ORIGINAL RESEARCH

A flexible robust model for blood supply chain network design problem

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Abstract

World Health Organization (WHO) declared COVID-19 as a pandemic On March 12, 2020. Up to January 13, 2022, 320,944,953 cases of infection and 5,539,160 deaths have been reported worldwide. COVID-19 has negatively impacted the blood supply chain by drastically reducing blood donation. Therefore, developing models to design effective blood supply chains in emergencies is essential. This research offers a novel multi-objective Transportation-Location-Inventory-Routing (TLIR) formulation for an emergency blood supply chain network design problem. We answer questions regarding strategic, operational, and tactical decisions considering disruption in the network and blood shelf-life. Since, in real-world applications, the parameters of the proposed mathematical formulation are uncertain, two flexible uncertain models are proposed to provide risk-averse and robust solutions for the problem. We applied the proposed formulations in a case study. Under various scenarios and realizations, we show that the offered robust model handles uncertainties more efficiently and finds solutions that have significantly lower costs and delivery time. To make a reliable conclusion, we performed extensive worst-case analyses to demonstrate the robustness of the results. In the end, we provide critical managerial insights to enhance the effectiveness of the supply chain.

Keywords Blood supply chain · Flexible programming · Chance constraint · Flexible robust optimization

1 Introduction

Natural and man-made disasters could disrupt the blood supply chain. In December 2019, a new strain of coronavirus called SARS-Cov-2 was discovered in Wuhan, China. The virus

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causes a respiratory disease called COVID-19. Despite early reactions such as lockdown applied by the government of China, the virus spread to 213 countries resulting in 320,944,953 cases and 5,539,160 deaths by January 13, 2022. COVID-19 pandemic negatively impacted the blood supply chain in most countries worldwide. One of the most critical impacts is that the pandemic has significantly reduced the number of blood donations (Ngo et al., 2020). Canadian Blood Services has reported that blood donation has fallen 30% during the pandemic [https://www.blood.ca/en]. The pandemic has also affected the blood supply chain network by disrupting several services such as blood collection and elective surgeries, which resulted in fluctuations in demand and supply in the blood supply chain. For instance, American Red Cross has closed some of its permanent and mobile blood collection sites due to the pandemic [https://www.redcross.org/]. Besides, schools that are significant sources of blood donations are closed due to the pandemic [https://www.redcross.org/]. Moreover, it has been reported that hospitals are willing to pay less for blood from blood banks. However, with the emergence of new viruses such as Zika, the blood banks face higher testing costs. Furthermore, the pandemic has affected the healthcare workers, and the blood supply chain has slowed down due to fewer available healthcare workers.

Having an efficient blood supply chain is especially important during disasters. For example, after an earthquake, hospitals face a surge in the number of injured people, which requires them to call for emergency blood supply. In this situation, if the blood supply chain is not efficient, only a tiny portion of the donated blood may arrive in the disaster area. For example, Khalilpourazari and Khamseh (2019) reported that only 1.3% of the donated blood reached the affected region in a real earthquake case. This real case disclosed the vital role of an efficient blood supply chain in emergencies. Based on these observations, it is essential to present efficient methodologies to optimize blood supply chains in disruptions and natural disasters like pandemics and earthquakes. These methodologies will help policymakers minimize blood shortages in blood banks and enable the supply chain to respond to the surge in demand adequately. Readers could refer to (Das et al., 2021) and (Das et al., 2020c) for more information about recent supply chain models.

Designing blood supply chains in disasters has been widely studied in the literature. Jabbarzadeh et al. (2014) carried out one of the first researches in the field and proposed a model for the blood supply chain network design (BSCND) problem. The authors used robust optimization to model a three-echelon network, including donors, blood collection, and storage facilities. Fahimnia et al. (2017) suggested a stochastic model for the problem. The authors address the minimization of total time for the first time. In another research, Kohneh et al. (2016) targeted minimizing costs and maximizing coverage in the problem. Zahiri and Pishvaee (2017) proposed a new model to minimize costs and maximize unsatisfied demand in more recent research. Their main novelty was to consider the blood compatibility in the mathematical model. Salehi et al. (2019) used a robust two-stage model to optimize the network. They considered the blood compatibility in their model as well.

Ramezanian and Behboodi (2017) considered social aspects in the BSCND and considered encouraging donors to donate blood on the supply chain. Samani et al. (2018) established a Mixed Integer Programming (MIP) model to minimize costs and time while minimizing unsatisfied demand. Khalilpourazari and Khamseh (2019) extended the model offered by Jabbarzadeh et al. (2014) and considered transportation and disruption. Besides, they considered the earthquake destruction radius for the first time. Fazli-Khalaf et al. (2019) considered a blood supply chain and considered transportation among different echelons and new echelons such as laboratories and hospitals, which was ignored in previous studies. Their model is designed to optimize cost, time, and blood testing reliability. Because of uncertainties, they used a robust approach to formulate uncertainties. They implement their model on a

case study in Iran. Gorashi et al. (2019) offered a new model for the BSCND problem that addresses routing decisions and location-allocation of the centers and donors. The authors considered cost and reliability as their objective functions. Haeri et al. (2020) proposed a new formulation for the BSCND problem and established a resilient network. The authors considered social aspects in their model and used an interactive fuzzy approach to solve the model.

Khalilpourazari et al. (2020) proposed a novel model for the BSCND problem considering a six-echelon network. The authors considered helicopters to transport donated blood and injured people for the first time to optimize the blood supply chain network and avoid shortages. Araújo et al. (2020) considered waste and perishability in the BSCND problem and developed a two-stage approach. Dehgani et al. (2021) proposed a stochastic programming approach for the BSCND problem and took many realistic assumptions into account, including uncertain demand and perishability, to minimize waste and shortages. Hosseini Motlagh et al. (2020) considered a three-echelon BSCND problem and proposed a new model considering the blood compatibility and priority rules between the groups. The authors also considered shelf-life in their model. Samani and Hosseini Motlagh (2020) offered a new model and studied donors' behavior on the BSCND problem.

Although the existing models are applicable, some unrealistic assumptions limit their application. In the following, the limitations of each model presented in the literature are discussed, then the new model is illustrated. First, most researchers mainly focused on minimizing the total costs (Jabbarzadeh et al., 2014; Ramezanian & Behbodi, 2017; Zahiri & Pishvaee, 2017; Salehi et al., 2019; Habibi-Kouchaksaraei et al., 2018). Conversely, in emergencies, minimizing cost is not the primary objective of blood transfusion services because other critical objectives such as minimizing delivery time are decision makers' first choice. Second, during or after a severe disaster, which results in a sudden increase in blood demand, the actual blood demand occurs at hospitals. Therefore, determining how to send the blood units to hospitals and the best delivery routes are of great importance. A few papers in the literature addressed routing decisions (Ghorashi et al., 2019). However, most researchers ignored other vital factors such as shelf-life in their model. Third, except for Khalilpourazari and Khamseh (2019), no research in the literature has considered destruction radius in the blood supply chain. Although Khalilpourazari and Khamseh (2019) have considered earthquake destruction radius in their proposed model, the authors considered it a deterministic parameter. However, this parameter is highly uncertain in real-world applications and depends on many factors.

In this research, we fill the aforementioned gaps by (a) considering a new network for the problem and (b) formulating a new mathematical model to optimize the network. From a network structure perspective, this paper considers a new and more complex four-echelon network for the problem in contrast to the common three-echelon supply chain, which is widely used in the literature. In addition, we propose a new mathematical model for the problem to optimize strategic, operational, and tactical decisions. The model consists of two objective functions to minimize the total costs and transportation time. This research considers several transportation modes such as ambulances and helicopters with limited capacities and different speeds to make a proper trade-off between optimizing time and cost. Besides, the offered model determines the best routes to deliver the donated blood to the demand points. In order to take disruption into account, we consider the effect of the earthquake on the availability and capacity of the facilities. Moreover, we consider blood shelf-life in our model to develop a realistic model for the problem that has been widely ignored in the literature. Although some of the main assumptions of this research may have been addressed in the

literature, this research presents a new comprehensive mathematical model that addresses routing decisions while considering realistic assumptions such as shelf-life and disruption.

Since, in a real-world application, most of the main parameters of the model are subject to variation and uncertainties, it is essential to present a model capable of providing reliable and robust solutions. Uncertainty modeling approaches help decision makers find a proper solution to an optimization problem in an uncertain environment. Based on the given illustrations by Ghelichi et al. (2021) and Khorshidvand et al. (2018), we can categorize uncertainty modeling techniques considering the uncertain nature of the parameters. Deep uncertainty is considered the first category in which there is no sufficient data to estimate the probability distribution of the uncertain parameters. In this case, Robust Optimization methods are among the best techniques to model uncertainty. In the second category, randomness uncertainty is considered in which one can estimate the probability distribution of the uncertain parameters. In this category, stochastic programming methods are used to model uncertainty. In the third category, we have epistemic uncertainty due to the unavailability of data. Robust Possibilistic methods can be utilized in this case.

In this work, we are planning before the disaster, and on the other hand, in most cases, we do not have enough historical data to estimate the probability distribution of the uncertain parameters. Therefore, we use the Robust Possibilistic method to model uncertainties. In this method, Fuzzy Programming (FP) enables us to use experts' opinions about uncertainties. On the other hand, Fuzzy programming allows us to determine the confidence level of the probabilistic constraints. The main issue with FP is that it has some limitations, such as the nonoptimality of the generated confidence levels and the computational burden of the solution process. In Sect. 3, we use robust optimization to address these issues.

In this research, to model real-world uncertainties in our model, we propose two flexible uncertain methods, including Flexible Robust Fuzzy Chance Constraint Programming (FRFCCP) and Flexible Fuzzy Chance Constraint Programming (FFCCP), to deliver robust risk-averse solutions to the decision makers. To assess the effectiveness of the proposed robust model, we apply the new formulation to real data from Tehran, Iran. Based on the results, we show that the proposed FRFCCP model can handle uncertainties and take into account significant variations in the main parameters such as demand or donation rates and provide risk-averse solutions. Given the results, we provide some managerial insights by analyzing the robust model's performance in worst-case scenarios. Based on the given illustrations, the main contributions of this research are as follows:

- To the best of our knowledge, our work is the first to consider a new network structure for the blood supply chain network design problem.
- We formulate a new Transportation-Location-Inventory-Routing (TLIR) model for the problem. The proposed model optimizes cost and delivery time in the network.
- Our model takes into account many complicating factors such as considering disruption, the shelf-life of donated blood, and different transportation means in the network.
- We also propose a flexible robust formulation to model the problem with uncertain parameters.
- We apply the proposed models to a real case study in Iran and provide several managerial insights to optimize the blood supply chain.

The remainder of this paper is organized as follows: In Sect. 2, we propose the problem definition and define all the sets, parameters, and decision variables. Then we present the new mathematical model for the problem. In Sect. 3, we propose Flexible Robust Fuzzy Chance Constraint Programming (FRFCCP) and Flexible Fuzzy Chance Constraint Programming (FFCCP) models to formulate uncertainties. In Sect. 4, we implement our models to real

data from Tehran. In this section, we generate realizations under several different scenarios and evaluate the performance of the FRFCCP and FFCCP models. We also carry out worst-case analyses to study the performance of the models in worst-case scenarios of uncertain parameters. At the end of Sect. 4, we offer several managerial insights to improve the blood supply chain efficiency in Iran. Finally, in Sect. 5, we conclude the paper and present several directions for future studies.

2 Problem definition and mathematical model

In this study, we offer a four-echelon network for the BSCND problem. The network contains donors, collection sites, blood banks, and hospitals. The donors donate blood at permanent or mobile collection centers. The donated blood in collection facilities is then transported to blood banks using ambulances and helicopters for testing and storage. The blood demand for hospitals is met by ambulances. The ambulances start from blood banks, deliver blood to several hospitals, and return to the corresponding blood bank. Ambulances are homogenous with limited capacity. To make the model more realistic, we also consider the destruction effect of earthquakes on blood collection centers and blood banks and their coverage and capacity parameters. Since the donated blood has a shelf-life, we also considered the shelf-life of the blood in our model. In addition, Hosseinifard and Abbasi (2018) showed that blood inventory centralization could increase the blood supply chain effectiveness. Therefore, it is considered that the blood banks are in control for holding blood inventory and satisfying blood demand at hospitals. Figure 1 presents a schematic view of the proposed supply chain.

To sum up, our model aims to answer the following questions.

1. How to allocate the donors to the established collection sites?
2. How much blood do we need to collect at each center at each period?
3. How many donation buses do we need?
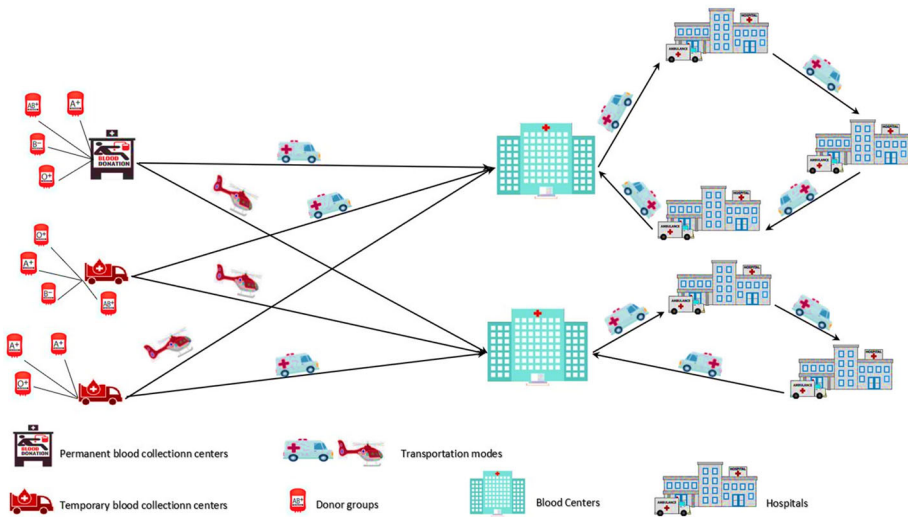4. Where do we have to locate the collection facilities?

Fig. 1 A schematic view of the proposed blood supply chain

5. How much inventory should be maintained in each blood bank at each period?
6. How many vehicles and helicopters do we need?
7. How much blood should be transfused?
8. Which routes should be used?

In order to develop the mathematical model, we used the notations presented in Table 1. The final model of the problem is presented as follows.

$$
\min\ z_1 = \sum_{j\in J}\widetilde{f_j}g_j + \sum_{j\in J}\sum_{l\in L}\sum_{t\in T}\widetilde{v_{jlt}}z_{jlt} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\widetilde{o_{ijt}}Q_{ijt} + \sum_{k\in K}\sum_{t\in T}\delta_{kt}M
$$
$$
+ \sum_{k\in K}\sum_{p\in P}\sum_{t\in T}\widetilde{c_{kpt}}(x_{0pkt} + x_{p0kt}) + \sum_{k\in K}\sum_{p\in P}\sum_{p'\in P}\sum_{t\in T}\widetilde{c'_{pp't}}x_{pp'kt}
$$
$$
+ \sum_{g\in G}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T}\sum_{v\in V}\widetilde{a_{jkv}}Qa_{jkgtv} + \sum_{k\in K}\sum_{g\in G}\sum_{t\in T}\widetilde{hc_k}In_{kgt}
$$
$$
+ \sum_{j\in J}\sum_{k\in K}\sum_{t\in T}\sum_{v\in V}\widetilde{ac_v}N_{jktv} \tag{1}
$$

$$
\min\ z_2 = \sum_{j\in J}\sum_{k\in K}\sum_{t\in T}\sum_{v\in V}\widetilde{ta_{jktv}}va_{jktv} + \sum_{k\in K}\sum_{p\in P}\sum_{t\in T}\widetilde{t_{kpt}}\left(x_{0pkt} + x_{p0kt}\right)
$$
$$
+ \sum_{k\in K}\sum_{p\in P}\sum_{p'\in P}\sum_{t\in T}\widetilde{t'_{pp't}}x_{pp'kt} \tag{2}
$$

subject to

$$
In_{kg-1t-1} + \sum_{j\in J}\sum_{v\in V}Qa_{jkgtv} - In_{kgt} + \delta_{kt} = \sum_{p\in P}vr_{pkgt}\quad \forall k\in K, t\in T, g\le sl, g\in G \tag{3}
$$

$$
g_j + \sum_{\substack{l\in L\\ j\neq l}}z_{jlt} \le 1\quad \forall j\in J, t\in T \tag{4}
$$

$$
z_{jlt} = 0\quad \forall j\in J, l\in L, \in T, j = l \tag{5}
$$

$$
\sum_{\substack{l\in L\\ j\neq l}}z_{jlt} \le \sum_{\substack{l\in L\\ j\neq l}}z_{ljt-1}\quad \forall j\in J, t\in T \tag{6}
$$

$$
y_{ijt} \le g_j + \sum_{\substack{l\\ j\neq l}}z_{jlt}\quad \forall i\in I, j\in J, t\in T \tag{7}
$$

$$
y_{ijt} \le \widetilde{cov}\left(1 - \widetilde{\chi_{jt}}\right)\quad \forall i\in I, j\in J, t\in Tr_{ijt} \tag{8}
$$

$$
Q_{ijgt} \le \widetilde{m_i}y_{ijt}\quad \forall i\in I, j\in J, g = 1, g\in G, t\in T \tag{9}
$$

$$
\sum_{j\in J}\sum_{t\in T}Q_{ijgt} \le \widetilde{m_i}\quad \forall i\in I, g = 1, g\in G \tag{10}
$$

$$
\sum_{g\in G, g=1}\sum_{i\in I}Q_{ijgt} \le \widetilde{CAP_{jt}}g_j\left(1 - \widetilde{\varrho_{jt}}\right) + \widetilde{b_{jt}}\sum_{\substack{l\\ j\neq l}}z_{jlt}\quad \forall j\in J, t\in T \tag{11}
$$

Table 1 Notations

Sets and indexes	
I	Set of donor groups $I = \{1,2,\ldots,n\}$
J	Set of potential locations for blood collection centers $J = \{1,2,\ldots,n\}$
K	Set of blood banks $K = \{1,2,\ldots, b'\}$
G	Set of the age of the blood $G = \{1,2,\ldots,f'\}$
T	Set of periods $T = \{1,2,\ldots,t'\}$
V	Set of transportation means $V = \{1,2,\ldots,v'\}$
P	Set of hospitals $P = \{1,2,\ldots,p'\}$
H	Set of hospitals and 0 index $H = \{0,1,2,\ldots,p'\}$
i	Index for donors
j	Index for potential locations for blood collection centers
k	Index for blood banks
g	Index for the age of the blood
t	Index for periods
v	Index for transportation means
p	Index for hospitals
$h = p \cup \{0\}$	Index for hospitals and 0 (shows that the routes start from and end at blood centers)
$p' = p$	Index for hospitals
$l = j$	Index for potential locations for blood collection centers
$h' = h$	Index for hospitals and 0 (shows that the routes start from and end at blood centers)
Parameters	
f_j	Establishment cost of fixed blood collection sites
v_{jlt}	Transportation cost from site l to site j at period t
χ_{jt}	Partial coverage disruption in the radius of the collection site j at period t
ϱ_{jt}	Partial capacity disruption in of the fixed collection site j at period t
ψ_{kt}	Partial disruption in the capacity of the blood bank k at period t
o_{ijt}	Operational cost for collecting blood from group i at site j at period t
a_{jkv}	Transportation cost from collection site j to blood bank k with vehicle type v
hc_k	Inventory holding expenses at site k
ac_v	Fixed cost of vehicle type v
ta_{jktv}	Transportation time from site j to blood bank k at timeslot t with vehicle v
m_i	Maximum available blood by group i
CAP_{jt}	The capacity of fixed the site j at period t
b_{jt}	The capacity of mobile site j at period t
uc_k	Blood center k capacity
dis_j	Distance of site j from the earthquake epicenter
ca_{jktv}	The capacity of vehicle v

Table 1 (continued)

Na_{jv}	Available vehicle v at site j
Q'	The capacity of ambulances in the routing stage from blood banks to demand points (hospitals)
d_{pt}	The demand of hospital p at period t
C_{kpt}	Cost of moving ambulance from blood bank k to hospital p at period t
$C'_{pp't}$	Cost of moving ambulance from hospital p to hospital p' at period t
t_{kpt}	Average transportation time of ambulance from blood bank k to hospital p at period t
$t'_{pp't}$	Average transportation time of ambulance from hospital p to hospital p' at period t
r_{ij}	Distance from group i to collection site j
cov	Coverage radius of collection centers
dr	Destruction radius of the possible earthquake
sl	Shelf-life of the donated blood
Decision variables	
Qa_{jkgtv}	Quantity of transfused blood from facility j to blood center k at period t using vehicle v with age $g = 1$
u_{pt}	Variables used to prevent exceeding the ambulances capacity and for sub-tour elimination. It represents the load of the ambulance after visiting hospital p at period t
vr_{pkgt}	Blood units sent from collection site k to hospital p at period t with age g
Q_{ijgt}	blood donated by group i at collection site j at period t with age $g = 1$
z_{jlt}	equal to 1 if temporary collection site is relocated from region l to region j at period t, 0 otherwise
y_{ijt}	equal to 1 if donor i is assigned to collection site j at period t, 0 otherwise
In_{kgt}	Blood inventory in blood bank k at period t with age g
N_{jktv}	Number vehicle v required at collection site j at period t to transfuse blood to blood bank k
g_j	equal to 1 if fixed collection site is established at region j, 0 otherwise
va_{jktv}	equal to 1 if vehicle v transport blood from collection site j to blood center k at period t 0 otherwise
$x_{hh'kt}$	equal to 1 if the ambulance goes from site h to site h' on the route related to blood bank k at period t; 0 otherwise
za_{pkt}	equal to 1 if hospital p is allocated to blood bank k at period t, 0 otherwise
δ_{kt}	shortage in blood bank k at period t

$$\sum_{g \in G, g \leq sl} In_{kgt} \leq \widetilde{uc_k}\left(1 - \widetilde{\psi_{kt}}\right) \quad \forall k \in K, t \in T \tag{12}$$

$$dis_j \geq \widetilde{dr}\left(g_j + \sum_{\substack{l \in L \\ j \neq l}} z_{jlt}\right) \quad \forall j \in J, t \in T \tag{13}$$

$$\sum_{k \in K} \sum_{v \in V} Qa_{jkgtv} = \sum_{i \in I} Q_{ijgt} \quad \forall j \in J, t \in T, g = 1, g \in G \tag{14}$$

$$Qa_{jkgtv} \leq va_{jktv} \sum_{i \in I} \widetilde{m_i} \quad \forall j \in J, k \in K, g = 1, g \in G, t \in T, v \in V \tag{15}$$

$$Qa_{jkgtv} \leq \widetilde{ca_{jktv}} N_{jktv} \quad \forall j, k \in K, g = 1, g \in G, t \in T, v \in V \tag{16}$$

$$\sum_{k \in K} N_{jktv} \leq \sum_{k \in K} Na_{jv} va_{jktv} \quad \forall j \in J, t \in T, v \in V \tag{17}$$

$$va_{jktv} \leq g_j + \sum_{\substack{l \\ j \neq l}} z_{jlt} \quad \forall j \in J, k \in K, t \in T, v \in V \tag{18}$$

$$\sum_{k \in K} za_{pkt} = 1 \quad \forall p \in P, k \in K, t \in T \tag{19}$$

$$\sum_{p \in P} x_{0pkt} = \sum_{p \in P} x_{p0kt} \quad \forall k \in K, t \in T \tag{20}$$

$$\sum_{\substack{h \in H \\ h \neq p+1}} x_{hpkt} = za_{pkt} \quad \forall p \in P, k \in K, t \in T \tag{21}$$

$$\sum_{\substack{h \in H \\ h \neq p+1}} x_{phkt} = za_{pkt} \quad \forall p \in P, k \in K, t \in T \tag{22}$$

$$u_{pt} - u_{p't} + Q' \sum_{k \in K} x_{pp'kt} \leq Q' - \sum_{g \in G, g \leq sl} \sum_{k \in K} vr_{pkgt} \quad \forall p \in P, p' \in P, t \in T, p \neq p' \tag{23}$$

$$\widetilde{d_{pt}} \leq u_{pt} \leq Q' \quad \forall p \in P, k \in K, t \in T \tag{24}$$

$$\sum_{g \in G, g \leq sl} vr_{pkgt} \geq \widetilde{d_{pt}} za_{pkt} \quad \forall p \in P, k \in K, t \in T \tag{25}$$

$$Q_{ijgt}, Qa_{jkgtv}, In_{kgt}, u_{pt}, vr_{pkgt} \geq 0 \quad \forall j \in J, g \in G, v \in V, i \in I, p \in P, k \in K, t \in T \tag{26}$$

$$N_{jktv} \geq 0, \text{int} \quad \forall j \in J, k \in K, t \in T, v \in V \tag{27}$$

$$g_j, z_{jlt}, y_{ijt}, va_{jktv}, x_{hh'kt}, za_{pkt} \in \{0, 1\} \quad \forall h \in H, h' \in H, j \in J, 1$$
$$\in L, v \in V, i \in I, p \in P, k \in K, t \in T \tag{28}$$

The first objective function minimizes the total costs of the supply chain. The first term, $\sum_j \widetilde{f_j} \ g_j + \sum_j \sum_l \sum_t \widetilde{v_{jlt}} \ z_{jlt}$, calculates the total cost of establishing the permanent blood collection facilities and the transportation cost of the temporary blood collection facilities, respectively. The second term, $\sum_i \sum_j \sum_t \widetilde{o_{ijt}} \ Q_{ijt}$, calculates the operational cost of the blood collection. The subsequent two terms, $\sum_k \sum_p \sum_t \widetilde{c_{kpt}}(x_{0pkt} + x_{p0kt})$ and $\sum_k \sum_p \sum_{p'} \sum_t \widetilde{c'_{pp't}} x_{pp'kt}$, determine the cost of delivering blood from blood centers to hospitals (demand points) in the last echelon of the supply chain. The expression $\sum_g \sum_j \sum_k \sum_t \sum_v \widetilde{a_{jkv}} \ Qa_{jkgtv}$ calculates the variable transportation cost from blood collection centers to blood centers using different transportation modes. Also, $\sum_k \sum_g \sum_t \widetilde{hc_k} \ In_{kgt}$ determines the holding costs of blood in the blood banks. Finally, $\sum_j \sum_k \sum_t \sum_v \widetilde{ac_v} \ N_{jktv}$ calculates the fixed transportation cost from blood collection centers to blood centers.

The second objective function targets reducing the transportation time. Constraint (3) guarantees a correct blood transfusion among facilities to meet the demand in hospitals and displays a correct inventory management model in different periods to meet the next period's demand. Constraint (4) offers that no more than one collection site is allowed to be located in a location. Constraints (5–6) enable temporary blood collection centers to move within sites. Constraint (7) allocates donors to blood collection sites. Constraint (8) determines the coverage radius for blood collection sites while considering the effect of disruption. Constraints (9–10) ensure that the donated blood cannot be more than the available blood supply by each donor group. Constraint (11) limits the capacity of blood collection sites while considering disruption. Constraint (12) introduces the maximum stock level at blood banks. Constraint (13) suggests that the earthquake can destroy blood collection facilities within its destruction radius. Constraints (14–15) confirm the correct flow of collected blood among facilities. Constraints (16–17) control the available transportation means to transport blood, considering that a limited number of equipment are available. Since the donors donate blood in the first echelon of the supply chain, the age of the donated blood is considered 1. Hence, Constraints (9) and (10) are valid for g = 1. In addition, since the collection centers are not able to hold donated blood, the age of the transfused blood from collection centers to other facilities should be one as well, which is ensured by Constraints (14) to (16). Then blood centers are responsible for holding blood. Therefore, the donated blood could be stored for more than one period in order to meet the demand. Thus, the aging process of the donated blood is considered in Constraint (3) in the blood centers for other ages. Constraint (18) ensures that the transportation means could dispatch from located collection centers. Constraint (19) shows the allocation of hospitals to blood banks. Constraint (20) guarantees that if an ambulance leaves a blood center, it must return to the same blood center. Constraint (21–22) ensures two main points. First, these constraints guarantee that each hospital must be visited immediately after exactly one blood center or after another hospital. Second, we could create routes between demand points allocated to the same blood center. To avoid surpassing ambulance capacity in the routing stage and avoid the generation of sub-tours, constraints (23–24) are added. Please note that these constraints are similar to the constraints provided by Miller et al. (1960) and Martínez-Salazar (2014). Constraint (25) shows that the amount of transfused blood from one blood center to a hospital should be larger than the demand of that hospital. Constraints (26–28) show the variables and their possible values.

In reality, the parameters of the suggested formulation are inexact. These uncertainties usually occur in donation rate, demand rate, transportation cost (mostly in developing countries), transportation time (weather and road conditions and the amount of debris on the streets), and capacities (due to disruption). Therefore, new formulations should be developed.

3 Background on robust optimization

Robust optimization (RO) is one of the best methods to express and formulate uncertainties in mathematical models. RO focuses on two main definitions, including feasibility and optimality robustness. The former guarantees that the solution remains feasible for nearly all realizations of uncertainties. The latter confirms that the solution of the robust model remains near-optimal for all possible levels of uncertainty. In other words, robust optimization expresses uncertainties and offers an answer resistant to deviations in uncertain parameters (Farrokh et al., 2018; Inuiguchi & Ramík, 2000; Phuc et al., 2017; Pishvaee & Khalaf, 2016; Ramezani et al., 2014; Torabi & Hassini, 2008). In the following, we propose

a robust programming model to formulate the problem. The main reason for proposing a robust programming model is that the main application of the blood supply chain network design problem is in the case of an emergency where the blood supply chain must be reliable and robust to effectively support saving human lives even in the worst case. There are many uncertain parameters in a blood supply chain network that the proposed robust programming model takes into account in the case of a disaster. In our research, we determine the uncertain parameters in our model using the $\sim$ symbol. We considered uncertainty in the cost and delivery time, the destruction radius parameter of the earthquake, the amount of donated blood and the blood demand, and the capacity of the facilities. These parameters are uncertain in real-world applications for several reasons. Since we are planning before the disaster, the transportation costs could significantly change due to economic reasons in a developing country by the time the disaster happens. On the other hand, the transportation time could also change significantly due to blocked roads by debris. In addition, other environmental factors such as weather could also affect the transportation time. Besides, we considered the destruction radius parameter of the earthquake as an uncertain parameter because the destruction radius of an earthquake significantly depends on the soil type and depth of the earthquake (Khalilpourazari & Khamseh, 2019). The amount of donated blood and the blood demand is uncertain parameters because they change significantly in the case of an emergency. Blood donation could drop due to the unavailability of the blood collection centers (reduced coverage radius) or blocked roads, and the blood demand could remarkably increase due to the surge of injured people. We considered the percentage of the disruption in the capacity of the facilities as an uncertain parameter since it heavily depends on the disaster scale. Please refer to Mondal & Roy, 2021a; Mondal & Roy, 2021b; Das et al., 2020a; Das et al., 2020b) for more information about uncertainty modeling.

3.1 Flexible fuzzy chance constrained programming

The compact form of the proposed mathematical model is presented as follows to make it easier to define the Flexible Fuzzy Chance Constrained Programming (FFCCP) formulation.

$$
\begin{aligned}
&\text{Min } Z = \tilde{c}x + \tilde{f}y \\
&\text{Subjected to} \\
&Nec\left\{Gx \geq \tilde{d} - \tilde{\vartheta}(1-\gamma)\right\} \geq \psi \\
&Bx = 0 \\
&Nec\left\{Dx \leq \left\{\tilde{S} + \tilde{\theta}(1-\delta)\right\}y\right\} \geq \xi \\
&Ix \geq 0 \\
&Vx \leq 1 \\
&x \geq 0, \; y \in \{0, 1\}
\end{aligned} \tag{29}
$$

It is considered that the uncertain parameters follow triangular fuzzy distributions such as $\tilde{d} = (d^{(p)}, d^{(m)}, d^{(o)})$. Based on the given illustrations by Inuiguchi and Ramík (2000), we cannot determine the value of a possibilistic linear function due to uncertainties in the coefficients. In addition, it is hard to handle when a constant is limiting the value of a possibilistic constraint. To handle these constraints, one can use possibility or necessity measures. A possibly optimal solution is defined as an answer that is optimal for at least one realization of uncertain parameters. A necessarily optimal solution is an answer that is optimal for all realizations of the uncertainty parameters. Inuiguchi and Ramík (2000) showed that necessity measure is the most reasonable solution to these constraints. For more information

about the necessity constraints, please refer to Inuiguchi and Ramık (2000). Considering the given illustrations by Inuiguchi and Ramik (2000) and Liu and Iwamura (1998), we utilize the expected value to reformulate the model as follows:

$$
\begin{aligned}
&Min\ Z = \left(\frac{c^{(p)}+c^{(m)}+c^{(O)}}{3}\right)x + \left(\frac{f^{(p)}+f^{(m)}+f^{(O)}}{3}\right)y \\
&\text{Subjected to} \\
&Gx \geq \left[\psi\left(\frac{d^{(m)}+d^{(o)}}{2}\right) + (1-\psi)\left(\frac{d^{(p)}+d^{(m)}}{2}\right)\right] - \left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon'_t}{3}\right)(1-\gamma)\right] \\
&Kx = 0 \\
&Dx \leq \left[\xi\left(\frac{S^{(p)}+S^{(m)}}{2}\right) + (1-\xi)\left(\frac{S^{(m)}+S^{(o)}}{2}\right)\right]y + \left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta'_r}{3}\right)(1-\delta)\right]y \\
&Ix \geq 0 \\
&Vx \leq 1 \\
&x \geq 0,\ y \in \{0, 1\}
\end{aligned}
\tag{30}
$$

In the model above, we control the flexibility of constraints by presenting potential violation of flexible constraints (i.e., $\left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon'_t}{3}\right)(1-\gamma)\right]$, $\left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta'_r}{3}\right)(1-\delta)\right]y$). Parameters ε_t, ε'_t, ζ_r, and ζ'_r present the distance of lateral margins of uncertain parameters and their most possible value.

$$
\varepsilon_t = \vartheta^{(o)} - \vartheta^{(m)}
$$

$$
\varepsilon'_t = \vartheta^{(m)} - \vartheta^{(p)}
\tag{31}
$$

We can adjust the risk averseness of the outcome by enhancing the satisfaction level of soft constraints. Although the model above has some advantages, a few key disadvantages bound the applicability in real-world applications. First, the best confidence levels selected by the DM are not essentially ideal since the DM determines the confidence levels of chance constraints by experience. Second, the solution process would become challenging by considering many flexible chance constraints. To overcome these problems in FFCCP, Pishvaee et al. (2012) suggested a Robust Fuzzy Chance Constraint Programing (RFCCP) method using the basic concepts behind chance constraint programming. RFCCP has some limitations as well (Fazli-Khalaf et al., 2019). Therefore, we develop a new flexible, robust model based on Pishvaee and Fazli Khalaf (2016).

3.2 Flexible robust fuzzy chance constrained programming

The FRFCCP model presented in this research is formulated as follows:

$$Min \; Z \; = \left(\frac{c^{(p)}+c^{(m)}+c^{(O)}}{3} \right) x + \left(\frac{f^{(p)}+f^{(m)}+f^{(O)}}{3} \right) y$$

$$+ \sigma \left\{ c^{(O)} x + f^{(O)} y \right\}$$

$$+ \pi \left\{ d^{(m)} - \left[\psi \left(\frac{d^{(m)}+d^{(o)}}{2} \right) + (1-\psi) \left(\frac{d^{(p)}+d^{(m)}}{2} \right) \right] \right\} + \varphi \left\{ \left[\xi \left(\frac{S^{(p)}+S^{(m)}}{2} \right) + (1-\xi) \left(\frac{S^{(m)}+S^{(o)}}{2} \right) \right] - S^{(p)} \right\} y$$

$$+ \tau \left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon_t'}{3} \right) (1-\gamma) \right] + \eta \left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta_r'}{3} \right) (1-\delta) \right] y$$

Subjected to

$$Gx \geq \left[\psi \left(\frac{d^{(m)}+d^{(o)}}{2} \right) + (1-\psi) \left(\frac{d^{(p)}+d^{(m)}}{2} \right) \right] - \left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon_t'}{3} \right)(1-\gamma) \right]$$

$$Kx = 0$$

$$Dx \leq \left[\xi \left(\frac{S^{(p)}+S^{(m)}}{2} \right) + (1-\xi) \left(\frac{S^{(m)}+S^{(o)}}{2} \right) \right] y + \left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta_r'}{3} \right)(1-\delta) \right] y$$

$$Ix \geq 0$$

$$Vx \leq 1$$

$$x \geq 0, 0.5 < \psi, \xi \leq 1, 0 \leq \gamma, \delta \leq 1, y \in \{0,1\}$$

$$(32)$$

where the objective function aims to ensure optimality robustness and feasibility robustness besides the previous objective function. The introduced formulation for FRFCCP model is nonlinear programming. So, it is crucial to linearize the FRFCCP model. For this purpose, we define auxiliary variables as follows:

$$\Omega = \xi y \qquad (33)$$

$$\emptyset = \delta y \qquad (34)$$

Using the newly defined variables, the linear FRFCCP model is presented below:

The FRFCCP formulation has numerous advantages. First, the confidence levels are handled as variables in the new model; therefore, by solving the FRFCCP, the best levels are determined. In addition, the new model enables us to consider many chance constraints since there is no need to solve the model for every possible combination of confidence levels. For more information about Fuzzy mathematical programming, the readers could refer to Tirkolaee et al., 2020; Goli et al., 2021; Goli et al., 2020).

4 Model implementation and evaluation

Earthquakes have caused many injuries and fatalities in Iran in the past years. From the Manjil–Rudbar earthquake in 1990 that had a magnitude of 7.4 and caused 40,000–50,000 deaths to the Bam earthquake in 2003 with a magnitude of 6.6, which caused 30,000 deaths in Iran. In 2017 several destructive earthquakes hit major cities of Iran such as Kermanshah, Sanandaj, Kerman, Tabriz, Urmia, Hamedan, etc. The Iran/Iraq border earthquake with a magnitude of 7.3, which hit Kermanshah province on November 12, 2017, killed 630 people, injured more than 8000 people, and was named the deadliest earthquake of 2017. After the earthquake, the Iranian Blood Transfusion Organization (IBTO) called for emergency blood donation to fulfill hospitals' demand in the disaster zone due to the high number of injured people. However, because of the inefficiency of the blood supply chain, only a tiny portion of donated blood was delivered on time to the disaster area. Tehran is the capital of Iran, with a population of over 16 million. The city is situated on thirteen active faults, which could generate over seven magnitude earthquakes. Recent researches show that the urban growth of Tehran city has been inappropriate, and more than 8 million people are located in the high

danger zone (Wikipedia).

$$
\text{Min } Z = \left(\frac{c^{(p)} + c^{(m)} + c^{(O)}}{3}\right)x + \left(\frac{f^{(p)} + f^{(m)} + f^{(O)}}{3}\right)y
$$
$$
+ \sigma\left\{\left[c^{(O)}x + f^{(O)}y\right]\right\}
$$
$$
+ \pi\left\{d^{(m)} - \left[\psi\left(\frac{d^{(m)} + d^{(o)}}{2}\right) + (1-\psi)\left(\frac{d^{(p)} + d^{(m)}}{2}\right)\right]\right\}
$$
$$
+ \varphi\left\{\left[\Omega\left(\frac{S^{(p)} + S^{(m)}}{2}\right) + (y-\Omega)\left(\frac{S^{(m)} + S^{(o)}}{2}\right)\right] - S^{(p)}\right\}
$$
$$
+ \tau\left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon_t'}{3}\right)(1-\gamma)\right] + \eta\left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta_r'}{3}\right)(y - \emptyset)\right]
$$

subject to

$$
Gx \geq \left[\psi\left(\frac{d^{(m)} + d^{(o)}}{2}\right) + (1-\psi)\left(\frac{d^{(p)} + d^{(m)}}{2}\right)\right] - \left[\left(\vartheta^{(m)} + \frac{\varepsilon_t - \varepsilon_t'}{3}\right)(1-\gamma)\right]
$$
$$
Kx = 0 \tag{35}
$$
$$
Dx \leq \left[\Omega\left(\frac{S^{(p)} + S^{(m)}}{2}\right) + (y-\Omega)\left(\frac{S^{(m)} + S^{(o)}}{2}\right)\right] + \left[\left(\theta^{(m)} + \frac{\zeta_r - \zeta_r'}{3}\right)(y - \emptyset)\right]
$$
$$
\Omega \leq My
$$
$$
\Omega \geq M(y-1) + \xi
$$
$$
\Omega \leq \xi
$$
$$
\emptyset \leq My
$$
$$
\emptyset \geq M(y-1) + \delta
$$
$$
\emptyset \leq \delta
$$
$$
Ix \geq 0
$$
$$
Vx \leq 1
$$
$$
x, \Omega, \emptyset \geq 0, \, 0.5 < \psi, \xi \leq 1, \, 0 \leq \gamma, \delta \leq 1, \, y \in \{0, 1\}
$$

In geological research, Asgary et al. (2007) indicated that a 7 M earthquake in Tehran would destroy 640,000 households and cause millions of deaths and injuries. Data showed that every 158 years, a big earthquake is probable in the region (Asgary et al., 2007). Up to date, it has been 170 years that a big earthquake has not occurred in the Tehran region; thus, Tehran is a potential and dangerous location for an earthquake. In December 2017, multiple 4.5–5.5 Richter magnitude earthquakes hit Tehran city, which worried many organizations such as the Iranian Blood Transfusion Organization (Sabzehchian et al., 2006). Iranian Blood Transfusion Organization (IBTO) is the only organization responsible for transfusing blood (Cheraghali, 2012; Khalilpourazari & Khamseh, 2019). IBTO is responsible for (i) developing standards for blood transfusion. (ii) planning for blood collection and distribution and (iii) conducting tests on donated blood. One of the main concerns of the IBTO is to construct an effective supply chain in Tehran. One of the main reasons for this concern is that multiple 4.5–5.5 Richter magnitude earthquakes hit Tehran in 2017. Therefore, to handle this issue, this paper aims to implement the proposed robust transportation-location-inventory-routing model on real data from Tehran city. To implement the mathematical model, 22 donor groups are considered in this research, each representing the blood donation capacity of each region. The average blood donation rate is considered to be 22.05 per 1000 people, and an average of 13 percent deferral rate is considered to take into account that some donors are rejected due to medical and safety reasons (Jabbarzadeh et al., 2014). The geographical coordinates of the donors and maximum blood donation are presented in Khalilpourazari and Khamseh (2019), Khalilpourazari et al. (2020). We note that some data in the current case study has been derived from other papers (Ghorashi et al. 2019; Khalilpourazari & Khamseh 2019; Khalilpourazari et al. 2020). Most of the blood demand of Tehran's hospitals is satisfied

by three main IBTO's blood centers. These centers are the most important blood centers of Tehran city, including IBTO north blood center, IBTO east center, and IBTO central blood center. Detailed information about the capacity of these centers is presented in Table A1 in the supplementary material. We note that two of these centers are presented in Ghorashi et al. (2019). Also, a graphical presentation of the location of the blood centers is given in Figure A1 in the supplementary material.

Since the demand occurs in hospitals, this research considers the seven largest hospitals of Tehran city as demand locations. Detailed information about geographical coordinates and the location of the hospitals are presented in Table A2 and Figure A2 in the supplementary material. We note that some of the data are derived from Ghorashi et al. (2019).

As mentioned earlier, we consider two types of transportation, including ambulances and helicopters. The capacity of ambulances and helicopters is 100 and 300 units, respectively. The travel time and cost between collection centers and blood banks using standard ambulances and helicopters are calculated using this information. To deliver the collected blood from blood centers to hospitals, homogenous ambulances with limited capacity are considered. This is because to implement the model on a larger scale, blood collection centers and blood centers are most likely to be far from each other, and the blood centers are most likely to be close to demand points (hospitals). To make this situation clear, consider that a severe earthquake occurs in a particular city. Regional blood centers call for an emergency blood supply to satisfy the blood request. Then, in many cities around the country, blood collection centers collect blood from donors and then send the collected blood to blood centers in the disaster zone. Then, the collected blood is distributed among hospitals in the disaster area. Due to the lack of precise information about blood demand after a severe earthquake in Tehran city, the blood demands of the hospitals are estimated using the information given in the literature. Detailed information about the case study data is presented in Tables A3-A8 in the supplementary material and in Khalilpourazari and Khamseh (2019); Ghorashi et al., (2019); Khalilpourazari et al., (2020).

It is worth mentioning that the blood holding cost at each period in each blood center is considered to be \$1 (Jabbarzadeh et al., 2014). Considering the Iranian Seismological Center (ISC) report, the Karaj Eshtehard fault is activated and is one of the most probable locations for an earthquake. In December 2017, two earthquakes with 5.2 and 3.2 magnitudes occurred in the Eshtehard fault. These significantly increased worries about a big earthquake in Tehran. Therefore, we assume that a 7.2RM earthquake has occurred on the southern fault of Tehran city.

Since usually in Multi-Objective Optimization (MOO) models, the objective functions conflict, a sole answer cannot be suggested. As a replacement, a set of solutions can be provided. First, we implement the real data on the deterministic model to show the conflicting objectives. To do so, each objective is optimized separately.

We used the e-constraint method to find the Pareto optimal solutions for the problem because there are more than one objective functions in the mathematical model, and they cannot be optimized simultaneously. To do so, we need to apply lexicographic or Multi-Objective Decision Making (MODM) methods such as e-constraint to solve the model and determine the Pareto optimal sets for the problem. It should be noted that the objectives, including minimizing the total cost and the total transportation time, are conflicting because their individual optimal solutions are not the same. This is because when minimizing the cost function, the solution uses the cheapest (slower) transportation mode; however, when optimizing the second objective, it uses the more expensive (faster) transportation mode to deliver the collected blood to demand points. Therefore, there is no single optimal solution that could optimize both objectives at the same time which means that the objectives are in conflict.

Table 2 Pareto solutions of the deterministic model

	Z1	Z2
Optimal_Z1	42,554.43	440.612
Pareto_Sol_1	42,559.90	412.962
Pareto_Sol_2	42,970.65	381.203
Pareto_Sol_3	43,859.82	352.864
Pareto_Sol_4	75,074.93	319.321
Pareto_Sol_5	86,210.30	317.807
Pareto_Sol_6	134,725.5	308.275
Pareto_Sol_7	136,402.2	307.245
Pareto_Sol_8	160,775.5	305.659
Pareto_Sol_9	302,844.4	304.927
Optimal_Z2	450,312.1	300.998

Therefore, using the e-constraint approach, nine Pareto solutions are calculated. Table 2 offers the outcomes. Based on the outcomes, it becomes apparent that the objectives conflict since they are not optimized simultaneously. To assess the performance of the uncertain models, the data are applied to all formulations. Consider specific parameter d, to produce a fuzzy version of this parameter; we use $d\_fuzzy = (d(p) = 0.7 * d, d(m) = 1.0 * d, d(o) = 1.3 * d)$ where d is considered to be the defuzzified value of d_fuzzy.

In the following, the two uncertain models are resolved. For this purpose, the FFCCP model is solved at three confidence levels, including 0.9, 0.8, 0.7. Then, the efficiency of the solutions provided by FRFCCP and FFCCP (0.9, 0.8, 0.7) models are evaluated in eleven realizations. For each realization, the solutions provided by models are replaced in the realization formulation as follows:

$$Min\ Z = c^{real}x^* + f^{real}y^* + p_1 K_1 + p_2 K_2,$$
$$s.t.\ Gx^* + K_2 \geq d^{real},$$
$$Bx^* = 0,$$
$$Dx^* \leq S^{real}y^* + K_1,$$
$$Ix^* \geq 0,$$
$$Vx^* \leq 1,$$
$$K_1, K_2 \geq 0 \tag{36}$$

where K_1 and K_2 are variables, and p_1 and p_2 are penalty values for infeasible solutions by the models in different scenarios. Table 3 shows the results of eleven realizations in different scenarios.

The outcomes of Table 2 indicate that the FRFCCP delivers robust solutions compared to the solutions offered by FFCCP through meaningfully lower costs. The suggested robust formulation benefits from various advantages over other formulas. First, it considers the worst case of the objectives. Therefore, it offers solutions robust to variations in uncertain parameters. Second, considering penalties to violations in the FRFCCP, we observe that the solution of the robust model is always feasible.

Consequently, the FRFCCP will offer the best solution with the lowest cost and time in diverse situations even in the worst cases. Figure 2 offers a visual assessment of the outcomes.

Table 3 Results of eleven realizations

Realization	FRFCCP	FFCCP 0.7	FFCCP 0.8	FFCCP 0.9
1	50,454.83	54,529.2	61,686.25	61,901.23
2	53,535.26	58,370.71	68,245.42	69,220.24
3	52,938.96	57,623.08	68,860.41	69,683.59
4	51,691.4	56,070.4	64,738.1	65,257.09
5	54,727.86	59,865.97	69,135.45	70,413.55
6	53,546.25	58,382.19	69,315.88	70,290.88
7	53,546.25	911,382.2	733,715.9	266,290.9
8	53,535.26	911,370.7	733,705.4	266,280.2
9	52,927.97	910,611.6	733,250	265,672.9
10	52,960.94	910,646	731,161.3	263,584.9
11	506,490.9	1,631,982	1,214,116	906,490.9
Average	**94,214.17**	510,984.9	413,448.2	215,916.9
median	**53,535.26**	59,865.97	69,315.88	70,413.55
Std Dev	**130,377.7**	533,491.5	401,093.8	237,106.8

Based on the outcome, we conclude that first, the FRFCCP model performs significantly better than the FFCCP models. Second, the performance of the FFCCP model, at different confidence levels, significantly differs from each other.

The results presented in Fig. 2disclose that the values of the uncertain parameters in different realizations significantly affect the performance of the FFCCP models. If most uncertain parameters take values to make the model less conservative, then the FFCCP 0.7 would perform the best since it is a less conservative model. However, as the values of the uncertain parameters move toward worst cases, we observe that the FFCCP 0.9 performs better because it is a more conservative model. It is worth mentioning that we do not observe such extreme variations in the performance of the FRFCCP model due to the optimality and feasibility robustness considerations in the objective function of this model. Based on the outcomes, we observe that the average, the standard deviation, and the median of the
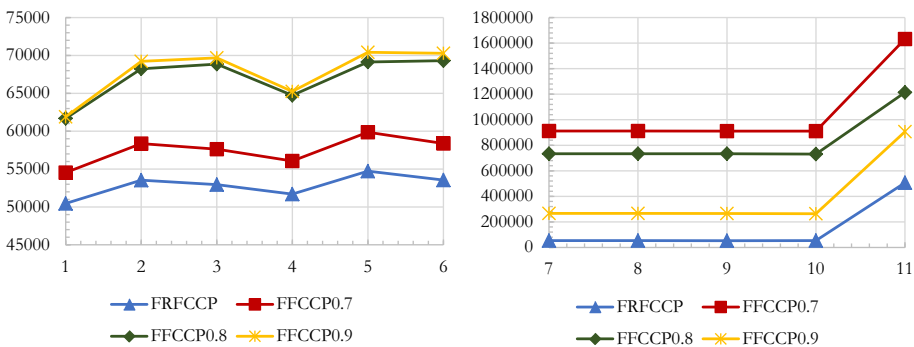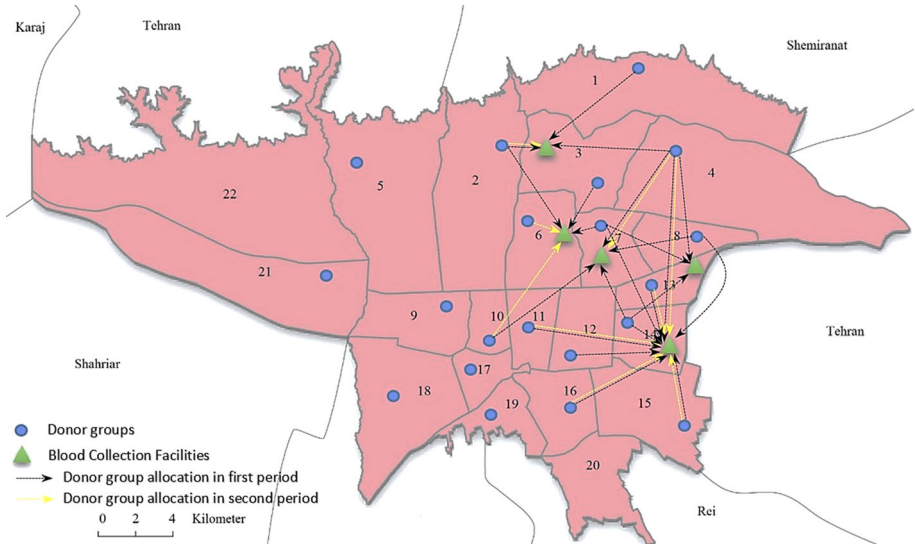

Fig. 2 A schematic view of the realizations

Fig. 3 Solution of the FRFCCP model- allocation and transfusion stages

objective function value in the FRFCCP model are significantly lower than those of FFCCP models.

Although the results mentioned above display that the FRFCCP is an efficient method in formulating uncertainties, more analyses are needed to highlight the significance of the results. By evaluating detailed information about the values of the decision variables in the FRFCCP and FFCCP models, important managerial insights can be derived.

By solving the FRFCCP model (results are shown in Figs. 3, 4 and 5), we observe that fixed collection sites are established at districts 3, 6, 7, 14, and a temporary blood collection facility (blood collection bus) is located at district 13. As is shown in Fig. 3, selected blood collection facilities are located to ensure decentralization. This orientation has several advantages. First of all, the collection sites are spread over the region, increasing the robustness of the network. Consider a change in the destruction radius. In that scenario, if the blood collection centers are close to the destruction zone, no blood collection center would survive the disaster. However, by locating blood collection facilities far from each other, the FRFCCP model aims to decrease the earthquake's impact on supply chain performance. Second, as mentioned earlier, the blood supply of the donor groups is approximated based on several factors, such as population. It can be seen in the results of the FRFCCP; the model has established collection centers in the most populated regions of the city. This way, the FRFCCP model minimizes total costs. As is presented in Fig. 4, IBTO's central and east blood centers are chosen to satisfy the demand of the hospitals. Considering two crucial notes, the accuracy and validity of the proposed FRFCCP model are ensured. First, the selected blood centers are close to blood collection centers and donor groups, which minimizes the total costs and delivery time. Second, IBTO's central blood center has an excellent location among hospitals. So, it could easily send blood to the hospitals. This can significantly decrease the total delivery time in an emergency. One important managerial insight obtained from the results is that the IBTO's central blood center plays a prominent role in the supply chain. So, its availability after a destructive earthquake is of great importance. Increasing its reliability and storage capacity and providing a sufficient
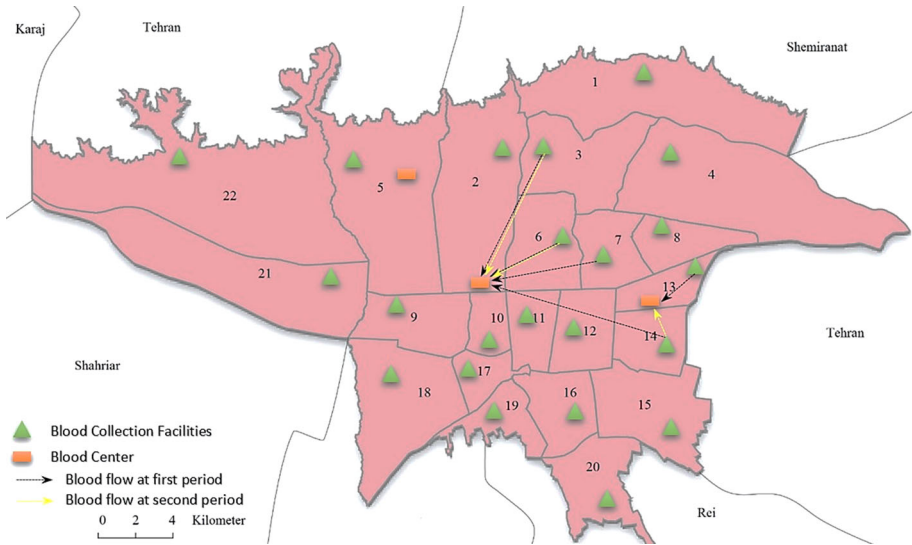
Fig. 4 Solution of the FRFCCP model- transfusion stage
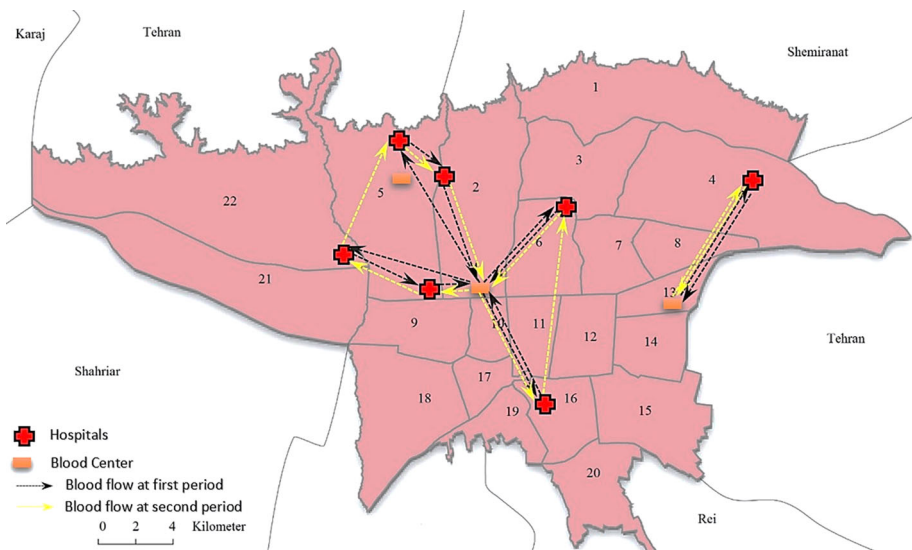

Fig. 5 Solution of the FRFCCP model- blood transfusion and routing stage

number of ambulances are vital to this center. We note that based on the results of the FRFCCP model, it is determined that two ambulances are needed at each fixed collection site. Besides, a single ambulance is enough at district 13, where a blood collection bus is located. The blood inventory level in the blood centers at the end of the first 24 h (first period) are determined to be 53 and 28 units, respectively. The best routes determined by solving the FRFCCP model to deliver blood to demand points are shown in Fig. 5.

From the results, it is clear that the IBTO's central blood bank could satisfy the demand of six of the hospitals in both periods. IBTO's east blood center is the only center responsible for sending blood to Alghadir hospital. The results indicate that at least two ambulances are needed in the IBTO's central blood center since two delivery routes are established. The length of the two routes is similar, ensuring the minimum delivery time of blood to the hospitals. Although it is shown that the FRFCCP could design an efficient network, however, it should design a robust network that is resistant to variations in the main parameters. In the following, we evaluate the performance and efficiency of the proposed FRFCCP model against the FFCCP models in more detail. To make challenging situations for both models, we consider the most essential three parameters of the proposed mathematical model, including, dis_j, cov, and m_i. Any significant change in these parameters may influence the efficiency of the models. To evaluate the FRFCCP and FFCCP models under critical situations, we change the values of these parameters at different stages and check the performance of the proposed solutions. In other words, the case study is solved one time by FRFCCP and FFCCP models, and we evaluate the efficiency of the proposed solutions in different scenarios. We call this worst-case analysis since we focus on the worst scenarios. In the following, three main parameters are considered. Then, the value of each parameter in the case study is increased/decreased, and the effectiveness of FRFCCP and FFCCP models is evaluated in those worst scenarios. Table 4 presents the results of realizations in worst-case scenarios. Please note that these variations are beyond the corresponding boundries of the fuzzy values of these parameters.

Table 4 Worst case analyses of FRFCCP and FFCCP

Parameter	Change (%)	FRFCCP	FFCCP 0.7	FFCCP 0.8	FFCCP 0.9
dis_j	+ 40	73,738.104	101,070.398	75,191.398	74,257.089
	+ 30	62,691.398	67,070.398	64,738.104	65,257.089
	+ 28	57,691.398	62,070.398	64,738.104	65,257.089
	+ 27	52,691.398	57,070.398	64,738.104	65,257.089
	+ 20	51,691.398	56,070.398	64,738.104	65,257.089
	0	51,691.398	56,070.398	64,738.104	65,257.089
cov	−40	86,691.398	229,070.398	207,738.104	88,257.089
	−35	51,691.398	157,070.398	129,738.104	76,257.089
	−30	51,691.398	92,070.398	76,738.104	66,257.089
	−28	51,691.398	73,670.398	65,938.104	65,257.089
	−27	51,691.398	67,670.398	64,738.104	65,257.089
	−25	51,691.398	58,070.398	64,738.104	65,257.089
	0	51,691.398	56,070.398	64,738.104	65,257.089
m_i	−30	51,691.398	909,070.398	729,138.104	261,257.089
	−28	51,691.398	582,470.398	396,938.104	65,257.089
	−27	51,691.398	419,170.398	230,838.104	65,257.089
	−25	51,691.398	165,070.398	64,738.104	65,257.089
	−20	51,691.398	56,070.398	64,738.104	65,257.089
	0	51,691.398	56,070.398	64,738.104	65,257.089

The first parameter is dis_j, this parameter shows the destruction radius. This paper assumes that the earthquake could disrupt the supply chain by destroying the blood collection. To investigate how a significant increase in earthquake magnitude could affect the supply chain, the destruction radius of the earthquake is increased at different percent rates, and the objective function value of the FRFCCP and FFCCP models is calculated and reported in Table 4.

Although estimating the destruction radius of an earthquake before its occurrence is possible, it significantly depends on many factors, such as soil type. Thus, uncertainty in the destruction radius of an earthquake is inevitable.

As is evident, in 0% change, the results show that without making any changes to values of the uncertain parameters, the robust model performs significantly better than the FFCCP model by providing much lower supply chain costs. By increasing the destruction radius up to 20% (which means the destruction radius is now $25 + 0.2*25 = 30$ km), all models perform the same. This means that all models are risk-averse and robust at this level. At this level, no change was expected due to the basics of the models. In the second stage, the destruction radius is increased by + 27%, resulting in an earthquake with a 32.5 km destruction radius. This change affects the solution provided by FFCCP 0.7 and increases its overall costs to $57,070.398. Using the realization model, the solution of the FRFCCP model results in a network with $51,691.398 cost, and the FFCCP 0.9 model results in $65,257.089 cost for supply chain network design. In other words, in this situation, the FRFCCP model can still provide much better solutions with lower costs.

This is because the FRFCCP model considered the worst case of the parameter dis_j. Again, by increasing the destruction radius by + 40 percent, the FRFCCP provides much lower costs for the designed supply chain.

Note that this situation is very critical. Since the worst case of dis_j parameter in the case study was considered equal to 1.3*(its deterministic value), thus increasing the value of this parameter by + 40 percent goes far beyond considered uncertainties in the model and challenges the solutions provided by the models. Figure 6 presents the results of realizations by increasing the destruction radius of the earthquake.

These analyses prove that FFCCP 0.9 aims to provide risk-averse solutions than FFCCP 0.7. Although the FFCCP model performs well, the FRFCCP model provides significantly better solutions at a lower cost. Thus, the FRFCCP model performs robustly in the worst case

Fig. 6 Worst-case analyses of FRFCCP and FFCCP on dis_j parameter
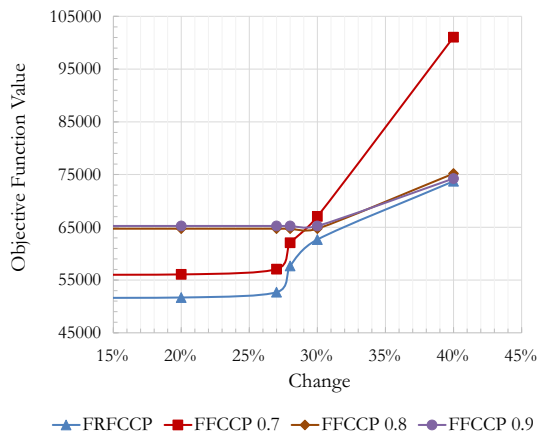

Figure 6: Worst-case analyses of FRFCCP and FFCCP on   parameter.

of this parameter. The second parameter, which is considered in the worst-case analyses, is *cov*. After a destruction earthquake, the coverage radius may be reduced for different reasons. Debris from destroyed infrastructures, traffic, blocked roads, and streets are the most common factors that could significantly reduce the coverage radius. Therefore, it is vital to consider the worst situation when the coverage radius is condensed and see how the solutions provided by FRFCCP and FFCCP models respond. For this aim, this parameter is reduced by different percent rates, and the efficiency of the provided solutions is evaluated. Considering the results given in Table 4, by reducing the coverage radius by -25 percent, both solutions provided by FRFCCP and FFCCP 0.8 and 0.9 perform the same as when no change has occurred. However, FFCCP 0.7 responds very poorly to this variation and results in significantly higher costs. In this situation, the FRFCCP model performs significantly better by providing an emergency blood supply chain network, which costs $51,691.398, compared to FFCCP, 0.8, and FFCCP, 0.9. In the second scenario, we decrease the coverage by −27 percent. In this case, the solution provided by the FRFCCP is still robust to variations in this parameter. However, the answer provided by FFCCP 0.7 turns out to be infeasible, and the total cost provided by this model results in a higher cost equal to $67,670.398.

In the other scenarios, we decrease the coverage from −28 to −40 percent. In this situation, the solution of FFCCP 0.8 turns out to be slightly infeasible at 28 percent, and the solution provided by FFCCP 0.9 becomes infeasible at a −30 percent decrease in *cov*parameter. Conversely, the FRFCCP model is resistant to even −35 percent change, which is beyond considered uncertainties. To make the scenarios much worst, *cov*parameter is decreased by −40 percent where the FRFCCP, FFCCP 0.7, FFCCP 0.8 and FFCCP 0.9 result in blood supply chains with $86,691.398, $229,070.398, $207,738.104, $88,257.089 costs, respectively. Therefore, the FRFCCP is the best and most robust model for handling uncertainties in this parameter and provides promising solutions. A schematic view of the results is given in Fig. 7. As is shown in Fig. 7, by decreasing the coverage radius by -40 percent, the solution of the FRFCCP starts to become infeasible, which increases the total costs. On the other hand, the solution provided by the FFCCP model has the same situation. However, the FRFCCP is more robust than the FFCCP model since it results in lower costs.

In the last part, we consider variations in m_i parameter that determines the maximum blood supply of donor groups. The blood supply of donor groups could significantly vary due to the lack/limitation of blood collection equipment, people's participation in blood donation (i.e., in a pandemic), and traffic. Therefore, it is vital to consider this worst situation when the blood supply significantly decreases from the forecasted value. To examine the efficiency of

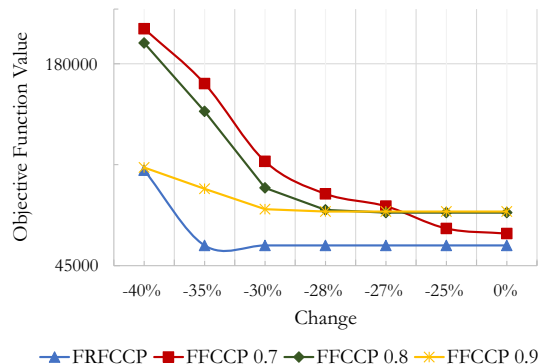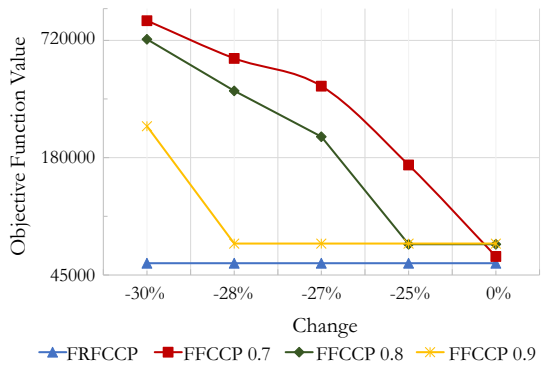**Fig. 7** Worst-case analyses of FRFCCP and FFCCP on *cov*parameter

Fig. 8 Worst-case analyses of FRFCCP and FFCCP on m_i parameter

the FRFCCP and FFCCP models in these situations, the value of the maximum blood supply of the donor groups is reduced by different percent rates. Considering the results given in Table 4, by reducing the supply parameter by -20 percent, all the models perform robustly, but the FRFCCP model provides the lowest costs. By decreasing the m_i parameter by -25 percent, the solution provided by FFCCP 0.7 becomes infeasible and results in a supply chain with a \$165,070.398 cost. The solutions provided by FFCCP 0.8 and FFCCP 0.9 become infeasible at -27 and -30 percent rates, respectively. However, the solution provided by the FRFCCP model remains unchanged and results in significantly lower costs than the FFCCP model. Figure 8 presents a graphical representation of the results. As a conclusion, the analyses revealed that:

- IBTO's central blood center plays a significant role in the supply chain. Thus, its reliability, safety, and availability should be increased in order to establish a robust blood supply chain in Tehran city.
- The results indicate that the collection hubs at 3, 6, 7, 14 districts play a prominent role in the blood supply chain. Therefore, their reliability and availability should be increased.
- At least two ambulances are needed in the permanent blood collection centers.
- At least two ambulances are needed in IBTO's central blood center and one ambulance at IBTO's east blood center.
- The FRFCCP model is able to design a robust blood supply chain resistant to variations in critical parameters.
- Worst case analyses revealed that the FRFCCP model is robust to variations in cov parameter up to -35 percent. However, a -40 percent decrease in cov parameter can increase the cost and delivery time.
- Worst case analyses revealed that the solution of the robust model remains resistant to up to $+40$ percent increase in the destruction radius of the earthquake and provides the lowest cost for the problem.
- Worst case analyses revealed that the solution of the robust model remains resistant to up to -30 percent decrease in m_i parameter, which is an outstanding performance compared to the FFCCP model.
- Enough storage equipment should be available at IBTO's central and east blood centers since they may stock donated blood to meet the subsequent periods' demand.

5 Conclusion and future directions

This study offered a novel mathematical model for blood supply network design in emergencies. The model considered several new assumptions compared to existing literature. For the first time, a Transportation-Location-Inventory-Routing (TLIR) model was introduced for designing an efficient blood supply chain network. The goal of the proposed model was to make decisions at strategic, tactical, and operational levels to establish the blood supply chain. Two blood transportation means were used to determine how to deliver the collected blood to facilities in a cost-efficient and timely manner. Besides, the new model aimed at determining the best routes to deliver blood to the demand points. In order to take the disruption into account, we considered the effect of the earthquake on the availability and capacity of the facilities. Moreover, we considered the blood shelf-life to develop a realistic model for the problem.

Since most of the main parameters of the model are under uncertainty in the real world, we used two approaches, including Flexible Robust Fuzzy Chance Constraint Programming (FRFCCP) and Flexible Fuzzy Chance Constraint Programming (FFCCP), to obtain risk-averse and resistant solutions for the problem. We applied the proposed models to a case study in Tehran, Iran. After the solution of the case study using the FRFCCP model and the FFCCP model under three different confidence levels, different solutions were obtained. Under various scenarios and realizations, we showed that the FRFCCP model is able to handle uncertainties more efficiently and could lead to a solution that has significantly lower cost and delivery time. Furthermore, the results indicated that the IBTO's central blood center plays a prominent role in the blood supply chain, and its availability after a severe earthquake is essential. The results indicated that the FRFCCP model resulted in a total cost of \$94,214.17 compared to \$510,984.9, \$413,448.2, and \$215,916.9 for FFCCP (0.7), FFCCP (0.8), and FFCCP (0.9), respectively, which is 81%, 77%, and 56% better in terms of the total costs.

We performed a series of worst-case analyses to compare FRFCCP and FFCCP models in terms of robustness. The results showed that the FRFCCP model is robust to any increase in dis_j parameter up to + 40%, and cov up to −40% and m_i up to −30%, where FFCCP models could not perform well in these variations and resulted in significantly higher cost and delivery time. Based on the results, we showed that the FRFCCP model was able to handle uncertainties very efficiently and provided risk-averse solutions for the problem. In the first worst-case scenario, we reduced the blood donation by 30%, and the total cost of the supply chain obtained by FRFCCP increased by 0% compared to 1658%, 1310%, and 405% by FFCCP (0.7), FFCCP (0.8), and FFCCP (0.9), respectively. In another worst-case scenario, we increased the destruction radius of the disaster by 40% and observed that the total cost of the supply chain in FRFCCP increased by 42% compared to 95%, 45%, and 43% in FFCCP (0.7), FFCCP (0.8), and FFCCP (0.9), respectively. In the third worst-case scenario, we decreased the coverage radius of collection centers by 40%, and demonstrated that the total cost of the supply chain in FRFCCP increased by 67% compared to 343%, 301%, and 70% in FFCCP (0.7), FFCCP (0.8), and FFCCP (0.9), respectively.

There are several limitations in the current research, such as ignoring the effect of queuing in blood collection facilities and the possibility of revising decisions dynamically based on the most revealed information. For future research, it is worthwhile to investigate the effect of these two factors in the blood network design problem. This will help us have a realistic estimate of the number of required servers and blood collection facilities. In addition, it is interesting to provide efficient solution methodologies for the problem in order to solve the problem in large instances. Presenting new methodologies to obtain the Pareto optimal set for the problem is another research direction.

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