Vehicle Routing Problem in Relief Supply under a Crisis Condition considering Blood Types

Mahsa Rezaei Kallaj,1 Milad Abolghasemian,2 Samaneh Moradi Pirbalouti,3 Majid Sabk Ara,4 and Adel Pourghader Chobar5

1Faculty of Industrial Engineering and Management System, Amirkabir University of Technology, Tehran, Iran
2Faculty of Engineering, Industrial Engineering Department, Islamic Azad University, Branch of Lahijan, Lahijan, Iran
3School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
4Faculty Member in Guilan ACECR, Educational Member in Guilan UAST, Guilan, Iran
5Department of Industrial Engineering, Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

Correspondence should be addressed to Milad Abolghasemian; m.abolghasemian.bt@mehrastan.ac.ir

Received 2 August 2021; Accepted 25 October 2021; Published 16 November 2021

Academic Editor: Alireza Goli

Copyright © 2021 Mahsa Rezaei Kallaj et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Despite the advances achieved in Medical Sciences, no substitute has been found for blood as a vital factor. Therefore, preparing sufficient and healthy blood in crisis conditions is a challenge that health systems encounter. Along with examining the conducted investigations in this field, the main contribution of current research is to develop a biobjective Mixed-Integer Linear Programming (MILP) model for relief supply under crisis condition. For this purpose, this paper proposes a model for routing of bus blood receiver under crisis conditions considering different blood groups. Besides, hours of unnecessary travel by bloodmobiles (buses) between each blood station (BS) and the crisis-stricken city for dispatching the collected blood is prevented thanks to considering a helicopter. The mentioned model has two objectives: maximizing the amount of blood collected by bloodmobiles and minimizing the arrival time of the blood receiver buses and a helicopter to a crisis-stricken city after the collected blood is used up. The model is coded by CPLEX software, and the results obtained from solving the model indicate that, without considering a helicopter, the demand is not supplied within the critical period after crisis. Given that blood cannot be artificially produced, its primary resource is blood donors. Concerning the importance of this issue under crisis conditions, this research investigates the relief vehicles’ routing problem, including bus and helicopter, in a crisis considering supply and transfer of different blood groups to a crisis-stricken city for maximum relief supply and blood transfer within the shortest period.

1. Introduction

Today, supply chain network design has been a demanding question and attracted great interest in a wide range of fields, such as medical industry. The important aspect of the entire discipline of the medical industry is the concept of blood management which recently brought striking attention among managers and decision-makers [1]. Blood transfusion is one of the most vital medical actions and interventions. However, blood is a highly scarce resource. Since blood cannot artificially be produced, the only blood resource is blood donors. It is reported that the demand for blood is 92 million units per year worldwide, while regular blood donors merely account for 5% of the world population [2]. Generally, the blood network consists of main centers, temporary facilities, bloodmobiles, and laboratory centers. The schematic of the blood supply chain is indicated in Figure 1. The main centers with preservation capacity and equipped with high technologies are responsible for collecting blood. Creating these centers requires very high investment. However, temporary facilities with a limited level of facilities for supplying demand and increasing the
number of donors are highly flexible. Effective use of the bloodmobiles may be helpful and increase the number of donors. The bloodmobiles are vehicles equipped with essential equipment for processing the received transfusion blood from donors. Compared to fixed blood donation centers, these vehicles can attract more donors by staying in crowded regions. Besides, employing this system prevents blood scarcity in blood transfusion centers and hospitals in a crisis and reduces blood wastes and system costs [3]. Blood donation starts when an individual visits a blood transfusion center or a service-provider bus. Bloodmobiles start their route from a particular location. Afterward, they follow their route to more centers in each city or even neighboring cities to collect more blood. It may take them several days to continue their routes. In order to prevent the blood collected by bloodmobiles from spoilage during their routes or deliver the collected blood to the patients on time, a helicopter visits bloodmobiles at the end of a day and dispatches the blood collected by bloodmobiles to the crisis-stricken city so that the bloodmobiles do not have to return to the crisis-stricken city at the end of the day. In the blood collecting centers, the blood units are processed and its components are separated. Ultimately, it is transferred to a hospital or a clinic according to the demand [4]. Even though blood units as a product may not be highly subject to spoilage, their separated components can be completely spoiled and destructed within a particular time [4]. Blood units are broken down into blood products, including white blood cells, platelets, and plasma. Red blood cells and platelets can be stored for 42 and 5 days, respectively. Each parameter can be divided into four groups of O, B, A, and AB, which can also be classified into other groups with positive or negative RH depending on the existence of special antigens [4]. Thereby, eight blood groups must be controlled simultaneously. Also, there are recipients (as chain customers) who are in dire need of various blood units and will suffer serious injury and death if they do not receive blood in the time of need. Therefore, not only are the different levels in such networks of a greater importance than those in other supply networks, but also the availability of network flow can determine the recipients’ life at lower levels of the chain [1]. Consequently, for making better use of available resources, advanced approaches for decision-making are needed. Also, better planning for receiving and collecting leads to better handling in times of scarcity such as crisis, i.e., COVID-19 pandemic, earthquake, etc. [5]. Therefore, one of important decisions in blood transfusion is the substitution of blood groups. Ideally, the transfused blood group must be identical to the patient’s blood type, while this is not always possible. When a blood group is not available at the time of the request, a compatible blood group with the desired blood group must be provided [6]. According to Table 1, the donated blood types are categorized based on the blood receiver and donor [3].

In general, the term “crisis” refers to any situation that temporarily limits the capability of services to preserve, store, and supply blood more than usual or creates a situation that increases the sudden demand for blood more than usual [6]. Disasters often lead to many problems, such as damage, financial losses, fatalities, and transportation problems in the damaged regions. Eighty-three thousand disasters have occurred from 2000 to 2012 worldwide [2]; for instance, demand is usually more than supply during the first 24 hours after the earthquake. Another concern regarding the design of blood supply chain networks is the limitation in the storage and transportation of blood products [7]. Compared to normal conditions, there is more demand for water, food, shelter, medical equipment, and other vital requirements, such as blood as a vital product after a disaster [2]. In order to tackle the challenges mentioned above, a novel and effective collecting system is proposed in this research for the vehicle routing problem, such as bloodmobiles and relief supplier helicopters after a
criterion employing the concept of routing and using mathematical modeling. Besides, it is assumed that crises happened in a city, and the blood receiving bloodmobiles collect blood from certain cities. Accordingly, in the mathematical model, a bloodmobile is allowed to stop at each visited city in order for the collected blood to be maximized. In addition, given that a crisis has taken place, the arrival time of the bloodmobiles and helicopters to the crisis-stricken city is minimized. Besides, the relief helicopters collect and dispatch the blood left in the bloodmobiles in the cities to the crisis-stricken city. Indeed, this investigation carries out the routing of blood receiving bloodmobiles and relief helicopters in the crisis-stricken location such that the maximum amount of blood is collected within the shortest period. Since the number of injured individuals suddenly increases in a crisis, patients wait to receive blood when the blood is being collected. Thus, the earlier each donation vehicle arrives at the blood bank, the more patients receive blood and are healed. Hence, this research accords a high priority to the minimum arrival time of the blood receiving bloodmobile and helicopter to the crisis-stricken city. The following suppositions are the main objectives of the paper:

(i) Developing a blood network to consider both amount of collected blood and arrival time to service
(ii) Maximizing the amount of collected blood and minimizing the arrival time of service provider into the crisis-stricken city
(iii) Utilizing deterministic programming to evaluate the model behavior in the real-world case study

The following of this article is arranged as follows: In Section 2, a historical review of the issue is presented. In Section 3, along with introducing the methodology, the problem assumptions and mathematical model are presented. The problem-solving results are indicated in Section 4. Finally, in Section 5, a conclusion and some suggestion for future researches are presented.

2. Literature Review

The investigations into the management of spoilable products’ supply chain and blood products specifically started in 1960 and culminated in the early 1980s [8]. During these years, various studies have been conducted on the blood supply chain, addressing different problems, such as the location of regional centers, blood banks, inventory, and routing problems of vehicles for blood collection and distribution. In recent years, some investigations into blood supply chain management have been conducted, which are introduced in the following. For instance, considering the location and allocation of them to the closest blood bank, Prastacos [9] proposed a mathematical model. This model aimed to minimize the total costs of the supply chain. In 2017, Haghjoo et al. [10] proposed a random bistage mathematical model for the design of a blood supply chain network and inventory management. Sha and Huang [11] proposed a multiperiod location-allocation mathematical model for the design of a blood supply chain network under emergency circumstances. They employed the Lagrange Relaxation method to solve the proposed mathematical model. Jabbarzadeh et al. [7] proposed a robust optimization mathematical model for the design of the blood supply chain network in an earthquake. They aimed to design a blood supply chain network with costs of three levels, including blood donors, blood centers, and blood collecting centers. The blood centers aimed to minimize the total costs of the supply chain. Zahiri and Pishvaee [12] proposed a biobjective mathematical model aiming to minimize the total costs of the supply chain and the unsupplied demands. This article designs a supply chain network by considering the compatibility of blood groups. For this purpose, a biobjective mathematical model is developed that minimizes the total costs and addresses the maximum undesired demand. Gunpinar and Centeno [13] modeled a vehicle routing problem employing an integer programming approach to simultaneously identify the number of blood transfusion buses and minimize the traveled distance. Besides, this model is developed to consider the uncertainty in the blood donation potential and the variable length in the visitors of the bloodmobiles. Rodriguez-Espindola et al. [14] proposed a collaborative humanitarian approach for disaster preparedness for logistic resource management when a natural disaster happens. In this model, the multiobjective optimization model is employed for making emergency logistic management decisions. Paul and Wang [15] proposed a robust network of allocation of relief supply pieces of equipment for earthquake preparedness. This robust network can optimize the number of equipment, capacities, and distribution centers and reduce social costs. Parameters with uncertainty in this model are listed as follows: Damaged facilities, casualties because of the intensity of an incidence, and the travel time of the relief supplier vehicles. In a recent study, Adarang et al. [16] proposed a temporary robust biobjective location-routing model for providing emergency medical services. This model aimed to minimize the relief supplying time and total cost. Total costs are the sum of spatial costs and the cost of covering the route by vehicle (ambulance and helicopter). Arani et al. [17] presented a novel mixed-integer programming model for designing a sustainable lateral resupply blood supply chain network. In this paper, we addressed a blood inventory-routing problem with supply and demand uncertainties. Also, we developed a scenario-based stochastic optimization model and revised multichoice goal programming approach to solve.

| Receptor blood type | Donor blood type |
|---------------------|------------------|
| O                   | +AB -AB +B -A -A +O -O |
| +O                  |                   |
| +O                  |                   |
| +A                  | +A +B -B -A -A +O -O |
| +B                  |                   |
| +B                  |                   |
| -AB                 |                   |
| +AB                 | +AB +AB +AB +AB +AB +AB |

Table 1: Blood groups that are compatible with each other.
Goodarzian et al. [18] considered an economic green medicine supply chain network under uncertainty. In this study, we developed multiperiod, three-echelon, multi-product, and multimodal transportation based fuzzy biobjective Mixed-Integer Linear Programming. Davoodi and Goli [19] presented an integrated model for location, allocation, and routing in disaster relief response. In this paper, minimizing last visit time is used as a suitable objective function in rural areas disasters. For faster convergence, Benders decomposition was developed using metaheuristics. Finally, we analyzed a real case to demonstrate the applicability of the research methodology. Samani and Hosseini-Motlagh [20] presented a novel capacity sharing mechanism to collaborative activities in the blood collection process during the COVID-19 outbreak. According to this research, a two-stage optimization tool for coordinating activities to mitigate the shortage in this urgent situation is considered. In the first stage, a blood collection plan considering disruption risk in supply to minimize the unmet demand will be solved. Then, 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. Tirkolaee et al. [21] presented a robust biobjective mathematical model for disaster rescue unit’s allocation and scheduling with learning effect. For this purpose, the effect of learning in the disaster management problem is considered. Then, a biobjective robust MILP model for rescue units allocation and scheduling is designed. Finally, a multichoice goal programming (MCGP) with utility functions to cope with the biobjectiveness of the model is applied. Wang et al. [22] presented a framework for optimization of warehouse location and resources distribution for emergency rescue under uncertainty. For this purpose in this paper, a mixed-integer programming (MIP) model based on time cost under uncertainty is proposed, which helps solve the emergency warehouse location and distribution problem. Mamashli et al. [23] presented a heuristic-based multichoice goal programming for the stochastic sustainable-resilient routing-allocation problem in relief logistics. The proposed model aims at minimizing total travel time, total environmental impacts, and total demand loss. The fuzzy robust stochastic optimization approach is utilized to cope with uncertain data arising in disaster conditions. Then, due to the complexity of the research problem, a hybrid approach based on the multichoice goal programming method and a heuristic algorithm is developed to solve the problem in a reasonable time. Mousavi et al. [1] evaluated an integrated sustainable medical supply chain network during the COVID-19 pandemic. Three hybrid metaheuristic algorithms, namely, ant colony optimization, fish swarm algorithm, and firefly algorithm, are suggested, hybridized with variable neighborhood search used to solve the sustainable medical supply chain network model.

Although several studies on vehicle routing under crisis conditions have been introduced in the literature review, a study that addresses the defined condition mentioned in this study has not been found despite the carried-out examinations. Therefore, in this research, the routing of the blood receiver bus and relief supplier helicopter in the crisis-stricken area is carried out such that the maximum amount of blood is collected within the shortest possible period. In this case, the arrival time of the blood receiver bus and the relief supplier helicopter from the defined cities to the crisis-stricken city is minimized.

3. Methodology

3.1. Problem Statement. This study aims to determine which of the equipped buses visit which stations. Also, it determines in what order and how much time the stations should be visited. Besides, it specifies in what order the helicopter visits the stations to take delivery of the collected blood. With such a case, the collected blood by the bloodmobiles (buses and helicopters) is maximized until the end of the day. Since the condition is critical, the lower the blood collection time is, the more the individuals are saved. Accordingly, this is a problem with two objective functions. The first objective is to maximize the collected blood by considering the blood type. The second objective is to minimize the longest time for arrival of the equipped buses and the helicopter to the crisis-stricken city. Since the amount of collected blood is inversely proportional to the blood collection time, our objective is to determine the variables such that a balance is struck between the blood collection time and collected blood amount.

3.2. Model Structure. Generally, proposed blood supply chain consists of main centers, mobile centers, and laboratory centers. Mobile centers are a few numbers of equipped bloodmobiles (bus). Blood buses are equipped with several beds, the pieces of equipment required for receiving blood from a donor, and a lab for monitoring the blood accuracy, a few nurses, and one physician. Shuttle, which is indeed a helicopter, prevents unnecessary hourly bus travels for receiving the collected blood between each BS and the crisis-stricken city. In this case, the buses are not required to transfer the collected blood to the crisis area, and a helicopter will take this responsibility. Thus, we assume that a crisis has happened in a city. This problem consists of a blood bank located in the crisis-stricken city and several nodes that are the cities and the defined villages of the city. The blood bank is equipped with a specific number of bloodmobiles (a number of buses) and a relief helicopter. The equipped buses (bloodmobiles) start moving from the blood bank and visit the blood stations (BS) for blood collection; they should return to the blood bank until the end of the day. Concerning the proposed model, the buses decide for how much time (hours) they make a stop in each BS to maximize the collected blood. Besides, an excessive stop in a city confines the opportunity of visiting other cities. Therefore, making more stops in a city does not necessarily mean more blood collection. Since a shortage would be at the cost of more human lives, it is not allowed in the problem, and all of the demands should be satisfied. The buses can provide the collected blood from each BS to that station by considering the blood preservation condition until the helicopter reaches that point. The main objective of the
helicopter is to visit the buses leaving or that have left the stations each hour, taking delivery of their collected blood. In this case, they can deliver the collected blood to the crisis-stricken city. This approach enables the buses to continue the predefined routes and make complete use of the other blood stations without having to return to each station of the crisis-stricken city at the end of being in service time. However, at the end of each route, the buses deliver the remaining collected blood to the blood bank. Therefore, the helicopter does not visit every blood station (BS).

3.3. Model Assumption and Notation. In this section, all elements of the assumption are presented in Table 2.

3.4. Model Notation and Formulation. In current section, objectives and constraints of the mentioned problem are modeled as follows. The objective function includes two sections:

\[
\text{Max } Z_1 = \sum_{b=1}^{4} Q_{b}, \tag{1}
\]

Equation (1) formulates the first objective. This objective firstly maximizes the amount of collected blood.

\[
\text{Min } Z_2 = \text{max } (\text{TB, TM}), \tag{2}
\]

Equation (2) indicates second objective, that is, minimizing the arrival time of the service-provider bus and helicopter to a crisis-stricken city that separate under assumptions intended for TB and TS in equations (3) and (4), respectively. Thus, the objective of the model is to minimize the arrival time of the service-provider bus and the helicopter to the crisis-stricken city if the collected blood is maximized by considering the blood type.

\[
X_{ijk} = 0, \quad \forall i \in (1, \ldots, n + 1), k \in K. \tag{5}
\]

Constraint (5) indicates that bloodmobile k (buses) cannot travel from city i to city j (loop is not allowed).

\[
X_{1n+1k} = 0, \quad \forall k \in K. \tag{6}
\]

Constraint (6) indicates that bloodmobiles k (buses) cannot travel directly from the starting city to the crisis-stricken city.

\[
\sum_{i=1}^{n} X_{ijk} = \sum_{i=1}^{n+1} X_{jik} = Y_{jk}, \quad \forall j \in (1, \ldots, n), K \in (1, \ldots, k). \tag{7}
\]

Constraint (7) is the flow balance; based on this constraint, if bloodmobile k (buses) enters the BS of city j from each point, it should drive to other stations merely from the BS of city j only if the mentioned bus (bus k) has visited city i. In order words, for each input, one output should exist.

\[
Y_{ik} \leq \sum_{j=2}^{n} X_{1jk}, \quad \forall i \in (1, \ldots, n + 1), k \in (1, \ldots, k). \tag{8}
\]

Constraint (8): bloodmobile k (buses) should start visiting from starting city.

\[
Y_{ik} \leq \sum_{j=2}^{n} X_{j+1k}, \quad \forall i \in (1, \ldots, n + 1), k \in (1, \ldots, k). \tag{9}
\]

Constraint (9) confines the bloodmobile k (buses) at the end of their route to return to the crisis-stricken city.

\[
X_{ijk} \leq Y_{jk}, \quad \forall i, j \in (1, \ldots, n + 1), k \in (1, \ldots, k). \tag{10}
\]

\[
X_{ijk} \geq Y_{jk}, \quad \forall i, j \in (1, \ldots, n + 1), k \in (1, \ldots, k). \tag{11}
\]

Constraints (10) and (11) guarantee that when bloodmobile k (buses) travels from city i to city j, it should visit city i at first and then visit city j.

\[
\sum_{k=1}^{K} Y_{ik} \leq 1, \quad \forall i \in (2, \ldots, n). \tag{12}
\]

Constraint (12) guarantees that the maximum number of buses visiting a city is 1.

\[
\sum_{i=2}^{n+1} X_{ijk} \leq 1, \quad \forall k \in (1, \ldots, k). \tag{13}
\]

Constraint (13) indicates that, at the time of operation start, each bloodmobile k (buses) can either be used or not. It is obvious that each blood mobile k (bus) travels to merely one city at first.

\[
Y_{Dik} \leq Y_{ik}, \quad \forall i \in (2, \ldots, n), k \in (1, \ldots, k). \tag{14}
\]

Constraint (14) indicates that if bloodmobile k (buses) visits city i, bus k cannot transport the collected blood from city i or leave it there to be transported by the helicopter to the same point.
Table 2: Detail of the proposed model.

| Notation | Description |
|----------|-------------|
| $N$      | Maximum number of points chosen as the station |
| $K$      | The number of bloodmobiles (buses) |
| $D$      | The donors’ population |
| $\alpha$| The blood type percentage in that population (the normality of universal blood type) |
| $R_b$    | The demand of blood types |
| $t_{ij}$ | The interval (time) that a bus travels from city $i$ to city $j$ |
| $r_{ij}$ | The interval (time) a helicopter travels from city $i$ to city $j$ |
| $\beta$ | The population of donors frequently donating blood |

**Binary variable**

$$X_{ijk} = \begin{cases} 1, & \text{bus k travels from city i to j}, \\ 0, & \text{otherwise.} \end{cases}$$

$$Z_{ij} = \begin{cases} 1, & \text{the helicopter travels from city i to j}, \\ 0, & \text{otherwise.} \end{cases}$$

$$Y_{ik} = \begin{cases} 1, & \text{bus k visits city i}, \\ 0, & \text{otherwise.} \end{cases}$$

$$YD_{ik} = \begin{cases} 1, & \text{after receiving the collected blood, if bus k leaves at city i}, \\ 0, & \text{otherwise.} \end{cases}$$

$$w_j = \begin{cases} 1, & \text{the helicopter visits city j}, \\ 0, & \text{otherwise.} \end{cases}$$

**Nonnegative variable**

$$TT_i$$ The required time for arriving city $i$  
$$S_{ik}$$ The stop time (hours) of bus at city $k$  
$$SS_{ij}$$ The stop time (hours) of the helicopter at city $j$  
$$Q_{1kb}$$ The amount of collected blood of blood types by bloodmobiles (buses)  
$$Q_{2k}$$ The amount of collected blood of blood types by the helicopter  
$$Q$$ The total amount of collected blood by the bloodmobiles (buses) and the helicopter per blood type  
$$F_k(S_{ik}) = S_{ik}, D_j, \alpha, \beta$$ Function of the amount of collected blood type $b$ by bus $k$ at city $i$, when it stopped $S_{ik}$ hours

Constraint (15) is related to the schedule of each bloodmobile (buses). Indeed, it strikes a balance between the entrance and exit time of bloodmobile (buses) from cities.

$$Z_{ii} = 0, \quad \forall i \in (1, \ldots, n + 1), k \in (1, \ldots, k). \quad (16)$$

Similar to constraint (5), constraint (16) guarantees that the helicopter cannot travel from city $i$ to $i$ (loop is not allowed).

$$Z_{i1 \ldots n + m} = 0, \quad \forall k \in (1, \ldots, k). \quad (17)$$

Similar to constraint (6), constraint (17) indicates that the helicopter cannot travel directly from starting city to the crisis-stricken city.

$$\sum_{i=0}^{n} Z_{ij} = \sum_{j=1}^{n+1} Z_{ji} = W_j, \quad \forall j \in (1, \ldots, n). \quad (18)$$

Constraint (18) is the flow balance constraint of the helicopter, such that if the helicopter enters from each city to city $j$, it should travel to other cities only from city $j$ (only if it has visited city $j$).

$$W_i \leq \sum_{j=2}^{n} Z_{ij}, \quad \forall i \in (1, \ldots, n + 1). \quad (19)$$

Constraint (19) guarantees that the helicopter starts routing from the starting city.

$$W_i \leq \sum_{j=2}^{n} Z_{jn+1}, \quad \forall i \in (1, \ldots, n + 1). \quad (20)$$

Constraint (20) guarantees that the helicopter visits the crisis-stricken city at the end of the route.

$$Z_{ij} \leq W_i, \quad \forall i, j \in (1, \ldots, n + 1). \quad (21)$$

$$Z_{ij} \leq W_j, \quad \forall i, j \in (1, \ldots, n + 1). \quad (22)$$

Constraints (21) and (22) guarantee that when the helicopter is going to travel from city $i$ to city $j$, it should visit city $i$; afterward, it visits city $j$. 

...
Constraint (23) guarantees that when the operation starts, the helicopter can either be used or not. It is clear that the helicopter can travel to only one city at first.

\[ \sum_{j=2}^{m} Z_{ij} \leq 1. \quad (23) \]

Constraint (25) is related to the helicopter’s schedule. Indeed, it strikes a balance between the entrance and exit of the helicopter from cities.

\[ (S_{ik} + T_{ik}) \cdot YD_{ik} \leq TT_i \cdot W_i, \quad k \in (1, \ldots, K), i \in (1, \ldots, N). \quad (26) \]

Constraint (26) is about the helicopter’s schedule for collecting blood, such that the helicopter should arrive at that location after delivering the collected blood to city \(i\) by bus if city \(i\) is not the final station of the route.

\[ Q_{1kb} = \sum_{i=1}^{n} F_{b}(S_{ik}) \cdot (1 - YD_{ik}), \quad \forall b \in (1, \ldots, 4), k \in (1, \ldots, K). \quad (27) \]

Constraint (27) is the total blood type \(b\) delivered to the crisis-stricken city by bloodmobile \(k\) (buses).

\[ Q_{2b} = \sum_{k=1}^{K} \sum_{i=1}^{n} F_{b}(S_{ik}) \cdot YD_{ik} \cdot W_{i}, \quad \forall b \in (1, \ldots, 4). \quad (28) \]

Constraint (28) is the total blood type \(b\) delivered to the crisis-stricken city by the helicopter.

\[ Q_{b} = \sum_{k=1}^{K} Q_{1kb} + Q_{2b}, \quad \forall b \in (1, \ldots, 4). \quad (29) \]

Constraint (29) is the buses’ total collected blood and the helicopter per blood type.

\[ Q_{1} \geq R_{1}, \quad (30) \]

\[ Q_{1} + Q_{2} \geq R_{2}, \quad (31) \]

\[ Q_{1} + Q_{3} \geq R_{3}, \quad (32) \]

\[ Q_{1} + Q_{3} + Q_{4} \geq R_{4}. \quad (33) \]

Constraints (30) to (33): the collected blood by the bloodmobiles (buses) and the helicopter should be equal or greater than the demand of each group. In fact, constraints emphasize that shortage is not allowed.

\[ X_{ijk}, Y_{ik}, YD_{ik}, W_{i}, Z_{ij} \in \{0, 1\}, \quad \forall i, j \in (1, \ldots, n), \forall K \in (1, \ldots, k). \quad (34) \]

In the end, constraint (34) specifies the limits of variables.
Also, the route of the helicopter has been from Qazvin to Danesfahan, Lak, and Avaj.

4.1. Sensitivity Analysis. In this section, the effect of changing the key parameters including the blood mobiles and helicopter quantity on the decisions of proposed model is examined. In Table 6 all considered changing is shown. As depicted in Table 6, changing blood mobiles and helicopter quantity have the remarkable effect on time and collected blood quantity.

Figures 2 and 3 show a comparison of the optimal situation with each of the scenarios considered for sensitivity analysis. According to Figure 2, it is shown that, based on
time of the bloodmobiles (the buses) to the crisis-stricken city is minimized. By changing the models’ assumptions, such as lowering the number of bloodmobiles, the blood collection time increases, reaching 44 hours. In addition, we considered a model without any helicopter, observing that the required blood in the crisis-stricken area cannot be transported and supplied on time. The main limitations of this work can be described as follows:

(i) Some limitations to access operational data that must be obtained from indirect sources
(ii) Challenges to determine demand for each blood type

Data Availability
No data were used to support this study.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

Authors’ Contributions
Mahsa Rezaei Kallaj contributed to software, investigation, and writing of the original draft. Milad Abolghasemian participated in conceptualization, resources, reviewing, and editing. Samaneh Moradi contributed to software, reviewing, and editing. Majid Sabkara contributed to methodology and native editing. Adel Pourghader Chobar contributed to translation to English and formal analysis.

References

[1] R. Mousavi, A. Salehi-Amiri, A. Zahedi, and M. Hajiaghaei-Keshmiri, “Designing a supply chain network for blood decomposition by utilizing social and environmental factor,” Computers & Industrial Engineering, vol. 160, p. 107501, 2021.
[2] F. Şahinyazan, B. Kara, and M. Taner, “Selective vehicle routing for a mobile blood donation system,” European Journal of Operational Research, vol. 245, no. 1, pp. 22–34, 2015.
[3] S. Gunpinar and G. Centeno, “An integer programming approach to the bloodmobile routing problem,” Transportation Research Part E: Logistics and Transportation Review, vol. 86, pp. 94–115, 2016.
[4] M. Eskandari-Khanghahi, R. Tavakkoli-Moghaddam, A. A. Taleizadeh, and S. H. Amin, “Designing and optimizing a sustainable supply chain network for a blood platelet bank under uncertainty,” Engineering Applications of Artificial Intelligence, vol. 71, pp. 236–250, 2018.
[5] B. Fahimnia, A. Jabbarzadeh, A. Ghavamifar, and M. Bell, “Supply chain design for efficient and effective blood supply in disasters,” International Journal of Production Economics, vol. 183, pp. 700–709, 2017.
[6] K. K. S. Kuruppu, “Management of blood system in disasters,” Biologicals, vol. 38, no. 1, pp. 87–90, 2010.
[7] A. Jabbarzadeh, B. Fahimnia, and S. Seuring, “Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application,” Transportation Research Part E: Logistics and Transportation Review, vol. 70, pp. 225–244, 2014.
[8] Q. Duan and T. W. Liao, “Optimization of blood supply chain with shortened shelf lives and ABO compatibility,” *International Journal of Production Economics*, vol. 153, pp. 113–129, 2014.

[9] G. P. Prastacos, “Blood inventory management: an overview of theory and practice,” *Management Science*, vol. 30, no. 7, pp. 777–800, 1984.

[10] N. Haghjoo, R. Tavakkoli-Moghaddam, H. Shahmoradi-Moghadam, and Y. Rahimi, “Reliable blood supply chain network design with facility disruption: a real-world application,” *Engineering Applications of Artificial Intelligence*, vol. 90, p. 103493, 2020.

[11] Y. Sha and J. Huang, “The multi-period location-allocation problem of engineering emergency blood supply systems,” *Systems Engineering Procedia*, vol. 5, pp. 21–28, 2012.

[12] B. Zahiri, “A multi-stage stochastic programming approach for blood supply chain planning,” *Computers & Industrial Engineering*, vol. 122, pp. 1–14, 2018.

[13] S. Gunpinar and G. Centeno, “Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals,” *Computers & Operations Research*, vol. 54, pp. 129–141, 2015.

[14] O. Rodriguez-Espíndola, P. Albores, and C. Brewster, “Disaster preparedness in humanitarian logistics: a collaborative approach for resource management in floods,” *European Journal of Operational Research*, vol. 264, no. 3, pp. 978–993, 2018.

[15] J. A. Paul and X. Wang, “Robust location-allocation network design for earthquake preparedness,” *Transportation Research Part B: Methodological*, vol. 119, pp. 139–155, 2019.

[16] H. Adarang, A. Bozorgi-Amiri, K. Khalili-Damghani, and R. Tavakkoli-Moghaddam, “A robust bi-objective location-routing model for providing emergency medical services,” *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 10, no. 3, 2020, in Press.

[17] M. Arani, Y. Chan, X. Liu, and M. Momenitabar, “A lateral resupply blood supply chain network design under uncertainties,” *Applied Mathematical Modelling*, vol. 93, pp. 165–187, 2021.

[18] F. Goodarzian, S. F. Wamba, K. Mathiyazhagan, and A. Taghipour, “A new bi-objective green medicine supply chain network design under fuzzy environment: hybrid metaheuristic algorithms,” *Computers & Industrial Engineering*, vol. 160, p. 107535, 2021.

[19] S. M. R. Davoodi and A. Goli, “An integrated disaster relief model based on covering tour using hybrid Benders decomposition and variable neighborhood search: application in the Iranian context,” *Computers & Industrial Engineering*, vol. 130, pp. 370–380, 2019.

[20] M. R. G. Samani and S.-M. Hosseini-Motlagh, “A novel capacity sharing mechanism to collaborative activities in the blood collection process during the COVID-19 outbreak,” *Applied Soft Computing*, vol. 112, p. 107821, 2021.

[21] E. B. Tirkolaee, N. S. Aydin, M. Ranjbar-Bourani, and G.-W. Weber, “A robust bi-objective mathematical model for disaster rescue units allocation and scheduling with learning effect,” *Computers & Industrial Engineering*, vol. 149, p. 106790, 2020.

[22] B. C. Wang, Q. Y. Qian, J. J. Gao, Z. Y. Tan, and Y. Zhou, “The optimization of warehouse location and resources distribution for emergency rescue under uncertainty,” *Advanced Engineering Informatics*, vol. 48, p. 101278, 2021.

[23] Z. Mamashli, A. Bozorgi-Amiri, I. Dadashpour, S. Nayeri, and J. Heydari, “A heuristic-based multi-choice goal programming for the stochastic sustainable-resilient routing-allocation problem in relief logistics,” *Neural Computing & Applications*, vol. 33, pp. 1–27, 2021.