Towards Smart Society: Deployment of Drones in Optimizing the Allocation of Covid-19 Vaccines, the Case of Qatar

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Abstract
Large-scaled distribution of vaccines can be highly complex and dynamic. This paper aims to propose an integrated framework that addresses the limitations of former literature in optimizing vaccine allocation for controlling the covid-19 outbreak in Qatar. First, we predicted the total positive cases in Doha for the upcoming 14 days using Autoregressive Integrated Moving Average (ARIMA) modeling. The best fit model was ARIMA (4,2,4) based on BIC (Bayesian Information Criteria) with an overall MAPE of 4.86% and R^2 of 0.9973 values. Then, we formulated a mathematical model to optimally allocate covid-19 vaccines to the twenty-five Primary Healthcare Centers (PHCCs) considering the total associated disease spread risk among the population, operational capacity limitations, and the transfer of ATP (Available to Promise) quantities between the centers. The obtained results provided managerial insights on how decision-makers can create efficient logistical capabilities for covid-19 vaccine allocation.

Keywords
Available to Promise, Covid-19, Vaccines Distribution, Optimization models.

1. Introduction
Two years since the covid-19 outbreak, it claimed more than 6 million lives worldwide, including 678 deaths in Qatar (MOPH 2022). According to a report issued by the Asian Development Bank, the estimated global economic loss could reach 5.8 trillion to 8.8 trillion USD (Sawada & Sumulong 2021), pushing millions into poverty and contributing to the rising rates of domestic abuse and mental health issues. Despite these dark numbers, global efforts contributed to breakthroughs in developing safe covid-19 vaccines at a wrapping speed. However, ending the covid-19 pandemic is not about the development of vaccines; it is about the administration of vaccines (Mak et al. 2021). The American center for disease control and prevention stated that although 14 million doses have already been produced in late 2020, only 2 million doses were administered. Adding to the urgency of distributing vaccines, the virus continues to spread rapidly and mutate. Thus, racing against the time, the current mass vaccination effort can be challenging in terms of:

1.1. Vaccine Production
The availability of the raw material, such as the enzymes used to convert DNA to mRNA for Pfizer and Moderna vaccines and packaging material, such as vials and stoppers, can limit the vaccine production rate. Also, the production yield can be unpredictable because of the uncertainty imposed in the production process. For example, AstraZeneca's vaccine requires cells' growth inside bioreactors, which is a very delicate process that causes significant delays in its delivery. As a result, more than 130 countries have not received a single covid-19 vaccine dose by February 2021 (Beaubien 2021). Notably, any modifications to scaling up the vaccine production capacity require regulatory approvals, which take a long duration.

1.2. Variability and Eligibility of the Demand
Vaccine hesitancy can be one factor contributing to demand variability. As per (Brenan 2021), 29% of healthcare workers in the U.S. hesitated to take the vaccine. Accordingly, the demand variability can impact the amount of vaccine wastage given the sensitive process of administering the mRNA vaccine.

1.3. Distribution
The transportation, storage, and administration of covid-19 vaccines can impose another challenge. As they require low storing temperatures also, their preparation process is very delicate. For example, the vaccine developed by Pfizer requires temperature settings to be between – 80℃ to -60℃ for a long storage duration. In comparison, the vaccine developed by Moderna requires temperature settings to be between 2℃ and 8 ℃. However, both vaccines must be administered within a maximum duration of 6 hours once diluted, and unopened vials should be discarded after exceeding the recommended period (World Health Organization 2021).

1.4. Inventory Management
Pfizer and Moderna vaccines require two dose regimens, which create a unique timing challenge. For example, the Moderna vaccine requires two doses with a recommended 28-day interval in between. To ensure adherence to the necessary two-dose regimen, countries initially followed a "hold-back policy," which implies that for each dose offered to a first-time recipient, one additional dose is reserved until the recipient returns for the second dose. Although the hold-back policy can ensure the supply of two doses for each recipient, it can cause delays for other individuals who did not yet receive their first dose (Mak et al. 2021).

2. Search Strategy
We started our searching strategy by selecting the top 10 journal databases in the "Operation Research" category as per Google scholar rankings. The investigation was confined to peer-reviewed journal articles with a publications period covered between 2014 and 2021, with older exceptions pertaining to papers of relevance. Multiple keywords such as "Vaccine," Vaccination," immunization," "Humanitarian logistics," "Cold Supply Chain," "Relief Supply chain," "Emergency Response Supply Chain," and "Covid 19" were used in the searching criteria. The investigation resulted in a total of 834 unique publications.

•Not scientific articles such as editorial statements, book reviews, and conference papers were disregarded.
•Papers related to healthcare management and clinical trials were disregarded; the scope was specified as Decision Science, Engineering, and Business Management.
•Articles written in languages other than English were also disregarded.
•Papers that lack healthcare or logistics terminology were disregarded. These publications were cited with one of the keywords in the title.

Eventually, 87 publications in the top operation research journals dealing with vaccines logistics, and supply chain topics and 3 books were selected and studied thoroughly. An additional supporting literature review search using the SCOPUS database and following the same criteria was conducted to have more comprehensive results.

3. Literature Review
The vaccine Supply Chain and Logistics (VSCL) systems have supported achieving the required vaccination coverage by overcoming enduring challenges in vaccine storage, allocation, and management. Despite many efforts, the immunization programs for most developing countries are already struggling to meet the demand and respond to any introduction of new vaccines. The expansion of the target population, the increasing cold chain infrastructure requirements, and insufficient funding are some challenges that can stress VSCL systems. The existing systems cannot keep pace with the changes, resulting in ineffective vaccine administration, vaccine wastage, and stock-outs, all of which have performance and cost implications(Bown et al. 2021). There are several differences between the vaccine supply chain (VSC) and the traditional supply chain, which can provide unique characteristics of VSC. For instance, the non-profit identity of the buyer, high associated risks in terms of products' perishability, supply and demand uncertainties, and very limited reliable information (Shamsi G. et al. 2018).

3.1 Policies & Strategies
Vaccination is one of the widely known methods in effectively controlling the spread of diseases such as SARS, Influenza, H1N1, Ebola, and Covid-19. After developing and producing vaccines, the main concern will be acquiring herd immunity as fast as possible. (Randolph & Barreiro 2020)defined herd immunity as " the indirect protection from infectious disease that can occur with some diseases when a sufficient percentage of a population has become immune to an infection." Thus, once the community acquires it, the infection will be effectively contained. 67% is the estimated herd immunity threshold for covid-19 which implies that the number of infected individuals will reduce once the percentage of immune individuals exceeds it (Randolph & Barreiro 2020). Vaccination can help in obtaining

herd immunity by enhancing the immunity of the vaccinated individuals and, thus, reducing the exposure of the disease for the unvaccinated individuals. Various vaccination strategies can be implemented like mass, random and targeted vaccination. Mass vaccination tends to administer a large number of vaccine doses among the population in a short time. While random vaccination tends to vaccinate randomly selected individuals. In contrast, targeted vaccination tends to focus on a specific group of the population.

With the limitation in supplying vaccines, prioritizing vaccine distribution or targeted vaccination can be one of the best strategies in mitigating the impacts of the pandemics. It has the potential to reduce economic losses, mortality, and protect population health significantly. (Ng et al. 2018) formulated a multi-objective MILP model that determines the optimal number of influenza vaccine doses under different vaccination strategies. Their study revealed that vaccinating a target group can be more effective compared to other vaccination strategies when there is a high demand and limited supply of vaccines. Accordingly, a stream of research focused on determining the priority groups under various objectives using mathematical models, population studies, and computer-based simulations. For example, (Russo et al. 2021) present a population-based cohort study that identifies high-risk categories worth targeting and prioritizing to minimize the number of future deaths.

Given the strong correlation between age and risk associated with covid-19 infection, (Hogan et al. 2021) propose a mathematical model of covid-19 transmission across various countries to assess the impact on public health using age-based prioritization. The majority of research that focuses on vaccine allocations assumes one strategy. In light of this, (Lee et al. 2021) present a mixed strategy modeling framework aiming to reduce the covid-19 death rate by determining when the strategy should be shifted from prioritized to non-prioritized vaccination. The paper adopts a systematic prioritized vaccination that considers healthcare workers, pregnant women, children, and individuals with chronic diseases as a high-risk group; hence they will be the first to get vaccinated. However, when the vaccine supply level is higher, the model facilitates vaccine dispensing to the general population.

Similarly, (Duijzer et al. 2018) develop a disease progression model using SIR and study the switching curve between strategies considering the timing of vaccination and the efficacy of vaccines. Since infectious diseases can spread rapidly, it is better to start immunizing people as soon as possible. But responding effectively to a breakout cannot always be initiated directly because the disease's characteristics are not yet known or because vaccines' production and allocation take time. Their model shows that a hybrid vaccination strategy outperformed the other strategies as it could decrease the number of infections by more than 50%.

3.2 Intermodal Transportation

Decision-makers tend to combine the available transportation modes to enhance the overall efficiency of the distribution network. For example, in disasters, the key roads to affected areas can be cut off, or distances between the distribution center and demand nodes are too far. Thus, (Ruan et al. 2016) propose an intermodal transportation network using helicopters and trucks to deliver medical supplies during large-scale disasters. Moreover, technological developments in automation (e.g., unmanned vehicles, robots, and drones) represent an opportunity to develop more innovative, sustainable, and efficient delivery models characterized by integrating different and complementary transportation modes. Several studies focused on the possibility of integrating trucks with robots for last-mile delivery. For instance, (Simoni et al. 2020) derive an optimization algorithm using IP formulation for a robot-assisted truck delivery system, where the robot can leave the truck to perform deliveries.

The results reveal that the system can be quite beneficial when a small number of customers are located in congested areas. Another study by (C. Chen et al. 2021) adopt robots for contactless delivery during the covid-19 pandemic. The paper considers a vehicle routing problem where robots are dispatched to serve close customers while a driver serves another customer; it introduces a MILP model that aims to minimize the total route times. The numerical experiments unveil the value of autonomous delivery robots by highlighting their operational limitations in urban areas.

Drones' systems or drones-trucks combined systems have attracted the attention of Academica as well as the industry. Although a stream of research focused on this area, it is still not covered extensively in the literature because the concept is new to researchers, the complexity of these systems, and most importantly, the technology is still in the emerging stage (Chung et al. 2020). Accordingly, we selected key papers that study drone systems and drone-truck systems focusing on optimization methods or humanitarian logistics. To start with, (Rejeb et al. 2021) investigate the capabilities, performance measures, and limitations of adopting drones in humanitarian logistics. The study derives several research directions like studying the capability of drones to improve humanitarian organizations' capacities and estimating the cost savings attained from integrating drones into humanitarian logistics. In the context of medical delivery, in particular, vaccine transportation, (Haidari et al. 2016) illustrate that using drones can increase the availability of vaccines and reduce costs if their use is frequent enough to exceed the capital costs of installing and maintaining the system. Given the limited range of drones, (Ghelichi et al. 2021) studies the problem of selecting locations for drone charging stations, then assigning the fleet of drones that belong to some medical suppliers to multiple demand nodes, and finally scheduling the trips such that the total time required to satisfy the demand nodes is minimized. The results revealed correlations among the number of charging stations, the frequency of charging, and the payload capacity. The number of papers that focus on the deployment of drones to contain covid-19 infection is extremely low.

An overview of the current knowledge is presented by (Poljak & Šterbenc 2020). According to the authors, drones have been already implemented in various healthcare applications such as transporting samples for laboratory testing, blood bags, vaccines, etc. Also, (Kunovjanek & Wankmüller 2021) provided a feasibility study of using drones in distributing viral tests to potentially affected individuals, the empirical evidence found various scenarios where cost or time benefits can be obtained.

Drones can travel faster than trucks and are not restricted to following a particular path as long as it's a permitted flying area. Still, their load capacity and travel range are limited. Hence, the applicability of drones in delivery systems can be further enhanced when used with vehicles like trucks. Since two modes of transportation are involved, the research focuses on drone-trucks systems that can be classified based on their role. Either both can take the main role of the operation, or one of them will play the main role, and the other mode takes a supporting role. In addition, synchronization between the two modes is important as it can be related to the system's overall efficiency depending on the application areas (Chung et al. 2020). (Moshref-Javadi et al. 2020) is an example of a synchronized one truck and several drone systems. The truck plays the supporting role of transporting the drones to a specific demand node to serve multiple customers.

The objective of the proposed MILP model is to minimize the total customer waiting times. The experimental results show considerable waiting times reduction compared to TRP (i.e., Travelling Repairman Problem). Similarly, (Zhang et al., 2021) study a system where the truck launches a drone equipped with a camera to collect data after a disaster; the supporting role of the truck is to recharge the drone's battery. The objective of the model is to maximize the value of the collected information. On the other hand, the truck can play the primary role, and drones may support it in many ways. For instance, after the disaster, a fleet of ambulances may work as the main vehicle for providing support, and drones facilitate communication among the ground vehicles (Ladosz et al. 2018). Another example is (Dayarian et al., 2020), where the truck is the main method to conduct the delivery, and the drones support resupplying the trucks whenever they are stationary.

4. Existing Distribution Models

Responsive vaccine distribution can be a critical factor in the effectiveness and efficiency of the pandemic mitigation plan. More specifically, designing a vaccine distribution system can impact the overall performance of the healthcare system. The review shows the research in this field is immature, especially in the context of covid-19 disease. As a result, the scope of the literature was expanded to include epidemic resource allocation. Operation research and mathematical modeling methods have been widely used in controlling infectious diseases by determining optimal resource allocation strategies. Those most used approaches by practitioners include but are not limited to simulation models and OR models, which are discussed in the following sub-sections.

4.1 Optimization Models

Optimization-based models use algorithms to determine the best solution that maximizes or minimizes a specific objective. These models tend to solve problems such as optimal selection of locations, identification of transport routes that minimize time and costs, determination of capacities, and evaluation of various key performance indicators. In OR modeling, the problem can be characterized by various objective functions, modeling frameworks, and solution approaches based on the scope (e.g., strategic, tactical, or operational). Referring to table 1, most studies aim to minimize the associated costs. However, since metrics related to service levels like satisfying demand, reducing total service time, or equitable distribution are more critical in the humanitarian/vaccine supply chain, some studies attempt to capture two objectives related to both the cost and service level. Concerning modeling frameworks, integer programming models seem to be the most common quantitative OR methods in the distribution and allocation of vaccines problems[(Tavana et al. 2021); (Rastegar et al. 2021); (Singh et al. 2018); (Zhong et al. 2020); (Büyüktahtakın et al. 2018); (Ismail 2021); (Yang et al. 2021); (Noyan et al. 2016); (Cook & Lodree 2017); (Moreno et al. 2016)]. Since the disease transmission rates are highly uncertain, some studies considered the uncertain parameters. Those OR models used stochastic dynamic programming or two-stage stochastic programming [(Noyan et al. 2016), (Cook & Lodree 2017),(Moreno et al. 2016)]. Accordingly, the solution methods include commercial optimization solvers to get an exact solution to small-scale problems, and heuristics methods are applied for large-scale problems. Moreover, most studies prioritize the distribution of vaccines on an age basis because of the strong correlation between age and risk associated with future death [(Rastegar et al. 2021); (Yang et al. 2021); (Foy et al. 2021); (X. Chen et al. 2020)].

4.2 Simulation Models

Although simulation models have remarkable acceptance as an evaluation and decision analysis tool that mimics the real environment and captures changes in output parameters by allowing the user to change input parameters, these modeling approaches have well-known limitations (Rausser & Johnson 1975). One of them is that translating the simulation model's output into useful decisions can be challenging since it provides a wide range of possible outputs for each input parameter. More importantly, it is restricted by the level of systems abstraction and representation. For example, systems dynamics represent the global view of the system as it follows a top-down approach. In contrast, ABS (i.e., Agent-based simulation) follows a bottom-up approach by defining agents' attributes, behaviors, and interactions. In this sense, ABS provides a more flexible approach that enables the study of the epidemic at multiple levels (Kasaie & Kelton 2014). Some studies used agent-based simulation models to predict disease propagation and analyze interventions such as resource allocation strategies [(Yarmand et al. 2014), (Shamil et al. 2021); (Kerr et al. 2021); (Kasaie & Kelton 2014)].

One of the most popular simulation models that study epidemiology dynamics are compartmental models (e.g., SIR and SEIR) because of their simplicity and intuitiveness, for example [(Foy et al. 2021); (Enayati & Özaltın 2020); (Shamsi Gamchi et al. 2021); (Long et al. 2018); (X. Chen et al. 2020); (Gillis et al. 2021)]. These models split the population into different compartments, and the individual's status changes from one compartment to another at different rates, for example, the (S) compartment presents the individuals that are susceptible to the diseases, the (E) compartment presents the individuals who have been exposed (i.e., infected but not yet infectious), the (I) compartment consists of individuals who have been infected and capable of spreading the disease, and finally, the (R) compartment include the individuals who gained immunity and cannot spread the disease to others (Gillis et al. 2021). Since Simulation-based techniques can relax assumptions and provide a realistic representation of the disease transmission, several studies tend to couple the simulation and optimization approaches to analyze the system's behavior and seek optimal allocations simultaneously [(Kasaie & Kelton 2014); (Gillis et al. 2021); (Ghamizi et al. 2020)].

5. Demand Forecasting

Providing suppliers with a precise demand forecast can reduce the mismatch between the demand and the supply. As a result, the chain-wide inventories, vaccine wastage, and the associated costs can reduce significantly (Casella et al. 2000). Also, the reliability of infectious disease spread rate prediction models can impact the development of new combating strategies and determine the efficiencies of the imposed ones. Although most studies tend to use traditional epidemic models, for instance, SEIR (Susceptible-Exposed-Infective-Recovered), to forecast the epidemic trajectory, these methods have some limitations. For example, their validity depends on the precise estimation of the infection transmission parameters like R0 (reproductive quantity) and Incubation period, which can be difficult to calculate in a real-world context (Ghafouri-Fard et al. 2021a). To overcome these challenges; several studies proposed using machine learning techniques in predicting the number of infections, deaths, and recoveries. According to (Ghosh & Dutta 2021), machine learning can be defined as the process of making computers learn automatically by looking for patterns in historical observations aiming to make better decisions. One of the most efficient models that outperformed complex ones in short-term forecasts is the ARIMA (Autoregressive integrated moving average) model (Ghafouri-Fard et al. 2021b). (Alzahrani et al. 2020) used ARIMA (2,1,1) to predict the total covid-19 positive cases in the Kingdom of Saudi Arabia. Their model yielded 21.1 RMSE, 14.9 MAE, and 2.16 MAPE. Similarly, (Khan & Gupta, 2020) and (Nesa et al. 2021) adopted the ARIMA model to estimate the daily number of covid-19 cases. The model parameters selection criteria were based on BIC (Bayesian Information Criteria), and R^2 (coefficient of determination). The proposed model of (Khan & Gupta 2020) outperformed the nonlinear autoregressive (NAR) neural network model.

5.1 Gap Analysis

The previously discussed studies have made remarkable contributions to infectious disease control literature. However, there are still research gaps in vaccine allocation problems to control epidemics. To start with, our literature review indicates that most of the studies use either simulation modeling approaches or differential equations to predict the transmission of the disease, which can be difficult to incorporate in optimizing decisions. Although few papers attempted to bridge this gap by proposing simulation-optimization models, a limited number of papers have planned and built an efficient vaccine distribution network (refer to table 1).

Table 1. Classification of selected vaccines distribution articles

Modeling Approach	Number of Articles	Percentage of Articles	Publications
Integer Programming Models	7	28%	(Tavana et al., 2021), (Rastegar et al., 2021), (Singh et al., 2018), (Zhong et al., (Büyüktahtakın et al., 2018), (Ismail, 2021), (Y. Yang et al., 2021).
Stochastic Programming Models	3	12%	(Noyan et al., 2016), (Cook & Lodree, 2017), (Moreno et al., 2016)
Compartmental Models	5	20%	(Foy et al., 2021), (Enayati & Özaltın, 2020), (Shamsi Gamchi et al., 2021), (Lon 2018), (X. Chen et al., 2020)
Simulation Models	6	24%	(Yarmand et al., 2014), (Shamil et al., 2021), (Kerr et al., 2021), (Kasaie & Kelton (Gillis et al., 2021), (Ghamizi et al., 2020).
Other Models	4	16%	(Sadjadi et al., 2019), (Olivares & Staffetti, 2021), (Bulula et al., 2020), (Zahed 2020)

and even these studies did not fully consider the levels of susceptibility and exposure within which vaccine distribution network can be optimized to reduce the risk of infection. To our best knowledge, none of the previous studies have:

- Incorporate the transfer of available to promise vaccine quantities between healthcare centers.
- Investigate how recent technologies can achieve greater responsiveness in managing the last-mile delivery during the pandemic —specifically, the integration of drones with other transportation modes to ensure an efficient supply of vaccines.
- Incorporate the level of susceptibility and exposure risk in the optimization model.

In this paper, we address these shortcomings and the research gaps in the literature by formulating a forecasting-optimization model that optimizes the allocation of vaccines to control disease outbreaks such as covid-19 based on the risk of exposure, susceptibility, and the capacity of medical centers, and various mode of transport.

6. Problem Modeling

we propose an integrated approach to address the challenges of covid-19 vaccine allocation and to improve the effectiveness of the vaccine supply chain. As illustrated in Figure 1, our approach tends to integrate two models in a loop. Model 1 is a forecasting model that will predict the disease transmission dynamics and provide inputs specifically, the number of infections per area per age group for Model 2 (i.e., the optimization model). Similarly, the optimization model will feed its output into Model 1.

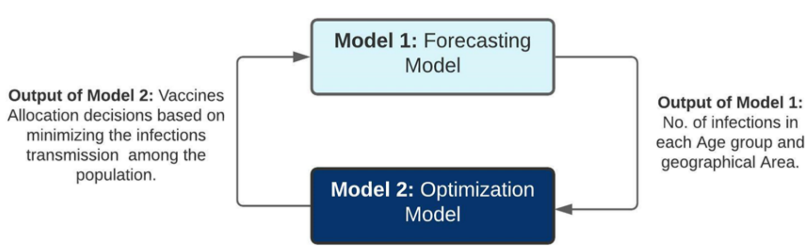

Figure 1. Integration Framework of Models 1 & 2

The forecasting model is developed using time series analysis (i.e., the ARIMA method), where the raw data is split into a training and testing set. As demonstrated in Figure 2. the first step is to check if the data is stationary or not. In other words, to check if it has a trend or a seasonality component. In case of the data is stationary, a difference technique can be applied. Then, the best parameters (p,d,q) of the ARIMA model will be configured using the Bayesian Information Criterion (i.e., BIC), verified using residual ACF, and finally, the model will be validated by calculating the mean absolute percentage error (i.e., MAPE) and coefficient of determination (i.e., R^2) for the forecasted data.

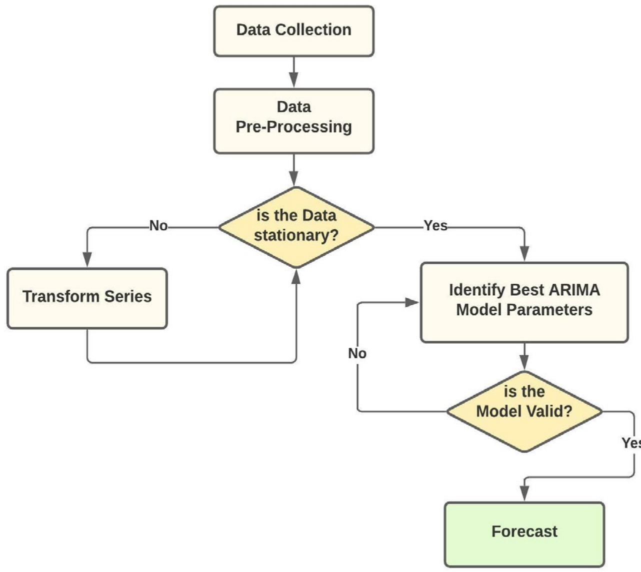

Figure 2. Methodology to Apply ARIMA Model for Forecasting

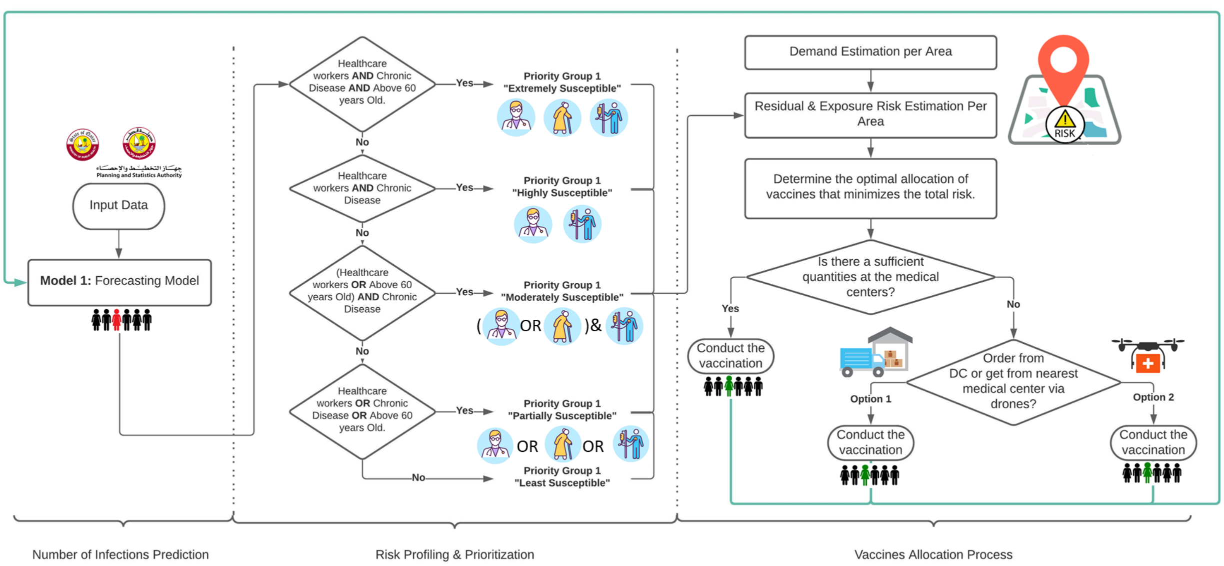

Figure 3. Methodology of Optimal Vaccines Distribution

The optimization model aims to minimize the infection transmission among the community throughout the planning horizon by allocating vaccines to healthcare centers based on the total risk of the individuals that a healthcare center is serving. Aligning with the world health organization's recommendations that have prioritized vaccinating individuals at risk of acute symptoms (World Health Organization 2021), the model proposes to segment individuals into specific risk priority groups, including Extremely Susceptible, Highly Susceptible, Moderately Susceptible, Partially Susceptible, and Least Susceptible. As shown in Figure 3, these priority groups are based on combinations of the criteria such as age, health condition, and nature of work.

The model also incorporates limited vaccine supply and healthcare capacities. Therefore, it assumes that any required supplies can be satisfied through option 1 (i.e., a central distribution center, where the stock can be replenished regularly) or option 2 (i.e., transfer of the available to promise quantities from nearest medical centers via drones). The obtained results include the number of individuals that are supposed to be vaccinated in each healthcare center from each priority group. These results will be sent back to model 1 to forecast the number of infections in the next period.

6.1 Development of Model 1 (Forecasting Model)

The data used in the development of the model is retrieved from the official website of the Qatar ministry of health (Ministry of Public Health 2022). The data from the first 94 days of the pandemic (29th Feb 2020 to 1st June 2020) were retrieved because no interventions were made. Thus, it is assumed that these data will provide better insights into the transmission of the virus. The data was split into two sets, namely training and testing. The training set consists of 80 data points, while the testing set consists of the remaining 14 data points. two differentiation processes were required to make the series stationary. Accordingly, the d element in our model is assumed to be 2. The parameters of the model were estimated based on goodness-of-fit measures by selecting the minimum Bayesian Information Criteria (BIC) value from multiple ARIMA models. From the table below, 999.46 is the least BIC Value and it corresponds to the ARIMA model (4,2,4).

Table 2. BIC Matrix for Different MA and AR Terms

q in MA(q)	**p in AR(p)**				
	0	1	2	3	**4**
0	1E+30	1E+30	1E+30	1E+30	1E+30
1	1E+30	1000.887	1001.19	1002.931	1004.814
2	1E+30	1003.29	1002.504	1000.869	1002.801
3	1E+30	1004.438	1001.042	1002.372	1003.983
4	1E+30	1006.05	1002.998	1004.343	**999.4649**

The autocorrelation of the model's residuals for different orders was inspected for verification purposes. In the time series model, the residual refers to the discrepancy between the observed value and the fitted value. In other words, they are the training set errors (Casella et al. 2000). Residuals can be useful for examining whether the model can capture all the information in the dataset. We observe that all the lags lie within the 95% confidence level and all coefficients are not statistically significant, implying that the model is a good fit. The final model was used to forecast the number of positive cases for the upcoming 14 days. Then, the mean absolute percentage error and coefficient of determination were estimated. From Figure 4, we can observe that the actual and forecasted values in the validation dataset are close which illustrates the promising result of the developed model as the MAPE of the 14 days is 4.86% and $R^2 = 0.9973$.

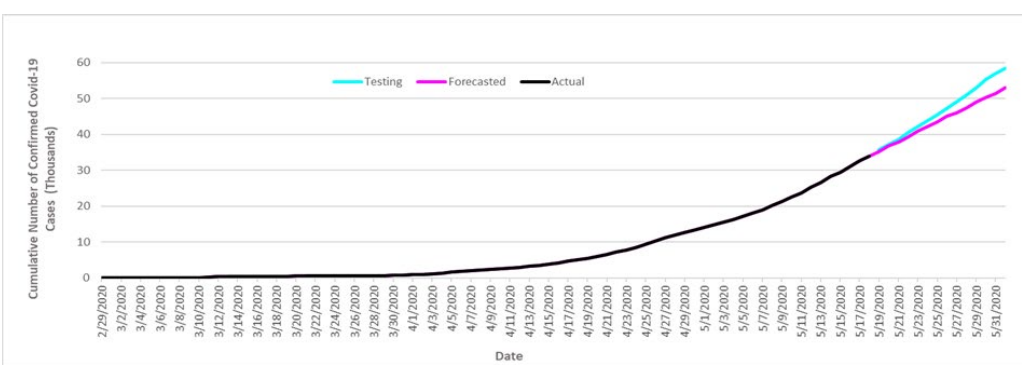

Figure 4. Graphical Comparison Between the Predicted Values and the Actual Values.

6.2 Development of Model 2 (Optimization Model)

we have developed a MILP model to optimize the distribution of covid-19 vaccines among various healthcare centers. IBM ILOG CPLEX optimization software was used in solving the model. The mathematical model presented in this paper is derived from the formulations shown in (Avila-Torres et al., 2020). Unlike the earlier formulations, the proposed model considers numerous healthcare centers with various delivery priorities and two types of transporting modes (by truck or by drone) with similar capacities. Also, the model is driven by minimizing the total associated risk among the society instead of minimizing the total associated costs. The problem can be formulated using the parameters, sets, and indices represented in Table 3 and Figure 5.

Table 3. Notations and Parameters

Notation	Definition
	Sets & Indices
G	The set of defined priority groups $G = \{1,2,...G\}$, index j.
H	The set of available healthcare centers in the country $H = \{1,2,...H\}$, index i.
	Parameters
Ps	The package size, and the number of vaccines in each package.
n_{ij}	The number of registered individuals to take the vaccine shot in a particular healthcare center $i \in H$ who belong to priority group j $\in G$.
S	The available supply in the distribution center.
w_j	The weight of each priority group j $\in G$ to get vaccinated. It is defined for each group such that $\sum_{j=1}^{G} w_j = 1$.
C_i	The maximum number of vaccine doses that a healthcare center $i \in H$ can administer per period.
Big M	A large number.
ϵ	Small positive number.
dev	indicates the minimum deviation between the weight of two priority groups, Min$(w_j - w_{j-1})$.
$T[1 \dots i][1 \dots k]$	t_{ik} indicates the travel time between healthcare centers. $\dot{t}$ = max (t_{ik})
TRD	Defined to limit the number of available times for drones in the network.
V_{ij}	a binary parameter guarantees that each healthcare center is linked to at least H other centers that have non-zero demand to facilitate the movement of vaccines among them.

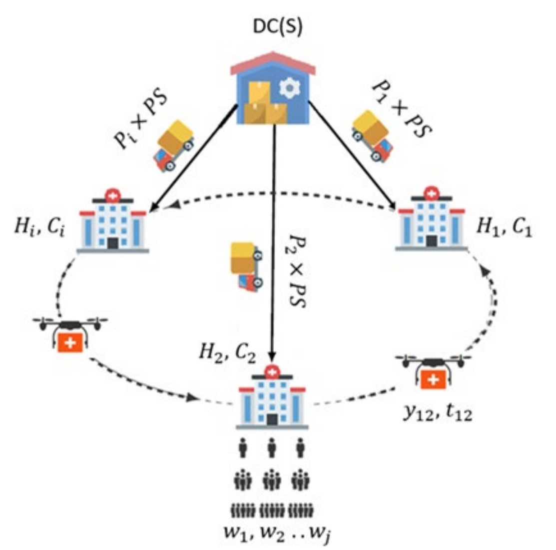

Figure 5. Schematic Sketch of the Proposed Model with Notations.

6.3 Case Study – Qatar Vaccination Program

The effectiveness of the proposed model will be assessed by applying it to allocating COVID-19 vaccines to the residents of Qatar. Qatar's population is estimated to be 2,794,000 in December 2021 (Planning & Statistics Authority, 2021). We assume that the Qatari government has set a target horizon of 60 days to vaccinate 85% of the total population. The information regarding Qatar's medical centers is obtained from PHCC (i.e., Primary Health Care Corporation). Figure 7 presents the spatial distribution of the 25 PHCC medical centers. The centers are distributed into three regions, namely Central, Western, and Northern.

7. Discussion of the Results

The analysis was conducted on a computer with a CPU @ 2.21 GHz, 64 GB. The model was solved optimally using the branch and cut algorithm in CPLEX IDE 20.1 solver. The model was executed for the entire planning horizon and continued until all the population was vaccinated. It is worth noting that any unmet demand due to operational capacity limitations, demand uncertainties, insufficient vaccine supply, or drones' transferring capabilities was added to the following day's requirements. Moreover, the daily available vaccine quantities per period for all 25 healthcare centers were set to be 36,000 doses per day. Figure 6 illustrates the total associated risk among the population per period considering the optimal covid-19 vaccine allocation decisions.

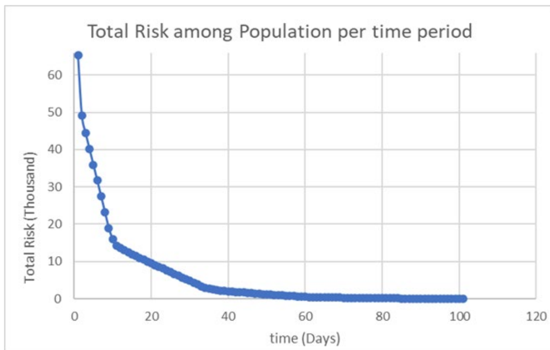

Figure 6. Total Risk among Population per Period.

Under the given assumptions, the obtained results indicate that 100 days is needed to fully immunize the Qatar population (2,404,776 individuals). The optimal allocation decisions to immunize 95% of the total population incorporated a combination of allocation mechanisms namely direct supply from the distribution center and transfer of an average of 1390 ATP doses among healthcare centers which account for 6% of the total daily administered vaccines. Clearly, the results demonstrate the need of considering the transfer of ATP into vaccine distribution systems. It is worth noting that by the end of the immunization program, allocating vaccines directly from distribution centers was enough to meet the needs of the 25 healthcare centers as there was no trigger for the transfer of ATP quantities. As a result, vaccine surplus started to accumulate at the 25 healthcare centers (refer to Figure 7 and Figure 8).

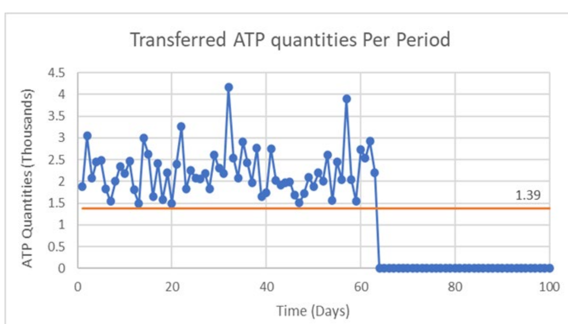

Figure 7. Total Transferred ATP Quantities among Healthcare Centers per Period.

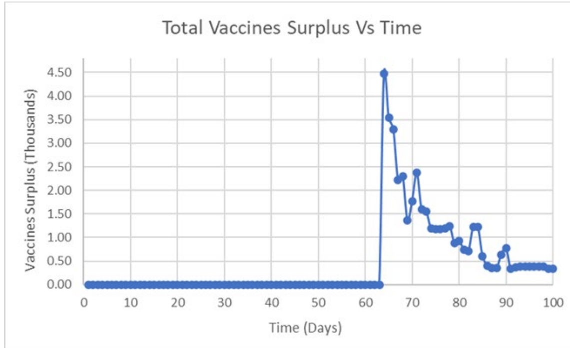

Figure 8. Total Vaccines Surplus per Period.

7.1 Sensitivity Analysis

To better understand the model, sensitivity analysis is conducted artificially for the capacity of Medical Centers (C_i), the number of available vaccine packs (S), and the size of the pack (L) parameters.

Impact of healthcare centers' operational capacities

Decision-makers need to take into consideration the impact of the medical center's capacity on the obtained total associated risk among the population. To study the impact, the same initial parameter was used except the value of S was increased to 80 instead of 72. Because we want to relax the capacity of S to provide an opportunity to investigate an unbiased impact of (C_i) on the proposed model. The capacities of the medical centers were increased by a factor of 0.8, 1.2,1.4, and 2. From Table 4, it can be noticed that the obtained risk decreased with the increase in the medical centers' capacities. In the case of Qatar, enhancing the capacities by 20% can decrease the total associated risk by approximately 3%. Although the capacity was doubled, it yielded almost the same impact because the daily number of registered individuals were all vaccinated. Hence, it can be said that capacity is a binding constraint.

Table 4. Impact of Operational Capacities on Total Associated Risk

C_i	Base Line (Total No. of Registered Individual)	20% decrease	20% increase	40% increase	100% increase
Objective Function	63,790	69,900	61,831	61,830	61,829
Difference %		9.57%	3.071%	3.072%	3.074%

Impact of the available vaccine supply

The daily number of available vaccine packs (i.e., Stock) is an important factor in the timely fulfillment of medical centers' demands. To study the impact of (S), the same initialization was used where (C_i) is the total number of registered individuals from all groups. The table below illustrates the daily total associated risk of each experiment for various values of S = {40, 60, 90,120}. Intuition suggests that increasing the stock levels will lead to lower levels of associated risk among the population. However, to be realistic - vaccinating the entire population of Qatar within a pre-determined target horizon relies on a minimum level of stock availability in the main distribution center. From the obtained results in Table 5, it can be seen that a minimum level of roughly 90 packs is required daily to complete the administering process within 60 days under low residual risk of disease transmission. The previously done experiments emphasize that the capacity decisions should be made considering operational and logistical restrictions to ensure that additional investment in capacity is worth the marginal benefits.

Table 5. Impact of Available Vaccine Supply on Total Associated Risk.

S	Base Line (80 Packs)	40 Packs	60 Packs	90 Packs	120 Packs
Objective Function	63,790	79,218	70,524	63,790	63,790
Difference		24.18%	10.55%	0.0%	0.0%

7.2 Impact of pack size

To effectively manage the operational risk of the transfer of ATP quantities, we investigated how the number of transferred ATP quantities is being impacted by changing the pack size. To conduct this experiment, the same initialization was used except S was recalculated to ensure the same total number of vaccines is available. The selected pack size Ps = {100,200,400,800}. From Table 6, it is noted that increasing the pack size (Ps) leads to a higher number of daily ATP quantities transferred between healthcare centers. Intuitively, when Ps=1, there will be no transfer of quantities in the network. Thus, increasing Ps increases the probability of union events which yields a situation where there is a surplus at the medical centers; the unused vaccines can be transferred. It is essential to highlight that the ATP transfer mechanism is triggered only when:

- There is an unsatisfied demand.
- There is an opportunity to provide the vaccine to an individual in a higher priority group.

Table 6. ATP Units Transferred among Healthcare Centers under Different Supplies.

Ps	Base Line (500 Units, S=80)	100 Units, S=400	200 Units, S=200	400Units, S=100	800 Units, S=50
Total No. of Transferred Units	1,215	424	936	1,387	3,615
Difference %		65.10%	22.96%	14.15%	197.53%

7.3 Recommendations & Managerial Insights

The findings of this paper can have the following managerial implications:

- The proposed framework can be used as a strategic and tactical tool for decision-makers to structure policies and operation plans that can contain pandemics by mitigating the potential risk of disease spread among the communities considering the limitation of resources.

- The obtained results emphasized the significant impact of considering the transfer of ATP (available to promise) quantities among healthcare centers and its ability in enhancing the operational efficiency of the vaccines allocation model as it lets the unused vaccines at specific nodes serve other unsatisfied demand nodes and hence vaccinating higher priority individuals. Consequently, decision-makers should consider the integration of drones in the transfer of ATP units. However, the cost of deploying this mechanism should be studied further.

- The sensitivity analysis provides useful managerial insights. For example, we have observed that the operational capacities of healthcare centers could impact the total associated risk and hence the length of the vaccinating horizon. Accordingly, decision-makers can shorten the target horizon by accommodating mobile vaccination units to support the high-demand nodes. Also, the analysis has shown that a larger pack size can lead to a higher surplus, which in turn increases the number of ATP units being transferred among the centers. Thus, a high-capacity transfer mode will be required across the network to manage the transfer of vaccines. This can provide a guideline for decision-makers that if the available vaccine supplier can only ship large packs, a high-capacity transfer mechanism should be designed.

- Concerning the available daily supply, we have observed a threshold value where increasing the supply can no longer reduce the total associated risk. Identifying this critical point can be useful in managing unexpected supply disruption.

- From a solution feasibility point of view, it is important to get the results from the proposed model in a reasonable computational time. Otherwise, heuristics algorithms should be applied to guide the model in solving large-scale problems. In the Qatar case study, the model achieved the solution within a fraction of a minute. Thus, no complementary heuristic algorithm was required.

Conclusion

In conclusion, efficient vaccine allocation and distribution mechanisms are crucial for successful emergency response. Although each disease has unique epidemiological characteristics, a robust resource allocation model is commonly needed in any emergency response plan. This thesis proposed an integrated framework that allows decision-makers to optimally allocate their finite resources aiming to mitigate the disease transmission risk proactively by developing two models.

The first model is a time series prediction model that forecasts the cumulative number of confirmed covid-19 cases in Qatar for the upcoming two weeks. The best-obtained model is ARIMA (4,2,4) with a MAPE of 4.86% and $R^2 = 0.9973$. Using the model, the estimated total number of cases can reach up to 46,142. Then, the estimated values can be imported into the optimization model.

The optimization model aims to minimize the infection transmission among the community throughout the planning horizon by allocating vaccines to healthcare centers based on the total risk of the individuals that a healthcare center is serving. The model was applied to 2.4 million residents of Qatar (about 40,080 daily individuals per period) by assigning the population to 25 healthcare centers according to the demographic data provided by the planning and statistics authority, the maximum time between medical centers was estimated using the geospatial data from google mapping services, and the risk for each priority group was calculated using the total deaths from covid-19 per age group. Then, the model was verified and validated as it successfully incorporated the susceptibility rating and exposure risk in the allocation decisions. Finally, sensitivity analysis for different parameters namely pack size, available stock, and operational capacities was conducted to have a better insight into the model's reliability.

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