ERASMUS UNIVERSITEIT ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS

Master Thesis Econometrics and Management Science
Operations Research and Quantitative Logistics

Innovating Health Care Supply in Developing Countries: Cost-effectiveness of Drones for Inventory Management of Essential Medicines

Author
S.E.H. Poiesz

Student number
386299

Supervisor
Prof. dr. A.P.M. Wagelmans

Second assessor
Dr. P.C. Bouman

August 20, 2020

Abstract

The aim of this research is to analyse the cost effectiveness of incorporating drones in the health care supply structure of developing countries. The drones, modelled complementary to truck transport, are used for inventory management against stockouts. In this thesis, an analytical model is developed as a first step towards conclusions for this optimization problem. Continuous approximations are used to model the transportation costs and a dual sourcing inventory policy is used to find an approximation of the optimal solution of the model with both drone and truck transport for the supply of essential medicines to health facilities. This analytical model is based on fixed parameters and limiting assumptions. To investigate the suitability of this analytical model for application to a real-world situation, a validation study is performed trough simulation using data of malaria medication and its distribution structure in Zambia. The model indicates that incorporating drones can be cost effective, when using the model developed in this thesis and stochastic truck lead time is considered. However, in case of deterministic truck lead time, no cost savings are achieved. Additionally, the model for dual sourcing is subject to multiple unrealistic assumptions. Relaxing some of these assumptions to create a more realistic setting can result in poor performance of the model. Therefore, the conclusion is the cost effectiveness of drones in the supply of health care in developing countries should be evaluated numerically in each specific situation.

Contents

1 Introduction

1.1 The Problem Field

New technologies allow for new opportunities. This is certainly true for the fast-evolving technology of drones and its opportunities for improving health care in developing countries. In developing countries, the need for health care is just as urgent as in western countries, but often much harder to facilitate as environmental conditions can prevent health care from reaching the people in need (Vledder et al., 2019). Average availability of (essential) medicines in local health facilities is sometimes as low as 29.4 % (Cameron et al., 2009). Integrating innovative technologies could very well be the key to developing an alternative system of health care supply.

In the past years there has been some publicity about the use of drones for delivering supplies in a humanitarian context (Tatham et al., 2017). In 2014, the Office for Coordination of Humanitarian Affairs had already proposed the potential effective use of Unmanned Aerial Vehicles (UAVs) in the area of logistics for small medical supplies (OCHA, 2014) and projects have already been launched by innovative companies (Braun et al., 2019).

In Africa, only one third of the people live within two kilometres of a road that is accessible year-round, making it difficult to reach other than just local health facilities in case of medical need (Khazan, 2016). However, these health facilities are sometimes inaccessible and therefore cannot supply the patients with proper health care. UAVs, commonly known as drones, have the ability to traverse heavy terrain and blocked roads under difficult circumstances, reaching places that would normally be unreachable (Rabta et al., 2018). The application of drones as transport in the health care supply chain of these developing countries could therefore be effective in improving health care. However, to date, a comprehensive framework on how drones can be economically deployed in health care systems has not been developed.

1.2 Academic, Practical and Social Relevance

Ineffective supply chains are a cause of bad health care supply, putting peoples' health at risk (Yadav, 2015). This is especially the case in developing countries, where many people suffer from diseases. For example, 213 million people in the WHO African Region suffer from malaria every year. While malaria is a potentially life-threatening disease, it is actually very treatable when the proper medication is available. Strengthening the health care supply chain by increasing medicine availability at health facilities can, therefore, directly save lives (Kazaz et al., 2016).

A proposed solution by academics to strengthen the supply chain has been the incorporation of drones into the supply chain (Braun et al., 2019; Eichleay et al., 2019). However, only relatively little research has been done to a profound understanding of the potential effective use of drones in the health care supply chain in developing countries. There have been some studies that, in specific settings, investigate if and under what circumstances drones could be feasibly incorporated in the existing health care systems. Analytical models of incorporating the use of drones have been developed, but mainly for different settings such as commercial delivery networks or disaster relief operations. This research aims to develop a general model that can give insights in the factors influencing a drone system implementation, but then focused specifically on health care supply of essential medicines in developing countries.

In general people are hesitant to invest in new technologies, especially when its use has not yet been properly analysed. A clear understanding of the expected potential and possible risks associated with the use of drones can guide societal change towards accepting and incorporating drone programs as possible solutions to better performance of health care systems (Otto et al., 2018).

1.3 Definition of the Problem

In this research, the central question is under what conditions is it economically favourable and, therefore, feasible, to use drones for health care supply in developing countries with potentially difficult to access health care facilities. The answer to this question is influenced by aspects such as costs, density of demand, or drone capabilities. Therefore, the aim is to identify how and to what extent these aspects are of influence on the feasibility of drone use for inventory management of essential medicines specifically.

As Wright et al. (2018) stated, due to the complexities of this problem it is difficult to find a proper model that provides definitive answers to the problem. Therefore, as a first step, the aim of this thesis is to create an analytical model that incorporates the use of drones for resupply of essential medicines. Then, the aim is to validate this model and to determine its suitability in practice.

1.4 Data and Methods

To answer this research question inventory models accounting for inventory and transportation costs are used to develop an analytical model. Because these integrated transportation and inventory models are often $\mathcal{NP}$-hard problems (Ansari et al., 2018), the transportation costs will be estimated using continuous approximations. This way, the problem can be solved finding a near-optimal solution (Langevin et al., 1996). The inventory policy that will be used is based on an appropriate policy as recommended in the dual sourcing literature.

To determine if the conclusions of this (simplified) analytical model also hold for real-world cases, it is used as a basis for a numerical study that focuses on the supply of malaria medication in Zambia. An inventory model with fixed base parameters and the same assumptions as those in the analytical model is used as a starting point. Then different (cost) factors and assumptions will be altered sequentially to analyse the effect of each of these factors and assumptions. The numerical study is conducted by simulation.

Data on malaria medication and the demand thereof in Zambia is retrieved from research done by Leung et al. (2016). The data contains accounting of medicine inventory at various facilities in multiple regions of Zambia. The focus in this thesis is on a malaria drug because supply of this drug has a large impact on health in developing countries and also provides a distribution challenge that is representative for other health care products (Leung et al., 2016).

1.5 Structure of the Thesis

This thesis is organized by chapters. Chapter 2 presents a literature review of previously published research. Chapter 3 provides a detailed description of the data used in this thesis. Chapter 4 details the methods that are used in this research, including the analytical model and the approach for the numerical study. Main findings of this thesis are discussed and compared in Chapter 5. Chapters 6 and 7, conclude the research with an overview of the main findings and a discussion that addresses limitations of this research and suggestions for further research.

2 Literature Review

2.1 The Use of Drones in Health Care

The technology of drones has expanded in the last several years. Drones, or Unmanned Aerial Vehicles (UAVs), are small, unmanned air crafts that can fly autonomously or that can be navigated by remote control (OCHA, 2014). They operate in an Unmanned Aerial System (UAS). Drones mostly fly on batteries, resulting in a limited flying range and cargo capability. Due to new technologies, drones can fly further, carry more weight or equipment, and be used under more circumstances (Braun et al., 2019). As drone technology has expanded, the interest in their possible applications has expanded as well, including in the delivery of supplies in both commercial and humanitarian context (Tatham et al., 2017).

In the context of humanitarian applications, and specifically medical applications, some research has already been done on the possibilities of incorporating drones. Most research is done on the practical aspects of incorporating drones, such as technological capabilities (for example Thiels et al. (2015); Braun et al. (2019); Tatham et al. (2017)). In general, these papers conclude that drones can be feasibly used for the transportation of small medical items. In some countries, the use of medical drones has already been implemented, such as Zipline in Rwanda and Ghana (blood transport and medicines), Matternet in North Carolina (transport of laboratory specimens), DHL in Tanzania (medicines) or Dr. One in Ghana (contraceptives and medicines) and there are more projects ongoing (Braun et al., 2019). All projects are considered successful medical delivery systems promising a future of drone health care transport.

However, a full understanding of the financial implications of such a system has not been established. There are some models that incorporate drones in delivery networks, but most are for commercial delivery services. The factors that determine the feasibility of incorporating a drone system for health care supply are different than in these commercial settings, and trade-offs are likely to turn out differently (Otto et al., 2018).

In order to investigate whether the use of drones would be beneficial for the distribution of health care products in developing countries, a clear overview of the current situation of the health care distribution and challenges therein is needed. This will be presented in the next section.

2.2 Supply Chain Models for Health Care in Developing Countries

At the moment, health care in developing countries is commonly transported to the local health facilities using a traditional multi-tiered land transport system (TMLTS) (Vledder et al., 2019; Haidari et al., 2016). Each tier is an echelon in the inventory model and a level in the transportation supply chain. One frequently used traditional system is a three-tiered system. A central (e.g. national) warehouse provides multiple district stores or regional warehouses with supplies. Local health facilities then get supplies from the regional warehouses. Personnel in these local health facilities administer health care to the local people (Vledder et al., 2019). The last stage of distribution (from regional warehouses to local health care facilities) is referred to as the last mile transport and is the final stage of a (humanitarian) supply chain (Balcik et al., 2008).

The supply chain in developing countries has challenges, with most issues related to transport. Lack of reliable transport results in a bottleneck for proper supply of products such as medicines and is caused by a number of factors. One factor is insufficient vehicles, due to poor maintenance and high break down levels caused by bad roads (Vledder et al., 2019). This results in a limitation of loading capacities on these vehicles (Rabta et al., 2018). Bad roads also result in some health facilities being entirely cut off for months in the rainy season because the roads become inaccessible. This seasonal inaccessibility mainly applies to last mile transport (Vledder et al., 2019).

Drones can overcome the inaccessibility to certain health facilities since they can traverse bad weather, blocked roads and flooded areas (Rabta et al., 2018). This could potentially save lives, as essential medicines can be distributed to people in need when time is of the essence (Ling and Draghic, 2019).

Since drones have limited payload and range but potential high costs, a trade-off is required. Given this trade-off, it is likely that drones would be deployed for the last mile transport, complementing a TMLTS system (Eichleay et al., 2019). For transport from the origin (central/national warehouse) to the regional warehouses road transport is still very possible, since these roads are usually in better condition with almost at no risk of being cut off. This last mentioned transport is also usually required over large distances (Walia et al., 2018).

Different measures can be used to evaluate the supply chains of medical provision. The measures can be categorized in six main groups: supply, demand, agility, costs, demand fulfillment and resource utilisation. These last four measures incorporate both supply and demand. Each category contains several specific measures that influence each other within the category and between categories (Haidari et al., 2017). Some measures are more relevant to this research than others. Relevantly identified factors include those in the agility category, costs of transport and storage, capacity for storage and transport on the supply side, and service rates that relate to demand fulfillment. The most common service rate in health care facilitation is the service level of health care availability, defined as the number of people that directly receive a health care product as a proportion of the entire number of people that come to the facility asking for that product (Haidari et al., 2016).

All these factors can be incorporated into an inventory model that represents a distribution network with transportation of goods and inventory holding of these goods. This research focuses on the inventory models of (essential) medicines in developing countries. Transportation in these models can be done by either the TMLTS system alone or TMLTS complimented with drone transport. Necessary here is to identify factors that are relevant in these models.

Therefore, a short review on supply chain, transportation and inventory models relevant for this research is presented, followed by a discussion of analytical approaches that provide general understanding and suggestions to model the problem analytically. Then numerical models that incorporate drones in health care distribution will be reviewed to identify factors that influence the model with respect to specific drone or health care aspects.

2.3 Supply Chain Optimisation

Humanitarian logistics is the process of planning and controlling the distribution and storage of goods in an efficient and cost effective way, such that the goods come from a point of origin to the point of consumption,s meeting requirements for the end user (Thomas and Mizushima, 2005). The methodology of humanitarian logistics is, for the most part, the same as other logistic problems, but the objectives can be different and its effect might be more critical (Chowdhury et al., 2017). In planning a robust network, both the distribution to the people who need it and the availability of the goods for these people is essential; therefore, a good supply chain network is key.

The objective of supply chain network design, containing inventory and transportation problems, is to minimise total costs that come with distribution systems. It analyses the interdependencies of different logistic factors and identifies the cost trade-offs (Langevin et al., 1996). The basic trade-off is that a higher frequency of deliveries often results in reduced inventory costs but increased transportation costs (Ansari et al., 2018). This can be subject to other objectives, such as reaching a particular service level.

The main focus of this research is on a three-level distribution structure, as explained earlier in this chapter. In the literature this is formally called a distribution network with transshipment of goods. The transshipment happens at transshipment terminals where goods may change vehicles or even transportation modes. In the distribution network of health care in developing countries, transshipment terminals are the regional warehouses. Distribution from the first to the second level is called linehaul, from the second to the third (the destination), is called local (Langevin et al., 1996).

This multi-level distribution structure is also called a multi-echelon system, where delivery of stock is not only dependent on lead times, but also on availability of the goods at the higher level echelon (for the three level health care system, the health facility is echelon one, the transshipment terminals are echelon two and the central warehouse is echelon three). Clark and Scarf (1960) first introduced the use of echelon inventory used to determine optimal inventory policies of a multi-echelon system. The echelon stock is the inventory of that echelon and all the inventory of downstream echelons.

There are two main solution approaches in logistic problems: one based on mathematical programming and one on continuous approximations. In this research, focus lays on the continuous approximations, that use summaries of data and work with analytical models. These analytical models are usually simplified models that can give insights to the effect of certain factors of the model on the problem and give understanding of the trade-offs (Langevin et al., 1996; Ansari et al., 2018). Next to the analytical approach a numerical approach can be used to model logistic systems. The insights gained in the analytical models can provide information on numerical models (Langevin et al., 1996).

2.4 Transportation and Inventory Models

As mentioned in the previous section, continuous approximation models can be used to closely approximate the optimal costs in a model, for example costs of difficult (logistic) problems. It uses approximated information to gain an understanding of the effects of different factors in the model. Therefore, in inventory models that are approached by continuous approximations, the demand is based on spatial density and average distribution (Langevin et al., 1996).

In the past literature has been developed to approximate both transportation models and inventory models. There is also research that incorporates both transportation and inventory models in distribution network optimisation. The location of distribution centres and local facilities in the distribution networks is often also incorporated in these models. Because the current research assumes a fixed and yet established distribution structure, the last mentioned aspect of the supply chain models is not discussed.

Transportation cost in a distribution network can be estimated in two ways, depending on the type of transport. For distance from a demand point to a central point, such as a warehouse, approximations have been made of the average distance given the shape and size of a service region. The shape of the service region has been found to have little impact on the optimal solution value (Dasci and Verter, 2001). In case of routing amongst multiple stops in a tour, a problem that is commonly called a travelling salesman problem, approximations have been made based on the size of the demand area and the number of stops (Daganzo, 1984a,b). This is used in problems where the costs of routes need to be estimated, but it does not matter what the exact routes are (Franceschetti et al., 2017).

In transportation research, both periodic and continuous inventory review policies are considered. A periodic review is more realistic for practical applications (Johansen and Thorstenson, 2014). However, the protection against stockouts is required over a longer period when using a periodic review policy, yielding a higher safety stock to provide the same costumer service level (Tagaras and Vlachos, 2001).

Inventory costs are approximated by type of inventory management. A fixed order quantity or an order-up-to policy can be used, the latter being an order of which the size is such that the inventory position is increased to the order-up-to level. The inventory position is defined as the on-hand stock plus the outstanding orders and minus the backorders. In case of a lost sales inventory model, backorders are non-existent and the inventory position can therefore not be negative (Axsäter, 2015). Periodic review systems with complete backordering are commonly approximated by an economic order quantity (EOQ) model. The model approximates costs using the average time between arrival of the product at the facility and the use of that product (Burns et al., 1985). Modifications of the EOQ model are made to account for specific types of inventory models. To make sure service levels are achieved, safety stock can be held. Depending on the demand distribution, the appropriate level of safety stock can be calculated. In contrast to the relative simplicity of the models with complete backordering, models with lost sales, both continuous and periodic review systems, are, in general, difficult to analyse and solve (Bijvank and Vis, 2012). Most inventory models work with a holding cost for the units stored and an ordering cost charged either per order or per product. In some models, the ordering costs contain transportation costs (Axsäter, 2015).

Models that explicitly incorporate transportation cost as a part of the inventory model have also been developed. Burns et al. (1985) have created an analytical model to approximate inventory and transportation cost under known demand. They use the estimation of travel distance based partly on the approximation of Daganzo (1984a,b). Contrary to most studies that have been published up to then, Tyworth and Ruiz-Torres (2000) state that, because the transportation costs increase disproportionately with decrease of the size of the shipment, transportation costs should be treated separately instead of implicitly as a cost of placing an order.

The performance of an inventory model or, more importantly, the objective to be reached with a policy is often defined for a certain service level. A widely used service level is the availability of the product for the consumer. It is represented by a percentage calculated from the number of consumers that receive a product as soon as they arrive at the facility, out of the total number of consumers at that facility. In this research specifically, it is defined as the number of people receiving the medication directly as they arrive at the facility divided by the total number of people that come to a facility requesting that medication. This is used as the performance measure, since directly receiving this medication can be crucial and, moreover, it is difficult to measure patient impact for receiving modified or delayed treatment (Haidari et al., 2016).

In light of the necessity of directly receiving treatment, it is also evident that, in inventory models for health care in developing countries, placing an order for health care when it is not directly available, so backlogging, is for some patients not a viable option. It is often difficult for these people to reach the facilities and usually it is urgent that they receive the health care (Khazan, 2016). Therefore, inventory models with lost sales seem to be applicable to this research. However, there are schemes to facilitate patients that receive part of the medication immediately and later return for the rest. In practice, for people that do not have enough payment on hand for full treatments, it is even appreciated to buy an incomplete dosage and return later for the rest (Peters et al., 2008). For this reason, making the assumption of backlogging is not completely misplaced. Models with backlogging are more easily analysed than lost sales models (Bijvank and Vis, 2011).

2.5 Single Sourcing with Fixed Replenishment Intervals

In developing countries truck delivery for essential medicine replenishment is often done in a fixed monthly schedule (Leung et al., 2016) A policy developed with fixed replenishment moments is an (R, S) policy, with R the replenishment interval and S the order-up-to level. This policy is beneficial as it can facilitate coordination with other supply chain stages and other issues such as work force planning and maintenance. This type of policy is also attractive as it allows effective use of transportation resources (Van Houtum et al., 2007). There are no final answer yet as to what the optimal policy for such problems is. However, (R, S) policies are found to be cost effective compared to other forms of ordering with fixed replenishment intervals. Rao (2003) show that using an economic order interval retrieved from deterministic analysis also provides a good approximation for a case with stochastic demand, but where lead time is still deterministic.

Another common single sourcing policy that requires reordering at certain fixed order moments at equidistant times is a max-min policy. This policy works with a lower and an upper inventory level: in standard form an order is placed if it is below the lower level and ordered up to a maximum of the upper level (Moon and Gallego, 1994). When the forced ordering variant is used, stock is always ordered up to the maximum. Because this max-min policy is easy to work with, it is often used in practice (Leung et al., 2016). It is also recommended for the specific application in supply chain management of health care in developing countries (USAID | DELIVER PROJECT, 2011).

2.6 Dual Sourcing Inventory Policies

Dual sourcing policies are often used in the situation where there are two suppliers, one regular supplier that offers lower unit cost and a longer lead time compared to another supplier that performs emergency shipments (Chiang et al., 1996; Janakiraman et al., 2015). Generally, dual sourcing policies are divided into single- and dual-index policies, which depends on whether one or two inventory positions are being accounted, and single and dual base stock policies, which depends on whether one or two order-up-to levels are used (Allon and Van Mieghem, 2010). To find optimal policies in dual sourcing systems is in general not easy, as optimal ordering quantities are functions of vectors with a length equivalent to the difference of lead time between suppliers and so the problem has the issue of high dimensions (Janakiraman et al., 2015). Therefore, a wide range of policies have been proposed by researchers to solve the dual sourcing inventory problem, which will be discussed next.

In the past, related research has been done on periodic review inventory models where the regular and emergency orders are restricted in terms of lead times or reorder points. Early research studies regular lead times that are exactly one period of the inventory model and emergency shipments that are instantaneous (Barankin, 1963; Daniel, 1961). Later, researchers create models for the situation that lead times are longer but the difference is exactly one period. This one period difference relates to the difference in lead time, being a lead time of k periods for one transportation mode and $k+1$ periods for the other. Dual-base-stock policy is found to be an optimal policy when lead time difference is one period. This policy makes a regular order to get the stock level to a first base level and emergency orders to get it to the second, higher level (Fukuda, 1964). More complex models are developed that allow lead times to have a difference of multiple periods (Rosenshine and Obee, 1976). All these models assume that complete backlogging is allowed.

Continuous models have also been developed. Johansen et al. (1998) developed a continious review model that uses a standard (R, Q) policy for regular orders and a reorder point and order-up-to level for emergency shipments. In their model the order-up-to level is dependent on the time until the regular order will be received. They build on the work of Moinzadeh and Nahmias (1988), who created a model to relax restrictive assumptions that were used in earlier work, such as exact lead time differences. An approximate model, without proof of optimality, was made for the average cost per time unit using two ordering quantities and reorder points (s_1, Q_1, s_2, Q_2) for normal and emergency orders. Based on this work, Mohebbi and Posner (1999) create a model using approximations for a lost sales continuous review system. Following the concept of Moinzadeh and Nahmias (1988), Mohebbi and Posner (1999) find that adding emergency shipments to achieve a certain service level in the continuous review policy leads to cost reductions.

Tagaras and Vlachos (2001) create a periodic review inventory policy where only one emergency shipment can be made per inventory cycle, but this order is within the review period. Because chance of a stockout is highest near the end of the replenishment cycle, so just before the arrival of the regular order, this is when the emergency supply is considered. Chiang et al. (1996) allow emergency replenishments at any time in the cycle including the order time of the regular order. Therefore, this approach is seen as a combination of periodic and continuous review for the regular and emergency orders respectively. Although it seems useful in practice, their proposed solution approach is quite complex (Chiang et al., 1996).

Sheopuri et al. (2010) show that the problem of finding an optimal policy for dual sourcing is a generalisation of finding it in a single-supplier system where excess demand is lost. They show that an order-up-to policy is, therefore, not optimal based on the assumption that emergency orders are received immediately and are used to satisfy demand that was not met with the regular order in that period.

Another widely analysed and used policy for dual sourcing is a tailored base-surge (TBS) policy. Using this policy, the facility receives a constant quantity from the regular supplier and when needed it dynamically determines to get an emergency shipment. This way, the regular supplier is used to supply a base level of demand from a constant quantity and a base stock (order-up-to) policy is used for the emergency shipments (Janakiraman et al., 2015). This policy is completely independent of the lead time of the regular supplier (Boute and Van Mieghem, 2015). It is found to be most effective when there is a large difference in lead time between the suppliers (Janakiraman et al., 2015).

Allon and Van Mieghem (2010) create a TBS based model which is analytically tractable. They seek simple formulas to indicate the main drivers in the allocation between sources, the costs and the base stock levels. They find this using a Brownian model which is, for high sourcing volumes, asymptotically optimal (Allon and Van Mieghem, 2010).

Combining TBS and order smoothing policies, Boute and Van Mieghem (2015) develop a discrete-time inventory model with a linear control rule to smooth orders and allow for exact and tractable analysis of the single versus dual sourcing policies. Smoothing is a method to reduce variability and the safety stock can be reduced compared to other policies that are using demand replacing chase policies. Using this approach, they find that a TBS policy is a form of order smoothing policies, which is especially true when considering models with inflexibility of changing orders or supply modes, or models with larger difference in lead time. However, the model created does depend on full backordering (Boute and Van Mieghem, 2015).

A generalisation of the TBS policy is the modal split transport (MST) policy. It is a generalisation of the TBS policy because it contains a generalizing assumption that the fast and slow deliveries do not have to have identical delivery frequencies as is required in the TBS model. Dong et al. (2018) develop an analytical model starting with deterministic demand to identify key drivers of volume allocation between the slow and fast transport and based on this, making tailored approximations of the cost function for different parameter settings. The approximations lead to closed-form expressions for the MST policy (Dong et al., 2018).

2.7 Analytical Optimisation Models for the Use of Drones

Only little research has been performed on analytical models that incorporate the use of drones in the distribution of goods. In their review on continuous approximation models that have been developed over the last years, Ansari et al. (2018) identified amongst existing gaps in this field of research the integration of other application domains such as drones.

Research that does incorporate the use of drones in a humanitarian context is that done by Chowdhury et al. (2017). They propose a combined facility location and inventory allocation problem with use of drones in disaster affected regions. With a continuous approximation model they determine the locations of distribution centres and corresponding inventories, taking into account stochastic demand and restrictions on the drone flying range. Continuous approximation is also used to divide the solution space such that it has slow varying demand, after which they optimise the model using an approximation of distance and costs to estimate the transportation, facility and inventory costs. Key insights include that if road access decreases costs increase (due to an increase of drone transport which has higher unit costs) and that with an increase of drone speed the total system cost decreases (Chowdhury et al., 2017).

Another research that uses continuous approximations for modeling a distribution network with drones is done by Figliozzi (2017). However, this model is based on a delivery network using solely drones. They find that battery capacity has a crucial impact on the effectiveness of the system. Also, they conclude that using drones as a distribution mode is more effective in areas with higher demand densities.

2.8 Numerical Models for the Use of Drones for Health Care Replenishment in Developing Countries

Most research that has been done towards incorporating drones in a health care supply chain is focused on a numerical analysis into the benefits of drones, as opposed to analytical analysis. Next is presented a selection of these studies, their findings, and factors that are used in the presented models are identified.

Walia et al. (2018) perform a cost analysis on the incorporation of drones in the delivery system of medical supplies, comparing the costs of a system with only land transport to a system that potentially utilizes drones for the distribution from regional warehouses to local health facilities in Tanzania. Tanzania uses a system of a central warehouse that supplies zonal warehouses, which are connected by proper roads. The transport from the central to zonal warehouses will always be done by truck transport in the model of Walia et al. (2018). From the zonal warehouses, supplies are distributed to local health facilities. The model uses a road condition parameter and an environmental risk parameters for transport by truck and drone respectively. Using fixed demand and an estimated fixed number for the road condition and environmental risk parameters, they conclude that incorporating drones as an option for the transport from regional centres to local health facilities provides a cost benefit compared to solely utilizing land transport.

This simplified research with fixed parameters suggests possible cost advantages to incorporating drones into the health care supply chain, but lacks some real-world implications. It does not take stochasticity into account for demand or environmental factors. Moreover, it disregards costs for operating the drone network, such as labor costs.

A computational model that does include stochasticity of demand is the model developed by Haidari et al. (2016). The authors use a simulation model to investigate the impact of using drones in the supply chain of routine vaccination. They conclude that the vaccine availability at health facilities, which they use as a key performance measure, can be increased from 94 to 96 % in a baseline scenario. Moreover, a reduction of about 20 % of the cost per dose of vaccines administered was achieved by incorporating drones in that same scenario (Haidari et al., 2016). This scenario is based on a supply chain with one central warehouse and uses a reduction of the number of regional hubs when drones are included compared to the scenario with only land transport. The authors do argue that the drones should be used frequently enough to overcome the costs of installing and maintaining the UAS system.

Where Haidari et al. (2017) and Walia et al. (2018) minimise costs, Scott and Scott (2017) argue that it is of the importance to minimise delivery times. This importance stems from the idea that, since time is of the essence, a fast response could prevent medical trauma and therefore save lives. In their model, Scott and Scott (2017) optimise the positioning of central and regional warehouses to ensure timely delivery. A mixed integer programming formulation is used. Like the previous mentioned research, a tandem strategy is considered in which truck deliveries are used to stock regional warehouses and drones are used for transport from these warehouses to the local health facilities.

In all previous mentioned models, a benefit of incorporating drones is identified, whether costs or other performance measures are used as a metric. In all models, different factors are incorporated and sensitivity analyses are performed. All research uses parameters for demand and for specifics of drones. Other factors used, that differ across the research, are a road condition parameter and an environmental risk parameter for flying drones (Walia et al., 2018), which is also related to seasonality (Haidari et al., 2016). Speed of trucks are of influence (Scott and Scott, 2017). Haidari et al. (2016) also take into account the spreading of people between urban and rural areas and the size of demand of people needing treatment per health facility into consideration.

2.9 Issues Regarding the Incorporation of Drones

Although all previous mentioned research favours the use of drones for health care supply in developing countries, there are some important drawbacks of this implementation identified in the literature that should be shortly mentioned.

One major issue often mentioned in research conducted on the feasibility of drone use are legal challenges. These legal challenges arise from concerns about privacy and security (Eichleay et al., 2019; Thiels et al., 2015).

Concern has also been raised that when new systems are used in existing health care structures, the new system has the potential to fracture these existing structures, leading to time-consuming implementation and possible inefficiency in the future (Eichleay et al., 2019). Therefore, a profound understanding of impact of different factors on the implementation of a new system must be realized before decisions can be made. A thorough and complete understanding is still missing currently in the literature.

Another drawback identified is an opportunity cost. If a government invests in drone technology, the need to invest in proper roads becomes smaller, even though roads can strengthen a country's overall welfare due to their alternate purposes (Braun et al., 2019; Foth, 2017).

2.10 Malaria

The aim of this research is to develop general models and conclusions about the provision of health care in developing countries and the potential role of drones therein. Health care consists of various items such as blood, vaccines, drugs, and medical supplies. One of the specific medicines that has great impact on the well-being of people are drugs for treating or preventing malaria (USAID | DELIVER PROJECT, 2011). Malaria is a life-threatening disease that can result in severe anemia, hypoglycemia and brain involvement (Ling and Draghic, 2019). The World Malaria Report 2019, published by the World Health Organisation (WHO), indicates that most cases of malaria sickness in 2018 are in less developed countries. In particular, the WHO African Region has 93 % of all cases, equivalent to approximately 213 million patients. In terms of deaths caused by this disease, the WHO African Region has almost 94 % of all deaths. Children under the age of five years are most vulnerable to malaria (World Health Organization, 2019).

However, malaria is both preventable and curable. Antimalarial medicines exist that can prevent malaria. Additionally, when the disease is diagnosed, medicines exist to treat and cure patients. Problems arise when a patient does not have access to these medicines. Therefore, proper availability of essential medicines at all health facilities should be a goal for both governments and aid organisations (Kazaz et al., 2016).

3 Data

For the numerical part of this study data on malaria medication from a health care system in Zambia is used. Data was accessed through the public repository associated with the research performed by Leung et al. (2016), who analyse stock cards at different distribution centres and health facilities. Stock cards are cards on which stock accounting is recorded by clinic staff and includes reporting inventory transactions and historical storeroom stock levels for all medicines. Data was collected on lead times of both linehaul and local transport. While data used to model drones and their (technical) capabilities is retrieved from multiple sources, main source is from drone data developed by Zipline (2020). A detailed description on all these aspects of data and the collection process for each of these is given below.

3.1 Demand of Malaria Medicines

In this research, focus is on malaria medication, specifically the anti-malarial drug artemether-lumefantrine (AL). This drug was chosen as the focus because it is representative for typical drug distribution challenges in developing countries and the drug has a large impact on public health (Leung et al., 2016). AL comes in four dosage forms, namely 6, 12, 18 and 24 tablets, with 24 tablets equal to one adult regimen.

To estimate demand for this drug, commodity planners from 212 health facilities in Zambia regularly photographed their clinic's stock cards between June 2009 and June 2010. The photographed stock cards contained dates and quantities of issued medicines, deliveries and stock levels. These facilities involved are from 12 districts. In addition to the facility name, location and district, the following information was provided: daily patient count, yearly demand for AL, demand shape, and the probability per month of the year of facility accessibility for a delivery via truck transport. For each district, a mean primary and mean secondary lead time is estimated.

To represent weekly demand and a mean of the estimated average demand each week, Leung et al. (2016) estimate the demand distribution, after testing for different distributions, to be the lognormal distribution with a coefficient of variation of 50 %. They determined this average weekly demand by correcting the raw daily data to include only data that is complete, resulting in an average weekly demand (all dosages combined) approximated from data of 17 facilities in 5 different districts. The average weekly demand over the entire year is 37.5 on average and the average standard deviation is 18.75.

3.2 Distribution Network

In Zambia, health medication is mostly supplied by the public health system which mainly entails medicines financed by the Government of Zambia (37 %) and donor support (26 %). Zambia has a size of 752,612 square kilometres containing a health system of 9 provinces and 72 districts. On average, each district has a size of 10,453 square kilometres. With 1,787 reported health facilities Zambia has, on average, about 25 health facilities per district (Republic of Zambia Ministry of Health, 2006).

Medication is received at a central warehouse, the NDC, in Lusaka. From there, medications are transported to district stores (RDCs), following a reliable monthly schedule with approximately two weeks lead time. From the RDCs, the medications are further transported to local health facilities. This transport is reported by commodity planners' monthly reports between May 2009 and June 2010. Staff at each facility estimate the probability that in any week a shipment to their specific facility would be delayed due to inaccessibility of roads by weather conditions. Data contains delivery dates both per district and per health facility. Leung et al. (2016) have estimated the secondary lead time without accessibility problems as a geometric random variable where the first moment is the sample mean, which is estimated at 3.8 weeks. However, seasonal accessibility problems are estimated with a Bernoulli random variable with a monthly dependent success probability that is estimated from subjective estimates of health workers at the facilities. Monthly estimated accessibility probabilities are 0.78, 0.76, 0.78, 0.85, 0.93, 0.97, 0.97, 0.98, 0.99, 0.99, 0.95 and 0.85 for the months January through December respectively.

At the RDCs, there are two options for the products, cross docking and intermediate stocking. Cross docking means that the RDC is merely a point of transfer for pre-packaged shipments. Packaging is done at the national warehouse directly for a specific facility. Intermediate stocking means the RDC maintains a stock from which picking and packing are done. For the data collected between May 2009 and June 2010, at least 800,000 adult regimens equivalent available (where 100 strips of AL 6 are 25 adult regimens equivalent) are in stock at the NDC.

3.3 Drone Capabilities

In this study a drone developed by Zipline is considered. Zipline's drones have a cruise speed of 100 kilometres per hour, a flying range of 170 kilometres (equivalent to an 85 kilometre service radius), a load carrying capacity up to 1.75 kilograms and a shipping box volume of approximately $30 \times 20 \times 15$ (9,000 cm^3) (Zipline, 2020). This drone can service a hospital 80 kilometres away from a drone station in under 45 minutes (Ackerman and Koziol, 2019). The 85 kilometre service radius results in an area of approximately 22,698 square kilometres. Since the average district area is on average 10,453 square kilometres, all health facilities can be reached by drone from an RDC in that district. By placing a drone station at each RDC, the drones can cover all health facilities (Republic of Zambia Ministry of Health, 2006). However, in practice, some regions are highly dense areas but small in square kilometres, so fewer than one drone station per district is needed, which may lead to cost reduction.

Zipline has created a technique to speed up the launching of the drones allowing the drone to reach cruise speed quickly. This is done by an electric launcher, with acceleration from 0 to 100 kilometres per hour in 0.33 seconds. Additionally, the landing process is performed by pulling the drone from the air, making it unnecessary for the drone to decelerate much. Therefore, the drone is estimated to always fly at cruise speed and acceleration and deceleration time is not considered. Since the drone drops its load at a programmed point (corrected for environmental factors), it does not land for delivery (Zipline, 2020). For ease of computation it is assumed that the drone can always fly in a direct line and turn instantaneously.

A typical package of AL with 24 tablets (one adult regimen) weighs approximately 15 grams and has a volume of approximately ($2 \times 4 \times 10 =$) 80 cm^3. Therefore, for a Zipline drone, AL shipping capacity is limited by the drone volume to approximately 100 packages.

The choice to work with this model drone is due to the fact that it is already in use for cooled health care transport in Sub Saharan Africa (Zipline, 2020). Moreover, compared to other currently developed small medical supply delivery drones, the Zipline drone is relatively fast and, rather important for this research, has the one of the largest flying ranges for a single battery charge (Braun et al., 2019).

3.4 Costs of Truck and Drone Transport

For the cost of truck transport, different estimates have been made in the past. A standard rate for truck transport is estimated at \$ 0.87 per mile per lb. by Walia et al. (2018). The standard rate is then multiplied with a road parameter (set for a specific region) using the following formula: cost for truck delivery = standard rate $* e^{\alpha}$. Brown et al. (2014) estimate logistics cost for truck transport of vaccine delivery at \$ 0.03 per dose.

In 2018, Zipline has reached a contract with the government of Ghana for installing four distribution centres to distribute blood in about 100-150 deliveries per day. The whole project is estimated to cost \$ 12.5 million. The government of Ghana have estimated a cost of \$ 17.00 per delivery (Ackerman and Koziol, 2019). In their study, Wright et al. (2018) calculate a total transportation cost for Zipline drones in both costs per flight and costs per kilometre. Based on about 10,000 flights from a hub per year, the estimated costs per flights is \$ 20.00 and the costs per kilometre is \$ 0.20.

4 Methodology

The health care network studied is a three-echelon supply chain. Goods flow from higher level echelons to level zero where they reach the people that need it. The health care items arrive from an outside supplier (level three) to a national distribution centre (NDC), which is at level two. The health care items are then shipped to level one regional distribution centres (RDCs). Local health facilities, where the health care is administered to patients, are level zero. This distribution inventory system is an arborescent system, in which stock in a centre is from at most one other point, but each centre can serve multiple points in the lower level (Axsäter, 2015).

4.1 Analytical Model

4.1.1 General Model Assumptions

The asumptions upon which the analytical mathematical model is based are present first, followed by the model itself. Assumptions are related to the network structure, demand patterns, inventory policies, and availability and limits of transportation modes. These assumptions are made to help simplify the model, which is in itself quite complex, but to keep the essence of the problem.

As mentioned, the model is based on a fixed network that has one NDC, multiple RDCs, and multiple health facilities, all of whose locations are fixed and known. Moreover, each health facility is assigned one RDC from which it exclusively receives goods. This assignment is applicable for both truck and drone transport, and there is a drone station at each RDC. It is assumed that all district service areas are of such size that all health facilities within the service regions can be reached from the RDC by a drone. Although common in supply chain literature, lateral shipments between DCs and facilities are not considered. In the case of humanitarian health care supply, lateral shipments are more often ignored, due to the impracticality with real-world issues such as poor infrastructure (Chowdhury et al., 2017). Additionally, limits on capacity at any level of the distribution network and a probability of facility failure are not considered.

Demand at a health facility, i, is an independent distributed random variable, ξ, with mean λ_i and standard deviation σ_i. Because the rest of this analysis is focused on only one facility at a time and can be performed in the same way for each facility, the superscript i is not notated in the rest of this thesis. ξ has a cumulative distribution function (CDF) $\Phi(\cdot)$ and a probability density function $\phi(\cdot)$. The lead time for NDC-RDC is deterministic and notated by η. NDC-RDC transport is restricted to trucks. Distribution from RDC to a health facility can be either by truck or by drone, with lead times μ_t and μ_d respectively. It is assumed that drones have a maximum capacity and the number of trucks and drones available are sufficient serve all demand points. The need for maintenance and probability of breaking down are also ignored. Additionally, it is assumed that the inventory at the RDC from which the health facility orders

Table 1: Notations used in the research

ξ	demand distribution
λ	mean demand per week
σ	standard deviation of demand per week
η	lead time for the NDC-RDC echelon
μ_t	expected lead time for the RDC-health facility echelon for truck transport
μ_d	expected lead time for the RDC-health facility echelon for drone transport
A_r	surface of influence area for each RDC r
δ_r	facility density in influence area of RDC r
ζ	length of the planning horizon
N_r	the number of facilities supplied by RDC r
I_r	the number of items per monthly order dispatch for RDC r
L_r	the number of truck loads per monthly order dispatch for RDC r
M_r	the average number of stops per monthly order dispatch for RDC r
m_r	the average number of stops per truck load for RDC r
a_r	the subregion which can be supplied by one truck load in RDC r
n_r	the average number of destinations per truck load for RDC r
δ_r	the facility density per subregion a_r for RDC r
V_t	the truck capacity
V_d	the drone capacity
$C_{f,t}$	fixed transportation cost per item using truck transport
$C_{f,d}$	fixed transportation cost per item using drone transport
$C_{v,t}$	variable transportation cost per mile per item using truck transport
$C_{v,d}$	variable transportation cost per mile per item using drone transport
C_t	total transportation cost per item using truck transport
C_d	total transportation cost per item using drone transport
Δ	cost savings of truck over drone transport per item
h	holding cost per item per period
b	backlogging cost per item per period

is always sufficient to satisfy the facility's demand.

Costs incurred are those associated with inventory and transportation. It is assumed inventory costs are only incurred when the items are at a distribution centre or a facility and none are incurred while in transit. There are no fixed order costs incurred per order. Transportation costs are assumed to consist of a fixed and variable cost per unit distance for both trucks and drones. The distance between an RDC and a health facility is measured by the Eucledian distance, with travel distances based on continuous approximations.

In the model the linehaul transport is assumed to be deterministic, to have no disruptions and to be executed in such a way that there is always sufficient stock available at the RDCs to supply the local health facilities. Moreover, since this research focuses on the cost effectiveness of drone transport complementary to truck transport, which is only applicable for the local (last mile) transport, the linehaul transport is assumed the same in either model. Therefore, the model developed in the next section includes only the analysis for the last mile transport, and uses a typical health facility in terms of its inventory policy and costs. The assumption is made that this typical facility is representative for all facilities in the RDC, so results could be easily applied to an analysis of the entire RDC service region.

4.1.2 Delivery Transportation Costs

In continuous approximation approaches, transportation cost is estimated by the RDC service area and the health facility density in this area. The shape of the service region - circular or a somewhat irregular - has been found to be of little influence on the optimal solution value (Dasci and Verter, 2001).

Transportation by Truck

The delivery costs are based on a continuous approximation using the demand density in an RDC service region. The model assumes truck delivery transport is periodic with fixed delivery times. The delivery of supplies from the RDC to the various facilities is done by peddling, the dispatching of a truck that delivers to multiple facilities per load (Burns et al., 1985). It is assumed that the number of facilities in the region is larger than the number of loads required, so peddling is beneficial.

The total number of items demanded per dispatch, per month, at an RDC, r, is defined as

$$I_r = \sum_{j=1}^{N_r} \zeta \lambda_j \tag{1}$$

The number of truck loads required per dispatch is

$$L_r = I_r / V_t \tag{2}$$

In this section it is assumed that demand is approximately equally distributed over the distribution area. Blumenfeld and Beckmann (1985) have shown that for little demand variation, the average number of stops per dispatch can be estimated as

$$M_r = N_r(1 - (1 - \frac{1}{N_r})^{I_r} \tag{3}$$

The capacity of the truck is a limiting factor; therefore, the number of stops per truck load is

$$m_r = M_r / L_r \tag{4}$$

A subregion, a_r, for RDC r is defined as an area in which all facilities in that region on average can be fully supplied with the capacity of no more than a single truck. The average number of destinations per subregion is n_r and the density per subregion is δ_r. The formulas are

$$a_r = A_r/L_r \tag{5}$$

$$n_r = N_r/L_r \tag{6}$$

$$\delta_r = N_r/A_r = n_r/a_r \tag{7}$$

Following Burns et al. (1985), an estimation of the average peddling distance is made using the formula

$$d = K\sqrt{m_r a_r} = K\sqrt{\frac{m_r n_r}{\delta_r}} \tag{8}$$

where K is a constant. This formula is based on the analysis of the shortest path connecting m customers located randomly in a region using the Eucledian distance. K is estimated as 0.6 by Daganzo (1984a,b).

The transportation cost per item for transportation by truck is therefore given by

$$C_T = \left(C_{f,t} + C_{v,t}K\sqrt{\frac{m_r n_r}{\delta_r}}\right)/V_t \tag{9}$$

where $C_{v,f}$ is the fixed transport cost per load and $C_{v,t}$ is the variable transport cost per distance travelled and m_r and n_r are given by Equation (4) and (6) respectively.

Transportation by Drone

Drone delivery costs are also estimated using continuous approximations. However, drones carry less capacity and have limited flying range. For this reason, drone deliveries are only modelled using direct shipping from the RDC to a facility. As stated previously, the shape of the service region has little impact, so it is common to use approximations based on a circular service region (Dasci and Verter, 2001). Therefore, the average distance from the RDC to a facility, is the average distance travelled by each item and, can be approximated by the formula

$$d = f\sqrt{A_r} \tag{10}$$

where f is estimated to be approximately 0.382 if the demand region is compact and the RDC is centrally located (Langevin et al., 1996). However, it is estimated as $\frac{2}{3\sqrt{\pi}}$, which is approximately 0.376, in cases of correlated disruptions in the transportation network (Li and Ouyang, 2010). Since it is assumed drones can fly anywhere regardless of environmental factors, there are no disruptions, so the first mentioned factor is used in the analysis. Because the drone must also return to its starting point, the distance the drone travels is doubled:

$$d = 2f\sqrt{A_r} \tag{11}$$

It is assumed that the costs are not dependent on the number of items carried. Thus, the average transportation cost per item of a drone delivery can be estimated by

$$C_D = (C_{f,d} + C_{v,d}\ 2f\sqrt{A_r})/V_d \tag{12}$$

This equation provides linearization resulting in an underestimation of the transport costs per item, as the costs incurred are per full drone. Flying a drone with less items than full capacity results in lower attributed drone transportation costs, but the costs are fully incurred in practice.

4.1.3 Lead Times

For model tractability the lead time of truck delivery, μ_t, is assumed to be deterministic and four weeks. Moreover, the truck delivery frequency is monthly. Therefore, one inventory cycle is assumed to be one month starting from the day a truck delivery arrives at the facility. A period in the inventory model is defined as one week.

Drones have a very short lead time, because they can fly 80 kilometres in under an hour (Zipline, 2020) and it is assumed that a drone is always available to be dispatched. For model tractability the lead time for drones, μ_d, is therefore assumed to be zero: $\mu_d = 0$.

4.1.4 Inventory Policy Single Sourcing

For a single sourcing policy a simple periodic review with one supply mode and complete backlogging is used. It is a service-based model using an order-up-to level for the truck transport and is called the base model with optimal solution value C_{single} for four periods, one delivery cycle. The truck transport is assumed to arrive every delivery cycle. Holding costs, h, are charged per unit per period. Any unmet demand is backlogged with a unit cost of b per period. The policy with fixed ordering intervals is used both to be able to relate it better to the chosen dual sourcing policy, but also to comply it with a realistic situation of health care distribution in developing countries, which is commonly done at a fixed order intervals (Leung et al., 2016).

The policy used for single sourcing comes from a newsvendor equation to efficiently determine the optimal order quantity. It is based on the estimation of demand during the review period and the ordering quantity such that $P(Y(T) \leq R(T)) = \frac{b}{b+h}$, where $Y(T)$ is the demand during the review period, T, and $R(T)$ is the order amount per review period, which is the optimal base stock level.

The order-up-to level for a given service level is defined as

$$S_{single} = \Phi^{-1}(\frac{b}{b+h}) \tag{13}$$

This leads to the total costs of the single sourcing model:

$$C_{single} = C_T(2\lambda) + L(S_{single}) \tag{14}$$

where (S^*_{single}) is the optimal order-up-to level that minimises the total steady state costs given a certain service level. The inventory mismatch costs are $L(S_{single}) = h\int_0^{S_{single}}(S_{single} - \xi)\phi(\xi)d\xi + b\int_{S_{single}}^{\infty}(\xi - S_{single})\phi(\xi)d\xi$.

4.1.5 Inventory Policy Dual Sourcing

The inventory policy used in this paper to model the drone transport complimentary to truck transport comes from the dual sourcing inventory policies where there is one regular transportation mode which is relatively cheap but slow and one emergency transportation mode that is fast but more expensive. The resulting cost savings per item shipped through the slow mode are: $\Delta = C_D - C_T > 0$.

Mohebbi and Posner (1999) create a lost sales model using compound Poisson process for demand, finding an explicit expression for s_1, Q_1, s_2, Q_2 using the stationary distribution of the inventory level. Although a similar approach is applicable in this research, the complexity of the derived expressions prevents the model from being applied analytically. In contrast, Sheopuri et al. (2010) find that dual sourcing can be seen as a generalisation of a lost sales problem, showing that dual sourcing can, like lost sales models, not be solved optimally. These models can, however, provide analytical insights. The assumptions used in their proof, such as a zero lead time for emergency replenishments, are also applicable in the settings of this research.

This complexity has yielded, as mentioned Section 2.6, different methods being developed to approximate good policies for the dual sourcing problem. However, most methods that lead to analytical conclusions are methods for models with complete backlogging. As argued before, backlogging allows for easier analysis, so this assumption is used. One relevant method in the literature is a tailored base-surge (TBS) policy which is often favoured because it is simple and easy to use in practice, yet still captures the trade-off between cost and responsiveness (Allon and Van Mieghem, 2010). For this reason, analysing a TBS policy is a suitable way to understand the trade-offs in the optimal policy for truck and drone transport in the setting of this research.

Within this policy, Allon and Van Mieghem (2010) have created a relatively simple analytical model to analyse the key drivers in the TBS policy. However, their analysis assumes that the regular and the emergency supplier have the same delivery frequencies, so both modes are available every period in the inventory model. More realistic is that drone transport can be ordered more often than the monthly delivery of truck transport. The MST model of Dong et al. (2018) considers different delivery frequencies between the regular and the emergency supply mode but is structurally the same as the TBS policy. The model solves the problem with simple and analytically tractable solutions.

In their model, Dong et al. (2018) assume that the emergency delivery can be utilized every period in the inventory model and the regular delivery only received every other period. The model cannot be analysed by simply minimising the expected cost per period. Rather, a cycle structure with two periods has to be analysed, with each period having a specified base stock level for the emergency replenishments. The time between two deliveries of the regular supplier is considered a delivery cycle. Thus, for this model a period is defined as two weeks, such that the delivery cycle is still four weeks. This means that whenever λ, σ or cost parameters, for example, are used, these constitute two weeks. General characteristics of the inventory model will be presented next followed by the resulting model used in this research and an outline of the steps to get this model.

It has been shown that a TBS or MST model cannot be exactly analysed, mainly due to the overshoot analysis. Overshoot is the phenomenon that occurs when the inventory position exceeds the base stock levels (Allon and Van Mieghem, 2010) and is defined as O_t where t is the overshoot in period $t, (t = 1, 2, \ldots, \infty)$. This is a stochastic process and emerges because, in a regular inventory system, the base stock policy is an order-up-to policy. However, with MST or TBS also a regular order with a constant quantity Q is brought into the inventory, and the inventory position might shoot "over" the base stock levels. The main question in the policy is how to split the demand between the transport modes such that the costs are minimised. The costs consist of the expected transportation costs for both modes and the inventory mismatch cost.

The quantity ordered from the regular supplier is fixed at Q and is also shipped in a fixed delivery frequency, therefore, the lead time of the slow mode can be neglected (Dong et al., 2018). Flexible orders can be placed at the emergency source according to a base stock policy. Since there are two periods in each delivery cycle, the periods are numbered by an index i: $i = 1$ for the first period in which both a regular and an emergency replenishment can be received, and $i = 2$ for the second period in which only an emergency replenishment can be received. The model consists of three parameters: Q, S_1, S_2 that are the quantity of the regular supply mode and the order-up-to level for the emergency replenishment in the first and the second period of the steady state cycle respectively. Holding costs, h, are charged per unit per period and any unmet demand is backlogged with a unit cost of b per period. It is assumed that $b > C_D$, such that pure backlogging without emergency replenishment is not an optimal solution.

It is assumed that $Q < 2\lambda$ because the slow mode should not exceed demand since this would result in a divergent system where inventory would build up infinitely. Additionally, the overshoots are bounded since by the fast mode deliveries being adjusted based on the overshoot in a period, the overshoots do not accumulate infinitely. The overshoot can occur in the odd periods in which Q arrives, but also in the even periods indirectly. They are however different: if t is an odd period the inventory position at the end of the period is a function of O_t, $S_1 + O_t - \xi$. If t is an even period, the inventory position at the end of the period is $S_2 + O_t - \xi$. For the next period, the overshoot can be recursively written as:

$$O_{t+1} = \begin{cases} (O_t + S_1 - \xi - S_2)^+ & \text{when } t \text{ is odd} \\ (O_t + S_2 + Q - \xi - S_1)^+ & \text{when } t \text{ is even} \end{cases} \tag{15}$$

The overshoot in the steady state cycle is $E[O_{\infty,1}]$ and $E[O_{\infty,2}]$ for each period and is nonnegative. Since the inventory position before demand occurs is $S_i + E[O_{\infty,i}]$ with $i \in \{1, 2\}$, the expected mismatch cost is:

$$L_i(S_i + E[O_{\infty,i}]) = hE[(S_i + E[O_{\infty,i}] - \xi)^+] + bE[(\xi - S_i - E[O_{\infty,i}])^+] \tag{16}$$

This leads to the total costs of the model:

$$C_{dual} = C_T Q + C_D(2\lambda - Q) + \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}]) \tag{17}$$

where (Q^*, S_1^*, S_2^*) are the parameter settings that minimise the total expected cost in a steady state cycle. Also, $C_T Q$ is the total transportation cost for the regular truck transport and $C_D(2\lambda - Q)$ is the total expected transportation cost for the emergency drone transport. The last term is the expected total mismatch cost over the cycle.

Following the analysis of Dong et al. (2018), the following equations state the approximate optimal order-up-to levels $\hat{S}_1$ and $\hat{S}_2$ and approximate optimal reorder quantity $\hat{Q}$ for the dual sourcing policy that assumes $\Delta > h$. This last mentioned assumption is a realistic situation in the health care supply chain in developing countries.

$$\hat{S}_1 = 0 \tag{18}$$

$$\hat{S}_2 = \Phi^{-1}\left(\frac{b}{b+h}\right) - \sigma\sqrt{\frac{\Delta - h}{2h}} \tag{19}$$

$$\hat{Q} = 2\lambda - \sigma\sqrt{\frac{2h}{\Delta - h}} \tag{20}$$

Below provides a short analysis on the derivation of these equations. For a full analysis, refer to Dong et al. (2018).

Intuitively, $\Delta > h$ results in the facility using a higher Q for not only the demand of the first period but also part of the second. This is not possible for the entire second period demand, otherwise the system could go into an unstable equilibrium as explained previously. For this reason the probability of running out of stock in the first period is zero. Therefore, S_1 is not utilized and there is no $E[O_{\infty,1}]$. Also, there are no backorders after the first period so the inventory mismatch cost is $h(S_2 + E[O_{\infty,2}] + Q - 2\mu)$. Because S_2 now only depends on Q, it can be minimised by taking the first order derivative and equating it to zero, yielding an approximate optimal S_2 in terms of overshoot. By bounding the overshoot and using bounds on the optimal level of Q a bound on cost saving is achieved. Minimising the lower bound of the cost savings by taking the derivatives with respect to Q and equating these to zero, yields the equations as stated above.

The equations show that if the cost difference increases, more items are ordered through the regular transport. However, if demand is more volatile, shipments are more likely to occur through the emergency supply mode. The order-up-to level S_2 shows that the slow mode is more attractive if cost savings are higher, as captured in the decreasing of S_2 in Δ.

The inventory model shows that the effect in the transport costs influence the inventory model only through the difference between the costs of both transport modes. Even with the difference the effect on parameter setting is not captured with a linear relationship. However, the cost difference between the two transport modes has a direct linear effect on total cost savings through the number of products shipped with the regular, cost saving transport mode.

The downside of this approach is that it only considers the case in which the drone transport occurs twice as often as the regular truck transport. The case in which more than two periods (in which emergency shipments can be done) are considered per replenishment cycle, can be analysed similarly to this reduction but results in more decision variables. To analyse this and derive closed-form expressions would require the elimination of more terms of the cost function, which, while possible, would increase the approximation error. Therefore, it is suggested that for larger cycle lengths, a numerical analysis, such as complete enumeration, for each specific instance is the appropriate method to find the optimal costs in that instance (Dong et al., 2018).

4.2 Numerical Analysis

To test the model developed in the previous section, a numerical study is performed. The numerical part of this research is a case study using data from health facilities in Zambia. The study relies on a discrete-event simulation model of the inventory of AL products in a typical health facility using the inventory control policy as presented above: ordering products from its regional warehouse. Using a discrete-event simulation, a common approach in research on inventory models, entails a sequence of events in time, which are deliveries, replenishment orders and demand for products. The model is developed in the Java programming language (Leung et al., 2016).

The simulation is run with weekly time increments. The stochasticity is present in factors such as the random demand realisations. Inventory levels and the outstanding orders are the simulated variables that are tracked. During the simulation, different performance measures are monitored. The main performance measure is service level, which is part of the total demand that is satisfied directly at the moment when the patient arrives. Other important measures are the cost spend on different replenishments modes, holding costs, average demand, the number of drone replenishments (if applicable), and the demand backlogged due to a stockout.

Following the results and approach of Leung et al. (2016), it is assumed there is always sufficient inventory available in higher order echelons. At the beginning of the simulation there is no outstanding order and assumed stock availability equal to the order-up-to level in the case of single sourcing, or equal to Q_{truck} in the case of dual sourcing. To account for the impact an initial state might have, a warm up period of two years will be run, followed by a three year simulation from which to collect data. The simulation is run in different settings, such as different cost components, different drone capacities or different lead time settings. Because of the random elements in the simulation, 100,000 replications will be run to obtain representative results.

Several sequential steps are taken each week in the simulation:

1. if it is the first week of the month (corrected for the assumption of four weeks per month), a regular replenishment order can be placed. The order quantity is determined by the used inventory policy and added to the outstanding order quantity. At this moment the delivery week of the order is determined;

2. if a regular replenishment order is scheduled to be received that week it is added to the inventory level and the outstanding order quantity is updated. The costs of this order delivery are calculated and added to the total costs spent on regular orders together with the number of items delivered with regular orders;

3. in each week, demand is generated from the random variable drawn from the demand distribution as described in Chapter 3 and is added to the total demand. The demand is satisfied from the available inventory. Issued stock is calculated as the minimum between the inventory level and the demand, and these issues are subtracted from the inventory level. If there is not enough stock available to satisfy demand and drone use is incorporated, an emergency replenishment can be placed if allowed according to the current inventory policy. This replenishment is added to the inventory level immediately, can be issued directly, and these issues subtracted from the inventory level. Costs and order quantities for drones are updated. If with the emergency replenishment demand still cannot be met, another emergency delivery is considered in the same way. If any demand is not met, these are backlogged.

Inventory replenishment will be performed using the following inventory policy, which is based on the inventory replenishment model developed in the analytical part of this research. This is from now on called the base case. If it is the first week of the month a regular replenishment will be placed to the order-up-to level as given by Equation (13) in the single sourcing model or an order of size Q in the dual sourcing case which is calculated by Equation (20). The lead time is in the base case fixed at one month and, when investigating the effect of the assumption of deterministic lead time, drawn from a distribution to get a stochastic lead time. At the beginning of every third week of the month, if drone deliveries are allowed, a drone order can, in the base case, be placed of the size equal to the difference between the current inventory position and the order-up-to level estimated by Equation (19).

Sensitivity analysis will be performed to investigate the effect of several parameter settings, including different drone capacities and different costs of drone and truck transport, and different service levels. Additionally, to validate the model and gauge its performance in practice, several assumptions of the analytical model will be loosened to investigate its effect and identify crucial assumptions. Assumptions and their influence on the performance of the model that will be researched are, amongst others, the stochastic lead time of the truck transport, the reorder moment in the cycle, and the number of possible drone replenishments during the cycle.

5 Results

In this chapter, several results regarding the influence of different parameters and assumptions on the feasibility of drones for supply of malaria medication in Zambia are presented with respect to the applicability of the analytical model to real-world settings. First, results of the base case are presented with several different parameter settings. The base case refers to the model (either with or without drones) as described in Section 4.2 which follows the assumptions of the analytical model. Next, several assumptions are relaxed to analyse their influence. In the last part of this chapter, various assumptions are simultaneously relaxed to investigate their common effect on the applicability of the model to the real-world case.

5.1 The Base Case and Some Parameter Settings

Based on the discussion in Chapter 3 and the section above, several parameters are set that are used as base parameters. The unit holding costs are generally a part of the value of the product (Dong et al., 2018). It is difficult to estimate the product value of essential medicines in developing countries. Although research has been performed to find a proper estimation, an appropriate number was not found. Therefore the estimation of the holding costs have been set such that it is convenient for analysis of the model in relation to estimated transportation costs (which is estimated below). For this research, the holding cost is set at \$ 0.01 per item per period. The backorder cost is set such that it indirectly forces the firm to reach a service level, obtained using the newsvendor ratio $\frac{b}{b+h}$. For example, a service level target of 95 %, results in the backorder cost $b = 0.19$ per item per period. Other settings, such as the service area of the RDC and the demand distribution are taken from Chapter 3.

In the base case, the costs per item of the drone transport are based on the estimation of Wright et al. (2018) with the costs per kilometre including both fixed and variable costs, as presented in Chapter 3. Using Equation (12) with no fixed costs (since these are already included in the estimation per kilometres); a variable cost, $C_{f,d}$, of \$ 0.20; an average area, A_r, of 10,453 square kilometres; and a capacity, V_d, of 100 items results in a cost, C_D, of \$ 0.16 per item.

For truck transport an estimation can be made based on the continuous approximation approach as presented in Section 4.1.2. However, since the main aim and interest of this thesis are to find the applicability of the analytical model to a real-world setting, interest is in the relative cost advantage. When comparing the dual sourcing to the single sourcing case, only the relative advantage of the first to the latter is relevant. Therefore, in the base position, the costs of truck transport are chosen such that the ratio between the cost advantage of truck transport over drone transport and the holding costs in the dual sourcing model is 2. It has been found in the TBS literature that the approximation error is larger when the cost difference between the two transportation modes increases (Allon and Van Mieghem, 2010; Dong et al., 2018). However, with a ratio close to one, Dong et al. (2018) find that the approximation of the model is also not correct. This is the reason for setting the ratio at 2, leading to a cost per item for truck transport, C_T, of \$ 0.12, where it is used that the holding costs used for this ratio is required over two weeks, yielding holding costs of \$ 0.02. In the further part of this chapter, when results in terms of costs are discussed, these are average yearly costs.

Single Sourcing

The simulation was run in the base case setting both with and without drones. When drones were not part of the simulation, an order-up-to level for trucks was used and calculated by Equation (13). The items are ordered from the current inventory level up, before the arrival of the previous order (so an order is placed at the end of the replenishment cycle). This resulted in total costs of \$ 256.11 on average per year but an actual realized service level of 0.5899, well below the 95 % targeted service level. Therefore, the model seems inappropriate for the case of supplying malaria medication in developing countries. One main issue that may have caused the poor performance is the seasonality ratio that Leung et al. (2016) found in the data, which is estimated as high as 2.2, suggesting high volatility in the demand.

Leung et al. (2016) analysed the resupply of AL medication using the traditional max-min policy and also found that high volatility leads to under performance of inventory models. In a max-min policy, stock is ordered if it, at the reorder point, is below a minimum level. If it is below the miminum level, stock is ordered up to the maximum inventory level. Leung et al. (2016) set the order-up-to level to the demand of a certain month multiplied by a safety factor, which is usually around 2-4.

To properly compare the base case without drones to the dual sourcing model with drones, the base case without drones is run with a max-min policy with different multiples of the average demand of AL medication as the maximum. The minimum is set equal to the maximum, suggesting that when an order can be placed, and the inventory level is below this maximum, it is ordered up to that level. Always placing an order at the reorder moments is called forced ordering (USAID | DELIVER PROJECT, 2011). All other assumptions and parameters are similar to the base case.

(a) Service Level

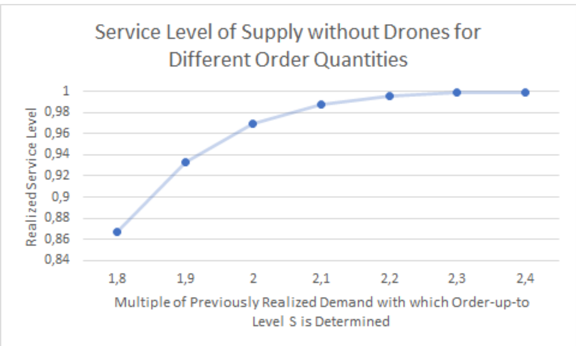
(b) Total Costs

Figure 1: Model Performance for Different Values of Order-up-to Level S for Trucks in the Max-min Policy for Supply without Drones using Average Monthly Demand

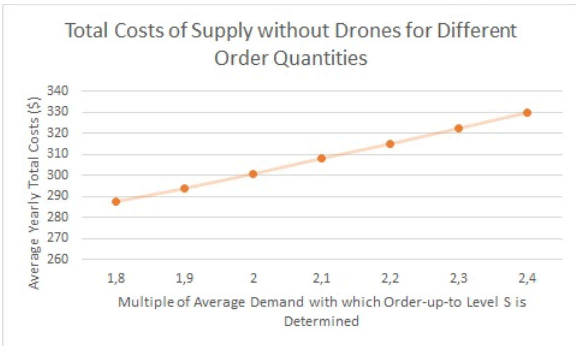
Figure 1 shows that when the order-up-to level is set to approximately 2.1 months of average monthly demand or higher, a service level of 95 % or higher was achieved. The costs increased as the order-up-to level increased, but this coincides with a higher service level. Costs increase when the maximum is increased, which is expected since a higher maximum leads to a higher average inventory. The costs associated with 2.1 months of average monthly demand are $ 308.04. However, when stochastic lead time, following the distribution presented in Chapter 3, is modelled, the attained service level for 2.1 months of average monthly demand is only 71.3 %. To get a service level of 95 %, the multiple with which the average monthly demand should be multiplied is 3.1. Costs increase to $ 358.29 due to the higher holding costs as a result of a higher inventory level. Compared to the model with 2.1 months of demand and deterministic lead time, the average yearly number of items ordered are approximately similar.

However, this is based on a very simple max-min model using average demand and no seasonality. The results of Leung et al. (2016), who researched the optimal max-min policy for malaria medication, show that improvement within max-min policies can be achieved. However, the research did not take costs of the model into account, but merely looked at the service level. Therefore, the main findings of optimal policies of Leung et al. (2016) are analysed in terms of costs. The model in this analysis does, however, use monthly demand data, something that the dual sourcing model does not require.

The max-min policy that considers the average demand of the next three calendar months of the previous year as a base for a maximum level, is considered to be the best policy in terms of service level out of all policies recommended by the USAID | DELIVER PROJECT (2011) for the distribution of malaria medication. Additionally, this policy results in relatively acceptable inventory levels given the attained service level (Leung et al., 2016). The best policy is 4 times the average demand over the next three months of the previous year. This model is also a forced ordering model.



(a) Service Level



(b) Total Costs

Figure 2: Model Performance for Different Values of Order-up-to Level S for Trucks in the Max-min Policy for Supply without Drones using the Demand of the Next Three Calendar Months of the Previous Year

When the policy that is described above is used in the simulation with deterministic demand, the attained service level is 100 % with costs $ 378.78. This service level is much higher than estimated by Leung et al. (2016) due to the difference in deterministic vs. stochastic lead time. The service level is extremely high, at the expense of extra costs. Therefore, when a service level of 95 % is aimed, a multiple of 2 for this policy is sufficient with deterministic truck lead time, see Figure 2. For a service level of 96.9 % the costs are $ 235.31.

When a stochastic lead time is used in the model with a factor of 2 a service level 75.0 % was attained with average yearly costs of $ 284.21. To attain a service level of at least 95 %, the multiplication factor was 3.1 and the resulted costs are $ 364.16. A targeted service level of approximately 97 % yields a cost of $ 387.75. The previous results show a high dependency of the policy on the lead time of truck transport: to attain a service level of about 97 %, the costs for variable lead time are about 65 % higher compared to the costs for the model with fixed lead time.

A standard max-min policy, in contrast to a forced ordering policy, is not considered in this thesis because fixed order costs are not used in this model. Moreover, the assumption was made that truck transport is utilized every month, as was given for the analytical dual sourcing model. For compliance with the dual sourcing model, the single sourcing model is also based on truck transport performed every month.

Dual Sourcing

Running the simulation for the base case with drones (with a fixed, deterministic lead time of 4 weeks, a drone capacity of 100, and the costs as described above) gives a Δ to h ratio of 2. Table 2 provides the statistics found for targeted service levels of 90, 95 and 98 %.

Table 2: Results of the Base Case with Drones for Different Service Levels

Targeted service level	**90**	**95**	**98**
Realized service level	0.9681	0.9783	0.9890
Average backorder duration (in weeks)	1.00	0.99	0.98
Average inventory level	94.11	100.90	111.01
Average yearly holding costs ($)	45.70	48.81	53.47
Average number of drone transports per year	3.75	3.76	3.75
Average number of items delivered by drone per year	163.75	163.15	162.77
Average yearly costs for drone transport ($)	26.04	26.10	26.04
Average number of items delivered by truck per year	1488	1488	1488
Average yearly costs for truck transport ($)	178.56	178.56	178.56
Average total costs ($)	250.30	253.47	258.07

From the results, it can be concluded that, for each targeted service level, the service level actually realized is higher. A higher service level also results in a higher average inventory level, which is consistent, since a higher stock level increases the probability that all demand can be satisfied. A higher inventory associated with a higher targeted service level, increases the average holding costs. This increase in holding costs is the only factor that increases the total costs since both the average number of drone transports and the average number of items delivered by drones are approximately equivalent regardless of the targeted service level. The results of the simulation are consistent with the findings of the analytical model, where the costs, for different service levels, only differ in the expected mismatch costs. These mismatch costs depend on the inventory level and the expected overshoot. The inventory level is then dependent on the order-up-to level of the drones, which is directly related to the service level. The transportation costs are similar regardless the targeted service level, which is also predicted in the analytical model: the transportation costs only depend on a similar, fixed Q and the realized demand (which is the same regardless the inventory policy).

Based on the formulas used to calculate the order-up-to level of the drone transport, a higher inventory level is consistent with a higher order-up-to level. The number of items delivered by drone are approximately the same for all targeted service levels, which suggests that when the stock falls below the order-up-to level, the number with which it is lower than that level is approximately the same for all service levels. That the amount ordered by drone is approximately similar regardless service level, is consistent with a higher average inventory level.

Single vs. Dual Sourcing

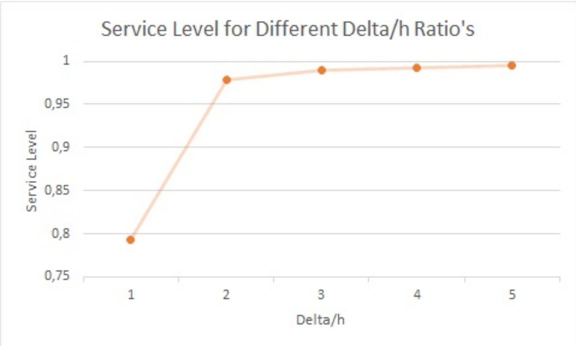
For the model using single sourcing with no monthly data, in the case of an achieved service level of approximately 97 % (for comparison to the findings of the 95 % targeted service level in Table 2), the average cost was $ 315.23, which was achieved at a multiple of 2.2 months of average monthly demand as a maximum. Comparing the average total costs from the achieved service level of 97 % for each model, the costs of the dual sourcing model are lower than the costs for single sourcing using the current parameter values: $ 315.23 and $ 253.47 for single and dual sourcing respectively. This cost difference suggests cost effectiveness in using drones complementary to truck transport compared to using truck transport exclusively. The reason for the difference is mainly due to the much higher average inventory level that was held.

However, when monthly data is used and a more sophisticated max-min policy is used, there are, with the current parameter values, no cost benefits for incorporating drones when a service level of approximately 97 % is realized (corresponding to the targeted service level of 95 % in case of dual sourcing): $ 235.31 and $ 253.47 for single and dual sourcing respectively.

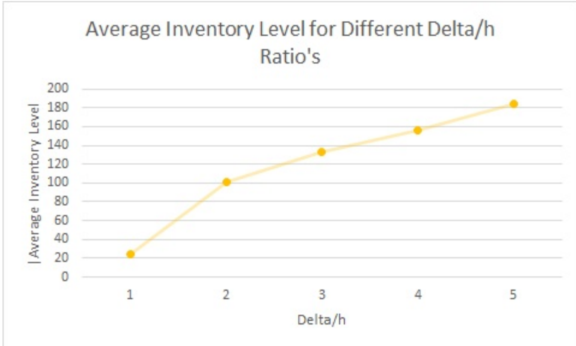
The next part of this chapter focuses on the different cost factors and their influence on the performance of the inventory policy within the dual sourcing model. When not further specified, in the next part of this chapter a targeted service level of 95 % is used.

5.1.1 Cost Factors

Following Dong et al. (2018), the influence of the ratio of delta to the holding costs is also analysed. Because in the model with drones a period is considered two weeks, the holding costs are doubled in calculating the order quantities and order-up-to level.



(a) Service Level



(b) Average Inventory Level

Figure 3: Model Performance for Different Ratios of Δ to h and a Targeted Service Level of 95 %

Figure 3(a) shows that when the ratio of the cost savings between the transportation modes (Δ) to the holding costs (h) is higher, the proposed analytical model works better in terms of higher service level. When the ratio is 1, the policy performs badly, since the service level is only around 80 %, which is much lower than the targeted level of 95 %, indicating that the model is not applicable for these settings. This poor performance at a ratio of 1 is consistent with Dong et al. (2018) who also conclude that the model is not correct for findings with a Δ/h ratio close to 1. For all other ratios, the achieved service level is higher than targeted.

As expected, when cost savings on transport are relatively high, this was the favoured cost advantage, at the expense of increased holding costs. More inventory was ordered by truck transport, which resulted in more stock being held during the inventory replenishment cycle, see Figure 3(b). This is also in accordance with the fact that, if more is shipped through the regular mode and held in inventory, less emergency transports are needed. This is consistent with the results that are shown in Figure 4.

When costs are considered, it is difficult to compare the total costs for each ratio to one another, since the cost of drone transport was changed and, therefore, it directly influences the total incurred costs. However, comparing various cost components between the models with different ratio's and comparing components within the results of one ratio, show the following.

First, the total costs increase as the ratio increases. This is, as previously mentioned, partly due to the increased inventory level, which results in increased holding costs. Additionally, the total costs are increased with the costs of truck transport, also consistent with the findings that more items are shipped with the regular transport mode. A larger delta to h ratio, while keeping

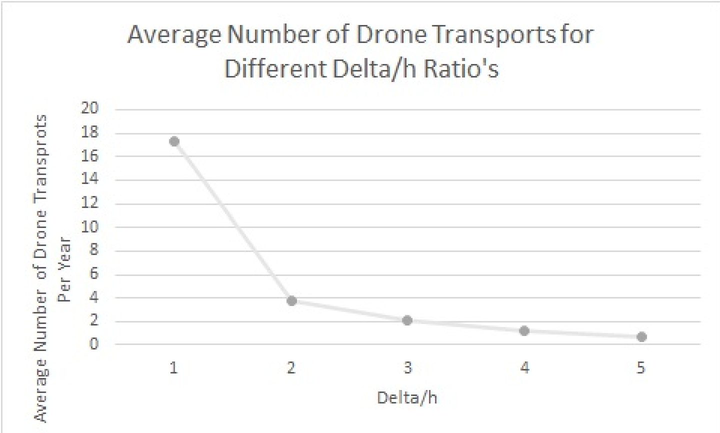


Figure 4: Average Number of Drone Transports per Year for Different Ratios of Δ to h and a Targeted Service Level of 95 %

truck transportation costs the same, results in higher drone transportation costs. However, since there are less items shipped through the, when the ratio increases, relatively more expensive, emergency transport, total costs spent on this transportation mode are smaller, even though the costs per item increase. The extra cost per item for drone transport is completely offset by the number of items shipped. The analytical model predicts that the costs for truck transport increase when more items are shipped through the regular transport mode. This directly results in less (cost for) items shipped trough the emergency transport mode. Also, holding a higher inventory level, due to the higher order-up-to level, increases costs.

In order to get a linear relationship and use the cost per item for calculating delta, the costs of drones are an underestimation of real costs. The costs per item are calculated as if the drone would fly with full capacity with each item carrying an equal portion of the flight costs. If there are less items in the drone, only costs for those items is taken into the cost calculation. It is, however, more realistic to incur the costs per drone instead of per item. The effect of incurring fixed costs per drone versus variable costs is reviewed in Section 5.1.3.

5.1.2 Demand Rate

In this section the influence of the demand rate is evaluated. First, the model was run for a targeted service level of 95 % using a lower and several higher demands. This is presented with a mean of the higher/lower demand as a multiple of the actual mean demand while keeping the same coefficient of variation. Keeping the same coefficient of variation with higher demand results in more volatile demand. Figure 5 shows the achieved service levels, with varying demand rate. The demand rate of 1 is the base case with demand estimated from the data. The results show that the achieved service level is above the targeted service level as well as approximately equivalent and for all demand levels. This indicates that the model works also for higher demand and more volatile demand. A comparison in terms of (total) costs is not possible, since higher demand per definition results in higher costs. What was observed is that, apart from a higher inventory level resulting in higher holding costs, both truck and drone transport (costs) increased, which is consistent with the prediction of the analytical model, that imposes a higher Q when demand is higher. Moreover, higher inventory mismatch costs are expected with more volatile demand.

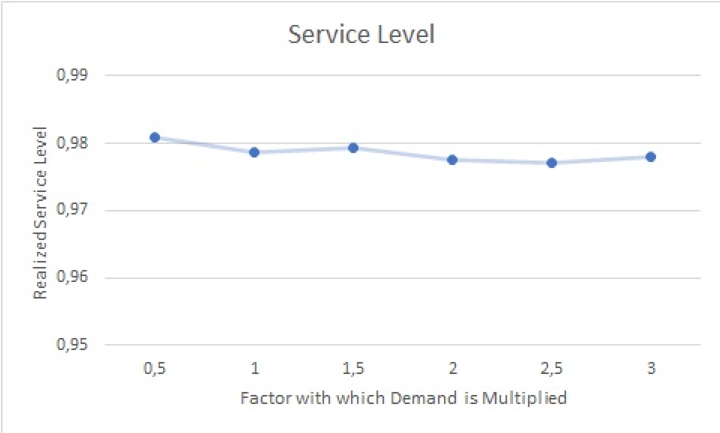


Figure 5: Realized Service Level for Different Demand Volumes as Factor of the Estimated Demand and a Targeted Service Level of 95 %

Due to the higher demand it is expected that, when costs are incurred per drone deployed rather than per item, the cost difference will be smaller. Likewise, when the demand is lower, the cost difference will be larger. Because of higher demand, higher volumes need to be ordered, and more of a drone's capacity will be utilized. This is confirmed by the results presented in Figure 6, which show the results which model the percentage with which the costs relatively increase when fixed costs per flight are incurred instead of variable costs. The absolute costs are not shown because, due to higher volatility with higher average demand (as the coefficient of variation is kept the same), the allocation between the truck and drone transport is different. The costs converge if the demand is higher.

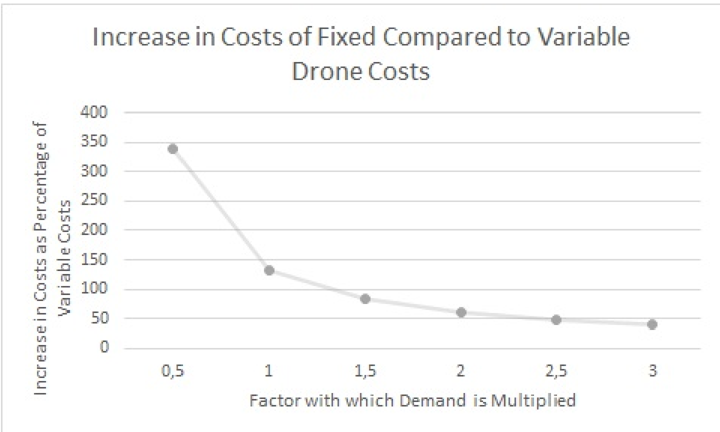


Figure 6: Percentage with which Using Fixed Relative to Variable Costs of Drone Transport Increases for Different Demand Volumes as Factor of the Estimated Demand and a Targeted Service Level of 95 %

5.1.3 Drone Capacity

In this section, the influence of drone capacity is analysed. Since an order-up-to level is used for drone transport and costs are calculated per item, it is expected that changing this parameter does not influence the costs generated in the model. This was confirmed by the simulation. However, drone capacity did affect the average number of drone flights per year as shown below in Figure 7.

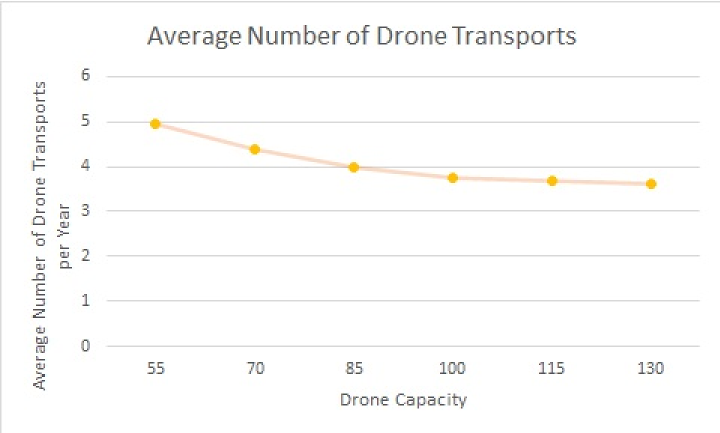


Figure 7: Average Number of Drone Transports per Drone Capacity and a Targeted Service Level of 95 %

Figure 7 shows that the number of drones flown per year on average decreases with increasing the drone capacity. However, the decrease attenuates as the capacity increases until a capacity of 115 and 130, at which point the curve is becomes almost flat, indicating that drone orders did not often exceed those high capacities when drones needed to be deployed.

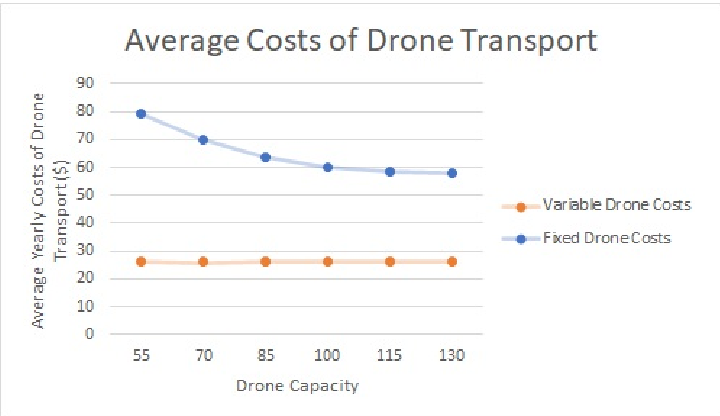


Figure 8: Average Costs of Drone Transports per Year per Drone Capacity Using Fixed or Variable Drone Transportation Costs and a Targeted Service Level of 95 %

As mentioned before, the total transportation costs for drone transports were not changed, since these were calculated per item. In practice, these costs are an underestimation of the real costs, since costs are more realistically incurred per flight then per item. Therefore, the influence of capacity should also be investigated in terms of costs incurred per drone, regardless of the number of items that are transported in that drone. The results of the costs per item (variable cost) versus per drone (fixed cost) are shown in Figure 8, which shows that the costs did increase with lower capacity and costs charged per drone. Moreover, the costs for all capacities, when incurred per deployed drone, are at least twice as high as the estimated costs when charged only per item. For the capacity of 55 regimens, this cost increase was more than three times higher. The minimal variation in the results when using variable costs are due to the random element in the simulation runs.

5.1.4 Fixed Order Quantity and Order-up-to Level

For the dual sourcing inventory policy the fixed order quantity, Q, for regular orders and the order-up-to level, S, for emergency replenishments, have been determined by the formulas in Section 4.1.5. To investigate the validity of these calculated levels in the case of malaria medication, a sensitivity analysis for different levels of Q and S is performed.

With base case settings and a targeted service level of 95 %, the fixed order quantity of AL medication via truck, Q, is set in the base case to 124 regimens, the order-up-to level for drone transports, S, is set to 84 regimens. Results of different analyses are shown in Figures 9 and 10.

(a) Service Level

(b) Total Costs

(c) Number of Items Delivered by Drone

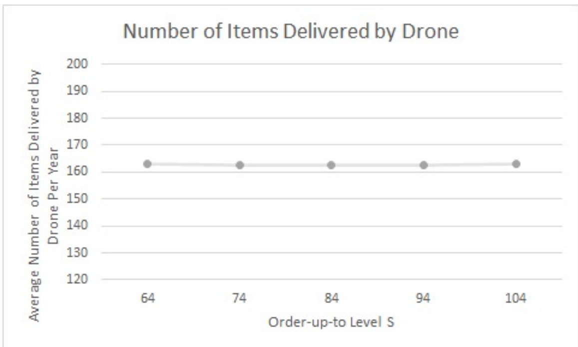
Figure 9: Model Performance for Different Values of Fixed Order Quantity Q and a Targeted Service Level of 95 %

It was expected that the model would give a lower value when estimating costs using Q as 124 items compared to other values of Q, since, according to the analytical model, this value was minimising costs for a service level of 95 %. In contrast, as shown in Figure 9(b), it is observed that with Q set at 109 items, the costs are lower and a service level of over 95 % is reached. However, since the drone costs are an underestimation of the actual costs, in reality, drone costs are much higher. Changing Q from 124 to 109 resulted in approximately double the number of items delivered by drones: therefore, in reality when fixed costs are likely charged, increasing the drone deliveries would increase the costs more than was estimated using the approximation if a (not necessarily full) drone would need to be deployed more frequently.

Using a Q of 94 and lower, both increased the annual costs and did not meet the targeted service level. An order quantity of 139 (higher than the suggested order quantity) gave a very high service level but the costs were also increased significantly. This suggests that a higher order quantity increases service level, but the service level was already overestimated in the base case using 124 items. A higher order quantity did result in very few items delivered by drones. In this case the drone costs are also highly underestimated, since the cost of drone transport is calculated based on frequent use and full drones.

(a) Service Level

(b) Total Costs



(c) Number of Items Delivered by Drone

Figure 10: Model Performance for Different Values of Order-up-to Level S and a Targeted Service Level of 95 %

Figure 10 shows that for different order-up-to levels, the costs only increased in S, yet the number of items ordered on average stayed approximately the same. This indicates that ordering up to a higher inventory level results in higher holding costs that was not offset by less items being ordered at a later point in time. The targeted service level is met from an order-up-to level of 74 and higher, indicating a smaller order-up-to level than suggested in the model also provides the appropriate service level while resulting in smaller costs. An order-up-to a level lower than 74 decreases costs, but does not provide a sufficient service level.

That the costs are higher when the order-up-to level for drones is higher, is consistent with the cost estimation of the analytical model. The costs are, in the analytical model, dependent on transportation costs and the inventory mismatch costs. The latter is directly dependent on the order-up-to level, which, if higher, results in higher inventory mismatch costs and, likewise, if lower, results in lower inventory mismatch costs.

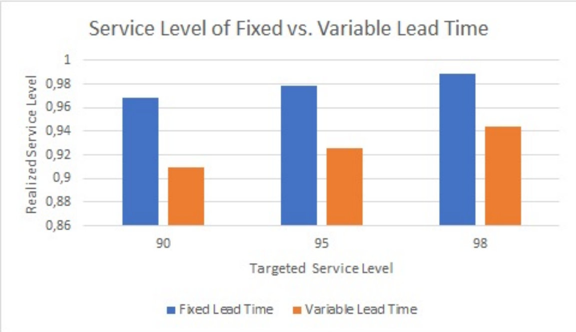
When adjusting Q and S, it was seen that the cost minima were attained at other than the, by the formula's of the analytical model, calculated order quantity and order-up-to level. Whether this changes in any way by using fixed instead of variable costs for drone transports (even though this is not what the analytical model uses), is analysed in Section 5.3.1.

5.2 The Impact of Assumptions

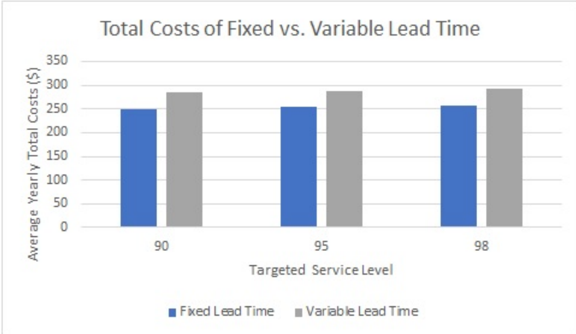
In the analytical model several strong assumptions have been made in order to analyse the inventory replenishment model. In practice however, some of these assumptions are not necessary or are highly unlikely. To determine the effect relaxing some of these assumptions would have on the performance of the model, the assumptions are relaxed one by one. All other assumptions and parameters are kept similar to the base model, this to be able to investigate the individual effects of these assumptions. In Section 5.3 the effect of relaxing multiple assumptions simultaneously will be analysed.

5.2.1 Deterministic vs. Stochastic Lead Time for Truck Transport

The data used indicate that for the local transport, trucks have a stochastic lead time. This secondary lead time is approximated by Leung et al. (2016) as a geometric random variable. Moreover, the truck transport can be delayed due to seasonal weather problems, resulting in the need to account for a monthly accessibility probability. Therefore, the assumption that truck transport follows exactly a deterministic, monthly schedule is highly unlikely. However, the analytical model for dual sourcing is developed based on this notion as one of the key assumptions. Therefore, if lead time is stochastic, the performance of the model could be affected, leading to results very different from the targeted service levels and targeted cost minimisation.



(a) Service Level



(b) Total Costs

Figure 11: Model Performance under Fixed and Variable Lead Time for Different Targeted Service Levels

Figure 11(a) shows the performance of the model with fixed versus variable lead time for different service levels. The variable lead time is modeled using distributions given in Chapter 3. The results show that, although the targeted service level is reached when this is targeted at 90 % for both fixed and variable lead times, the model with fixed lead time gave a much higher service level. For a targeted service level greater than 90 %, a stochastic lead time prevented achieving the targeted service level. Figure 11(b), shows that the costs are higher for the model with variable lead time versus a fixed lead time.

The cause of the extra costs are shown in Figure 12. The costs are split into truck transportation costs, drone transportation costs and holding costs. The results show that, when lead time of the regular transport is variable in the model, the costs of truck and drone transports are approximately equivalent, but holding costs increased more than 65 %. This indicates that more items were not necessarily delivered by drone, but due to the random element in delivery, stock is held longer in the inventory leading to a higher holding costs. The analytical model predicts that the transportation costs are, on average, only dependent on the total expected demand. This is not changed by relaxing the assumption of fixed lead time and, therefore, the findings of the simulation are in line with the prediction of the analytical model. However, the higher inventory level leads to higher inventory mismatch costs.

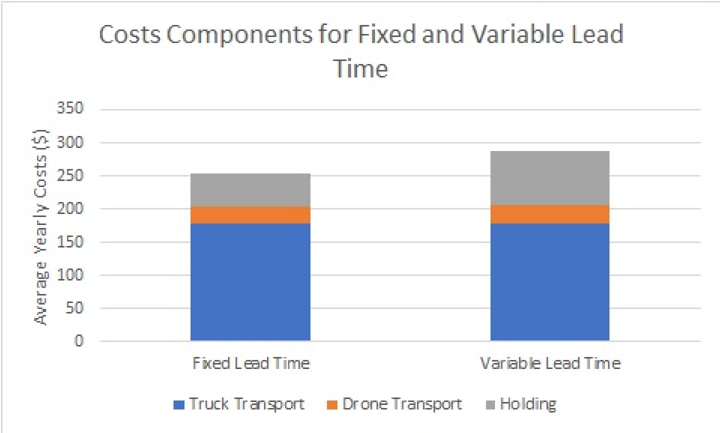
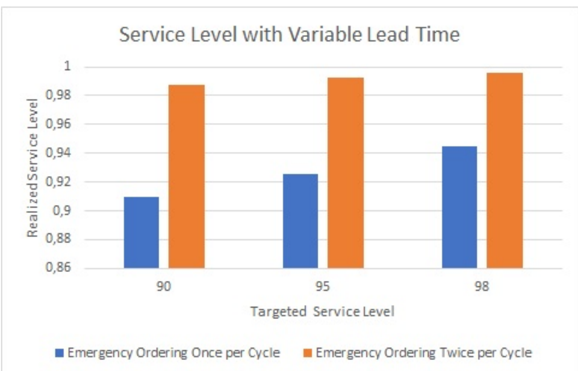


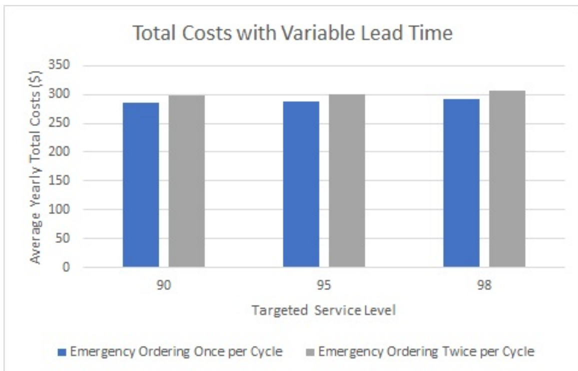
Figure 12: Cost Components of the Total Costs for a Model with Fixed and Variable Lead Time and a Targeted Service Level of 95 %

Comparing the dual to the single sourcing model with stochastic lead time results in, for a realized service level of approximately 95 %, a cost advantage of using drones over the model without drones. The model with drones results in a total average yearly costs of \$ 292.37 whereas the model without drones results in \$ 364.16.

An assumption of the analytical model is that emergency deliveries can be ordered twice as often as regular deliveries. This means that emergency replenishments can be placed in both the first and the third week of a month. In the case of deterministic lead time, placing an order in the first week was never utilized, because in that first week also the regular order arrived and with $\Delta > h$ the better option is always to fully stock the first half of the replenishment cycle with the regular transport. However, with stochastic lead time for regular replenishments, the truck may not arrive in the first week of a month. Therefore, the effect of the possibility of a drone replenishment in the first week of a month has been modeled. The order-up-to level is kept similar to the base case, even though the theory for which it is developed is not correct, as the expectation of the overshoot is no longer accurate.



(a) Service Level



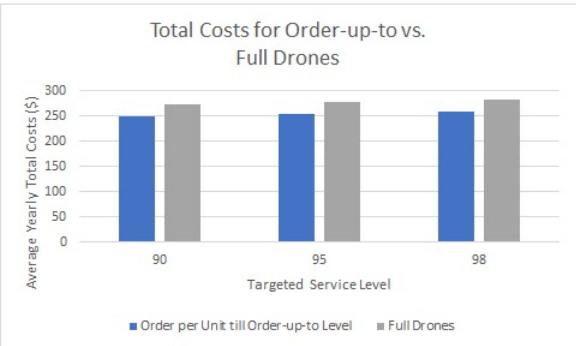
(b) Total Costs

Figure 13: Model Performance under Fixed and Variable Lead Time for Different Targeted Service Levels and Biweekly Emergency Replenishments

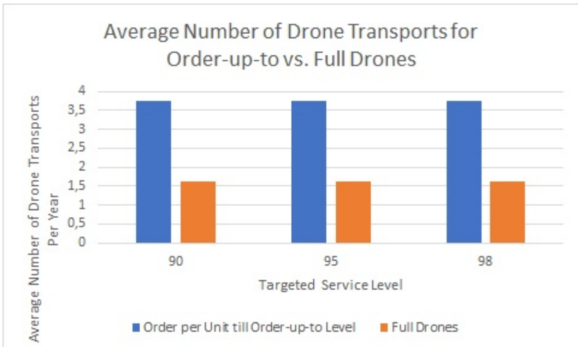
The results of this last-mentioned variation is shown above in Figure 13. The figure shows that, when an emergency drone replenishment order can also be made in the first week of the month, the service level is higher, such that the targeted service level is met and even higher than in the base case with a fixed, deterministic lead time. The costs, however, increase for every targeted service level. This is mainly due to the increase in inventory level. When adjusting for the possibility of ordering from the emergency replenishment twice a month, the order-up-to level was not changed. The effect of the order-up-to level in the situation of stochastic lead time and biweekly ordering is analysed in Section 5.3.2.

5.2.2 Per Item vs. Per Full Drone Emergency Replenishment

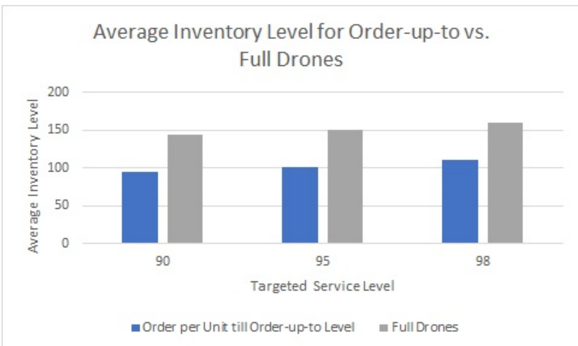
The analytical model is based on a fixed order quantity for regular orders but uses an order-up-to replenishment policy for the emergency shipments. However, always flying a drone at full capacity, also called batch replenishment, may be more cost effective since drones are associated with high fixed costs due to things such as personnel to launch the drone and the battery charge for each flight. To analyse the effect of flying a drone always at full capacity, the model is set such that, whenever there would be any emergency replenishment according to the order-up-to policy as used in the base case, the amount to be ordered is set to the first multiple of the drone capacity that is at least the number of items as would have been ordered using the order-up-to policy.



(a) Total Costs



(b) Number of Drone Transports



(c) Inventory Level

Figure 14: Model Performance for Order-up-to Replenishments and Full Drone Replenishments for Different Targeted Service Levels

For all targeted service levels, the realized service level when delivering full drones was always above 99 %. Although this higher service level is achieved, the costs were higher as well. This is due to the increased holding costs, see Figures 14(a) and 15. The higher holding costs, an increase of 48 %, are consistent with a higher average inventory level which is shown in Figure 14(c).

Figure 14(b) shows that when drones are flown at full capacity, less drones were deployed. The increased average inventory level could have resulted in the threshold for drone orders not being reached. In contrast, even though less drones were deployed, each drone carried at least as many items as in the base case, resulting in an approximately similar number of items shipped and drone costs, since these costs are linear. See Figure 15.

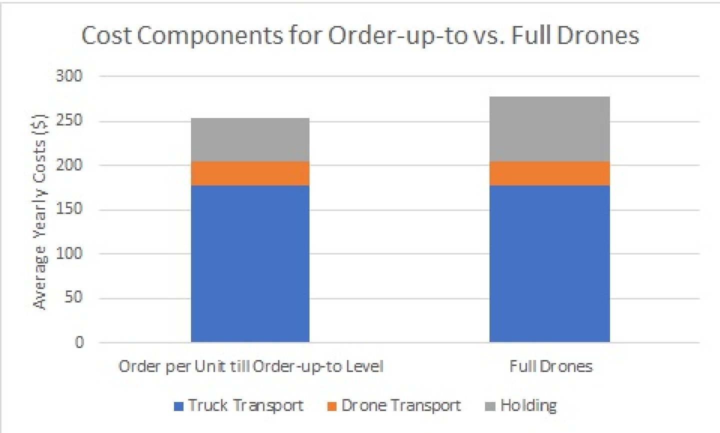
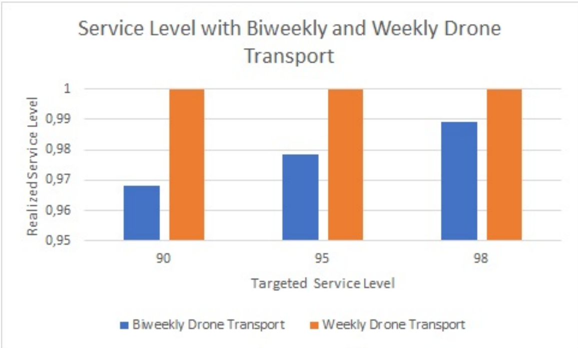


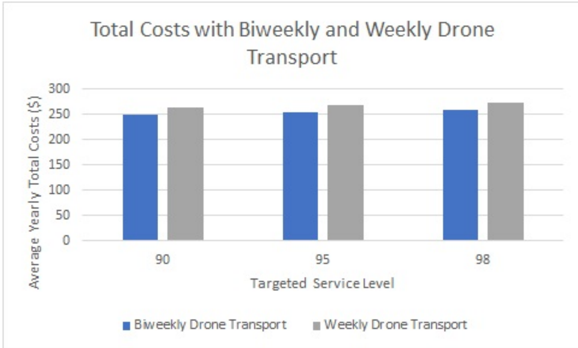
Figure 15: Cost Components of the Total Costs for a Model with Order-up-to Replenishments and Full Drone Replenishments and a Targeted Service Level of 95 %

5.2.3 Biweekly vs. Weekly Drone Transport

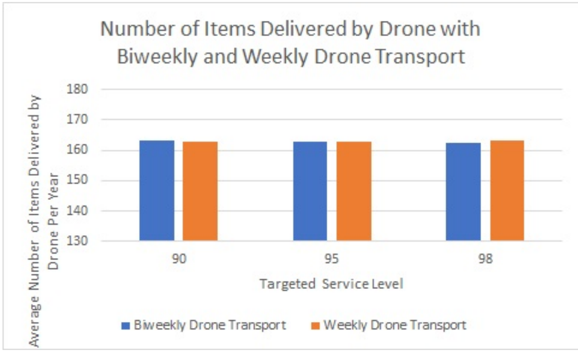
The analytical model developed in Section 4.1.5 assumes that drone transport can be done every other week, which is defined as every period for the dual sourcing model. After deriving the analytical results for a model with this assumption, Dong et al. (2018) stated that allowing more frequent emergency replenishments would rather complicate the analysis and enlarge the approximation errors. However, in practice drones could be deployed every week (or even more often, however, since the study is based on weekly increments, more frequent intervals are not researched). Results of several main performance measures are shown below in Figure 16.



(a) Service Level



(b) Total Costs



(c) Number of Items Delivered by Drone

Figure 16: Model Performance for Weekly and Biweekly Emergency Order Moments for Different Targeted Service Levels

The figure above shows that, when drone orders can be placed every week, the service level is much higher, as high as greater than 99 % for each targeted service level. This was expected since, when stock falls below the order-up-to level, an order can be placed. This order-up-to level is based on supply for one period (two weeks) of demand. When the stock is replenished to that level, the demand of the upcoming week will be met in most cases. The average time orders are backlogged, for a targeted service level of 95 %, is only 0.05 weeks. However, total costs increase. Figure 16(c) shows that approximately the same, or even less items are delivered by drone on average. The increase in costs is again due to the increased inventory level with increased holding costs. This is visualized in Figure 17. Due to the higher average inventory level, a higher service level is obtained at the expense of higher inventory costs.

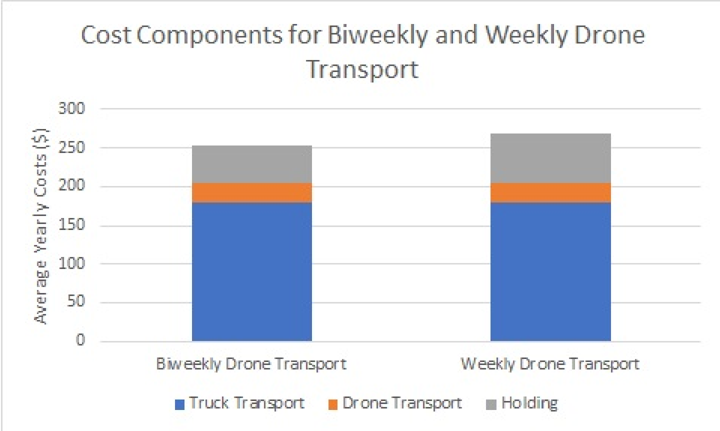


Figure 17: Cost Components of the Total Costs for a Model with Weekly and Biweekly Emergency Replenishments and a Targeted Service Level of 95 %

The previous analysis has been performed again with an order-up-to level of 74, similar to the one calculated in the base case, suggesting that having weekly replenishment moments mostly facilitates better coordination when demand is higher than expected. However, by having more replenishment moments, the amount of safety stock until the next replenishment moment is less as well, suggesting a lower order-up-to level would suffice for emergency replenishments. This is dependent on the interaction between the decrease in holding costs and the extra drone replenishment costs. As Dong et al. (2018) argue, this requires a new analysis of the expected overshoot each period, but this is prone to estimation errors. The effect of different order-up-to levels when weekly drone replenishment is performed is analysed in Section 5.3.3.

5.2.4 Backlogging vs. Lost Sales

One of the main assumptions in the model developed is that all unmet demand is completely backlogged. This has enabled the model remain analytically tractable through working with a continuous and potentially negative inventory position. The approximation of the overshoot each period in the dual sourcing inventory replenishment model and the optimal policy, using the overshoot approximation, for minimal costs is depended on this assumption as well. However, as was seen in the literature, in developing countries, a more realistic scenario may be to have (at least part of) the demand lost in case of a stockout. In this section, to see how it affects the model, demand is considered lost in case of a stockout, which leads to the following results.

When the model was changed to a lost sales model, the results showed not much difference from the base case. As expected, the service level for the lost sales model was slightly higher for each service level, because the service level, similar to the backlogging model, is based on the number of patients that receive treatment as soon as they arrive at the health facility (regardless of the time they would have to wait for treatment in the case of backlogging). The likely cause of the slight increase in the service level is that backlogged demand that also needs to be supplied from either the regular or emergency replenishment does not exist, allowing the full replenishment to go into the current inventory.

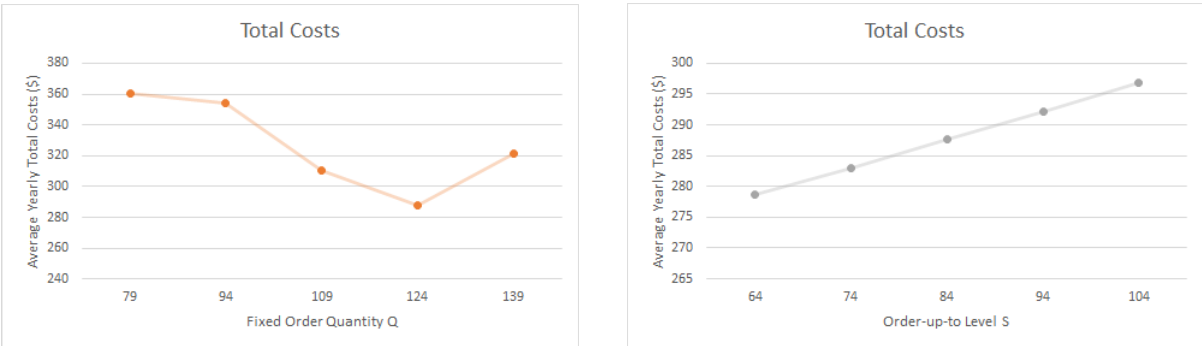
The slight increase (of 2 % only) in the inventory level, is due to the fact that it cannot be negative and, when an order arrives, the full load is added to the inventory level. The increase in inventory level resulted in less items that were ordered by emergency replenishment, which has resulted in a slight decrease in total costs. The slight cost decrease was, however, less than 2 % for the model with a targeted service level of 95 %.

5.3 Different Assumptions Combined

In this section multiple assumptions and parameters are simultaneously analysed to find the effect the combination has on the model. The combinations, suggested from the previous sections, are investigated based on relevance to a real-world scenario.

5.3.1 Fixed Costs and Q and S

It is more realistic to incur fixed instead of variable costs for drone transport. When this is the case, the parameters for the fixed order quantity or the order-up-to level may be optimal for different values than predicted by the analytical model, which uses variable costs for drone transport. Results of this analysis are shown in Figure 18.



(a) Fixed Order Quantity Q

(b) Order-up-to Level S

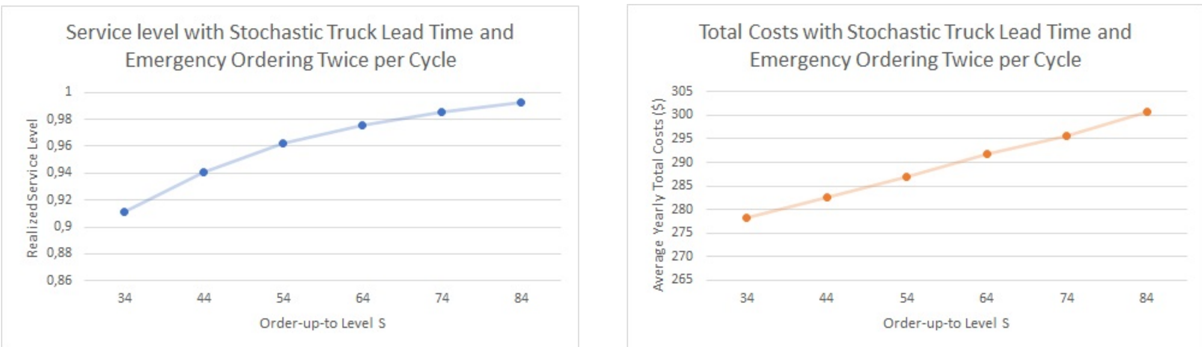
Figure 18: Model Performance for Different Values of the Fixed Order Quantity Q and the Order-up-to Level S and a Targeted Service Level of 95 %

Changing only the cost factor of drone transportation does not change any other performance measure except total costs and drone transportation costs. Therefore, only the impact on the total costs is shown. Figure 18(a) shows that, when fixed costs are incurred instead of variable costs, the optimal reorder quantity is actually reached at the, by the analytical model proposed, order quantity of 124. Compared to the findings of the analysis of the model with variable costs, which shows that the optimal order quantity is less than the quantity set by the analytical model, the model with fixed costs for drones reaches optimality at a higher quantity of truck transport. That more items should be shipped through the regular transport mode makes sense, since in the model with fixed drone costs, drones are relatively more expensive (the variable cost were an underestimation of the drone costs). If the emergency transportation is more expensive, more items should be shipped by regular transportation.

The total costs for different values of the order-up-to level for drone transport shows a similar trend as in the simulation using variable costs. The analytical model shows that costs are dependent on the transportation and inventory mismatch costs. The transportation costs depend on the truck transportation costs which are fixed in Q and the drone transportation costs which is based on the demand during the period minus the amount shipped through the regular transport mode. The drone costs did, compared to the model with variable costs, increase systematically. Inventory mismatch costs are still similar to the model with variable costs. Since truck transportation costs and inventory mismatch costs did not change, the results showed that using fixed or variable costs results in a similar positive trend with increase of the order-up-to level.

5.3.2 Stochastic Lead Time, Biweekly Ordering and Order-up-to Level S

The effect of drone orders both in the first week and third week (so in both periods) of the replenishment cycle with stochastic lead time of truck transport, was analysed in the second half of Section 5.2.1 and it showed that the service level was very high with a slight increase in costs. As was mentioned, the order-up-to level was not adjusted even though relatively more often a drone could be deployed. Below the sensitivity analysis of different order-up-to levels with regards to service level and total costs are shown below. These are all calculated for a service level of 95 %.



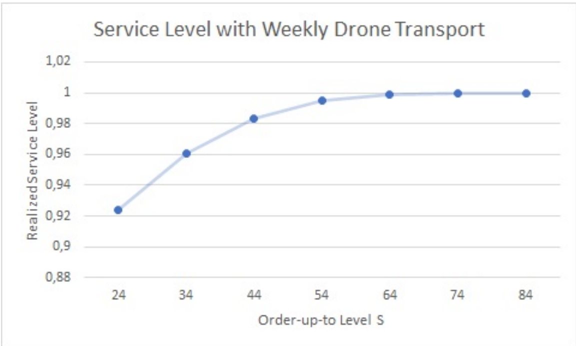
(a) Service Level (b) Total Costs

Figure 19: Model Performance for Different Values of Order-up-to Level S, Stochastic Lead Time, Emergency Ordering Twice per Cycle and a Targeted Service Level of 95 %

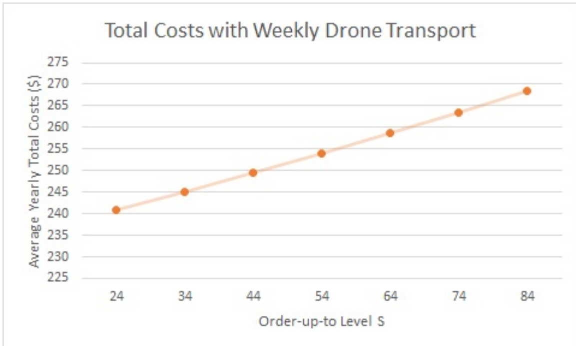
Figure 19(a) shows that the targeted service level is met at an order-up-to level of 54 and higher. Figure 19(b) shows that the lower the order-up-to level, the lower the costs. These findings combined show that, with emergency ordering twice a month and stochastic lead time, the order-up-to level S can be lowered to 54 while still meeting the targeted service level. This results in a cost reduction, which is again due to lower average inventory that needs to be held. The number of flights per drone are approximately similar for the various order-up-to levels. Consistent with the analytical model, the transportation costs did not change, only the inventory mismatch costs, which is dependent on the order-up-to level and overshoot analysis, did.

5.3.3 Weekly Ordering and Order-up-to Level S

In the previous section, it was shown that, when weekly drone ordering is allowed, the service level was always above 99 % at the expense of higher costs. It was suggested the order-up-to level, due to the now incorrect estimation of the overshoot, should be adapted to obtain the targeted service level without increased costs. Therefore, a sensitivity analysis of different order-up-to levels in combination with weekly ordering is performed. The results are shown below in Figure 20. The base case uses an S of 84 items.



(a) Service Level



(b) Total Costs

Figure 20: Model Performance for Different Values of Order-up-to Level S, Weekly Drone Transport and a Targeted Service Level of 95 %

In Section 5.1.4, it was seen that total costs decreased when the order-up-to level for drone transports were lower. However, at a level lower than 74 items, the targeted service level was not met. For that reason, the sensitivity analysis for weekly transport was conducted for an order-up-to level below 84. Combined with weekly transport, the costs decrease when the order-up-to level is lower. However, from a level of 24 the service level was no longer met, which is lower than the level for biweekly drone transport, suggesting that with weekly drone ordering the optimal order-up-to level should be lower.

According to the order-up-to level with the lowest cost while still meeting the targeted service level of 95 %, weekly ordering leads to cost reductions. For biweekly ordering the order-up-to level is 74 with average yearly costs of \$ 248.89. For weekly transport this level was 34 with average yearly costs of \$ 244.94.

6 Conclusion

In this thesis the main objective has been to analyse the cost effectiveness of incorporating drones into the supply of essential medicines in developing countries. The aim was to model this in terms of different (cost) factors and to find the effect of each of these on the model. To this end, as a first step, an analytical model has been developed. To see whether this model is suitable to be used in practice, a validation research through a simulation study has been performed on malaria medication distribution in Zambia. The following conclusions can be drawn.

In developing countries, some health facilities are often hard to reach. Inaccessibility is especially high during the rainy season, in which part of the road network is flooded. Drones, on the contrary, can traverse difficult terrain as they can be deployed in most circumstances. However, not much research is conducted about the cost effectiveness of drone deliveries complementary to truck transport in the supply of health care to local health facilities. This is due to the complexity of the problem to model the inventory policies at the health facilities.

As a first step to answering the main question, the aim has been to model the problem analytically. This model was developed in the thesis. Continuous approximations were used to estimate the average distance a product has to travel from a certain (central) point in an area to another. To model the inventory policy that uses both a regular transportation mode, trucks, and an emergency transportation mode, drones, the theory of modal split transport (MST), which is a generalisation of the tailored base surge (TBS) policy, is used. This policy works with the assumption that the regular order arrives every replenishment cycle with a fixed quantity and emergency replenishment can be done twice as often with flexible quantities. By analysing the overshoot that occurs in the second period, when the emergency order can be placed again, the cost minimising order quantity for regular and order-up-to level for emergency transport is derived. This results in an optimal split between the two transport modes.

The next research question was whether the analytical model that was developed is suitable for application to a real-world situation. To that end, the analytical model was validated by simulation of the outcomes of the analytical model on data of demand for malaria medication for a typical health facility in Zambia. It was found that the classical order-up-to level model for supply of AL medication using only trucks performed poorly. This is likely due to the high seasonality of the demand, which the model with drone replenishment was able to deal with. A higher order-up-to level, found using a simple max-min policy, showed significant improvement in terms of service level, but resulted in higher costs than when drones were allowed. A more sophisticated max-min policy, using previously realised demand data, did show that drones were not cost effective. However, this is under the assumption of deterministic lead time for truck transport.

Also, different settings of the base case with drones, that followed the assumptions of the analytical model, have been tested via simulation. It can be concluded that the analytical model is only applicable when the ratio between the relative cost advantage per product of shipping with the regular, truck transport over shipping with the emergency, drone transport and the holding costs is 2 or larger. The analysis on the proposed levels of the fixed order quantity for regular and order-up-to levels for emergency replenishment show that lower costs were attained at a lower fixed order quantity than proposed. A slightly lower order-up-to level did also result in lower costs, while still reaching the targeted service level. Overall, when cost advantage of regular versus emergency replenishment increases, less items are shipped by drone.

With stochastic instead of deterministic lead time of the regular transport it was found that the model was able to attain the targeted service level, although costs did increase. However, adjusting the order-up-to level for drones produced cost savings. Also, with stochastic lead time the dual sourcing model produced cost savings over the single sourcing model. With the possibility of weekly emergency ordering instead of biweekly, the service level goes up. Adjusting the order-up-to level for drones also resulted in cost savings. Additionally, in practice, costs are incurred per drone flight, as opposed to transportation cost per item. The higher the demand, the less difference is observed between both types of costs. Drone capacity has little influence on the outcome of the model in terms of total costs if the capacity is 100 or more when fixed drone costs per flight are considered.

These conclusions indicate that cost savings can be achieved, when drones are used complementary to truck transport for the resupply of essential medicines in developing countries, using the analytical model developed in this thesis, when stochastic lead time for truck transport is considered or when only average data is used to determine inventory policies. However, when monthly data is used and deterministic lead time for truck transport is used, implementing drones did not result in cost savings, given the parameter settings used in this thesis. Additionally, the results indicate that the developed analytical model can be applied in real-world scenarios regarding the influence of several factors that influence the cost effectiveness. However, no final conclusions can be made since the analytical model relies too heavily on unrealistic assumptions. When these assumptions are relaxed to generate a real-world setting, the model was in most cases not able to meet the targeted performance objectives. Therefore, to make a proper analysis of the cost benefits, a tailored approach per situation is required.

7 Discussion

As Wright et al. (2018) found, modeling the possible use of drones for resupplying essential medicines against stockouts is rather complex. In fact, this modeling is so complex that it is not possible to derive any definitive conclusions about the viability of the drones without strong assumptions. Nevertheless, this research found a model that shows cost benefits of incorporating drones in the supply of essential medicines in developing countries when stochastic lead time for truck transport is considered or when only average data is used to determine inventory policies. However, the research also found that certain assumptions are crucial for the model but not realistic in practice. Therefore, restrictions and possible extensions of this research are discussed in this chapter.

With the aim in mind to fill an existing gap in the literature on the use of drones, connection between this problem and dual sourcing inventory problems has been made. Therefore, this thesis can be relevantly placed in both the dual sourcing and the drone deployment literature. A model developed by Chowdhury et al. (2017), who model the use of drones in a disaster relief setting, most resembles the problem investigated in this thesis. The main difference between Chowdhury et al. (2017) and the current thesis is that this thesis is focuses on a structural inventory management problem, whereas the disaster relief problem is only short term. Wright et al. (2018) do analyse long term replenishment of health care supply, but only draw conclusions about specialized cases such as the extreme rare situation of antivenom use. The complexity of analysing the use of drones for inventory replenishment and protection against stockouts for essential medicines, prevented these authors to make any conclusions.

The application of this research in a practical sense is to evaluate the settings in which drones could be effectively deployed. With the strong assumptions as given in the analytical model, this model might not be directly applicable, but could give a guideline on how to split the supply between the supply modes should a full drone network be implemented. By having a better structural and analytical assessment of the possible outcomes of the drone supply network, its development could be more easily accepted or investors might be more inclined to invest in the drone network, which is found to be cost effective while also attaining higher service levels when protection against stockouts in case of accessibility problems is the target.

The application of drones can be widely used. Modeling the cost-effectiveness of drones for health care replenishment in developing countries can also guide the analysis for the use of drones in other fields of research that use either probabilistic access or stochastic lead time. Assessing the factors influencing the viability in health care can also stimulate the use of drones in a wider range of segments (Haidari et al., 2017).

The main disadvantage of this model is that it is developed with strong assumptions that are not realistic for a real-world application. Relaxing these assumptions sometimes indicates that the model no longer performs well. Therefore, the translation between the analytical model and practice is not direct. The relationship between factors in the analytical model cannot be taken as a direct basis for conclusions in specific cases.

For the simulation used to validate the analytical model, averaged data is used to create a typical health facility. In practice, much variation exists between the facilities concerning demand and/or accessibility issues, although in almost all facilities, both urban and rural, substantial stockouts occur regularly (Wright et al., 2018). Additionaly, the distance that items need to travel is roughly estimated with continuous approximations, but this can actually vary widely amongst facilities. Moreover, the data is focused on a specific type of medication, questioning the validity of the model and conclusions made in this thesis for other (health care) products.

Wright et al. (2018) argue that the cost effectiveness response to only transport a single product is not optimal. They further argue that combining different health care items may lead to cost savings compared to models that involve only one specific item of health care since economies of scale can be used. The argument of Wright et al. (2018) is consistent with the findings in this research, which showed that if demand is higher, then the number of items to be shipped is also higher and the cost gap between drone transportation per item versus per drone is smaller. Allowing for multiple use of drones, the cost will decrease with the increase in the number of flights. Therefore, the actual viability of incorporating drones in the supply chains could be more easily achieved then determined in this research.

Apart from single item analysis of only one type of medication, the developed model only considers drones on the level of one facility. However, a drone system can only be installed on a large scale, for example on national level, so this analysis only considers part of the issue at hand.

The disadvantages at hand lead to multiple suggestions for future research. One such topic is the incorporation of multiple echelons in the analysis to get a full understanding of the cost effectiveness to set up a drone network nationally. This would require incorporation of an analysis of the linehaul transport between the NDC and RDCs and the inventory policy at the DCs in addition to optimising the inventory policies and estimating transportation cost at the local health facilities that was analysed in this thesis.

Another research opportunity relevant for the analysis of the cost effectiveness is the number of drone stations that should be placed. For policy makers, this number may influence the adoption of a drone network due to costs. Fewer hubs from which drones can start and land lowers the large set up costs that are involved with investing in a drone network. During this thesis the approximate costs of the drone transport is based on 10,000 flights per year. Strategically placing the hubs is an optimization problem in itself but is related to the research of this thesis. A key assumption in this research has been a zero lead time for the emergency orders fulfilled by drones. However, more facilities needing to be serviced may lead to a scenario in which all drones are already deployed when a new order is placed, imposing a positive lead time on the emergency replenishment orders.

New technologies allow for new opportunities. This was the beginning statement of this thesis which concludes that the aspects of the viability of drone use are still dependent on specific settings. Although in case of deterministic lead time for trucks and an inventory policy for single sourcing that uses monthly demand data, no cost savings were achieved, the use of drones can be cost effective when used complementary to a truck transportation system for the supply of health care in developing countries in case of, more realistically, stochastic lead time for trucks. In any case, the promising application of this new technology is worth researching further.

References

Ackerman, E. and Koziol, M. (2019). In the air with zipline's medical delivery drones. *IEEE Spectrum: Technology, Engineering, and Science News.*

Allon, G. and Van Mieghem, J. A. (2010). Global dual sourcing: Tailored base-surge allocation to near-and offshore production. *Management Science*, 56(1):110–124.

Ansari, S., Başdere, M., Li, X., Ouyang, Y., and Smilowitz, K. (2018). Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. *Transportation Research Part B: Methodological*, 107:229–252.

Axsäter, S. (2015). *Inventory control*, volume 225. Springer.

Balcik, B., Beamon, B. M., and Smilowitz, K. (2008). Last mile distribution in humanitarian relief. *Journal of Intelligent Transportation Systems*, 12(2):51–63.

Barankin, E. (1963). A delivery-lag inventory model with an emergency provision. *Naval Research Logistics Quarterly*, 8:285–311.

Bijvank, M. and Vis, I. F. (2011). Lost-sales inventory theory: A review. *European Journal of Operational Research*, 215(1):1–13.

Bijvank, M. and Vis, I. F. (2012). Lost-sales inventory systems with a service level criterion. *European Journal of Operational Research*, 220(3):610–618.

Blumenfeld, D. E. and Beckmann, M. J. (1985). Use of continuous space modeling to estimate freight distribution costs. *Transportation Research Part A: General*, 19(2):173–187.

Boute, R. N. and Van Mieghem, J. A. (2015). Global dual sourcing and order smoothing: The impact of capacity and lead times. *Management Science*, 61(9):2080–2099.

Braun, J., Gertz, S. D., Furer, A., Bader, T., Frenkel, H., Chen, J., Glassberg, E., and Nachman, D. (2019). The promising future of drones in prehospital medical care and its application to battlefield medicine. *Journal of trauma and acute care surgery*, 87(1S):S28–S34.

Brown, S. T., Schreiber, B., Cakouros, B. E., Wateska, A. R., Dicko, H. M., Connor, D. L., Jaillard, P., Mvundura, M., Norman, B. A., Levin, C., et al. (2014). The benefits of redesigning Benin's vaccine supply chain. *Vaccine*, 32(32):4097–4103.

Burns, L. D., Hall, R. W., Blumenfeld, D. E., and Daganzo, C. F. (1985). Distribution strategies that minimize transportation and inventory costs. *Operations research*, 33(3):469–490.

Cameron, A., Ewen, M., Ross-Degnan, D., Ball, D., and Laing, R. (2009). Medicine prices, availability, and affordability in 36 developing and middle-income countries: a secondary analysis. *The lancet*, 373(9659):240–249.

Chiang, C., Gutierrez, G. J., et al. (1996). A periodic review inventory system with two supply modes. *European Journal of Operational Research*, 94(3):527–547.

Chowdhury, S., Emelogu, A., Marufuzzaman, M., Nurre, S. G., and Bian, L. (2017). Drones for disaster response and relief operations: A continuous approximation model. *International Journal of Production Economics*, 188:167–184.

Clark, A. J. and Scarf, H. (1960). Optimal policies for a multi-echelon inventory problem. *Management science*, 6(4):475–490.

Daganzo, C. F. (1984a). The distance traveled to visit n points with a maximum of c stops per vehicle: An analytic model and an application. *Transportation science*, 18(4):331–350.

Daganzo, C. F. (1984b). The length of tours in zones of different shapes. *Transportation Research Part B: Methodological*, 18(2):135–145.

Daniel, K. H. (1961). A delivery-lag inventory model with emergency. Technical report, CALIFORNIA UNIV BERKELEY STATISTICAL LAB.

Dasci, A. and Verter, V. (2001). A continuous model for production–distribution system design. *European Journal of Operational Research*, 129(2):287–298.

Dong, C., Transchel, S., and Hoberg, K. (2018). An inventory control model for modal split transport: A tailored base-surge approach. *European Journal of Operational Research*, 264(1):89–105.

Eichleay, M., Evens, E., Stankevitz, K., and Parker, C. (2019). Using the unmanned aerial vehicle delivery decision tool to consider transporting medical supplies via drone. *Global Health: Science and Practice*, 7(4):500–506.

Figliozzi, M. A. (2017). Lifecycle modeling and assessment of unmanned aerial vehicles (drones) co2 emissions. *Transportation Research Part D: Transport and Environment*, 57:251–261.

Foth, J. (2017). We haven't considered the true cost of drone delivery medical services in Africa. *https://qz.com/africa/1090693/zipline-drones-in-africa-like-rwanda-and-tanzania-have-an-opportunity-cost/*.

Franceschetti, A., Jabali, O., and Laporte, G. (2017). Continuous approximation models in freight distribution management. *Top*, 25(3):413–433.

Fukuda, Y. (1964). Optimal policies for the inventory problem with negotiable leadtime. *Management Science*, 10(4):690–708.

Haidari, L. A., Brown, S. T., Ferguson, M., Bancroft, E., Spiker, M., Wilcox, A., Ambikapathi, R., Sampath, V., Connor, D. L., and Lee, B. Y. (2016). The economic and operational value of using drones to transport vaccines. *Vaccine*, 34(34):4062–4067.

Haidari, L. A., Brown, S. T., Wedlock, P., and Lee, B. Y. (2017). Map of different vaccine supply chain efficiency measures. *Vaccine*, 35(1):199–200.

Janakiraman, G., Seshadri, S., and Sheopuri, A. (2015). Analysis of tailored base-surge policies in dual sourcing inventory systems. *Management Science*, 61(7):1547–1561.

Johansen, S. G. and Thorstenson, A. (2014). Emergency orders in the periodic-review inventory system with fixed ordering costs and compound poisson demand. *International Journal of Production Economics*, 157:147–157.

Johansen, S. G., Thorstenson, A., et al. (1998). An inventory model with poisson demands and emergency orders. *International Journal of Production Economics*, 56(57):275–289.

Kazaz, B., Webster, S., and Yadav, P. (2016). Interventions for an artemisinin-based malaria medicine supply chain. *Production and Operations Management*, 25(9):1576–1600.

Khazan, O. (2016). A drone to save the world. *The Atlantic*.

Langevin, A., Mbaraga, P., and Campbell, J. F. (1996). Continuous approximation models in freight distribution: An overview. *Transportation Research Part B: Methodological*, 30(3):163–188.

Leung, N.-H. Z., Chen, A., Yadav, P., and Gallien, J. (2016). The impact of inventory management on stock-outs of essential drugs in Sub-Saharan Africa: secondary analysis of a field experiment in Zambia. *PloS one*, 11(5).

Li, X. and Ouyang, Y. (2010). A continuum approximation approach to reliable facility location design under correlated probabilistic disruptions. *Transportation research part B: methodological*, 44(4):535–548.

Ling, G. and Draghic, N. (2019). Aerial drones for blood delivery. *Transfusion*, 59(S2):1608–1611.

Mohebbi, E. and Posner, M. J. (1999). A lost-sales continuous-review inventory system with emergency ordering. *International Journal of Production Economics*, 58(1):93–112.

Moinzadeh, K. and Nahmias, S. (1988). A continuous review model for an inventory system with two supply modes. *Management science*, 34(6):761–773.

Moon, I. and Gallego, G. (1994). Distribution free procedures for some inventory models. *Journal of the Operational research Society*, 45(6):651–658.

OCHA (2014). Unmanned aerial vehicles in humanitarian response. *Policy Briefs and Studies*.

Otto, A., Agatz, N., Campbell, J., Golden, B., and Pesch, E. (2018). Optimization approaches for civil applications of unmanned aerial vehicles (uavs) or aerial drones: A survey. *Networks*, 72(4):411–458.

Peters, D. H., Garg, A., Bloom, G., Walker, D. G., Brieger, W. R., and Hafizur Rahman, M. (2008). Poverty and access to health care in developing countries. *Annals of the New York Academy of Sciences*, 1136(1):161–171.

Rabta, B., Wankmüller, C., and Reiner, G. (2018). A drone fleet model for last-mile distribution in disaster relief operations. *International Journal of Disaster Risk Reduction*, 28:107–112.

Rao, U. S. (2003). Properties of the periodic review (r, t) inventory control policy for stationary, stochastic demand. *Manufacturing & Service Operations Management*, 5(1):37–53.

Republic of Zambia Ministry of Health (2006). Service Availability Mapping (SAM) .

Rosenshine, M. and Obee, D. (1976). Analysis of a standing order inventory system with emergency orders. *Operations Research*, 24(6):1143–1155.

Scott, J. and Scott, C. (2017). Drone delivery models for healthcare. In *Proceedings of the 50th Hawaii international conference on system sciences.*

Sheopuri, A., Janakiraman, G., and Seshadri, S. (2010). New policies for the stochastic inventory control problem with two supply sources. *Operations research*, 58(3):734–745.

Tagaras, G. and Vlachos, D. (2001). A periodic review inventory system with emergency replenishments. *Management Science*, 47(3):415–429.

Tatham, P., Stadler, F., Murray, A., and Shaban, R. Z. (2017). Flying maggots: a smart logistic solution to an enduring medical challenge. *Journal of Humanitarian Logistics and Supply Chain Management*, 7(2):172–193.

Thiels, C. A., Aho, J. M., Zietlow, S. P., and Jenkins, D. H. (2015). Use of unmanned aerial vehicles for medical product transport. *Air medical journal*, 34(2):104–108.

Thomas, A. and Mizushima, M. (2005). Logistics training: necessity or luxury. *Forced Migration Review*, 22(22):60–61.

Tyworth, J. E. and Ruiz-Torres, A. (2000). Transportation's role in the sole-versus dual-sourcing decision. *International Journal of Physical Distribution & Logistics Management.*

USAID | DELIVER PROJECT (2011). Guidelines for managing the malaria supply chain: A companion to the logistics handbook.

Van Houtum, G.-J., Scheller-Wolf, A., and Yi, J. (2007). Optimal control of serial inventory systems with fixed replenishment intervals. *Operations Research*, 55(4):674–687.

Vledder, M., Friedman, J., Sjöblom, M., Brown, T., and Yadav, P. (2019). Improving supply chain for essential drugs in low-income countries: Results from a large scale randomized experiment in Zambia. *Health Systems & Reform*, 5(2):158–177.

Walia, S. S., Somarathna, K., Hendricks, R., Jackson, A., and Nagarur, N. (2018). Optimizing the emergency delivery of medical supplies with unmanned aircraft vehicles. In *Proceedings of the 2018 IISE Annual Conference.*

World Health Organization (2019). World malaria report 2019.

Wright, C., Rupani, S., Nichols, K., Chandani, Y., and Machagge, M. (2018). What should you deliver by unmanned aerial systems? *White paper for JSI Research & Training Institute, Inc., and Llamasoft.*

Yadav, P. (2015). Health product supply chains in developing countries: diagnosis of the root causes of underperformance and an agenda for reform. *Health Systems & Reform*, 1(2):142–154.

Zipline (May 5 2020). *https://flyzipline.com/*.