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Designing a new sustainable Test Kit supply chain network utilizing Internet of Things

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ABSTRACT

The advent of COVID-19 put much economic pressure on countries worldwide, especially low-income countries. Providing test kits for Covid-19 posed a huge challenge at the beginning of the pandemic. Especially the low-income and less developed countries that did not have the technology to produce this kit and had to import it into the country, which itself cost a lot to buy and distribute these kits. This paper proposes a sustainable COVID-19 test kits supply chain network (STKSCN) for the first time to fill this gap. Distribution and transportation of test kits, location of distribution centers, and management of used test kits are considered in this network. A mixed integer linear programming Multi-Objective (MO), multi-period, multi-resource mathematical model is extended for the proposed supply chain. Another contribution is designing a platform based on the Internet of Things (IoT) to increase the speed, accuracy and security of the network. In this way, patients set their appointment online by registering their personal details and clinical symptoms. An augmented ε-constraint2 (AUGMECON2) is proposed for solving small and medium size of problem. Also, two meta-heuristic algorithms, namely NSGA-II and PESA-II are presented to solve the small, medium and large size of the problem. Taguchi method is utilized to control the parameters, and for comparison between meta-heuristic, five performance metrics are suggested. In addition, a case study in Iran is presented to validate the proposed model. Finally, the results show that PESA-II is more efficient and has better performance than the others based on assessment metrics and computational time.

1. Introduction

In late 2019, the outbreak of an unknown virus in Wuhan, China, took the world by surprise. The COVID-19 virus quickly became widespread around the world. Based on the World Health Organization, more than 220 countries around the world have been affected by the pandemic so far, more than 169 million people have been infected with this disease, and more than 3 million have died. The mortality rate of the virus is estimated at 1 to 5 percent, which varies depending on each patient's immune system (Chen et al., 2020). Of course, the amount of medical and health facilities and equipment in each country is definitely effective in increasing or decreasing the number of infected people and the rate of deaths. Table 1 shows the morbidity, mortality, and recovery rates of some countries according to WHO.

The coronavirus pandemic has devastated governments and people in many ways. In the COVID-19 condition, the demand for plastic products such as masks, gloves, and corona test kits increased dramatically, leading to an increase in plastic waste. If these products are not disposed of, or appropriately recycled after consumption, they can negatively affect the environment and people (Klemeš et al., 2020). Countries' economic indicators, such as GDP, fell sharply, and many jobs and businesses were disrupted (Wang and Su, 2020). Naturally, the short-term negative and contractionary effects on the economies of countries and the sustainable deployment of energy following the outbreak of the virus are definite, but with ingenuity and proper management, some of the COVID-19 threats can be turned into golden opportunities for sustainable deployment and green energy production (Hosseini, 2020).

According to the new conditions this pandemic has created for countries and governments, it is essential to have a comprehensive and accurate plan to combat the virus and ensure people's health. Hence, an efficient Supply Chain (SC) should be designed to present the medicines and equipment needed for health centers and hospitals (Navaei et al., 2021). In addition to protecting people's health, we must also look for a way to reduce the prevention of its destructive economic and environmental effects. With the advent of coronavirus, the importance of sustainability and its application in the macro programs of governments

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Table 1
The number of infected cases, total deaths, and total recovered case (12/27/2021) (https://www.worldometers.info/coronavirus/).

Country	Total cases	Total recovered	Total deaths
USA	53,891,852	41,203,698	839,605
India	34,799,691	34,243,945	480,290
Brazil	22,246,276	21,414,318	618,575
UK	12,209,991	10,126,656	148,003
Russia	10,437,152	9,337,447	306,090
Turkey	9,33,223	8,965,748	81,733
France	9,146,451	7,864,693	122,898
Germany	7,028,368	6,217,800	111,304
Iran	6,186,729	6,028,495	131,434
Spain	5,932,626	5,031,961	89,139
Italy	5,678,112	5,003,855	136,753
Argentina	5,480,305	5,270,844	117,066

and various industries is becoming increasingly felt. Demand for some equipment such as masks, gloves, and corona test kits for hospitals and clinics has significantly increased during pandemics. Due to the novelty of this issue, little research has been done to address the issue of SC and allocation in epidemic conditions and to include aspects of sustainability.

Nowadays, digital technologies are widely used in the field of healthcare. The Internet of Things (IoT) use in this area has accelerated the process, increased accuracy, and made the process safer from violations. While it can reduce additional costs, it can also increase customer satisfaction. The IoT is a network of intelligent devices, sensors, and applications that can be used to collect data, analyze existing systems, and make informed decisions (Rahman et al., 2020). Using the Internet of Things makes it possible to control SC violations and help SC management by tracking and sending sensory data into the cloud space (Hasan et al., 2019).

In this paper, a sustainable SC network of coronavirus test kits is designed. According to the emphasis on the importance of applying the concept of sustainability, it has been tried to consider all three aspects of it in the proposed network. For this aim, a MO MILP model is proposed to decrease the network's total cost, adverse environmental effects, and negative social impact. In this paper, IoT, which has been rarely utilized in healthcare studies, was used to estimate the required demand and allocate hospitals to patients. Three methods, one exact method, and two meta-heuristic methods have been used to solve the proposed model. The small and medium size of the problem is solved using the augmented ϵ-constraint2 (AUGMECON2) method, and for the large size of the problem, two meta-heuristic algorithms, namely, non-dominated sorting genetic algorithm (NSGA-II) and Pareto envelope-based selection algorithm (PESA-II), are developed. Then the results of the proposed methods were compared with each other.

The rest of the paper is summarized as follows. The related studies are shown in next section. Section 3 describes the structure of the presented network, and presents notation and mathematical models. The solution approach and encoding scheme are illustrated in Section 4. A numerical example, computational experiments, parameter tuning, case study, sensitivity analysis, and managerial insights are provided in Section 5, and the conclusion and future works is discussed in final section.

2. The related works

As regards the outbreak of COVID-19 has had a severe effect on people's lives, applying appropriate management methods in various economic, social, and environmental aspects is necessary to cope with it. According to evaluations, the issue of Waste Management (WM) during the outbreak of the disease has faced a serious challenge that can also affect the environment. Also, the lack of an integrated SC in the production, allocation and distribution of test kits, disinfectants, and plastic equipment, including masks, gloves, syringes, etc. has created problems during the pandemic outbreak. This section will deal with related works to further explore the field.

Regarding the healthcare SC, Moslemi et al. (2017) presented a MO model for the multi-echelon closed-loop medicine SC and multi-product with quality consideration. They provided a conceptual model in the medical SC, taking into account the concepts of the environment. The proposed model includes three objective functions: minimizing production costs, including transportation, purchase, maintenance, breakdown, commissioning, collection, and disposal cost. Maximizing the quality of products and minimizing the environmental impact of products and transportation. Savadkoohi et al. (2018) proposed a three-echelon, multi-period medicine SC network with a distribution-location-inventory model considering perishable products. Then, they developed a possibilistic programming approach to tackle with uncertain parameters. They also presented a real case study to give a practical description of the proposed model. Sabouhi et al. (2018) have investigated a combined method based on Data Envelopment Analysis and mathematical programming method. Also, a two-stage possibilistic-stochastic programming model to design an integrated pharmaceutical SC network, and supplier selection is developed. Assumptions such as minor and complete disruption of suppliers and consideration of small discounts for raw materials were considered. Eventually, a case study has been applied to the pharmaceutical industry. Roshan et al. (2019) developed a two-stage method to manage the medicine SC with perishable products in crisis, intending to minimize unmet demand, decreasing total costs, and increasing social responsibility satisfaction. A robust optimization method to reverse drug SC coordination under reversible strategies was proposed by Taleizadeh et al. (2019) to maximize the benefits of reverse drug chain members. Zhang et al. (2019) developed a two-stage pharmaceutical SC from the perspective of the pharmaceutical manufacturer. They aimed to decrease the whole cost. They first show the NP-hard problem and then provide a pseudo-polynomial-time algorithm to solve their problem. Nasrollahi and Razmi (2019) developed a mathematical model for an integrated multi-period, multi-echelon pharmaceutical SC network with maximum expected coverage under uncertainty. A particle swarm optimization algorithm and faulty sorting genetic algorithm were used to solve the model. Aghababaei et al. (2019) proposed a two-stage fuzzy optimization model for the rationing problem of rare medicines under uncertainty. The first stage is to minimize the maximum profit of the supplier and the second stage is to minimize the maximum amount of shortage. Goodarzian et al. (2020) designed a comprehensive integer nonlinear MO mathematical model for the medicine SC network that includes production, distribution, procurement, ordering, inventory maintenance, allocation, and routing. Some of the proposed model objectives were to minimize network costs, minimize total network flow time, and maximize SC reliability. Five MO meta-heuristic algorithms named MOSEO, MOSA, MOPSO, MOKA, and MOFFA are proposed to achieve the optimal solution. Sazvar et al. (2021) developed a scenario-based MO integer linear programming model to design a sustainable pharmaceutical close-loop SC. The SC provided includes the reverse flow of expired medicines divided into three categories: disposable, reproducible, and recyclable. Then, they combine the LP-metrics method and a heuristic algorithm, and suggest a new hybrid method. A network for vaccine distribution in developing countries is provided (Yang et al., 2021). A MIP model to reduce the cost of the entire network is presented, and then an innovative algorithm that is suitable for very large problems is proposed. Eventually, the performance of the model and algorithm was measured with real data from four countries in South Africa.

Singh et al. (2021) proposed a network distribution system simulation model with three scenarios to investigate problems in the food SC under pandemic conditions. They placed great emphasis on resilient SC flexibility during the pandemic. They claimed that the proposed simulation model could create a resilient and responsive food SC. An outbreak of a pandemic can profoundly affect the workforce, as the

Table 2
Summary of literature review.

Reference	Type of model	Sustainability measures			Product	COVID-19	Case study	IOT	Solution approach	
		EC.	EV.	S.					E.	H/M.
Moslemi et al. (2017)	MIP	✓	✓	✓	Medical					✓
Savadkoohi et al. (2018)	MINLP	✓			Medicine		✓		✓	
Sabouhi et al. (2018)	MILP	✓			Medicine		✓		✓	
Taleizadeh et al. (2019)	MINLP	✓			Medicine		✓			
Roshan et al. (2019)	MINLP	✓		✓	Medicine		✓		✓	
Zhang et al. (2019)	IP	✓			Medicine					✓
Nasrollahi and Razmi (2019)	MINLP	✓		✓	Medicine		✓			✓
Aghababaei et al. (2019)	NLP	✓			Medicine		✓		✓	
Goodarzian et al. (2020)	MINLP	✓		✓	Medicine					✓
Singh et al. (2021)	simulation				Food	✓				
Yu et al. (2020)	MIP	✓			Waste	✓	✓		✓	
Nagurney (2021)	MP	✓			Goods	✓			✓	
Sazvar et al. (2021)	MILP	✓	✓	✓	Medicine		✓			✓
Yang et al. (2021)	MIP	✓			Vaccine		✓			✓
Kargar et al. (2020a)	MINLP	✓		✓	Waste	✓	✓		✓	
Kargar et al. (2020b)	MILP	✓			Waste		✓		✓	
Tirkolaee et al. (2021)	MILP			✓	Waste	✓	✓		✓	
Goodarzian et al. (2021a,b)	MILP	✓	✓	✓	Medicine	✓	✓			✓
Zahedi et al. (2021)	MINLP			✓	Relief	✓	✓	✓		✓
This study	MILP	✓	✓	✓	Test kit	✓	✓	✓	✓	✓

* EC: Economic/ EV: Environmental/ S: Social/ E: Exact/ H: Heuristic/ M: Meta-heuristic.

availability of labor for various SC activities may be disrupted by disease, fear of transmission, the need for social/physical distance, and so on. Zambrano-Monserrate et al. (2020) examined the indirect effects of the virus on the environment. They summarized their studies on the effects of the virus in six cases, three of which were positive and three of which were negative. Increased organic and inorganic wastes, disruption of the waste recycling cycle, and some specific adverse effects such as contamination of sewage systems due to the use of disinfectants to prevent the spread of the virus in some countries such as China were among the negative effects of coronavirus. They also claimed that COVID 19 reduced air pollution and emitted gases such as nitrogen dioxide, in addition to helping to clean up beaches and reduce noise that was harmful to the environment. However, they eventually concluded that some of the positive effects of the virus do not appear to be lasting and require serious and intelligent management to deal with its negative effects in the long run. Ivanov and Dolgui (2021) investigate the various SCs and identified the disruptions in them. Their goals are collect SC disorders, and identify and classify methods to deal with it. Nagurney (2021) presented an optimization model for a SC in a pandemic situation, considering the workforce as an important element in linking the economic activities of the SC network and its related capacities. The chain provided includes medical and protective equipment and some special food items. Goodarzian et al. (2021a) due to the lack of mathematical model in the field of sustainability in the pharmaceutical industry and also the new conditions created by COVID-19 to design a comprehensive medicine SC including production, distribution, inventory control, they assigned and located. A MO, multi-product and multi-level model was presented. They presented three hybrid algebraic algorithms called ant optimization Algorithm, fish swarm algorithm and firefly algorithm and they were hybridized by variable local search to solve the corresponding network model. Due to the sensitivity of meta-heuristic algorithms to the input parameters, they used the response surface approach to adjust the parameters. They eventually used a real case study and concluded from numerical results that the fish swarm algorithm was more efficient than the other algorithms. A systematic review of studies that focus on the impact of the COVID-19 epidemic on SCs has been conducted by Chowdhury et al. (2021). They investigated 74 related articles. Zahedi et al. (2021) designed a relief SC in a corona pandemic utilizing the IoT in healthcare management. The proposed model consists of two stages. 1. Prioritization stage (decreases the maximum response time of ambulances) 2. Assignment stage (minimizes the total critical response time). Both stages were validated by numerical examples of a real case study in Iran. Finally, three efficient meta-heuristic algorithms, namely SA, SEO and PSO, and their combination (hybrid), are used to optimize the proposed models.

A MIP model for reverse logistics network design in epidemic outbreaks is developed (Yu et al., 2020). This model looks for optimal locations for temporary equipment, and different transportation methods for medical WM. With the prevalence of the COVID-19, consequent adherence to personal hygiene protocols, and increased referrals to medical centers, the amount of medical and infectious waste has raised significantly. An efficient and reliable infectious medical waste reverse logistics network was designed (Kargar et al., 2020a). A linear programming model purposes to decrease the total costs and the risk associated and maximize the amount of uncollected waste in medical waste generation centers is presented. Then, a real case study from Tehran is designed to validate their model. Kargar et al. (2020b) provided a linear programming multi objective model under uncertain parameters to design a medical waste reverse SC. A robust possibilistic programming method is used to tackle with uncertain parameters, and a fuzzy goal programming approach is suggested to solve a MO model. Tirkolaee et al. (2021) presented a MILP model to design the sustainable problem with time windows for medical WM in the coronavirus pandemic. Minimizing travel time, contravention from time windows, and total environmental impact inflict on the population around disposal sites are aims of the model. The classification of papers reviewed is shown in Table 2.

According to the literature, we find that there are very few studies that examine all three aspects of sustainability in pandemic conditions with operational research (OR) methods. The coronavirus detection test kit is an essential tool that some developing or poor countries may not be able to produce it, or it may take a long time to reach production capacity. In this research, a test kits SC network is included, which includes distribution, allocation, location and WM. Finally, the proposed model is solved by exact and meta-heuristics algorithms. The novelties of the current study that, distinguish it from other study are as follow:

- Designing a new distribution, allocation, and WM SC network for the coronavirus test kits for the first time.
- Proposing all sustainability aspects: economic, environmental, and social in proposed test kits SC.
- Considering the rate of population density in the routes between different echelons of the network to select the best route with the aim of reducing the destructive social effects.

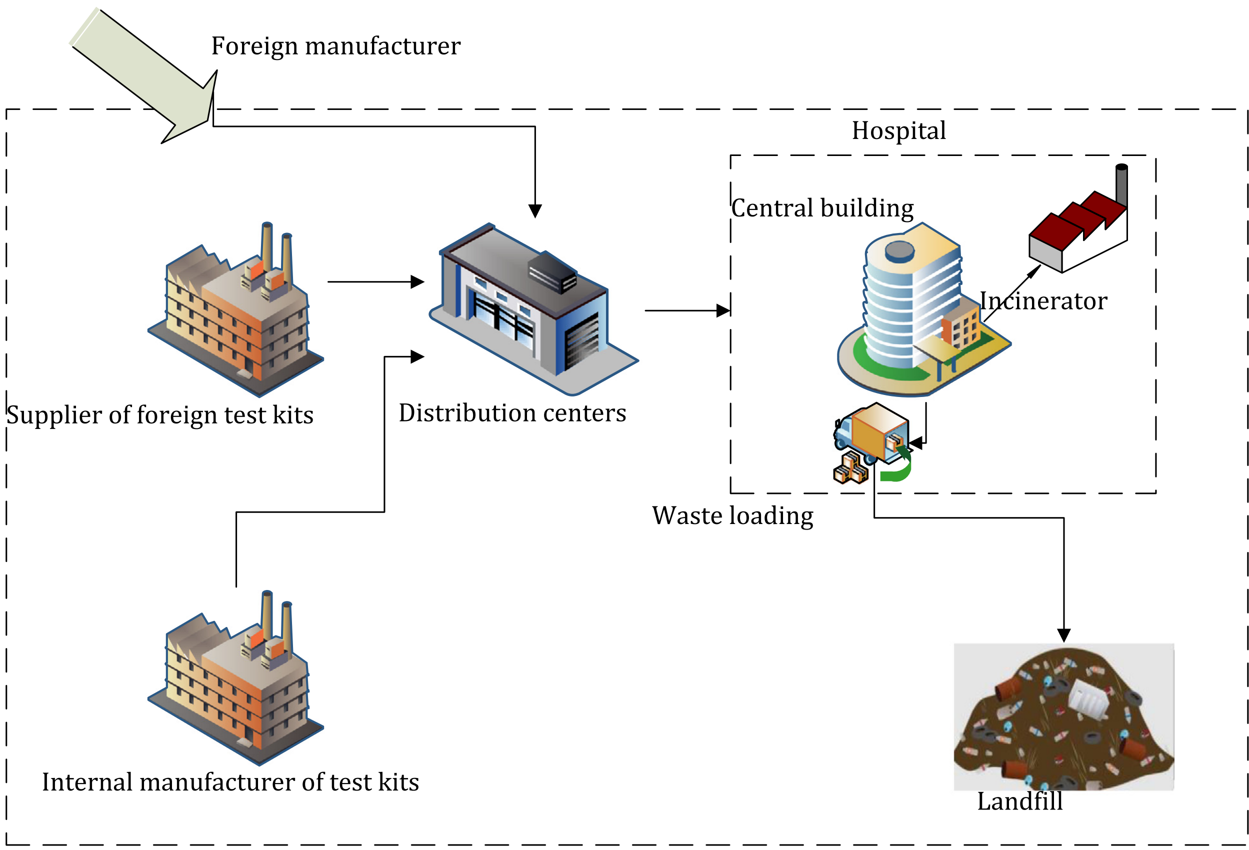

Fig. 1. The network of Supply chain and waste management.

- Providing the IoT application to identify patients and accelerate and organize health care services.
- Using one exact method (AUGMECON2) and two meta-heuristic algorithms to solve presented model in small, medium and large size. Then, comparing and validating presented methods by utilizing five performance metrics and a real case study in Iran.

3. The description of the model and mathematical modeling

Problem statement, related figures, notations and mathematical modeling are provided in this section.

3.1. Problem statement

In this study, a sustainable SC of coronavirus test kits network (STKSCN) is designed. An MO, multi-period, and multi-resource mathematical model is formulated to implement this network. The proposed network has four levels, suppliers, Distribution Centers (DCs), hospitals and WM centers, which are interconnected respectively. To better understand the network, Fig. 1 is depicted. According to the health of patients is a priority, and we may see a sudden increase in hospital referrals and the need for more test kits, and also the lack of a large number of kits in the country, in the network provided, both internal manufacturer of coronavirus test kits and external supplier of these kits are used. There are two types of test kits in this network: PCR and Anti-body tests. Patients with suspected COVID symptoms should have a PCR test, and patients who have been through the disease and want to make sure they have antibodies in their body want to have Anti-body test. The kits are first transported to DCs that located and constructed by the government. After packing, they are sent to hospitals according to the declared demand. After use, the test kits are immediately placed by the operator in a special box (safety box) that is placed in each hospital room and are collected at the end of the day and sent directly to the waste disposal unit to be incinerated and disinfected by the incinerator. Of course, not all hospitals have incinerators. Due to the weakness of our country's health system and the critical situation in this chain, we considered that hospitals that do not have incinerators, take their medical waste to appropriate locations for landfilling to be buried there following health protocols.

An IoT-based application that can be installed on a mobile phone or computer is designed. Data is collected by this application and after analysis, decision and allocation, the necessary information is sent to hospitals and patients. The data gathering process is shown in Fig. 2. The way this application works is that the patient has to answer a few questions after entering the application and registering their first and last name and address. Questions about their clinical symptoms or previous tests. For the PCR test, if at least 2 out of 5 questions are answered in the affirmative, the patient is allowed to take the test, and the nearest hospital is assigned to their based on their geographical location. The hospital address is also sent to the patient in the same application. For the Anti-body test, if the patient has two necessary conditions, they are allowed to take this test, and the same steps are performed for them. The steps that the patient must go through in the application are shown in Figs. 3 and 4.

Cost management in the health logistics network is essential during the pandemic condition. On the other hand, the amount of plastic waste and infectious waste has increased significantly. In the long run, the increase of plastic waste will cause irreparable damage to the environment, and improper management of infectious waste will be dangerous for public health. The purposes of the proposed model in this research are to minimize network costs, minimize negative environmental impacts and increase the level of social indicators so that it includes all three aspects of sustainability. The assumptions of current problem are explained as follow:

- There are two types of test kits. The first category is PCR test kits that indicate the presence or absence of the virus, and the second

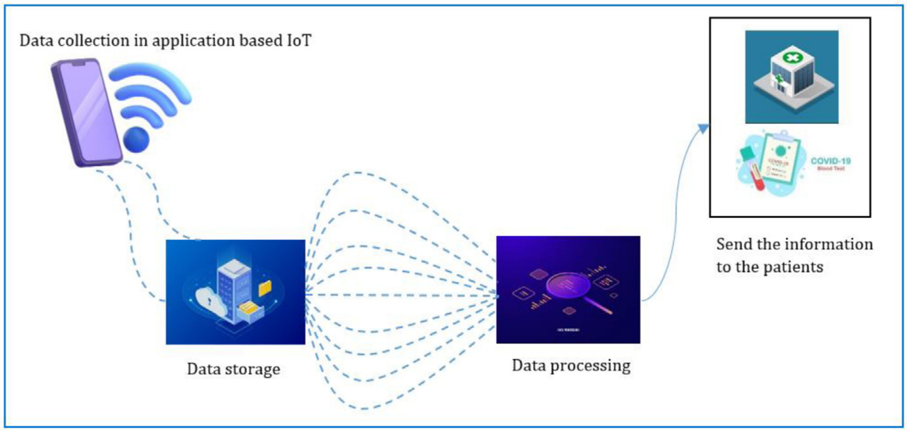

Fig. 2. The procedure of data gathering based on IoT.

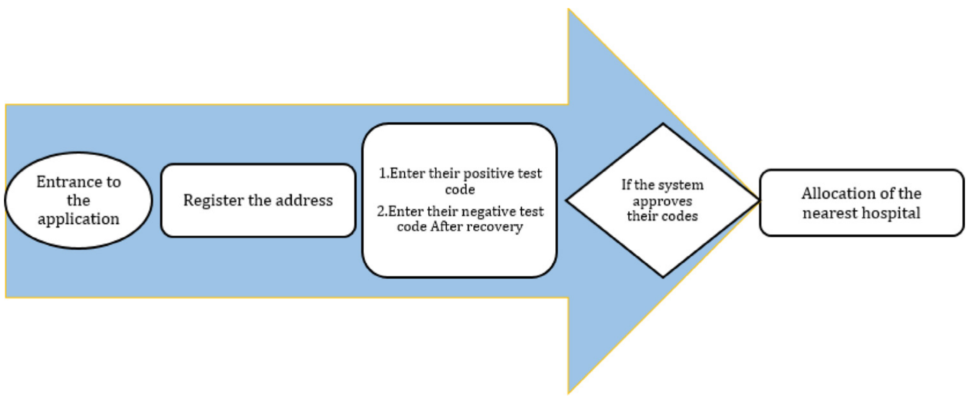

Fig. 3. The main steps that patient must pass in application to take PCR test.

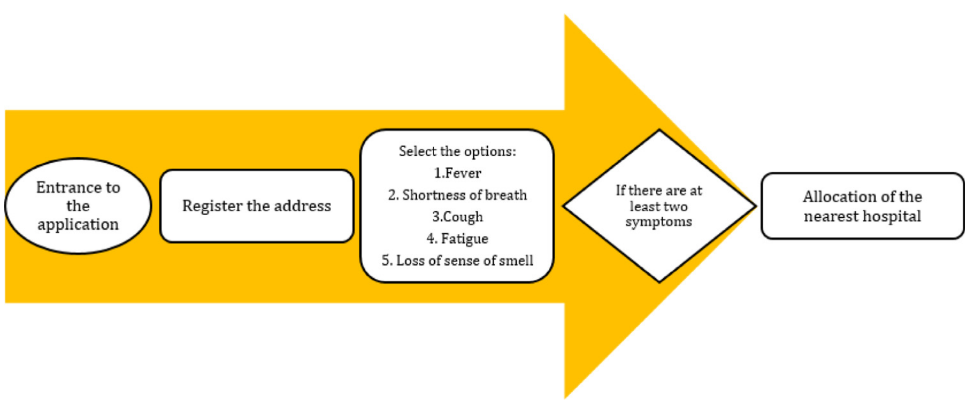

Fig. 4. The main steps that patient must pass in application to take Anti-Body test.

category is Antibody test kits that are used to assess the patient's immune system.

- The DCs and landfills must be located.
- The hospitals, manufacturers, and foreign suppliers are pre-determined.
- Some hospitals are not equipped with incinerators. These hospitals transfer their waste to the landfill at the end of each period.
- DCs and landfills have a fixed establishment cost.
- The DCs, manufacturers, and foreign suppliers have limited capacity.

3.2. *Notations*

The notations, parameters, and decision variables are stated.

Indices	
i	Set of test kits.
H	Set of hospitals
$h \subset H$	Set of Hospitals with incinerators
$h' \subset H$	Set of Hospitals without incinerators
t	Set of time periods

r	Set of candidate locations for the DC
k	Set of candidate locations for the landfill
p	Set of manufacturers of internal test kits
p'	Set of suppliers of foreign test kits
Parameters	
TC_{pir}	The cost of transporting a test kit type i from the manufacturer P to the DC r per unit distance
$TC_{P'ir}$	The cost of transporting a test kit type i from the supplier P' to the DC r per unit distance
TC_{riH}	The cost of transporting a test kit type i from the DC r to the hospital H per unit distance
$TC_{h'ik}$	The cost of transporting a test kit type i from the hospital h' to the landfill k per unit distance
LC_i	Cost of product landfilling operations i
OC_i	Cost of product burning operation i
PEC_i	The cost of purchasing each Iranian test kit i
PFC_i	The cost of purchasing each foreign test kit i
FC_r	The cost of establishing DC r
FC_k	The cost of establishing landfill center k
D_{iHt}	The amount of demand for product i in hospital H at period t
EG	Carbon emission rate of kit incineration
EV	Carbon emission rate due to the transporting the kits by vehicle per unit distance
CC	The capacity of each vehicle
CI	The limited capacity of DC
DS_{pr}	The amount of distance between manufacturer p and DC r
$DS_{p'r}$	The amount of distance between supplier p' and DC r
DS_{rH}	The amount of distance between DC r and hospital H
$DS_{h'k}$	The amount of distance between hospital h' and landfill center k
IC_i	The inventory holding cost for product i at each period
R_{pr}	Population density rate, in the path of manufacturer p to the DC r
$R_{p'r}$	Population density rate, in the path of supplier p' to the DC r
R_{rH}	Population density rate, in the path of DC r to the hospital H
$R_{h'k}$	Population density rate, in the path of hospital h' to the landfill center k
CB_i	The penalty cost of shortage for kit i at each period.
M	The big number
Decision variables	
Y_r	If DC r is opened:1; otherwise, 0
Y_k	If landfill center k is opened:1; otherwise, 0
Q_{pirt}	The number of kits type i transported from the manufacturer p to the DC r at period t
$Q_{P'irt}$	The number of kits type i transported from the supplier P' to the DC r at period t
X_{riHt}	The number of kits type i transported from the DC r to the hospital H at period t
RS_{iht}	The number of products i that must be incinerated in hospital h at period t
$RD_{h'ikt}$	The number of products i that must be transported from the hospital h to the landfill center k to be buried at period t
I_{rit}	Inventory level of Kit i in the DC r at the end of each period t.
E_{prt}	If DC r is assigned to manufacturer p in period t :1 and; otherwise, 0
$E_{p'rt}$	If DC r is assigned to supplier p' in period t :1 and; otherwise, 0
E_{rHt}	If hospital H is assigned to DC r in period t :1 and; otherwise, 0
$E_{h'kt}$	If landfill center k is assigned to hospital h' in period t :1 and; otherwise, 0
B_{iHt}	The amount of shortage for each type of product i in hospital H at period t
N_{prt}	The number of vehicles used in the rout of manufacturer p to DC r at period t
$N_{p'rt}$	The number of vehicles used in the rout of supplier p' to DC r at period t
N_{rHt}	The number of vehicles used in the rout of DC r to hospital H at period t
$N_{h'kt}$	The number of vehicles used in the rout of hospital h' to landfill center k at period t

3.3. Mathematical modeling

A MO, multi-period, multi-resource, distribution-location–allocation-inventory-WM model is presented in subsection aims to minimizing total network costs, negative environmental effects and negative social effects.

Objective function1 (Total cost):

$$
\begin{aligned}
MinZ_1 = & \sum_p \sum_i \sum_r \sum_t Q_{pirt} \cdot PEC_i + \sum_{p'} \sum_i \sum_r \sum_t Q_{p'irt} \cdot PFC_i \\
& + \sum_p \sum_i \sum_r \sum_t N_{prt} \cdot DS_{pr} \cdot TC_{pir} + \sum_r FC_r \cdot Y_r \\
& \sum_{p'} \sum_i \sum_r \sum_t N_{p'rt} \cdot DS_{p'r} \cdot TC_{p'ir} \\
& + \sum_r \sum_i \sum_H \sum_t N_{rHt} \cdot DS_{rH} \cdot TC_{riH} \\
& + \sum_i \sum_h \sum_t OC_i \cdot RS_{iht} + \sum_k FC_k \cdot Y_k \\
& + \sum_{h'} \sum_i \sum_k \sum_t N_{h'kt} \cdot DS_{h'k} \cdot TC_{h'ik} \\
& + \sum_{h'} \sum_i \sum_k \sum_t RD_{h'ikt} \cdot LC_i \\
& + \sum_r \sum_i \sum_t I_{rit} \cdot IC_i + \sum_i \sum_H \sum_t B_{iHt} \cdot CB_i
\end{aligned}
\tag{1}
$$

The objective function (1) seeks to minimize total costs of network. Respectively, two first equations are Purchasing cost, transportation cost between manufacturer and DCs, fixed establishing cost of DC, transportation cost between suppliers and DCs, transportation cost between DCs and hospitals, incinerator cost, establishing cost of landfill centers, transportation cost between hospitals and landfill centers, landfilling cost, and two last equations consider inventory holding cost and penalty shortage cost.

Objective function2 (Environmental impacts):

$$
\begin{aligned}
MinZ_2 = & EV \Bigg(\sum_p \sum_r \sum_t N_{prt} \cdot DS_{pr} + \sum_{p'} \sum_r \sum_t N_{p'rt} \cdot DS_{p'r} \\
& + \sum_r \sum_H \sum_t N_{rHt} \cdot DS_{rH} + \sum_{h'} \sum_k \sum_t N_{h'kt} \cdot DS_{h'r} \Bigg) \\
& + \sum_i \sum_h \sum_t RS_{iht} \cdot EG
\end{aligned}
\tag{2}
$$

This objective function (2) aims to reduce adverse environmental impact on SC. The parentheses contain amount of carbon emission during transportation from manufacturer to DC, supplier to DC, DC to hospital, and hospital to landfill center. The second equation calculate amount of carbon emission in burning Used kits with incinerator.

Objective function3 (Social impacts):

$$\boldsymbol{MinZ_3} = \sum_p \sum_r \sum_t E_{prt} \cdot R_{pr} + \sum_{p'} \sum_r \sum_t E_{p'rt} \cdot R_{p'r} + \sum_r \sum_H \sum_t E_{rHt} \cdot R_{rH} + \sum_{h'} \sum_k \sum_t E_{hkt} \cdot R_{h'k} \tag{3}$$

This Eq. (3) purpose to minimize the adverse social index with considering population density rate in routes between manufacturer to DC, supplier to DC, DC to hospital, and hospital to landfill center.

Constraints:

$$\sum_p \sum_i Q_{pirt} + \sum_{p'} \sum_i Q_{p'irt} \le CI \cdot Y_r \qquad \forall r, t \tag{4}$$

$$\sum_r Q_{pirt} \le C_{pit} \qquad \forall p, i, t \tag{5}$$

$$\sum_r Q_{p'irt} \le C_{p'it} \qquad \forall p', i, t \tag{6}$$

Constraints (4)–(6) ensure that DC, manufacturer and supplier cannot receive, produce and supply kits exceed of their limited capacity at each period.

$$\sum_r X_{riHt} + B_{iHt} = D_{iHt} \qquad \forall i, H, t \tag{7}$$

Constraint (7) is demand constraint, and refer to amount of shortage in each hospital per period.

$$\sum_p \sum_i \sum_t Q_{pirt} \le M \cdot Y_r \qquad \forall r \tag{8}$$

$$\sum_{p'} \sum_i \sum_t Q_{p'irt} \le M \cdot Y_r \qquad \forall r \tag{9}$$

$$\sum_i \sum_H \sum_t X_{riHt} \le M \cdot Y_r \qquad \forall r \tag{10}$$

$$\sum_{h'} \sum_i \sum_t RD_{h'ikt} \le M \cdot Y_k \qquad \forall k \tag{11}$$

Constraints (8)–(11) ensure that kits are transported to or from DC, and transported to landfill center if they are opened.

$$N_{prt} \cdot CC \ge \sum_i Q_{pirt} \qquad \forall p, r, t \tag{12}$$

$$N_{p'rt} \cdot CC \ge \sum_i Q_{p'irt} \qquad \forall p', r, t \tag{13}$$

$$N_{rHt} \cdot CC \ge \sum_i X_{riHt} \qquad \forall r, H, t \tag{14}$$

$$N_{h'kt} \cdot CC \ge \sum_i RD_{h'ikt} \qquad \forall h', k, t \tag{15}$$

Constraints (12)–(15) calculate the number of vehicles used between manufacturers to DCs, suppliers to DCs, DCs to hospitals and, hospitals to landfill centers at each period.

$$I_{rit} = I_{ri(t-1)} + \sum_p Q_{pirt} + \sum_{p'} Q_{p'irt} - \sum_H X_{riHt} \qquad \forall r, i, t \tag{16}$$

This Eq. (16) indicates balancing for inventory level of each DC during each period.

$$\sum_i \sum_H X_{riHt} \le \sum_p \sum_i Q_{pirt} + \sum_{P'} \sum_i Q_{p'irt} + I_{ri(t-1)} \qquad \forall r, t \tag{17}$$

Constraint (17) Specifies an upper limit for amount of kit type i transported to DC r at period t.

$$RS_{iht} = \sum_r X_{riht} \qquad \forall t, i, h \tag{18}$$

$$\sum_k RD_{h'ikt} = \sum_r X_{rih't} \qquad \forall t, i, h' \tag{19}$$

Constraints (18) and (19) determine number of used kits that must be burn and number of used kits that must be transported to landfill, respectively.

$$\sum_p E_{prt} \le 1 \qquad \forall r, t \tag{20}$$

$$\sum_{p'} E_{p'rt} \le 1 \qquad \forall r, t \tag{21}$$

$$\sum_k E_{h'kt} \le 1 \qquad \forall h', t \tag{22}$$

$$\sum_r E_{rHt} \le 1 \qquad \forall H, t \tag{23}$$

Constraints (20)–(23) ensure that, at most, each DC is allocated to one manufacturer, each DC is allocated to one supplier, each landfill center is allocated to one hospital, and each hospital is allocated to one DC.

$$Q_{pirt}, Q_{i'Ht}, Q_{p''jrt}, X_{riHt}, X_{ri'Ht}, X_{rjHt}, RS_{iht}, RD_{h'ikt}, N_{prt}, N_{p'rt}, N_{rHt}, N_{h'kt}, B_{iHt} \ge 0 \tag{24}$$

$$E_{h'ht}, E_{Hkt}, E_{prt}, E_{p'rt} \in \{0, 1\} \tag{25}$$

Constraints (24) and (25) define domain of decision variables.

4. Solution approach

In this section, to solve the current model, cope with three objectives, and then find the Pareto optimal solution, the augmented ϵ-constraint2 (AUGMECON2) method will be applied. This method is effective in proposing the Pareto set in mathematical programming problem compared to the original version of ϵ-constraint method and some other methods, like weighted sum method.

Because of the complexity of the problem, it is hard to solve the large size of the problem with this method, or it takes a lot of time; NSGA-II and PESA-II are utilized to cope with NP-hard problem. The algorithms are selected to develop because these methods are swift and flexible and search in a wide range to find Pareto solutions. Enhance, the implementation is not complex.

4.1. Augmented ϵ-constraint2 (AUGMECON2)

AUGMECON2 improves the AUGMECON which uses slack variables in each iteration. Additional iterations are eliminated and calculation times are reduced (Mavrotas and Florios, 2013). The formulation of this method according to our presented model is defined as follows:

$$Min \left[f_1(x) - eps \cdot \left(\frac{S_2}{r_2} + \left(10^{-1} \cdot \frac{S_3}{r_3} \right) \right) \right] \tag{26}$$

s.t.

$$f_2(x) + S_2 = e_2$$

$$f_3(x) + S_3 = e_3$$

$$x \in S, S_i \in R$$

where e_2, e_3 are parameters for RHS that are plotted for specific iterations of the network points of Objective 2 and 3. The parameters r_2 and r_3 are the domains of the objective functions. $\{S_2, S_3\}$ are the slack variables of the constraints and eps $\in [10^{-6}, 10^{-3}]$.

4.2. Non-dominated sorting genetic algorithm (NSGA-II)

NSGA-II is one of the most successful and widely used algorithms introduced by (Deb et al., 2002). The advantages of this algorithm include less computational complexity and compatibility with constraints. The NSGA-II process consists of three main phases: generating the population, computing crowding distance for members, and selecting the solution which satisfies all objective functions. Crowding distance is a factor for better selection of solutions in terms of dispersion. More information about this method can be in some other studies (Taleizadeh et al., 2008, 2011; Farrokhi-Asl et al., 2020; Ghasemi et al., 2019, 2020;

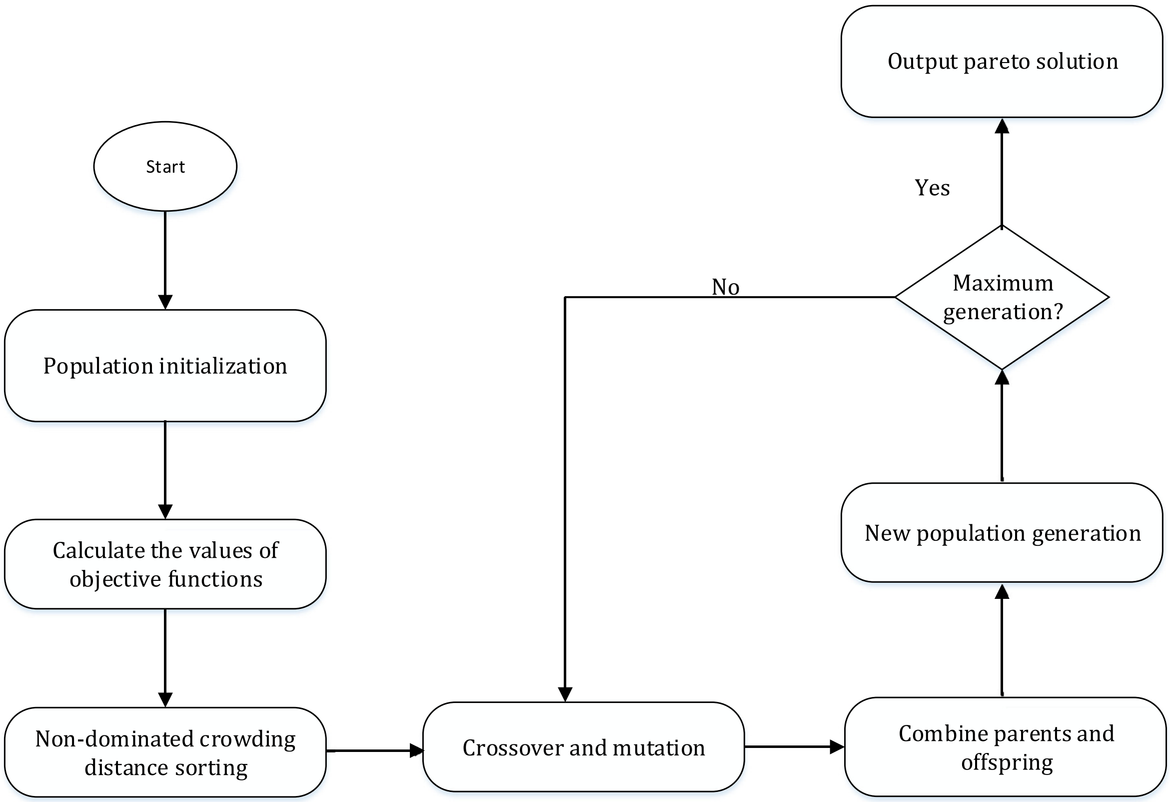

Fig. 5. The main steps of NSGA-II.

```
Input: P // initialize population ;
Generate population (size N) ;
Calculation the values of objective functions ;
Sorting based on Pareto ;
Generate child population ;
    Crossover and mutation ;
    combination;
For i = 1 to k do
    For each parent and child in population do
        Sorting based Pareto ;
        Generate set of non-dominated solutions ;
        Calculate crowding distance ;
        Start the loop by adding solutions to the next generation from the first until to N individuals ;
    end
    Create next generation ;
        Crossover and mutation ;
        Recombination ;
end
```

Fig. 6. The pseudo code of NSGA-II.

Zhang et al., 2017). The main steps and the pseudo code of the NSGA-II are presented in Figs. 5 and 6.

4.3. Pareto envelope-based selection algorithm (PESA-II)

PESA-II was introduced by (Corne et al., 2001). This algorithm is an evolutionary optimization algorithm that solves MO problems based on Pareto selection and according to the concept of genetic algorithm. This algorithm actually improves the PESA algorithm. Region-based selection is considered an individual selection feature. Selective fitness is to be assigned to the region of the objective space. This selection enhances the Pareto frontier. For more information about PESA-II, scholars can read these studies (Arjmand et al., 2020; Omidi Brojeni et al., 2021). The main steps and the pseudo code of the PESA-II are depicted in Figs. 7 and 8.

5. Computational experiment

In this study, for solve proposed multi objective model, AUGMECON2 is applied with GAMS software (24.1.2) and baron solver on a

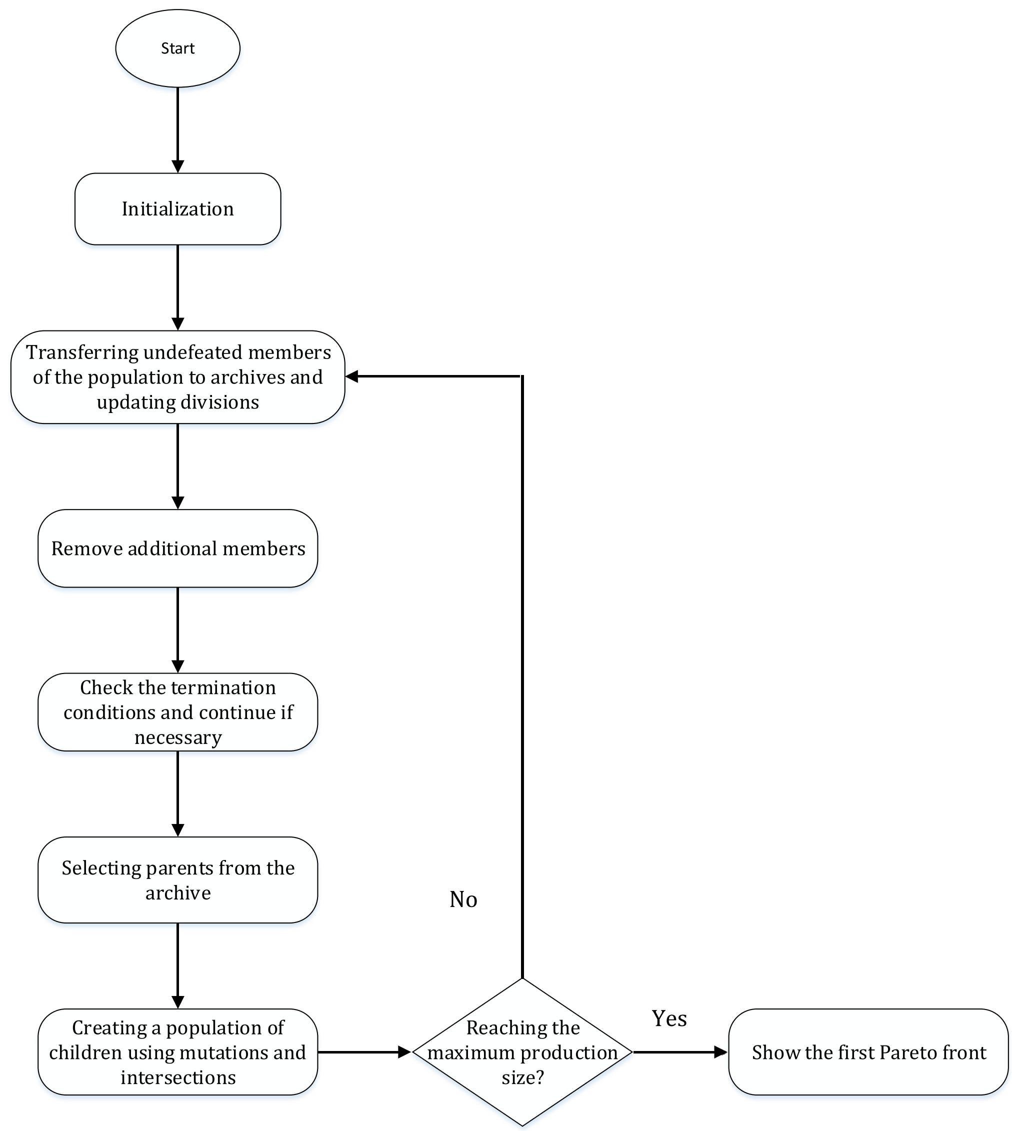

Fig. 7. The main steps of PESA-II.

computer with technical specifications of 16 GB of RAM and 2.70 GHz CPU. Hence, two meta-heuristic algorithms, namely NSGA-II and PESA-II, are utilized to solve medium and large size of the problem. The proposed methods are implemented in MATLAB R2018b on the same PC. Finally, a real case study in Iran is presented to validate current model.

5.1. Numerical example

The price of foreign and domestic kits is estimated according to the information announced by the Ministry of Health. Distance between manufacturer and supplier to DC and, DC to hospital and, hospital to landfill center are generated randomly by uniform distribution. Other parameters are estimated based on Expert opinion. Several numerical tests problem in small, medium, and large scale are presented in Table 3. The examples contain the number of test kits, manufacturer, supplier, DCs, landfills, hospitals, and periods. The range of parameters is shown in Table 4.

The results of solving the model by exact methods are shown in Fig. 9 and Table 5. Small and medium size of problem are solved by AUGMECON2.

5.2. Performance metrics

For measure the quality of the solution obtained by proposed algorithms, several performance metrics are presented. Convergence, diversity and number of solutions are aspects that metrics considered (Riquelme et al., 2015). In order to take these features into account and compare meta-heuristic algorithms, a number of performance metrics namely SM, CM, SNS, IGD and MID are purposed.

- MID (Goodarzian et al., 2021b)
- MS (Farrokhi-Asl et al., 2020)
- IGD (Zhang et al., 2009)
- SNS (Goodarzian et al., 2020)
- NPS (Zahiri et al., 2018; Govindan et al., 2015)

5.3. Parameter tuning

Adjusting the parameters can raise the performance of the proposed methods, and makes the conditions for comparing them fairer. In this study, Taguchi method is utilized to tuning parameters. Taguchi was introduced by Taguchi (1986). Taguchi method is different from

Table 3
Generated test problem.

Scale	Indices	Test kit	Manufacturer	Supplier	DC	Landfill	Hospital	Period
Small	Test problem1	2	1	1	2	1	2	2
	Test problem2	2	2	2	2	1	2	3
	Test problem3	2	2	2	2	2	2	5
	Test problem4	2	2	2	3	2	3	6
Medium	Test problem5	4	4	5	6	5	6	12
	Test problem6	5	5	7	8	6	8	15
	Test problem7	5	6	10	12	10	10	20
	Test problem8	6	8	15	18	15	15	30
Large	Test problem9	8	10	18	20	18	16	32
	Test problem10	8	10	20	25	19	18	35
	Test problem11	9	12	25	30	20	20	40
	Test problem12	10	15	30	40	25	25	50

```
Initialize population;
Archive = ∅ ;
Evaluate population;
Create grid;
Iteration = 0 ;
While iteration < Max iteration
    Archive = Archive + new population;
    Archive = Archive (non-dominated members);
    If |Archive| > N
        Delete extra members;
    end
    Update grid;
    Evaluate new population;
    Iteration = iteration + 1
end
    Report results in external archive ;
end
```

Fig. 8. The pseudo code of PESA-II.

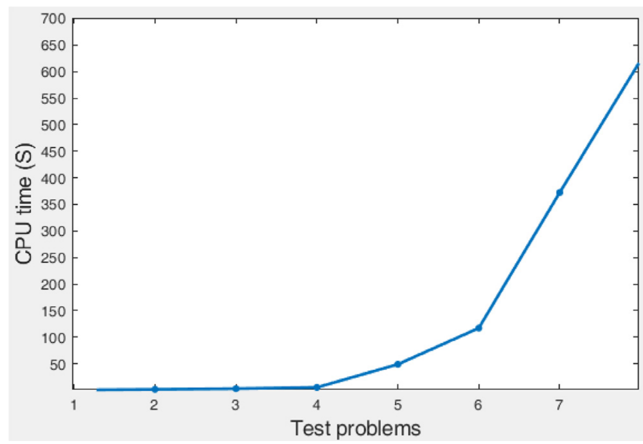

Fig. 9. CPU time of AUGMECON2 for small and medium size of problem.

Table 4
The range of parameters.

Parameters	Size of parameters	Parameters	Size of parameters
PEC_i	U~(10, 80)	FC_k	U~(600, 1000)
PFC_i	U~(30,100)	DS	U~(15, 60)
OC_i	U~(5, 15)	Re	U~(0.2, 0.8)
CI	U~(2000, 4000)	EV	U~(200, 400)
CC	U~(300, 500)	EG	U~(50, 200)
FC_r	U~(800, 1200)	TC	U~(2, 10)

Table 5
The solutions of exact method.

Test problem	F_1	F_2	F_3
Test1	3979	404	17.5
Test2	4042	432	17.5
Test3	4339	479	17.7
Test4	4570	575	18
Test5	7302	753	29.5
Test6	7793	887	30.7
Test7	8113	1003	34.5
Test8	8351	1259	35.5

Table 6
The factors and levels of parameter tuning for meta-heuristic algorithms.

NSGA-II	**Level1**	**Level2**	**Level3**
Number of population (nPop)	100	200	300
Crossover Rate (Pc)	0.2	0.4	0.55
Mutation rate (Pm)	0.1	0.3	0.5
Maximum iteration (MaxIt)	400	450	500
PESA-II	**Level1**	**Level2**	**Level3**
Number of population (nPop)	100	200	300
Crossover Rate (Pc)	0.2	0.4	0.55
Mutation rate (Pm)	0.1	0.3	0.5
Maximum iteration (MaxIt)	400	450	500
Archive size (As)	5	10	15

common engineering methods. Taguchi emphasizes on quality control during product and process design, while other common methods are based on inspection during the production process or after product production. Taguchi uses common statistical tools in his quality improvement methods and has simplified this method by identifying a set of powerful solutions in designing experiments and analyzing the results. Parameters are divided into controllable and uncontrollable factor. Taguchi design uses orthogonal arrays. Two different orthogonal designs are used for these two sets of parameters. Internal array for controllable variables and outer array for intrusive variables. The combination of two internal and external arrays provides a crossed array that provides information about the interactions between controllable and intrusive variables. By facilitating the experimental design process, orthogonal arrays make it possible to examine main and interaction effects by performing the least number of experiments in a reasonable amount of time. The factors and levels of algorithms are shown in Table 6.

In this approach, after adjusting the parameters of the algorithms by using a number of orthogonal arrays, the total number of experiments is reduced (Goodarzian et al., 2021a). The Taguchi method is used for the NSGA-II and PESA-II, the Orthogonal Array L9 and L27 with three levels, which specified in Tables 7 and 8 respectively. To attain the optimum level between the proposed levels for the proposed methods, Relative Percent Deviation (RPD) and S/N indices have been calculated.

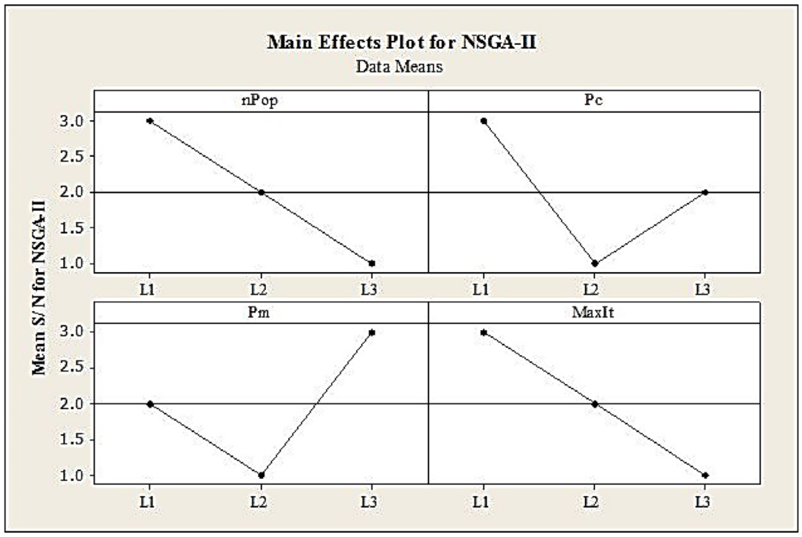

Fig. 10. The S/N ratio of NSGA-II.

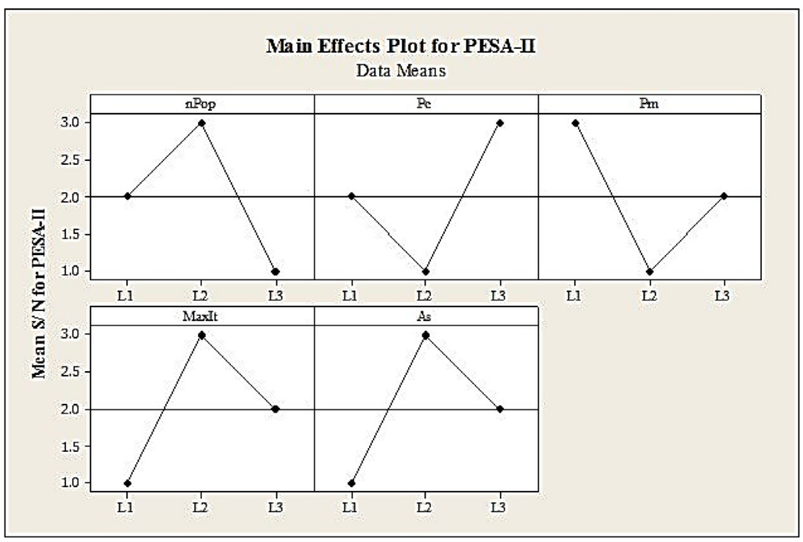

Fig. 11. The S/N ratio of PESA-II.

In Taguchi method, a loss function (L_i) is used to calculate the changes between the results and the desired value. The formulation of the S/N, is shown in Eq. (27).

$$\frac{S}{N} \text{ ratio } = -10. \log \left(L_i\right) \tag{27}$$

Since the model's objective functions are aimed to minimized, the formula for the loss function is calculated as follows in Eq. (28) and S/N ratio is provided in Eq. (29).

$$L_i = \frac{1}{n} \sum \left(y_i\right)^2 \tag{28}$$

$$\frac{S}{N} \text{ ratio } = -10. \log \sum \frac{\left(y_i\right)^2}{n} \tag{29}$$

n indicates the orthogonal array and y_i illustrates the value of the solution for the orthogonal array. Figs. 10–11 show the S/N ratio for the proposed algorithms, respectively.

5.4. Comparison of the proposed methods

In this section, the solution of meta-heuristic algorithms is compared together by their CPU time and purposed assessment metrics. The objective function values in each algorithm are provided in Table 9. Also, the behavior of algorithms is compared by their CPU time in Fig. 12, and based on figure, it is obvious that PESA-II is swifter than NSGA-II for each test problem. As mentioned earlier, five performance metrics were proposed for better and fairer comparison of algorithms. The results are provided in Tables 10 and 11. In Figs. 13 and 14, some examples are run and the obtained Pareto front of each algorithm is shown. Furthermore, according to the Pareto optimal analyses, a set of statistical comparison is presented to find the best method. Relative Deviation Index (RDI) that is common metric is calculated.

The formulation of RDI is as follow (Mehdizadeh et al., 2015):

$$RDI = \frac{\left|A\,\mathrm{lg}_{sol} - Best_{sol}\right|}{\mathrm{Max}_{sol} - \mathrm{Min}_{sol}} \times 100 \tag{30}$$

Alg_{sol} shows the value obtained with a specific measurement scale of the method. $Best_{sol}$ indicates the best solution between all algorithm, and Max_{sol} and Min_{sol} are maximum and minimum values between all resulted. The results are indicated in Fig. 15. The lower value of RDI is better. So PESA-II is More efficient.

Table 7
The proposed Orthogonal Array L9 for NSGA-II algorithm.

L9	nPop	Pc	Pm	MaxIt
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 8
The proposed Orthogonal Array L27 for PESA-II algorithm.

L27	nPop	Pc	Pm	MaxIt	As	L27	nPop	Pc	Pm	MaxIt	As
1	1	1	1	1	1	**15**	2	2	3	1	3
2	1	1	1	1	2	**16**	2	3	1	2	1
3	1	1	1	1	3	**17**	2	3	1	2	2
4	1	2	2	2	1	**18**	2	3	1	2	3
5	1	2	2	2	2	**19**	3	1	3	2	1
6	1	2	2	2	3	**20**	3	1	3	2	2
7	1	3	3	3	1	**21**	3	1	3	2	3
8	1	3	3	3	2	**22**	3	2	1	3	1
9	1	3	3	3	3	**23**	3	2	1	3	2
10	2	1	2	3	1	**24**	3	2	1	3	3
11	2	1	2	3	2	**25**	3	3	2	1	1
12	2	1	2	3	3	**26**	3	3	2	1	2
13	2	2	3	1	1	**27**	3	3	2	1	3
14	2	2	3	1	2						

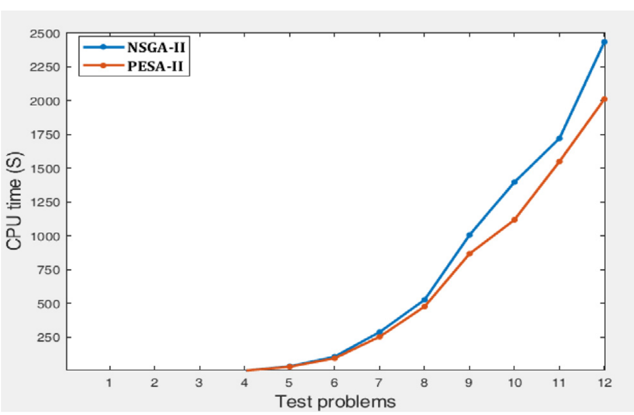

Fig. 12. The behavior of CPU time for algorithms.

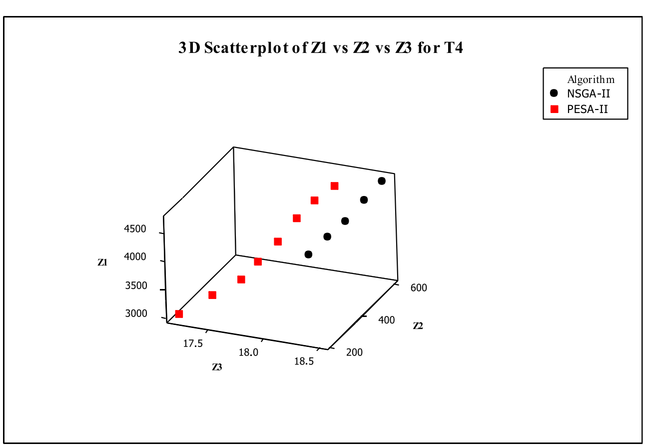

Fig. 13. The Pareto frontier for test problem 4.

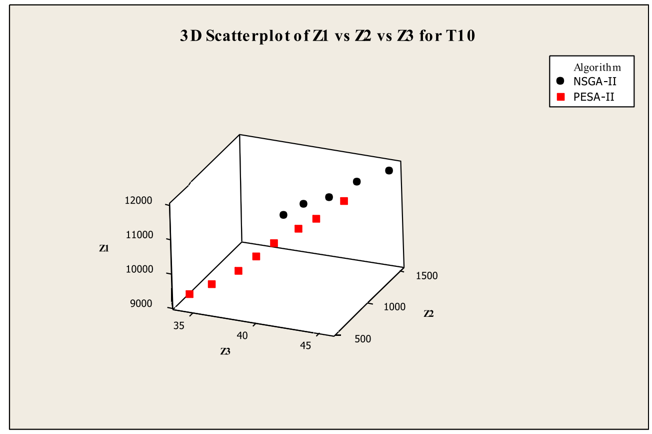

Fig. 14. The Pareto frontier for test problem 10.

5.5. Comparison of results

In this article, to compare and evaluate the presented meta-heuristic algorithms, five different assessment metrics named MID, IGD, SNS, NPS, and MS are presented. According to the results of Tables 10 and 11, we come to the conclusion that the PESA-II algorithm is more efficient and better than the NSGA-II algorithm. In order, the (higher the MS performance metrics, higher the NPS, higher the SNS, lower the IGD, and lower the MID), the more efficient the algorithm is. Also, based on Fig. 12, the amount of time needed to solve the PESA-II algorithm is less than NSGA-II, as a result, this algorithm is faster and smoother. Also, for additional analysis, we proposed the RDI index, which is calculated according to Eq. (30), and its results are shown in Fig. 15. It is worth pointing out that the lower RDI value indicates better quality and efficiency. Therefore PESA-II is more efficient.

5.6. Case study

In order to validate the proposed model and come conditions closer to real world, a case study in Tehran is investigated. Tehran is the capital of Iran. Fig. 16 indicates its location. With the outbreak of the corona pandemic, the distribution and allocation of COVID test kits has become big challenges for decision makers due to the shortage of test kits and the sudden increase in cases suspected of having COVID19. Eight hospitals, six DCs, four landfills, four suppliers, and three manufacturers are considered in case study. Their locations are shown in Fig. 17. Other information is provided in Tables 12–14. Also, two types of test kits, and fifteen units of time period are determined. The dataset of case study is obtained from Application of IoT, google map, ministry of health and treatment, and Municipality of Tehran city. The amount of distance between network components are calculated by google map. The amount of demand for each hospital in each period is obtained from IoT application, the ministry of health and municipality of Tehran provided other data.

5.7. Case study results

The outcomes of case study are investigated by PESA-II algorithm. Tables 15–20 shows case study solutions. It should be noted that Nikan, Milad and Erfan hospitals are equipped with incinerators and do not need to transfer their infectious waste to landfills.

As you can see in Table 15, Saadat Abad, Nobonyad, Piroozi and Rah Ahan are the locations that obtained for DC, but Haft-e-Tir and Jomhoury are rejected locations. Also, according to Table 16 Ariashahr, Khaksefid and Darband are selected for landfill locations, whereas

Table 9
The objective functions values of purposed algorithms.

Algorithm	NSGA-II			PESA-II		
objective function	OF1	OF2	OF3	OF1	OF2	OF3
T1	3997	427	17.5	3986	412	17.5
T2	4287	448	17.6	4112	439	17.5
T3	4472	508	18	4344	489	18
T4	4699	601	18.5	4575	574	18.1
T5	7306	754	29.1	6911	711	28.5
T6	7673	846	29.5	7214	793	28.6
T7	7952	963	32.6	7563	889	31.5
T8	8117	1084	33	7761	1002	32.8
T9	10658	1325	44.5	9841	1236	41.1
T0	11813	1513	45.5	10995	1391	42.5
T11	13227	1695	48.8	12236	1509	45.5
T12	14597	1822	54.1	14589	1688	52.6

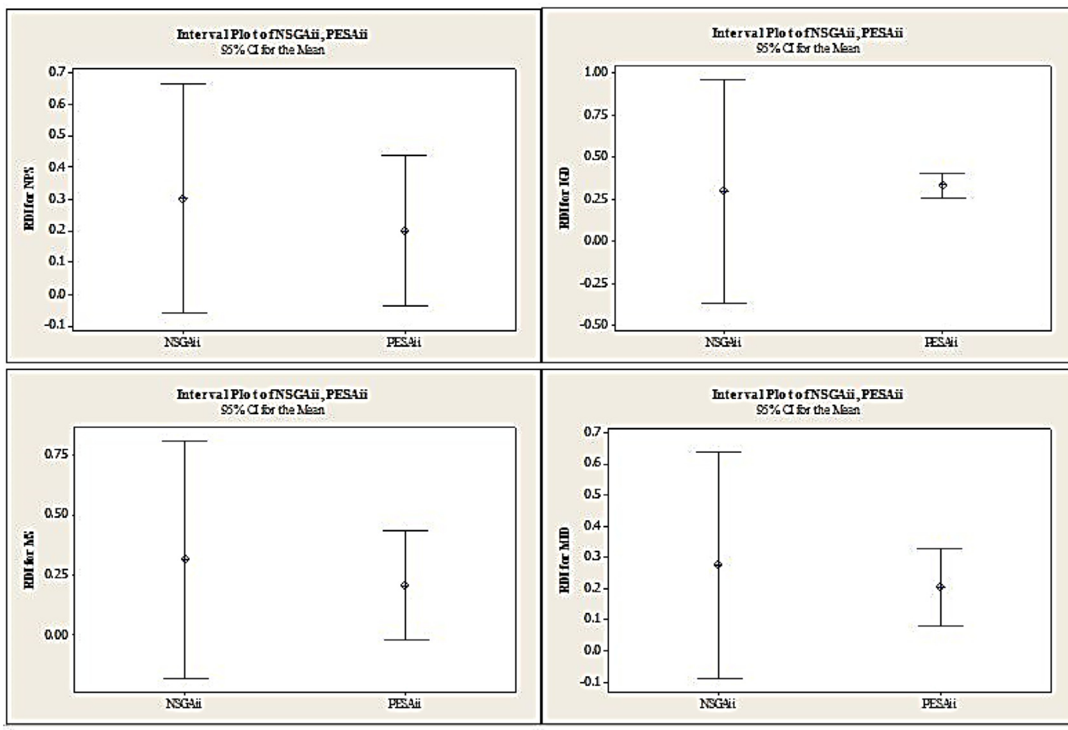

Fig. 15. The RDI means plot for proposed algorithms.

Table 10
The results of performance metrics for NSGA-II algorithm.

Algorithm	NSGA-II				
Performance metric	MS	NPS	SNS	IGD	MID
T1	4595	4	3552	0.048	1.86
T2	4629	6	3763	0.048	2.24
T3	4705	4	3914	0.049	2.95
T4	4876	5	4186	0.051	3.18
T5	6993	7	4368	0.055	3.68
T6	7210	7	4618	0.058	3.81
T7	7324	8	4878	0.06	4.28
T8	7541	9	5029	0.061	4.62
T9	9782	10	5297	0.065	5.09
T10	10536	8	5559	0.069	5.72
T11	11949	7	5732	0.072	6.17
T12	13178	6	5998	0.076	6.59

Table 11
The results of performance metrics for PESA-II algorithm.

Algorithm	PESA-II				
Performance metric	MS	NPS	SNS	IGD	MID
T1	4821	6	3751	0.042	1.27
T2	4903	7	3898	0.044	1.73
T3	5021	5	4079	0.045	2.11
T4	5111	8	4285	0.049	2.59
T5	7339	10	4488	0.051	3.04
T6	7456	10	4753	0.053	3.51
T7	7578	10	4992	0.054	3.88
T8	7909	12	5177	0.056	4.52
T9	10819	13	5332	0.061	4.83
T10	11981	10	5609	0.064	5.42
T11	12322	9	5884	0.068	5.95
T12	14768	8	6199	0.071	6.31

Yaftabad is rejected. Table 17 indicates the amount of case study solution for each objective function. Tables 18–20 shows the allocation relationship between manufacturers and DCs, suppliers and DCs, hospitals and DCs, and hospitals and landfills. For example, the manufacturer that stated in Sedeghie location is allocated to Saadat Abad DC, or Kasra hospital is allocated to Piroozi DC.

Fig. 16. The exact location of Tehran city.

Fig. 17. The exact locations of manufacturers, suppliers, hospitals, DCs and landfills.

Table 12
Distance between DCs and hospitals (km).

DC	Hospital							
	Nikan	Iran Mehr	Milad	Payambaran	Kasra	Taleghani	Erfan	Firoozgar
Saadat Abad	17	9.2	7.8	13	13	4.2	2.8	15
Haft-e-Tir	14	12	13	12	3.4	14	16	1.9
Nobonyad	2.2	9.5	19	21	14	15	16	16
Piroozi	15	13	21	20	12	23	21	10
Jomhouri	17	17	11	13	8.7	16	14	3.6
Rah Ahan	25	21	15	16	12	19	17	6.6

Table 13
Distance between DCs and manufacturers/suppliers (km).

DC	Manufacturer			Supplier			
	1 (Sadeghie)	2 (Tehranpars)	3 (Shoosh)	Poonak	Vanak	Enghelab	Narmak
Saadat Abad	14	22	25	8.1	8.2	14	21
Haft-e-Tir	9.8	15	11	15	9.2	5.4	14
Nobonyad	23	14	21	18	16	18	8.2
Piroozi	22	6.7	14	24	18	11	9.5
Jomhouri	5.5	15	12	14	9.3	1.8	21
Rah Ahan	13	23	8.6	20	14	5.7	26

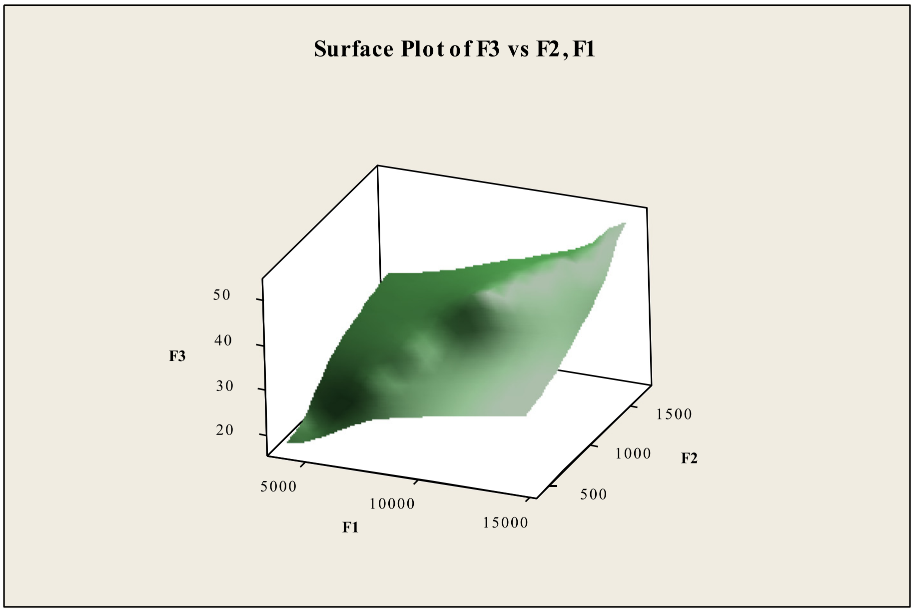

Fig. 18. The behavior of objective function with each other.

Table 14
Distance between hospitals and landfills (km).

Hospital	Landfill			
	Yaftabad	Ariashahr	Khak Sefid	Darband
Nikan	30	20	14	12
Iran Mehr	28	17	19	7.3
Milad	17	7.4	26	17
Payambaran	13	2.8	22	21
Kasra	22	12	14	13
Taleghani	24	14	25	7
Erfan	21	11	25	14
Firoozgar	16	8.7	20	16

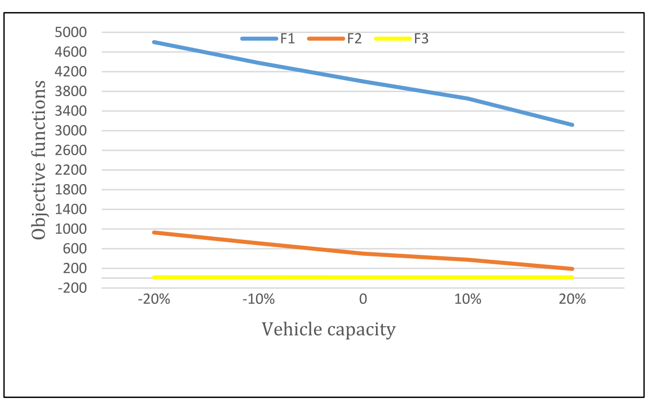

Fig. 19. The effect of changing vehicle capacity on objective functions.

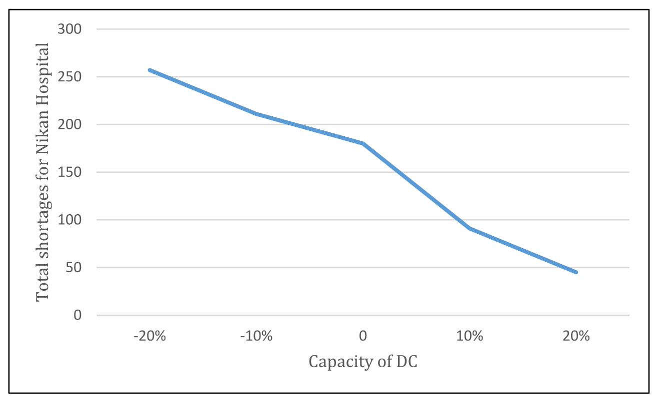

Fig. 20. The effect of DC capacity on shortage.

5.8. Sensitivity analysis

A set of sensitivity analysis is performed to evaluate and identify purposed model. The proposed case study (two kinds of COVID test kits, three manufacturers, four suppliers, six DCs, four landfills, eight hospitals and fifteen periods of time) is selected for this section. Objective functions, several important parameters like demand (D_{iH_t}), capacity of vehicle (CC) and Capacity of DCs (CI) are considered to sensitivity analysis. The variations of objective functions relative to parameters are measured relative. In Fig. 18, 3D plot of three objective function is shown. For instance, the behavior of the objective functions and other parameters are measured in variation of a ±%30 fluctuation in demand. Figs. 19–20 illustrate the results of analysis.

According to Fig. 19, As the capacity of vehicles increases, the first objective function decreases because the number of vehicles used in a period decreases dramatically and the cost of transportation decreases dramatically, which ultimately reduces the final cost. For example, when vehicle capacity increase 10%, total cost decreases 3653. Objective functions 2 and 3 are also reduced because environmental pollution and social harms are reduced by reducing vehicle traffic. Then, increasing the capacity of vehicles can have better results.

As you can see in Fig. 20, as the capacity of DCs increases, the total shortfall for a hospital decreases dramatically. Here Nikan hospital has been selected as a sample. When the capacity of DC increases 20%, the total shortage of Nikan hospital decreases to 45.

5.9. Managerial insight

As mentioned in the literature section, there is a lack of mathematical modeling in research investigating COVID 19, and most of them are conceptual. In this study, a MILP model is presented with three objective functions, and several mathematical constraints. Also, it solves by exact and meta-heuristic algorithms, and the results are compared. Healthcare decision makers can utilize the methods used in

Table 15
The establishment of DCs.

DC	Saadat Abad	Haft-e-Tir	Nobonyad	Piroozi	Jomhouri	Rah Ahan
Is opened?	1	0	1	1	0	1

Table 16
The establishment of landfills.

Landfill	Yaft Abad	Arya Shahr	Khaksefid	Darband
Is opened?	0	1	1	1

Table 17
The solution of case study.

Objective	F1	F2	F3
	7014	758	28.5

this paper to handle their plans for pandemic and reduce its harmful effects.

Nowadays, cities are going to smartness in every aspect. Internet of things (IoT) is one of the smartness elements that play a key role in decision makers' plans. In recent years, IoT has made a major contribution in medical progression in developed countries. Fig. 21 indicates influences that IoT can be in healthcare management, but still in developing countries has not remarkable role in this aspect.

Using a platform based on the IoT for a health supply chain during a pandemic primarily increases the speed of the process, which is the most important point in crisis control and management. In addition, due to the reduction of direct human intervention and human errors, it also improves the accuracy and security of the network. It reduces people's visit to get their turn and crowding in this condition, and as a result, costs and environmental damages are also reduced. Therefore, it can be concluded that in all aspects, the use of such a network can be effective and profitable for supply chain managers. This research which has also been investigated in Iran can help decision makers to develop and use IoT systems to prioritize Suspicious patients to take the COVID test. IoT leads to appropriate allocation, location and distribution in healthcare systems. Also, in these fatal situations where the number of test kits is low in developing countries, more critical patients will have access to the kit sooner with proper planning and prioritization.

Also, if the capacity of vehicles that carry test kits or other medical products related to the pandemic is increased, it can reduce the total costs. Due to the decrease in the number of required cars, the amount of emission of polluting gases is also reduced and the environmental indicators are improved, of course, on the condition that managers pay attention to the emission rate of polluting gases of the cars that are going to be replaced.

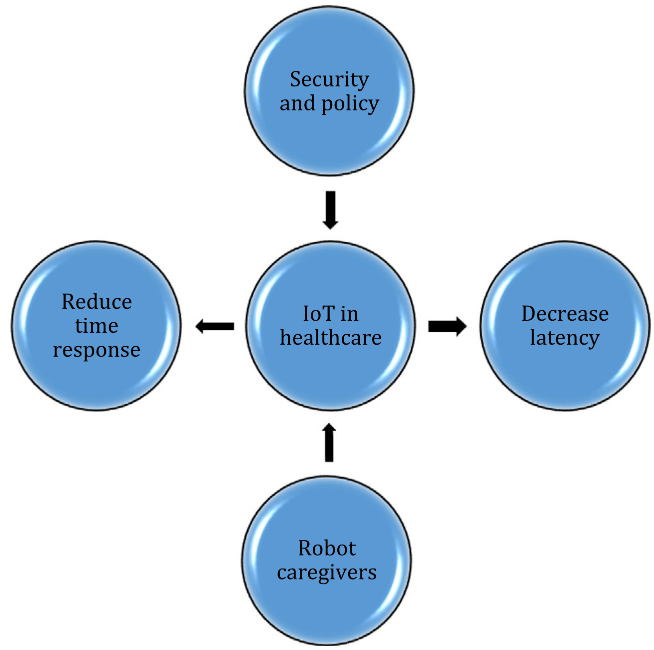

Fig. 21. IoT impacts on healthcare management.

6. Conclusion

In the current study, a multi-period multi-echelon sustainable COVID-19 test kits SC network (STKSCN) is designed to address the location–allocation-distribution problem for medical test kits for COVID19. Manufacturer/supplier, DC, hospital are four echelons of proposed network. Two types of test kits (domestic and foreign) are considered for problem. There are two types of hospitals: some of them have incinerators and others do not. The hospitals that do not have incinerator must transport their used test kits to landfill centers at the end of each period. A MILP MO model is presented that aims to minimize total network costs, negative environmental effects, and negative social impacts. To estimate the amount of required demand for each hospital in each period, an IoT-based application is provided that gets information from patients, gives them permission to test, and determines which hospital is allocated to them. One exact method (AUGMECON2), and two meta-heuristic algorithms (NSGA-II and PESA-II) are provided to solve the proposed STKSCN. Finally, a case study in Iran is presented, and a set of sensitivity analysis are performed to validate the model and compare parameters and objective functions.

Some of the limitations we faced include the lack of database in the field of transportation cost, we had to ask some taxi drivers as experts, and there were different answers, and by averaging them, we recorded the exact amount related to the cost in the case study. Also, another problem that can be mentioned is the issue of access to the Internet for all people. This issue may be trivial for developed countries, but some poor and underdeveloped countries are facing the problem of accessing to the internet in some of their rural areas. This problem can disrupt the healthcare supply chain based on the IoT.

The final results of model solving show that PESA-II is better than other presented algorithms. It is approved by comparing the results of assessment metrics and CPU chart. Also, the results of case study indicates that four distribution centers and three landfill centers must be established. As can be seen by increasing the capacity of vehicles regarding to their carbon emission, managers can reduce the costs.

For future research, the fallowing matters are suggested:

- machine learning methods can be used to forecasting demand, supplier selection or other matters.
- Also, the concept of uncertainty can be considered. For example, fuzzy or stochastic programming can be presented.
- Another concept that should be contributed in future research is resiliency, which can be crucial for healthcare SCs.

Table 18
The allocation of manufacturer and supplier to DCs.

DC	Manufacturer			Supplier			
	1 (Sadeghie)	2 (Tehranpars)	3 (Shoosh)	Poonak	Vanak	Enghelab	Narmak
Saadat Abad	1	0	0	1	0	0	0
Haft-e-Tir	0	0	0	0	0	0	0
Nobonyad	0	1	0	0	0	0	1
Piroozi	0	1	0	0	0	0	1
Jomhouri	0	0	0	0	0	1	0
Rah Ahan	0	0	1	0	0	1	0

Table 19
The allocation of DCs to hospitals.

DC	Hospital							
	Nikan	Iran Mehr	Milad	Payambaran	Kasra	Taleghani	Erfan	Firoozgar
Saadat Abad	0	0	1	0	0	1	1	0
Haft-e-Tir	0	0	0	0	0	0	0	0
Nobonyad	1	1	0	0	0	0	0	0
Piroozi	0	0	0	0	1	0	0	1
Jomhouri	0	0	0	0	0	0	0	0
Rah Ahan	0	0	0	1	0	0	0	0

Table 20
The allocation of landfills to hospitals.

Hospital	Landfill			
	Yaftabad	Ariashahr	Khak Sefid	Darband
Nikan	0	0	0	0
Iran Mehr	0	1	0	0
Milad	0	0	0	0
Payambaran	0	1	0	0
Kasra	0	0	1	0
Taleghani	0	0	0	1
Erfan	0	0	0	0
Firoozgar	0	0	1	0

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

No data was used for the research described in the article.

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