Transportation Research Interdisciplinary Perspectives 11 (2021) 100453

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

A simulation-based analysis for effective distribution of COVID-19 vaccines: A case study in Norway

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ARTICLE INFO

Keywords:
Vaccine distribution
COVID-19 vaccines
Cold chain logistics
Vaccine supply chain
Simulation
Vaccine logistics

ABSTRACT

Since December 2020, the vaccines from several manufacturers, e.g., Pfizer/BioNTech, Moderna, etc., have been approved for mass vaccination to control the COVID-19 pandemic, which has caused more than 100 million infections and 2.4 million deaths. These vaccines are produced and transported in large quantities to suffice the needs of several countries. Before arriving at the end-users, the vaccines need to be stored at extremely low temperatures and distributed through reliable cold chain logistics networks. Thus, the timely and cost-effective distribution of COVID-19 vaccines via cold chain logistics has become a complex operational challenge. In this paper, we develop a simulation-based approach combining both route optimization and dynamic simulation to improve the logistics performance for COVID-19 vaccine distribution. A state-of-the-art simulation package called anyLogistix is used to perform a real-world case study in Norway. With the data of periodic vaccine demands, customer and warehouse locations, vehicle-related costs and emissions, and expected service levels, implications are obtained based on the analysis of several scenarios. Our experimental results reveal that the service level, cost-effectiveness, environmental performance, and equity of a cold chain vaccine logistics system can be significantly influenced by the fleet size, the fleet composition, the type of vehicle used, and the route optimization. Thus, these factors need to be holistically considered in the planning of an effective COVID-19 vaccine distribution system.

1. Introduction

The catastrophic effect of the novel coronavirus disease (COVID-19) has swept the entire globe, which has drastically affected global healthcare systems, economies, and many industries. By March 2021, the pandemic has caused more than 100 million confirmed cases, and the COVID-19's mortality rate has been fatal with associated deaths of more than 2.4 million, according to the World Health Organization (WHO) (WHO, 2021). This infectious disease was first found in Wuhan, China, in December 2019, and it was declared a pandemic by the WHO on January 30th, 2020, causing a major stir worldwide. Given the severity of this pandemic, the WHO, together with several industry-leading pharmaceutical companies is in a haste to find means to curb the widespread of this infectious disease. While control measures are put in place, several studies have been conducted to develop reliable vaccines that can prevent the spread of this infectious disease.

According to the WHO, approximately 2–3 million deaths can be prevented with mass vaccination and immunization, which may expunge COVID-19 by converting it to a vaccine-preventable disease (W. H. Organisation, 2021). To achieve this great obligation, the WHO has collaborated with several stakeholders through the Access to COVID-19 Tools (ACT) Accelerator to expedite the global response to the pandemic. Along with the ACT-Accelerator, COVAX is another important scheme put in place to facilitate an equitable vaccination (GAVI, 2021). This program is led by the Vaccine Alliance (GAVI) and the Coalition for Epidemic Preparedness Innovations (CEPI) in collaboration with the WHO, with the purpose of accelerating the development of several COVID-19 vaccines and of ensuring the availability and fair access across the globe to COVID-19 vaccines.

Data from a WHO report show that 69 vaccines have been in clinical development (W.H.O., 2021). On December 2nd, 2020, the vaccine from Pfizer/BioNTech was first approved in the UK for emergency use to flatten the sharp increase in COVID-19 infections at the end of the year. Shortly after, this vaccine was approved in the US, the EU, and many other countries. Currently, the COVID-19 vaccines from several manufacturers, i.e., Moderna, AstraZeneca, Johnson & Johnson, Serum

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https://doi.org/10.1016/j.trip.2021.100453
Received 18 May 2021; Received in revised form 12 August 2021; Accepted 16 August 2021
Available online 24 August 2021

Institute of India, etc., have been approved or are in the process of approval in several countries. While many research efforts have been given to the development of reliable COVID-19 vaccines in several countries, supply chain experts are also burdened with the tasks of ensuring these potential vaccines reach the end-user population through the appropriate cold chain distribution channels right from the manufacturing plants to the points of administration (Kartoglu et al., 2020).

The development of COVID-19 vaccines is the first step toward the eradication of the disease. Vaccine production and distribution are crucial stages in mass vaccination and immunization programs, which require appropriate planning and implementation due to the enormous demands. While attention has been given to the COVAX program for guaranteeing the equitable allocation and distribution of large quantities of COVID-19 vaccines to affected countries, a more imminent challenge is the effective distribution at the last mile. Many influencing factors such as the strict temperature requirement and the timeliness have put significant challenges to a country's cold chain logistics network for effective vaccine distribution. For example, Pfizer-BioNTech's COVID-19 vaccine requires an ultra-low freezing temperature at −70 °C during transportation and storage to stay effective (Pfizer, 2021). The primary aim of the COVID-19 immunization program is to have a large proportion of the entire world population vaccinated as early as possible, so higher and timely immunization coverage is crucial. It could be an unfavorable situation that the COVID-19 vaccines can reach all countries in need of them, but the end-users may not be able to access them due to poor cold chain logistics facilities and practices.

Therefore, in this paper, we present a simulation-based analysis to improve the cold chain logistics performance for effective COVID-19 vaccine distribution through a case study in Norway. Several scenarios with different configurations were tested with a professional optimization-simulation package, named anyLogistix. Based on customer demands, the fleet size, and the types of vehicles, the transportation routes and vehicle assignments are first optimized, and these decisions are then evaluated in a dynamic and more realistic simulation environment. This study shows the applicability of a powerful tool for decision-makers to better organize the distribution of COVID-19 vaccines. Besides, several generic managerial implications are obtained based on the simulation analyses, which can help logistics managers to better understand the interactions among the key influencing factors of a cold chain vaccine distribution system.

The structure of the paper is given as follows. Section 2 presents a comprehensive literature review of vaccine supply chains and the relevant methods used in vaccine supply chain design and operations. Section 3 introduces the COVID-19 vaccine distribution program in Norway and gives the problem description. Section 4 presents the simulation-based methods, the results of a set of experiments, and managerial implications. Section 5 concludes the paper with a summary and an outlook.

2. Literature review

In this section, we present an extensive literature review of the vaccine supply chain and the relevant methods. Then, the literature gaps are identified.

2.1. Vaccine supply chain

A vaccine supply chain is defined by Lee (2016) as a complex system consisting of locations, storage equipment, vehicles, transport routes, and personnel that handle these vaccines from the production to the points of administration. The uncertainty, risks, and disruptions associated with the vaccine supply chain make it delicate and complex. Because of this, the setup and operations of a vaccine supply chain require thorough planning and implementation (Lemmens et al., 2016). The vaccine supply chain is distinctively different from other supply chains due to several unique attributes such as decentralized decision making, the influence of political decisions on vaccine allocation, the importance of making decisions and acting on time (Duijzer et al., 2018). To achieve the timely and cost-efficient distribution of vaccines across the globe during the COVID-19 pandemic, it is necessary to implement a resilient and responsive supply chain that can bridge the gap in demand and supply uncertainties. Four main stages of the vaccine supply chain are defined by Rastegar, et al. (Rastegar et al., 2021):

- Product – (what type of vaccine is needed?)
- Production – (when and how many vaccines should be produced?)
- Allocation – (who should receive the vaccines?)
- Distribution – (how should the vaccines be distributed?).

To ensure the viability of vaccines at the points of administration, it is crucial to maintain effective and efficient cold chain logistics. A vaccine supply chain is said to be effective if it can meet the full demands by ensuring that the number of vaccines needed for the target population is available in potent conditions and at an affordable cost (Brison and LeTallec, 2017). Therefore, the effective distribution through the last stage of the vaccine supply chain is important when large immunization coverage is expected. In this regard, several studies have been conducted for designing emergency supply chains and epidemic control supply chains (Yang et al., 2021b; Saif and Elhedhli, 2016; Leng et al., 2020; Leng et al., 2020). Other studies on the vaccine supply chain address the associated challenges (Privett and Gonsalvez, 2014; Yong et al., 2020; Dasaklis et al., 2012; Dwivedi et al., 2018) and the need for collaboration among stakeholders of a vaccine supply chain (Duijzer et al., 2018; Dasaklis et al., 2012; Lee and Haidari, 2017). Duijzer et al. (2018) revealed the need for system integration and suggested that the decisions made in each stage of the vaccine supply chain might affect the downstream components.

Privett and Gonsalvez (2014) suggested that, with an increasing number of vaccine production, the vaccine supply chain might suffer from a lack of capacity. To tackle this challenge, integrating the vaccine logistics with other pharmaceutical products' supply chains is considered a possible solution, which can reduce both fixed and operational costs associated with transportation, warehousing, and distribution. Although this integration is beneficial to the upstream stakeholders, it could be ineffective in managing product variety and customer requirements in some cases (Privett and Gonsalvez, 2014). Thus, the decisions to integrate the vaccine supply chain with other medical products need to be made cautiously with selected products at certain stages of the supply chain. This approach is more effective at the downstream stages of the supply chain, i.e., warehousing and transportation (Privett and Gonsalvez, 2014).

Many studies highlight the need for collaboration and the importance of stakeholder involvement in decision-making. Lee and Haidari (2017) identified the key stakeholders of a vaccine supply chain and the implications of their actions. The results emphasized the need for enhanced communication between decision-makers and supply chain experts. De Boeck et al. (2019) pointed out that, although real-life data had been used in modeling vaccine supply chains, the models' applicability was still low due to the lack of stakeholder involvement. Brison and LeTallec (2017) suggested that strong coordination among various stakeholders in a cold chain logistics system would improve fair and timely access to vaccines. One major operational challenge of a vaccine supply chain is related to human interference. Ashok et al. (2017) developed a dependency model to uncover the challenges faced by a global vaccine supply chain, which revealed the most significant influencing factor is human resource dependency. Lloyd and Cheyne (2017) investigated the prevailing issues associated with the exposure of vaccines to improper temperatures. The findings showed that there was a lack of adequate knowledge of health workers regarding the effect of freeze damage on vaccines and the temperature monitoring. Thus, the key players in the vaccination and cold chain logistics need to be adequately trained.

2.2. Methods for vaccine supply chain planning and operations

Optimization and computer-based simulation are the most powerful tools for decision support of vaccine supply chain design and operations.

2.2.1. Optimization method

Supply chain network design (SCND) is to systematically make key decisions at both strategic and tactical levels, mathematical optimization models have been widely used for SCND to achieve highly effective and efficient operations. By optimizing the decision-making of SCND, various benefits, e.g., reduced operating costs, improved customer experience, improved environmental impacts, and efficient production and distribution, etc., can be achieved (Yu and Solvang, 2020). The SCND for vaccines is usually modeled to achieve low operating costs, while simultaneously, to be capable of rapid distribution of vaccines to end-users, especially during the pandemic. The most extensively used modeling techniques are linear programming (LP), mixed integer programming (MIP), and multi-objective programming (MOP). The MIP model consists of two types of variables, namely, integer variable and continuous variable, where integer variables determine the facility locations, and continuous variables determine the demand allocations. When multiple influencing factors, e.g., costs, responsiveness, etc., are considered, the MOP can be used to model and balance the trade-off among these conflicting factors. Based on these techniques, several optimization models have been formulated with the focuses on reducing the total costs (Saif and Elhedhli, 2016; Song et al., 2020; Al Theeb et al., 2020b; Huai et al., 2019; Dou et al., 2020; Shahparvari et al., 2020; Yang et al., 2020), reducing cargo damage (Leng et al., 2020a; Dou et al., 2020), minimizing carbon emissions (Al Theeb et al., 2020b; Zhang et al., 2019; Leng et al., 2020a; Leng et al., 2020b), and improving customer satisfaction (Leng et al., 2020b; Yang et al., 2020).

At the operational level, the vehicle routing problem (VRP) is one of the most important issues affecting the operational efficiency of vaccine distribution. The VRP is to determine the routes of a set of transport vehicles through which all the customer demands can be satisfied with the minimum cost. Several VRP algorithms have been developed to improve the operations of cold chain logistics. Song et al. (2020) modeled a canonical VRP, where the varied time windows, the types of vehicles, and the different levels of energy consumption were modeled as the main control parameters. Al Theeb et al. (2020a) proposed a generic mixed-integer optimization model to support the decisions related to the VRP and inventory allocation problems of cold chain logistics. Huai et al. (2019) formulated a multi-objective model to reduce the freight damage and distribution costs of a cold chain logistics system.

Combined location and routing problems have recently received much attention in vaccine supply chain management. Lim et al. (2019) developed a MIP model for planning a vaccine distribution network using intermediate distribution networks. Rastegar et al. (2021) investigated a novel MIP for a location-inventory problem to ensure the fair allocation of influenza vaccines in developing countries during the COVID-19 pandemic. Pg Petroianu (2020) developed a user-friendly optimization tool for the VRP of vaccine distribution in Mozambique. Lin et al. (2020) presented the impacts of different cold chain transportation policies in a vaccine supply chain. Yang et al. (2021) developed a MIP model to improve the vaccine supply chains in low-income countries, and a novel MIP-based disaggregation-and-merging algorithm was also proposed to improve the computational efficiency. Li (2020) proposed a MOP model to locate vaccination stations considering the balance between accessibility and costs.

2.2.2. Simulation method

Simulation has been increasingly used in supply chain analysis. The volatility of demands, the cost variability, and the turbulence associated with supply chains can be well addressed using simulation techniques (Giacomo, 2012). Simulation models are digital and virtual representations of real-world problems, and they can help to evaluate different scenarios of a vaccine supply chain. Ingalls (2014) argued that many real-world conditions could not be well addressed by mathematical optimization models. Thus, simulation has more advantages in the processes where the demands and other parameters change over time. In supply chain and logistics, simulation can be used to validate the solutions obtained by optimization models (De Boeck et al., 2018; Sun et al., 2019; Yu et al., 2021). For example, Dai et al. (2020) used a numerical simulation to test their decision-making time-delay model for vaccine transportation. Simulation methods can be used to better model the real-world characteristics of a complex supply chain. Besides, Vieira et al. (2020) suggested that simulation tools could be used as data integration tools in solving the dynamics and uncertainties associated with supply chains.

In an international vaccine supply chain, the vaccines from foreign sources arrive in a country by air or by sea and are stored in a central warehouse before being further transported to the rest of the country through intermediate distribution centers (Lim et al., 2019). The vaccine distribution at the country level can be broken down into four stages: (1) the sourcing at the national level; (2) the storage of vaccines; (3) the transportation between different levels, and (4) the administration of vaccines (De Boeck et al., 2018). The decisions on these four stages can be analyzed by computer-based simulation tools, e.g., HERMES, AnyLogic, etc. With the help of HERMES, Lee (2016) developed a simulation model for evaluating the weaknesses of Mozambique's vaccine supply chain, and several suggestions were made for improving the supply chain operations. Usually, the studies using HERMES software considered the entire vaccine supply chain (Lee, 2016; Lee and Haidari, 2017; Mueller, 2016). In addition, Shittu et al. (2016) addressed the problems related to vaccine storage facilities in Nigeria, where a simulation model was applied to analyze the effect of the fluctuations of the vaccine supplies and demands on the storage capacity requirements.

The recent advancement in computational science and its applications have caused a surge in the hybrid application of both simulation and optimization methods, referred to as SIM-OPT. The advantages of both methods can be combined to yield a better analysis and solution to complex decision-making problems in vaccine supply chains. For instance, Dillon and Colton (2014) developed a SIM-OPT-based approach to determine the cost-effective design of vaccine warehouses in developing countries. The results from their experiments indicated that the proposed method not only yields a more accurate analysis but also makes the problem becoming less computationally expensive.

2.3. Literature gaps

Even though significant efforts have been spent in vaccine supply chains and cold chain logistics, there are still three gaps identified as follows:

1. The COVID-19 pandemic has brought new challenges for effective vaccine distribution, e.g., supply uncertainty, and these challenges cannot be well tackled by the existing methods.
2. Less research effort has been given to explore the strengths of both optimization and simulation in vaccine distribution.
3. The interactions among different influencing factors in vaccine distribution, e.g., fleet size, type of vehicle, etc., have not been thoroughly investigated.

Thus, to fill these gaps, a simulation-based approach combining both route optimization and dynamic simulation is developed to improve the COVID-19 vaccine distribution. A state-of-the-art simulation package called anyLogistix is used to investigate the interactions among the key influencing factors.

Table 1
Dosage per vial for the usage of different COVID-19 vaccines (Health, 2021).

COVID-19 Vaccine	Dosage/vial
Pfizer/BioNTech	6 doses/vial
AstraZeneca	10 doses/vial
Moderna	10 doses/vial

3. Problem description

In this section, the COVID-19 vaccine distribution program in Norway is first introduced, and then the problem description is given.

3.1. COVID-19 vaccination program in Norway

Before a vaccine is introduced into the Norwegian Immunization Program, it needs to be approved by the Norwegian Medicines Agency. The approval of COVID-19 vaccines in Norway is conducted through the review for use by the European Medicines Agency (EMA). Vaccine manufacturers must send their research to the EMA for 'rolling review' before a COVID-19 vaccine can be recommended for use (CORONAVIRUS, 2021). The recommended COVID-19 vaccines by the EMA will then be approved by the European Union (EU) Commission for use across Europe. The Norwegian government, through the European Economic Area (EEA) agreement, approves the COVID-19 vaccines from the EU Commission to be used for vaccination in Norway (CORONAVIRUS, 2021). The first approved COVID-19 vaccine is from Pfizer/BioNTech, which has been used since Christmas, 2020, for vaccination starting from the priority groups set by the Norwegian Institute of Public Health (NIPH), e.g., the elderly at nursing homes across the country and people with higher risks due to other diseases. Currently, there are three COVID-19 vaccines from Pfizer/BioNTech, Moderna, and Oxford/AstraZeneca that are being used by the Norwegian government in its Coronavirus Immunization Program, all of which are required for two doses to be fully effective. Table 1 shows the dosage per vial for the usage of different COVID-19 vaccines in Norway. In February 2020, Johnson & Johnson applied for approval of its COVID-19 vaccine candidate to the EMA (Johnson, 2021).

3.2. COVID-19 vaccine distribution in Norway

The NIPH is responsible for the purchase, storage, and distribution of COVID-19 vaccines (NIPH, 2020). When the vaccine vials arrive in Norway, they will first be received by the NIPH and be stored in its central warehouse, and then they will be transported to the municipalities/health trusts throughout the country on a weekly basis (CORONAVIRUS, 2021a). Initially, due to the consideration of supply uncertainty, the NIPH reserved a portion of the received COVID-19 vaccines in its warehouse, and the aim was to ensure that the people who got the first dose would get the second one in three weeks. The rest was then equally allocated and responsively distributed to all municipalities across the country based on several given criteria (NIPH, 2020). From March 2021, the NIPH suggested a new vaccine allocation strategy, in which the COVID-19 vaccines would be differentially allocated to the municipalities based on the level of infection rate. With this plan, the municipalities with the highest infection pressure will receive 20% more vaccine doses, while the portions allocated to the others will be decreased by 3% (VG, 2021).

The weekly distribution of the COVID-19 vaccines to the municipalities is controlled by the NIPH with real-time tracking. The direct distribution from the warehouses to various reception centers is done either by refrigerated trucks or by other vehicles with cooling boxes, and the COVID-19 vaccine delivery is usually within 0–8 h in Eastern Norway and within 24–36 h to the other parts of Norway (Health, 2021). Due to strict temperature requirements, coldtainers are used for the transportation of COVID-19 vaccines in Norway. The Norwegian Directorate of Health has provided coldtainers for road transportation and internal transportation in community healthcare service centers. Fig. 1 shows the three types of coldtainers used in Norway, whose volumes are 10.5 L, 22 L, and 32 L, respectively. The capacities of the coldtainers are dependent on the package of different vaccines when they are being transported (Helsedirektoratet, 2021).

3.3. Problem description of vaccine distribution

In this paper, we analyze the cold chain logistics performance for effectively distributing the COVID-19 vaccines in the Oslo area and Viken county, both of which are in the southern part of Norway. These two areas have higher infection rates and a large number of municipalities, so the effective distribution of COVID-19 vaccines is of paramount importance in the control of disease spread. As shown in Fig. 2, the vaccine distribution system under investigation consists of the NIPH's central warehouse and, in total, 66 customers located in these two adjacent regions. There are 16 vaccination centers in the Oslo area, which are represented by the purple nodes in Fig. 2(A) (Municipality, 2021), and the other 50 blue nodes in Fig. 2(B) are the vaccination centers located in Viken county (CORONAVIRUS, 2021b). Based on the currently available data, the time horizon for the analysis is set from December 21th, 2020 to March 9th, 2021, and the COVID-19 vaccine used in Norway during this period is from Pfizer/BioNTech. Due to the extraordinary temperature requirements for shipping and storage, COVID-19 vaccines need to be distributed under temperature control, and several distribution centers are used to improve the operational efficiency of vaccine delivery to different municipalities and health trusts throughout the country (NIPH, 2020). The vaccine is mainly transported by refrigerated trucks in the southern part of Norway, and the cooling packaging is used when necessary in the transportation to the northern part of Norway (NIPH, 2020).

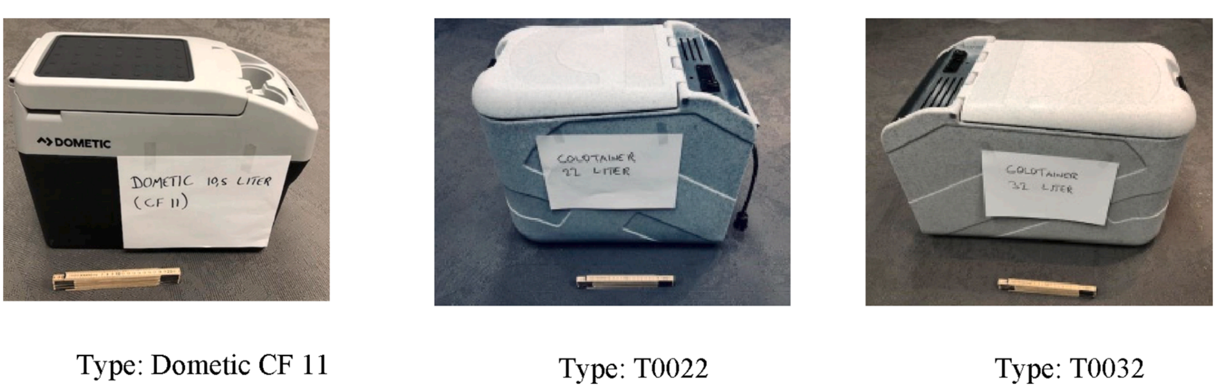
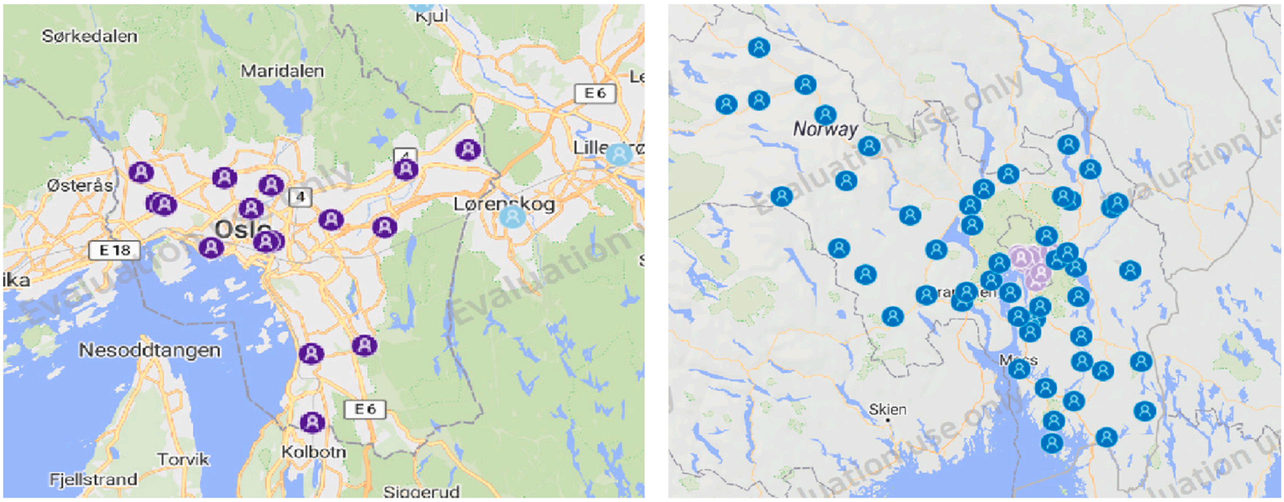


Fig. 1. The three types of coldtainers (Helsedirektoratet, 2021).



(A) Oslo Area (B) Viken County

Fig. 2. COVID-19 vaccination centers in Oslo and Viken.

Because of the low proximity between the municipalities and the FIPH's central warehouse, the vaccines are distributed directly to respective customers in the Oslo area and Viken County. The amounts of weekly vaccine distribution to the customers in the study period are provided by the NIPH (CORONAVIRUS, 2021b), which are given in Appendix A. The delivery of COVID-19 vaccines needs to be highly responsive in order to effectively control the spread of this infectious disease, while simultaneously, the operations of the cold chain logistics system should stay cost-effective. Currently, there are two major challenges to the COVID-19 vaccine supply chain in Norway. First, at the municipalities' level, they cannot order the vaccines by themselves. Instead, they can only receive the COVID-19 vaccines distributed by the NIPH per week with an uncertain amount and uncertain time of delivery, which results in a planning challenge for the local vaccination. On the other hand, due to the limited supplies of COVID-19 vaccines in the study period, the delivery of a small number of vaccines over a large number of geographically dispersed customers makes it difficult to achieve a balance between service responsiveness and cost-effectiveness. Therefore, through a simulation-based analysis, we aim at evaluating several fleet configurations for the effective distribution of COVID-19 vaccines.

4. Simulation-based analyses

Mathematical models can solve complex optimization problems, while on the other hand, simulation-based analyses can provide decision-makers with implications in a more realistic environment. In this paper, the anyLogistix software package was used to perform the simulation-based analyses. AnyLogistix is a state-of-the-art and highly integrated platform, which provides an off-the-shelf solution to conduct both optimization and simulation for a logistics system (Ivanov, 2020; Ivanov, 2019). Several mathematical optimization models are built-in to support different supply chain decisions, i.e., facility location and vehicle routing, and these models are solved by a powerful optimization solver called CPLEX. With these integrated optimization models and the geographical information system (GIS), anyLogistix allows a quick setup for the optimization of several decision-making problems in a real-world logistics system. The simulation module of anyLogistix is based on the AnyLogic simulation software. The decisions obtained from the optimization can be automatically converted into the simulation module, where more realistic requirements and parameters, e.g., service level requirement for vaccine distribution, traffic conditions, daily working hours, etc., can be added to test the performance of the logistics system in a dynamic and realistic environment. Besides, the results can be easily visualized. The integration of these powerful tools in anyLogistix provides a way to realize the concept of the digital supply chain twin (Ivanov and Dolgui, 2020).

4.1. Model development and inputs

The current cold chain COVID-19 vaccine distribution network in Norway is, by nature, a demand-pull system restricted by the capacity of vaccine supplies. Based on availability, it aims at delivering the COVID-19 vaccines to customers in a timely and efficient fashion. In this model, we assumed that the customer demands were generated at the beginning of each week and were equal to the amount of the weekly vaccine distribution to respective municipalities set by the NIPH in the study period, as shown in Appendix A. The COVID-19 vaccines are required to be directly delivered from the central distribution center to the end customers preferably within the time window of 8 h, say, one working day (NIPH, 2020). Thus, the expected lead time (ELT) was set to one day in the experiments, and the vaccine delivery out of the normal working time was not considered. The ELT is a key performance indicator to assess the responsiveness and service level of a cold chain vaccine distribution network. If a customer order can be delivered within the time window, it is on-time delivery. Otherwise, it is considered a delayed delivery. The delayed deliveries directly affect the ELT service level of the system, which is calculated by the ratio between the on-time deliveries and the total deliveries within the study period.

In this simulation, the distribution of COVID-19 vaccines is considered a temporary endeavor and is performed by specialized logistics companies, which already have the existing capacity to perform this weekly vaccine distribution in a discrete manner. For instance, based on customer demands, vaccine delivery only occurs in one or two days within a week to satisfy the responsiveness requirements, so the fixed costs of maintaining the fleet were not considered in the experiments. The transportation costs are trip-based and calculated in accordance with the usage of the fleet. We assumed that two types of vehicles would be used for the shipment of COVID-19 vaccines, namely, small refrigerated trucks and small box vans with mobile cooling containers. These two types of vehicles have different capacities, fuel consumption, and costs. In the experiments, the transportation costs for vaccine delivery consist of two parts. The first part is tour-related fixed costs determined by the driver's salary and indirect costs, the vehicle's depreciation cost and maintenance cost, etc. The second part is variable costs, which are determined by the fuel consumption and other relevant costs directly

Table 2
Input data used in the simulation model.

Parameters	Description	Value	Unit
Vehicle capacity	Small box van	2 (Ltd, 2021)	m^3
	Small refrigerated truck	9 (Ltd, 2021)	m^3
Vehicle speed	Variable speed	Triangular (40;70;50)	km/h
Transportation cost	Variable cost (box van/ refrigerated truck)	6/12	NOK/km
	Fixed cost (box van/ refrigerated truck)	1000/1500	NOK/ tour
CO_2 emissions	Small box van	155 (Ltd, 2021)	g/km
	Small refrigerated truck	213 (Ltd, 2021)	g/km
Shipping	Shipping time	Monday to Friday8 AM to 4 PM	day
Processing time	Inbound shipment	Uniform (10;15)	minute/ m^3
	Outbound shipment	Uniform (5;15)	minute/ m^3
Periods	Experiment duration	12/21/20–03/09/ 21	day

Table 3
Test scenarios.

Scenarios	Type of vehicle	Fleet size	Number of vehicles/UAV		
			Small box van	Small refrigerated truck	UAV
Scenario 1	Small box van and small refrigerated truck	2	1	1	0
Scenario 2	Small box van and small refrigerated truck	4	2	2	0
Scenario 3	Small box van and small refrigerated truck	4	1	3	0
Scenario 4	Small box van and small refrigerated truck	4	3	1	0
Scenario 5	Small box van and small refrigerated truck	6	3	3	0
Scenario 6	Small box van and small refrigerated truck	6	2	4	0
Scenario 7	Small box van and small refrigerated truck	6	4	2	0
Scenario 8	Small box van and small refrigerated truck	8	4	4	0
Scenario 9	Small box van	6	6	0	0
Scenario 10	Small refrigerated truck	6	0	6	0
Scenario 11	Small box van, small refrigerated truck, and UAV	4 + 2	2	2	2
Scenario 12	Small box van, small refrigerated truck, and UAV	4 + 4	2	2	4

proportional to the travel distance. The two cost components in the experiments were estimated based on the data from Statistics Norway (Norway, 2020) and other relevant documents, as shown in Table 2. Considering the uncertainty, the vehicle speed and processing time were assumed to be stochastic.

Using different vehicles and fleets will affect the performance of the COVID-19 vaccine distribution in several aspects, i.e., ETL service level, transportation costs, and CO_2 emissions. Thus, in order to understand the impacts on these performance indicators, ten scenarios were first generated with changes in both the fleet size and the type of vehicle. The comparison among these scenarios can help to identify the most important influencing factors to effective COVID-19 vaccine distribution. In addition, considering the increasing use of unmanned aerial vehicles (UAVs) in logistics operations, another two scenarios with UAVs were considered in the experiment, as illustrated in Table 3. Even though the potential benefits of using UAVs for improving the responsiveness and the environmental impacts of fast delivery service have been discussed (Shavarani et al., 2018), there is still a lack of solid analysis for quantifying the relevant parameters in a cold chain vaccine distribution system. Different types of UAVs are capable of delivering packages weighing between 4 and 30 kg with a flying speed up to 100–130 km/h (Hader and Baur, 2020; Wikipedia, 2021). For example, the M-series UAV used by China's e-commerce giant JD.COM for fast delivery can carry a maximum load of 30 kg flying up to 30 km (Valley, 2017). On the other hand, the Elroy drone developed by a US startup can carry 225 kg loads with a maximum distance of 500 km in its detachable pod (Hader and Baur, 2020). Furthermore, because UAVs have not been used in the real world for COVID-19 vaccine delivery yet, the relevant data for UAVs were estimated by considering several parameters in order to provide implications close to real-world conditions. First, to fulfill the temperature requirement, the coldtainers are used for COVID-19 vaccine transportation by the UAV. Based on several studies (Valley, 2017; Chiang et al., 2019; Phillips et al., 2016; Dhote and Limbourg, 2020), we set the variable costs to 2 NOK/km. The trip-based fix costs are related to the personnel costs of the operators, the depreciation costs, and the maintenance costs, which are estimated based on Statistic Norway (Norway, 2020). Considering the safety issue of flying a UAV in the urban area, we assumed the maximum speed of the UAV was 30 km/h, and the delivery radius was thus within 15 km from the warehouse. By analyzing the results given by Stolaroff et al. (2018), the unit CO_2 emissions of the UAV were set to 40 g/km. Due to the battery limits, the UAV could only perform a point-to-point delivery.

Based on the given data, the analytical models were established in anyLogistix. Fig. 3 illustrates the methodological framework. The transportation optimization (TO) models were first developed in anyLogistix to obtain the optimal vehicle assignments and the optimal vehicle routings or milk runs in the test scenarios. The customer locations, customer demands, vehicle-related transportation costs and capacity, and GIS-based paths are needed to optimize the routing decisions by minimizing the total transportation costs. Considering the balance between costs and service levels for COVID-19 vaccine distribution, we set the maximum tour capacity to 20 municipalities per trip to maintain high responsiveness to customer demands. Thus, the vehicle assigned to each tour needs to simultaneously fulfill both vehicle capacity constraint and tour capacity constraint, Furthermore, the travel segment limit and the returning segment limit were set to 500 km and 100 km, respectively.

The various combinations of the fleet size and the types of vehicles led to different vehicle assignments and routing decisions, which were then outputted to the simulation (SIM) module and validated in a dynamic and realistic environment. Fig. 4 presents an example of the optimal routing decisions obtained by the TO and visualized in the SIM. As shown, the number and sequence of the customers and the paths of each tour can be determined by the TO module. To run the simulation, more detailed and practical information, e.g., the working hour requirement, the stochastic processing time, etc., need to be given in order to generate a comprehensive and more accurate analysis of several performance indicators, e.g., transportation costs, ELT service level, lead time, vehicle capacity utilization, etc. With the use of stochastic parameters generated from different data distributions, a simulation is, by nature, a stochastic problem. In this regard, the stability of the simulation results obtained is important in order to avoid the noises from the parameter generation process (King and Wallace, 2012). In this paper, we conducted variation experiments of 30 replications in the SIM module for each scenario to ensure the stability and reliability of the

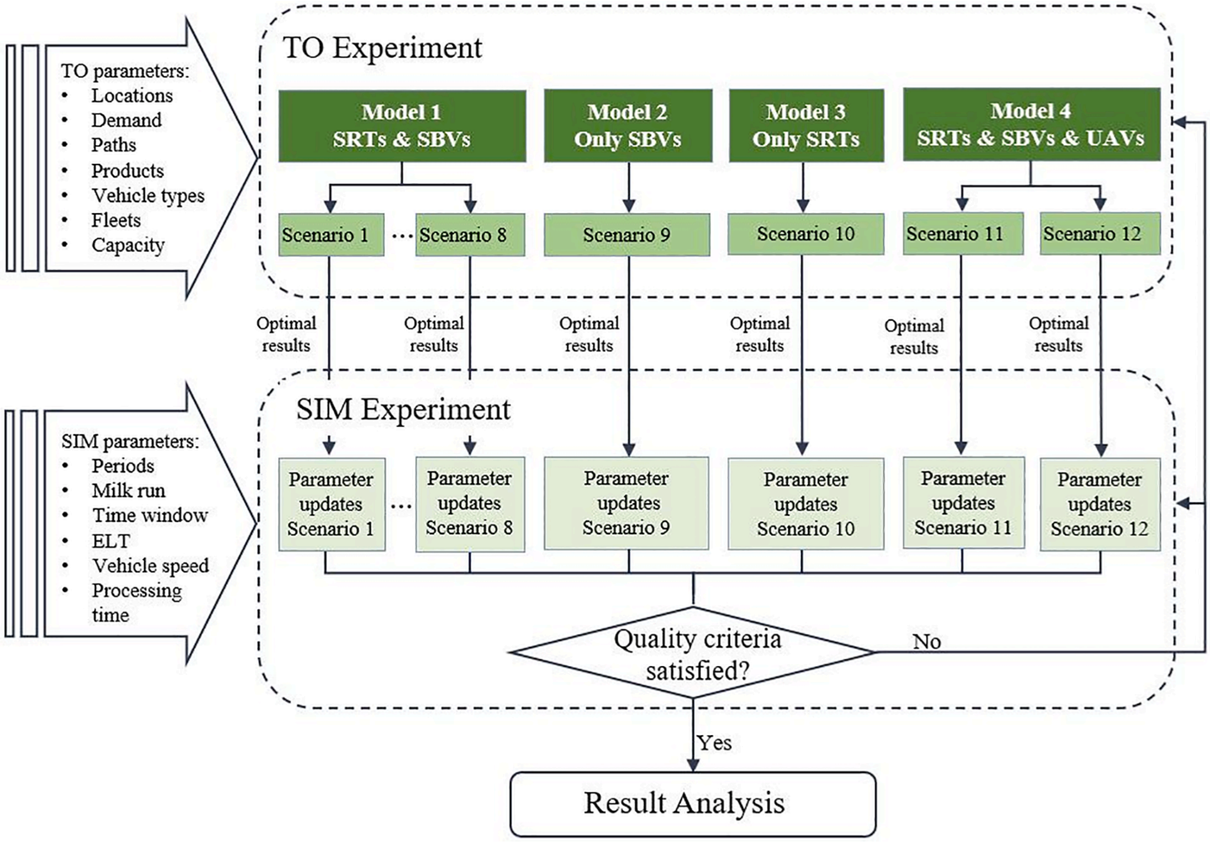


Fig. 3. The methodological framework.

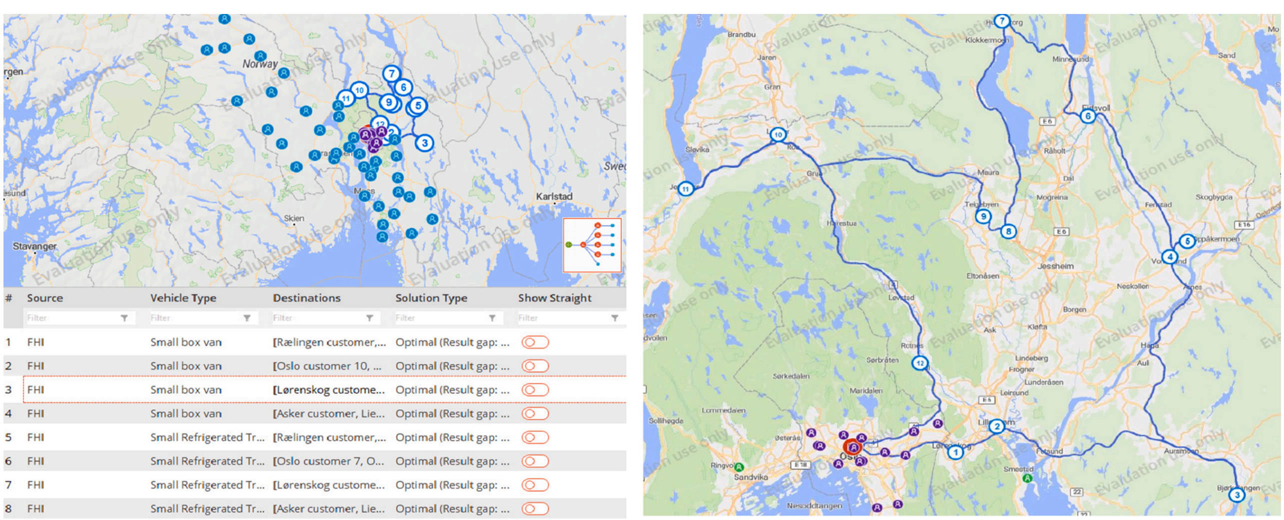


Fig. 4. An example of the optimal routes generated by the TO model.

analytical results. In addition, the simulation horizon was set accordingly based on the real period of investigation.

4.2. Results and discussions

Table 4 presents the simulation results, and Fig. 5 shows the comparison of the transportation costs and the CO_2 emissions of each scenario. Figs. 6, 7, and 8 present vis-à-vis comparisons of the ELT service level by customers, the lead time by customers, the maximum number of vehicles used, and the number of trips in each period of the 12 test scenarios. In Fig. 6, the vertical axis shows the measures of the service levels at each customer, which are represented by different colors. In Fig. 7, the vertical axis shows the lead time (days) of vaccine delivery at each customer over the planning horizon. As can be seen, in Scenario 1, only 31% of vaccines can be delivered within one day, and the average lead time for vaccine delivery is 1.3 days. Furthermore, the maximum lead time may be up to 3.512 days, and the long delay of the delivery of COVID-19 vaccines to several municipalities drastically reduces the service level and the fairness of the system, as shown in Figs. 6 and 7. The results show that the fleet size limit under the working hour constraint significantly reduces the responsiveness of this COVID-19 vaccine distribution system. When the fleet size is increased from 2

Table 4
Simulation results.

Scenarios	Transportation cost (NOK)	Lead time (day)		ELT Service Level by Products	Vehicle capacity utilization	Transportation CO_2 emissions (kg)
		Max	Mean			
Scenario 1	295,200	3.512	1.30	0.31	0.67	3,593
Scenario 2	292,607	1.67	0.73	0.73	0.65	3,481
Scenario 3	287,743	1.55	0.66	0.84	0.60	3,394
Scenario 4	303,662	1.84	0.80	0.68	0.77	3,484
Scenario 5	294,623	1.50	0.58	0.96	0.69	3,479
Scenario 6	284,949	1.26	0.57	0.96	0.62	3,396
Scenario 7	293,742	1.51	0.59	0.93	0.71	3,451
Scenario 8	282,027	1.04	0.54	0.98	0.66	3,419
Scenario 9	325,329	1.64	0.72	0.76	0.89	3,935
Scenario 10	274,986	1.36	0.57	0.96	0.6	3,363
Scenario 11	283,279	1.67	0.61	0.93	0.55	3,243
Scenario 12	283,124	1.58	0.60	0.93	0.55	3,241

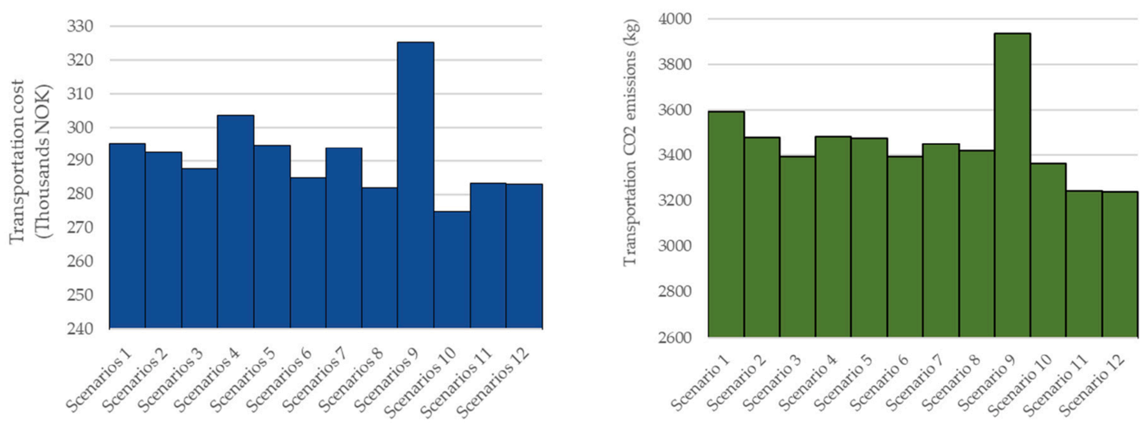


Fig. 5. Comparison of transportation costs and CO_2 emissions of the test scenarios.

vehicles to 4 vehicles in Scenarios 2 to 4, both the average lead time and the average ELT service level can be drastically improved by at least 38.5% and 119%, respectively.

By changing the fleet composition, the performance of the cold chain COVID-19 vaccine distribution system is by no means identical. First, Scenarios 1 and 2 are compared, both of which have the same number of heterogeneous vehicles in their fleets. In Scenario 2, the total transportation costs are reduced by 0.9%, and the total CO_2 emissions are decreased by 3.1%. Moreover, approximately 73% of vaccines can be delivered within 8 h, which is equivalent to a 135% improvement compared with that in Scenario 1. The average lead time has been reduced to 0.73 days. When the fleet composition is changed to include 3 small refrigerated trucks and 1 small box van in Scenario 3, the overall performance of the cold chain COVID-19 logistics system can be further improved. Compared with Scenario 2, the transportation costs, the CO_2 emissions, and the average lead time can be reduced by 1.7%, 2.5%, and 9.6%, respectively. The rate of on-time delivery can also be increased to 84%, the delivery delays happen to fewer customers. However, when the fleet composition is changed to have one small refrigerated truck and 3 small box vans in Scenario 4, the system's performance decreases drastically compared to the previous two scenarios with the same fleet size. The results show that, due to the capacity limitation of the small box van, they need to perform more trips during the high-demand periods to maintain a high level of service and responsiveness, which leads to higher transportation costs. Compared with Scenarios 2 and 3, this fleet composition yields a reduced performance in both cost-effectiveness and service level.

When the fleet size is increased to 6 in Scenarios 5, 6, and 7, the ELT service level can be further improved. The best performance is achieved in Scenario 6 with 2 small box vans and 4 small refrigerated trucks, in which 96% COVID-19 vaccines can be delivered to respective customers within 8 h. In this scenario, the average lead time can be reduced to 0.57 days, and the total transportation costs and the CO_2 emissions are 284,949 NOK and 3,396 kg, respectively. When the number of small box vans is increased in Scenarios 5 and 7, the same phenomenon is observed, where the total transportation costs, the CO_2 emissions, and the average lead time are increased. However, the change of these key performance indicators is not that significant, and the minimum ELT service level can be maintained at 93%. Besides, it is also observed that the maximum lead time for vaccine delivery in Scenario 6 is 1.26 days, and this implies that the service level is affected by small delays of the vaccine delivery at three municipalities. Furthermore, from the observation of Fig. 7, the variations of the lead time among all customs are much lower, which results in higher equity and fairness of vaccine distribution. Besides, the reduced system performances in Scenarios 5 and 7 are mainly caused by the service delays at several municipalities from day 60 due to the increased customer demands and the limited vehicle capacities of small box vans.

In Scenario 8, the fleet size is increased to 8 with 4 vehicles of each type. Without significant changes in the transportation costs and the CO_2 emissions, the average lead time can be further reduced to 0.54 days, and the ELT service level can reach 98%. The maximum lead time becomes 1.04 days, which is the lowest among all test scenarios. Besides, a high level of service equity is also observed. In Scenarios 9 and 10, the fleet each with 6 single-type transport vehicles is tested. When 6 small box vans are used in Scenario 9, the system has the highest level of both transportation costs and CO_2 emissions, and the ELT service level is reduced to 76%, which is close to the three 4-vehicle scenarios. Both the maximum lead time and the average lead time are increased to 1.64 days and 0.72 days, respectively. Furthermore, compared with Scenarios 4–8, the service fairness is significantly reduced due to the long delays of vaccine delivery to several municipalities. The reason behind this is the

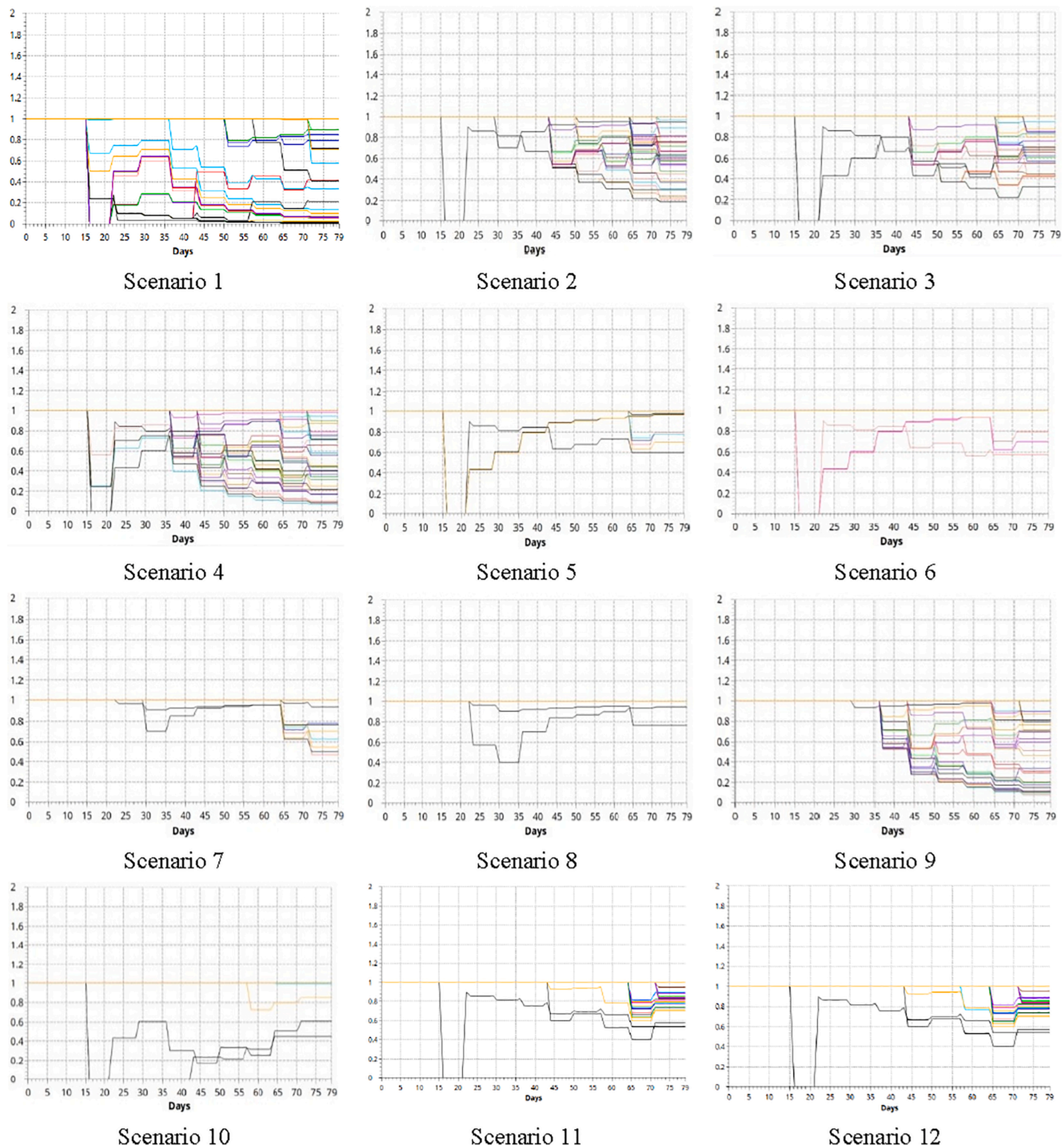


Fig. 6. Comparison of the ELT service level by customers over the planning horizon in each scenario.

capacity limitation of small box vans, and more trips are needed to maintain the service level of vaccine delivery, as observed in Scenarios 4 and 7. However, on the other hand, using 6 small refrigerated trucks in Scenario 10 yields much better performance in comparison with the other 6-vehicle scenarios. Providing with the same level of responsiveness as Scenario 6, both the total transportation costs and the CO_2 emissions in Scenario 10 can be reduced by 3.5% and 1%, respectively.

The experimental results reveal that, in general, the increase in fleet size will lead to a reduced lead time for COVID-19 vaccine delivery, an improved service level and responsiveness, and improved service equity. However, due to the different characteristics of transport vehicles, the fleet composition has large impacts on the overall system performance related to service level, transportation costs, CO_2 emissions, and fairness. In this case study, because of their larger capacity, small refrigerated trucks have better performance than small box vans to provide a responsive vaccine distribution service with more affordable transportation costs and lower CO_2 emissions. Notably, only the trip-based transportation costs are calculated in the simulation. This is because the delivery of COVID-19 vaccines is on a discrete basis, for example, one or two days per week. However, the fixed fleet-operating costs with different numbers and types of vehicles in a cold chain are by no means identical, so it may be taken into further account in a holistic economic analysis. Besides, as shown in Fig. 8, the use of vehicles and the number of trips performed are proportional to customer demands, and more vehicles are needed in the weeks with higher demands of vaccine delivery to fulfill customer requirements with high

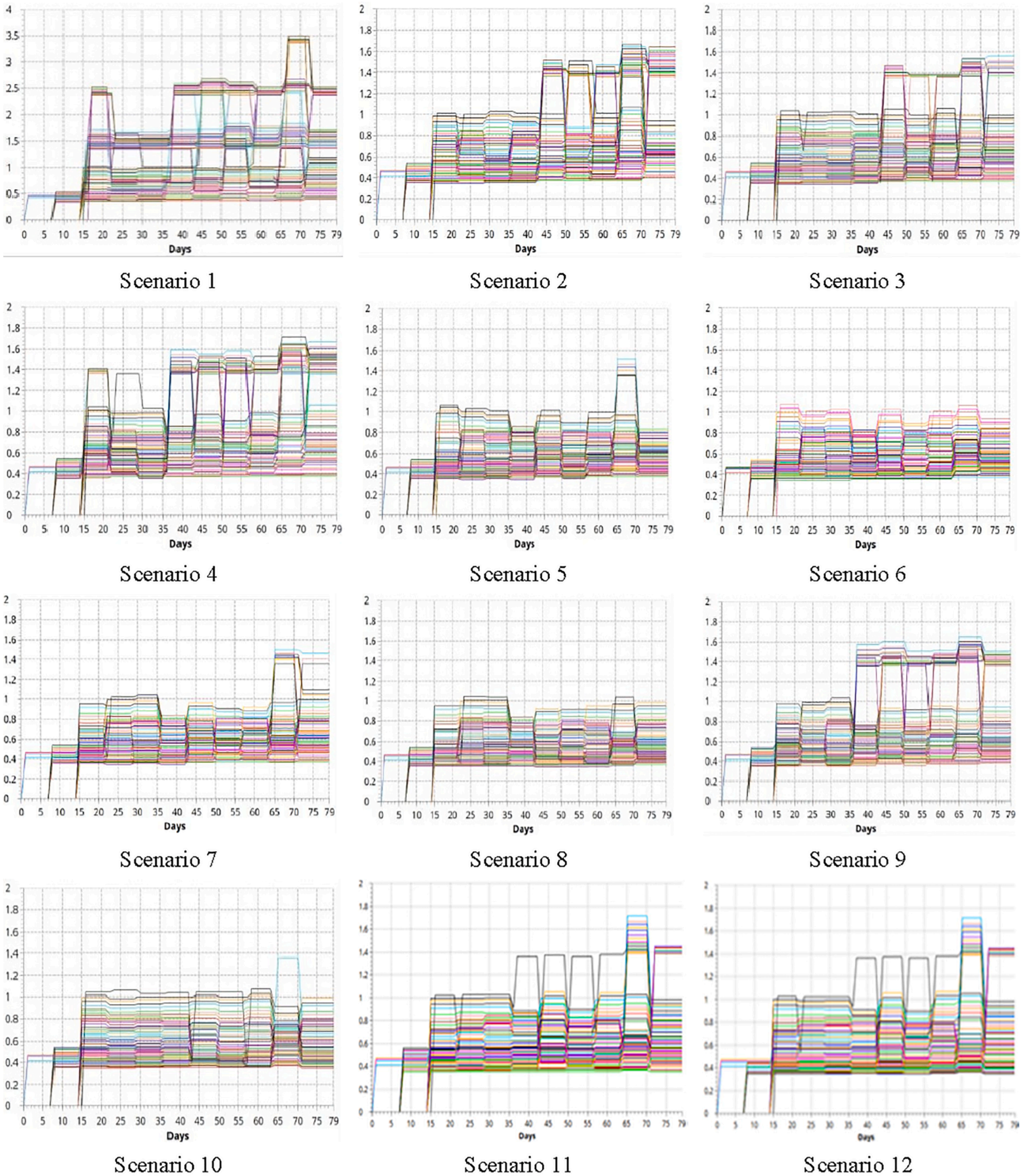


Fig. 7. Comparison of the lead time by customers over the planning horizon in each scenario.

responsiveness. This reveals that fleet flexibility is important to maintain effective operations under highly fluctuate demands.

We are interested in the potential impacts of using UAVs in the rapid delivery of COVID-19 vaccines. Compared with Scenario 2, by introducing 2 and 4 more UAVs in Scenarios 11 and 12, the ELT service level can be improved by 27.4%, and the total lead time, the transportation costs and the CO_2 emissions can be reduced by at least 16.4%, 3.2%, and 6.8%, respectively. Figs. 9 and 10 illustrate, in Scenario 11, the components of transportation costs and CO_2 emissions contributed by small refrigerated trucks, small box vans, and UAVs, respectively. In this scenario, the UAV operations occupy 16.4% of transportation costs, while the associated CO_2 emissions are only 2%. The simulation results show that UAVs are preferred choices for vaccine delivery within their ranges. Compared with the reduction of transportation costs, the use of UAVs in COVID-19 vaccine delivery is more appealing due to the improvements in service responsiveness and environmental impacts.

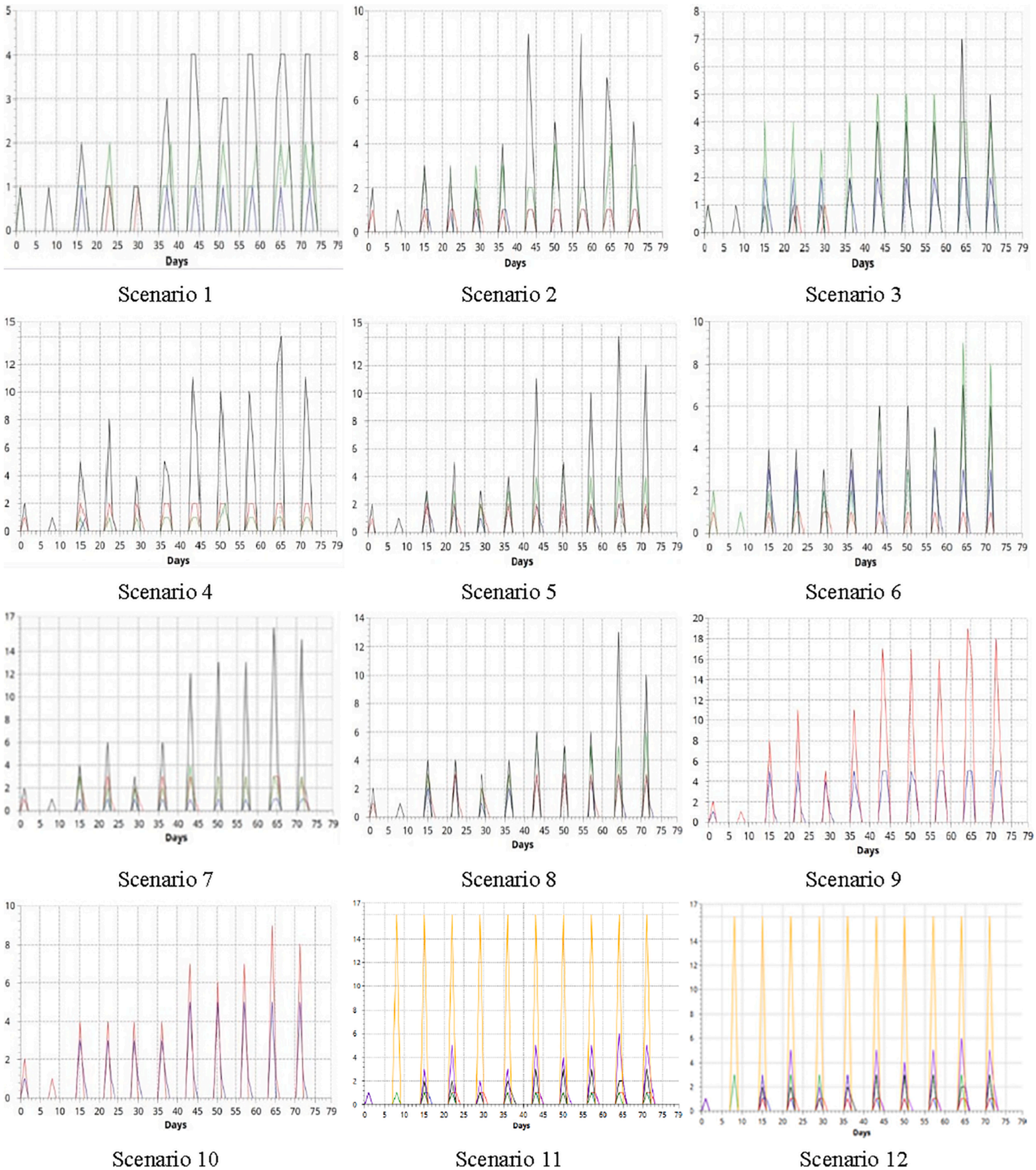


Fig. 8. Comparison of the total number of trips performed and the maximum number of different vehicles used in each period.

4.3. Managerial implications

Based on the simulation-based analyses, five generic managerial implications related to the operations of a cold chain logistics system for effective COVID-19 vaccine distribution are obtained as follows:

- The overall system performance in terms of transportation costs, lead time, service levels, CO_2 emissions, and service equity are affected by the fleet size, the fleet composition, the types of refrigeration vehicles employed, and the routing optimization.
- Generally, a larger fleet size leads to a higher service level and higher equity of the vaccine distribution due to its higher flexibility for better managing demand fluctuations. However, considering the impacts from different vehicles and from the transportation planning, the fleet expansion may not always guarantee an improved service level.
- To improve the responsiveness, cost-effectiveness, environmental impacts, and service equity of a cold chain logistics system for COVID-19 vaccine distribution, both the fleet configuration and the individual vehicle's routing and scheduling decisions need to be optimized.

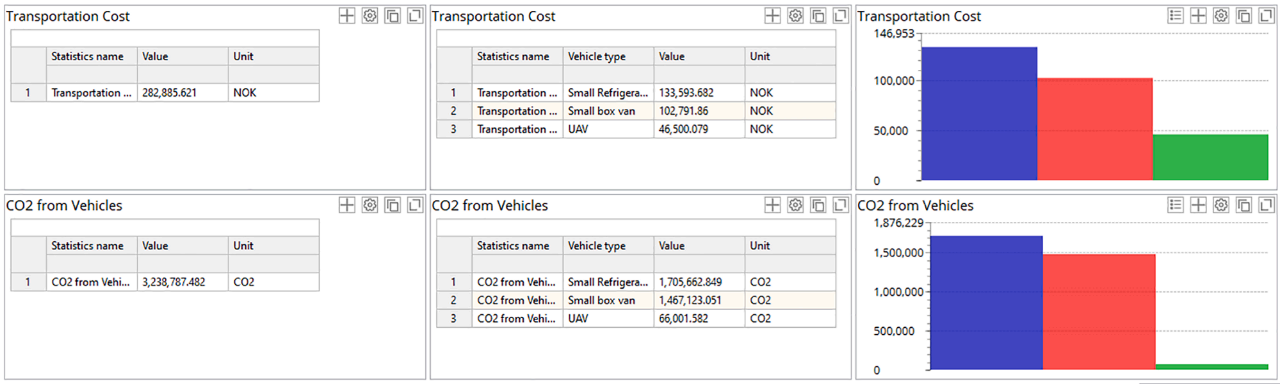


Fig. 9. Comparison of the different components of transportation costs and CO_2 emissions in scenario 11.

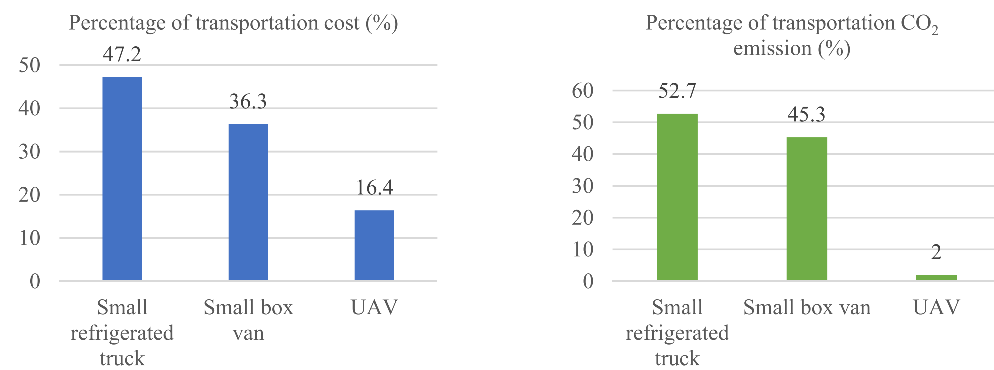


Fig. 10. Comparison of the different components of transportation costs and CO_2 emissions by percentage in scenario 11.

- The use of UAVs within short ranges, if well planned, can improve the service level, environmental impacts, and cost-effectiveness of COVID-19 vaccine distribution.

5. Conclusions

With a large number of infections and deaths, the COVID-19 pandemic has led to catastrophic impacts on the worldwide healthcare systems and economy, and the people's wellbeing and lifestyles have been dramatically altered due to various infection control measures implemented, e.g., city lockdown, travel restrictions, online education, etc. Besides, the pandemic has also caused significant challenges to logistics systems and global supply chains (Sarkis, 2020; Yu et al., 2020; De Boeck et al., 2019). Mass vaccination is considered the most promising way to control the disease spread and to restore normal life. However, the planning of a responsive and cost-effective distribution of COVID-19 vaccines is a complex problem due to several influencing factors, i.e., uncertainty related to the vaccine supplies, strict temperature requirements for storage and transportation, change of policies for vaccine distribution, and resource limitation. Thus, it is important to support transportation planning in a timely and reliable way. In this paper, considering different fleet configurations, we present a simulation-based analysis of the cold chain logistics system for effective COVID-19 vaccine distribution in the Oslo area and Viken county, Norway. Based on the number and the types of transport vehicles, the optimal routing and vehicle assignment decisions were first determined by the TO models established in anyLogistix, whose results were then tested and validated in a dynamic and realistic simulation environment. The experimental results provide several generic managerial implications, which can help decision-makers with better transportation planning of COVID-19 vaccine distribution.

The contributions of this research are summarized as follows:

- This research presents a two-stage optimization-simulation analysis for improving the cold chain logistics operations for COVID-19 vaccine distribution, and the method is implemented through a state-of-the-art simulation package.
- This research provides a case study to show the applicability of the method in the real world.
- This research shows the impacts of different fleet sizes, fleet composition, type of vehicle used, and routing decisions on the service level, cost-effectiveness, environmental performance, and equity of a cold chain vaccine logistics system.
- This research provides some ideas to test new technologies, e.g., UAV, in COVID-19 vaccine distribution in a risk-free simulation environment.

In addition, from the practical perspective, this method can help practitioners to easily and rapidly generate optimal operational decisions for effective COVID-19 vaccine distribution under fluctuate supplies and resource limitations. Real-time transportation planning can be used via digital platforms for better communication with the municipalities so that they can plan vaccine admissions in a timely and more resource-efficient fashion. Furthermore, the managerial implications obtained will also help developing countries, which suffer from poor infrastructures and limited cold chain logistics accesses (Chen et al., 2014; Zhang et al., 2020), to better plan the effective distribution of COVID-19 vaccines with scarce resources. The enhanced coordination among different stakeholders in a cold chain COVID-19 vaccine distribution network such as the government, the logistics companies, the municipalities, and the end-users will drastically improve the operations and overall resource efficiency.

The limitations of the current research are identified for future improvements:

Table A1
COVID-19 vaccine allocation to different municipalities in the study period (Ivanov, 2020).

Municipality	Distribution of vaccine doses (Week by week)											
	W 52	W 53	W 1	W 2	W 3	W 4	W 5	W 6	W 7	W 8	W 9	In total
Oslo	6	534	1,674	3,398	1,110	3,984	9,282	9,310	6,198	13,886	7,368	56,750
Øvre Eiker	0	0	72	54	42	168	288	150	234	434	620	2,062
Ås	0	0	60	60	48	144	270	228	304	410	298	1,822
Ål	0	0	24	18	12	54	90	42	72	72	136	520
Våler (Viken)	0	0	18	18	12	42	78	66	60	160	160	614
Vestby	0	0	66	66	48	156	300	246	322	334	322	1,860
Ullensaker	0	0	108	108	84	258	498	414	466	690	466	3,092
Skiptvet	0	0	12	12	12	30	60	54	48	48	148	424
Sigdal	0	0	18	12	12	42	66	36	60	54	130	430
Sarpsborg	444	0	222	210	168	528	990	968	844	1,280	284	5,938
Rælingen	0	0	54	54	42	126	246	204	280	392	280	1,678
Råde	0	0	36	30	24	84	150	126	114	220	214	998
Rollag	0	0	6	6	6	18	30	18	24	24	18	150
Flesberg	0	0	12	12	6	30	48	24	42	36	124	334
Nore og Uvdal	0	0	12	12	6	30	54	24	42	42	124	346
Ringerike	0	0	132	102	84	306	528	276	532	626	1,016	3,602
Rakkestad	0	0	36	36	24	84	156	126	114	220	214	1,010
Nordre Follo	0	0	210	204	162	504	948	862	808	1,244	272	5,214
Nittedal	0	0	72	72	54	174	330	276	346	458	346	2,128
Asker	0	0	318	252	204	744	1,308	684	1,262	1,756	2,846	9,374
Nesodden	0	0	72	66	54	168	306	258	334	440	328	2,026
Frogn	0	0	66	66	54	162	306	258	228	340	328	1,808
Nesbyen	0	0	18	12	12	42	66	36	60	54	130	430
Nes	0	0	84	78	60	198	366	300	376	488	370	2,320
Nannestad and Gjerdrum	0	0	42	90	48	126	312	234	204	422	404	1,882
Moss	0	0	210	198	156	498	924	774	796	1,126	790	5,472
Modum	0	0	60	48	36	138	246	126	198	298	496	1,646
Marker	0	0	18	18	12	42	84	72	60	66	166	538
Aremark	0	0	6	6	6	18	30	24	24	24	24	162
Halden	0	0	132	126	102	318	594	498	550	768	544	3,632
Drammen	0	0	354	282	222	828	1,458	756	1,388	1,976	3,206	10,470
Lørenskog	0	0	138	132	102	324	612	510	556	880	556	3,810
Lunner	0	0	42	42	30	84	174	132	96	232	226	1,058
Lillestrøm	0	0	276	264	210	654	1,230	1,210	1,118	1,666	508	7,136
Lier	0	0	90	72	54	210	366	186	400	494	744	2,616
Krødsherad	0	0	12	6	6	24	36	18	30	30	118	280
Kongsberg	0	0	108	84	66	252	438	228	460	554	880	3,070
Jevnaker	0	0	30	24	18	66	114	60	90	190	348	940
Indre Østfold	0	0	180	174	138	426	804	672	700	1,030	694	4,818
Hvaler	30	0	30	24	18	66	120	108	90	96	190	772
Hurdal	0	0	12	12	12	30	60	48	42	48	142	406
Hole	0	0	24	18	18	60	102	54	84	184	142	686
Hol	0	0	18	18	12	48	84	42	72	66	136	496
Hemsedal	0	0	6	6	6	18	30	18	30	24	118	256
Gol	0	0	18	18	12	48	84	42	72	66	136	496
Fredrikstad	654	0	324	282	264	780	1,440	1,364	1,304	1,858	496	8,766
Flå	0	0	6	6	6	12	24	12	18	18	12	114
Enebakk	0	0	36	36	30	84	162	138	120	226	220	1,052
Eidsvoll	0	0	90	84	66	210	390	324	388	506	388	2,446
Bærum	0	0	426	342	270	996	1,758	912	1,728	2,416	3,832	12,680
Aurskog-Høland	0	0	72	66	54	168	318	270	334	352	340	1,974

- Even if anyLogistix provides an off-the-shelf solution to perform the optimization-simulation analysis of cold chain vaccine logistics systems, it suffers from flexibility problems. For example, the setups of different routing objectives cannot be achieved. In this regard, mathematical models with different or multiple objectives can be used to generate routing decisions with more flexibility (Laporte, 2009).
- As a complex optimization problem (Wang and Sheu, 2019), vehicle routing decisions may be calculated through state-of-the-art algorithms to improve computational efficiency.
- The simulation results can be validated with more real-world data to provide more accurate implications for decision-makers. For example, a recent study shows, from the life cycle analysis perspective, the use of UAVs to deliver large items over long distances may generate more environmental impacts (Stolaroff et al., 2018; Stolaroff et al., 2018), so this needs to be further investigated with more accurate data.
- Recent technological advancements in Industry 4.0 have provided new solutions to various logistics problems, future research may be conducted to test these innovative solutions. For example, the use of a drone-and-truck system (Macrina et al., 2020) may be an effective solution in COVID-19 vaccine distribution, especially for sparsely populated areas.

CRediT authorship contribution statement

Xu Sun: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing - original draft. **Eugenia Ama Andoh:** Conceptualization, Methodology, Data curation, Writing - original draft. **Hao Yu:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The invaluable comments from the reviewers are highly appreciated, which help to significantly improve the quality of this paper. We would like to express our deep gratitude to all the interviewees of this paper. This research was supported by the Idea Factory Project from UiT—The Arctic University of Norway for promoting active learning of Industrial Engineering.

Appendix A

See Table A1..

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