Applied Soft Computing 112 (2021) 107821

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A novel capacity sharing mechanism to collaborative activities in the blood collection process during the COVID-19 outbreak

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ARTICLE INFO

Article history:
Received 29 May 2021
Received in revised form 7 August 2021
Accepted 10 August 2021
Available online 13 August 2021

Keywords:
Blood supply chain
COVID-19 outbreak
Capacity sharing concept
Two-stage optimization tool
Mixed uncertainty approach
Rolling horizon planning

ABSTRACT

Because of government intervention, such as quarantine and cancellation of public events at the peak of the COVID-19 outbreak and donors' health scare of exposure to the virus in medical centers, the number of blood donors has considerably decreased. In some countries, the rate of blood donation has reached lower than 30%. Accordingly, in this study, to fill the lack of blood product during COVID-19, especially at the outbreak's peak, we propose a novel mechanism by providing a two-stage optimization tool for coordinating activities to mitigate the shortage in this urgent situation. In the first stage, a blood collection plan considering disruption risk in supply to minimize the unmet demand will be solved. Afterward, in the second stage, the collected units will be shared between regions by applying the capacity sharing concept to avoid the blood shortage in health centers. Moreover, to tackle the uncertainty and disruption risk, a novel stochastic model combining the mixed uncertainty approach is tailored. A rolling horizon planning method is implemented under an iterative procedure to provide and share the limited blood resources to solve the proposed model. A real-world case study of Iran is investigated to examine the applicability and performance of the proposed model; it should be noted that the designed mechanism is not confined just to this case. Obtained computational results indicate the applicability of the model, the superior performance of the capacity sharing concept, and the effectiveness of the designed mechanism for mitigating the shortage and wastage during the COVID-19 outbreak.

1. Introduction

A disaster is an event that happens quickly and whose result may escalate the severity level of routine situations; it stops society from daily routines and causes damages to economies, life, and the environment. Disaster management includes the preparedness of operations before, during, and after the disaster strike to mitigate its detrimental impacts [1]. An epidemic outbreak as a kind of disaster makes a significant interruption at all levels of healthcare systems, and prerequisites of all operations need to be adapted quickly in response to changes in this condition [2]. The newfound disruptive virus called COVID-19 has triggered the sharpest slump in the past few decades and causing immense hurt to people's health and businesses [3]. This outbreak, which was first reported in December 2019 in Wuhan, China, has already spread through almost all countries worldwide. COVID-19 is spread rapidly and effectually, and the infected person transmits the disease to two or three more people on average [4]. Based on the WHO report, 197,237,527 confirmed COVID-19 cases, and 4,211,702 deaths were reported till July 2021 [5].

An epidemic outbreak usually lowers the blood supply and adversely affects blood supply network (BSN) activities. Blood activities should plan and given to patients proportionately and adequately. Monitoring blood supply and demand to mitigate the shortage is assumed primary BSN activity during the epidemic outbreak [6]. Therefore, coordination among all managers and beneficiaries in BSN should be performed to support blood availability and its by-products for patients. A decrease in blood donation before, during, and after an outbreak is a significant risk. Therefore, decision-makers should have an appropriate plan for a suitable response during the epidemic outbreak [7]. Collaboration among blood systems decision-makers to control the inventory level to mitigate shortages helps create a balance between supply and demand. Hence, BSN members need to be connected and healthcare professionals responsible for transfusion activities to ensure that blood is used in a clinically fitting way [8].

On 19 February 2020, the first positive case of COVID-19 was confirmed in Iran. Then, the disease spread quickly throughout the country [9]. In this situation, one of the main challenges for healthcare system managers is the healthy donation of blood by donors in an epidemic time, ensuring staff and blood donors'

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https://doi.org/10.1016/j.asoc.2021.107821
1568-4946/

safety, and providing a sufficient blood supply. Accordingly, the countries need an emergency vision to plan, manage, and control the supply of blood and its by-products. For these reasons, the IBTO (Iranian Blood Transfusion Organization) suffered from a fall in blood donation rate [10–12]. Due to the dynamic nature of peak outbreaks in different regions of the country, some blood collection centers in regions in the non-peak time of the outbreak (white status) can collect the blood more than the demand. Otherwise, some blood collection centers in other regions in the peak time of the outbreak (red status) may be faced a decrease in the number of donors simultaneously. Therefore, IBTO should consider the tradeoff between shortage and leftover capacity in blood supply in different regions. In this regard, the capacity sharing concept and transshipment strategy between regions is a practical approach that can enhance the BSN's flexibility.

According to the above-mentioned explanation, the main aim of this study is to develop an analytical approach by presenting a mathematical formulation for BSN management during the COVID-19 outbreak, taking into account the particular characteristics of blood such as perishability, demand uncertainty, various collection methods, and disruption risk in blood supply. The proposed approach in this study has excellent potential for making the appropriate decision on the blood collection process in different regions with different statuses of the COVID-19 outbreak. Also, the capacity-sharing strategy between regions at the peak of the outbreak can mitigate the blood shortage and wastage in this urgent situation. Accordingly, this study aims to provide a collaborative mechanism in BSN to coordinate activities between regions to mitigate the shortage in this network. Motivated by a real case study in Iran, this study tries to recommend the appropriate answer to the following main research questions:

- Which approach should be adopted to mitigate the blood shortage, especially at the peak of the outbreak?
- What policy should be considered in regions for blood collection procedures at the peak and non-peak times of the outbreak?
- What strategy should be applied for blood sharing between regions when the actual demand is realized in each period?
- Which policy should be used to deal with disruption and operational risks in blood supply and demand during the outbreak?

In this paper, to answer the first question, we utilize mathematical optimization programming to model BSN activities to coordinate the blood banks for collecting blood units from donors to mitigate shortages. To answer the second question, we develop a novel mechanism based on a two-stage optimization tool. In the first stage, blood collection centers try to collect the blood from donors as much as possible, and in the second stage, blood centers are coordinated to share the blood units between regions to respond to the demand of health centers. To answer the third question and dynamic nature of this network, by applying a capacity sharing concept, the sharing process between regions will be done. For avoiding the level of wastage and shortage, the proposed model will be solved by a rolling-horizon strategy. Finally, to answer the last question, we propose a novel mixed possibilistic-flexible programming method to cope with uncertainty (operational risk), and a new strategy is also devised to deal with disruption risk in this network. To the best of our knowledge, this study is the first research in BSN literature that proposes a novel real case-based collaborative mechanism to coordinate blood collection activities between regions in the outbreak of COVID-19. The main contributions of this study that differentiate it from previous studies are provided as follows:

- Developing a medium-term plan to manage the blood collection process during the outbreak of COVID-19 by applying transshipment between regions to mitigate the fluctuation of demand and supply, especially at the peak of the outbreak;
- Proposing a novel two-stage optimization tool combining mixed uncertainty approach and rolling-horizon strategy to tackle the uncertain and dynamic essence of BSN;
- Applying a reactive model to update the collection planning for fulfilling the blood shortage in regions in the peak time of the outbreak;
- Selecting a real-world case study of Iran to evaluate the practicality of the proposed model in collaboration with IBTO;
- Some useful managerial insights are concluded by implementing our collaborative mechanism for a real-life case study.

This study is organized as follows. Section 2 provides a systematic background on BSN. Section 3 extends this study using mathematical formulations and methodology for managing the concerned BSN is proposed in Section 4. The practicality of the proposed methodology by a real case study is dedicated to Section 5. The computational results and sensitivity analysis of this study are provided in Section 6. Section 7 provides research implications and future directions, and finally, Section 8 presents the final remarks of this study.

2. Related literature

The study of BSN came to interest in recent years. Regarding the review paper by Beliën and Forcé [13], the studies published up to 2012 are conducted based on several perspectives, such as hierarchical level, solution methodology, performance measures, the problem, and methodology types, and practical implementation. Another review paper on BSNs is provided by Osorio et al. [14], which organized the papers published between 2012 and 2017 based on BSNs echelons: collection, production processes, inventory control, distribution, and integrated models. Also, Pirabán et al. [15] updated the literature review of BSN papers focusing on issues in the design of the BSNs, planning decisions, operational processes, modeling, solution methodologies, and data characteristics, published between 2005 and February 2019, to find the possible gaps. Overall, the main focus of the current study is on blood collection strategy during the COVID-19 disaster. Therefore, the related literature can be divided into two main categories: BSN in disaster conditions and blood collection management. Consequently, we address these two categories separately in the following related literature. First, in Section 2.1, a targeted review on BSN in the disaster condition is provided. Then, in Section 2.2, a review on blood collection management in BSN is presented. Also, a comprehensive review on BSN in disaster and normal situations in recent years is provided and presented in Table A.1 in Appendix.

2.1. BSN in disaster condition

Several studies in the literature investigated BSN management under disaster conditions. Sha and Huang [16] have developed a multi-period location–allocation mathematical formulation for emergency blood supply to minimize the total transportation cost, reposition cost of temporary facilities, and punishment cost (the penalty cost for unfulfilled demand). They rendered a Lagrangian relaxation-based algorithm to solve the proposed mixed-integer programming model. The applicability of their proposed model was illustrated by implementing a real case in

Beijing. In another effort, Fahimnia et al. [17] developed a mathematical model for blood collection in disaster using a bi-objective two-stage stochastic mathematical formulation. Total network cost and the average delivery time are minimized over multiple planning horizons, and the ε-constraint and Lagrangian relaxation methods are applied to solve the proposed model. Habibi et al. [18] addressed a bi-objective robust model for the multi-echelon BSN in disaster relief cases, aiming to reduce the total cost and shortage. The authors handled the plurality of objective functions by employing a goal programming method. Also, they tested the performance of the proposed model through a real-world case study. In another study, Samani et al. [19] presented a mixed-integer multi-objective model to design and plan for BSN in a disaster condition. They did a tradeoff between total network cost, perishability, and reliability of blood facilities. A mixed two-stage stochastic-possibilistic approach is tailored to handle the uncertainty of the parameter. A real data study from Mashhad city in the northwest of Iran is applied to explore the model applicability.

Fazli-Khalaf et al. [20] proposed a mixed possibilistic-flexible robust model for designing an emergency BSN. Their model aims to minimize the total cost of the network and the total time transportation between blood facilities and maximize the collected blood reliability. In another study in the context of disaster, Fereiduni and Shahanaghi [21] proposed a robust optimization model for controlling BSN after a striking natural disaster. Their model aims to minimize the total network cost and find the allocation pattern, location, and blood distribution decisions for a multi-period planning horizon. In another effort, Ma et al. [22] proposed a blood supply chain to find an optimal blood allocation strategy after striking disasters assuming blood group compatibilities. The computational results revealed that the concept of blood compatibility singularly enhances network efficiency. also, they used a greedy heuristic algorithm for solving the proposed mathematical model in large-size instances. Khalilpourazari and Khamesh [23] applied a bi-objective optimization model to select the optimal allocation pattern, location, inventory, and transportation decisions in the context of an earthquake event. The authors tailored multiple transportation modes, and the objectives function aim to minimize the total blood network expenses along with the delivery time of collected blood to blood centers. Sharma et al. [24] modeled a Min–Max problem to optimize the location–allocation pattern for mobile blood facilities after a disaster condition. They applied a mixed approach in which the Tabu search algorithm fixes the location of mobile blood facilities. The priority of locations for mobile blood facilities is determined by using the Bayesian belief network.

Salehi et al. [25] developed a robust-stochastic programming model to manage a BSN in pre and post-disaster phases by considering compatibility between blood groups and safety stock in blood inventories. The first stage of the model decides on the location decisions and the safety stock level, and then blood allocation decisions are made in the second stage. In another research, Cheraghi and Hosseini-Motlagh [26] proposed a relief-based BSN, which considered the priority level of patients, equity in blood distribution, and disruption and operational risks in a disaster situation. In addition, they applied a multi-objective model to minimize the total cost and the shortage level between demand zones. There are several studies recently published that addressed the application of analytical techniques during the COVID-19 outbreak. The impact of this epidemic outbreak on different aspects of the supply chain networks is considered by several researchers such as Choi [3], Ivanov et al. [5], Arcot et al. [27], Ojha et al. [28], Raturi and Kusum [29], and Govindan et al. [1]. A review on application of operation research (OR) techniques in the COVID-19 outbreak reveals that a substantial ratio of the researchers has worked on OR techniques to analyze economic situations made by the COVID-19 outbreak in the supply chains. Due to the limited number of blood donors in this situation and the daily needs for blood and its by-products, discussing the planning and management of BSN in the COVID-19 outbreak is necessary and unavoidable. However, to the best of our knowledge, no research has addressed this issue during the COVID-19 outbreak until now. To fill this gap, due to the potentiality of OR techniques, this study seeks to apply an analytical model for the management of BSN to balance the supply and demand to mitigate the shortage during this epidemic outbreak.

2.2. Blood collection management

This subsection reviews the related literature on published papers on BSN, focusing on the blood collection process. Blood collection management is considered by Zahiri et al. [30] through a mixed-integer linear model in both strategic and tactical levels. The location of temporary blood facilities besides permanent blood centers as strategic decisions, and the allocation of donors to blood facilities and blood volume, distributed from blood facilities to demand zones in each period as tactical decisions, are determined via the proposed model. Also, data uncertainty was tackled by applying a robust fuzzy approach, and model application is evaluated by applying a real case of Babol city in Iran. Şahinyazan et al. [31] developed a bi-objective model for blood systems in the context of the selective vehicle routing problem, including bloodmobiles, shuttles, and a specific depot in which the collected blood is transferred by the shuttle at the end of each period. The model calculates both bloodmobile tours and shuttles, reduces transportation costs, and optimizes the number of collected blood. They employed a two-stage heuristic method based on integer programming for solving the proposed model in the large-size instance. The model and its solution technique are examined using real data of the Turkish Red Crescent.

In another study, Alfonso et al. [32] proposed two mathematical models, i.e., annually and weekly, for a bloodmobile collection system. The annual blood collection planning aims to ensure each region's self-sufficiency for red blood cell supply and minimize the total red blood cell supplied by other regions. The weekly blood collection planning aims to minimize total working time, including setup, collection, and transportation time. Blood donation was also estimated through a proposed model for forecasting donation based on donor availability and population. To evaluate the performance of the proposed model, they used data from the French Blood Service. Chen et al. [33] developed a dynamic programming model for a joint decision-making problem of blood collection and platelet inventory control based on different demand priorities and freshness requirements. The model's practicality is validated by the real data obtained from most countries, especially the developing ones.

Various collection approaches are evaluated by a simulation model proposed by Lowalekar and Ravichandran [34]. Both fixed and variable quantities collected by the collection policies and the donation times are assumed in the proposed study. The obtained results revealed that blood collecting as much as possible is not necessarily beneficial. Considering social aspects, Ramezanian and Behboodi [35] designed a BSN in the collection phase. The distance between donors and blood facilities, donors' experience, and advertisement in blood facilities, are assumed to formulate the donors' utility function. For modeling the stochastic nature of the parameters, a robust optimization approach is utilized. In continue, Hosseini-Motlagh et al. [36] proposed advertisement, education, and medical credits to increase the donors' utility and control the supply amount more efficiently. They applied an augmented version of the data envelopment analysis model to find the optimal location of blood collection facilities. A mixed stochastic-possibilistic robust approach is developed to cope with operational and disruption risks simultaneously. A real case study in Mashhad city in the northwest of Iran is used to validate the applicability of the proposed model.

Samani et al. [37] outlined a multi-attribute group decision-making technique to evaluate the best-fit candidate location to establish blood collection facilities based on qualitative criteria. This study presented a multi-objective model for designing an integrated BSN based on quantitative factors. Then, to deal with the uncertainty of input data, they used a robust formulation technique. Larimi and Yaghoubi [38] investigated the impact of different types of donors, the number of non-scheduled and scheduled donors, social impacts, and different production technologies on platelet donation. They developed a bi-objective stochastic-robust model to deal with the uncertainty of critical parameters. The first objective aims to minimize the total cost of the network, and the second one aims to maximize the number of delivered platelets. In another study, Ensafian et al. [39] rendered a discrete Markov chain process to evaluate the number of donors for the platelet supply network. To mitigate the shortage in this network, the possibility of ABO-RH group compatibility is considered in the model. For handling the data uncertainty, a two-stage stochastic programming model is applied. Reviewing the related literature on blood collection management in BSN reveals that no research focused on the impact of disruption risk in blood supply and using the capacity sharing concept to mitigate the shortage in disaster situations like the COVID-19 outbreak. Also, the presented study considers the fluctuations of blood demand in this situation and applying a rolling horizon planning mechanism to fulfill the demand in an efficient way.

3. Problem description and formulation

In this section, a real problem that the IBTO in the COVID-19 outbreak is considered a case study of this paper. A two-stage optimization model with a multi-period planning horizon using a rolling planning horizon approach is developed to this aim. Fig. 1 illustrates the schematic view of the proposed two-stage optimization model. As shown from this figure, there are two stages in each iteration. In the first stage, a blood collection plan in each region considering disruption risk in blood supply in the event of peak outbreak to minimize the total unfulfilled demand will be solved. In this stage, the collection procedure is tailored by the whole-blood collection mechanism. Therefore, by solving the first-stage model, the quantity of collected blood in each region in each period is determined. It should be noted that the collection procedure is planned based on the total nominal demand of regions in this stage. Then in the second stage of the model, based on sharing strategy concept, the quantity of collected blood from regions in blood collection centers is shared between central blood banks in different regions to fulfill the demand. It is worth mentioning that, due to the maximum allowable distance between blood collection centers and central blood banks, the assignment procedure is done based on the maximum coverage radius between each pair of nodes. In the second stage model, the quantity of blood units which is delivered to each central blood bank is determined based on solving the first-stage model. It can be said that the output variables of the first-stage model are specified as the input parameters for the second-stage model. In central blood banks, the collected blood units are tested to assure that they have no infectious diseases. The safe blood units are stored in the central blood banks while considering the respective shelf life and distributed to the hospitals of the regions to fulfill the demand. The second stage model aims to minimize the total delivery time and total cost of the network simultaneously. At the end of each period, by applying a rolling planning horizon approach, based on the realized (actual) demand in each region, the inventory level value of the central blood banks is updated, and make a plan for the next periods. It is worth mentioning that if the unfulfilled demand occurred in the regions based on actual demand, it should be covered by the apheresis collection mechanism.

List of sequences

The sequence of events in each period are listed below:

1. In each period, the quantity of blood collection in each region by considering disruption risk is determined;
2. Blood collection centers transport the collected units to central blood banks;
3. Central blood banks receive the collected units and kept as inventory of blood banks after the testing process;
4. The inventory level in each period uses to fulfill the demand of regions; otherwise, leftover units is transferred to the inventory of the next period;
5. If the actual demand is greater than the inventory level in each period, the demand is fulfilled by the apheresis method in central blood banks;
6. When each period ends, the inventory of each central blood bank is updated after realizing the actual demand;
7. Based on updated inventory at the end of each period in central blood banks, the collection plan is updated from next periods;

List of assumptions

The main assumptions of the first and second stage models made in this research are as follows:

- The location of blood collection centers and central blood banks are predetermined;
- The capacity of blood collection centers and central blood banks in each period is considered to be limited;
- The considered model is a multi-period problem in which each period equals one week;
- Donation of blood from each region is considered to be the supply amount of each region as it seems impracticable to plan for blood collection separately for each donor;
- As blood is a critical product for the lifesaving of patients and shortage can result in death, the quantity of shortage at the end of each period is fulfilled by the apheresis collection method. In other words, the shortage is not allowed in regions in each period;
- Both disruption and operational risk are counted in the model. Disruption risk is considered in blood supply, and the demand parameter is assumed to be uncertain. These parameters are handled according to Section 4.1 and Section 4.2, respectively.

3.1. Nomenclature

The notations used in the following model are addressed in this subsection, and then the mathematical formulation is presented.

Indices and sets

$j \in \mathcal{J}: \{1, 2, \ldots, J\}$ Set of blood collection centers;

$i \in \mathcal{I}: \{1, 2, \ldots, I\}$ Set of regions;

$k \in \mathcal{K}: \{1, 2, \ldots, K\}$ Set of central blood banks;

$l \in \mathcal{L}: \{1, 2, \ldots, L\}$ Set of shelf-life;

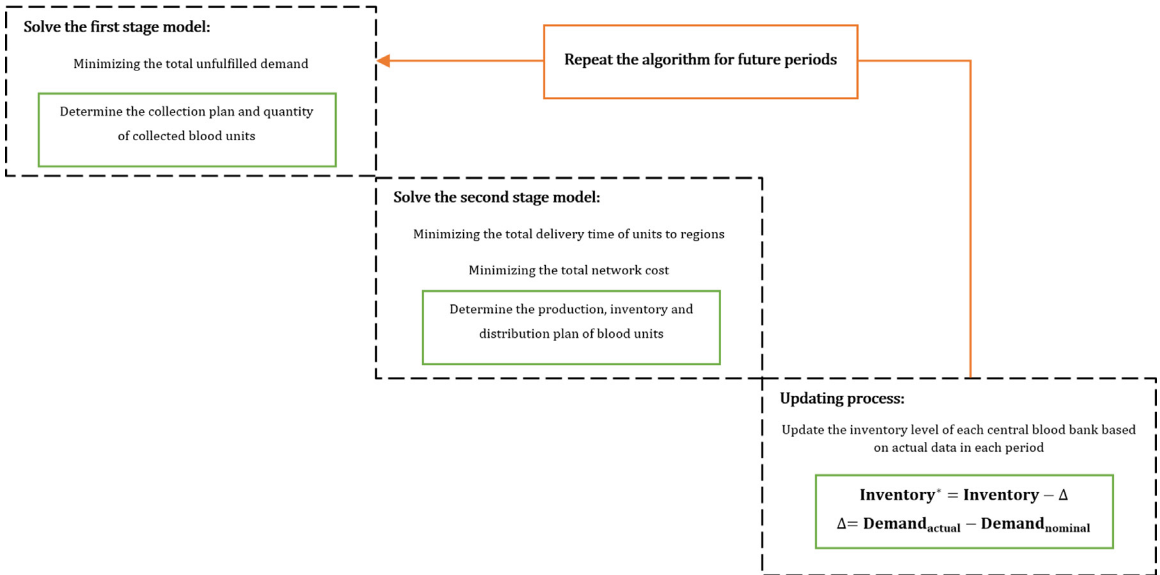

Fig. 1. The schematic of the proposed two-stage optimization tool for the concerned problem.

$t \in \mathcal{T}$: $1, 2, \ldots, T$ Set of periods;

$r \in \mathcal{R}$: $1, 2, \ldots, R$ Set of prevalence levels of COVID-19;

$s \in \mathcal{S}$: $1, 2, \ldots, T$ Set of scenarios.

Parameters

$\mathscr{p}_i$ The population of region $i \in \mathcal{I}$;

$\theta_{it}^{\min}$ The minimum blood donation rate in region $i \in \mathcal{I}$ in period $t \in \mathcal{T}$;

$\theta_{it}^{\max}$ The maximum blood donation rate in region $i \in \mathcal{I}$ in period $t \in \mathcal{T}$;

$\mathcal{C}_j$ The maximum capacity of blood collection center $j \in \mathcal{J}$;

$\mathscr{e}_k$ The maximum capacity of central blood bank $k \in \mathcal{K}$;

ζ_{ij} The distance between blood collection centers $j \in \mathcal{J}$ and region $i \in \mathcal{I}$;

ζ'_{jk} The distance between blood collection centers $j \in \mathcal{J}$ and central blood bank $k \in \mathcal{K}$;

ζ''_{ki} The distance between central blood bank $k \in \mathcal{K}$ and region $i \in \mathcal{I}$;

ξ The maximum coverage radius between blood collection centers and regions;

ξ' The maximum coverage radius between blood collection centers and central blood banks;

ξ'' The maximum coverage radius between central blood banks and regions;

λ_{irt}^{s} The available (non-disrupted) fraction of blood donation in region $i \in \mathcal{I}$ with prevalence level of $r \in \mathcal{R}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

t_{jk} The travel time between blood collection centers $j \in \mathcal{J}$ and central blood bank $k \in \mathcal{K}$;

t'_{ki} The travel time between central blood bank $k \in \mathcal{K}$ and region $i \in \mathcal{I}$;

β The historical discard rate per unit in testing and production process in central blood bank;

$\mathscr{m}_k$ The capacity of central blood bank $k \in \mathcal{K}$;

$\tilde{d}_{it}$ The demand in hospitals of region $i \in \mathcal{I}$ in period $t \in \mathcal{T}$ (uncertain parameter);

a_{jk} Transportation cost per unit from collection center $j \in \mathcal{I}$ to central blood bank $k \in \mathcal{K}$;

b_{ki} Transportation cost per unit from central blood bank $k \in \mathcal{K}$ to region $i \in \mathcal{I}$;

e Expiration cost per unit in central blood bank;

h Inventory holding cost per unit in central blood bank;

o Collection cost of blood by apheresis method in central blood bank;

$\mathscr{g}$ Collection cost of blood by whole blood method;

ρ^{s} The probability of scenario $s \in \mathcal{S}$;

$\mathcal{M}$ A very large number.

Decision variables

X_{ij} It is equal to 1; if donors' region $i \in \mathcal{I}$ is assigned to blood collection center $j \in \mathcal{J}$; and 0 otherwise;

X'_{jk} It is equal to 1; if blood collection center $j \in \mathcal{J}$ is assigned to central blood bank $k \in \mathcal{K}$; and 0 otherwise;

X''_{ki} It is equal to 1; if region $i \in \mathcal{I}$ is assigned to central blood bank $k \in \mathcal{K}$; and 0 otherwise;

Y_{ijt}^{s} Quantity of blood donated by donors' region $i \in \mathcal{I}$ to blood collection center $j \in \mathcal{J}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

Z_{jkt}^{s} Quantity of collected blood in collection center $j \in \mathcal{J}$ transferred to central blood bank $k \in \mathcal{K}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

I'^{s}_{klt} Inventory level with shelf-life of $l \in \mathcal{L}$ in central blood bank $k \in \mathcal{K}$ at the beginning of period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

I'^{s}_{klt} Inventory level with shelf-life of $l \in \mathcal{L}$ in central blood bank $k \in \mathcal{K}$ at the end of period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

I^{s}_{kt} Total inventory level in central blood bank $k \in \mathcal{K}$ at the end of period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

U^{s}_{it} Unfulfilled demand in region $i \in \mathcal{I}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

G^{s}_{kt} Expired units in central blood bank $k \in \mathcal{K}$ at the end of period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

W^{s}_{kilt} Quantity of units in central blood bank $k \in \mathcal{K}$ used to fulfill the demand of region $i \in \mathcal{I}$ with shelf-life of $l \in \mathcal{L}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$;

V^{s}_{it} Quantity of unfulfilled demand which is covered by apheresis method in region $i \in \mathcal{I}$ in period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$.

In this section, the concerned problem is modeled by applying a two-stage optimization tool in Sections 3.2 and 3.3.

3.2. First stage model

In this subsection, the mathematical model is formulated to present the first stage decisions discussed earlier in this paper.

$$\min \sum_{s} \rho^{s} \sum_{i,t} U^{s}_{it} \tag{1}$$

subject to

$$X_{ij}.\zeta_{ij} \leq \xi \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} \tag{2}$$

$$Y^{s}_{ijt} \leq \mathcal{M}.X_{ij} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3}$$

$$p_i.\theta^{\min}_{it}.\lambda^{s}_{irt} \leq \sum_{j} Y^{s}_{ijt} \leq p_i.\theta^{\max}_{it}.\lambda^{s}_{irt} \qquad \forall i \in \mathcal{I}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{4}$$

$$\sum_{i} Y^{s}_{ijt} \leq \mathcal{C}_j \qquad \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{5}$$

$$\sum_{i,j} Y^{s}_{ijt} + \sum_{i} U^{s}_{it} = \sum_{i} \bar{d}^{nominal}_{it} - \sum_{k} I^{*s}_{k,t-1} \qquad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{6}$$

$$Y^{s}_{ijt}, U^{s}_{it} \geq 0 \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7}$$

$$X_{ij} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} \tag{8}$$

The aim of the first stage model is to minimize the total unfulfilled demand in regions in each period. This objective is shown in Eq. (1). Constraint (2) shows that each region can be assigned to a blood collection center only if the distance between the region and the facility is not more than the maximum standard distance between them. Constraint (3) allows blood collection only if donors' regions are assigned to a blood collection facility in each period. In this constraint, if X_{ij} equals to zero, the blood collection process in region i is not allowed. Each region can donate blood no more than its potential capacity. The potential capacity of each region is calculated by multiplying the population of regions (p_i) and percentage blood donation rate (θ_{it}). This subject is bounded by Constraint (4). In this constraint (λ^{s}_{irt}) shows the non-disrupted fraction of blood donation in each region. Constraint (5) limits the capacity of each blood collection center in each period. Eq. (6) guarantees the quantity of blood collected units for demand satisfaction in each period. In this equation ($I^{*s}_{k,t-1}$) determines the updated inventory level in the previous period by applying the rolling horizon mechanism. The domain of decision variables is specified by Constraints (7) and Constraint (8).

3.3. Second stage model

In this subsection, the mathematical model is formulated to present the second stage decisions, which were previously discussed in this paper. In this stage, the quantity of $\overline{Y}^{s}_{ijt}$ is considered as input according to solving the first-stage optimization model.

$$\min \sum_{s} \rho^{s} \Big(\sum_{j,k,t} t_{jk}.Z^{s}_{jkt} + \sum_{k,i,l,t} t'_{ki}.W^{s}_{kilt}\Big) \tag{9}$$

$$\min \sum_{s} \rho^{s} \Big(\sum_{j,k,t} a_{jk}.Z^{s}_{jkt} + \sum_{k,i,l,t} b_{ki}.W^{s}_{kilt} + \sum_{i,j,t} g.\overline{Y}^{s}_{ijt} + \sum_{k,t} h.I^{s}_{kt} + \sum_{k,t} e.G^{s}_{kt} + \sum_{i,t} o.V^{s}_{it}\Big) \tag{10}$$

subject to

$$\sum_{i} \overline{Y}^{s}_{ijt} = \sum_{k} Z^{s}_{jkt} \qquad \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{11}$$

$$Z^{s}_{jkt} \leq \mathcal{M}.X'_{jk} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{12}$$

$$X'_{jk}.\zeta'_{jk} \leq \xi' \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K} \tag{13}$$

$$\sum_{j} Z^{s}_{jkt} \leq m_k \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{14}$$

$$\sum_{j} Z^{s}_{jkt}.(1-\beta) = I'^{s}_{k,L,t} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{15}$$

$$I'^{s}_{klt} = I'^{s}_{klt} + \sum_{i} W^{s}_{kilt} \qquad \forall k \in \mathcal{K}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{16}$$

$$I''^{s}_{k,l+1,t} = I'^{s}_{k,l,t+1} \qquad \forall k \in \mathcal{K}, \forall l \in \mathcal{L}\backslash\{L\}, \forall t \in \mathcal{T}\backslash\{T\}, \forall s \in \mathcal{S} \tag{17}$$

$$I''^{s}_{k,1,t} = G^{s}_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{18}$$

$$\sum_{l \in \mathcal{L}\backslash\{1\}} I'^{s}_{klt} = I^{s}_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{19}$$

$$I^{s}_{kt} \leq e_k \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{20}$$

$$W^{s}_{kilt} \leq \mathcal{M}.X''_{ki} \qquad \forall k \in \mathcal{K}, \forall i \in \mathcal{I}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{21}$$

$$X''_{ki}.\zeta''_{ki} \leq \xi'' \qquad \forall k \in \mathcal{K}, \forall i \in \mathcal{I} \tag{22}$$

$$\sum_{k,l} W^{s}_{kilt} + U^{s}_{it} = \tilde{d}^{real}_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{23}$$

$$U^{s}_{it} = V^{s}_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{24}$$

$$Y^{s}_{ijt}, Z^{s}_{jkt}, U^{s}_{it}, I'^{s}_{klt}, I'^{s}_{klt}, I^{s}_{kt}, W^{s}_{kilt}, V^{s}_{it} \geq 0 \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{25}$$

$$X'_{jk}, X''_{ki} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall k \in \mathcal{K} \tag{26}$$

The first aim of the second stage model in Eq. (9) minimizes the total delivery time of whole blood units from blood collection centers to central blood banks ($\sum_{j,k,t} t_{jk}.Z^{s}_{jkt}$) and blood units from central blood banks to demand zones ($\sum_{k,i,l,t} t'_{ki}.W^{s}_{kilt}$). The second aim of the model in Eq. (10), including six terms, is to minimize the total cost of the network. In the first term ($\sum_{j,k,t} a_{jk}.Z^{s}_{jkt}$) shows the transportation cost between collection centers and central blood banks. The second term ($\sum_{k,i,l,t} b_{ki}.W^{s}_{kilt}$) counts the transportation cost between central blood banks and regions. The third term ($\sum_{i,j,t} g.\overline{Y}^{s}_{ijt}$) denotes the collection cost of whole blood units from donors. The fourth term ($\sum_{k,t} h.I^{s}_{kt}$) points to the inventory holding cost in central blood banks. The fifth term

($\sum_{k,t} e.G^s_{kt}$) is composed of expiration cost. Finally, the last term ($\sum_{i,t} o.V^s_{it}$) displays the collection cost of unfulfilled demand by the apheresis method.

Eq. (11) shows the total blood units transferred from blood collection centers to central blood banks in each period. In this equation, $\overline{Y}^s_{ijt}$ is determined in the first stage model. A blood collection center can be assigned to the central blood bank only if the central blood bank has been selected. Similar to Constraint (3), Constraint (12) allows flow between blood collection centers and central blood banks only if blood collection centers are assigned to the central blood banks. Constraint (13) limits the transferred units between blood collection centers and central blood banks based on the maximum coverage radius. Constraint (14) limits the capacity of each central blood bank in each period. Eq. (15) determines the number of healthy blood units in the central blood bank in each period. β determines the historical discard rate during the production process. Eq. (16) presents the balancing inventory equation between inventory and blood units used to fulfill the demand. Eq. (17) models the aging process of inventory level. Blood units with the age of $l+1$ at the end of period t, goes to the age of l at the beginning of period $t+1$. Eq. (18) calculates the expired units of blood in each period. The total inventory level in each central blood bank in each period is determined by applying Eq. (19). The capacity limitation of each central blood bank in each period is bounded in Eq. (20). Similar to Constraint (2) and Constraint (3), the assignment role between central blood banks and regions are specified in Constraint (21) and Constraint (22). Eq. (23) calculates the number of blood units used to fulfill the demand of each region. Eq. (24) represents that the quantity of unfulfilled demand in each region is fulfilled by the apheresis method. Finally, Constraint (25) and Constraint (26) display the type of decision variables.

4. Solution methodology

Supply chain components are surrounded by various risks, and accordingly, the supply chains are planned in a stochastic environment and disruption risk. The BSN is no exception, and they encounter different kinds of risks such as uncertainty in demand and disruption in supply. In order to prevent supply chain malfunctions, appropriate strategies should be taken by policy-makers, and in this study, a hybrid stochastic possibilistic-flexible programming approach is presented to handle risks in the proposed BSN.

4.1. The formulation for disruption risk in blood supply

Experience of COVID-19 outbreak implied that there would be a meaningful impact on blood supply due to the reduction in blood donors. The COVID-19 epidemic can decrease the blood supply and its by-products and negatively affect blood network activities. When a region faces a peak of the COVID-19 outbreak, one of the major impacts of this situation on blood transfusion services is that it leads to remarkable shortages in blood donation due to donors' fear of exposure to the virus in a medical center. Generally, in this situation, blood banks should deal with a disruption in blood supply. The solution to cope with supply disruption can include advertisement, encouraging healthy donors to visit blood centers and other motivational initiatives. It should be noted that in this situation, several time periods are required for disappearing the effect of disruption and blood donation returns to the normal status.

This study is proposed for multiple periods that are long sufficient to make disruptions independent from each other. The striking disruption in one period has no effect on the probability of disruption risk in the next periods. In such a problem, disruption in blood supply parameters has a Bernoulli distribution. Furthermore, disruption risk is a particular kind of yield uncertainty in which the yield is considered a Bernoulli random variable [40]. It is presumed that the disruption probability for blood supply in each region within a period at the peak of the outbreak follows a Bernoulli distribution with parameter $0 < \mathcal{P}_i < 1$, which addresses disruption probability in region $i \in I$. In this regard, if a disruption in region i with a prevalence level of $r \in \mathcal{R}$ under scenario s within period t happens, parameter φ^s_{irt} is equal to 1, and 0 otherwise [41,42].

According to a normal distribution $N(\mu_i, \sigma_i)$ that $i \in I$, it is assumed that a percentage of maximum blood supply will be interrupted if a disruption happens. Indeed, if a disruption occurs at the peak of the outbreak during the period t under scenario s, the percentage of available blood supply in region i with a prevalence level of $r \in \mathcal{R}$ will be gone, which is presented by τ^s_{irt}. When a disruption occurs in blood supply for a region at the outbreak's peak, initiative strategies should be executed to return its original supply. By considering a linear recovery function, if the recovery time equals to δ_j, the percentage of the recovered supply for a region in a period t equals to $\frac{1}{\delta_j} \times 100\%$. Fig. 2 shows the linear recovery of blood supply over a planning horizon at the outbreak's peak. In the following equation, parameter λ^s_{irt} represents the available blood supply in region i with a prevalence level of r during period t under scenario s. As can be seen, $\min(1-\lambda^s_{irt}), (\frac{1}{\delta_j})$ is the recovered blood supply at the beginning of period t. $(1-\varphi^s_{irt} \times \frac{\tau^s_{irt}}{100})$ denotes the fraction of the available supply when a disruption occurs in the period t. It is worth mentioning that parameter λ^s_{irt} is always a positive value between zero and one.

$$\lambda^s_{irt} = \max\{0, (\lambda^s_{i,r,t-1} + \min\{\left(1-\lambda^s_{i,r,t-1}\right), (\frac{1}{\delta_j})\})(1-\varphi^s_{irt} \times \frac{\tau^s_{irt}}{100})\} \tag{27}$$

4.2. The formulation for uncertainty in blood demand

To deal with uncertainty, there are many different methods in the literature. On the other hand, fuzzy programming is considered as a frequently used approach to tackle epistemic uncertainties [43]. When access to sufficient information is not available, or the available information is ill-known, this approach is adopted. The fuzzy programming approach can be divided into two groups: flexible programming used to handle flexible constraints and objective functions and possibilistic programming used to handle data uncertainty [44,45]. Herein, in order to cope with different sources of uncertainty, fuzzy and stochastic approaches have been utilized simultaneously in the form of proposed hybrid stochastic possibilistic flexible programming, which are provided as follows.

Step 1: The compact form of the first and second stage models proposed in Sections 3.2 and 3.3 are as follows. A, B, C, C', E, E' and F are matrices of the models, which consist of deterministic parameters and $\mathcal{M}$ denotes a very large positive number. X and X' are binary variables associated with the first and second stages, which are independent scenario variables, respectively. Also, Y^s and U^s are continuous variables in the first-stage model and $\overline{Y}^s, Z^s$, and U^s show the continuous scenario-based variables in the second stage model. Additionally, s denotes disruption scenarios, and its occurrence probability is ρ^s ($\sum_s \rho^s = 1$). In these models, the last constraint of the first stage model is a flexible constraint. Violation is allowed in this constraint, controlled according to the decision-makers' opinions by assigning a penalty (see Box I).

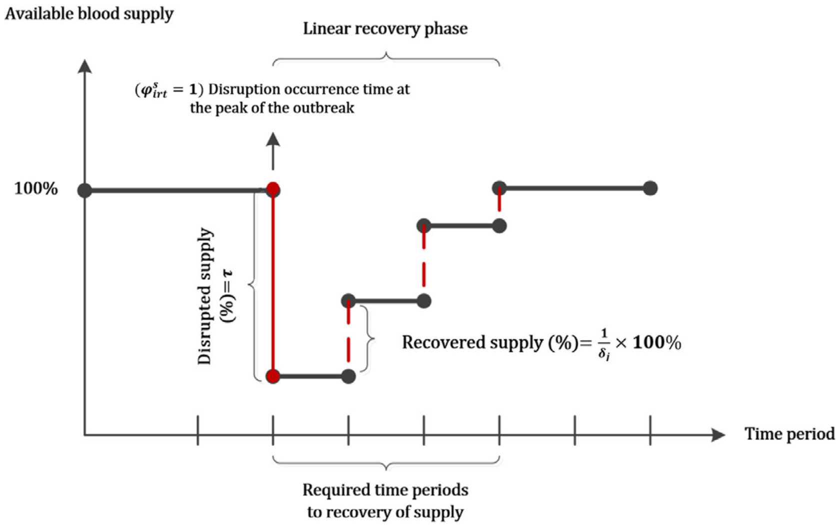

Fig. 2. The recovery process for disruption in blood supply at the peak of the outbreak.

$$
\begin{array}{llll}
\min & \sum_s \rho^s \sum U^s & \min & \sum_s \rho^s \sum A.\overline{Y}^s \\
 & & \min & \sum_s \rho^s \sum B.Z^s \\
\text{subject to} & \theta^{\min}.\lambda^s \leq Y^s \leq \theta^{\max}.\lambda^s & \text{subject to} & Z^s \leq \mathcal{M}.X' \quad \forall s \\
 & Y^s \leq \mathcal{M}.X & & Z^s \leq F \quad \forall s \\
 & C.X \leq E & & C'.X' \leq E' \\
 & Y^s + U^s \tilde{=} \overline{d}^{nominal} & & Z^s + U^s = \tilde{d}^{actual} \quad \forall s \\
 & Y^s, U^s \geq 0; X \in \{0,1\} & & \overline{Y}^s, Z^s, U^s \geq 0; X' \in \{0,1\} \quad \forall s
\end{array} \tag{28}
$$

Box I.

$$
\begin{array}{llll}
\min & \sum_s \rho^s \sum U^s & \min & \sum_s \rho^s \sum A.\overline{Y}^s \\
 & & \min & \sum_s \rho^s \sum B.Z^s \\
\text{subject to} & \theta^{\min}.\lambda^s \leq Y^s \leq \theta^{\max}.\lambda^s & \text{subject to} & Z^s \leq \mathcal{M}.X' \quad \forall s \\
 & Y^s \leq \mathcal{M}.X & & Z^s \leq F \quad \forall s \\
 & C.X \leq E & & C'.X' \leq E' \\
 & Y^s + U^s \tilde{=} \overline{d}^{nominal} - \tilde{\tau}(1-\sigma) & & Z^s + U^s = \tilde{d}^{actual} \quad \forall s \\
 & Y^s, U^s \geq 0; X \in \{0,1\} & & \overline{Y}^s, Z^s, U^s \geq 0; X' \in \{0,1\} \quad \forall s
\end{array} \tag{29}
$$

Box II.

Step 2: The amount of violation in flexible constraint is shown by $\tilde{\tau}$ which is triangular fuzzy numbers. Besides, for flexible constraint, a parameter is assigned that indicates the minimum satisfaction level (σ in this model). The above model changes to the following form [46,47]:(see Box II).

Step 3. $\tilde{\tau}$ is shown in the triangular fuzzy forms of $\tilde{\tau} = (\tau^1, \tau^2, \tau^3)$, which can be defuzzified as follows [48,49]:

$$(\tau^2 + \frac{\varphi_\tau - \varphi'_\tau}{3}) \tag{30}$$

which φ_τ, φ'_τ are calculated as follows:

$$\varphi_\tau = \tau^3 - \tau^2; \varphi'_\tau = \tau^2 - \tau^1 \tag{31}$$

$$
\begin{array}{llll}
\min & \sum_s \rho^s \sum U^s & \min & \sum_s \rho^s \sum A.\overline{Y}^s \\
 & & \min & \sum_s \rho^s \sum B.Z^s \\
\text{subject to} & \theta^{\min}.\lambda^s \le Y^s \le \theta^{\max}.\lambda^s & \text{subject to} & Z^s \le \mathcal{M}.X' \quad \forall s \\
 & Y^s \le \mathcal{M}.X & & Z^s \le F \quad \forall s \\
 & C.X \le E & & C'.X' \le E' \\
 & Y^s + U^s \tilde{=} \overline{d}^{nominal} - (\tau^2 + \frac{\varphi_\tau - \varphi'_\tau}{3})(1-\sigma) & & Z^s + U^s = \tilde{d}^{actual} \quad \forall s \\
 & Y^s, U^s \ge 0; X \in \{0,1\} & & \overline{Y}^s, Z^s, U^s \ge 0; X' \in \{0,1\} \quad \forall s
\end{array} \tag{32}
$$

Box III.

Step 4: According to the above-mentioned descriptions, the crisp equivalent of Model (29) is as given in Box III.: where $(\tau^2 + \frac{\varphi_\tau - \varphi'_\tau}{3})(1-\sigma)$ is the violation of the flexible constraint.
Step 5: In Model (32), the value of σ is determined based on decision-makers' opinions.
Step 6: According to the compact models of first and second stage models, the basic hybrid stochastic possibilistic programming model is as follows:

$$
\begin{aligned}
&\min \sum_s \rho^s \sum U^s \\
&\text{subject to} \\
&\theta^{\min}.\lambda^s \le Y^s \le \theta^{\max}.\lambda^s && \forall s \\
&Y^s \le \mathcal{M}.X && \forall s \\
&C.X \le E \\
&Y^s + U^s \tilde{=} \left[\delta\left(\frac{\tilde{d}^m + \tilde{d}^o}{2}\right) + (1-\delta)\left(\frac{\tilde{d}^p + \tilde{d}^m}{2}\right)\right] && \forall s \\
&Y^s, U^s \ge 0; X \in \{0,1\} && \forall s \\
&\min \sum_s \rho^s \sum A.\overline{Y}^s \\
&\min \sum_s \rho^s \sum B.Z^s \\
&\text{subject to} \\
&Z^s \le \mathcal{M}.X' && \forall s \\
&Z^s \le F && \forall s \\
&C'.X' \le E' \\
&Z^s + U^s = \tilde{d}^{actual} && \forall s \\
&\overline{Y}^s, Z^s, U^s \ge 0; X' \in \{0,1\} && \forall s
\end{aligned} \tag{33}
$$

In this model, the parameter d is considered as triangular fuzzy numbers in which the actual value of this parameter is realized in the second stage model at the end of each period. δ addresses the confidence level of fuzzy constraint so that $0.5 < \delta \le 1$.
Step 7: To eradicate the mentioned shortcomings, the hybrid stochastic possibilistic-flexible programming model is presented as follows:

$$
\begin{aligned}
&\min \sum_s \rho^s \sum U^s \\
&\text{subject to} \\
&\theta^{\min}.\lambda^s \le Y^s \le \theta^{\max}.\lambda^s && \forall s \\
&Y^s \le \mathcal{M}.X && \forall s \\
&C.X \le E \\
&Y^s + U^s \tilde{=} \left[\delta\left(\frac{\tilde{d}^m + \tilde{d}^o}{2}\right) + (1-\delta)\left(\frac{\tilde{d}^p + \tilde{d}^m}{2}\right)\right] \\
&\quad -(\tau^2 + \frac{\varphi_\tau - \varphi'_\tau}{3})(1-\sigma) && \forall s \\
&Y^s, U^s \ge 0; X \in \{0,1\} && \forall s \\
&\min \sum_s \rho^s \sum A.\overline{Y}^s \\
&\min \sum_s \rho^s \sum B.Z^s \\
&\text{subject to} \\
&Z^s \le \mathcal{M}.X' && \forall s \\
&Z^s \le F && \forall s \\
&C'.X' \le E' \\
&Z^s + U^s = \tilde{d}^{actual} && \forall s \\
&\overline{Y}^s, Z^s, U^s \ge 0; X' \in \{0,1\} && \forall s
\end{aligned} \tag{34}
$$

In Model (34), σ indicates the satisfaction level of flexible constraint. Furthermore, the values of the δ and σ are selected based on the experts' opinions. In the above model, based on actual data when is realized at the end of each period, the inventory level is updated. If $\tilde{d}^{actual} > \overline{d}^{nominal}$ then $I^*_t < 0$ and system faces with unfulfilled demand, which should be covered by apheresis method (Please refer to the second-stage model in Section 3.3). On the other hand, if $\tilde{d}^{actual} < \overline{d}^{nominal}$ then $I^*_t > 0$ and system faces leftover blood units, which should be transferred to the future period to avoiding extra blood collection. This procedure will be done according to the rolling horizon approach, which is presented in Section 4.3. According to Section 4.1 and Section 4.2, Algorithm 1 describes the disruption and operational risks formulation procedure.

Algorithm 1: The procedure of the disruption and operational risks formulation

To cope with disruption and operational risks

- **Step 1:** Determine the disruption scenario, flexible constraint, and uncertain parameters in the mathematical formulation
- **Step 2:** Determine the amount of violation in flexible constraint by triangular fuzzy numbers
- **Step 3:** Defuzzify the triangular fuzzy form
- **Step 4:** Convert the flexible model to the crisp equivalent model
- **Step 5:** Determine the allowable violation of the flexible constraint by decision-maker
- **Step 6:** Consider the uncertain parameters as triangular fuzzy numbers and defuzzify by possibilistic programming
- **Step 7:** Solve the hybrid stochastic possibilistic-flexible programming model

4.3. Rolling horizon approach

An appropriate plan must be flexible enough to solve uncertainties in a system at multiple levels. It is identified as a necessary requirement for responding to input data about the past and the future in the planning process of a dynamic environment. In an uncertain environment, it needs continuing planning since the database constantly updates. The rolling horizon approach is an integrated procedure to deal with optimization problem iteratively [50]. In each iteration, the mathematical model is only made for a sector of the planning horizon, and the remaining part is illustrated from a general perspective. The rolling horizon has a unique framework within which each scheduling sub-horizon is successively solved, and its leftover demands are carried over the next periods. Finally, the practical solutions are achieved with a remarkable decrease in computational requirements [51,52].

A rolling horizon procedure is based on forecasting the future and adjusting to disruptive influences. This procesure is regarded as a flexible instrument for making adaptations to a planning horizon with data uncertainty comprising unpredictable data to plan a schedule at the lowest error rate. The rolling horizon decision-making process proves to be a flexible planning tool in environments with low level of data availability, including data with a different performance level. It would be better to say; the rolling horizon sets a connecting link between past incidents and their updated status. Consequently, it offers DMs (decision-makers) the possibility for using the data acquired over the planning horizon. Rolling horizon aims to analyze the results achieved by adopting optimal solutions over a planning horizon. It is worth mentioning that the optimal solutions for period t are the given optimal decisions that must be made by solving the problem with $| T |- t + 1$ periods before uncertainty realization at period t. The schematic of the rolling horizon approach is depicted in Fig. 3.

In this study, due to the uncertainty in demand and disruption risk in supply, a rolling horizon approach is adopted to perform continuous runs for models to implement the decisions with the capability to reconsidering them. To preserve the dynamic essence of the decision-making process, the mathematical formulation is integrated into a rolling horizon approach, that is, while the decisions are made over a planning horizon. The procedure is continually repeated in each period of the planning horizon. Preliminary data per period such as supply and demand, leftover demand of each region are generated by decisions made in its previous period. In Algorithm 2, the steps of the rolling horizon planning approach to solve the mathematical formulation are presented.

4.4. Handling the multiple objectives

Various methods for handling multiple objectives have been applied in the literature. However, the techniques of the compromise programming approach, goal programming approach, and epsilon constraint approach are three of the most well-known methodologies in the literature [54]. In this study, the compromise programming approach is applied to handle the multiple objectives of the second stage model. We consider that two objective functions of the second stage model are called $\varkappa_1$ and $\varkappa_2$. According to the compromise programming approach, the mathematical model should be optimized for each objective function separately. We consider that the optimal values for two objective function are $\varkappa_1^*$ and $\varkappa_2^*$, the converted single objective model can now be formulated as follows:

$$\min \left[w^1 . \frac{\varkappa_1 - \varkappa_1^*}{\varkappa_1^*} + w^2 . \frac{\varkappa_2 - \varkappa_2^*}{\varkappa_2^*} \right] \tag{35}$$

where $0 \leq w \leq 1$ is the weight of each objective function that is given by the decision-maker. The procedure of the compromise programming approach to solve the bi-objective model is described in Algorithm 3. According to the above-mentioned strategies in this section, the flowchart of the proposed solution methodology of this study is depicted in Fig. 4.

5. Case study

Managing blood supply is a vital activity; hence blood transfusions are considered as a lifesaving process in many situations. For example, the SARS-COV outbreak in 2003 hurt blood supply. In an outbreak situation like COVID-19, blood banks confront challenges in preparing an adequate and safe blood supply due to decreasing blood donors. WHO predicted that the COVID-19 outbreak caused about 20% to 30% reduction in countries, and it was noted that the donation rate has dropped by approximately 10%–30% in the US and by about 30% at Canadian Blood centers [7]. The blood centers in many countries reported their lowest blood supply levels since the beginning of the COVID-19 outbreak. Blood donation proceeded to be canceled since many organizations, schools, and businesses remained closed due to quarantine roles. In some other countries, such as Saudi Arabia, were reported the blood supply and donation at blood collection centers showed a fall of 39.5% [8]. In Malaysia, the supply of blood at blood banks throughout the country had decreased by 40% compared with the same years before the COVID-19 outbreak. Also, in Iran, the blood donation rate and RBC inventory decreased about 29.5% during this outbreak [10].

As a result, blood bank managers should take precautionary measures to reduce any changes in blood stocks as much as possible. Blood and its products are continuously required during the COVID-19 outbreak for patients suffering from cancers, trauma, blood diseases, and also emergency surgeries. It is clear that not adopting an appropriate management approach of blood demand and supply in BSN, hospitals, and clinics will face a shortage to service the patients who need blood, and consequently, many patients may suffer or even die unnecessarily. In this section, about an actual problem that the IBTO in the COVID-19 outbreak is deal with, the proposed model and approach for BSN is applied

Algorithm 2: The Procedure of the rolling horizon planning

for t=1..., T do

Step 1: Calculate the s disruption scenario for the next T periods

Step 2: Estimate the nominal blood demand and formulate the uncertainty approach

Step 3: Run the first stage model to determine the collection plan based on initial inventory at the current period t

Step 4: Implement the sharing strategy of collected blood units between regions

Step 5: Obtain the actual blood demand in each region at the end of period T

Step 6: Update the inventory level of blood banks according to sharing strategy and actual demand

Step 7: Use the apheresis mechanism to cover the unfulfilled demand at the end of period T

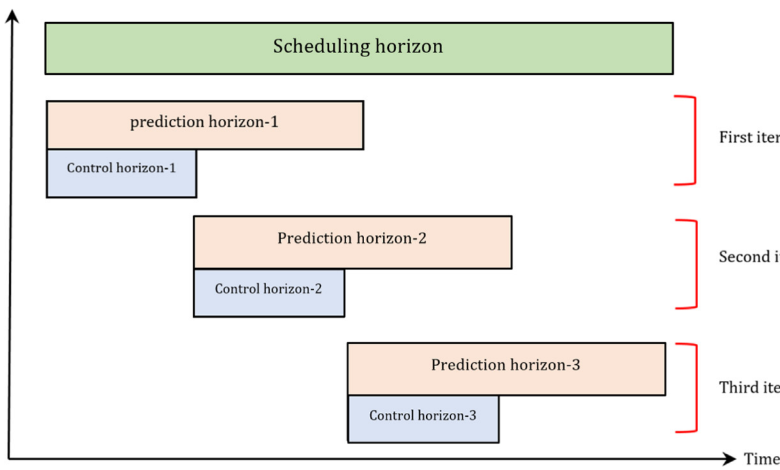

Fig. 3. Rolling horizon approach framework.
Source: Adopted from Silvente et al. [53].

Algorithm 3: The procedure of the compromise programming approach

for solving the bi-objective model

Step 1: Determine the ideal solution of the first objective function called z_1^*

Step 2: Determine the ideal solution of the second objective function called z_2^*

Step 3: Covert the bi-objective model to a single objective function by min $\left[w^1.\frac{z_1-z_1^*}{z_1^*}+w^2.\frac{z_2-z_2^*}{z_2^*}\right]$

Step 4: Determine the weight of each objective function by decision-maker

Step 5: Optimize the converted single objective function according to the weight of each objective function

for the whole of Iran through a collaboration with the IBTO's specialists, and experts will be then provided with the outcomes of it.

Iran is the seventeenth most populous country globally, with an area of over 1,648,000 km ^{2}. Iran, with a population of approximately 82 million, comprises 31 provinces and 430 counties [55,56]. The geographical depiction of counties in Iran is depicted in Fig. 5. According to the investigations of IBTO's experts, the BSN in Iran in the COVID-19 outbreak deserves special consideration to reschedule the blood collection plan because the number of donors dramatically decreased, especially in the cities that are at the peak of the outbreak (http://fna.ir/f0r603; https://tn.ai/2407890). Based on the professional experts' knowledge in IBTO, this condition arises from the fact that donors in cities at the peak of COVID-19 with quarantine situations are less inclined to donate their blood than the people in cities with normal situations [57]. Consequently, blood inventories have decreased almost in the counties with the outbreak's peak, and shortages occurred in some hospitals (www.irna.ir/news/84423945/). It should be mentioned that currently, the system for announcing the status of blood inventory in Iran has been set up (https://www.isna.ir/news/1400011103961/), and IBTO is upgrading its system to share the blood units between the regions of the country to mitigate the shortage and wastage in this outbreak situation

Regarding this challenge during the COVID-19 outbreak, IBTO has decided to prepare a plan for BSN to coordinate the blood collection processes among the counties of the country. Therefore, blood collection centers in the counties with a normal situation in terms of COVID-19 outbreak collect blood from donors as much as possible and, after fulfilling the needs of their city, share their leftover collected blood to the counties that are at the peak of the outbreak. It should be noted that the counties at the peak of the outbreak mostly face shortages to fulfill the demand of their hospitals. The characteristics of blood collection centers and central blood banks in Iran are provided in Table 1 and Table 2,

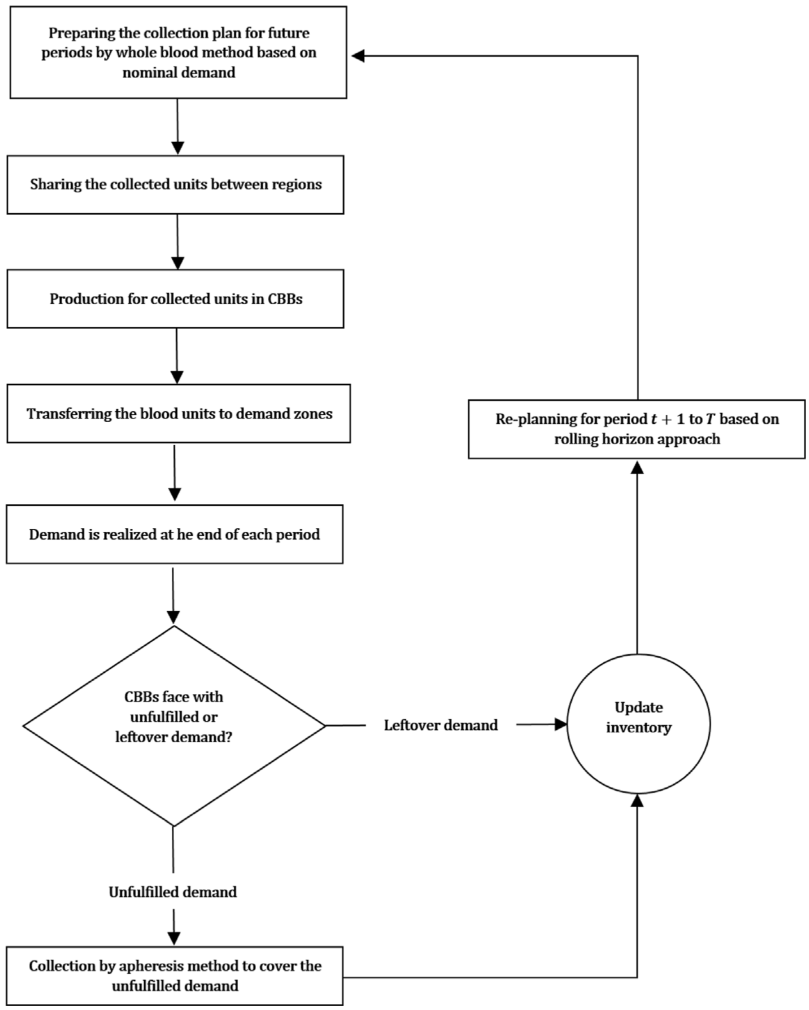

Fig. 4. Flowchart of the proposed methodology based on sharing mechanism and rolling horizon approach.

Fig. 5. Geographic desperation of counties in Iran.

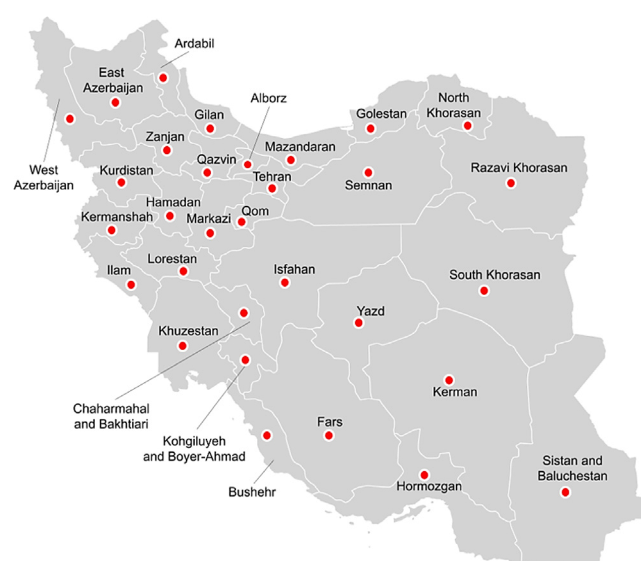

Fig. 6. Geographic depiction of central blood banks in Iran.

respectively. Also, the geographical schematic of central blood banks in the provinces of Iran is presented in Fig. 6.

According to IBTO protocols, people in the range of 18–60 can donate blood, which approximately 60% of the population of Iran are in this age range. Another hand, regarding the documented donation in IBTO, the rate of donation is between 10%–15%.

Table 1
The properties of blood collection centers in Iran.

Number	Province	Blood collection center	Number	Province	Blood collection center	Number	Province	Blood collection center
1	Ardebil	Ardebil	55	Alborz	Mehrbano	109	Khozestan	Andimeshk
2	Ardebil	Pars Abad	56	Ghom	Ghom	110	Kohliloye Boirahmad	Yasouj
3	Ardebil	Meshkin Shahr	57	Ghom	Roholah	111	Kohliloye Boirahmad	Dehdasht
4	Ardebil	Khalkhal	58	Semnan	Emam Reza	112	Kohliloye Boirahmad	Gachsaran
5	Azarbaijan Gharbi	Oromieh	59	Semnan	Shahrood	113	Boushehr	Boushehr
6	Azarbaijan Gharbi	Khoy	60	Semnan	Damghan	114	Boushehr	Kangan
7	Azarbaijan Gharbi	Mahabad	61	Semnan	Garmsar	115	Boushehr	Genaveh
8	Azarbaijan Gharbi	Miandoab	62	Golestan	Gonbad Kavoud	116	Boushehr	Dashtestan
9	Azarbaijan Gharbi	Naghadeh	63	Golestan	Ali Abad	117	Fars	Ghavami
10	Kurdestan	Sanandaj	64	Golestan	Bandar Gaz	118	Fars	Namazi
11	Kurdestan	Saghez	65	Golestan	Kourkoy	119	Fars	Marvdasht
12	Zanjan	Sadi	66	Golestan	Azad Shahr	120	Fars	Jahrom
13	Zanjan	Abhar	67	Golestan	Mena	121	Fars	Bani Hashemi
14	Gilan	Lahijan	68	Khorasan Shomali	Bojnoord	122	Fars	Darab
15	Gilan	Roudsar	69	Khorasan Shomali	Shirvan	123	Fars	Abadeh
16	Gilan	Anzali	70	Tehran	Vesal	124	Fars	Fasa
17	Gilan	Fouman	71	Tehran	Satari	125	Hormozgan	Hormozgan
18	Gilan	Talesh	72	Tehran	Tehranpars	126	Hormozgan	Bandar Lengeh
19	Gilan	Astara	73	Tehran	Rey	127	Hormozgan	Minab
20	Gilan	Langroud	74	Tehran	Sadr	128	Hormozgan	Gheshm
21	Hamedan	Hamedan	75	Tehran	Pirouzi	129	Kerman	Azadi
22	Hamedan	Malayer	76	Tehran	Narmak	130	Kerman	Jirouft
23	Kermanshah	Kermanshah	77	Tehran	Emam Khomeini	131	Kerman	Bam
24	Kermanshah	Kangavar	78	Tehran	Shahriar	132	Kerman	Sirjan
25	Kermanshah	Ghasre Shirin	79	Tehran	Robat Karim	133	Kerman	Rafsanjan
26	Kermanshah	Eslam Abad	80	Tehran	Shahre Ghods	134	Sistan va Balochestan	Emam Mahdi
27	Lorestan	Khoram Abad	81	Tehran	Varamin	135	Sistan va Balochestan	Zabol
28	Lorestan	Alavi	82	Chahar Mahal Bakhtiari	Shahrekord	136	Sistan va Balochestan	Chabahar
29	Lorestan	Boroujerd	83	Chahar Mahal Bakhtiari	Boroujen	137	Sistan va Balochestan	Iranshahr
30	Lorestan	Aligodarz	84	Chahar Mahal Bakhtiari	Ben	138	Sistan va Balochestan	Saravan
31	Ilam	Ilam	85	Esfahan	Khajoo	139	Sistan va Balochestan	Khash
32	Markazi	Shahid Rajaei	86	Esfahan	Ashegh Esfahani	140	Khorasan Jonobi	Kantiner
33	Markazi	Saveh	87	Esfahan	Shahin Shahr	141	Khorasan Jonobi	Tabas
34	Markazi	Khomein	88	Esfahan	Khomeini Shahr	142	Khorasan Jonobi	Ferdous
35	Markazi	Delijan	89	Esfahan	Najaf Abad	143	Khorasan Jonobi	Ghaen
36	Markazi	Tafresh	90	Esfahan	Khansar	144	Khorasan Razavi	Emam Reza
37	Markazi	Mahalat	91	Esfahan	Golpayegan	145	Khorasan Razavi	Soleimani
38	Markazi	Ashtian	92	Esfahan	Kashan	146	Khorasan Razavi	Karimi
39	Ghazvin	Ghazvin	93	Esfahan	Naeen	147	Khorasan Razavi	Omid
40	Ghazvin	Takestan	94	Esfahan	Shahreza	148	Khorasan Razavi	Samen
41	Ghazvin	Bein Zahra	95	Esfahan	Zarin Shahr	149	Khorasan Razavi	Mehr
42	Mazandaran	Sari	96	Yazd	Yazd	150	Khorasan Razavi	Ghochan
43	Mazandaran	Amol	97	Yazd	Azad Shahr	151	Khorasan Razavi	Torbat Heidarieh
44	Mazandaran	Babol	98	Yazd	Hosseini poor	152	Khorasan Razavi	Sabzevar
45	Mazandaran	Tonekabon	99	Yazd	Meibod	153	Khorasan Razavi	Neyshabour
46	Mazandaran	Chalos	100	Khozestan	Ahvaz	154	Khorasan Razavi	Gonabad
47	Mazandaran	Ramsar	101	Khozestan	Amanieh	155	Khorasan Razavi	Torbat Jam
48	Mazandaran	Noor	102	Khozestan	Behbahan	156	Khorasan Razavi	Kashmar
49	Mazandaran	Ghaem Shahr	103	Khozestan	Izeh	157	Azarbaijan Sharghi	Tabriz
50	Mazandaran	Behshahr	104	Khozestan	Dezfol	158	Azarbaijan Sharghi	Masjed Kabod
51	Mazandaran	Gelogah	105	Khozestan	Masjed Soleiman	159	Azarbaijan Sharghi	Maragheh
52	Mazandaran	Joybar	106	Khozestan	Abadan	160	Azarbaijan Sharghi	Mianeh
53	Alborz	Alborz	107	Khozestan	Khoram Shahr	161	Azarbaijan Sharghi	Ahar
54	Alborz	Tohid	108	Khozestan	Shoshtar	162	Azarbaijan Sharghi	Marand

Consequently, it is considered that between 6%–9% of the people can donate their blood. The population of each county in Iran is collected from the Statistical Center of Iran. Accordingly, the minimum and maximum supply of blood in each county are estimated by multiplying the blood donation rate and population of each county. In this research, the maximum shelf life of blood is considered three weeks. The demand for blood in each county is gathered based on documentation of hospitals in each county and assumed as fuzzy numbers based on experts' opinions. The geographical coordinates of each county, blood collection centers, central blood banks, and the transportation time between these nodes are calculated based on Google Map. As reported by IBTO, the wastage rate of blood over the production process is assumed 7%. The reference of parameters in this research is reported in Table 3.

Table 2
The properties of central blood banks in Iran.

Number	Province	Number	Province	Number	Province
1	Azarbaijan Gharbi	11	Ghazvin	21	Yazd
2	Azarbaijan Sharghi	12	Mazandaran	22	Khozestan
3	Kurdestan	13	Ardebil	23	Kohliloye Boirahmad
4	Zanjan	14	Ghom	24	Boushehr
5	Gilan	15	Semnan	25	Fars
6	Hamedan	16	Golestan	26	Hormozgan
7	Kermanshah	17	Khorasan Shomali	27	Kerman
8	Lorestan	18	Tehran	28	Sistan va Balochestan
9	Ilam	19	Chahar Mahal Bakhtiari	29	Khorasan Jonobi
10	Markazi	20	Esfahan	30	Khorasan Razavi
				31	Alborz

Table 3
The value of parameters.

Parameters	Value/Reference
p_i	Statistical Center of Iran
θ_{it}^{min}	6% (IBTO report)
θ_{it}^{max}	9% (IBTO report)
$\mathcal{C}_j$	500 units per week (IBTO report)
e_k	500 units per week (IBTO report)
$\zeta_{ij}, \zeta_{jk}^{'}, \zeta_{ki}^{''}$	Google Map
$\xi, \xi^{'}, \xi^{''}$	20 km, 400 km, 400 km
λ_{irt}^{s}	Based on Section 4.1
$t_{jk}, t_{ki}^{'}$	Google map
β	7% (IBTO report)
m_k	300 units per period (IBTO report)
$\tilde{d}_{it}$	Documentation of hospitals
a_{jk}, b_{ki}	0.0001($*10,000/Km)
e	0.015($*10,000/Unit)
h	0.00015($*10,000/Unit)
g	0.5($*10,000/Unit)
o	0.1($*10,000/Unit)

6. Implementation and evaluation

The applicability and performance of the proposed model and methodology of this research during the COVID-19 outbreak are investigated in this section, and experts in IBTO will be provided with its outcomes. We solved the model using GAMS (General Algebraic Modeling System) software version (25.1.2) with the CPLEX solver version (12.5.1.0) on a laptop with Intel Core i7 3.9 GHz and 32 GB of RAM. The number of equations and variables are 50083 and 48578, respectively. The model is solved in a reasonable processing time in which obtained computational results have no gap (0.00%), and all running times are less than 20 min. Then, the general results and sensitivity analysis are reported in Section 6.1 and Section 6.2, respectively.

6.1. Computational results

Table 4 summarizes the computational results along with the number of collected units at each province in each period during the planning horizon. The results have been implemented for six weeks from 21 March 2021 to 02 May 2021, in which the prevalence level of COVID-19 outbreak in each county is determined based on Fig. 7 (https://www.irna.ir/). As reported in this figure, five prevalence levels from low to very very high are obtained in the counties. In each prevalence level, the available blood supply in each region and each period are different. The rate of very very high (please refer to Fig. 7) affects the blood donation rate in regions more than other statuses. On the other hand, the minimum affected rate in blood donation happens at a low rate of COVID-19 prevalence.

Applying the formulation for disruption risk in blood supply which is proposed in Section 4.1, the mathematical model was solved, and then, results were reported. It is worth mentioning that due to the large-size number of outputs for all counties, for simplicity and better-displaying results, the output of the counties of each province are aggregated and presented in the form of a result obtained for a province. The number of collected units in each province is computed based on the first-stage optimization model. Notably, due to the limited capacity of blood supply, it is possible that all of the demand may not be fulfilled completely. Therefore, as shown in this table, the provinces with more population have more collected units based on the available capacity for blood donation rate. This table shows that Tehran and Ilam have the highest and lowest portion for blood collection among provinces, respectively. In Table 4, columns 3–8 demonstrate the number of collected units in each period in each province, column 9 shows the average collected units per period in each province, and finally, column 10 reflects the participation ratio of each province for blood collection in comparison to the total collected units in the country.

The allocation pattern of transferring for collected units between different provinces is shown in Table 5. Due to the limited transfer time of collected units (Maximum 8 h), the possibility of transferring is determined based on the maximum coverage radius in the model. It can be realized from this pattern that the sharing of collected units is usually done between neighboring provinces to prevent the shortage. As can be seen from Table 5, the provinces located in central Iran, due to their geographical location, have more ability to share the blood units than provinces located near border areas. Table 6 represents the number of transferred units from central blood banks to each province in each period. It is determined according to the second stage model. Results show that Tehran and Ilam receive the largest and lowest portion of blood units transferred from central blood banks. In Table 6, columns 3–8 demonstrate the number of transferred units to each province in each period, column 9 shows the average of arrived units per period in each province, and finally, column 10 shows the ratio of received units in each province to the total units transferred from all central blood banks in the country. The average collection and consumption rates in each province during the planning horizon are depicted in Fig. 8.

In the continuation, Table 7 demonstrates the total number of unfulfilled units in each province in each period. The results show that by applying the capacity sharing mechanism, the demand is completely fulfilled at most periods and provinces. In 27 provinces, no unfulfilled demand has occurred. From this table, it can be seen that the shortage has occurred mostly in the border provinces (except Kerman) of Iran. Due to the geographical location, the far distance of Hormozgan province from other neighboring provinces, the severity of the COVID-19 outbreak, and more disruption in blood supply, the largest portion of shortage have occurred in this province. It should be noted that the number of unfulfilled demand in each province should be covered

Table 4
The summary of the collected units during the planning horizon in each province.

Number	Province	Week #1	Week #2	Week #3	Week #4	Week #5	Week #6	Average	Ratio (%)
1	Azarbaijan Gharbi	385	321	334	268	281	282	312	5.01
2	Azarbaijan Sharghi	233	213	240	202	207	308	234	3.75
3	Ardebil	88	108	97	98	120	91	100	1.61
4	Esfahan	276	475	507	456	248	434	399	6.41
5	Alborz	195	192	279	176	167	120	188	3.02
6	Ilam	41	44	61	29	38	43	43	0.69
7	Boushehr	85	94	114	91	71	106	93	1.50
8	Tehran	819	1112	1337	1409	1261	1003	1157	18.57
9	Chahar Mahal Bakhtiari	50	72	70	63	72	103	72	1.15
10	Khorasan Jonobi	54	66	72	59	41	56	58	0.93
11	Khorasan Razavi	545	399	502	416	623	558	507	8.14
12	Khorasan Shomali	90	61	66	58	78	56	68	1.09
13	Khozestan	373	435	438	355	416	352	395	6.34
14	Zanjan	99	75	80	96	47	84	80	1.29
15	Semnan	55	55	43	50	30	59	49	0.78
16	Sistan va Balochestan	280	219	208	265	179	216	228	3.66
17	Fars	342	372	452	403	349	405	387	6.22
18	Ghazvin	109	104	73	81	92	84	90	1.45
19	Ghom	65	129	81	122	104	108	101	1.63
20	Kurdestan	124	162	79	120	121	162	128	2.06
21	Kerman	215	288	244	202	251	243	241	3.86
22	Kermanshah	162	154	193	182	162	112	161	2.58
23	Kohliloye Boirahmad	45	58	64	43	60	59	55	0.88
24	Golestan	186	166	115	107	160	126	143	2.30
25	Gilan	193	145	184	193	146	200	177	2.84
26	Lorestan	100	141	155	155	95	148	132	2.12
27	Mazandaran	237	267	200	263	155	161	214	3.43
28	Markazi	89	115	110	95	65	100	96	1.54
29	Hormozgan	112	134	124	130	90	146	123	1.97
30	Hamedan	107	167	105	83	55	108	104	1.67
31	Yazd	70	96	108	84	111	97	94	1.51

Table 5
The allocation pattern of transferring for collected units between different provinces.

From		To
Azarbaijan Gharbi	→	Azarbaijan Gharbi/Azarbaijan Sharghi/Ardebil/Zanjan/
Azarbaijan Sharghi	→	Azarbaijan Gharbi/Azarbaijan Sharghi/Ardebil
Ardebil	→	Azarbaijan Gharbi/Azarbaijan Sharghi/Ardebil/Zanjan/Gilan
Esfahan	→	Esfahan/Chahar Mahal Bakhtiari/Ghom/Kohliloye Boirahmad/Lorestan/Markazi/Yazd
Alborz	→	Alborz/Tehran/Zanjan/Semnan/Ghazvin/Ghom/Gilan/Mazandaran/Markazi/Hamedan
Ilam	→	Ilam/Kurdestan/Kermanshah/Lorestan/Hamedan
Boushehr	→	Boushehr/Fars/Kohliloye Boirahmad
Tehran	→	Alborz/Tehran/Zanjan/Semnan/Ghazvin/Ghom/Golestan/Gilan/Mazandaran/Markazi/Hamedan
Chahar Mahal Bakhtiari	→	Esfahan/Chahar Mahal Bakhtiari/Ghom/Kohliloye Boirahmad/Lorestan/Markazi
Khorasan Jonobi	→	Khorasan Jonobi
Khorasan Razavi	→	Khorasan Razavi/Khorasan Shomali
Khorasan Shomali	→	Khorasan Razavi/Khorasan Shomali/Golestan
Khozestan	→	Khozestan/Lorestan
Zanjan	→	Azarbaijan Gharbi/Ardebil/Alborz/Tehran/Zanjan/Ghazvin/Ghom/Kurdestan/Gilan/Hamedan
Semnan	→	Alborz/Tehran/Semnan/Ghazvin/Ghom/Golestan/Mazandaran
Sistan va Balochestan	→	Sistan va Balochestan
Fars	→	Boushehr/Fars/Kohliloye Boirahmad
Ghazvin	→	Tehran/Zanjan/Semnan/Ghazvin/Ghom/Gilan/Mazandaran/Markazi/Hamedan
Ghom	→	Esfahan/Alborz/Tehran/Chahar Mahal Bakhtiari/Zanjan/Semnan/Ghazvin/Ghazvin/Lorestan/Mazandaran/Markazi/Hamedan
Kurdestan	→	Ilam/Zanjan/Kurdestan/Kermanshah/Lorestan/Markazi/Hamedan
Kerman	→	Kerman/Yazd
Kermanshah	→	Ilam/Kurdestan/Kermanshah/Lorestan/Markazi/Hamedan
Kohliloye Boirahmad	→	Esfahan/Boushehr/Chahar Mahal Bakhtiari/Fars/Kohliloye Boirahmad/Yazd
Golestan	→	Tehran/Khorasan Shomali/Semnan/Golestan/Golestan
Gilan	→	Ardebil/Alborz/Tehran/Zanjan/Ghazvin/Gilan/Mazandaran/Hamedan
Lorestan	→	Esfahan/Ilam/Chahar Mahal Bakhtiari/Khozestan/Ghom/Kurdestan/Kermanshah/Lorestan/Markazi/Hamedan
Mazandaran	→	Alborz/Tehran/Semnan/Ghazvin/Ghom/Golestan/Gilan/Mazandaran
Markazi	→	Esfahan/Alborz/Tehran/Chahar Mahal Bakhtiari/Ghazvin/Ghom/Kurdestan/Kermanshah/Lorestan/Markazi/Hamedan
Hormozgan	→	Hormozgan
Hamedan	→	Alborz/Ilam/Tehran/Zanjan/Ghazvin/Ghom/Kurdestan/Kermanshah/Gilan/Lorestan/Markazi/Hamedan
Yazd	→	Esfahan/Kerman/Kohliloye Boirahmad/Yazd

from the apheresis collection method in the same province in each period.

6.2. Sensitivity analysis

In this section, the sensitivity analysis on critical aspects and important parameters of BSN is presented. In continue, the analyses on solution methodology, uncertainty approach, coverage

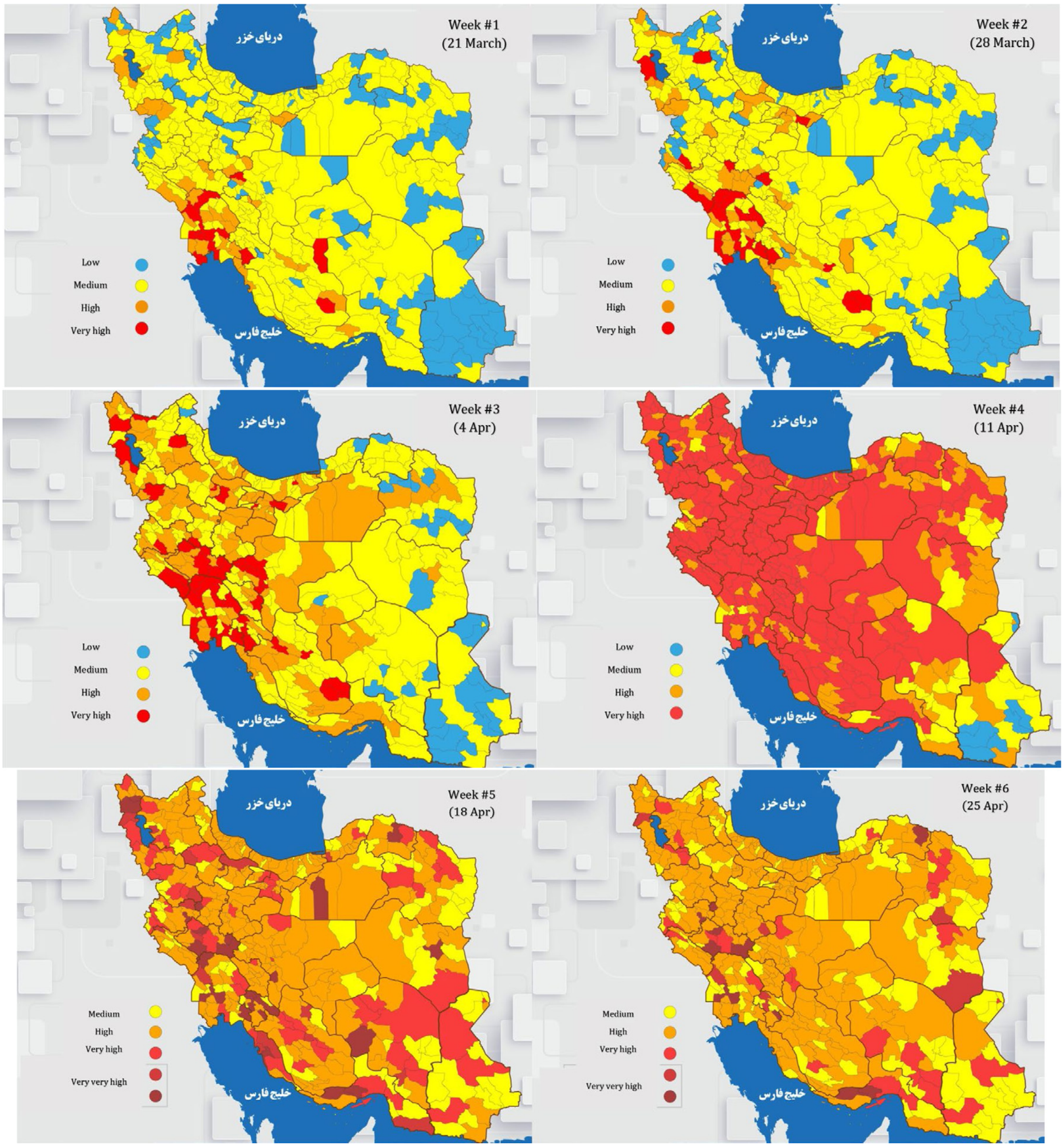

Fig. 7. The prevalence of COVID-19 in counties of Iran during the planning horizon.

radius, cost parameters, and multi-objective programming are investigated.

6.2.1. Methodology analysis

In Table 8, the results of the adopted approach in this study are compared to the non-capacity sharing mechanism and non-rolling horizon approach, which are common approaches in BSN literature. As shown in the table, the total network cost of the BSN by the adopted method in comparison to the others decrease significantly, in which the total cost decreases by about 61.03% in comparison to the non-capacity sharing status, and about 9.11% reduces in comparison to the non-rolling horizon approach status. Furthermore, the unmet demand that occurs in our approach is significantly lower than the unmet demand of other statuses. Therefore, by applying the capacity sharing and rolling horizon mechanisms in the BSN, the total network cost and unfulfillment rate decrease remarkably. Finally, between two other statuses were used for comparison in this study, the capacity sharing strategy with the non-rolling horizon strategy outperforms another status in the context of cost and unfulfilled demand measures. In status #2, because the sharing of blood units is impossible, the inventory range compared to other statuses decreases. On the other hand, in status #1, in comparison to status #3, by applying the rolling horizon approach and the possibility of updating the inventory level at the end of each period, the inventory rate in central blood banks decreases by about 5.63%. In the last column of Table 8, the running time of each status is presented. The computational times of all statuses are almost equal and slightly different together, which is negligible. Noteworthy, all computational times have been carried out with reasonable processing time, and therefore, we did not develop heuristic or metaheuristic algorithms to solve the model.

Table 6
The summary of the transferred units to each province during the planning horizon in each province.

Number	Province	Week #1	Week #2	Week #3	Week #4	Week #5	Week #6	Average	Ratio (%)
1	Azarbaijan Gharbi	291	320	342	301	240	265	293	4.84
2	Azarbaijan Sharghi	217	287	253	231	217	243	242	3.98
3	Ardebil	276	203	161	153	95	88	162	2.68
4	Esfahan	409	517	434	318	331	360	395	6.51
5	Alborz	192	246	209	202	181	180	202	3.32
6	Ilam	47	46	45	39	34	38	41	0.68
7	Boushehr	202	203	128	79	65	89	128	2.10
8	Tehran	1012	1025	1172	867	772	877	954	15.73
9	Chahar Mahal Bakhtiari	62	80	73	72	57	62	68	1.11
10	Khorasan Jonobi	59	61	59	51	41	47	53	0.87
11	Khorasan Razavi	494	496	509	480	435	419	472	7.79
12	Khorasan Shomali	139	92	73	61	52	54	79	1.30
13	Khozestan	323	446	366	335	294	320	347	5.73
14	Zanjan	76	204	87	147	67	73	109	1.79
15	Semnan	53	56	56	52	42	51	51	0.85
16	Sistan va Balochestan	205	244	211	199	185	192	206	3.39
17	Fars	385	439	419	306	307	313	361	5.96
18	Ghazvin	83	117	98	83	75	84	90	1.49
19	Ghom	96	218	111	97	74	89	114	1.88
20	Kurdestan	117	137	137	106	102	110	118	1.95
21	Kerman	203	246	248	232	207	241	229	3.78
22	Kermanshah	132	161	148	127	112	149	138	2.28
23	Kohliloye Boirahmad	54	72	55	54	40	53	55	0.90
24	Golestan	140	159	149	124	126	118	136	2.25
25	Gilan	193	222	223	182	168	157	191	3.15
26	Lorestan	132	158	139	111	110	121	128	2.12
27	Mazandaran	213	278	266	243	227	235	244	4.02
28	Markazi	110	116	123	90	99	90	105	1.73
29	Hormozgan	141	139	142	118	109	128	129	2.13
30	Hamedan	118	143	139	126	111	108	124	2.05
31	Yazd	76	102	126	135	79	80	100	1.64

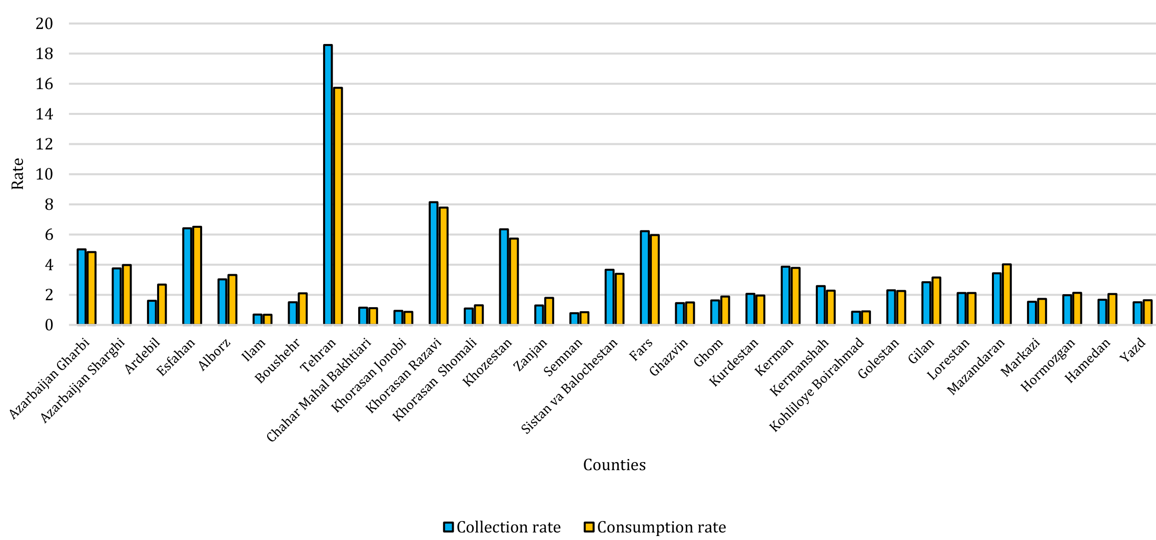

Fig. 8. The average collection and consumption rates in each province during the planning horizon.

Table 7
The summary of the unfulfilled demand during the planning horizon at each scenario in each province.

Number	Province	Week #1	Week #2	Week #3	Week #4	Week #5	Week #6	Average	Ratio (%)
10	Khorasan Jonobi	0	0	0	1	5	4	1.7	20.8
12	Khorasan Shomali	0	0	0	0	0	2	0.3	3.4
21	Kerman	0	0	0	3	0	0	0.5	6.2
29	Hormozgan	0	0	13	8	12	2	5.7	69.6

6.2.2. Uncertainty analysis

In this subsection, the role of uncertainty on BSN is investigated. The performance of the deterministic and hybrid stochastic possibilistic-flexible programming (HSPFP) models are compared with different values of confidence level parameters (σ, δ). The results of Table 9 shows that the HSPFP model with parameter setting of $\sigma, \delta = 0.9$ has minimum total network cost, and by increasing (or decreasing) in the value of confidence level parameters, the total cost increases (decreases). Therefore, it is clear that if the stakeholders of BSN focus on minimizing the total network cost, the parameter setting of ($\sigma, \delta = 0.9$) can achieve

Table 8
Comparison between different statuses in BSN.

		Total cost ($ * 10'000)	Unfulfillment demand (Blood units)	Inventory rate (Per period)	Computational time (min)	Gap (%)
Status #1	Capacity sharing and rolling horizon (our approach)	5477.8	49	5431	14:37	0.00%
Status #2	Non-capacity sharing status	8820.0	207	4830	12:56	0.00%
Status #3	Capacity sharing strategy with the non-rolling horizon mechanism	5976.2	72	5737	13:28	0.00%

Table 9
Performance of objective functions of the second-stage model under the different realizations.

	Deterministic model	HSPFP ($\sigma, \delta = 0.6$)	HSPFP ($\sigma, \delta = 0.7$)	HSPFP ($\sigma, \delta = 0.8$)	HSPFP ($\sigma, \delta = 0.9$)	HSPFP ($\sigma, \delta = 1.0$)	Gap (%)
Total delivery time	9783.4	9875.2	9919.3	9926.5	9962.0	10008.9	0.00%
Total network cost	5629.4	5654.0	5511.4	5477.8	5547.4	5545.7	0.00%
Computational time (min)	14:04	13:56	15:18	14:37	12:41	13:27	

Table 10
Performance of cost objective functions in each realization.

	Deterministic model	HSPFP ($\sigma, \delta = 0.6$)	HSPFP ($\sigma, \delta = 0.7$)	HSPFP ($\sigma, \delta = 0.8$)	HSPFP ($\sigma, \delta = 0.9$)	HSPFP ($\sigma, \delta = 1.0$)	Gap (%)
Realization #1	5611.9	5546.6	5498.1	5490.0	5539.4	5539.2	0.00%
Realization #2	5628.0	5559.4	5518.3	5475.8	5553.8	5549.1	0.00%
Realization #3	5633.5	5553.3	5515.3	5488.3	5543.2	5543.6	0.00%
Realization #4	5642.1	5549.1	5514.8	5469.9	5540.4	5539.2	0.00%
Realization #5	5640.6	5579.2	5499.3	5476.4	5541.9	5538.6	0.00%
Realization #6	5628.3	5582.0	5504.6	5463.4	5552.6	5550.4	0.00%
Realization #7	5609.6	5574.7	5512.4	5479.7	5557.2	5554.8	0.00%
Realization #8	5644.5	5561.2	5522.3	5491.1	5546.3	5542.2	0.00%
Realization #9	5627.1	5559.5	5518.8	5460.4	5552.1	5551.1	0.00%
Realization #10	5628.4	5575.2	5510.0	5482.9	5547.5	5548.5	0.00%
Average	5629.4	5654.0	5511.4	5477.8	5547.4	5545.7	0.00%
Standard deviation	11.73	12.83	8.302	10.77	6.220	5.821	0.00%

a minimum cost in an uncertain environment of COVID-19 outbreak. On the other hand, because in deterministic conditions, a lower level of blood units collected, the deterministic model has a better performance in total delivery time. In Fig. 9, the comparison between the performance of various models in terms of total network cost and total delivery time is depicted.

The obtained results in Table 9 are calculated based on an average of 10 random realizations. The performance of HSPFP models and deterministic model are compared and evaluated by uniformly generating 10 random realizations from the respective uncertainty intervals of uncertain demand. The performance of both deterministic and HSPFP models in each realization are reported in Table 10. As can be seen, HSPFP ($\sigma, \delta = 0.8$) outweighed other models in terms of the average cost of the network. Also, the superiority of the HSPFP model with the confidence level of $\sigma, \delta = 1.0$ in terms of standard deviation can be seen in the last row of Table 10. The trend of average cost and standard deviation in different models is shown in Fig. 10.

6.2.3. Coverage radius analysis

In this subsection, the role of coverage radius variation on BSN measures is devised. To better evaluate the proposed approach in this study, we analyze the changes in some important parameters of the mathematical model in this subsection. The sensitivity analysis of variations in coverage radius for sharing blood units is illustrated in Fig. 11. In Fig. 11-a, the effect of increasing coverage radius on total unfulfilled demand is depicted. Figs. 11-b and 11-c demonstrate the effect of this variation on total delivery time and total network cost. Fig. 11-a shows that blood units can be transshipped between provinces with farther distance by increasing the maximum coverage radius. By increasing the coverage radius, more blood units are capable of being shared between provinces. Increasing shared blood units can lead to a lower number of unfulfilled demand in provinces, and for this reason, the total network cost of the BSN decreases because the cost of unfulfilled demand is more than transportation cost in this network. This fact is shown in Fig. 11-c. It can be realized from Fig. 11-b that further increase in the coverage radius imposes increases in the total delivery time of blood units. Because in this situation, more blood units are delivered to provinces, and consequently, the total delivery time increases.

6.2.4. Cost analysis

In this subsection, the role of considering different cost parameters is analyzed. Table 11 analyzes the impact of variation in cost parameters on the total unfulfilled demand, total network cost, and total delivery time. As can be seen in this table, an increase in o, decreases the total unfulfilled demand of blood units in the BSN. This model prefers fewer blood collections by the apheresis method to meet the demand, and the whole blood collection mechanism covers more percentage of the demand. On the other hand, by increasing blood collection by the whole blood mechanism, total delivery time increases because more blood units are collected and need more time to be delivered to the provinces. Since the collection cost by the apheresis method dominates the transportation cost of the network, the total network cost increases in this situation. In the second row of Table 11, the opposite trend is visible for decreasing in parameter o. The changes of parameters e, and h have not significant impact on the quantity of unfulfilled demand and total delivery time because varying this parameter does not affect the quantity of blood collection. Thus, unfulfilled demand and delivery time remain constant. Increasing (decreasing) in parameters e, and h results in more (less) cost in the expired units and inventory units, and consequently, the total network cost increase (decreases). When the parameters of a_{jk}, and b_{ki} increase, the rate of collection unit by whole blood mechanism decreases, and for this reason, the number of unfulfilled demand increases. Consequently, provinces

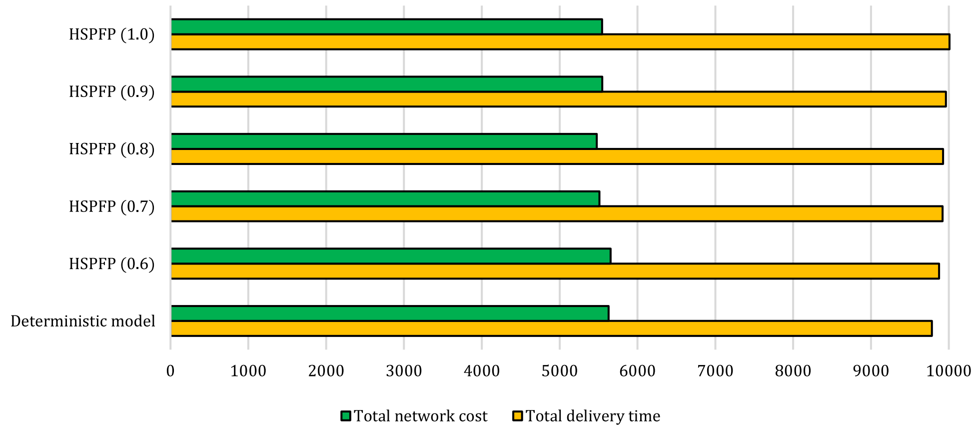

Fig. 9. Performance of measures under the different realizations.

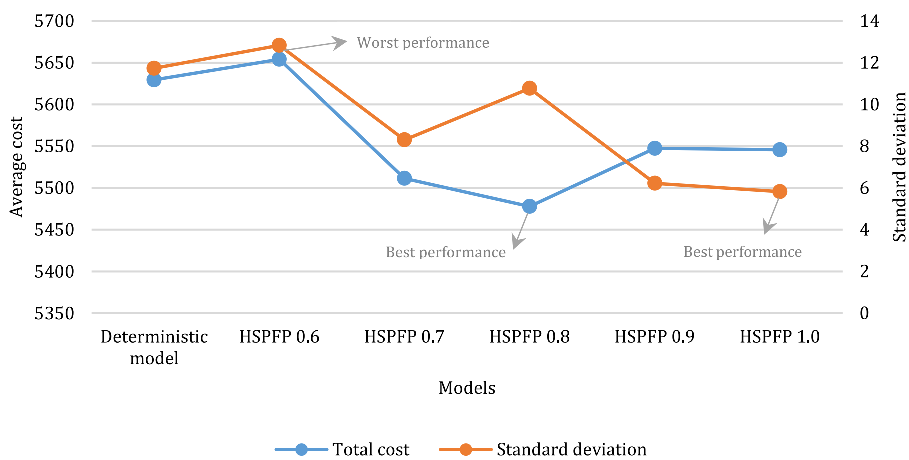

Fig. 10. The trend of average cost and standard deviation in different models.

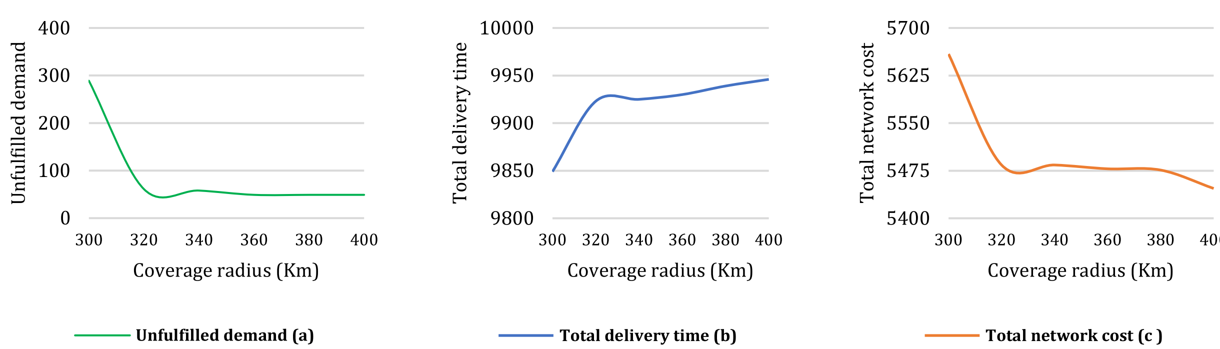

Fig. 11. The impact of coverage radius on performance measures.

receive fewer blood units by sharing mechanism, and the total delivery time decreases. Also, the total network cost leads to an increase in this status. Another general observation can be seen in decreasing in parameters a_{jk}, and b_{ki} in Table 11.

6.2.5. Multi-objective programming analysis

In this subsection, the trade-off between different weights of objective functions is investigated. In the second stage of the model, a bi-objective optimization model has presented in which the first objective minimizes the total delivery time of blood units from collection centers to provinces, and the second one calculates the total network cost of the BSN. This bi-objective model is handled by the compromise programming approach proposed in Section 4.4. The trade-off between these objective functions is done by varying in different weights of these objective functions $\left(w^1, w^2\right)$. As shown in Table 12, the first objective (total delivery time) and the second objective (total network cost) conflict. As can be seen in Table 12 and Fig. 12, increasing the value of w^1 leads to a decrease and better solution for the first objective function, which reveals the higher importance of the delivery time in the model. By increasing the value of the w^1 the delivery time of blood units becomes more important for BSN stakeholders. They prefer to use the apheresis method in the same province more than receive the blood units from neighboring provinces. Because blood collection by the apheresis method has more cost than the whole blood method, the total network cost increases by assigning more important weight to w^1. The values of w^1 and w^2

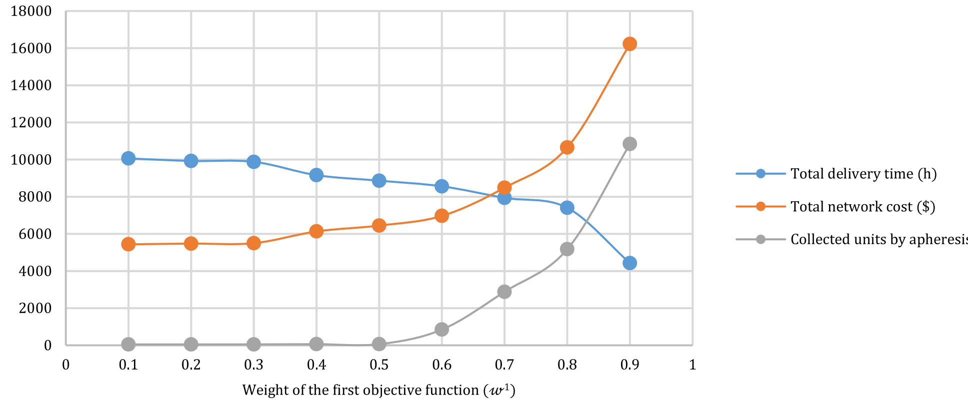

Fig. 12. The trend of total delivery time versus total network cost and collected units by apheresis collection method.

Table 11
Impacts of variation on cost parameters.

Parameter	Unfulfilled demand (Blood units)	Total network cost ($)	Total delivery time
$o\uparrow$	↙	↗	↗
$o\downarrow$	↗	↙	↙
$e\uparrow$	No change	↗	No change
$e\downarrow$	No change	↙	No change
$h\uparrow$	No change	↗	No change
$h\downarrow$	No change	↙	No change
$a_{jk}\uparrow$	↗	↗	↙
$a_{jk}\downarrow$	↙	↙	↗
$b_{ki}\uparrow$	↗	↗	↙
$b_{ki}\downarrow$	↙	↙	↗

can be selected based on the preferences of healthcare system managers, and this table helps stakeholders of BSN to have a better choice between alternatives of blood collection methods in different situations of COVID-19 outbreak. It should be noted that the running time of each model is provided in the last row of Table 12, and all running times are less than 20 min.

7. Research implications, limitations, and future directions

The obtained results reveal that the capacity sharing concept can enhance the service level of the BSN and lower the amount of shortage during the COVID-19 outbreak. The proposed two-stage optimization tool is resilient to cope with fluctuation in blood donation in this situation. Applying a rolling horizon mechanism due to the dynamic nature of BSN and both disruption risk in blood supply and uncertainty in blood demand during the outbreak can prevent low blood service levels in regions of the country. The following key insights for managers of BSN concluded by applying the capacity sharing concept and results of this research:

- Stakeholders of BSNs can benefit from capacity sharing concept due to the reduction in blood donors during the COVID-19 outbreak; as it results in a more service level in hospitals, resilient network, and thus, quicker response level to the blood demand;
- Applying an HSPFP approach to tackle disruption risk in blood supply and uncertain demand in BSN, especially in outbreak peak, can result in better performance and more service level than the deterministic condition and considering just one aspect of risk measures;
- The rolling horizon technique has more remarkable performance in extra blood collection and reducing the shortage due to the dynamic nature of the COVID-19 prevalence and new information in this situation;
- Employing motivational aspects for blood donation during the COVID-19 outbreak and planning for blood collection via an apheresis method from booked donors can be beneficial to cope with disruption in blood supply. On the other side, the possibility of blood sharing between blood banks by maximum possible distance can mitigate the shortage and result in less wastage and more service quality for patients;
- Although the proposed model and methodology in this research were applied for real data of IBTO in Iran, our designed mechanism can be beneficial for other BSN in countries that face the challenge of reducing blood donation during the COVID-19 outbreak.

Several directions for future study can be suggested. Due to the limited blood supply and donors in disaster situations like the COVID-19 outbreak, motivational initiatives can be considered to encourage blood donations in blood collection centers. Furthermore, different exact or heuristics solution approaches can be developed for this problem, resulting in optimal solutions quickly for large-sized problems. The proposed model could be applied to another future research avenue by taking other uncertainty approaches such as data-driven or distributionally robust optimization approaches. Another domain for future research could also be extended this model by considering different blood groups and compatibility rules to satisfy the patient's demands and reduce the shortage level during the epidemic outbreak. Moreover, when a disaster strikes, preparing a scheduling plan for blood collection via an apheresis mechanism from booked donors can help this network to cover the unfulfilled demand in hospitals.

Table 12
The summary of second-stage model based on different w levels.

	(w^1, w^2) (0.9, 0.1)	(w^1, w^2) (0.8, 0.2)	(w^1, w^2) (0.7, 0.3)	(w^1, w^2) (0.6, 0.4)	(w^1, w^2) (0.5, 0.5)	(w^1, w^2) (0.4, 0.6)	(w^1, w^2) (0.3, 0.7)	(w^1, w^2) (0.2, 0.8)	(w^1, w^2) (0.1, 0.9)
Total delivery time (w^1)	4425.0	7402.2	7939.2	8562.9	8865.4	9162.4	9879.6	9926.5	10061.6
Total network cost (w^2)	16226.3	10654.0	8488.7	6968.5	6447.6	6133.9	5499.6	5477.8	5437.2
Collected units by apheresis	10840	5177	2883	847	63	62	52	49	47
Computational time (min)	15:01	14:52	12:11	11:29	13:39	09:47	13:11	14:37	18:31

Table A.1
A review on BSN research.

Reference	Situation		Hierarchical level					Planning horizon			Products				Modeling approach	Collection mechanism		Objective function		Performance measure								Planning horizon		Type of uncertainty						Transshipment	Methodology		Case study
	Normal	Disaster	Collection	Production	Inventory	Distribution	Integrated	Strategic	Tactical	Operational	Whole blood	Platelet	Plasma	Red blood cell		Whole blood	Apheresis	Single	Multi	Cost	Distance	Shortage	Wastage	Freshness	Delivery time	Risk	Service level	Single period	Multi-period	Flexible programming	Possibilistic programming	Stochastic programming	Robust optimization	Possibilistic-robust	Possibilistic-stochastic		Exact	Metaheuristic	
[58]	*				*					*				*	MINLP	*		*					*						*			*						*	Yes
[59]		*	*					*	*		*				MINLP	*		*		*									*				*				*		Yes
[60]	*				*					*		*			DP	*		*					*						*			*					*		No
[61]	*				*					*		*		*	ILP	*		*		*									*			*					*		No
[30]	*		*					*	*		*				MILP	*		*		*									*					*					Yes
[31]	*		*						*		*				MIP	*			*	*							*		*									*	Yes
[62]	*		*						*	*	*			*	MILP	*		*							*				*								*		No
[63]	*		*							*		*	*	*	Simulation	*			*	*		*	*						*									*	Yes
[64]	*				*				*		*				Simulation	*			*	*		*	*	*					*			*				*		*	No
[32]	*		*					*	*			*	*		Simulation	*		*							*		*		*			*					*		Yes
[65]	*				*					*				*	Simulation	*			*				*						*									*	No
[66]	*				*					*		*	*	*	MILP	*			*	*		*							*			*				*	*		No
[18]		*					*	*	*		*				MILP	*			*	*		*							*				*				*		Yes
[20]		*					*	*	*		*				MILP	*			*	*					*	*			*					*			*		Yes
[24]		*					*		*	*	*				MILP	*		*			*								*								*		Yes
[67]	*				*				*	*		*			MILP	*			*	*		*							*					*			*		Yes
[39]	*						*		*	*		*			MILP	*	*	*		*									*			*					*		Yes
[23]		*					*	*	*		*				MILP	*			*	*					*				*								*		Yes
[25]		*	*					*	*			*	*	*	MILP	*		*		*									*				*				*		Yes
[17]		*					*	*	*		*				MILP	*			*	*					*				*			*					*		Yes
[68]	*						*	*	*			*	*	*	MILP	*			*	*		*							*					*		*	*		Yes
[69]	*				*					*				*	MILP	*			*	*		*	*						*			*					*		Yes
[70]	*				*				*					*	DP	*		*		*									*							*	*		Yes
[71]	*						*		*	*		*			MILP	*			*	*				*					*				*				*		Yes
[35]	*		*					*	*		*				MILP	*		*		*									*				*				*		Yes
[19]		*					*	*	*			*	*	*	MILP	*			*	*		*		*					*						*		*		Yes
[72]	*						*	*		*		*	*	*	SO	*		*		*									*				*				*		Yes
[73]	*						*	*			*				MILP	*	*	*		*								*									*		Yes
[74]	*						*	*	*			*			MINLP	*			*	*									*		*							*	No
[75]							*		*			*	*	*	MILP	*			*	*		*							*				*					*	No
[76]		*					*	*	*		*				MILP	*		*		*									*				*					*	Yes
[77]	*				*			*			*				MILP	*			*	*					*				*				*					*	No
[37]	*						*	*	*			*	*	*	MILP	*		*		*									*					*			*		Yes
[78]	*						*	*	*			*	*	*	MILP	*	*		*	*				*		*			*				*				*		Yes
[79]	*				*				*			*			MILP	*	*		*	*							*		*				*			*	*		Yes
[80]	*						*	*	*					*	MILP	*			*	*					*				*			*					*		Yes
[81]	*						*	*	*			*	*	*	MILP	*			*	*							*		*					*			*		Yes
[82]	*						*		*	*				*	MILP	*		*											*								*		No
[36]	*						*	*	*			*	*	*	MILP	*	*	*		*								*		*				*			*		Yes
[83]	*				*					*				*	MILP	*		*		*									*			*				*	*		No
[84]	*						*	*	*			*	*	*	MILP	*	*		*	*						*	*		*				*				*		Yes
[85]	*						*	*	*					*	MILP	*			*	*							*		*				*				*		Yes
[86]		*			*	*			*	*		*			MILP	*			*	*		*							*					*			*		Yes
[87]		*					*	*	*		*				MILP	*		*		*									*				*				*		Yes
[88]	*			*	*	*			*	*		*			MILP	*	*	*		*									*					*		*	*		Yes
This study		*	*	*	*	*	*		*					*	MILP	*	*		*	*		*	*		*	*			*	*	*	*				*	*		Yes

Abbreviations: MINLP=Mixed Integer Non-Linear Programming; DP=Dynamic Programming; ILP=Integer Linear Programming; MILP=Mixed Integer Linear Programming; MIP=Mixed Integer Programming; SO=Simulatio-Optimization.

Finally, as further extensions for this study, transshipment of blood units between hospitals and collaboration to sharing the leftover blood units in blood banks to cover the total unfulfilled demand can significantly mitigate the shortage in this urgent situation.

8. Conclusion

A considerable reduction in blood donations was observed in epidemic outbreaks like the SARS epidemic in 2003; Similarly, during the Influenza pandemic in 2009 and in the recent COVID-19 outbreak. Monitoring the supply and demand for blood and its by-products should be escalated during and after the epidemic outbreaks like COVID-19 due to their effects on patients so that adequate blood is maintained to support ongoing critical needs. Some reasons such as fear of infection, inconvenient location, weakened immune system, and avoidance of public places has been lead to a reduction in blood donation in regions at the peak of the outbreak. While in this situation, regions with a low prevalence rate of the epidemic frequently have no challenges in preparing the required blood units. A proper strategy in blood collection management should be implemented to reduce the shortage of blood and its by-products in regions of the country. In this research, by conducting a capacity sharing concept, a two-stage optimization tool to coordinate the blood collection activities in BSN was proposed to lower the shortage and wastage during the COVID-19 outbreak. To prevent BSN malfunctions in this urgent situation, a novel hybrid stochastic possibilistic-flexible robust programming approach was developed. Due to the dynamic nature of the COVID-19 outbreak, a rolling horizon mechanism was adopted to implement the decisions by the capability to reconsideration in blood collection activities. In collaboration with IBTO, the applicability and performance of the proposed model and methodology were implemented on real data in Iran country. The computational results and sensitivity analysis revealed that the capacity sharing concept has a good potential to mitigate the shortage level of blood units in regions, especially at the peak of the COVID-19 outbreak.

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.

Appendix

See Table A.1.

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