 1 \end{bmatrix}$$

Figure 35. Step 3: Sites vs Criterion

$$\begin{bmatrix} & RoadSlopeIndex & AccessbyTruckIndex & PopulationDensityLevelIndex & Score \\ DhadingBesi & \textsc{Row average after normalization} & \cdots & \cdots & RowSum \\ Aginchok & \textsc{Row average after normalization} & \cdots & \cdots & RowSum \\ \vdots & \vdots & \vdots & \vdots & \cdots \\ Semjong & \textsc{Row average after normalization} & \cdots & \cdots & RowSum \end{bmatrix}$$

Figure 36. Step 4: Preference Matrix a.k.a Rating

Step 4 provides us with a scoring system on a 3 point basis: easy, medium, difficult. In figure 37. We present the summary of results for Dhading and the Consistency Ratio and Index for the decision making on criteria rating.

Dhading		Nuwakot	
Easy	8	Easy	8
Medium	33	Medium	44
Difficult	6	Difficult	9
Inaccessible Sites	13	Inaccessible Sites	10
Total Sites	47	Total Sites	61

	CI first step	CI second step
	0,904762	3,095023
	1,988095	3,170886
	0,243651	3,019672
		9,285581
λmax		3,095194

Consistency Inde:	Consistency Ratio
0,047596805	0,04
	Satisfactory

Figure 37. Step 5: Results and Criteria Consistency Index

If Consistency Ration is smaller than 0.1, it implies that the decision and the process was Satisfactory. The index and ration are calculated as follows:

$$CI = (\lambda_{max} - n)/n - 1CR = CI/RI \tag{1}$$

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