

# Designing a sustainable reverse supply chain network for COVID-19 vaccine waste under uncertainty

Erfan Amani Bani<sup>a</sup>, Ali Fallahi<sup>a</sup>, Mohsen Varmazyar<sup>a,\*</sup>, Mahdi Fathi<sup>b</sup>

<sup>a</sup> Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran

<sup>b</sup> Department of Information Technology and Decision Sciences, University of North Texas, Denton, TX, USA

## ARTICLE INFO

### Keywords:

Vaccine waste management  
COVID-19 pandemic  
Reverse supply chain  
Multi-objective optimization  
Robust optimization  
Lagrangian relaxation

## ABSTRACT

The vast nationwide COVID-19 vaccination programs are implemented in many countries worldwide. Mass vaccination is causing a rapid increase in infectious and non-infectious vaccine wastes, potentially posing a severe threat if there is no well-organized management plan. This paper develops a mixed-integer mathematical programming model to design a COVID-19 vaccine waste reverse supply chain (CVWRSC) for the first time. The presented problem is based on minimizing the system's total cost and carbon emission. The uncertainty in the tendency rate of vaccination is considered, and a robust optimization approach is used to deal with it, where an interactive fuzzy approach converts the model into a single objective problem. Additionally, a Lagrangian relaxation (LR) algorithm is utilized to deal with the computational difficulty of the large-scale CVWRSC network. The model's practicality is investigated by solving a real-life case study. The results show the gain of the developed integrated network, where the presented framework performs better than the disintegrated vaccine and waste supply chain models. According to the results, vaccination operations and transportation of non-infectious wastes are responsible for a large portion of total cost and emission, respectively. Autoclaving technology plays a vital role in treating infectious wastes. Moreover, the sensitivity analyses demonstrate that the vaccination tendency rate significantly impacts both objective functions. The case study results prove the model's robustness under different realization scenarios, where the average objective function of the robust model is less than the deterministic model ones' in all scenarios. Finally, some insights are given based on the obtained results.

## 1. Introduction

Coronavirus disease 2019, briefly known as COVID-19, is a contagious disease identified in December 2019 in Wuhan, China. The high mortality and prevalence rate of COVID-19 plunged the world into a global crisis, and the World Health Organization (WHO) recognized it as a pandemic (Tison, 2020; Lotfi et al., 2022). According to WHO data, nearly 513 million people have already contracted COVID-19 by April 2022 (Worldometer, 2022). From the beginning of the pandemic, various policies, such as social distancing and travel bans, were implemented by governments to control the spread of the virus. On the other hand, medical experts sought efficient cures for COVID-19 in different ways. Convalescent plasma therapy and consumption of some medicines, such as RemeSivir and Favipiravir, were the first treatment methods utilized for severely infected patients (Goodarzi et al., 2021; Abolghasemi, 2020). Although these procedures provided some benefits in managing the pandemic, they were not as efficient as expected due to

their limitations and the unique features of the virus.

Consequently, various research groups widely focused on the COVID-19 vaccine, where >100 companies started studies to develop this product from the beginning of COVID-19 (Degeling, 2021). Vaccination is a defensive behavior that can play a critical role in controlling the prevalence of pandemics and epidemics. This powerful tool showed excellent performance and efficiency for previous infectious diseases like influenza and Ebola (Rastegar et al., 2021). The efforts were successful, and some of these vaccines got the emergency approval of the WHO for injection after three trial phases. Therefore, many countries planned mass vaccination programs for their target communities to reduce the transmission of the virus, and the most extensive vaccination program in history was started (Georgiadis and Georgiadis, 2021). The global scope of vaccination and some properties, such as cold chain requirements and the necessity of equitable access, caused the need to manage vaccine supply chains. The first COVID-19 vaccine supply chain network design problem is investigated by Taviana, et al. (Taviana et al.,

\* Corresponding author at: Department of Industrial Engineering, Sharif University of Technology, Azadi Ave, Tehran 1458889694, Iran.

E-mail address: [varmazyar@sharif.edu](mailto:varmazyar@sharif.edu) (M. Varmazyar).

2021).

Alongside vaccine logistics, managing the COVID-19 vaccine waste supply chain network is another critical problem in vaccination programs. In the current stage of COVID-19, there is a mass generation of vaccine waste, and the environment is confronting troubles due to this phenomenon (Hasija et al., 2021). However, this is not the end, and Crommelin, et al. (Crommelin et al., 2021) estimate that  $5 \times 10^9$  to  $9 \times 10^9$  vaccine doses are required to end the pandemic and provide global immunization. COVID-19 vaccine waste management, as a waste supply chain network design problem, falls into the category of reverse supply chain networks (Kargar et al., 2020), and it is so important that WHO has issued a new special instruction for managing COVID-19 vaccination waste as “Waste management of used COVID-19 vaccine vials and ancillary supply” (World Health Organization, 2022). The COVID-19 vaccine waste reverse supply chain (CVWRSC) network has some unique features which distinguish it from the other waste management networks; some of them are as follows:

- The behavior of COVID-19 is still mysterious, and we do not have enough information about the future of this virus.
- While patient referrals to hospitals are unmanageable in other medical waste networks, the allocation of vaccination applicants to vaccination sites can be managed to increase CVWRSC network efficiency (Kargar et al., 2020; World Health Organization, 2022).
- CVWRSC planning should be integrated with the vaccine supply chain network decisions based on WHO instructions (World Health Organization, 2022).

Therefore, it is necessary to provide a different management framework and design a special reverse supply chain network to optimize the generated waste of COVID-19 vaccines (Hasija et al., 2021). This study aims to fill that gap by taking into account the real-world challenges of the vaccination systems that the WHO mandates. Therefore, the main contributions and components of this work can be summarized as follows:

- Developing a new multi-objective mixed-integer mathematical model to design a CVWRSC network under uncertainty. This model can determine the optimal decision of the network considering the unique feature of the vaccination program during the COVID-19 pandemic so that the system's total cost and total carbon emission are minimized.
- Providing a robust optimization method to cope with the uncertainty of the model. The presented robust optimization approach is able to efficiently handle the uncertainty in the vaccination tendency rate of candidate groups considering the lack of historical data.
- Using an interactive fuzzy approach to handle the multiple objectives of the problem. This method is able to consider the decision-maker's preferences during the solving process directly and enables the decision-maker to determine the satisfaction level of objectives.
- Proposing a Lagrangian relaxation (LR) algorithm to find efficient solutions to the large-scale problem of the CVWRSC network optimization. This algorithm is able to deal with the problem's complexity and provide the proper solutions for large-size networks in a reasonable time.
- Analyzing the model's performance for a real-world CVWRSC network from Tehran, the capital of Iran, as one of the largest metropolitans in middle-east with a 9,423,702 population, and providing managerial insights for the managers of the vaccination programs.

To the best of our knowledge, no research addresses the CVWRSC network design problem considering the mentioned features.

The remainder of the paper is organized as follows. In Section 2, the related research literature is reviewed, and the research gap is clarified.

Section 3 defines the new problem for the CVWRSC, and a mixed-integer multi-objective mathematical model is developed. In addition, a three-phase methodology is presented for the problem. Section 4 provides random numerical examples and a real-life case study from Iran's capital, Tehran, to assess the model's performance and applicability. In Section 5, managerial insights are presented. In Section 6, the paper is concluded, and some suggestions as the future research directions are discussed.

## 2. Literature review

This section presents a literature review of the related studies for CVWRSC planning, focusing on medical waste and vaccine supply chain management.

### 2.1. Medical waste management

Various researchers have recently addressed the supply chain planning models for medical waste management in recent years. Shi, et al. (Shi et al., 2009)'s research is one of the earliest network design problems for medical waste management. They applied a mixed-integer programming model to minimize the system's overall cost and solved the model with an enhanced genetic algorithm. Mantzaras and Voudrias (Mantzaras and Voudrias, 2017) used a new methodology based on the geographical information system (GIS) to determine the candidate locations for treatment facilities in a waste management problem by minimizing the total cost. Nikzamir and Baradaran (Nikzamir and Baradaran, 2020) presented a stochastic green location-routing problem in which the traveling time between nodes was considered a random variable. They considered the carbon emission of the vehicles depending on random travel time. Kargar, et al. (Kargar et al., 2020) used a possibilistic optimization approach for a multi-objective model of a medical waste management system. This approach is applied to the model for covering the uncertainty in the supply side of the system. The recent outbreak of the COVID-19 pandemic causes some research questions for medical waste management worldwide, which results in a very new research line in the literature. Zambrano-Monserrate, et al. (Zambrano-Monserrate et al., 2020) pointed out that the outbreak of COVID-19 has indirect effects on the environment. They concluded that increasing medical waste is one of the significant results of these side effects. Yu, et al. (Yu et al., 2020) investigated a reverse supply chain network problem for medical waste management in Wuhan, the city which the prevalence of the pandemic began. Kargar, et al. (Kargar et al., 2020) extended a three-objective model that minimizes the total generated waste, total cost, and the transportation risk of infectious medical waste. The multi-objective model is handled using the goal programming technique. Valizadeh and Mozafari (Valizadeh and Mozafari, 2021) discussed a cooperation policy between the waste collectors of the system and concluded that the collaboration reduces the system's total cost. They analyzed the problem with four-game theory methods. Valizadeh, et al. (Valizadeh et al., 2021) studied another extension of the problem where the aiding role of government in providing the necessary services is also considered by a stochastic model and solved by the benders decomposition approach. Govindan, et al. (Govindan et al., 2019) presented a location-routing waste management problem by formulating the load-dependent fuel consumption, vehicle failure, and vehicle scheduling assumptions in the problem. Tirkolaee, et al. (Tirkolaee et al., 2021) also focused on the location-routing problem of medical waste during COVID-19 and developed a multi-trip extension of the problem. The goal of the model was to minimize the total travel time, time window violation, and the risk of disposal sites. Lotfi, et al. (Lotfi et al., 2021) discussed the role of flexible capacity as a resilience strategy for the medical waste supply chain during the COVID-19 pandemic. An energy-efficient model is developed for this problem which also considers the carbon emission of the system. Tirkolaee, et al. (Tirkolaee et al., 2022) presented a closed-loop supply chain network for COVID-19

face masks. The total cost, total emission, and the total human risk were the objectives of the problem, and they solved this sustainable model using MOGWO and NSGA-II metaheuristics. The novelty of our work against the previous research in medical waste-management literature is highlighted in Table 1.

## 2.2. Vaccine supply chain management

In this research scope, Jacobson et al. (Nikzamir and Baradaran, 2020) developed an inventory control model to manage the supply of pediatric vaccines in the United States. They considered disruption scenarios for vaccine production and suggested some effective inventory policies. Abrahams and Ragsdale (Abrahams and Ragsdale, 2012) worked on the vaccination scheduling problem and tried to optimize the total cost of the scheduling system by a mixed-integer binary model. Samii, et al. (Samii et al., 2012) considered the reservation and allocation decisions in an inventory planning model for the influenza vaccine. Hovav and Tsadikovich (Hovav and Tsadikovich, 2015) presented a mathematical model for designing an influenza vaccine supply chain. The goal was to optimize the distribution and inventory decisions of the influenza vaccine supply chain. Saif and Elhedhli (Saif and Elhedhli, 2016) investigated a green cold vaccine supply chain. This is one of the few studies on carbon emission alongside the total cost in the vaccine supply chain. They solved the model using a simulation–optimization method. Lim, et al. (Lim et al., 2019) addressed the redesign problem of the vaccine supply chain, which determines distribution centers' location in an existing network. Due to problem complexity, a hybrid metaheuristic is developed to find the solutions to the model. Lin, et al. (Lin et al., 2020) studied a distributor-retailer vaccine supply chain with two inspection policies for the received vaccine on the retailer side. They concluded that one of these policies is more effective in managing the flow of vaccines in the network. Gamchi, et al. (Gamchi et al., 2021) proposed a new vehicle routing problem (VRP) formulation to optimally determine transportation decisions in a vaccine supply chain. The bi-objective models aimed to simultaneously minimize transportation costs and the social cost of the network. This problem is solved by using augmented epsilon constraint and dynamic programming methods. Enayati and Özaltın (Enayati and Özaltın, 2020) researched the vaccine distribution problem in the epidemic situation. Their mathematical model aimed to control the prevalence of the disease by equitable distribution of vaccines to the population. Rastegar, et al. (Rastegar et al., 2021) addressed some emerging accessibility problems for the influenza vaccine supply chain during the COVID-19 pandemic, especially in developing countries. Considering these concerns, a mathematical model with a new objective function is developed. Chandra and Vipin (Chandra and Vipin, 2021) presented a subsidy contract for coordination in the vaccine supply chain. They analyzed the performance of the model for a case in India. Finally, as mentioned before, the first network design problem for a multi-product supply chain of COVID-19 vaccine was introduced by Tavana, et al. (Tavana et al., 2021). They considered the assumptions in a developing country to model the problem where the objective was the equitable distribution of vaccines between the demand points. Other realistic assumptions are also considered, such as receive time and capacity limitation. Georgiadis and Georgiadis (Georgiadis and Georgiadis, 2021) presented a new mathematical model for the COVID-19 vaccine supply chain where strategic and tactical decisions are included. A decomposition algorithm is discussed to solve the problem in large-scale networks. Li, et al. (Li et al., 2022) investigated the production and pricing decisions in a manufacturer-retailer vaccine supply chain under government subsidies and Late Rebate contract. Uncertainty in production, transportation, and demand was also formulated in this work. Chowdhury, et al. (Chowdhury et al., 2022) developed a sustainable vaccine supply chain network considering the features of a developing country. They addressed three pillars of sustainability by modelling the total cost, total emission, and total negative value of employment as the objective functions. In another work, Gilani

and Sahebi (Gilani and Sahebi, 2022) studied a sustainable vaccine supply chain network with uncertainty in the unjust worldwide vaccine distribution. The uncertainty of the model was handled using a data-driven robust optimization approach. In the subject of the vaccination supply chain, literature review studies are also presented. Duijzer, et al. (Duijzer et al., 2018) categorized the works in vaccine supply chain planning based on criteria such as type of product, production, allocation, and distribution. De Boeck, et al. (De Boeck et al., 2020) provided another literature review focusing on vaccine distribution networks in low and middle-income countries. To the best of our knowledge, there is no research in the literature on CVWRSC network design problem, according to WHO instruction or other national or international organizations.

Although there are some studies for medical waste management during COVID-19 and vaccine supply chain planning, this paper is the first decision-making framework that focuses on the CVWRSC. The overall framework of the current research is schematically presented in Fig. 1.

## 3. Problem statement

### 3.1. Problem definition

The goal of the problem is to determine the optimal location, allocation, distribution, inventory control, treatment, and disposal decision of the CVWRSC network. The problem is defined based on the standard operating procedure of WHO to manage COVID-19 vaccine waste (World Health Organization, 2022). This reverse supply chain network includes six main echelons, including (1) candidate groups for vaccination, (2) vaccine distribution centers, (3) vaccination sites (fixed and mobile), (4) vaccine waste storage centers, (5) waste treatment facilities (existing and temporary), and (6) landfills. At the first echelon, some peoples are eligible for vaccination. The people can be categorized based on different criteria such as municipal district, age, and job.

All candidate people may not accept vaccination invitations and refuse to be vaccinated. Anxiety about the side effects, lack of awareness about the effectiveness, and distrust of imported vaccines are the primary reasons for vaccination refusal (Yigit et al., 2021). The vaccination dose's tendency rate remains fixed and changes in different periods (Robinson et al., 2021). Accordingly, an uncertain vaccination tendency rate is considered for each group to make the problem more realistic.

The candidate groups should be allocated to vaccination sites to receive their vaccine dose. Two categories of vaccination sites are considered: fixed and mobile vaccination sites. The fixed vaccination sites are located at the beginning of the planning horizon. In contrast, the mobile vaccination sites may not remain fixed, and they can move between a set of candidate locations during the planning horizon. The vaccination sites need to place vaccine package orders from the vaccine distribution centers. A vaccine package is assumed to include all the necessary items for the vaccination of an individual, e.g., vaccine vials, syringes, alcohol, and the required equipment for vaccination staff. One of our strategic decisions in the CVWRSC problem is to determine the optimal location of distribution centers.

After the vaccination, two types of vaccine waste are generated. The first type is infectious vaccine wastes, including vaccine vials, syringes, and needles. The hazardous infectious wastes need to be treated with special methods before disposal. The second type is the non-infectious vaccine wastes, including personal protective equipment (mask, face shield, gloves), wrap, and cotton (World Health Organization, 2022). In this way, the vaccine wastes are separated at the vaccination sites. The non-infectious vaccine wastes need no treatment and are directly transported to landfills for disposal. The infectious vaccine wastes need more processing and are sent to storage centers. The optimal locations of storage centers are another strategic decision of CVWRSC and should be determined. The held inventory of infectious vaccine wastes in the storage centers imposes a holding cost to the system at the end of each period.

**Table 1**

A review of the published research on medical waste management.

Article	Year	Main contributions	Waste type		Time period		Objective function			Treatment technology		Uncertainty type			Solution method	Case study
			Single	Multi	Single	Multi	Single	Multi	Measures	Single	Multi	Robust	Stochastic	Fuzzy		
Shi, et al. (Shi et al., 2009)	2009	Medical waste network design	x	✓	x	✓	✓	x	(C)	x	x	x	x	x	Metaheuristic	✓
Mantzaras and Voudrias (Mantzaras and Voudrias, 2017)	2017	A general infectious medical waste network design	✓	x	x	✓	✓	x	(C)	✓	x	x	x	x	Metaheuristic	✓
Nikzami and Baradaran (Nikzami and Baradaran, 2020)	2020	Carbon emission in medical waste network	x	✓	✓	x	x	✓	(C,E)	x	✓	x	✓	x	Metaheuristic	✓
Kargar, et al. (Kargar et al., 2020)	2020	Multi objective medical waste network design	x	✓	x	✓	x	✓	(C,T,W)	x	✓	✓	x	✓	Commercial solver	✓
Yu, et al. (Yu et al., 2020)	2020	Infectious waste network design during COVID-19	✓	x	x	✓	x	✓	(C,R)	✓	x	x	x	x	Commercial solver	✓
Kargar, et al. (Kargar et al., 2020)	2020	Infectious waste network design during COVID-19 considering all sources of waste generation	✓	x	x	✓	x	✓	(C,R,U)	✓	x	x	x	x	Commercial solver	✓
Valizadeh and Mozafari (Valizadeh and Mozafari, 2021)	2020	Infectious waste collection planning during COVID-19	✓	x	x	✓	✓	x	(C)	x	x	✓	x	x	Commercial solver, Metaheuristic	✓
Valizadeh, et al. (Valizadeh et al., 2021)	2021	Bi-level waste network planning	x	✓	✓	x	✓	x	(C)	x	x	✓	x	x	Commercial solver	✓
Govindan, et al. (Govindan et al., 2019)	2021	Medical waste location-routing during COVID-19	✓	x	x	✓	x	✓	(C,R)	x	x	x	x	✓	Commercial solver	✓
Tirkolaee, et al. (Tirkolaee et al., 2021)	2021	Multi-trip location-routing for medical waste during COVID-19	✓	x	x	✓	x	✓	(TT,TVW, R)	x	x	x	x	✓	Commercial solver	✓
Lotfi, et al. (Lotfi et al., 2021)	2021	Viable medical waste network design	x	✓	x	✓	✓	x	(C)	x	x	✓	✓	x	Commercial solver	✓
Tirkolaee, et al. (Tirkolaee et al., 2022)	2022	Face masks closed-loop supply chain	x	✓	x	✓	x	✓	(C,E,R)	x	x	x	x	x	Metaheuristic	✓
Current research	2022	Sustainable COVID-19 vaccine waste reverse network design	x	✓	x	✓	x	✓	(C,E)	x	✓	✓	x	x	Commercial solver, LR	✓

C: Cost, E: Emission, T: Technology score, W: waste inventory, R: Risk, U: Uncollected waste, TT: Travel time, TVW: Time window violation.

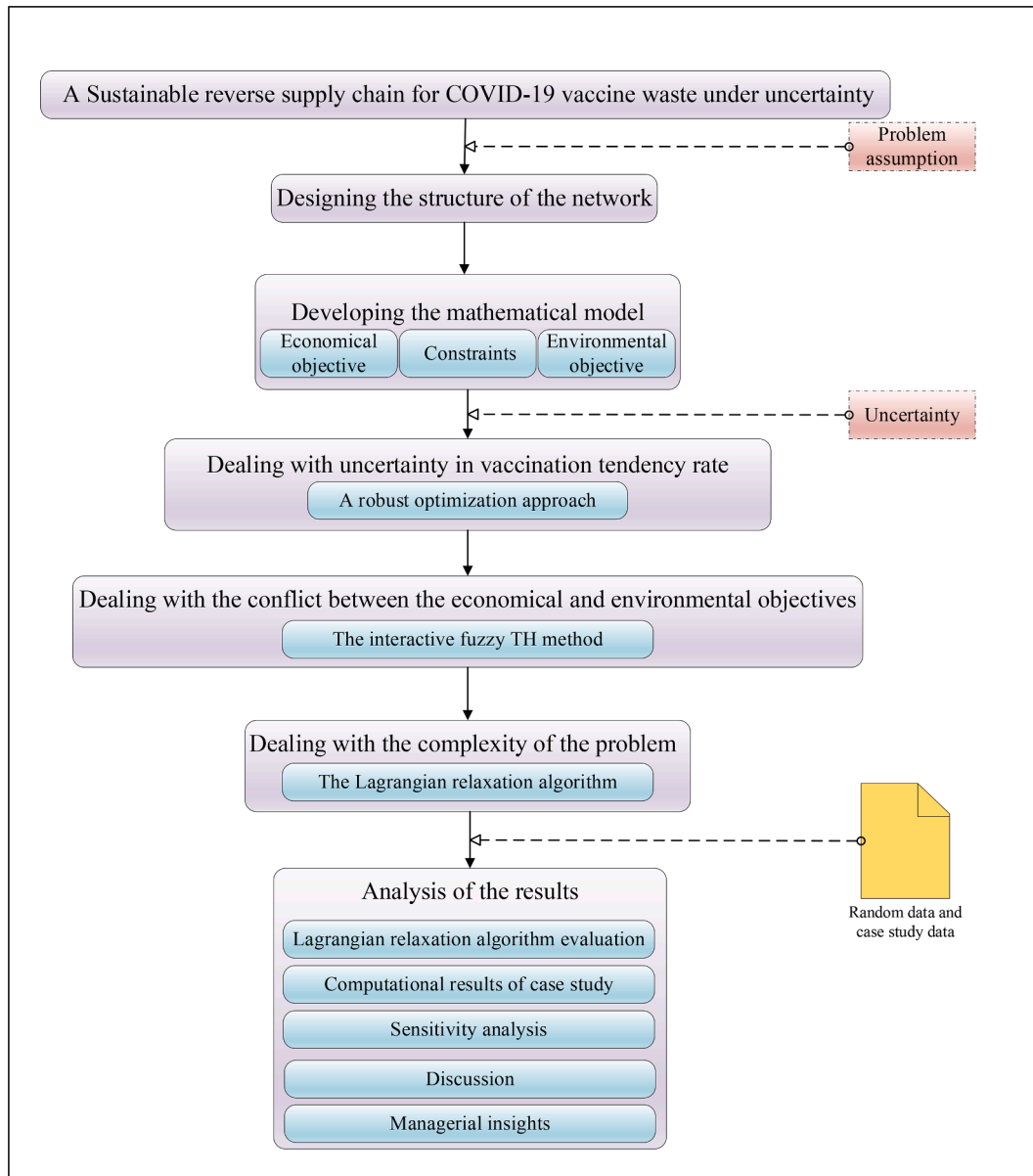


Fig. 1. The overall framework of the current research.

Next, the infectious vaccine wastes are transported to the treatment facilities. Some existing treatment facilities in the CVWRSC network are already used to treat other medical waste, such as hospitals and clinics west. Some candidate temporary treatment facilities are also considered and can be located to ensure the availability of enough treatment capacity. The vaccine waste treatment technologies in the treatment facilities are: 1) disinfection with the chlorine solution and 2) sterilization through the autoclaving process. The primary differences between these technologies are in their operational cost and capacity. While the autoclaving process is rapid and fast, disinfection with chlorine solution imposes less cost on the system. The treated wastes are transported to landfills for disposal and non-infectious vaccine wastes.

The first objective of the model is to minimize the overall cost of the CVWRSC network. On the other hand, academicians and practitioners have paid more attention to green operations management and environmentally responsible supply chains in recent years (Martins and Pato, 2019; Lotfi et al., 2022; Lotfi et al., 2022; Asadkhani et al., 2022; Fallahi et al., 2021). The role of environmental pollution in waste management networks is significant. Previous research addressed carbon emission as one of the objectives of the problems for various waste management

systems, e.g., medical waste and municipal waste (Govindan et al., 2019; Darmian et al., 2020; Harijani et al., 2017; Mohsenizadeh et al., 2020). Not only the air pollution problem and carbon emission concerns are not reduced during the COVID-19 pandemic, but they also intensified due to the role of the breathing system in the severity of the disease. Air pollution can result in more harm to COVID-19 patients (Goodarzi et al., 2021). Therefore, it is reasonable to consider the carbon emission of activities while planning CVWRSC (Hasija et al., 2021). Here, we aim to address the environmental concerns and use the second objective function of the problem as minimizing the total carbon emission of CVWRSC. Fig. 2 shows a schematic view of the proposed CVWRSC network.

### 3.1.1. Assumptions

The main assumptions of the problem are as follows:

- The problem is a multi-objective, multi-echelon, multi-product, multi-period CVWRSC network.
- There are some eligible candidate groups of people for vaccination.



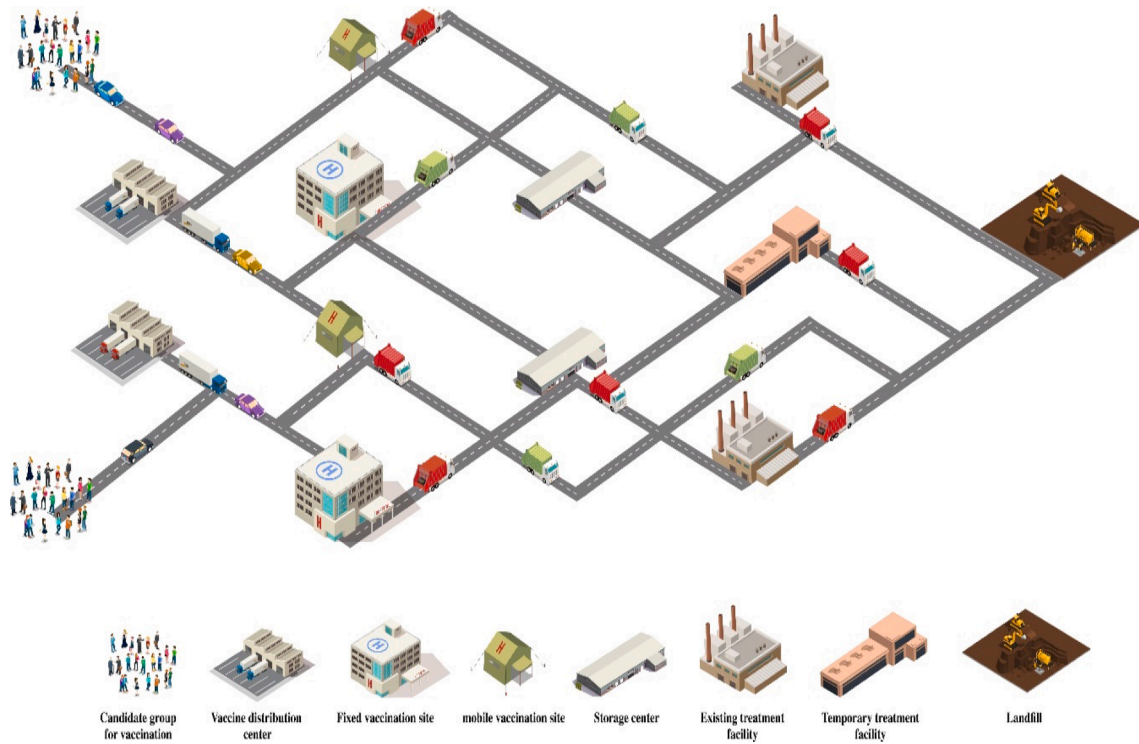


Fig. 2. An overview of the CVWRSC network.

- There is an uncertain vaccination tendency rate for each group at each period.
- There are fixed vaccination sites and mobile vaccination sites for vaccination.
- There are vaccine distribution centers.
- The vaccination sites generate two types of waste: infectious and non-infectious vaccine wastes.
- The non-infectious vaccine wastes are directly transported to landfills after vaccination for disposal.
- The infectious vaccine wastes should be transformed into storage centers after vaccination.
- Inventory of infectious vaccine wastes imposes a holding cost on the system at the end of each period.
- There are two treatment technologies in treatment facilities: disinfection with chlorine solution and sterilization through the autoclaving process.
- The treated infectious vaccine wastes are transported to landfills after vaccination for disposal.
- There are two objective functions: minimizing the total cost and total carbon emission.
- Transportation activities are the source of carbon emissions in the network.

### 3.2. Mathematical modeling

In this section, a mixed-integer linear programming (MILP) model is developed for the research problem.

#### 3.2.1. Notation list

The following notations, including sets, parameters, and decision variables, are used for the formulation of the model:

Sets	
$S$	Set of candidate groups for vaccination; $s \in \{1, \dots, S\}$
$D$	Set of potential locations for vaccine distribution centers; $d \in \{1, \dots, D\}$

(continued on next column)

(continued)

Sets	
$S$	Set of candidate groups for vaccination; $s \in \{1, \dots, S\}$
$V$	Set of potential locations for fixed vaccination sites; $v \in \{1, \dots, V\}$
$W$	Set of potential locations for mobile vaccination sites; $w \in \{1, \dots, W\}$
$P$	Set of vaccine waste types; $p \in \{1, \dots, P\}$
$C$	Set of potential locations for storage centers; $c \in \{1, \dots, C\}$
$J$	Set of potential locations for existing treatment facilities; $j \in \{1, \dots, J\}$
$K$	Set of potential locations for temporary treatment facilities; $k \in \{1, \dots, K\}$
$G$	Set of treatment technology types; $g \in \{1, \dots, G\}$
$L$	Set of landfills; $l \in \{1, \dots, L\}$
$T$	Set of periods; $t \in \{1, \dots, T\}$

#### Parameters

$POP_{st}$	The population of candidate groups $s$ in period $t$
$\theta_{st}$	The vaccination tendency rate of candidate group $s$ in period $t$
$ECD_d$	Establishment cost of vaccine distribution center $d$
$ECV_v$	Establishment cost of fixed vaccination site $v$
$MCV_{w'w''t}$	Moving cost of a mobile vaccination site from location $w'$ to $w''$ in period $t$
$CDV_{dvt}$	Unit transportation cost of a vaccine package from vaccine distribution center $d$ to fixed vaccination site $v$ in period $t$
$CDW_{dwt}$	Unit transportation cost of a vaccine package from vaccine distribution center $d$ to mobile vaccination site $w$ in period $t$
$CAV_{vt}$	Maximum vaccination capacity of fixed vaccination site $v$ in period $t$
$CAW_{wt}$	Maximum vaccination capacity of mobile vaccination site $w$ in period $t$
$VCF_{vt}$	Unit vaccination cost at fixed vaccination site $v$ in period $t$
$VCT_{wt}$	Unit vaccination cost at mobile vaccination site $w$ in period $t$
$INS_c$	Establishment cost of storage center $c$
$NTV_{vlt}$	Unit transportation cost of a non-infectious vaccine waste from fixed vaccination site $v$ to landfill $l$ in period $t$
$NTW_{wlt}$	Unit transportation cost of a non-infectious vaccine waste from mobile vaccination site $w$ to landfill $l$ in period $t$
$ITV_{vct}$	Unit transportation cost of an infectious vaccine waste from fixed vaccination site $v$ to storage center $c$ in period $t$
$ITW_{wct}$	Unit transportation cost of an infectious vaccine waste from mobile vaccination site $w$ to storage center $c$ in period $t$
$CAS_c$	Maximum inventory capacity of storage center $c$

(continued on next page)

(continued)

Parameters	
$POP_{st}$	The population of candidate groups $s$ in period $t$
$VSC_{ct}$	Vaccine waste unit holding cost in storage center $c$
$INT_k$	Establishment cost of temporary treatment facility $k$
$CSF_{jct}$	Unit transportation cost of a vaccine waste from storage center $c$ to existing treatment facility $j$ in period $t$
$CST_{ckt}$	Unit transportation cost of a vaccine waste from storage center $c$ to temporary treatment facility $k$ in period $t$
$CAF_{jg}$	Maximum capacity of treatment technology $g$ at existing treatment facility $j$
$CAT_{kg}$	Maximum capacity of treatment technology $g$ at temporary treatment facility $k$
$CTF_{jgt}$	Unit treatment cost by technology $g$ at existing treatment facility $j$ in period $t$
$CTT_{kgt}$	Unit treatment cost by technology $g$ in temporary treatment facility $k$ in period $t$
$CFL_{jlt}$	Unit transportation cost of a treated vaccine waste from existing treatment facility $j$ to landfill $l$ in period $t$
$CTL_{klt}$	Unit transportation cost of a treated vaccine waste from temporary treatment facility $k$ to landfill $l$ in period $t$
$CAL_{lt}$	Maximum disposals capacity of landfill $l$ in period $t$
$LBC_{lt}$	Unit disposal cost of a vaccine waste at landfill $l$ in period $t$
$\alpha_p$	The weight of generated type $p$ waste from a vaccination package
$ECW_{w'w''}$	Unit released carbon to move a mobile vaccination site from $w'$ to $w''$
$EDV_{dv}$	Unit released carbon to transport a vaccine package from vaccine distribution center $d$ to fixed vaccination site $v$
$EDW_{dw}$	Unit released carbon to transport a vaccine package from vaccine distribution center $d$ to mobile vaccination site $w$
$EVS_{vc}$	Unit released carbon to transport an infectious vaccine waste from fixed vaccination site $v$ to storage center $c$
$EWS_{wc}$	Unit released carbon to transport an infectious vaccine waste from mobile vaccination site $w$ to storage center $c$
$EVL_{vl}$	Unit released carbon to transport a non-infectious vaccine waste from fixed vaccination site $v$ to landfill $l$
$EWL_{wl}$	Unit released carbon to transport a non-infectious vaccine waste from mobile vaccination site $w$ to landfill $l$
$ESF_{cj}$	Unit released carbon to transport an infectious vaccine waste from storage center $c$ to existing treatment facility $j$
$EST_{ck}$	Unit released carbon to transport an infectious vaccine waste from storage center $c$ to temporary treatment facility $k$
$EFL_{jl}$	Unit released carbon to transport a treated vaccine waste from existing treatment facility $j$ to landfill $l$
$ETL_{kl}$	Unit released carbon to transport a treated vaccine waste from temporary treatment facility $k$ to landfill $l$
$M$	A big number

Decision variables	
$y_d$	1 if vaccine distribution center $d$ is established, 0 otherwise
$q_v$	1 if fixed vaccination site $v$ is established, 0 otherwise
$u_{w'w''t}$	1 if temporary vaccination site is moved from potential location $w'$ in period $t-1$ to potential location $w''$ in period $t$ , 0 otherwise
$z_c$	1 if storage center $c$ is established, 0 otherwise
$x_k$	1 if temporary treatment facility $k$ is installed, 0 otherwise
$tdv_{dvt}$	Quantity of transported vaccine packages from vaccine distribution center $d$ to fixed vaccination site $v$ in period $t$
$tdw_{dwt}$	Quantity of transported vaccine packages from vaccine distribution center $d$ to mobile vaccination site $w$ in period $t$
$naf_{svt}$	Number of vaccinated people of candidate group $s$ at fixed vaccination site $v$ in period $t$
$nam_{swt}$	Number of vaccinated people of candidate group $s$ at mobile vaccination site $w$ in period $t$
$tvw_{vt}$	Quantity of used vaccine packages at fixed vaccination site $v$ in period $t$
$tww_{wt}$	Quantity of used vaccine packages at mobile vaccination site $w$ in period $t$
$tvsv_{vt}$	Quantity of transported infectious vaccine wastes from fixed vaccination site $v$ to storage center $c$ in period $t$
$tnv_{vlt}$	Quantity of transported non-infectious vaccine wastes from fixed vaccination site $v$ to landfill $l$ in period $t$
$twsw_{wt}$	Quantity of transported infectious vaccine wastes from mobile vaccination site $w$ to storage center $c$ in period $t$
$tnw_{wlt}$	Quantity of transported non-infectious vaccine wastes from mobile vaccination site $w$ to landfill $l$ in period $t$
$inw_{ct}$	Inventory level of infectious vaccine wastes at storage center $c$ in period $t$
$tsf_{cjt}$	Quantity of transported infectious vaccine wastes from storage center $c$ to existing treatment facility $j$ in period $t$

(continued on next column)

(continued)

Decision variables	
$y_d$	1 if vaccine distribution center $d$ is established, 0 otherwise
$ts_{ckt}$	Quantity of transported infectious vaccine wastes from storage center $c$ to temporary treatment facility $k$ in period $t$
$twf_{jgt}$	Quantity of treated wastes by technology $g$ at existing treatment facility $j$ in period $t$
$twf_{kgt}$	Quantity of treated wastes by technology $g$ at temporary treatment facility $j$ in period $t$
$tf_{jlt}$	Quantity of transported treated vaccine wastes from existing treatment facility $j$ to landfill $l$ in period $t$
$ttl_{klt}$	Quantity of transported treated vaccine wastes from temporary treatment facility $k$ to landfill $l$ in period $t$
$qtl_{lt}$	Quantity of wastes disposal at landfill $l$ in period $t$

### 3.2.2. The model

The first objective function aims to minimize the total cost of the CVWRSC network, including:

- The location cost of vaccine distribution centers:

$$LDC = \sum_d y_d \times ECD_d \quad (1)$$

- The location cost of fixed vaccination sites:

$$LFC = \sum_v q_v \times ECV_v \quad (2)$$

- Movement cost of mobile vaccination sites

$$MMC = \sum_t \sum_{w'} \sum_{w''} u_{w'w''t} \times MCV_{w'w''t} \quad (3)$$

- Transportation cost of vaccine packages from vaccine distribution centers to fixed vaccination sites:

$$TFC = \sum_d \sum_v \sum_t tdv_{dvt} \times CDV_{dvt} \quad (4)$$

- Transportation cost of vaccine packages from vaccine distribution centers to mobile vaccination sites:

$$TMC = \sum_d \sum_w \sum_t tdw_{dwt} \times CDW_{dwt} \quad (5)$$

- Vaccination operational cost at fixed vaccination sites:

$$FOC = \sum_s \sum_v \sum_t naf_{svt} \times VCF_{vt} \quad (6)$$

- Vaccination operational cost at mobile vaccination sites:

$$MOC = \sum_s \sum_w \sum_t nam_{swt} \times VCT_{wt} \quad (7)$$

- Transportation cost of non-infectious vaccine wastes from fixed vaccination sites to landfills:

$$FIC = \sum_v \sum_l \sum_t tnv_{vlt} \times NTV_{vlt} \quad (8)$$

- Transportation cost of non-infectious vaccine wastes from mobile vaccination sites to landfills:

$$MIC = \sum_w \sum_l \sum_t tnw_{wlt} \times NTW_{wlt} \quad (9)$$

- The location cost of storage centers:

$$LSC = \sum_c z_c \times INS_c \quad (10)$$

- Transportation cost of infectious vaccine wastes from fixed vaccination sites to storage centers:

$$FSC = \sum_v \sum_c \sum_t tvs_{vct} \times ITV_{vct} \quad (11)$$

- Transportation cost of infectious vaccine wastes from mobile vaccination sites to storage centers:

$$MSC = \sum_w \sum_c \sum_t tws_{wct} \times ITW_{wct} \quad (12)$$

- Inventory holding cost at storage centers:

$$IHC = \sum_c \sum_t inw_{ct} \times VSC_{ct} \quad (13)$$

- Location cost of temporary treatment facilities:

$$LTC = \sum_k x_k \times INT_k \quad (14)$$

- Transportation cost of infectious vaccine wastes from storage centers to existing treatment facilities:

$$SEC = \sum_c \sum_j \sum_t tsf_{cjt} \times CSF_{cjt} \quad (15)$$

- Transportation cost of infectious vaccine wastes from storage centers to temporary treatment facilities:

$$STC = \sum_c \sum_k \sum_t tst_{ckt} \times CST_{ckt} \quad (16)$$

- Wastes treatment cost at existing treatment facilities:

$$TEC = \sum_j \sum_g \sum_t twf_{jgt} \times CTF_{jgt} \quad (17)$$

- Wastes treatment cost at temporary treatment facilities:

$$TTC = \sum_k \sum_g \sum_t twt_{kgt} \times CTT_{kgt} \quad (18)$$

- Transportation cost of treated wastes from existing treatment facilities to landfills:

$$ELC = \sum_k \sum_g \sum_t twt_{kgt} \times CTT_{kgt} \quad (19)$$

- Transportation cost of treated wastes from temporary treatment facilities to landfills:

$$TLC = \sum_j \sum_l \sum_t tfl_{jlt} \times CFL_{jlt} \quad (20)$$

- Wastes disposal operational cost at landfills:

$$DOC = \sum_k \sum_l \sum_t tll_{klt} \times CTL_{klt} + \sum_l \sum_t qtl_{lt} \times LBC_{lt} \quad (21)$$

Considering the above terms, the total cost objective function can be calculated as follows:

$$\begin{aligned} MinZ_1 = & LDC + LFC + MMC + TFC + TMC + FOC + MOC + FIC + MIC \\ & + LSC + FSC + MSC + IHC + LTC + SEC + STC + TEC \\ & + TTC + ELC + TLC + DOC \end{aligned} \quad (22)$$

The focus of the second objective function is to minimize the total carbon emission of the CVWRSC network, including:

- Carbon emission from the movement of mobile vaccination sites:

$$MME = \sum_{w'} \sum_{w''} \sum_t u_{w'w''t} \times ECW_{w'w''} \quad (23)$$

- Carbon emission from the transportation of vaccine packages from the vaccine distribution centers to fixed vaccination sites:

$$DFE = \sum_d \sum_v \sum_t tdv_{dvt} \times EDV_{dv} \quad (24)$$

- Carbon emission from the transportation of vaccine packages from the vaccine distribution centers to mobile vaccination sites:

$$DME = \sum_d \sum_w \sum_t tdw_{dwt} \times EDW_{dw} \quad (25)$$

- Carbon emission from the transportation of infectious vaccine wastes from the fixed vaccination sites to storage centers:

$$FSE = \sum_v \sum_c \sum_t tvs_{vct} \times EVS_{vc} \quad (26)$$

- Carbon emission from the transportation of infectious vaccine wastes from the mobile vaccination sites to storage centers:

$$MSE = \sum_w \sum_c \sum_t tws_{wct} \times EWS_{wc} \quad (27)$$

- Carbon emission from the transportation of non-infectious vaccine wastes from fixed vaccination sites to landfills:

$$FLE = \sum_v \sum_l \sum_t tvl_{vlt} \times EVL_{vl} \quad (28)$$

- Carbon emission from the transportation of non-infectious vaccine wastes from mobile vaccination sites to landfills:

$$MLE = \sum_w \sum_l \sum_t twl_{wlt} \times EWL_{wl} \quad (29)$$

- Carbon emission from the transportation of infectious vaccine wastes from storage centers to the existing treatment facilities:

$$SEE = \sum_c \sum_j \sum_t tsf_{cjt} \times EST_{cj} \quad (30)$$

- Carbon emission from the transportation of infectious vaccine wastes from storage centers to the temporary treatment facilities:

$$STE = \sum_c \sum_k \sum_t tst_{ckt} \times EST_{ck} \quad (31)$$

- Carbon emission from the transportation of treated wastes from the temporary treatment facilities to the landfills:

$$TLE = \sum_k \sum_l \sum_t tll_{klt} \times ETL_{kl} \quad (32)$$



- Carbon emission from the transportation of treated wastes from the existing treatment facilities to the landfills:

$$ELE = \sum_j \sum_l \sum_t tfl_{jlt} \times ETL_{jl} \quad (33)$$

Finally, the total carbon emission objective function can be expressed as follows:

$$\begin{aligned} MinZ_2 = & MME + DFE + DME + FSE + MSE + FLE + MLE + SEE + STE \\ & + TLE + ELE \end{aligned} \quad (34)$$

The constraints of the problem are as follows:

$$\sum_v \sum_t tdv_{dvt} \leq M \times y_d; \forall d \quad (35)$$

$$\sum_w \sum_t tdw_{dwt} \leq M \times y_d; \forall d \quad (36)$$

$$\sum_d \sum_t tdv_{dvt} \leq M \times q_v; \forall v \quad (37)$$

$$\sum_v \sum_t tvs_{vct} \leq M \times z_c; \forall c \quad (38)$$

$$\sum_w \sum_t tws_{wct} \leq M \times z_c; \forall c \quad (39)$$

$$\sum_c \sum_t tst_{ckt} \leq M \times x_k; \forall k \quad (40)$$

$$\sum_l \sum_t ttl_{klt} \leq M \times x_k; \forall k \quad (41)$$

$$\sum_{w'} u_{w'w''t} \leq 1; \forall w'', t \quad (42)$$

$$\sum_{w''} u_{w'w''t} \leq \sum_{w'} u_{w'w''t-1}; \forall w', t \geq 2 \quad (43)$$

$$\sum_s \sum_t naf_{svt} \leq M \times q_v; \forall v \quad (44)$$

$$\sum_s nam_{swt} \leq M \times \sum_{w'} u_{w'wt}; \forall w, t \quad (45)$$

$$\sum_s naf_{svt} \leq CAV_{vt}; \forall v, t \quad (46)$$

$$\sum_s nam_{swt} \leq CAW_{wt}; \forall w, t \quad (47)$$

$$POP_{st} \times \theta_{st} = \sum_v naf_{svt} + \sum_w nam_{swt}; \forall s, t \quad (48)$$

$$\sum_d tdv_{dvt} = \sum_s naf_{svt}; \forall v, t \quad (49)$$

$$\sum_d tdw_{dwt} = \sum_s nam_{swt}; \forall w, t \quad (50)$$

$$\sum_d tdv_{dvt} = tvw_{vt}; \forall v, t \quad (51)$$

$$\sum_d tdw_{dwt} = tww_{wt}; \forall w, t \quad (52)$$

$$\alpha_p \times tvw_{vt} = \sum_l tnw_{vlt}; \forall p = 1, v, t \quad (53)$$

$$\alpha_p \times tww_{wt} = \sum_l tnw_{wlt}; \forall p = 1, w, t \quad (54)$$

$$\alpha_p \times tvw_{vt} = \sum_c tvs_{vct}; \forall p = 2, v, t \quad (55)$$

$$\alpha_p \times tww_{wt} = \sum_c tws_{wct}; \forall p = 2, w, t \quad (56)$$

$$inw_{ct} = inw_{ct-1} + \sum_v tvs_{vct} + \sum_w tws_{wct} - \sum_j tsf_{cjt} - \sum_k tst_{ckt}; \forall c, t \quad (57)$$

$$inw_{ct} \leq CAS_c; \forall c, t \quad (58)$$

$$\sum_c tsf_{cjt} = \sum_g twf_{jgt}; \forall j, t \quad (59)$$

$$\sum_c tst_{ckt} = \sum_g twt_{kgt}; \forall k, t \quad (60)$$

$$\sum_g twf_{jgt} = \sum_l tfl_{jlt}; \forall j, t \quad (61)$$

$$\sum_g twt_{kgt} = \sum_l ttl_{klt}; \forall k, t \quad (62)$$

$$twf_{jgt} \leq CAF_{jg}; \forall j, g, t \quad (63)$$

$$twt_{kgt} \leq CAT_{kg}; \forall k, g, t \quad (64)$$

$$\sum_v tnw_{vlt} + \sum_w tnw_{wlt} + \sum_j tfl_{jlt} + \sum_k ttl_{klt} \leq qtl_{lt}; \forall l, t \quad (65)$$

$$y_d, q_v, u_{w'w''t}, z_c, x_k \in \{0, 1\}; \forall d, v, w', w'', t, c, k \quad (66)$$

$$tdv_{dvt}, tdw_{dwt}, naf_{svt}, nam_{swt} \geq 0 \text{ and integer } \forall d, v, t, w, s \quad (67)$$

$$tvw_{vt}, tww_{wt}, tnw_{vlt}, tws_{wct}, tnw_{wlt}, inw_{ct}, tsf_{cjt}, tst_{ckt}, twf_{jgt}, twt_{kgt}, tfl_{jlt}, ttl_{klt}, qtl_{lt} \geq 0 \quad (68)$$

$$\forall v, t, w, l, c, j, k, g \quad (68)$$

Constraint sets (35) to (37) ensure that the flow of vaccine packages between the vaccine distribution centers and vaccination sites (mobile and local) are possible only for the established ones. Constraint sets (38) and (39) limit the flow of infectious vaccine wastes to the established storage centers. Constraint sets (40) and (41) relate to the possibility of flow in the established temporary treatment facilities. Constraint set (42) ensures that only one mobile vaccination site is located in a candidate node in each period. In each period, the movement of mobile vaccination sites from a node is possible only for the located sites, which is indicated via constraint set (43).

Constraint sets (44) and (45) guarantee that the candidate groups are allocated only to the established fixed and mobile vaccination sites. Constraint sets (46) and (47) express the vaccination capacity limitation in fixed vaccination sites and mobile vaccination sites, respectively. Constraint set (48) compels the vaccination of all referral people to fixed and mobile vaccination sites. The population of referral people is calculated by multiplying the group's overall population and vaccination tendency rate. The flow equation of vaccines from vaccine distribution centers to fixed and mobile vaccination sites in each period is shown in constraint sets (49) and (50).

The number of used vaccine packages in fixed and mobile vaccination sites is calculated by constraint sets (51) and (52). Constraint sets (53) and (54) show the generated non-infectious vaccine wastes flow from the fixed and mobile vaccination sites to the landfills. The flow of the generated infectious vaccine wastes from the vaccination sites (fixed and mobile) is specified by constraint sets (55) and (56).

The inventory balancing equation of storage centers is formulated via constraint set (57). Constraint set (58) shows the limited inventory capacity of the storage centers. Constraint sets (59) and (60) balance the inflow of the vaccine wastes at the existing and temporary treatment facilities. The flow balancing of vaccine wastes from the treatment facilities (existing and temporary) to landfills is shown in constraint sets (61) and (62). Constraint sets (63) and (64) consider the limited capacity of each treatment technology in the existing and temporary treatment facilities. The inflow equation of vaccine wastes from the vaccination sites and treatment facilities to landfills is provided in constraint set (65). Constraint sets (66) to (68) show the types of decision variables.

### 3.3. The solution approaches

The presented problem is a multi-objective mixed-integer mathematical programming model under uncertainty. In this section, we provide a three-phase methodology to address these features of the problem as follows:

#### Phase 1: Robust optimization

In this phase, the problem is reformulated under a robust optimization approach to consider the uncertainty in the vaccination tendency rate parameter ( $\theta_{st}$ ). Due to the unavailability of reliable historical data, the probability distribution of this parameter cannot be estimated. Robust optimization is the commonly used approach to deal with uncertainty when there is no historical data. We adopt the Bertsimas and Sim (Bertsimas and Sim, 2004) approach to formulate the interval uncertainty in vaccination tendency rate and develop the robust counterpart of the model. To explain the details, consider the following problem:

$$\text{Min}cx \quad (69)$$

Subject to:

$$\sum_j \tilde{a}_{ij}x_j \leq b_i; \forall i \quad (70)$$

$$x \in F(x) \quad (71)$$

There is uncertainty in coefficient  $\tilde{a}_{ij}$  and the parameter is assumed to be in the interval  $[\bar{a}_{ij} - \hat{a}_{ij}, \bar{a}_{ij} + \hat{a}_{ij}]$ , where  $\bar{a}_{ij}$  is the nominal value of  $a_{ij}$  and  $\hat{a}_{ij}$  is the deviation from normal value. Note that the equality constraints can be converted to inequality forms to keep the problem feasible (Gorissen et al., 2015). These inequalities are tight at optimality regarding the structure of the problem. Bertsimas and Sim (Bertsimas and Sim, 2004) formulated the robust counterpart of the model using the duality theorem as follows:

$$\text{Min}cx \quad (72)$$

Subject to:

$$\sum_j \bar{a}_{ij}x_j + Z_i\Gamma_i + \sum_{j \in J_i} P_{ij} \leq b_i; \forall i \quad (73)$$

$$Z_i + P_{ij} \geq \hat{a}_{ij}x_j; \forall i, j \in J_i \quad (74)$$

$$Z_i \geq 0; \forall i \quad (75)$$

$$P_{ij} \geq 0; \forall i, j \quad (76)$$

$$x \in F(x) \quad (77)$$

In this model,  $J_i$  is the number of the uncertain parameters in constraints  $i$ . In addition,  $\Gamma_i \in [0, |J_i|]$  is the budget of uncertainty and  $Z_i$  and  $P_{ij}$  are the auxiliary variables.

For the presented model, assume that the vaccination tendency rate group  $s$  in period  $t$  with the nominal value  $\bar{\theta}_{st}$  and deviation  $\hat{\theta}_{st}$  is in the symmetric interval  $[\bar{\theta}_{st} - \hat{\theta}_{st}, \bar{\theta}_{st} + \hat{\theta}_{st}]$ . Considering  $P_{st}$  and  $Z_{st}$  as the

axillary variables, the robust formulation of CVWRSC under uncertainty includes constraint sets (35) to (47) and (49) to (68) plus the following constraint sets:

$$POP_{st} \times (\bar{\theta}_{st} + P_{st} + Z_{st}\Gamma) \leq \sum_v naf_{svt} + \sum_w nam_{swt}; \forall s, t \quad (78)$$

$$POP_{st} \times (\bar{\theta}_{st} + P_{st} + Z_{st}\Gamma) \geq \sum_v naf_{svt} + \sum_w nam_{swt}; \forall s, t \quad (79)$$

$$P_{st} + Z_{st} \geq \hat{\theta}_{st}; \forall s, t \quad (80)$$

#### Phase 2: An interactive fuzzy multi-objective method

In this phase, an interactive fuzzy multi-objective approach is presented to deal with the objectives of the problem. Generally, there are three categories of methods to deal with multi-objective problems as (1) prior, (2) posterior, and (3) interactive (Ehrgott, 2005). The interactive methods consider the decision-maker's preferences during the solving procedure. Torabi and Hassini (Torabi and Hassini, 2008) introduced the TH method as an efficient and powerful interactive fuzzy approach in the literature. TH method enables the decision-maker to determine the satisfaction level of objectives directly. The implementation of the TH method for a bi-objective problem involves the following steps:

**Step 1:** In this step, each objective function calculates the positive ideal solutions (PISs) and negative ideal solutions (NISs). ( $Z_1^{PIS}, x_1^{PIS}$ ) and ( $Z_2^{PIS}, x_2^{PIS}$ ) are PISs obtained by solving the crisp counterpart of the mathematical model for each objective function separately. In addition, the NISs can be calculated as:

$$Z_1^{NIS} = Z_1(x_2^{PIS}) \quad (81)$$

$$Z_2^{NIS} = Z_2(x_1^{PIS}) \quad (82)$$

**Step 2:** In this step, a linear fuzzy membership function for the objective functions is determined as follows:

$$\mu_j(x) = \begin{cases} 1 & \text{if } Z_j \leq Z_j^{PIS} \\ \frac{Z_j^{NIS} - Z_j}{Z_j^{NIS} - Z_j^{PIS}} & \text{if } Z_j^{PIS} \leq Z_j \leq Z_j^{NIS} \forall j = 1, 2 \\ 0 & \text{if } Z_j \geq Z_j^{NIS} \end{cases} \quad (83)$$

where  $\mu_j(x)$  is the satisfaction degree of  $j^{th}$  objective function.

**Step 3:** In this step, the TH aggregation function is used to convert the equivalent crisp model and establish a single objective model as follows:

$$\text{Min}\lambda(x) = \gamma\lambda_0 + (1 - \gamma)\sum_j \theta_j\mu_j(x) \quad (84)$$

Subject to:

$$\lambda_0 \leq \mu_j(x) \forall j = 1, 2 \quad (85)$$

$$x \in F(x) \quad (86)$$

$$\lambda_0, \lambda \in [0, 1] \quad (87)$$

where  $\lambda_0$  is the minimum degree of satisfaction for the objective functions and  $F(x)$  is the feasible region of the problem. Moreover, the compensation coefficient and importance weight of objective functions are denoted by  $\gamma$  and  $\theta_j$ , respectively. The decision-maker determined the value of these parameters based on his (or her) preference.

**Step 4:** The initial values are set for the objective function's weights  $\theta_j$  and compensation coefficient  $\gamma$ . The model is solved, and if the solution is satisfiable, the algorithm stops; otherwise, the parameters are changed to obtain another Pareto solution.

#### Phase 3: Lagrangian relaxation algorithm

The supply chain network design is in the class of NP-hard problems (Gourdin et al., 2000). Therefore, the complexity of the presented

mixed-integer programming model is also raised exponentially when the size of the problem increases, and the computational time may not be reasonable. In this phase, a LR algorithm is provided to find efficient lower-bound solutions in large-size problems. LR is a powerful algorithm that can find lower-bound solutions by relaxing some of the problem's hard constraints. LR was introduced by Held and Karp (Held and Karp, 1970), and it is utilized successfully to solve various supply chain planning problems (Diabat et al., 2019; Fahimnia et al., 2017; Lotfi et al., 2021; Lotfi et al., 2021; Fallahi et al., 2022). This solution method tries to find the complex constraints of the problem, relax, and move them to the objective function as a penalty. The goal is to enhance the computational speed and find a(n) lower (upper) bound for a minimi-

where  $UB$  is the upper bound,  $LB_{it}$  is the obtained lower bound of the current iteration, and  $Gr_{it}^2$  is the Euclidean norm of the relaxed constraints in the current iteration. The Euclidean norm for constraint  $Ax \leq b$  equals to  $(b - Ax)^2$ . The algorithm updates the value of the Lagrangian multipliers as follows:

$$\lambda_{it+1} = \lambda_{it} + Stp_{it} Gr_{it} \quad (90)$$

Finally, the maximum number of iterations is considered as the stopping criterion for the sub-gradient algorithm. Fig. 3 shows the flowchart of the Lagrangian relaxation algorithm.

#### 4. Computat

$$Min\lambda(x) = \gamma\lambda_0 + (1 - \gamma) \sum_j \theta_j \mu_j(x) + \sum_s \sum_t \beta_{st} (\hat{\theta}_{st} - P_{st} - Z_{st}) + \sum_l \sum_t \delta_{lt} \left( \sum_v tnv_{vlt} + \sum_w tnw_{wlt} + \sum_j tfl_{jlt} + \sum_k ttl_{klt} - qtl_{lt} \right) \quad (88)$$

Subject to :

Eqs. (35–47), (49–64), (66–68), (78–79).

zation (maximization) problem.

Regarding these details, the first step to implementing the LR is to identify the complex constraints of the problem. For this purpose, each set of problem's constraints is relaxed separately, and the model is run to determine the CPU time. After, the constraints with considerable effect on the CPU time are kept, and the problem is solved again with pair relaxation of these constraints. Table 2 shows a part of the constraints relaxation results of the proposed CVWRSC problem.

Based on the results, constraint sets (65) and (80) can be identified as complex constraints of the problem. These constraints are relaxed by removing them from the constraint sets and moving them into the objective function with penalty multipliers. Therefore, the LR form of the CVWRSC problem can be formulated as: where  $\beta_{st}$  and  $\delta_{lt}$  are the Lagrangian multipliers. A fixed value is set for Lagrangian multipliers, which are iteratively updated during the solving procedure of the algorithm. Here, we use the well-known sub-gradient method presented by Fisher (Fisher, 2004). In the sub-gradient algorithm, the Lagrangian multipliers and the lower bound of the problem are set to 0 and -inf, respectively. A fixed upper bound is also set for the problem. After, the relaxed problem's solution is considered a new lower bound. Therefore, the algorithm calculates the step size of the next iteration as follows:

$$Stp_{it+1} = \frac{UB - LB_{it}}{Gr_{it}^2} \quad (89)$$

**Table 2**  
The impact of constraints relaxation on the computational time problem.

Relaxation type	Relaxed constraints	CPU time (Second)
Separate relaxation	35	12.750
	37	14.007
	47	12.458
	65	13.078
	80	12.852
Pair relaxation	35–37	14.333
	35–47	46.980
	35–65	14.714
	35–80	13.121
	37–47	10.513
	37–65	11.847
	37–80	11.141
	47–65	12.902
	47–80	9.182
	65–80	8.888

#### ional results

In this section, some random numerical examples are provided to investigate the performance of the proposed LR algorithm. After, the model is applied to a real case study, and the results are analyzed. The LR algorithm and the presented case study are coded in GAMS 24.1.2 software on a supercomputer with 64 GB ram and Intel Xeon E312 CPU. The results are obtained using the CPLEX commercial solver.

##### 4.1. Numerical analysis

Different test problems are generated in three classes to evaluate the proposed LR algorithm. The details of the test problems are presented in Tables 3 and 4.

The details of the parameters randomly generated from a uniform distribution in the corresponding intervals, are shown in Table 4. To solve test problems, we set the importance weight of objective functions, compensation coefficient, and the budget of uncertainty  $\theta_1 = 0.7$ ,  $\theta_2 = 0.3$ ,  $\gamma = 0.3$ , and  $\Gamma = 0.5$ , respectively.

Each test problem is solved four times by CPLEX solver and LR algorithm. The details of comparing CPLEX solver and LR algorithm results in the context of total quality and CPU time are provided in Tables 5 and 6. The gap of obtained solutions by the Lagrangian relaxation algorithm is calculated using the following formula:

$$Gap_{CPLEX} = \frac{Bestsol_{LR} - Bestsol_{CPLEX}}{Bestsol_{CPLEX}} \quad (91)$$

where  $Bestsol_{LR}$  and  $Bestsol_{CPLEX}$  are the best-obtained solution by the lagrangian relaxation algorithm and CPLEX solver, respectively. Moreover, the gap between the obtained solutions by CPLEX solver is calculated as follows:

$$Gap_{LR} = \frac{|BP - BF|}{|BP|} \quad (92)$$

where  $BF$  and  $BP$  are the objective functions of the current best integer solution and the best possible integer solution, respectively. It is evident that the LR algorithm can find reasonable lower bounds in small- and medium-size classes, which have no significant gap to the optimal solution. However, the computational time of LR is higher than CPLEX due to the iterative procedure of the algorithm.

The main advantage of LR is for the large class example, where

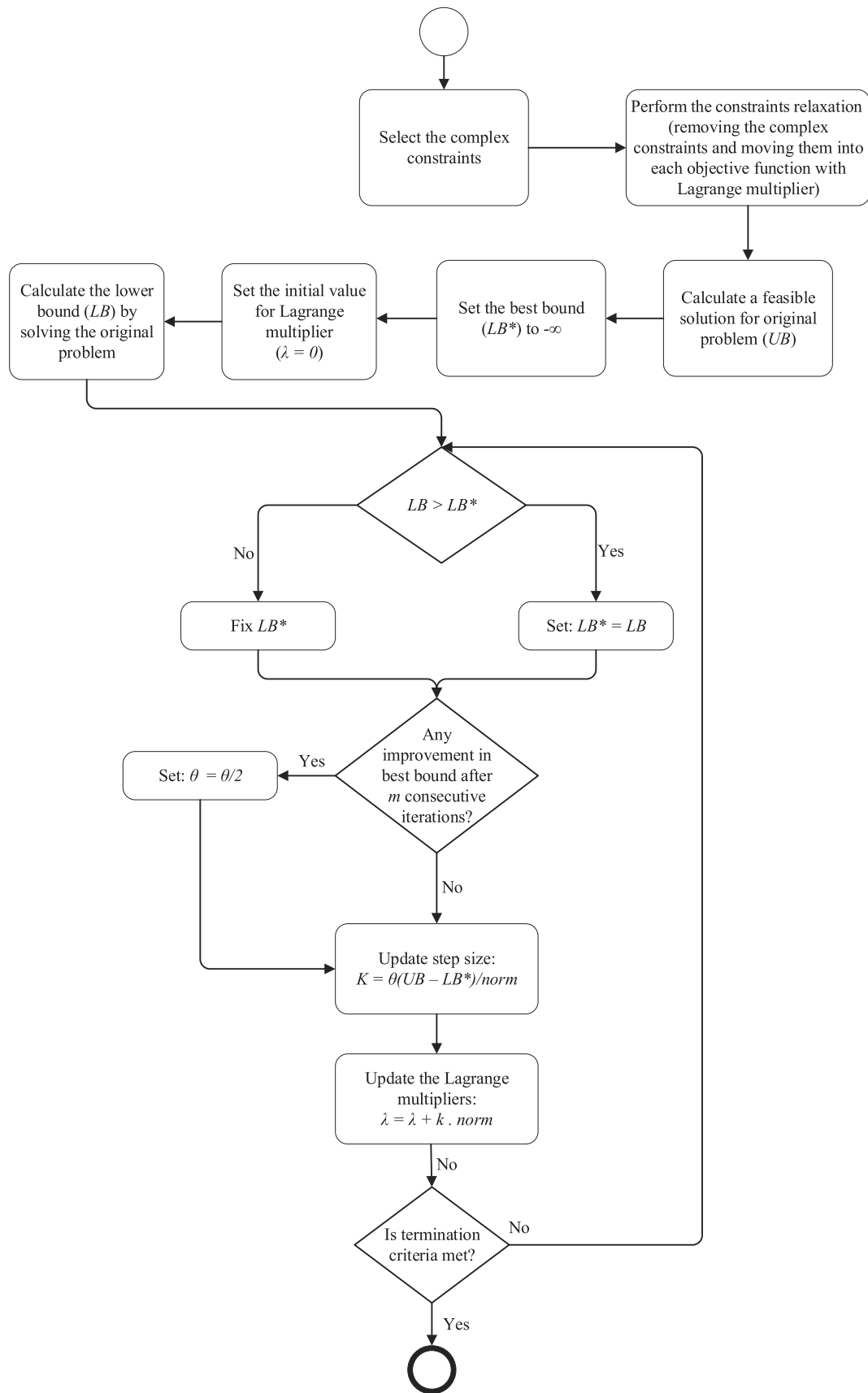


Fig. 3. The flowchart of Lagrangian relaxation algorithm.

**Table 3**  
Generated numerical test problems.

Class	Problem	Candidate groups for vaccination	Vaccine distribution centers	Fixed vaccination sites	Mobile vaccination sites	Vaccine waste types	Storage centers	Existing treatment facilities	Temporary treatment facilities	Treatment technology types	Landfills	Periods
Small	I1	7	7	7	7	2	7	7	7	7	4	3
	I2	9	9	9	9	2	9	9	9	9	4	4
	I3	12	12	12	12	2	12	12	12	12	6	5
	I4	13	13	13	13	2	13	13	13	13	6	6
Medium	I5	14	14	14	14	2	14	14	14	14	7	4
	I6	14	14	14	14	2	14	14	14	14	7	5
	I7	15	15	15	15	2	15	15	15	15	7	5
Large	I8	16	16	16	16	16	16	16	16	16	8	5
	I9	17	17	17	17	17	17	17	17	17	8	5
	I10	20	20	20	20	2	20	20	20	20	10	6

**Table 4**  
The input parameters numerical examples.

Parameter	Value	Parameter	Value
$POPIPOP_m$	$Uniform(50000, 75000)$ $Uniform(25000, 50000)$	$ITWPOP_s$	$Uniform(0.001, 0.016)$ $Uniform(10000, 25000)$
$\bar{\theta}$	$Uniform(0.7, 0.8)$	VSC	$Uniform(0.03, 0.036)$
$\hat{\theta}$	$Uniform(0, 0.2)$	CSF	$Uniform(0.0003, 0.014)$
MCV	$Uniform(0, 1)$	CST	$Uniform(0.0025, 0.0125)$
CDV	$Uniform(0.0002, 0.0008)$	CAF	$Uniform(1500, 2000)$
CDW	$Uniform(0.0001, 0.0011)$	CAT	$Uniform(800, 1300)$
CAV	$Uniform(60000, 80000)$	CTF	$Uniform(0.001, 0.0025)$
CAW	$Uniform(30000, 40000)$	CTT	$Uniform(0.001, 0.0025)$
VCF	$Uniform(0.0018, 0.0025)$	CFL	$Uniform(0.0005, 0.001)$
VCT	$Uniform(0.0018, 0.0025)$	CTL	$Uniform(0.0005, 0.0011)$
NTV	$Uniform(0.0004, 0.0011)$	CAL	$Uniform(1000000, 1500000)$
NTW	$Uniform(0.0005, 0.0009)$	LBC	$Uniform(0.00018, 0.00022)$
ITV	$Uniform(0.001, 0.014)$	ECW	$Uniform(0.4, 8)$
EDV	$Uniform(0.0001, 0.0005)$	EDW	$Uniform(0.0001, 0.0008)$
EVS	$Uniform(0.0003, 0.0033)$	EWS	$Uniform(0.0004, 0.0051)$
EVL	$Uniform(0.04, 0.11)$	EWL	$Uniform(0.07, 0.15)$
ESF	$Uniform(0.0005, 0.0185)$	EST	$Uniform(0.003, 0.0172)$
EFL	$Uniform(0.022, 0.031)$	ETL	$Uniform(0.016, 0.037)$
ECD	$Uniform(70, 80)$	ECV	$Uniform(50, 55)$
INS	$Uniform(30, 40)$	CAS	$Uniform(1000, 1250)$
INT	$Uniform(18, 22)$		

**Table 5**  
Comparing the total cost quality of CPLEX solver and LR algorithm.

Class	Problem	CPLEX						LR					
		Total cost			Gap			Total cost			Gap		
		Worst	Average	Best	Min	Average	Max	Worst	Average	Best	Min	Average	Max
Small	I1	3003.415	3162.865	3315.073	0.0000	0.0001	0.0000	3087.34	3101.852	3133.756	0.0547	0.0643	0.0687
	I2	4004.928	4329.546	4540.373	0.0001	0.0001	0.0001	3961.336	4068.084	4164.877	0.0827	0.1040	0.1275
	I3	4754.431	5418.304	5854.508	0.0000	0.0001	0.0000	4698.965	5336.686	5781.004	0.0126	0.0884	0.1974
	I4	5744.548	6186.207	6622.154	0.0001	0.0002	0.0001	5422.386	5866.476	6582.298	0.0060	0.1141	0.1812
Medium	I5	8050.733	8208.766	8290.501	0.0001	0.0010	0.0001	7422.144	7711.442	8009.814	0.0339	0.0698	0.1047
	I6	10088.89	10333.61	10470.17	0.0002	0.0004	0.0002	9364.809	9564.12	9668.513	0.0766	0.0865	0.1056
	I7	10347.31	10863.7	11511.22	0.0010	0.0018	0.0010	9833.691	10052.24	10316.326	0.1038	0.1267	0.1457
Large	I8	15330.39	15710.81	16261.42	0.0010	0.0020	0.0028	13713.22	15012.25	16062.394	0.0122	0.0768	0.1567
	I9	12657.86	12956.25	13624.17	0.0020	0.0026	0.0040	11875.42	12026.13	12187.873	0.1054	0.1173	0.1284
	I10	NS*	NS	NS	NS	NS	NS	14285.87	15470.19	16127.772	NA**	NA	NA

\*NS: No solution

\*\*NA: Not available

CPLEX cannot find the optimal solution after about 7200 s, but LR provides a lower bound in about 2700 s averagely.

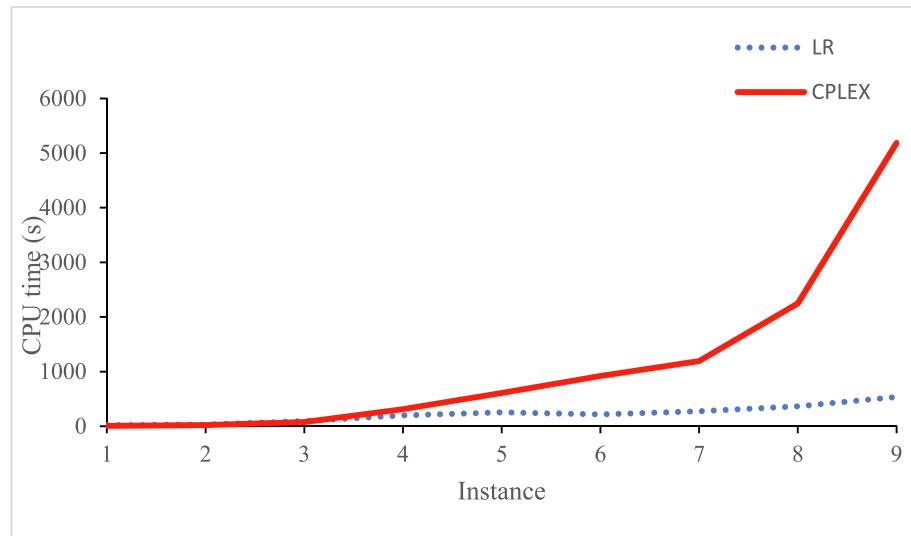
Moreover, as shown in Fig. 4, as the size of test problems increases, the average CPU time of the CPLEX solver increases exponentially. It is evident that due to the iterative nature LR algorithm, the computational

time of CPLEX is less than LR in the small-size and some medium classes. However, the results confirm that the LR algorithm can reduce the CPU time to find a solution, notably for large-size classes. However, the findings show that the LR algorithm may significantly reduce the CPU's time to discover a solution, especially for complex issues. As CPLEX

**Table 6**

Comparing the solution time (Second) of CPLEX solver and LR algorithm.

Class	Problem	CPLEX			LR		
		Min	Average	Max	Min	Average	Max
Small	I1	4.1	4.49	4.845	17.713	19.516	23.982
	I2	15.528	19.723	23.365	23.74	31.598	35.319
	I3	61.886	74.839	101.598	68.047	96.512	111.276
	I4	259.444	314.511	353.657	149.962	201.238	241.947
Medium	I5	538.394	609.937	751.499	174.093	256.249	317.129
	I6	1044.324	1194.152	1290.891	164.521	274.909	375.071
	I7	750.030	921.054	1225.068	166.924	217.398	295.243
Large	I8	1747.837	2245.941	2630.468	310.126	365.296	429.245
	I9	5056.496	5186.213	5220.865	490.781	537.223	629.539
	I10	> 10,000	> 10,000	> 10,000	665.643	779.143	856.823

**Fig. 4.** Comparing the CPU time of CPLEX and LR.**Table 7**

The properties of Tehran's municipal districts.

District	Population	Latitude	Longitude
1	531,274	35.8025	51.45972
2	749,022	35.7575	51.36222
3	369,502	35.75444	51.44806
4	990,146	35.74164	51.49194
5	928,738	35.74889	51.30028
6	278,947	35.73722	51.30028
7	336,550	35.72194	51.40583
8	479,005	35.72444	51.44611
9	207,624	35.68361	51.49833
10	342,223	35.68361	51.31722
11	333,127	35.67944	51.36667
12	256,601	35.6865	51.39583
13	265,796	35.70778	51.42639
14	538,073	35.67444	51.51417
15	706,844	35.63083	51.47028
16	289,077	35.63944	51.47361
17	309,230	35.65389	51.40917
18	445,429	35.65167	51.36306
19	282,598	35.62056	51.29278
20	395,088	35.59028	51.36694
21	196,874	35.69056	51.25778
22	191,934	35.74722	51.20417

**Table 8**

The properties of distribution centers.

Number	Facility	Latitude	Longitude
1	Iranian red crescent 1	35.65935	51.42911
2	Iranian red crescent 2	35.73318	51.54429
3	Iranian red crescent 3	35.79284	51.40218
4	Iranian red crescent 4	35.66618	51.26401

cannot find a solution in the large-size classes, the efficiency of LR can be concluded.

## 4.2. Case study

### 4.2.1. Case description

Here, a real-world network is investigated to demonstrate the model's applicability. The required data for the problem is collected from a CVWRSC from the capital of Iran, Tehran. Tehran is selected as the case study because it is the most populous city in Iran and one of the most populated cities in the Middle East, with a 9423702 population (Municipality, 2022). Iran's Ministry of Health and Medical Education and Tehran municipality manage the vaccination programs in Tehran. The main sources of the current case study are: (1) the documents of the



**Table 9**  
The properties of vaccination sites.

Number	Type	Facility	Latitude	Longitude
1	Fixed vaccination site	Kordestan complex hall	35.72721	51.39471
2	Fixed vaccination site	Saei complex hall	35.70796	51.44298
3	Fixed vaccination site	Mofatteh complex hall	35.72674	51.42815
4	Fixed vaccination site	Salem complex hall	35.58646	51.42593
5	Fixed vaccination site	Arash Miresmaeili complex hall	35.66165	51.32382
6	Mobile vaccination site	Shohadaye Ghavvas complex hall	35.68869	51.23573
7	Mobile vaccination site	Shahid Homayoun complex hall	35.65191	51.31529
8	Mobile vaccination site	Imam Khomeini complex hall	35.67895	51.23713
9	Mobile vaccination site	Shahid Kaafi complex hall	35.63471	51.36315
10	Mobile vaccination site	Sharbanoo complex hall	35.72366	51.45074

**Table 10**  
The properties of storage centers.

Number	Landfill	Latitude	Longitude
1	West Tehran health center	35.72817	51.41557
2	North Tehran health center	35.73996	51.44565
3	South Tehran health center	35.70421	51.39877
4	Shahid Kazemian health center	35.70493	51.34355

**Table 11**  
The properties of treatment facilities.

Number	Type	Facility	Latitude	Longitude
1	Existing treatment facility	Imam Hossein hospital	35.70658	51.45105
2	Existing treatment facility	Imam Khomeini hospital	35.70922	51.38054
3	Existing treatment facility	Shariati hospital	35.72236	51.38648
4	Existing treatment facility	Milad hospital	35.74582	51.38142
5	Existing treatment facility	Feyzbakhsh hospital	35.67587	51.26591
6	Existing treatment facility	Resalat hospital	35.74353	51.44884
7	Temporary treatment facility	Masih Daneshvari hospital	35.81704	51.49636
8	Temporary treatment facility	Payambaran hospital	35.73501	51.32788
9	Temporary treatment facility	Baqiyatallah hospital	35.75696	51.39529
10	Temporary treatment facility	Sina hospital	35.68669	51.41239

**Table 12**  
The properties of landfills.

Number	Landfill	Latitude	Longitude
1	Aradkooh waste processing plant 1	35.50241	51.35674
2	Aradkooh waste processing plant 2	35.46411	51.32344

Ministry of Health and Medical Education and Tehran municipality, (2) WHO instructions for vaccine waste management (World Health Organization, 2022), and (3) the relevant published papers in the literature (Kargar et al., 2020; Kargar et al., 2020).

The planning horizon is three months which consists of three one-

month periods. Tehran encompasses 22 municipal districts whose population and geographical coordinates are shown in Table 7. Each municipal district is considered a candidate group for vaccination. Five candidate nodes are considered potential locations for fixed and mobile vaccination sites. In addition, three Iranian red cross centers are the candidate points for the distribution centers. Currently, there are six existing treatment facilities in Tehran used to treat medical wastes. Based on the opinion of experts, four candidate locations are considered for temporary treatment facilities in the network. Finally, two landfills are used for vaccine waste disposal in Tehran. The network cost is measured by 10 million Rials (Iran currency).

Moreover, the kilogram is the unit for carbon emission and vaccine waste in the system. The detailed properties of the CVWRSC are provided in Tables 8–12. The locations of all concerned facilities in the network are shown in Fig. 5 schematically.

#### 4.2.2. Results

As mentioned before, one of the main features of CVWRSC that distinguishes this supply chain is the necessity of the integration between the vaccination and waste networks regarding the WHO instructions. First of all, we are going to show the gain of the integration for the presented case study against the separate solving models. To evaluate the performance of the model, we define two models separately as follows:

- 1- Model I: The vaccine supply chain network, including candidate groups for vaccination, vaccine distribution centers, fixed vaccination sites, and mobile vaccination sites.
- 2- Model II: The waste supply chain network, including fixed vaccination sites, mobile vaccination sites, storage centers, existing treatment facilities, temporary treatment facilities, and landfills.

We run the model for two extreme points ( $\theta_1 = 1, \theta_2 = 0$ ) and ( $\theta_1 = 0, \theta_2 = 1$ ), and the results are presented in Table 13.

As can be seen, the CVWRSC model outperforms the disintegrated models. Considering the results, the total cost and total carbon emission of studied points are reduced by about 0.47 and 9.08 percent, respectively.

Next, the model is solved with different values of  $\theta_1$  and  $\theta_2$  to provide a set of Pareto solutions for the decision-makers. Increasing the importance weight of an objective function results in better solutions for that function. The Pareto solutions are presented in Table 14.

As can be seen, the Pareto solutions are computed in a reasonable time with no significant gap. Hence, there is no need to apply the LR algorithm in this case study.

The components of the objective functions for each solution are reported in Table 15 to provide better insights into the Pareto front. As can be seen in Table 15, some components, such as vaccination cost, waste treatment cost, moving cost of mobile vaccination sites, and the carbon emission from the moving mobile vaccination sites, are equal for all Pareto solutions. This similarity is because all candidate groups should satisfy the vaccination demand. However, depending on the weight of each objective function, the model tries to determine the location of the facilities and the allocation and inventory policies to make a different trade-off between the total cost and total carbon emission objectives. Fig. 6 clearly shows the conflicts of objective functions. It is obvious that when we try to optimize the model for one objective, the model will have its greatest performance in terms of that objective, and the optimum solution will be produced for the measure. However, when we attempt to optimize the model by considering both objectives, the performance will be reduced in each of the objectives to get a reasonable trade-off. According to Fig. 6, the best possible solution for the total cost objective function is 1013.163, which is obtained in ( $\theta_1 = 1, \theta_2 = 0$ ). In addition, the best possible solution for the total carbon emission function is 224.152, which is obtained in ( $\theta_1 = 0, \theta_2 = 1$ ). In the same way, the worst solution in terms of total cost and total emission objective

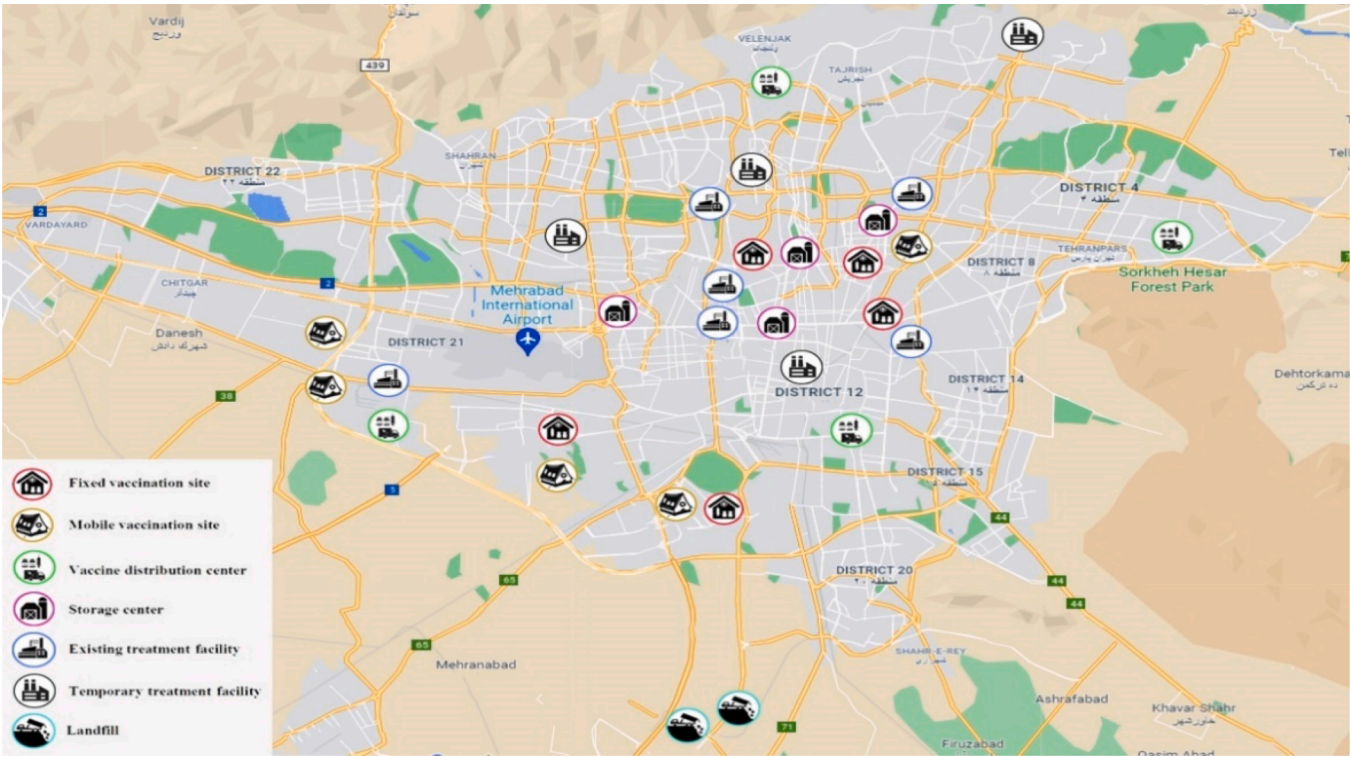


Fig. 5. Location of concerning facilities in Tehran’s CVWRSC.

Table 13  
Comparing the performance of CVWRSC and the disintegrated models.

$\theta_1$	$\theta_2$	Objective function	Model I	Model II	Model I + Model II	CVWRSC model	Reduction percentage
1	0	Total cost	864.598	153.879	1018.477	1013.608	0.47
0	1	Total carbon emission	13.268	225.952	239.22	217.482	9.08

Table 14  
The Pareto solutions of the case study.

$\theta_1$	$\theta_2$	$Z_1$	$Z_2$	$\mu_1(x)$	$\mu_2(x)$	$\lambda_0$	Gap	CPU time (S)
0.0	1.0	1140.219	224.152	0.604	0.944	0.842	0.0002	64.273
0.1	0.9	1140.208	224.158	0.604	0.944	0.818	0.0002	65.742
0.3	0.7	1062.174	244.751	0.791	0.791	0.791	0.0002	63.276
0.7	0.3	1052.179	247.739	0.815	0.769	0.791	0.0002	86.778
0.9	0.1	1019.967	259.419	0.892	0.682	0.814	0.0002	80.884
1	0.0	1013.163	262.425	0.908	0.659	0.833	0.0002	220.386

Table 15  
The components of objective functions in the Pareto front solutions.

$\theta_1$	$\theta_2$	Total cost component						Total carbon emission component			
		Establishment	Transportation	Infectious waste holding	Treatment	Vaccination	Moving mobile sites	Vaccine transportation	Infectious waste transportation	Non-infectious waste transportation	Moving mobile sites
0.0	1.0	581	82.747	13.255	9.423	494.73	0.000	26.155	60.485	131.534	0.000
0.1	0.9	527	96.237	13.005	9.235	494.73	0.000	20.088	63.616	140.446	0.000
0.3	0.7	453	96.056	13.005	9.235	494.73	0.000	18.032	80.152	146.567	0.000
0.7	0.3	453	87.454	13.005	9.235	494.73	0.000	15.831	70.866	159.601	0.000
0.9	0.1	378	125.016	13.005	9.235	494.73	0.000	30.594	70.725	158.089	0.000
1.0	0.0	378	118.194	13.005	9.235	494.73	0.000	27.996	73.243	161.187	0.000

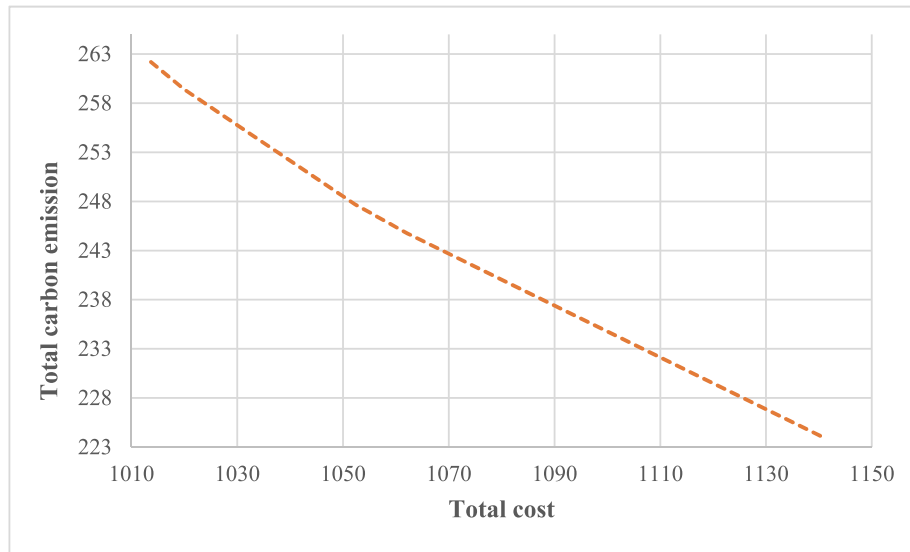


Fig. 6. The Pareto frontier of the case study.

Table 16

The location of established fixed vaccination sites.

	Kordestan complex hall	Saei complex hall	Mofatteh complex hall	Salem complex hall	Arash Miresmaeili complex hall
Establishment state	0	1	1	0	1

Table 17

The location of established mobile vaccination sites.

	Shohadaye Ghavvas complex hall	Shahid Homayoun complex hall	Imam Khomeini complex hall	Shahid Kaafi complex hall	Sharbanoo complex hall
$t = 1$	1	1	1	1	1
$t = 2$	1	1	1	1	1
$t = 3$	1	1	1	1	1

functions are 1140.219 and 262.425, which are obtained in  $(\theta_1 = 0, \theta_2 = 1)$  and  $(\theta_1 = 1, \theta_2 = 0)$ , respectively.

The Pareto solution with  $\theta_1 = 0.7$  and  $\theta_2 = 0.3$  is selected for further analysis of the results. The optimum location decisions of this solution are presented in Tables 16–20. In these tables, the value 1 shows that the facility is established in that location.

As shown in Table 16, all mobile vaccination sites are deployed in the

mobile vaccination sites, so in this respect, no cost is imposed on the network.

The components of the total emission function are also analyzed. The results in Fig. 8 show that most pollution is generated through the transportation of non-infectious vaccine wastes. As the mobile vaccination sites are not relocated, there is no carbon emission from the movement of these facilities.

The comparison of the usage percentages of treatment technologies is shown in Fig. 9. The autoclaving process generates approximately 90 % of the infectious vaccine wastes. It can be concluded that the treatment capacity of this technology is the main reason for this.

#### 4.2.3. Robustness evaluation

In this section, the performance of the proposed robust model against the deterministic model is investigated by using a realization model. 10 random realizations of the vaccination tendency rate are randomly generated  $[\bar{\theta}_{st} - \hat{\theta}_{st}, \bar{\theta}_{st} + \hat{\theta}_{st}]$  interval. The robust and deterministic models are solved separately, and their solutions are substituted in the realization model with the following compact form:

$$Max \lambda = \gamma \lambda_0 + (1 - \gamma) \left( \theta_1 \frac{Z_1^{NIS^*} - (q_{real} \cdot x^* + g_{real} \cdot y^*)}{Z_1^{NIS^*} - Z_1^{PIS^*}} + \theta_2 \frac{Z_2^{NIS^*} - (h_{real} \cdot x^* + f_{real} \cdot y^*)}{Z_2^{NIS^*} - Z_2^{PIS^*}} \right) - p(S_b^+ + S_b^-) \quad (93)$$

first period and remain fixed during the planning horizon. Therefore, mobile vaccination sites have no movement cost or transportation emissions. In addition, there is no need to use a temporary treatment facility in this network, and the infectious vaccine wastes is only treated in the existing treatment facilities.

To provide better insight, we divide the total cost of Tehran's CVWRSC into its sub-components. As shown in Fig. 7, a high portion of the network cost is related to establishing the facilities and vaccination of candidate groups. As mentioned before, there is no movement of

Subject to:

$$B_{real} x^* - S_b^+ + S_b^- = 0$$

$$Ax^* \leq C$$

$$Tx^* = 0$$

$$Dx^* \leq Ey^*$$

**Table 18**

The location of established distribution centers.

	Iranian red crescent 1	Iranian red crescent 2	Iranian red crescent 3	Iranian red crescent 4
Establishment state	1	0	0	1

**Table 19**

The location of established storage centers.

	West Tehran health center	North Tehran health center	South Tehran health center	Shahid Kazemian health center
Establishment state	1	1	1	1

**Table 20**

The location of established temporary treatment facilities.

	Masih Daneshvari hospital	Payambaran hospital	Baqiyatallah hospital	Sina hospital
Establishment state	0	0	0	0

$$Fy^* \leq 1$$

$$S_b^+, S_b^- \geq 0$$

where  $x^*$  and  $y^*$  the optimal obtained solutions for the deterministic and robust models. Here, there are two decision variables in the problem,  $S_b^+$  and  $S_b^-$ , which is the constraint violation value in the cases of infeasibility. The constraint violation is penalized in the objective function using  $p$  as the penalty multiplier. We investigate the realization in the different levels of price of robustness. The models are compared in the context of the average and standard deviation of the objective function. The results of realization are summarized in Tables 21 and 22.

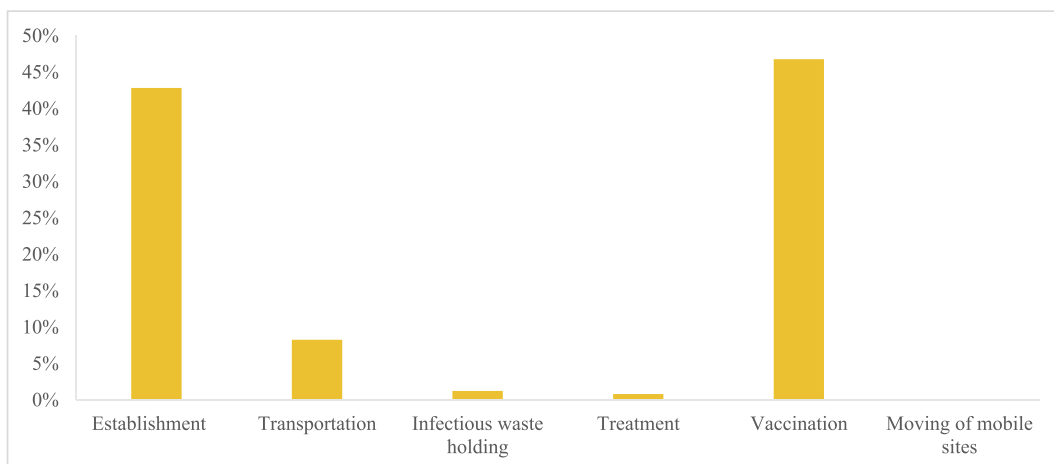
As evident, the robust model has better average objective functions than the deterministic model in all cases. Also, the robust model has a more reasonable standard deviation for both objective functions in most cases. The proposed robust approach is efficient for this problem in an uncertain situation regarding the mentioned description. A visual assessment of the results is also provided in Figs. 10 and 11.

#### 4.2.4. Sensitivity analysis

The decision-makers may have different opinions, and the parameters of the robust model and the TH method may change based on their preference. Therefore, we investigate the model's sensitivity to some of the main parameters of the presented approaches. We also analyze the variation in the value of total cost when robustness's price varies. As shown in Fig. 12, as the budget of uncertainty increases, the total cost function increases due to the imposed conservatism. A similar trend exists for the total emissions of the system, in which the second objective function rises when the uncertainty budget is increased. To respond to the vaccination demand, it is predictable that risk-averse decision-makers favor a price of robustness with higher levels of uncertainty. On the other side, risk-taking decision-maker favors lowering the cost of CVWRSC, which raises the probability of people not being vaccinated.

The model results under different values for the compensation coefficient of the TH method are shown in Fig. 13. The TH model's first term ( $\gamma\lambda_0$ ) seeks to balance and enhance the membership function values of the objective functions as much as possible, while the second term ( $(1-\gamma)\sum_j \theta_j \mu_j(x)$ ) prioritizes the weights of the objective functions. In this case, the first term of the TH model should be given more weight (the value is increased) if the decision-maker prefers to find efficient solutions with the balance of the membership function values. On the other hand, if the preference of the decision maker is to concentrate on the weights of objective functions and obtain solutions where the weight of the functions inside it is more important, the value of  $\gamma\lambda_0$  should be reduced so that the second term of the objective function will be more significant. As can be seen, the objective functions do not have similar behavior. Increasing the compensation coefficient results in an increasing trend in the total cost and a decreasing trend in the total carbon emissions. Fig. 13 shows that the model encourages the membership functions to become closer to each other as the compensation coefficient increases. On the other side, the lower levels of compensation coefficient improve the total cost objective function, which has a higher weight.

In reality, uncertainty is involved in decision-making, which results in less desirable outcomes. Finally, the vaccination tendency rate is the uncertain parameter of this model, which may vary in real-world situations and different countries. The success of vaccination programs can significantly impact people's trust in being vaccinated. Here, to examine the impact of the vaccination tendency rate, the parameter value is changed from 0.40 to 0.95, and the results are schematically provided in Figs. 14 and 15. As expected, increasing the vaccination tendency rate of candidate groups leads to a general increasing trend for both objective functions. In fact, the vaccination demand is increased, and if more people refer to the vaccination sites, the flow of CVWRSC will increase. In this situation, more facilities are required for vaccine distribution,

**Fig. 7.** The components of the total cost function.

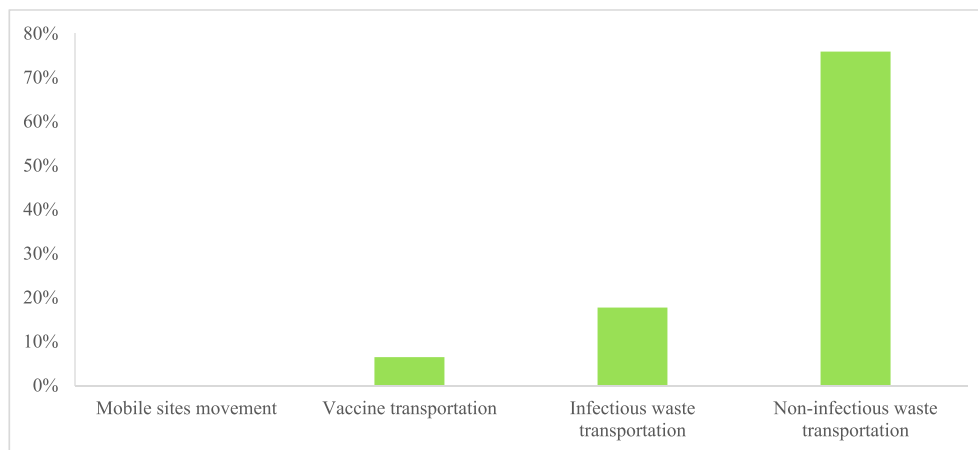


Fig. 8. The components of the total carbon emission function.

vaccination, storage, and treatment of the generated wastes. Consequently, higher costs and carbon emissions are imposed on the system. According to the results, the total carbon emission variation range is higher than the total cost.

#### 4.2.5. Discussion

In this paper, we study a sustainable CVWRSC network under uncertainty that aims to minimize the total cost and total carbon emission. The capital of Iran, Tehran, is the case study for evaluating the model. Through the literature investigation, we cannot observe a similar study that specifically addresses the vaccine waste management problems during the COVID-19 pandemic. The paper by Kargar, et al. (Kargar et al., 2020) is a medical waste management network that is somewhat close to our paper. However, significant deficiencies make this model not work well for managing the waste of the COVID-19 vaccine.

Kargar, et al. (Kargar et al., 2020) investigate a simple three-echelon medical waste reverse supply chain. They only consider waste generation centers, treatment facilities, and landfills. Consequently, their model locates the treatment facilities and location decisions for the treatment facilities, and the location decisions of the other facilities in CVWRSC, such as fixed vaccination sites, mobile vaccination sites, vaccine distribution centers, and storage centers, are not considered. In addition, they do not consider the allocation decisions for the candidate groups for vaccination, which is one of the most important decisions in COVID-19 vaccine waste management. It is simply assumed that a certain amount of waste is generated in each period. They also do not assume the presence of multiple types of treatment technologies in treatment centers. Moreover, Kargar, et al. (Kargar et al., 2020) do not consider the growing concerns of carbon emission, which may

significantly affect the severity of COVID-19 disease. Our work enables the managers and decision-makers to make a trade-off between the economic and environmental objectives of the network. Kargar, et al. (Kargar et al., 2020) ignore the uncertainty of the real-world environment. It is undeniable that various uncertainty sources may impact the performance of medical waste networks, and in the particular case of CVWRSC, the vaccination tendency rate is an influential parameter that is inherently stochastic. We consider the uncertainty and handle it via robust optimization, which is one of the most efficient methods when historical data are unavailable. From the solution approach viewpoint, the Kargar, et al. (Kargar et al., 2020) model is solved via the LINGO software package. Nevertheless, as mentioned before, the supply chain network design falls into the category of Np-hard problems, and commercial solvers are ineffective for problem-solving in large-size networks. Some other researchers also simply used commercial solvers to solve the medical waste management problems during COVID-19 (Govindan et al., 2019; Tirkolaee et al., 2021). The current work presents the Lagrangian relaxation algorithm as a powerful solution approach for large-size networks that can be utilized for other problems. It is also noteworthy to mention that the TH approach addresses the membership of the objective functions and the weight of each objective simultaneously, which is this method's main distinctive feature. Finally, the model's performance is evaluated by applying it to a case study from Tehran, the capital of Iran. This city is selected because Tehran is one of the largest metropolitans in the middle east, with a 9,423,702 population. However, Kargar, et al. (Kargar et al., 2020) and many other papers in the literature addressed the case studies with much smaller populations.

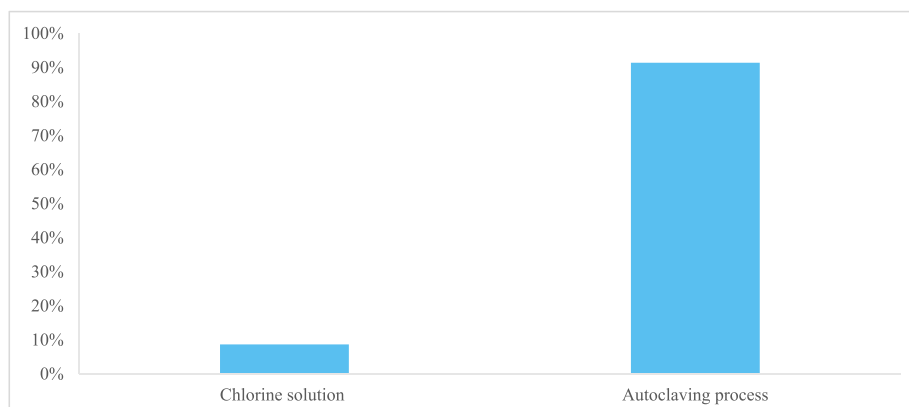


Fig. 9. Comparison of the usage percentage of treatment technologies.



**Table 21**

The total cost of models under the realization scenarios.

$\Gamma$	Mean		Standard deviation	
	Robust	Deterministic	Robust	Deterministic
0	<b>1934.01</b>	1967.96	172.20	<b>127.55</b>
0.1	<b>1883.94</b>	1999.50	<b>150.20</b>	212.35
0.2	<b>1910.87</b>	1974.35	166.70	<b>166.12</b>
0.3	<b>1948.68</b>	2051.36	183.81	<b>134.31</b>
0.4	<b>1871.20</b>	1939.27	<b>98.65</b>	201.83
0.5	<b>1864.96</b>	1920.06	<b>117.31</b>	136.62
0.6	<b>1901.64</b>	1965.46	<b>123.65</b>	129.66
0.7	<b>1889.55</b>	1988.28	192.82	<b>131.69</b>
0.8	<b>1973.43</b>	2006.58	<b>83.50</b>	164.00
0.9	<b>1886.40</b>	1952.34	<b>114.23</b>	174.95
1	<b>1922.73</b>	1997.62	<b>126.47</b>	132.45
Average	<b>1907.95</b>	1978.43	<b>139.05</b>	155.59

**Table 22**

The total carbon emission of models under the realization scenarios.

$\Gamma$	Mean		Standard deviation	
	Robust	Deterministic	Robust	Deterministic
0	<b>603.20</b>	616.78	68.88	<b>51.02</b>
0.1	<b>594.43</b>	640.65	<b>60.08</b>	84.94
0.2	<b>593.82</b>	605.34	66.68	<b>61.56</b>
0.3	<b>608.94</b>	650.02	73.52	<b>53.73</b>
0.4	<b>578.07</b>	605.30	<b>39.46</b>	80.73
0.5	<b>577.98</b>	608.87	<b>46.93</b>	54.65
0.6	<b>590.25</b>	615.78	<b>49.46</b>	51.86
0.7	<b>585.35</b>	624.84	77.13	<b>52.67</b>
0.8	<b>618.96</b>	632.22	<b>33.40</b>	65.60
0.9	<b>584.15</b>	610.53	<b>45.69</b>	69.98
1	<b>599.50</b>	629.45	<b>50.59</b>	52.98
Average	<b>594.06</b>	621.80	<b>55.62</b>	61.79

## 5. Managerial insights and practical implications

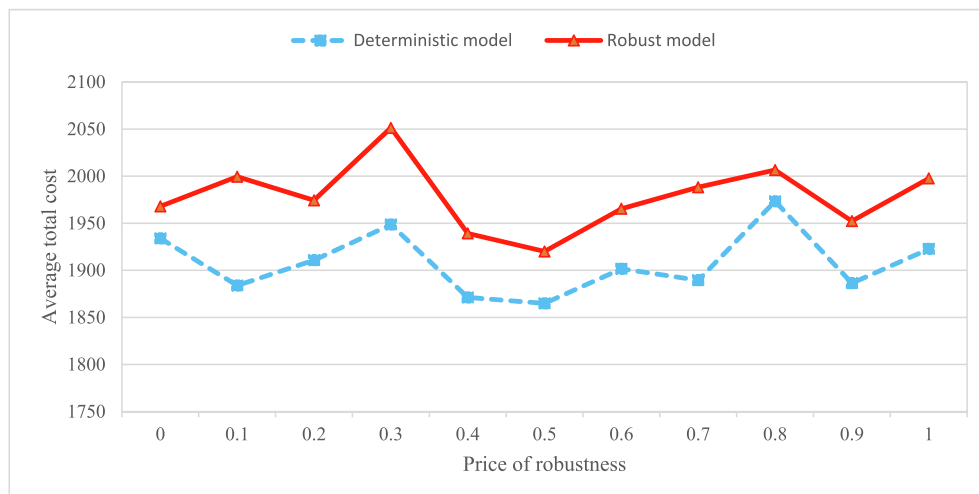
Based on the results of this study, some insight can be presented to the managers of vaccination programs for efficient planning of the CVWRSC network and to provide a decision support framework for managing COVID-19 vaccine waste. In this way, the goal is to determine the optimal decisions of the reverse supply chain network by the presented model so that the system's total cost and total carbon emission are minimized. Some of the extracted insights from the results of the case study, which is one of the greatest metropolises in the middle east, are

as bellow:

- 1) The vaccination operations impose a huge cost on the network regarding the components of the total cost of the network. Consequently, the proper infrastructure and human resources enable the managers to reduce the network's cost significantly.
- 2) The location cost of the facilities is the second high-cost component of the network. One main feature that distinguishes the current network from the other medical waste network is the need to establish particular vaccination facilities during the pandemic. This shows how much is necessary to use a structured framework to find the optimum location from a set of candidate points. Our model supports the managers in determining the location of facilities in the best possible way.
- 3) Most of the carbon emission is from the transportation of non-infectious vaccine wastes. Therefore, one of the best ways of controlling carbon emission is to invest in carbon emission reduction and use more environmentally friendly vehicles to transport this type of waste.
- 4) Although it seems at first glance that autoclaving is a highly cost treatment technology, the result of the case study shows that the autoclaving process performs about 90 percent of non-infectious waste treatment. Therefore, it seems logical that managers should focus on providing this technology for treatment facilities.
- 5) Both total cost and total emission objectives are highly impacted by the vaccination tendency rate, which is not also a deterministic parameter in the real-world environment. The presented model can cope with the parameter's uncertainty efficiently. However, the managers should do their best to predict the vaccination tendency rate as best as possible using a proper prediction mechanism.

## 6. Conclusion and outlook

The vast COVID-19 vaccination programs have caused a new problem in the west management research area. Based on the WHO reports, the reverse supply chain network of COVID-19 vaccine waste needs special attention due to its unique features. This paper addresses this problem for the first time by developing a new multi-objective mixed-integer mathematical programming model. The total cost and total carbon emissions are the two objective functions considered to be optimized. A robust optimization approach is utilized to deal with the inevitable uncertainty in the tendency rate of vaccination and a lack of data. The single objective counterpart of the model is established using the TH method as an efficient interactive fuzzy approach. Due to the complexity of the model, commercial solvers cannot solve large

**Fig. 10.** The total cost comparison under realization scenarios.



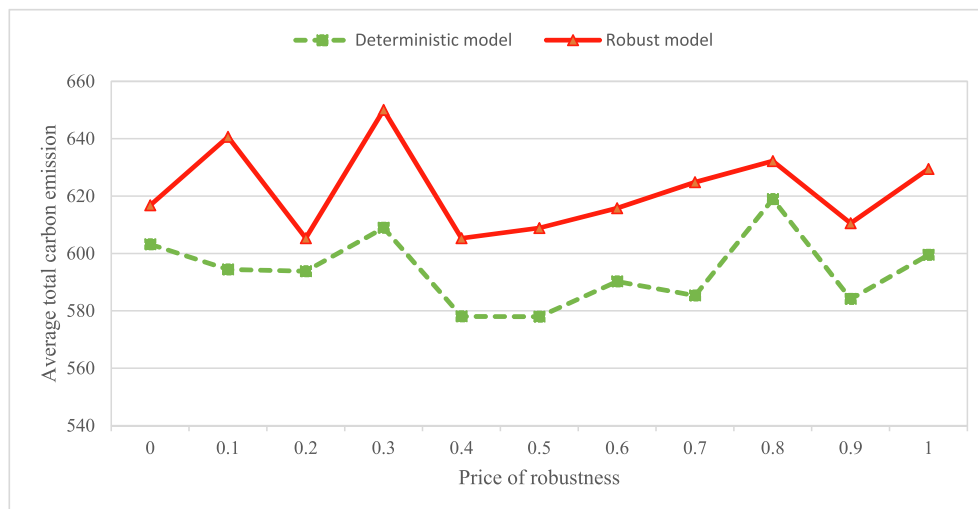


Fig. 11. The total carbon emission comparison under realization scenarios.

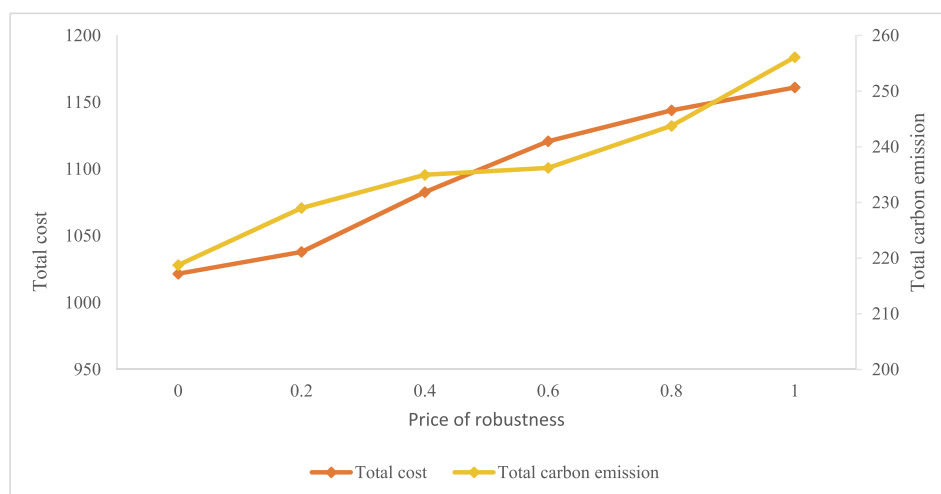


Fig. 12. The impact of the prices of robustness on the objective functions of the system.

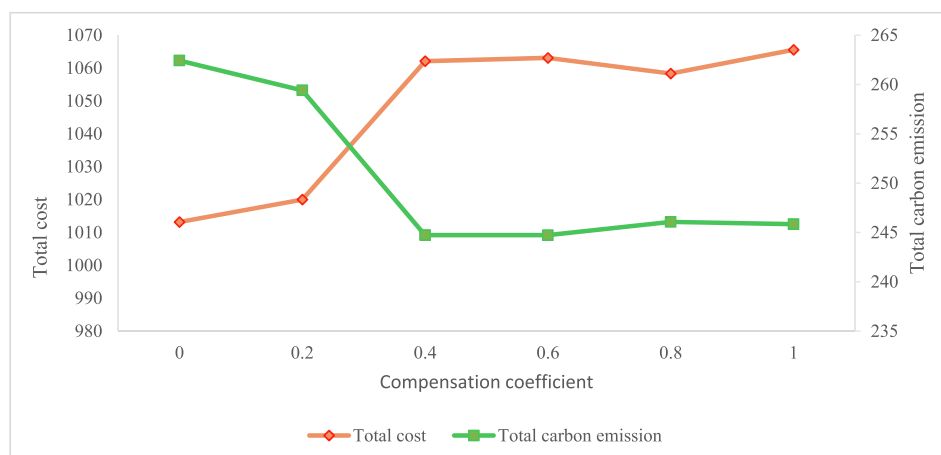


Fig. 13. The impact of the compensation coefficient on the objective functions of the system.

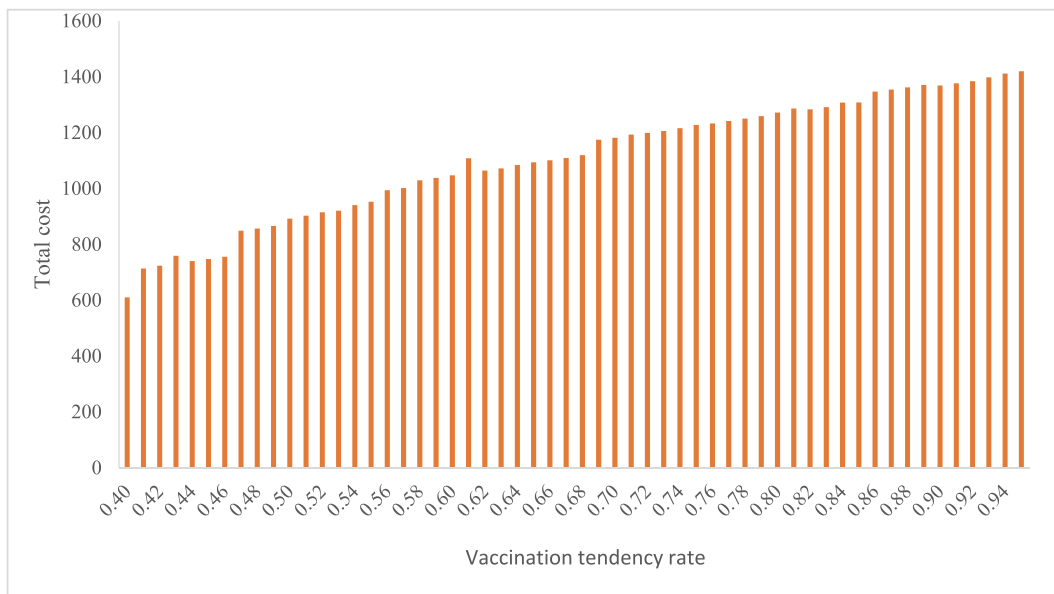


Fig. 14. The impact of the vaccination tendency rate on the total cost of the system.

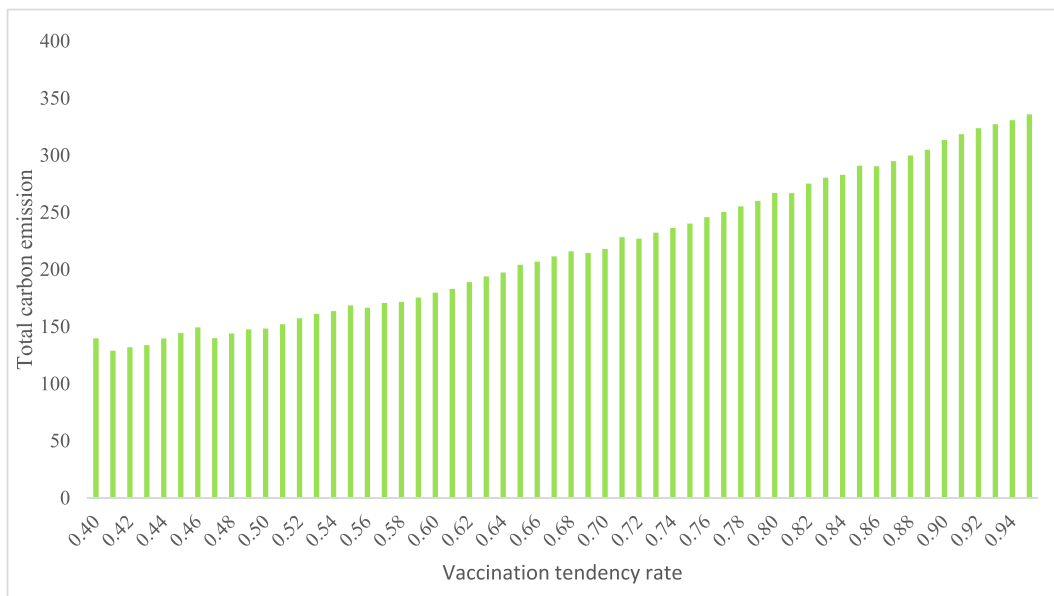


Fig. 15. The impact of the vaccination tendency rate on total carbon emission of the system.

instances. Therefore, a LR algorithm is presented to find the lower bound solutions. The algorithm's efficiency is shown by solving different random test problems and comparing the results with the CPLEX commercial solver. We also verify the applicability of the mathematical model by applying it to a real-world network. The main findings are as follows:

- The results demonstrate that increasing the tendency rate of vaccination imposes more cost and carbon emissions on the system. By increasing the tendency rate from 0.40 to 0.95, the total cost is increased from 6090 to 14,200 million Rials. Additionally, the total carbon emission is also increased from 140 to 335 kg.
- The autoclaving process has a significant role in treating infectious vaccine wastes, and this technology treats about 91 percent of infectious vaccine wastes.
- A large part of the cost of the network is related to the vaccination cost, and the vaccination process is responsible for about 46 percent of the overall cost of the system.
- A large part of the emission of the network is related to the transportation of non-infectious wastes, and the transportation of this type of waste is responsible for about 76 percent of the overall cost of the system.
- All mobile vaccination sites are located at the beginning of the first period, and there is no movement of these facilities in the subsequent period. As a result, the carbon emission and the movement cost of mobile vaccination sites are equal to zero.
- The random generation of realization scenarios and the performed robustness analysis demonstrate that the robust optimization approach can successfully deal with the uncertainty of the network. According to the results, the robust model's average total cost and total carbon emission are less than the deterministic one's in all cases.

For the future research, considering other objectives such as the potential risk (Kargar et al., 2020), using some other heuristics and metaheuristic algorithms to solve the problem, and comparing the results with the presented LR algorithm are some interesting suggestions to extend this work. In this way, various algorithms, such as fix-and-optimize (Lotfi et al., 2021; Zare Mehrjerdi and Lotfi, 2019; Lotfi et al., 2022), differential evolution (Fallahi et al., 2022; Niknamfar and Niaki, 2016), and particle swarm optimization (Moslehi and Mahnam, 2011; Mokhtari and Noroozi, 2018) can be utilized as the solution approach. Moreover, the mathematical model can address the routing decisions (Govindan et al., 2019).

### CRedit authorship contribution statement

**Erfan Amani Bani:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization. **Ali Fallahi:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Mohsen Varmazyar:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – review & editing, Supervision, Project administration. **Mahdi Fathi:** Validation, Writing – review & editing.

### 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.

### Data availability

Data will be made available on request.

### References

- Abolghasemi, H., et al. (2020). Clinical efficacy of convalescent plasma for treatment of COVID-19 infections: Results of a multicenter clinical study. *Transfusion and Apheresis Science*, 59(5), Article 102875.
- Abrahams, A. S., & Ragsdale, C. T. (2012). A decision support system for patient scheduling in travel vaccine administration. *Decision Support Systems*, 54(1), 215–225.
- Asadkhani, J., Fallahi, A., & Mokhtari, H. (2022). A sustainable supply chain under VMI-CS agreement with withdrawal policies for imperfect items. *Journal of Cleaner Production*, Article 134098.
- Bertsimas, D., & Sim, M. (2004). The price of robustness. *Operations research*, 52(1), 35–53.
- Chandra, D., & Vipin, B. (2021). On the vaccine supply chain coordination under subsidy contract. *Vaccine*.
- Chowdhury, N. R., Ahmed, M., Mahmud, P., Paul, S. K., & Liza, S. A. (2022). Modeling a sustainable vaccine supply chain for a healthcare system. *Journal of Cleaner Production*, 370, Article 133423.
- Crommelin, D. J., Volkin, D. B., Hoogendoorn, K. H., Lubiniecki, A. S., & Jiskoot, W. (2021). The science is there: Key considerations for stabilizing viral vector-based Covid-19 vaccines. *Journal of Pharmaceutical Sciences*, 110(2), 627–634.
- Darmian, S. M., Moazzeni, S., & Hvattum, L. M. (2020). Multi-objective sustainable location-districting for the collection of municipal solid waste: Two case studies. *Computers & Industrial Engineering*, 150, Article 106965.
- De Boeck, K., Decouttere, C., & Vandaele, N. (2020). Vaccine distribution chains in low- and middle-income countries: A literature review. *Omega*, 97, Article 102097.
- Degeling, C., et al. (2021). Priority allocation of pandemic influenza vaccines in Australia-Recommendations of 3 community juries. *Vaccine*, 39(2), 255–262.
- Diabat, A., Jabbarzadeh, A., & Khosrojerdi, A. (2019). A perishable product supply chain network design problem with reliability and disruption considerations. *International Journal of Production Economics*, 121, 125–138.
- Duijzer, L. E., Van Jaarsveld, W., & Dekker, R. (2018). Literature review: The vaccine supply chain. *European Journal of Operational Research*, 268(1), 174–192.
- Ehrgott, M. (2005). *Multicriteria optimization*. Springer Science & Business Media.
- Enayati, S., & Özalpın, O. Y. (2020). Optimal influenza vaccine distribution with equity. *European Journal of Operational Research*, 283(2), 714–725.
- Fahimnia, B., Jabbarzadeh, A., Ghavamifar, A., & Bell, M. (2017). Supply chain design for efficient and effective blood supply in disasters. *International Journal of Production Economics*, 183, 700–709.
- Fallahi, A., Bani, E. A., & Niaki, S. T. A. (2022). A constrained multi-item EOQ inventory model for reusable items: Reinforcement learning-based differential evolution and particle swarm optimization. *Expert Systems with Applications*, 207, Article 118018.
- Fallahi, A., Mahnam, M., & Akhavan Niaki, S. T. (2022). Direct Aperture Optimization for Intensity Modulated Radiation Therapy: Two Calibrated Metaheuristics and Liver Cancer Case Study (in eng). *International Journal of Industrial Engineering & Production Research*, 33(2), 1–14.
- Fallahi, A., Mokhtari, H., & Niaki, S. T. A. (2021). Designing a closed-loop blood supply chain network considering transportation flow and quality aspects. *Sustainable Operations and Computers*, 2, 170–189.
- Fisher, M. L. (2004). The Lagrangian relaxation method for solving integer programming problems. *Management Science*, 50, no. 12, supplement, 1861–1871.
- Gamchi, N. S., Torabi, S. A., & Jolai, F. (2021). A novel vehicle routing problem for vaccine distribution using SIR epidemic model. *OR Spectrum*, 43(1), 155–188.
- Georgiadis, G. P., & Georgiadis, M. C. (2021). Optimal planning of the COVID-19 vaccine supply chain. *Vaccine*, 39(37), 5302–5312.
- Gilani, H., & Sahebi, H. (2022). A data-driven robust optimization model by cutting hyperplanes on vaccine access uncertainty in COVID-19 vaccine supply chain. *Omega*, 110, Article 102637.
- Goodarzian, F., Ghasemi, P., Gunasekaran, A., Taleizadeh, A. A., & Abraham, A. (2021). A sustainable-resilience healthcare network for handling COVID-19 pandemic. *Annals of Operations Research*, 1–65.
- Goodarzian, F., Taleizadeh, A. A., Ghasemi, P., & Abraham, A. (2021). An integrated sustainable medical supply chain network during COVID-19. *Engineering Applications of Artificial Intelligence*, 100, Article 104188.
- Gorissen, B. L., Yanikoglu, İ., & den Hertog, D. (2015). A practical guide to robust optimization. *Omega*, 53, 124–137.
- Gourdin, E., Labbé, M., & Laporte, G. (2000). The uncapacitated facility location problem with client matching. *Operations Research*, 48(5), 671–685.
- K. Govindan, A. K. Nasr, P. Mostafazadeh, and H. Mina, “Medical waste management during coronavirus disease 2019 (COVID-19) outbreak: A mathematical programming model,” *Computers & Industrial Engineering*, p. 107668, 2021.
- Harijani, A. M., Mansour, S., Karimi, B., & Lee, C.-G. (2017). Multi-period sustainable and integrated recycling network for municipal solid waste—A case study in Tehran. *Journal of Cleaner Production*, 151, 96–108.
- Hasija, V., Patial, S., Raizada, P., Thakur, S., Singh, P., & Hussain, C. M. (2021). The environmental impact of mass coronavirus vaccinations: A point of view on huge COVID-19 vaccine waste across the globe during ongoing vaccine campaigns. *Science of The Total Environment*, Article 151881.
- Held, M., & Karp, R. M. (1970). The traveling-salesman problem and minimum spanning trees. *Operations Research*, 18(6), 1138–1162.
- Hovav, S., & Tsadikovich, D. (2015). A network flow model for inventory management and distribution of influenza vaccines through a healthcare supply chain. *Operations Research for Health Care*, 5, 49–62.
- Kargar, S., Paydar, M. M., & Safaei, A. S. (2020). A reverse supply chain for medical waste: A case study in Babol healthcare sector. *Waste Management*, 113, 197–209.
- Kargar, S., Pourmehdi, M., & Paydar, M. M. (2020). Reverse logistics network design for medical waste management in the epidemic outbreak of the novel coronavirus (COVID-19). *Science of the Total Environment*, 746, Article 141183.
- Li, B., Guo, H., & Peng, S. (2022). Impacts of production, transportation and demand uncertainties in the vaccine supply chain considering different government subsidies. *Computers & Industrial Engineering*, 169, Article 108169.
- Lim, J., Norman, B. A., & Rajgopal, J. (2019). Redesign of vaccine distribution networks. *International Transactions in Operational Research*.
- Lin, Q., Zhao, Q., & Lev, B. (2020). Cold chain transportation decision in the vaccine supply chain. *European Journal of Operational Research*, 283(1), 182–195.
- Lotfi, R., Kargar, B., Gharehbaghi, A., & Weber, G.-W. (2021). Viable medical waste chain network design by considering risk and robustness. *Environmental Science and Pollution Research*, 1–16.
- Lotfi, R., Kargar, B., Rajabzadeh, M., Hesabi, F., & Özceylan, E. (2022). Hybrid fuzzy and data-driven robust optimization for resilience and sustainable health care supply chain with vendor-managed inventory approach. *International Journal of Fuzzy Systems*, 24(2), 1216–1231.
- Lotfi, R., Kheiri, K., Sadeghi, A., & Babaee Tirkolae, E. (2022). An extended robust mathematical model to project the course of COVID-19 epidemic in Iran. *Annals of Operations Research*, 1–25.
- Lotfi, R., Nazarpour, H., Gharehbaghi, A., Sarkhosh, S. M. H., & Khanbaba, A. (2022). Viable closed-loop supply chain network by considering robustness and risk as a circular economy. *Environmental Science and Pollution Research*, 1–20.
- Lotfi, R., Safavi, S., Gharehbaghi, A., Ghaboulia Zare, S., Hazrati, R., & Weber, G.-W. (2021). Viable supply chain network design by considering blockchain technology and cryptocurrency. *Mathematical Problems in Engineering*, 2021.
- Lotfi, R., Sheikhi, Z., Amra, M., AliBakhshi, M., & Weber, G.-W. (2021). Robust optimization of risk-aware, resilient and sustainable closed-loop supply chain network design with Lagrange relaxation and fix-and-optimize. *International Journal of Logistics Research and Applications*, 1–41.
- Lotfi, R., Yadegari, Z., Hosseini, S., Khameneh, A., Tirkolae, E., & Weber, G. (2022). A robust time-cost-quality-energy-environment trade-off with resource-constrained in project management: A case study for a bridge construction project. *Journal of Industrial and Management Optimization*, 18(1), pp.
- Mantzaras, G., & Voudrias, E. A. (2017). An optimization model for collection, haul, transfer, treatment and disposal of infectious medical waste: Application to a Greek region. *Waste Management*, 69, 518–534.
- Martins, C., & Pato, M. (2019). Supply chain sustainability: A tertiary literature review. *Journal of Cleaner Production*, 225, 995–1016.
- Mohsenizadeh, M., Tural, M. K., & Kentel, E. (2020). Municipal solid waste management with cost minimization and emission control objectives: A case study of Ankara. *Sustainable Cities and Society*, 52, Article 101807.

- Mokhtari, H., & Noroozi, A. (2018). An efficient chaotic based PSO for earliness/tardiness optimization in a batch processing flow shop scheduling problem. *Journal of Intelligent Manufacturing*, 29(5), 1063–1081.
- Moslehi, G., & Mahnam, M. (2011). A Pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search. *International Journal of Production Economics*, 129(1), 14–22.
- T. Municipality. <https://en.tehran.ir/> (accessed 10 Jan. 2022).
- Niknamfar, A. H., & Niaki, S. T. A. (2016). Soft time-windows for a bi-objective vendor selection problem under a multi-sourcing strategy: Binary-continuous differential evolution. *Computers & Operations Research*, 76, 43–59.
- Nikzami, M., & Baradaran, V. (2020). A healthcare logistic network considering stochastic emission of contamination: Bi-objective model and solution algorithm. *Transportation Research Part E: Logistics and Transportation Review*, 142, Article 102060.
- Rastegar, M., Tavana, M., Meraj, A., & Mina, H. (2021). An inventory-location optimization model for equitable influenza vaccine distribution in developing countries during the COVID-19 pandemic. *Vaccine*, 39(3), 495–504.
- Robinson, E., Jones, A., & Daly, M. (2021). International estimates of intended uptake and refusal of COVID-19 vaccines: A rapid systematic review and meta-analysis of large nationally representative samples. *Vaccine*, 39(15), 2024–2034.
- Saif, A., & Elhedhli, S. (2016). Cold supply chain design with environmental considerations: A simulation-optimization approach. *European Journal of Operational Research*, 251(1), 274–287.
- Samii, A.-B., Pibermik, R., Yadav, P., & Verecke, A. (2012). Reservation and allocation policies for influenza vaccines. *European Journal of Operational Research*, 222(3), 495–507.
- Shi, L., Fan, H., Gao, P., & Zhang, H. (2009). Network model and optimization of medical waste reverse logistics by improved genetic algorithm. In *International Symposium on Intelligence Computation and Applications* (pp. 40–52). Springer.
- Tavana, M., Govindan, K., Nasr, A. K., Heidary, M. S., & Mina, H. (2021). A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. *Annals of Operations Research*, 1–34.
- Tirkolaee, E. B., Abbasian, P., & Weber, G.-W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Science of the Total Environment*, 756, Article 143607.
- Tirkolaee, E. B., Goli, A., Ghasemi, P., & Goodarzian, F. (2022). Designing a sustainable closed-loop supply chain network of face masks during the COVID-19 pandemic: Pareto-based algorithms. *Journal of Cleaner Production*, 333, Article 130056.
- Tison, G. H., et al. (2020). Worldwide effect of COVID-19 on physical activity: A descriptive study. *Annals of Internal Medicine*, 173(9), 767–770.
- Torabi, S. A., & Hassini, E. (2008). An interactive possibilistic programming approach for multiple objective supply chain master planning. *Fuzzy Sets and Systems*, 159(2), 193–214.
- Valizadeh, J., Hafezalkotob, A., Alizadeh, S. M. S., & Mozafari, P. (2021). Hazardous infectious waste collection and government aid distribution during COVID-19: A robust mathematical leader-follower model approach. *Sustainable Cities and Society*, 69, Article 102814.
- Valizadeh, J., & Mozafari, P. (2021). A novel cooperative model in the collection of infectious waste in COVID-19 pandemic. *Journal of Modelling in Management*.
- World Health Organization. "Standard Operating Procedure (SOP) : Waste management of used COVID-19 vaccines vials and ancillary supply." <https://www.afro.who.int/publications/standard-operating-procedure-sop-waste-management-used-covid-19-vaccines-vials-and> (accessed 13 Feb. 2022).
- Worldometer. "<https://www.worldometers.info/coronavirus/>." (accessed 29 Apr. 2022).
- Yigit, M., Ozkaya-Parlakay, A., & Senel, E. (2021). Evaluation of COVID-19 vaccine refusal in parents. *The Pediatric Infectious Disease Journal*, 40(4), e134–e136.
- Yu, H., Sun, X., Solvang, W. D., & Zhao, X. (2020). Reverse logistics network design for effective management of medical waste in epidemic outbreaks: Insights from the coronavirus disease 2019 (COVID-19) outbreak in Wuhan (China). *International Journal of Environmental Research and Public Health*, 17(5), 1770.
- Zambrano-Monserrate, M. A., Ruano, M. A., & Sanchez-Alcalde, L. (2020). Indirect effects of COVID-19 on the environment. *Science of the Total Environment*, 728, Article 138813.
- Zare Mehrjerdi, Y., & Lotfi, R. (2019). Development of a mathematical model for sustainable closed-loop supply chain with efficiency and resilience systematic framework. *International Journal of Supply and Operations Management*, 6(4), 360–388.