Abstract

The focus of this research is to evaluate the use of drones for the delivery of pediatric vaccines in remote areas of low-income and low-middle-income countries. Delivering vaccines in these regions is challenging because of the inadequate road networks, and long transportation distances that make it difficult to maintain the cold chain’s integrity during transportation. We propose a mixed-integer linear program to determine the location of drone hubs to facilitate the delivery of vaccines. The model considers the operational attributes of drones, vaccine wastage in the supply chain, cold storage and transportation capacities. We develop a case study using data from Niger to determine the impact of drone deliveries in improving vaccine availability in Niger. Our numerical analysis show a 0.71% to 2.12% increase in vaccine availability. These improvements depend on the available budget to build drone hubs and purchase drones, and the population density in the region of study.

Keywords: Drone delivery network; Vaccine supply chain in low-middle-income countries; Mixed-integer linear program; Niger’s vaccine supply chain.

1 Introduction

Immunization is an effective tool in public health intervention for reducing child morbidity and mortality (Bärnighausen et al. 2014). In 1974, to make vaccines available to all children worldwide regardless of their social or economic status, the WHO initiated the Expanded Program on Immunization (EPI) (Glo 2013). Many organizations such as the WHO, the United Nations Children’s Fund (UNICEF), the Global Alliance of Vaccines and Immunization (GAVI), the World Bank, national governments, and many non-governmental organizations collaborate to extend the scope and reach of the EPI. As a result of these efforts, several hundred million children worldwide have been vaccinated and millions of
lives have been saved (World Health Organization, 2018; Alliance, 2020; World Health Organization, 2019a).

However, despite all these successes, the EPI’s target of vaccinating 90% of all children in every country by 2020 has not been achieved (Glo, 2013; World Health Organization, 2019b). Recent reports indicate that especially low-income and low-middle-income countries (LICs and LMICs) are falling short of meeting these goals. For example, out of 19.4 million children who remained un- or under-vaccinated in 2018, about 8.5 million lived in Africa (World Health Organization, 2019b). Sub-Saharan Africa has a mortality rate of 77 per 1,000 live births of children under 5 years old and has a risk of child mortality 15 times higher than developed countries (World Health Organization, 2019b).

Several factors led to insufficient vaccine availability in LICs and LMICs. Most vaccines require a cold chain that keeps them properly refrigerated or frozen at all times until their use (World Health Organization, 2020c). However, the available cold chain capacity in LICs and LMICs is limited, frequently leading to stock-outs (Assi et al., 2011; Ministry of Public Health Niger, 2016). Another challenge is demand uncertainty, which complicates planning, leads to insufficient vaccine availability, and high vaccine wastage. Geographically, many areas lack access to immunization services (Metcalf et al., 2014; Blanford et al., 2012). In rural areas of many African countries, vaccination coverage is negatively impacted by the limited access to healthcare services, which makes it difficult for patients to seek routine immunization services and has led to a rural-urban disparity in vaccination rates (Metcalf et al., 2014; Blanford et al., 2012). To reach children in remote areas, many countries rely on outreach activities, in which health workers travel to under-served communities to offer immunization (Organization, 2000; Vandelaer et al., 2008). The success of these activities depends on adequate planning and on vaccine and personnel availability. However, reaching remote areas is often challenging due inadequate road networks, long distances, and the need to maintain the cold chain’s integrity during transportation.

Utilizing drones for vaccine delivery may address some of the existing vaccine distribution challenges in LICs and LMICs. Recent developments in drone and battery technology allow for the economical use of drones for civil applications (Zipline, 2019). Drones can fly on a direct path at high speed and could enable on-demand deliveries to mitigate stock-outs caused by lacking cold chain capacities. Furthermore, the drone’s independence of
road infrastructure could allow it to reach remote areas. This would help communities that
have been excluded from the benefits of vaccination due to lack of accessibility to medical
services.

There is precedence in the use of drone for the delivery of medical supplies. In 2016,
Rwanda successfully implemented drone delivery of blood for transfusions. Blood, like vac-
cines, also must be stored in a cooled environment, and its demand is uncertain (Ackerman
and Kozioł 2019). The implementation of drone delivery allowed centralizing the inventory,
which led to a reduction of stationary storage capacity and stock-outs. In 2017, this suc-
cessful project encouraged Tanzania to start using drones for delivering medical supplies. In
2018, the government of Ghana, in collaboration with UNICEF and a private partner, built
a drone delivery network for vaccines (Alliance 2019). In 2018, drone-delivered vaccines
reached remote communities in Vanuatu (UNICEF 2018). Since 2019, through commercial
contractors, Vanuatu has frequently used drones to deliver vaccines over the country.

Despite a growing interest in the operations research community to model vaccine supply
chains (VSC) and the successful implementation of drone delivery networks, research in
this area is limited (De Boeck et al. 2020). Studies by Haidari et al. (2016) and Walia
et al. (2018) conclude that using drones, instead of traditional land transportation, yields
potential cost savings and increases vaccine availability at clinics. However, these studies
focused mainly on costs and did not consider the potential to improve vaccination rates by
serving remote areas lacking access to immunization services.

Drone deliveries might help save the hard-fought gains in immunization coverage in LICs
and LMICs that were put at risk due to the COVID-19 pandemic (World Health Organiza-
tion 2020a). By 2020, more than 13 million children missed routine immunizations, and
close to 78 million children will miss routine immunizations due to COVID-19 pandemic-
induced disruptions (Roberts 2020). The WHO reported that in 2021 alone more than
25 million children missed out one or more doses of DTP through routine immunization
services (WHO 2022). This is due to canceled flights, temporarily suspended immuniza-
tion campaigns, and people’s reluctance to visit immunization session because they fear of
getting infected with COVID-19. These disruptions could lead to disease outbreaks (such
as measles, polio, yellow fever) which would additionally burden health systems already
fighting the impacts of COVID-19 (Roberts 2020).
This study proposes a mixed-integer optimization model that determines a drone delivery network to maximize the number of children who are vaccinated. This model captures (i) the trade-offs between the frequency of deliveries and inventory level, (ii) communities’ accessibility to immunization services, and (iii) the impact of drone deliveries for outreach activities on the efficiency of immunization programs. We validate the model via a case study using real-life data from Niger. We provide insights that could improve supply chain’s performance.

This study is organized as follows. In Section 2 we describe the structure of VSCs of LICs and LMICs and its operations. In Section 3 we discuss the relevant literature. Next, we provide a formal problem definition and mathematical model of a VSC in Section 4. In Section 5 we discuss the approach used to solve the model. This includes a pre-processing method to reduce the problem size. Section 6 introduces the case study. Finally, in Section 7 we conclude the study with a summary and potential future research directions.

2 Background on Vaccine Supply Chains

Most vaccines degrade under heat exposure and must be kept at low temperatures. Few vaccines need to be kept frozen (between -25°C to -15°C) and most need to be refrigerated (between 2°C to 8°C) \cite{WorldHealthOrganization2020}. Therefore, VSCs are equipped with cooling devices to maintain the required temperature ranges during storage and transportation. In LICs and LMICs, VSCs typically consist of three to five layers (i.e., echelons). In most countries, VSCs have four layers (see Figure 1) consisting of national-, regional-, district-level storage facilities, and clinics \cite{Lee2015}. At the national level, a central store delivers vaccines downstream to regional centers (RCs) and district centers, which function as transshipment nodes. These centers deliver vaccines to clinics and health centers (HCs), which offer immunization services to children.

In many LICs and LMICs, major parts of the population reside in rural areas lacking access to HCs because of poor road infrastructure, long travel times, and missing or not affordable public transportation \cite{Metcalf2014, Blanford2012, Jani2008, Toikilik2010}. Hence, additional immunization services are often provided via outreach activities \cite{Organization2000, Vandelaer2008}. To support outreach
activities, health care workers travel to rural areas. This service is typically provided at
regular time intervals (e.g., quarterly) and pre-determined locations (Organization, 2000;
Lim et al., 2016). However, the success of outreach activities depends on the availability of
resources.

Vaccines come in different vial sizes, have different cold storage requirements, and might
require a diluent for reconstitution before the administration (World Health Organization,
2020b,c). World Health Organization reports that vaccines are lost, damaged, destroyed,
or discarded. Vaccine wastage is typically classified into closed vial wastage (CVW) and
open vial wastage (OVW). CVW primarily includes wastage due to ineffective temperature
control, expiry, and breakage during handling processes. OVW occurs when multi-dose
vials are opened but not completely used within a given time frame and the remaining
doses have to be discarded. The OVW rate is determined by the session size, vial size, and
discard time. Historically, OVW wastage contributes more to the overall wastage rate and
can be quite high, with rates over 50% (World Health Organization, 2019c).

Figure 1: A typical four-layer VSC (adopted from Lee et al. (2015))
3 Literature Review

Relevant to our work is the literature on supply chain network design (SCND) for vaccines. Lemmens et al. (2016) surveyed the SCND literature and assessed its application to VSCs. The authors conclude that general SCND models are missing key issues unique to VSCs. Thus, researchers have to go beyond the existing SCND literature to optimize VSCs. In fact, many researches developed models explicitly for VSCs (Assi et al., 2011; Azadi et al., 2020; Chen et al., 2014; De Boeck et al., 2020; Haidari et al., 2016; Lim et al., 2016; McCoy and Lee, 2014; Walia et al., 2018; Yang et al., 2020); for an extensive review we refer to (Duijzer et al., 2018; De Boeck et al., 2020).

Discrete-event simulation models for VSCs were presented by Assi et al. (2011) and De Boeck et al. (2020). These simulation models consider cold chain capacities (inventory and transportation), shipping policies, vaccine characteristics and stochastic demand for vaccines. De Boeck et al. (2020) used their model to assess the impact of disruptions caused by the rainy season in Madagascar. The simulation model from Assi et al. (2011), called HERMES, was used in a number of studies to evaluate the impact of different changes to the VSC such as removing a supply chain layer, altering shipping policies, or using different vial sizes (Assi et al., 2011, 2013; Brown et al., 2014; Haidari et al., 2015; Lee et al., 2015, 2016; Wedlock et al., 2019). However, the most closely related simulation-based study is by Haidari et al. (2016) who extended HERMES by considering drone delivery from regional and district stores to clinics, instead of using land transportation. Through a case study for Mozambique’s VSC, Haidari et al. (2016) found that drone delivery can increase vaccine availability at clinics and decrease logistic costs in a broad range of settings (e.g., for different drone payloads and demand levels).

A number of optimization models have been proposed in the literature to optimize the performance of the VSCs (Azadi et al., 2020; Chen et al., 2014; Lim et al., 2016; McCoy and Lee, 2014; Walia et al., 2018; Yang et al., 2020). Yang et al. (2020) proposed a mixed-integer program (MIP) to reallocate cold capacities and reassign transportation routes to minimize inventory and transportation costs. Chen et al. (2014) proposed a linear program (LP) to make inventory, transportation, and vaccine administration decisions that maximize vaccination rates. Furthermore, the authors presented an extension to determine where in the supply chain, cold chain capacities must be added to satisfy demand at the minimum
investment costs. \cite{Azadi2020} extended this model by reformulating it as a stochastic program with uncertain demand and chance constraint to ensure that demand is satisfied with a certain probability. Both, \cite{Chen2014} and \cite{Azadi2020} used their model to investigate changes to the supply chain, such as removing a supply chain layer, or changing vaccine presentation. \cite{Walia2018} formulated an integer program (IP) to determine a cost efficient transportation mode (land transportation or drone delivery) for different transportation routes in a VSC. \cite{Lim2016} and \cite{McCoy2014} propose IPs to optimize the outcome of outreach services by improving accessibility to immunization services. \cite{McCoy2014} developed a model to determine allocation of motorcycles, needed for outreach services, to clinics to improve their services. \cite{Lim2016} compared different set covering models to maximize the number of people that have access to immunization services, assuming that only a limited number of outreach sessions can be conducted. For this purpose, \cite{Lim2016} modeled the access to services as a function of the distance between the vaccination center and locations.

4 Problem Description and Model

The objective of this section is to develop a mathematical model to support the design of a VSC that uses drones to deliver vaccines in LICs and LMICs. For this purpose, we introduce problem assumptions, notation, and provide an MIP formulation.

4.1 Assumptions

The focus of this research is on supporting sustained outreach activities for routine childhood immunization. Hence, we do not consider supplemental immunization programs, such as mass vaccination campaigns. Moreover, we focus on optimizing the VSC of a single country once it has vaccines available for distribution.

The following is a list of assumptions adopted in the proposed MIP model. (i) Cold storage and cold transportation capacities are limited, (ii) there is sufficient capacity to store and transport (via land) auxiliary supplies such as syringes, (iii) the lead time for delivering vaccines via land transportation, between any two centers in the country, is within one time period (i.e., a day), (iv) drone deliveries can be scheduled on-demand and
| Publication | Model type | Modeled key issues |
|-------------|------------|--------------------|
| Assi et al. (2011), Lee et al. (2011) | Discrete-event simulation | Limited Capacities, Transportation, Delivery |
| Lee et al. (2013), Haidari et al. (2015) | Discrete-event simulation | Limited Capacities, Transportation, Delivery, Uncertainty |
| Wedlock et al. (2019) | Discrete-event simulation | Limited Capacities, Transportation, Delivery, Outreach |
| Haidari et al. (2016) | Discrete-event simulation | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| De Boeck et al. (2020) | Discrete-event simulation and MIP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Chen et al. (2014) | LP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Lim et al. (2015), Yang et al. (2020) | MIP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Wells et al. (2018), Azadi et al. (2020) | IP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Dhamodharan et al. (2011), Azadi et al. (2019) | SP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Lim et al. (2016) | IP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
| Scott and Scott (2017), Kim et al. (2017) | IP | Limited Capacities, Transportation, Delivery, Outreach, Uncertainty |
have a negligible lead time, (v) drone deliveries are dedicated, single-trip deliveries (i.e., one beneficiary per delivery from the hub to the destination), (vi) drones and equipment used for cold storage and transportation are reliable and have negligible failure rates and causing no damage or vaccine spoilage, (vii) drones are shared among different hubs but remain stationed for a month before they can be relocated. (viii) there is no shortage of skilled personnel to administer vaccines at each location, (ix) vaccine wastage due to breakage, incorrect storage temperatures, equipment failure, and open-vial wastage is captured via the average wastage rates, (x) vaccine vial size is fixed. Thus, we model the flow of doses in the supply chain. For each dose, we calculated the corresponding volume in the vial, (xi) children are vaccinated at clinics or outreach posts that are located within a fixed distance from their homes.

4.2 Problem Definition

The following subsections provide a formal definition of the problem. A summary of the notation used can be found in Appendix 8.1.

4.2.1 Vaccines

Let $\mathcal{L}$ be a set of vaccines used by a country in its routine immunization schedule. For each vaccine $l \in \mathcal{L}$, $a_l$ represents the number of doses necessary for completing the country’s immunization regimen per child; $q_l$ represents the effective volume per doses; and, $r_l$ represents the dilutant volume needed to reconstitute a lyophilized vaccine dose (for vaccines stored in powder presentation). Furthermore, vaccines must be kept at low temperatures until administered. There is limited cold capacity in the supply chain.

4.2.2 Vaccine Supply Chain

Similar to Azadi et al. (2020) and Chen et al. (2014), we represent the VSC for a country as a graph $\mathcal{G} = (\mathcal{J}, \mathcal{A})$, where $\mathcal{J}$ represent its nodes and $\mathcal{A}$ represents its arcs. The set of nodes $\mathcal{J}$ consists of three subsets, $\mathcal{I}, \mathcal{O},$ and $\mathcal{K}$. Nodes in $\mathcal{I}$ represent facilities in different layers of the supply chain. Each facility $i \in \mathcal{I}$ has cold storage devices with a limited holding $^{1}$

$^{1}$r$_{l}$ = 0 for non-lyophilized vaccines
capacity $u_i$. Let $w_{ii}^b$ represent the expected fraction of vaccine $l \in \mathcal{L}$ that could be lost to breakage or inadequate cooling in facility $i \in \mathcal{I}$. Nodes in $\mathcal{I}$ are potential locations for hubs since they have the available space to store and launch drones. Nodes in $\mathcal{O}$ represent the outreach posts where storage is not available.

Nodes in $\mathcal{K}$ represent the communities. Let $\pi_{kl}^t$ represent the demand for vaccine $l \in \mathcal{L}$ at time $t \in \mathcal{T}$ at community $k \in \mathcal{K}$. Children from these communities seek immunization services at clinics or outreach posts nearby. Let $\Pi$ represent these vaccination centers. Note that, $\mathcal{K} \cap \Pi \neq \emptyset$.

We use $w_{ii}^o$ to represent open-vial wastage (OVW) during administration of vaccine $l$ in $i \in \Pi$.

The set of arcs $\mathcal{A}$ consists of three disjoint subsets; where $\mathcal{A}^*$ represents land transportation routes, $\hat{\mathcal{A}}$ represents potential drone transportation routes, and $\mathcal{A}'$ represents walking paths from a community to a vaccination center (clinic or outreach post). There is an arc
between any two locations \(i, j\) (thus, \((i, j) \in \mathcal{A}\)) if the distance \(d_{ij}\) between them is smaller than the maximum drone range. Arcs \(\mathcal{A}'\) between nodes in \(i \in \Pi\) and communities \(j \in \mathcal{K}\) exist if the community \(k\) is within the maximum acceptable travel distance from \(i\). Parameters \(w_{ijl}^f\) (\(w_{ijl}^d\)) represent the fraction of vaccines \(l\) wasted during transportation between \(i\) and \(j\) for \((i, j) \in \mathcal{A}^*\) (\((i, j) \in \mathcal{A}\)) because of breakage. Parameters \(u_{ij}^f\) (\(u^d\)) represent truck (drone) capacity along \((i, j) \in \mathcal{A}^*\) (\((i, j) \in \mathcal{A}\)).

Figure 2 provides a graphical representation of the proposed VSC. For simplicity, the figure does not include the communities and the walking paths to vaccination centers. The main differences between the proposed VSC and an existing/typical VSC (shown in Figure 1) are the addition of outreach posts, drone hubs, and drone transportation arcs.

### 4.2.3 Decision Variables and Additional Notation

Let \(\mathcal{T}\) represent the planning horizon for our model. We assume that, at the beginning of the planning horizon, a centralized decision maker determines where to open drone hubs and how many drones to use. The binary variable \(Y_i\) takes the value 1 if a drone hub opens in \(i \in \mathcal{I}\), and takes the value 0 otherwise. The cost of opening a hub in \(i\) is \(c_i\). The integer variable \(Z\) represents the number of drones procured. These drones are shared among hubs. The integer variable \(V_{it}\) represents the number of drones used by hub \(i\) in period \(t\). The cost of procuring a drone with an average speed \(s\) and payload \(u^d\) is \(\bar{c}\). The decision maker has a budget of \$b\ for opening drone hubs and purchasing drones. This study considers that the supply chain is already equipped with vehicles for land transportation.

At the beginning of the planning horizon, vaccines arrive at the central store. The decision maker determines the number of doses of vaccine \(l\) that should be delivered in period \(t\) from location \(i \in \mathcal{I}\) to location \(j \in \mathcal{J}\) using land (via \((i, j) \in \mathcal{A}^*\)), or using drones (via \((i, j) \in \mathcal{A}\)). These decisions, denoted by \(S_{ijlt}\) (land transportation) and \(D_{ijlt}\) (drone transportation), are affected by the availability of cold storage at the destination. These decisions impact the stockpile level \(I_{ilt}\) at each facility \(i(\in \mathcal{I})\), which in return determines the number of children that could be vaccinated in period \(t\). We use \(X_{ijlt}\) to represent the number of vaccines \(l\) administered at location \(i(\in \Pi)\) in period \(t\) to vaccinate children from community \(j(\in \mathcal{K})\).
4.2.4 Objective

The objective of routine childhood immunization is to maximize the number vaccinated children. A number of factors impact childhood immunizations, however, this study focuses on increasing vaccine availability at vaccination centers. We assume that if available, a vaccine is used to vaccinate a child in need of one. Thus, increasing availability could increase the number of children that are vaccinated.

Similar to De Boeck et al. (2020), we use the supply ratio (SR) as a measure of vaccine availability, and as a performance measure for the VSC. Let \( \text{SR}_{it} \) represents the proportion of children vaccinated via the proposed VSC in period \( t \) at vaccination center \( i \in \Pi \). Recall that, \( \pi_{klt} \) represent the number of children in need of vaccine \( l \) in community \( k \) in period \( t \) and \( X_{iklt} \) represents the number of vaccines administered at vaccination center \( i \) to children from community \( k \), then,

\[
\text{SR}_{it} = \frac{\sum_{k: (k, i) \in A'} X_{iklt}}{\sum_{k: (k, i) \in A'} \pi_{klt}}, \quad \forall i \in \Pi, t \in T.
\]  

(1)

Let \( N_k \) represent an upper bound on the number of fully immunized children of community \( k \). To calculate this bound we divide the number of vaccines administered in \( k \) during the planning horizon, with \( \alpha_l \) – the number of doses of vaccine \( l \) necessary for completing the immunization regimen.

\[
N_k \leq \sum_{l \in \mathcal{L}} \sum_{t \in T} \sum_{i: (k, i) \in A'} \frac{X_{iklt}}{\alpha_l}, \quad \forall l \in \mathcal{L}, k \in \mathcal{K}.
\]  

(2)

The objective function, \( f \), of the proposed model maximizes \( N_k \) and the total number of vaccines available via the VSC. The second term in the objective maximizes \( \text{SR}_{it} \). We adjust the relative importance of both terms in the objective via \( \epsilon \in (0, 1) \).

\[
f = \max \sum_{k \in \mathcal{K}} N_k + \epsilon \sum_{(k, i) \in A'} \sum_{l \in \mathcal{L}} \sum_{t \in T} X_{iklt}.
\]  

(3)

4.3 A Mixed-Integer Programming Model

We propose an MIP that extends the model proposed by Chen et al. (2014) by considering the establishment and operation of a drone network for vaccine delivery in addition to traditional land transportation. Drone deliveries improve vaccine availability at the community level. The proposed model is an extension of the traditional facility location-transportation
model. This model integrates planning (mid-term) and operational (short-term) decisions. The planning decisions focus on the establishment of a drone network. The operational decisions focus on vaccine transportation, storage, and administration. The operation of drones in the VSC depends on the drone network. Below we introduce the proposed model formulation, which we call model \((P)\).

\[
\begin{align*}
  z &= \max f \\
  \text{s.t.} & \quad \sum_{i \in I} c_i Y_i + \bar{c}Z \leq b, \\
  & \quad V_{it} \leq mY_i, \quad \forall i \in I, \ t \in \mathcal{T}, \\
  & \quad \sum_{i \in I} V_{it} \leq Z, \quad \forall t \in \mathcal{T}.
\end{align*}
\]

The objective function \([4]\) maximizes the number of fully and partially immunized children. This number is impacted by the structure of the proposed VSC, which incorporates a drone network. Constraint \([5]\) indicates that the available budget limits the establishment of drone hubs and the number of drones purchased. Recall that drones are shared in this VSC to increase utilization. Thus, constraints \([6]\) allow drones to be used by facility \(i\) if a hub is already established. Here, \(m\) is the maximum number of drones that could be purchased using the available budget. Constraints \([7]\) force the total number of drones utilized in the VSC during time \(t\) to be less than or equal to the total number of drones purchased.

\[
\begin{align*}
  I_{ilt} &= (1 - w_{ilt}^h)I_{ilt-1} - \sum_{j: (j,i) \in \mathcal{A}^*} S_{ijlt} + \sum_{j: (j,i) \in \mathcal{A}^*} (1 - w_{jilt}^b)S_{jilt-1} - \sum_{j: (i,j) \in \mathcal{A}} D_{jilt} + \\
  & \quad + \sum_{j: (j,i) \in \hat{\mathcal{A}}} (1 - w_{jilt}^d)D_{jilt} - \left(\frac{\sum_{k: (k,i) \in \mathcal{A}'} X_{iklt}}{1 - w_{ilt}^o}\right), \quad \forall i \in I, \ l \in \mathcal{L}, \ t \in \mathcal{T},
\end{align*}
\]

\[
\sum_{l \in \mathcal{L}} q_l \left[ I_{ilt} + \sum_{j: (j,i) \in \mathcal{A}^*} (1 - w_{jilt}^b)S_{jilt-1} + \sum_{j: (j,i) \in \hat{\mathcal{A}}} (1 - w_{jilt}^d)D_{jilt} \right] \leq u_i, \quad i \in I, \ t \in \mathcal{T}.
\]

\[
I_{ilt} = 0, \quad \forall i \in I, \ l \in \mathcal{L}.
\]

Constraints \([8]\) - \([10]\) are related to the inventory. Constraint \([8]\) determines inventory balance for each vaccine at each facility for each period. This constraint accounts for the
loss of vaccines in the supply chain due to breakage during transportation and inventory, and OVW. The constraint also accounts for the one-period lead time for land transportation. Constraints (9) limit the inventory based on the available cold chain capacity. Constraint (10) initializes the inventory.

Since the outreach posts do not carry inventory, its flow (inventory) balance constraints (11) are slightly different from the inventory balance constraints for facilities in (8).

\[
\sum_{j: (j,i) \in A^*} (1 - w^l_{jil}) S_{jilt} - 1 + \sum_{j: (j,i) \in \dot{A}} (1 - w^d_{jil}) D_{jilt} = \left( \frac{\sum_{k: (k,i) \in A'} X_{iklt}}{1 - w^d_{ilt}} \right), \quad \forall \, i \in O, \ l \in L, \ t \in T. \tag{11}
\]

The following set of constraints, (12) - (13), enforce transportation restrictions. Constraints (12) ensure that the volume of vaccines transported by land is limited by the associated vehicle capacities. The volume of vaccines delivered via drones is limited by the total number of operating hours of the drone fleet since drones can fly several times between locations. Thus, the right-hand-side of constraint (13) represents the total available operating hours for drone deliveries at facility (hub) \(i\) in period \(t\). The left-hand-side of constraint (13) represents the total number of operating hours that are required to deliver vaccines from hub \(i\) in period \(t\). The first term in the left-hand-side determines the number of trips per period, and the second term determines the number of hours per trip.

\[
\sum_{l \in L} q_l S_{ijlt} \leq u^l_{ij}, \quad \forall \ (i, j) \in A^*, \ t \in T, \tag{12}
\]

\[
\sum_{j: (i,j) \in \dot{A}} \sum_{l \in L} \left( \frac{(q_l + r_l) D_{ijlt}}{u^d_{ij}} \right) \left( \frac{2d_{ij}}{s} \right) \leq h V_{it}, \quad \forall \, i \in I, \ t \in T. \tag{13}
\]

Constraints (14) indicate that the number of vaccines administered is bounded by demand for vaccines. Constraints (15) provide an upper bound on the number of fully immunized children (i.e., children that received the complete vaccine regimen).

\[
\sum_{t \in T} \sum_{i: (k,i) \in A'} X_{iklt} \leq \sum_{t \in T} \pi_{klt}, \quad \forall \ k \in K, \ l \in L, \tag{14}
\]

\[
N_k \leq \sum_{t \in T} \frac{\sum_{i: (k,i) \in A'} X_{iklt}}{a_l}, \quad \forall k \in K, l \in L. \tag{15}
\]
Finally, we introduce the non-negativity, the binary constraints, and the integer constraints.

\[ N_k \geq 0, \quad \forall \ k \in K, \quad (16) \]
\[ S_{ijl} \geq 0, \quad \forall \ (i,j) \in A^*, \ l \in L, \ t \in T, \quad (17) \]
\[ D_{ijl} \geq 0, \quad \forall \ (i,j) \in \hat{A}, \ l \in L, \ t \in T, \quad (18) \]
\[ V_{it} \geq 0, \quad \forall \ i \in \mathcal{I}, \ t \in T, \quad (19) \]
\[ X_{ikt} \geq 0, \quad \forall \ (k,i) \in A', \ l \in L, \ t \in T, \quad (20) \]
\[ I_{lt} \geq 0, \quad \forall \ i \in \mathcal{I}, \ l \in L, \ t \in T, \quad (21) \]
\[ Y_i \in \{0,1\}, \quad \forall i \in \mathcal{I} \quad (22) \]
\[ Z \in Z^+ \cup \{0\} \quad (23) \]

5 Solution Methodology

The size of VSC, and consequently problem size, is impacted by the number of communities served. As preliminary test showed that the problem size for realistic instances is prohibitively large, we propose a pre-processing approach to reduce the size of the VSC. In this pre-processing stage, we aggregate nearby communities into demand clusters as depicted in Figure 3. Thus, the problem reduces to satisfy the vaccination needs of clusters, rather than single communities. After pre-processing, the corresponding MIP model, referred as model \((Q)\), is solved using the Benders Decomposition Algorithm \cite{Rahmaniani et al. 2017}.

The proposed pre-processing is motivated by the works of \cite{Metcalf et al. 2014, Blanford et al. 2012, Jani et al. 2008, Toikilik et al. 2010} that show that people prefer getting vaccinated in nearby clinics; and that long travel times often prevent people from seeking immunization services. Hence, to improve the accessibility to immunization services, we assume that communities that do not have a nearby clinic nearby must be served via outreach sessions. These outreach session can be supported by drones to ensure an adequate supply of vaccines cold chain. However, organizing an outreach session for every community is not efficient due to limited resources, such as, the number of available healthcare workers. Thus, it is reasonable that an outreach session pools resources to serve several communities. The challenge, however, is to determine where to locate such outreach sessions to ensure
that every community has access to at least one vaccination center. To determine what communities should serve as hosts for outreach sessions, we first solve a Set Cover model, and then use Algorithm [1] which assigns demand to the vaccination centers.

The objective of the Set Cover model is to determine the minimum number of communities that will host outreach sessions to ensure that all communities can access at least one vaccination center located within a reasonable distance (i.e., within a 5Km radius). Consistent with the notation used in Section 4, \( K \) represents the set of communities. Let \( \tilde{K} \) represent those communities that have access to a clinic (\( \tilde{K} \subset K \)). Let \( a_{ik} \) be an indicator parameter that takes the value 1 if vaccination center \( i \) is reachable (within 5Km) from community \( k \), and takes the value 0 otherwise. Let \( W_i \) be a binary variable that takes the value 1 if a vaccination center is located in \( i \), and takes the value 0 otherwise.

\[
\text{min} \sum_{i \in K} W_i, \tag{24}
\]

\[
s.t. \sum_{i \in K} a_{ik} W_i \geq 1, \quad \forall k \in \tilde{K}, \tag{25}
\]

\[
W_i = 1, \quad \forall i \in \tilde{K}, \tag{26}
\]

\[
W_i \in \{0, 1\}, \quad \forall i \in K. \tag{27}
\]

The objective function (24) minimizes the number of vaccination centers required to
ensure access to immunization services to everyone. Constraints (25) ensure that the outreach posts are selected such that each community has access to at least one vaccination center within walking distance. Furthermore, constraints (26) ensure that all clinics are considered as vaccination centers. (27) are the binary constraints.

After the vaccination centers are determined, we use Algorithm 1 to assign the communities’ demands to vaccination centers. Initially, each vaccination center is assigned the demand of the community where it is located. The demand of communities that are not co-located with a vaccination center but have access to at least one clinic are equally distributes among reachable clinics. For communities that have no access to a clinic, the demand is equally distributed among reachable outreach session.

Algorithm 1 Demand Aggregation

1: for community $i \in \mathcal{K}$ do
2:    if $i$ is selected as vaccination center then
3:       assign $i$’s demand to $i$
4:    else if $i$ has access to at least one clinic then
5:       assign $i$’s demand uniformly among accessible clinics
6:    else
7:       assign $i$’s demand uniformly among accessible outreach posts

Algorithm 1 by aggregating demand, reduces the size of graph $\mathcal{G}$. The set of nodes in the new graph is $\mathcal{J} = \mathcal{I} \cup \mathcal{O}$, and the set of arcs is $\mathcal{A} = \mathcal{A}^* \cup \dot{\mathcal{A}}$. As a result, in model $(Q)$, we use decision variables $X_{ilt}$ (rather than $X_{iklt}$), which represent the total number of vaccines administered at vaccination center $i \in \Pi$. Demand for vaccinations in $i(\in \Pi)$ is $\pi_{ilt}$. These updates impact the objective function and several constraints of $(P)$. We present formulation $(Q)$ in the Appendix.

6 Case Study

In this case study, we evaluate the proposed model and solution methodology using data from Niger, a low-income country in West Africa, mostly covered by the Saharan desert. Roughly 80% of its 23,196,000 inhabitants reside in rural areas with limited access to medical services (Ministry of Public Health Niger, 2016). Only 10% of the roads that connect the
main cities are paved (Blanford et al., 2012). As a result, about 60% of the population must travel longer than 1 hour to reach a clinic. Long travel times are one of the main reasons for low vaccination rates, which lead to immunization disparities in rural versus urban regions (Blanford et al., 2012; Metcalf et al., 2014). Therefore, road-independent drone deliveries seem promising to enhance Niger’s VSC performance.

6.1 Data Collection

Table 2 summarizes the data we have used and its sources. Additional details about the data are presented in the following subsections.

| Data                      | Source                                                                 |
|---------------------------|------------------------------------------------------------------------|
| Cold chain capacities     | Ministry of Public Health Niger (2016), Assi et al. (2011), and Haidari et al. (2013) |
| Population demographics   | National Institute of Statistics of Niger (2012); UN Office for the Coordination of Humanitarian Affairs (2018); World Bank (2020a,b) |
| Vaccines                  | World Health Organization (2020b,c, 2019c)                              |
| Drone specifications      | Zipline (2019); Dove Air (2021); Deutsche Post Group (2021); Wingcopter (2021); Scott and Scott (2017); Walia et al. (2018) |

6.1.1 Cold Supply Chain

In Niger, vaccines are distributed through a four-tier VSC as depicted in Figure 4. The vaccines are delivered from the manufacturer to cold rooms at the central store, located in the capital, Niamey. Then, cold trucks deliver vaccines to cold rooms at eight regional stores: Agadez, Diffa, Dosso, Maradi, Niamey, Tillabery, Tahoua, and Zinder. From here, vaccines are shipped in cold boxes via small trucks to the 44 district stores, where they are stored in chest refrigerators and freezers. Finally, healthcare workers pick up vaccines from the district stores with cars or motorcycles, using vaccine carries for cooling, to offer immunization at 695 clinics. Currently, Niger is expanding the number of its district stores
and clinics, however, we only have data for the 44 district stores and 695 clinics. The cold capacities at clinics are aggregated over all clinics in each region. Thus, we first allocate the regional capacity to districts based on population size, and then, allocate districts’ capacity uniformly among their clinics.

![Figure 4: Niger’s Cold Chain (L: liters)](image)

A clinic, on addition to servicing its patients, organizes outreach sessions to serve remote communities. Based on Niger’s immunization strategy, no one should travel longer than 5 Km to receive immunization services [Ministry of Public Health Niger, 2016]. Since the location of the outreach posts are not published, we use the location of communities, derived from [UN Office for the Coordination of Humanitarian Affairs, 2018], and the set cover aggregation algorithm (in Section 5) to determine locations of outreach posts. We estimated the demand for vaccination of communities using population size, and birth rates. We used the 2012 census data [National Institute of Statistics of Niger, 2012] weighted by population growth rates [World Bank, 2020a] to estimate population size of Niger in 2020 [World Bank, 2020b].

### 6.1.2 Vaccine Characteristics

Niger’s immunization schedule for routine childhood immunization includes nine vaccines administered during six appointments as depicted in Table 3. We compute vaccine wastage rates using the WHO vaccine wastage calculator [World Health Organization, 2019c].
Table 3: Vaccine Characteristics

| Vaccine      | Regimen          | Vial Size | Volume Per Dose [cm³] | Volume Per Diluent [cm³] | Storage Requirement |
|--------------|------------------|-----------|-----------------------|--------------------------|---------------------|
| BCG          | birth            | 20        | 0.879                 | 0.626                    | refrigerated or frozen |
| DTP-HebB-Hip | 6, 10, 14 weeks  | 10        | 3.062                 | -                        | refrigerated         |
| Pneumo       | 6, 10, 14 weeks  | 10        | 2.109                 | -                        | refrigerated         |
| IPV          | 14 weeks         | 10        | 2.440                 | -                        | refrigerated         |
| Measles      | 9, 16 months     | 10        | 2.109                 | 3.142                    | refrigerated         |
| MenA         | 9 months         | 10        | 2.109                 | 3.106                    | refrigerated         |
| Yellow Fever | 9,16 months      | 10        | 2.715                 | 4.730                    | refrigerated         |
| Rotavirus    | 6, 10 weeks      | 1         | 17.126                | -                        | refrigerated         |
| OPV          | birth, 6, 10, 14 weeks | 1    | 0.879                 | -                        | frozen               |

6.1.3 Drone Specifications

A growing number of companies offer drone delivery for medical supplies, using a variety of drone technologies (Zipline, 2019; Dove Air, 2021; Deutsche Post Group, 2021; Wingcopter, 2021; Scott and Scott, 2017). Depending on the employed technology, drones have different capabilities. For instance, fixed-wing drones have larger ranges and higher speeds compared to rotor drones. However, most fixed-wing drones cannot launch vertically and need more space or special equipment for take-off and landing. Also, there is a substantial difference in terms of range and payload between battery-powered and fuel-based drones. Purchase costs for single drones and investment costs for drone hubs are hardly available since most companies offer drone delivery only as a service. Thus, we derived the drone capabilities and estimated costs using data from several drone companies (Zipline, 2019; Dove Air, 2021; Deutsche Post Group, 2021; Wingcopter, 2021), other academic publications (Scott and Scott, 2017; Walia et al., 2018), and conversations with experts. We use drone specifications summarized in Table 4.
Table 4: Drone Specifications

| Parameter        | Value         |
|------------------|---------------|
| Range (one way)  | ~ 30 to 75 km |
|                  | ~ 900 km      |
| Payload          | ~ 1.0 to 2.0 liters |
|                  | > 10 liters   |
| Cruise speed     | ~ 75 km/h     |
| Investment costs | per drone $ 30,000 |
|                  | per drone Hub $ 1 Mil. |

6.2 Experimentation and Results

We conducted experiments to evaluate the computational performance of the pre-processing stage, and to evaluate the impact of the proposed VSC on SR. We focus on the regions Agadez, Diffa, Maradi, and Zinder and solve the model for each region separately because (i) the cold capacity at the central store is not a bottleneck of the cold chain [Ministry of Public Health Niger, 2016], (ii) each region serves its own population [Ministry of Public Health Niger, 2016], (iii) the selected regions represent diverse geographical settings, and (iv) considering only a subset of regions reduces the computational complexity of the model.

The experiments were run in C++ on a computer with Intel Core i7-5500 processor with 2.40 GHz using CPLEX 12.10.0 as solver.

6.2.1 Computational performance

To evaluate the impact of the pre-processing stage on the solution time and quality, we solved models (P) and (Q), which correspond to the original and aggregated networks. We used 5Km as the maximum acceptable travel distance to a vaccination center, which aligns with Niger’s immunization strategy [Ministry of Public Health Niger, 2016]. Table 5 reports the results of the experiments. Figure 5 presents Maradi’s VSC network before and after aggregation.

The results show that demand aggregation significantly reduces the network sizes and running times of CPLEX. For Agadez and Diffa the average running times were reduced...
Table 5: Network sizes and running times for the original and aggregated networks. (* no solution found within 10 hours)

| Region    | Nodes [-] | Arcs [-] | Run Time [sec] |
|-----------|-----------|----------|----------------|
|           | Orig.     | Agg.     | Orig.          | Agg.          | Orig.  | Agg.  |
| Agadez    | 1283      | 634      | 7282           | 1010          | 30 sec | 7 sec |
| Diffa     | 2144      | 629      | 15980          | 1135          | 155 sec| 8 sec |
| Maradi    | 5383      | 569      | 93079          | 2227          | *      | 81 sec|
| Zinder    | 7590      | 1058     | 141262         | 2624          | *      | 129 sec|

by 77% and 95%, respectively. For Maradi’s and Zinder’s original network, CPLEX failed to find a solution within 10 hours. However, after the network aggregation, the instances were solved within a few minutes. In fact, the computational challenges faced when solving the large problem instances, motivated the proposed pre-processing stage.

Figure 5: Maradi’s VSC network. Gray nodes are regional centers, blue nodes are distribution centers, red nodes are clinics, and green nodes are communities.

We found that both models, $(P)$ and $(Q)$, establish the same drone hubs in Agadez and Diffa. However, the SRs for model $(Q)$ are 1.62% smaller on the average. Nevertheless, solving model $(Q)$ yields near optimal solutions in reasonable time.
6.2.2 Discussion of results

The following discussion addresses some relevant questions related to our proposed research.

**What is the impact of outreach sessions and drone deliveries on SR?** We establish a baseline scenario, where there are no drone deliveries and no outreach sessions. This is achieved by setting the available budget to build the drone network to zero. Several researchers assume that families in LICs and LMICs have access to clinics (Azadi et al., 2020; Chen et al., 2014). Additionally, these researchers assign communities uniformly among clinics. These simplifying assumptions overestimate SR. To demonstrate this, we conducted a few experiments that solve the baseline scenario assuming full and limited access to clinics. Under the assumption of full access, we assign communities uniformly among clinics. Under the assumption of limited access, we assign a community to a clinic if located within 5Km of the clinic. Otherwise, the community does not have access to a clinic, and their children are not vaccinated. We measure the SR value for each clinic, and the SR value for each community.

| Region | Full access | Limited access |
|--------|-------------|----------------|
|        | Communities | Clinics | Communities | Clinics |
| Agadez | 93.59 %     | 93.59 % | 41.55 %     | 81.83 % |
| Diffa  | 99.51 %     | 99.51 % | 23.05 %     | 88.80 % |
| Maradi | 70.34 %     | 70.34 % | 23.51 %     | 75.24 % |
| Zinder | 81.49 %     | 81.49 % | 22.19 %     | 98.20 % |

Table 6 summarizes the results of these experiments. Assuming full access to a clinic overestimates SR, and consequently overestimates the proportion of children that could get vaccinated. The SR values for the regions of study are lower when accessibility to clinics is considered. Based on our results, 81.83% of the children who have access to a clinic in Agadez could be vaccinated. This is because of cold limited storage capacity at clinics. Overall, only 41.55% of the children of Agadez could be vaccinated. This is because of most children do not have access to a clinic and/or limited cold storage capacity.

The SR values in Table 6 are below 100% when we assume full access to clinics. This
Table 7: Region-Based SR Values for the Baseline Scenario: Changing Cold Capacity

| Region  | Bottleneck          | Limited Capacity Communities | Limited Capacity Clinics | Unlimited Capacity at Bottleneck Communities | Unlimited Capacity at Bottleneck Clinics |
|---------|---------------------|------------------------------|--------------------------|---------------------------------------------|------------------------------------------|
| Agadez  | Agadez City, Arlit  | 41.55%                       | 81.84%                   | 50.77%                                      | 100%                                     |
| Diffa   | Diffa City          | 23.05%                       | 88.80%                   | 25.96%                                      | 100%                                     |
| Maradi  | Maradi City         | 23.51%                       | 75.24%                   | 30.99%                                      | 100%                                     |
| Zinder  | -                   | 22.19%                       | 98.20%                   | 22.19%                                      | 98.20%                                   |

is because of limited availability of cold storage and transportation in the VSC. The SR values of a region are different under the assumption of full and limited accessibility. This is because of the approach followed in assigning communities to clinics. When we assume limited access, the large population of Agadez city, Arlit, Diffa city, and Maradi city is assigned to clinics located in these cities. This leads to a disproportional number of children assigned to clinics in major cities as compared to other areas of the country, and lower SR values because of limited cold storage. Such realities could prevent Niger from achieving the EPI target of vaccinating 90% of the children. Thus, increasing access to immunization services is crucial to close the gap in immunization coverage, and confirms the findings from Blanford et al. (2012). Using outreach sessions increases accessibility and shows a great potential to improving vaccination rates. Based on these experiments, providing access to vaccination (i.e., via outreach sessions) could increase SR between 1.2 to 4.3 times.

Motivated by the results presented in Table 6, we conduct one additional experiment for the baseline scenario with limited access. We resolve the baseline scenario assuming that the major cities of Niger have unlimited cold storage capacity. We calculate the SR values for the clinics and for the overall communities in the region, and present the results in Table 7. By increasing the cold storage capacity, the SR value of clinics in Agadez, Diffa, and Maradi increase. These clinics have the inventory necessary to vaccinate the children who live within 5Km. This resulted to a 12-32% increase of SR for the corresponding regions.

Let us summarize our observations: (i) outreach sessions supported by drone distribution networks have the potential to drastically increase accessibility to vaccines; (ii) increasing cold storage of clinics located in highly populated areas can lead to greater improvements of SR. However, such an approach does not ensure an equitable distribution of
resources.

**What are the bottlenecks of the VSC?** The results presented in Table 7 show that limited cold storage capacity of clinics in major cities of Niger impacts SR. In Figures 6a and 6b we present the utilization of cold storage and cold transportation for the baseline scenario, at all levels of the VSC. In these figures, the $x$-axis presents the utilization level, and the $y$-axis presents the number of observations. For example, trucks are used to deliver vaccines from the national-level central store to the 8 regional level stores. Since the size of vaccine vials is small, these trucks are underutilized. Cars and motorcycles are used to transport vaccines from 44 district stores to the 695 clinics. Thus, due to the small storage capacity, the utilization of these transportation vehicles is higher. Similarly, the cold storage capacity at the central store is underutilized since vaccines are moved downstream the VSC. However, for a few clinics, the cold storage utilization is over 80%. These are clinics located in major cities.

Motivated by the findings in Figures 6a and 6b, we decided to evaluate the impact of increasing storage capacity (SC) and transportation capacity (TC) on SR and the proportion of fully vaccinated children (FIC). We conducted experiments by increasing the values of TC and SC for the baseline scenario. Figure 7 summarizes the results of these experiments. These are our observations: (i) increasing TC, by increasing the frequency of shipments, has a greater impact in improving SR as compared to increasing SC; (ii) increasing both, TC and SC, has a greater impact in improving FIC, as compared to only increasing TC or SC.
How does budget size impact SR? We consider five budget levels, $0 (baseline scenario), $2 Millions, $3 Millions, $4 Millions, and $5 Millions. These budgets are used to purchase drones with ranges 30 km, 50 km, 75 km, and 900 km. We experimented with every combination of budget and drone ranges. The results of these experiments are summarized in Figure 8. These are our observations: (i) every positive budget results in higher SR than the baseline scenario for every region of Niger. This is because the budget is used to establish a drone delivery network; (ii) using drones of any range improves SR of every region. Using drones of range 900 km resulted in the highest values of SR, 100%. However, Maradi region benefits greatly from using drones of range 50 and 75 km. This region has the smallest area, and highest population density in the country (see Table 12 in the Appendix).

Do drones with higher payload or higher range have a greater impact on SR? We initially conduct a $2^6-2$ factorial design of experiments (DOE) (?) to determine what factors impact the value of SR. For each factor we determine two levels, low and high. The factors and the corresponding levels are: budget, $2 and $4 million; drone payload, 1 and
2 litters; drone range, 30 and 75 km; land TC, 100% an 125% of the existing capacity; cold SC, 100% an 125% of the existing capacity; and demand, 100% an 125% of the existing demand. The results of these experiments for Agadez are presented in Figure 9. We make the following observations: (i) drone range, rather than drone payload, greatly impacts the mean value of SR; (ii) budget size and drone range greatly impact the mean value of SR; (iii) investments on establishing a drone network result in higher SR than investments on land TC or cold SC.

We also conducted a full factorial design to gain further understanding on the impact that budget size and drone range have on SR. Figure 10 summarizes these results for Agadez. We make these observations: (i) when the budget is used to purchase short range drones, then, the initial increase of budget size greatly impacts SR. However, the maximum achievable SR from investments on short range drones is only 70%; (ii) the maximum
increase of SR comes from using long range drones, which improves accessibility of remote communities. Figure 11 presents the location and coverage of drone hubs that use drones with range 75 km. The total budget to establish this drone network is $5 million, which is used to establish 4 hubs and purchase the drones. The range of the drones does not cover communities located in remote areas.

What strategies to use in designing the drone network? Based on the results of Figure 8, budget size impacts decisions about the number and location of drone hubs, and the fleet size. In these experiments, we observed that drone hubs are typically located at regional centers. The inventory level of regional centers is larger than district centers and clinics. Drone deliveries provide clinics and outreach posts with access to the inventory of regional centers.

Since LICs and LMICs have limited resources, it is of interest to evaluate what strategies these countries can use to establish and expand the drone network to increase accessibility to vaccines. Our proposed strategy is to use regional centers as potential location for drone hubs. If budget is limited, priority should be given to regional centers that are close to highly populated areas. As additional budget becomes available, this network can be extended.

In order to evaluate the performance of this proposed strategy, we design the following experiment that mimics a potential expansion of the drone network. The experiment solves a variation of model \((Q)\) in which only regional centers are candidate locations to establish a drone hub. Let us call this model \((\bar{Q})\). We solve model \((\bar{Q})\) the first time assuming a $2 million budget to establish the drone hub and purchase drones. We solve model \((\bar{Q})\) a
second time assuming a budget of $3 millions, of which $2 million is already assigned to establishing the hub(s) open the first time we solved model ($\bar{Q}$). We continue in this fashion by changing the budget in increments of $1 million and resolving ($\bar{Q}$) till the total budget reaches $5 millions. The SR values for each of the solutions found are compared to the optimal solution of ($Q$) (at the corresponding budget level). The corresponding percentage decrease of SR values are summarized in Table 8. We observe that the proposed strategy is optimal in 78% of the problems solved, and in the worst case reduces SR by at most 2.12%.

7 Summary of Results and Future Research Directions

Achieving vaccination targets in low-income and low-middle-income countries (LICs and LMICs) is a challenging task. Therefore, this study examines the use of drones to improve vaccine distribution. For this purpose, we develop a mixed-integer linear program that determines where to establish drone hubs to improve access to vaccination. The model
Figure 11: Drone Network of Agadez: Budget $5 Million, Drone Range 75 km

Table 8: Percentage Difference of SR of the Proposed Drone Network Expansion and the Optimal Solution

|        | Agadez |                                      | Diffa |                                      |
|--------|--------|--------------------------------------|-------|--------------------------------------|
|        |        | Drone Range [km]                     |       | Drone Range [km]                     |
| Budget | Drone Range [km]   |       | Budget | Drone Range [km]          |       |
|        | [Million] | 30 | 50 | 75 | 900 | [Million] | 30 | 50 | 75 | 900 |
| 2.0    | 0.40%  | 1.36% | 2.12% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| 3.0    | 0.00%  | 1.36% | 2.12% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| 4.0    | 0.00%  | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| 5.0    | 0.00%  | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |

|        | Maradi |                                      | Zinder |                                      |
|--------|--------|--------------------------------------|--------|--------------------------------------|
|        |        | Drone Range [km]                     |        | Drone Range [km]                     |
| Budget | Drone Range [km]   |       | Budget | Drone Range [km]          |       |
|        | [Million] | 30 | 50 | 75 | 900 | [Million] | 30 | 50 | 75 | 900 |
| 2.0    | 0.00%  | 0.00% | 0.00% | 0.00% | 2.31% | 1.91% | 1.10% | 0.00% |
| 3.0    | 0.00%  | 0.00% | 0.00% | 0.00% | 0.78% | 1.16% | 0.00% | 0.00% |
| 4.0    | 0.16%  | 0.00% | 0.00% | 0.00% | 0.00% | 1.99% | 0.00% | 0.00% |
| 5.0    | 0.15%  | 0.00% | 0.00% | 0.00% | 0.00% | 1.62% | 0.00% | 0.00% |

30
captures transportation and inventory replenishment decisions in the vaccine supply chain (VSC). The model considers the spatial distribution of communities and the location of clinics in determining locations for drone hubs. We develop a case study using data from Niger. We develop a pre-processing algorithm to reduce the problem size. The aggregated model is solved via CPLEX.

Via the case study, we make a number of observations. The most relevant findings are:

- Improving accessibility to immunization services via outreach sessions is crucial to achieve vaccination targets >90%.

- Drones are capable to increase vaccination rates by mitigating bottlenecks in the cold chain via on-demand deliveries to clinics and by reaching undeserved hard-to-reach areas.

- The benefits of drone deliveries are mainly limited by the size of the drone network and reach of the drones. Thus, it is important to determine the location of drone hubs and the drone range to achieve vaccination targets.

- Our proposed strategy of using regional centers in highly populated areas as potential location for drone hubs, and extending the drone network as the budget becomes available, leads to high SR values (high quality solutions).

The efficacy of the proposed model is limited by assumptions made to deal with missing or incomplete data. Our proposed model does not consider vaccine hesitancy, and assumes that if vaccines are available within reach (within 5Km from the community), they are used. However, the actual demand for vaccines is influenced by many factors such as religious beliefs, education, attitude towards vaccination, accessibility of services, birth rates, and others [Toikilik et al. (2010)]. We did not have the data and knowledge about the impact of vaccine hesitancy on vaccination demand at the community level. The model can be extended by estimating vaccine hesitancy, and using these estimated to update demand in the VSC. Changes in demand impact the design of the drone network.

The proposed model considers dedicated, single-trip deliveries. Such a policy is simple and easy to implement. In contrast, supplying multiple locations in one trip could reduced the number of drones used in the VSC, and shift attention to the drone payload. We only
consider the initial investment cost for the drone network but do not include the operational costs due to lack of data. Extending the model to consider these options could improve the operations of VSC.

We assume that vaccination demand is deterministic. However, the model can be extended to evaluate the impact of stochastic demand on VSC decisions. Additionally, the model can be extended to capture the impacts of using drones for the delivery of vaccines during VSC disruptions caused by disasters, war and conflicts, pandemics, etc.

Finally, our case study focuses on Niger. The VSC and demographics of Niger are different from other Sub-Saharan countries. However, these countries have large rural population that remains under-served because of lacking access to clinics. Therefore, it can be assumed that in these countries, drone delivery has a similar impact and helps to improve vaccination rates by serving people in rural areas.

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32
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## 8 Appendix

### 8.1 Summary of Notation

Table 9: Sets

| Set | Description |
|-----|-------------|
| $\mathcal{A}$ | Arcs |
| $\mathcal{A}^*$ | Arcs that represent land transportation routes, $\mathcal{A}^* \subset \mathcal{A}$ |
| $\mathcal{A}'$ | Arcs that represent community’s access to a vaccination center, $\mathcal{A}' \subset \mathcal{A}$ |
| $\hat{\mathcal{A}}$ | Arcs that represent potential drone delivery routes, $\hat{\mathcal{A}} \subset \mathcal{A}$ |
| $\mathcal{I}$ | Facilities with available cold storage. These are potential locations for drone hubs. |
| $\mathcal{J}$ | Cold chain facilities and communities |
| $\mathcal{K}$ | Communities, $\mathcal{K} \subset \mathcal{J}$ |
| $\bar{\mathcal{K}}$ | Communities that have access to a clinic, $\bar{\mathcal{K}} \subset \mathcal{K}$ |
| $\mathcal{L}$ | Vaccines |
| $\mathcal{O}$ | Outreach posts, $\mathcal{O} \subset \mathcal{J}$ |
| $\Pi$ | Vaccination centers, $\Pi \subset \mathcal{J}$ |
| $\mathcal{T}$ | Discrete time periods |
Table 10: Parameters

| Parameter | Description |
|-----------|-------------|
| $a_l$     | Number of doses needed from vaccine $l \in \mathcal{L}$ to complete the vaccination regimen. |
| $a_{jk}$  | An indicator parameter that takes the value 1 if vaccination center $j \in \Pi$ is reachable (within 5Km) from community $k \in \mathcal{K}$, and takes the value 0 otherwise. |
| $b$       | Budget available to establish drone hubs and purchase drones. |
| $c_i$     | Costs to establish a drone hub at location $i \in \mathcal{I}$. |
| $\bar{c}$ | Unit purchase cost of a drone. |
| $d_{ij}$  | Distance (in Km) of arc $(i, j) \in \mathcal{A}$. |
| $\epsilon$ | A scaling factor. |
| $h$       | Total number of operating hours per drone hub per time period. |
| $q_l$     | Effective packed volume of one dose of vaccine $l \in \mathcal{L}$. |
| $m$       | The maximum number of drones that can be purchased using the available budget $b$. |
| $\pi_{klt}$ | Demand for (number of children in need of a) vaccine $l \in \mathcal{L}$ at community $k \in \mathcal{K}$ in period $t \in \mathcal{T}$. |
| $\pi_{ilt}$ | Demand for (number of children in need of a) vaccine $l \in \mathcal{L}$ at vaccination center $i \in \Pi$ in period $t \in \mathcal{T}$. |
| $r_l$     | Volume of the diluent for a single dose of vaccine $l \in \mathcal{L}$. |
| $s$       | Average travel speed of a drone. |
| $u^d$     | Drone payload. |
| $u_i$     | Cold storage capacity at facility $i \in \mathcal{I}$. |
| $u^t_{ij}$ | Cold land transportation capacity along $(i, j) \in \mathcal{A}^*$. |
| $u^b_{il}$ | Fraction of vaccine $l \in \mathcal{L}$ lost to breakage or inadequate cooling at facility $i \in \mathcal{I}$. |
| $u^o_{il}$ | Fraction of open-vial wastage during administration of vaccine $l \in \mathcal{L}$ at vaccination center $i \in \Pi$. |
| $w^t_{ij}$ | Fraction of vaccine $l \in \mathcal{L}$ lost to breakage or inadequate cooling during land transportation along $(i, j) \in \mathcal{A}^*$. |
| $w^d_{ij}$ | Fraction of vaccine $l \in \mathcal{L}$ lost to breakage or inadequate cooling during drone transportation along $(i, j) \in \mathcal{A}$. |
Table 11: Decision variables

| Variable | Description |
|----------|-------------|
| $D_{ijlt}$ | A continuous variable that represents the number of doses of vaccine $l \in \mathcal{L}$ shipped via drones from location $i$ to $j$ $((i,j) \in \mathcal{A})$ in period $t \in \mathcal{T}$. |
| $I_{ilt}$ | A continuous variable that represents the inventory of doses of vaccine $l \in \mathcal{L}$ at location $i \in \mathcal{I}$ at the end of time period $t \in \mathcal{T}$. |
| $N_{k}$ | A continuous variable that represents the number of fully immunized children of community $k \in \mathcal{K}$. |
| $S_{ijlt}$ | A continuous variable that represents the number of doses of vaccine $l \in \mathcal{L}$ shipped via land transportation from facility $i$ to $j$ $((i,j) \in \mathcal{A}^*)$ in period $t \in \mathcal{T}$. |
| $V_{it}$ | An integer variable that represents the number of drones used at facility $i \in \mathcal{I}$ during period $t \in \mathcal{T}$. |
| $W_{i}$ | A binary variable that takes the value 1 if an outreach post is established at community $i \in \mathcal{K}$, and takes the value 0 otherwise. |
| $X_{iklt}$ | A continuous variable that represents the number of doses of vaccine $l \in \mathcal{L}$ administered at vaccination center $i \in \Pi$ to children from community $k \mathcal{K}$ in period $t \in \mathcal{T}$. |
| $X_{ilt}$ | A continuous variable that represents the number of doses of vaccine $l \in \mathcal{L}$ administered at vaccination center $i \in \Pi$ in period $t \in \mathcal{T}$. |
| $Y_{i}$ | A binary variable that takes the value 1 if a drone hub is established at facility $i \in \mathcal{I}$, and takes the value 0 otherwise. |
| $Z$ | An integer variable that represents the number of drones purchased. |
8.2 Model \((Q)\)

The following is the formulation of model \((Q)\).

\[
z = \max \sum_{i \in \Pi} N_i + \epsilon \sum_{i \in \Pi} \sum_{t \in \mathcal{T}} \sum_{l \in \mathcal{L}} X_{ilt}. \tag{28}
\]

s.t. \((5) - (7), (10) - (12), (13), (22) - (19)\)

\[
I_{ilt} = (1 - \omega_{il}^b)I_{ilt-1} - \sum_{j: (i,j) \in \mathcal{A}^*} S_{ijlt} + \sum_{j: (j,i) \in \mathcal{A}^*} (1 - \omega_{ji}^f)S_{jilt-1} - \sum_{j: (i,j) \in \hat{\mathcal{A}}} D_{ijlt} + \sum_{j: (j,i) \in \mathcal{A}} (1 - \omega_{ji}^d)D_{jilt} - \left(\frac{X_{ilt}}{1 - \omega_{il}^o}\right), \quad \forall i \in \mathcal{I}, \ l \in \mathcal{L}, \ t \in \mathcal{T}, \tag{29}
\]

\[
\sum_{j: (j,i) \in \mathcal{A}} (1 - \omega_{ji}^d)D_{jilt} = \left(\frac{X_{ilt}}{1 - \omega_{il}^o}\right), \quad \forall i \in \mathcal{O}, \ l \in \mathcal{L}, \ t \in \mathcal{T}. \tag{30}
\]

\[
\sum_{t \in \mathcal{T}} X_{ilt} \leq \sum_{t \in \mathcal{T}} \pi_{ilt}, \quad \forall i \in \mathcal{I}, \ l \in \mathcal{L}, \tag{31}
\]

\[
N_i \leq \sum_{t \in \mathcal{T}} \frac{X_{ilt}}{a_i}, \quad \forall i \in \mathcal{I}, \ l \in \mathcal{L}. \tag{32}
\]

8.3 Data

Table 12: Geographical characteristics of the regions

| Region  | Population | Area  | Population density |
|---------|------------|-------|--------------------|
| Agadez  | 626,100    | 634,209 | 0.99               |
| Diffa   | 762,700    | 140,216 | 5.44               |
| Maradi  | 4,728,200  | 38,581 | 122.55             |
| Zinder  | 4,873,900  | 145,430 | 33.51              |