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MULTI-OBJECTIVE OPTIMIZATION MODEL FOR BLOOD SUPPLY CHAIN NETWORK DESIGN CONSIDERING COST OF SHORTAGE AND SUBSTITUTION IN DISASTER

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Abstract. The problem of network design of blood supply chains is traditionally studied considering a maximum of three objective functions. In the real world, however, there are always many conflicting objectives for different stakeholders. This paper addresses a blood supply chain (BSC) network design problem to optimize the costs of blood shortage and substitution in addition to other common objective functions. To this end, four important objectives that decision makers are always faced with in disaster are considered: (1) minimizing the total cost, (2) minimizing transportation time, (3) minimizing total unsatisfied demand, and (4) maximizing the total reliability. A mixed-integer linear programming (MIP) model is proposed to formulate the problem at hand. Since this problem is known to be strongly NP-hard, the intelligent NSGA-II algorithm is applied to solve it in a reasonable time. Data from a real case study is used to evaluate the performance of the proposed solution method. The comparison of the results of the proposed algorithm with the mathematical model confirms the accuracy of the proposed method. Furthermore, the analysis of the results indicates the superiority of the proposed model over previous studies. Moreover, the proposed algorithm provides a wide range of suitable solutions. Therefore, different alternatives are presented to the decision makers to make a trade-off according to their preferences.

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1. Introduction

Blood Supply Chain Management (BSCM) aims to meet the need for blood as an essential resource for people during or after disasters. After events, which can be natural or man-made, there is a great need for help and rescue. Blood is one of the most important supplies needed during and after disasters. Providing this help plays a vital role in saving the wounded. Therefore, the design problem of the blood supply chain is significant, especially in accident-prone areas, so this problem has been motivating researchers since 1960. In fact, research

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in this area has broadly contributed to the development of effective methods for managing perishable inventory [1]. In general, a BSC consists of three main features. (I) main blood donation centers with adequate facilities, (II) laboratory centers with large storage capacity and technology for necessary tests, and (III) distribution methods and facilities to meet the needs. On the other hand, temporary facilities with limited capacity are much cheaper and more flexible to meet demand and donors.

This topic has been explored to some extent in the literature due to its relevance to healthcare. Therefore, many different approaches have been introduced to model and solve this problem. These approaches are mainly based on integer or mixed-integer programming, simulation, dynamic programming, and goal programming. On the other hand, although this problem would have more than three objectives in the real world, researchers usually focus on designing this problem for a maximum of two or three objectives (multi-objective). Therefore, in this study, the design problem of the BSC is discussed in more than three objectives considering the real conditions. More objectives in BSCM could support more stakeholders and better meet their needs.

To the best of the authors' knowledge, existing studies on relief efforts can be categorized into two classes. Some of them relieve the supply chain for goods, and others investigate regarding blood [2]. A summary of efforts to design blood supply chain networks related to blood supply management is presented below.

Blood is a perishable product and the first study of perishable items was conducted by Whitin in 1957 [3]. Thereafter, research into regional and local management of the blood supply started in the 1960s. Elston *et al.* proposed the first statistical approach for ordering and usage policies for a hospital blood bank in 1963 [4]. They also presented some guidelines to inventory levels for a hospital blood bank determined. They simulated some operations of a particular blood bank on an electronic computer to obtain values that permit the establishment of inventory levels appropriate for critical ranges of mean uses and inputs [5]. For a full review of work on the BSC up to the mid-1980s, see Prastacos [6], particularly in relation to blood bank management policies and decisions. In addition, Nahmias [1] reviewed perishable inventory theories that researchers had introduced up to 1982.

Pierskalla [7] conducted a comprehensive supply chain design to answer the following questions: (1) where blood banks can be deployed, (2) how donor groups can be assigned to blood collection centers, (3) blood transfusion sites, and (4) how the blood in a blood transfusion facility can be allocated and collected to be sent to facilities and blood bank hospitals. Rajagopalan *et al.* [8] presented a multi-period coverage model for determining ambulance position. They proposed a new model to determine the minimum number of ambulances and their locations for an Emergency medical service (EMS) system.

Applications in health research have been extensively discussed by Papageorgiou [9] and Rais and Viana [10]. An article that focused heavily on health facility allocation refers to Syam and Côé [11]. They developed a model for location allocation of specialty healthcare systems based on four critical factors: mean, level of service orientation, role of patient care as a function of distance to treatment, and geographic density of the patient population. Belien and Force proposed a literature review on blood supply chain management and claimed that some research had been presented in this area [12].

Nagurney *et al.* [13] presented a seven-level mathematical BSC model with two objectives to minimize the total cost and risk. Sha and Huang [14] solved a single-objective two-layer model by the heuristic algorithm. Duan and Liao [15] introduced a new metaheuristic algorithm called TA-TS to solve a two-layer single-objective model. Arvan *et al.* [16] presented a four-layer multi-objective model to minimize cost and time by the ε-*constraint* method. The same research was conducted by Fahimnia *et al.* [17] with a hybrid solution. Belien *et al.* have considered the optimization of organ transplant networks [18].

Ghatreh Samani and Hosseini-Motlagh proposed an extended Perspective that included a two-phase preventive policy by reducing the risk of interference using the fuzzy analysis hierarchy process [19]. Hosseinifard and Abbasi studied the importance of inventory centralization at the second echelon of a two-echelon perishable supply chain. Their results indicated that centralization of hospital inventory is a critical factor in the BSC and can increase the resilience and sustainability of BSCs [20]. Yates *et al.* explained some methods commonly used in commercial supply chain management that can lead to efficiencies in waste management in the hospital and BSC. They state that an example of this case is the sharing of stock or lateral transshipment of blood units just before their expiration date between hospitals, thereby reducing waste in the supply chain [21]. Osorio *et al.* presented a location–allocation model that takes these factors into account to support strategic decision-making at different levels of centralization. A case study (Colombia) illustrated to redesign the national BSC under a set of realistic travel time constraints [22]. Dehghani *et al.* analyzed how a proactive transshipment policy can avoid future shortages; besides, they considered a network of hospitals with uncertain demand. Each hospital decided on the amount to order from a central blood bank and transfer to other hospitals in each period [23].

Some recent studies by Habibi-Kouchaksaraei *et al.* considered BSC networks under uncertain decision-making and social aspects [2]. They proposed a robust optimization model to design a bi-objective multi-period BSC network including three echelons. The authors proposed a scenario-based model to determine the number and location of facilities and the best strategy to allocate them under three different scenarios. Minimizing the overall cost and blood shortages are two considered objectives in their study. In addition, Hosseini-Motlagh *et al.* conducted this problem and developed a robust optimization approach to tackle the uncertainty of parameters in a bi-objective model [24]. A dynamic, robust location–allocation model was presented for designing a BSCM under facility disruption risks and uncertainty in a disaster situation by Haghjoo *et al.* [25]. Sun *et al.* presented a bi-objective robust optimization model for strategic and operational response to clarify the facility location and emergency resource allocation in a three-level problem including casualty clusters, temporary facilities, and hospitals [26]. Finally, Rajendran and Ravi Ravindran developed a stochastic integer-programming model to determine ordering policies along a BSC under uncertainty. They also proposed a stochastic genetic algorithm to solve the problem on the large scales [27].

The four studies that come closest to this research are as follows:

Salehi *et al.* [28] investigated a robust two-stage, multi-period stochastic model that accounts for the transfusion of one blood group and its derivatives to other species based on medical needs. They simultaneously overlooked the priority of blood supplements by the same blood and transportation mode in their model. Dillon *et al.* [29] performed well-known research on inventory management for the blood supply chain by introducing a two-stage stochastic programming model that considers blood group compatibility without the same blood priority. Zahiri and Pishvaee [30] presented a bi-objective mathematical programming model for BSC network design to minimize total network cost and maximum shortage. Although they addressed blood compatibility and blood products, their model did not deal with transport mode. Fazli-Khalaf *et al.* [31] conducted a three-objective model in 2017 with mode of transport and reliability of the blood tested, without considering blood compatibility and blood products. They define a new reliability objective function that aims to maximize the reliability of blood tests using different technologies in laboratories.

In this study, in addition to demonstrating a new area of investigation by considering four objectives for blood supply chain management (BSCM), the cost of the blood substitution penalty is discussed for the first time. Abdulwahab *et al.* [32] mentions that while it is a good way to use compatibility for blood supply, it also has its risks and problems for patients.

Das *et al.* considered the deterioration effect of the product and the preservation technology in BSCM. They developed an inventory model for items that do not immediately deteriorate, with demand dependent on the selling price of the product. The authors used the quantum-behaved particle swarm optimization (QPSO) algorithm to solve their problem. For each case, a numerical example was considered and solved with the different variants of QPSO algorithms [33]. Kang *et al.* discussed performance improvement and future sustainability in BSCM. The main objective of their study is to minimize the patient queue and required resources in a healthcare unit considering staff absenteeism [34]. Two cases of resource planning were presented. The first case looked at planning without desertion and the second at planning with an absenteeism factor. They showed that planning with an absenteeism factor improved the performance of healthcare systems in terms of the reduced patient queue and operational sustainability. Sardar *et al.* proposed a Machine Learning (ML) approach for on-demand forecasting using Long-Short-Term Memory (LSTM). The authors applied a consignment policy where the manufacturer controls inventory and the retailer receives a fixed fee and commission for the sale of each product. They developed two mathematical models using a classical optimization technique [35].

Table 1. Summary of literature review in blood supply chain network design.

Articles	Objectives				Solution approach	Main features						
	Cost	Shortage	Reliability	Time		# of layers	Blood compatibility	Substitution's penalty cost	Multi-products	Multi-period	Transportation	Case study
Nagurney *et al.* [13]	*				Decision making	7						
Sha and Huang [14]	*				Heuristic	2				*		
Duan and Liao [15]		*			TA-TS	2	*			*		
Jabbarzadeh *et al.* [39]	*				Robust	3				*		*
Hsieh [49]	*	*			NSGA-II	3						*
Arvan *et al.* [16]	*			*	ε-*constraint*	4						
Osorio *et al.* [22]	*				Simulation	3			*	*		*
Zahiri and Pishvaee [30]	*	*			Robust	5	*		*	*		*
Fahimnia *et al.* [17]	*			*	Hybrid solution	4				*		
Salehi *et al.* [28]	*				Simulation	3	*			*		*
Dillon *et al.* [29]	*				Stochastic programming	4	*			*		*
Ramezanian and Behboodi [38]	*				Robust	3				*		*
Fazli-Khalf *et al.* [31]	*		*	*	Robust	5				*	*	*
Habibi-Kouchaksaraei *et al.* [2]	*	*			GP Method	4				*		*
Haghjoo *et al.* [25]	*				Robust optimization	3					*	*
Hosseini-Motlagh *et al.* [24]	*	*			Robust optimization	4	*			*	*	*
Dehghani *et al.* [23]	*				Stochastic optimization	3				*		*
Asadpour *et al.* [50]	*				GP Method	3					*	*
This research	*	*	*	*	ε-*constraint* NSGA-II	5	*	*	*	*	*	*

In order to structure a relevant literature review of the considered problem and to show the main contributions of this study, we have classified the previous studies according to three characteristics: the objective functions, solution approach, and problem characteristics (see Tab. 1).

Although some different models for BSCM have been presented in recent years, according to the result presented in Table 1, there is still a certain vacuum that needs to be explored in this field of science. For example, only one of these models considered different vehicle types in transportation. In contrast, in real applications, there are usually different types of vehicle transport, capacity, cost, and speed. In addition, some studies considered blood compatibility by dividing blood products. In addition, none of the researchers considered the risk attitude of blood substitution. By considering this penalty in the cost function, the model attempts to reduce the amount of blood supply in the other group. However, every organization has its objective in an emergency, which can conflict with others. Therefore, this study is the first research to address the following four objectives in BSC modeling simultaneously:

- Minimizing the total cost of network considering the penalty of blood substitution.
- Minimizing transportation time between facilities.
- Minimizing total unsatisfied demand.
- Maximizing the total reliability of the tested blood in laboratories.

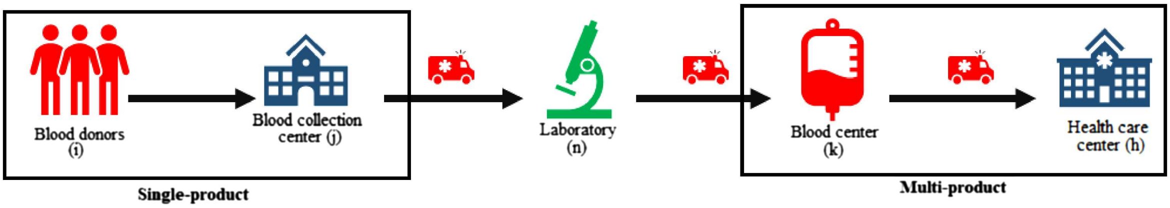


FIGURE 1. Graphic image of the blood supply chain network of proposed model.

Problems with many objectives are a new approach in mathematical modeling that few research in BSCM considers. Therefore, some of the stakeholders have been left out due to the number of objective limitations [36, 37].

This paper is organized as follows. Section 2 describes the problem in detail and presents the assumptions and mathematical models. Section 3 describes the proposed algorithms. The case study considered is presented in Section 4. The result of solving the case study by the proposed methods is discussed in Section 5. Finally, Section 6 describes conclusions and recommendations for future research.

2. Problem definition

This research focuses on a many-objective five-level BSC including candidate points for blood donation, blood collection facilities, laboratories, blood centers, and health centers (see Fig. 1). Two types of blood collection facilities are considered in this study, permanent and temporary. Blood collections collect blood and send it to labs for blood testing. Blood is then fractionated and converted into different types of blood products. All types of blood products such as red Blood Cells (RBC), platelets, plasma, whole blood and frozen blood are considered in this research. The blood products are then shipped to blood centers, which are responsible for the care and distribution of the blood to health centers. Among all supply chain facilities, different types of vehicles with different speeds and capacities are considered.

In these studies, the following assumptions are considered to model and solve the blood supply chain design problem.

- Each blood donor has a maximum blood supply.
- ABO compatibility is considered for each product.
- The capacity of the blood collection facilities, blood centers, laboratories, and transportation mode is limited.
- The demand rate of each health care center is known.
- The expiry time is only considered on the transport route.
- A single product is transported through the network before blood separation, then multiple products are transported.

In this research, an integrated mathematical model is proposed for the aforementioned problem by considering four objective functions: (1) minimizing the total cost, (2) minimizing the transportation time between facilities, (3) minimizing the total unsatisfied demand, and (4) maximizing the total reliability of the tested blood in the laboratory.

These four objectives are necessary to address essential needs that are essential to stakeholders in BSCM. The first objective is the total cost of the network, which is a notable objective in BSCM and shows the cost that most finance managers and CEOs are interested in. Transportation time is another notable objective that helps improve the reliability of BSCM. With increasing transportation time, the risk of blood perishability also increases. On the other hand, the most important purpose of BSCM is to provide the recipient with enough reliable and suitable blood at the right time.

Table 2. ABO matrix for RBC ($p = 1$).

Recipient	Donor O^-	O^+	A^-	A^+	B^-	B^+	AB^-	AB^+
O^-	*							
O^+	*	*						
A^-	*		*					
A^+	*	*	*	*				
B^-	*				*			
B^+	*	*			*	*		
AB^-	*		*		*		*	
AB^+	*	*	*	*	*	*	*	*

Table 3. ABO matrix for Plasma ($p = 2$).

Recipient	Donor O^-	O^+	A^-	A^+	B^-	B^+	AB^-	AB^+
O^-	*	*	*	*	*	*	*	*
O^+		*		*		*		*
A^-			*	*			*	*
A^+				*				*
B^-					*	*	*	*
B^+						*		*
AB^-							*	*
AB^+								*

Total unsatisfied demand is the rate of demand that is not provided in BSCM. This objective is helpful to make an important decision between the cost and uncertainty of BSCM for decision-makers. If the model does not consider this objective, the model prefers to increase this rate to cost reduction. The reliability of the tested blood in laboratories could be another operational objective that is considered to increase the technology used in the blood test. As the technology becomes more reliable, the cost of BSCM will increase, so this objective could strike a balance between the cost and blood test reliability for DM.

One of the most important issues researchers should consider when it comes to blood is blood compatibility. In emergencies or when a blood group is not available, a compatible blood group can be used [15]. For derivative products, compatibility is not the same for every blood type. Tables 2 and 3 show the ABO adjustment for RBC and Plasma (PLS), respectively [30]. It is also assumed that for Platelets (PLT) all types of groups are compatible with blood transfusions.

Another approach in this research is the number of objectives, which forces us to model our problem with more than three objectives to consider more aspects of a BSC mathematical model. To achieve this, we set the most repeatable objective in our model, such as cost, time, and shortage concepts. These three objectives are repeated several times in the literature, such as Abdulwahab and Wahab [32], Fahimnia *et al.* [17], Beliën *et al.* [18], Fazli-Khalaf *et al.* [31], Habibi-Kouchaksaraei *et al.* [2], Nagurney *et al.* [13], Zahiri and Pishvaee [30], Ramezanian and Behboodi [38], Jabbarzadeh *et al.* [39], and Khalilpourazari and Khamseh [40]. Some of them just model a parcel of BSC like Ramezanian and Behboodi [38], Duan and Liao [15], Sha and Huang [14], and Osorio *et al.* [22].

To notice more aspects of BSC for modeling a comprehensive model, some mathematical models in blood supply chain in recent years like Fazli-Khalaf *et al.* [31], Zahiri and Pishvaee [30], and Ramezanian and Behboodi

[38]. These models have some positive points, but none of these considered this problem in four objective conditions. Besides, the compatibility of blood groups considering its products and different vehicle types in transportation with different costs and capacities has not been investigated simultaneously in the previous studies. Therefore, from an integrated point of view, we have noticed all poses in real-world problems.

The following notations are used in this research to propose the mathematical programming model. Based on these notations, a comprehensive model inspired by some existing mathematical models in the BSC field such as Fazli-Khalaf *et al.* [31], Zahiri and Pishvaee [30], and Ramezanian and Behboodi [38] is developed.

2.1. Indices

i	Index for donor groups
j	Index for potential locations of blood facilities
k	Index for blood centers
t	Index for time periods
h	Index for health care centers
n	Index for laboratories
v	Index for transportation modes
g	Index for blood group types
p	Index for blood derived products
a	Index for blood testing technology of laboratories

2.2. Parameters

f_j	Fixed cost of establishment of permanent blood collection center j
fv_{na}	Fixed cost of establishment of laboratory n with blood testing technology a
v_{jlt}	Fixed cost of moving temporary blood collection centers from location l to location j at period t
oc_{ijt}	Cost of collecting blood from donor group i at blood collection facility j in period t
ccj_{jnvt}	Transportation cost of blood collection facilities j to laboratory n using transportation mode v in period t
ccg_{nkvt}	Transportation cost of blood from blood laboratory n to blood center k using transportation mode v in period t
tc_{na}	Testing cost of each unit of blood at laboratory n using blood testing technology a
cck_{khvt}	Transportation cost of blood from blood center k to demand zone h using transportation mode v period t
h_k	Unit holding cost of blood at blood center k
toc_v	Fixed cost of transportation mode v
S_{gpkt}	Unit shortage cost of g group blood from product p at blood center k in period t
$O_{gg'p}$	The ABO compatibility matrix with dimensions $g * g'$ for derived product p
tj_{jnvt}	Required time for each transportation mode type v to transport loaded blood from collection center j to laboratory n in period t
tk_{khvt}	Required time for each transportation mode type v to transport loaded blood center k to demand zone h in period t
tg_{nkvt}	Required time for each transportation mode type v to transport loaded blood from laboratory n to blood center k in period t
d_{gpht}	The demand of g group blood from product p blood at hospital h in period t
tr_{na}	Blood testing reliability of laboratory n using blood testing technology a
r_{ij}	Distance of donor group i from blood collection center j
b_{jt}	The capacity of temporary blood collection center j in period t
c_{jt}	The capacity of the permanent blood collection center j at period t
$potpop_i$	Potential population for blood donation of donor group i
sc_k	Maximum storage capacity in blood center k

M	A big constant number
ut_{ij}	Utility value for donor group i in blood facility of location j that calculated using equation $ut_{ij} = r_{ij}^{-\alpha} * p_j^{\beta} * e_j^{\lambda}$ [38]
$ubest_i$	The best utility value is accessible for donor group i based on utility equation $ut_{ij} = r_{ij}^{-\alpha} * p_j^{\beta} * e_j^{\lambda}$ and closest blood facility
tp_p	Expiry time of product p
ε	A very small positive number
dis	Coverage radius of blood collection centers
cp_n	Maximum capacity of laboratory n
$capa_v$	Maximum capacity of transportation mode v
pen	A penalty cost of blood compatibility

2.3. Decision variable

X_j	A binary variable; equal to 1 if a permanent facility is opened at site j; 0, otherwise
vn_{na}	The binary variable, is equal to 1 if a laboratory is established at location n with technology a; 0, otherwise
Y_{ijt}	A binary variable; equal 1 if blood facility at location j is assigned to donor group i in period t; 0, otherwise
Z_{jlt}	A binary variable; equal to 1 if a temporary facility is located at location l in period $t-1$ and moves to location j in period t; 0, otherwise
Q_{ijt}	Amount of blood collected at blood facility j from donor group i in period t
I_{gpkt}	Blood inventory level of g group blood from product p at blood center k at the end of period t
δ_{gpkt}	Under fulfillment of g group blood from product p at blood center k at the end of period t
at_{ijt}	Attractiveness utility of established facilities in location j in case of visiting that location by blood donor i in period t
$u_{nagpkvt}$	Amount of transported blood from laboratory n of group type g of the derived product p to blood center k using transportation v in period t tested by technology a
nj_{jnvt}	Number of transportation mode v needed at blood collection center j to transport collected blood to laboratory n in period t
ng_{nkvt}	Number of transportation mode v needed at laboratory n to transport blood to blood center k in period t
nk_{khvt}	Number of transportation mode v needed at blood center k to transport blood to demand zone h in period t
vj_{jnvt}	A binary variable; equal to 1 if transportation mode v is used to transport collected blood from blood collection center j to laboratory n in period t; 0, otherwise
vk_{khvt}	A binary variable, equal to 1 if transportation mode v is used to transport blood from blood center k to demand zone h in period t; 0, otherwise
vg_{nkvt}	A binary variable, equal to 1 if transportation mode v is used to transport blood from laboratory n to blood center k in period t; 0, otherwise
m_{gpkhvt}	Amount of transported of g group type blood from derived product p from blood center k to demand zone h with transportation mode v in period t
ot_{jnvt}	Amount of transported blood from blood collection center j to laboratory n using transportation mode v in period t
o_{jnt}	Amount of transported blood from blood collection center j to laboratory n in period t
y'_{gpkhvt}	Binary variable equals to 1 if $m_{gpkhvt} > 0$; 0, otherwise
$mg_{gg'pkhvt}$	Amount of g group type blood from derived product t which fulfill from g' group type blood from blood center k to demand zone h with transportation mode v in period t

2.4. Model formulation

The objective functions of the proposed model are as follows:

$$\begin{aligned}
\text{Min } Z_1 = &\sum_j f_j X_j + \sum_n \sum_a fv_{na} vn_{na} + \sum_j \sum_l \sum_t v_{jlt} z_{jlt} + \sum_i \sum_j \sum_t oc_{ijt} Q_{ijt} \\
&+ \sum_j \sum_n \sum_v \sum_t ccj_{jnvt} vj_{jnvt} + \sum_n \sum_a \sum_g \sum_p \sum_k \sum_v \sum_t (ccg_{nkvt} + tc_{na}) u_{nagpkvt} \\
&+ \sum_g \sum_p \sum_k \sum_h \sum_v \sum_t cck_{khvt} m_{gpkhvt} + \sum_g \sum_p \sum_k \sum_t h_k I_{gpkt} \\
&+ \sum_j \sum_n \sum_v \sum_t toc_v nj_{jnvt} + \sum_n \sum_k \sum_v \sum_t toc_v ng_{nkvt} + \sum_k \sum_h \sum_v \sum_t toc_v nk_{khvt} \\
&+ \sum_g \sum_p \sum_k \sum_t S_{gpkt} \left(\delta_{gpkt} - \sum_{g'} \sum_h \sum_v O_{gg'p} mg_{gg'pkhvt} \right) \\
&+ \sum_g \sum_{g'} \sum_p \sum_k \sum_h \sum_v \sum_t O_{gg'p} mg_{gg'pkhvt} pen
\end{aligned} \tag{1}$$

$$\begin{aligned}
\text{Min } Z_2 = &\sum_j \sum_n \sum_v \sum_t tj_{jnvt} vj_{jnvt} + \sum_n \sum_k \sum_v \sum_t tg_{nkvt} vg_{nkvt} \\
&+ \sum_k \sum_h \sum_v \sum_t tk_{khvt} vk_{khvt}
\end{aligned} \tag{2}$$

$$\text{Min } Z_3 = \sum_g \sum_p \sum_t \frac{\sum_k \left(\delta_{gpkt} - \left(\sum_{g'} \sum_h \sum_v O_{gg'p} mg_{gg'pkhvt} \right) \right)}{\sum_h d_{gpht}} \tag{3}$$

$$\text{Max } Z_4 = \sum_n \sum_a \sum_g \sum_p \sum_k \sum_v \sum_t tr_{na} * u_{nagpkvt} \tag{4}$$

$$\begin{aligned}
&\sum_k I_{gpkt-1} + \sum_n \sum_a \sum_k \sum_v u_{nagpkvt} - \sum_k I_{gpkt} + \sum_k \delta_{gpkt} - \sum_{g'} \sum_k \sum_h \sum_v O_{gg'p} mg_{gg'pkhvt} \\
&\qquad \geq \sum_k \sum_h \sum_v m_{gpkhvt} \qquad \forall g, p, t.
\end{aligned} \tag{5}$$

Subject to the following constraints:

$$X_j + \sum_l Z_{jlt} \leq 1 \qquad \forall j, t \tag{6}$$

$$\sum_l Z_{ljt} \leq \sum_l Z_{jlt-1} \qquad \forall j, t \geq 2 \tag{7}$$

$$Y_{ijt} \leq X_j + \sum_l Z_{jlt} \qquad \forall i, j, t \tag{8}$$

$$r_{ij} Y_{ijt} \leq dis \qquad \forall i, j, t \tag{9}$$

$$\sum_j Y_{ijt} \leq 1 \qquad \forall i, t \tag{10}$$

$$Q_{ijt} \leq M * Y_{ijt} \qquad \forall i, j, k, v, t \tag{11}$$

$$\sum_i Q_{ijt} \leq c_{jt} X_j + b_{jt} \sum_l Z_{jlt} \qquad \forall j, t \tag{12}$$

$$\sum_g \sum_p I_{gpkt} + \sum_n \sum_a \sum_g \sum_p \sum_v u_{nagpkvt} \leq sc_k \qquad \forall k,t \qquad (13)$$

$$\sum_j Q\_ijt \leq potpop_i \frac{\sum_j at_{ijt}}{ubest_i} \qquad \forall i,t \qquad (14)$$

$$at_{ijt} \leq ut_{ij} Y_{ijt} \qquad \forall i,j,t \qquad (15)$$

$$at_{ijt} \geq ut_{ij} - M(1 - Y_{ijt}) \qquad \forall i,j,t \qquad (16)$$

$$\sum_k \sum_v m_{gpkhvt} \geq d_{gpht} \qquad \forall g,p,h,t \qquad (17)$$

$$\left(\sum_v tk_{khvt} - tp_p\right) y'_{gpkht} \leq \varepsilon y'_{gpkht} \qquad \forall g,p,k,h,t \qquad (18)$$

$$vk_{khvt} \leq \sum_g \sum_p m_{gpkhvt} \qquad \forall k,h,v,t \qquad (19)$$

$$vj_{jnvt} \leq ot_{jnvt} \qquad \forall j,n,v,t \qquad (20)$$

$$vg_{nkvt} \leq u_{nagpkvt} \qquad \forall a,g,p,k,n,v,t \qquad (21)$$

$$ng_{nkvt} \leq vg_{nkvt} * M \qquad \forall n,k,v,t \qquad (22)$$

$$nj_{jnvt} \leq vj_{jnvt} * M \qquad \forall j,n,v,t \qquad (23)$$

$$nk_{khvt} \leq vk_{khvt} * M \qquad \forall k,h,v,t \qquad (24)$$

$$\sum_g \sum_p \sum_v u_{nagpkvt} \leq M * v_{na} \qquad \forall n,k,a,t \qquad (25)$$

$$\sum_j o_{jnt} = \sum_a \sum_g \sum_p \sum_k \sum_v u_{nagpkvt} \qquad \forall n,t \qquad (26)$$

$$ng_{nkvt} \geq \frac{\sum_a \sum_g \sum_p u_{nagpkvt}}{capa_v} \qquad \forall n,k,v,t \qquad (27)$$

$$nj_{jnvt} \geq \frac{ot_{jnvt}}{capa_v} \qquad \forall j,n,v,t \qquad (28)$$

$$nk_{khvt} \geq \frac{\sum_g \sum_p m_{gpkhvt}}{capa_v} \qquad \forall k,h,v,t \qquad (29)$$

$$\sum_{g'} \sum_h \sum_v mg_{gg'pkhvt} \leq \delta_{gpkt} \qquad \forall g,p,k,t \qquad (30)$$

$$\sum_j \sum_j Q_{ijt} \geq \sum_n \sum_a \sum_g \sum_p \sum_k \sum_v u_{nagpkvt} \qquad \forall t \qquad (31)$$

$$\sum_j o_{jnt} \leq \sum_a cp_n vn_{na} \qquad \forall n,t \qquad (32)$$

$$o_{jnt} = \sum_v ot_{jnvt} \qquad \forall j,n,t \qquad (33)$$

$$Q_{ijt} \cdot I_{gpkt} \cdot \delta_{gpkt} \cdot at_{ijt} \cdot u_{nagpkvt} \cdot m_{gpkhvt} \cdot ot_{jnvt} \cdot o_{jnt} \cdot mg_{gg'pkhvt} \geq 0; \qquad \forall i,j,l,n,v,g,p,k,h,t \qquad (34)$$

$$Y_{ijt} \cdot Z_{jlt} \cdot X_j \cdot vn_{na} \cdot vj_{jnvt} \cdot vk_{khvt} \cdot vg_{nkvt} \cdot y'_{gpkht} \in \{0.1\} \qquad \forall i,j,l,n,v,g,p,k,h,t \qquad (35)$$

$$nj_{jnvt} \cdot ng_{nkvt} \cdot nk_{khvt} \geq 0; \qquad int. \qquad (36)$$

According to relation (1) of the mathematical model, the total cost of the blood supply chain is minimized as the first objective function. This item includes the cost of establishing permanent blood collection facilities, laboratories with different test technologies, moving temporary blood collection, blood collection operation, transportation between facilities with a different mode, carrying out blood tests in laboratories with different technologies, blood centers holding, fixed costs of required transportation modes, the shortage cost and finally the penalty cost of using alternative blood. The cost of temporary blood collection vehicles is setting in the first movement of these facilities. The second objective function has been shown as relation (2). This objective aims to minimize the total transportation time between facilities. The total unsatisfied demand of different products is minimized by the third objective function that has been defined as relation (3). The fourth objective function aims to maximize the total reliability of the blood tested with different technologies in the laboratories with relation (4). Constraint (5) determines the inventory level at blood centers and the under-fulfillment of blood requirement, a control constraint. Constraint (6) purposes of avoiding locating more than one facility at each site. Constraint (7) enforces temporary facilities cannot move from a location where there is no facility located. Constraint (8) aims that donors only can be assigned to open facilities. Constraint (9) guarantees that donors covers within a distance "*dis*" of blood facilities assigned to them. Constraint (10) ensures that blood donors visit at most one facility in each period. Constraint (11) ensures that the volume of blood donated by a donor cannot be shipped from a facility not assigned to that donor. Constraint (12) restricts the capacity of the blood collection facility. Constraint (13) expresses the blood holding capacity at each blood center. Constraint (14) shows that collected blood is proportional to the potential population and the provided utility of blood donors. Constraints (15) and (16) declare that if blood donor i is allocated to facility j, then at_{ijt} is equal to the provided utility.

Constraint (17) shows the demand for health care centers. Constraint (18) is the time constraint, ensuring the derived products are transported to demand zones less than the expiry time. Constraints (19)–(21) ensure that blood can flow between facilities if transportation mode is defined. Constraints (22)–(24) show between which facilities, transportation means are used. Constraint (25) ensures the flow of collected blood between blood collection centers and laboratories. Constraint (26) ensures the flow of collected blood between facilities.

Constraints (27)–(29) determine the number of transportation means between facilities at each period. Constraint (30) guarantees that blood supplied from the compatibility matrix must be less than a shortage. Constraint (31) guarantees that collected blood from donors must be more than the amount of blood released from laboratories. Constraints (32) show the maximum capacity of laboratories. Constraint (33) ensured the equality between transported blood to laboratories with any transporting mode and transported blood from blood collection centers to laboratories. Constraints (34)–(36) represent the decision variables and their possible values.

In addition, the first level of the considered problem is devoted to blood donation. Considering the factors affecting blood donation, such as the distance from the blood donor to the blood recipient, the incentives for blood donors and the expertise of the staff in the health center, we use the utility function $ut_{ij} = r_{ij}^{-\alpha} * p_j^{\beta} * e_j^{\lambda}$ [38]. In this equation, r_{ij} is the distance between the ith donor candidate and the jth blood collection facility. p_j and e_j, respectively, are advertising budgets and an experience factor in the jth blood collection facility. α and β are also parameters that indicate the distance and cost sensitivity of donors respectively. The parameter λ is also a factor in donor rationality. In addition, for the first time in mathematical BSC modeling, this research takes into account the penalty conception of blood substitution. To this end, a statement is added to the first function to control the amount of blood supplied from another blood group as below. This formula can cause the model to use less blood in compatibility by increasing the BSC cost as follow:

$$C_{\mathrm{BSC}} = \sum_{g} \sum_{g'} \sum_{p} \sum_{k} \sum_{h} \sum_{v} \sum_{t} O_{gg'p} mg_{gg'pkhvt} pen$$

while *pen* is a blood compatibility penalty cost.

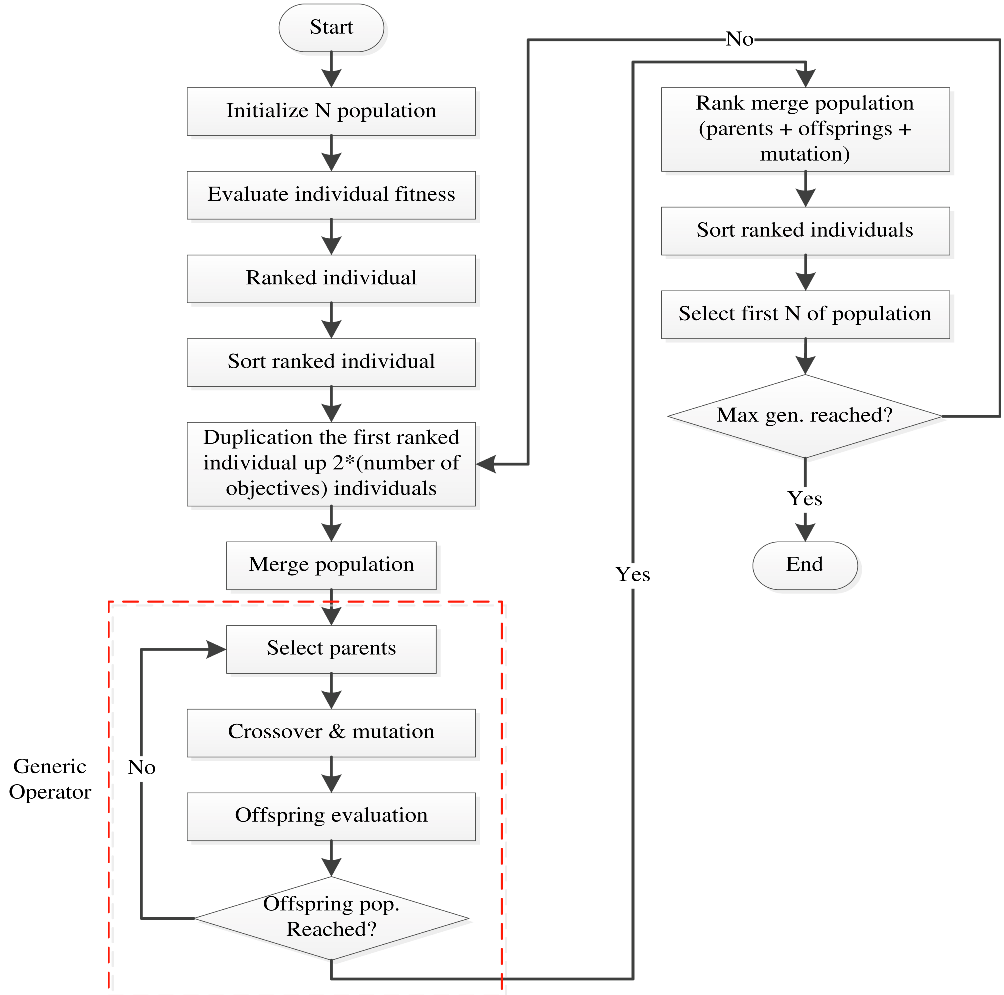


FIGURE 2. Proposed NSGA-II algorithm.

3. Solution approach

3.1. Proposed NSGA-II

In this section, the Non-dominated Sorting Genetic Algorithm (NSGA-II) is adjusted and used to solve the problem on the real-sized scales. This method is one of the population-based algorithms for solving multi-objective optimization problems. In this algorithm, some parameters like the number of the initial population, the number of iterations, the mutation and the crossover percentage affect the solution time and the quality of the result. Creating a more intelligent population is a way to improve a metaheuristic algorithm and the performance of evolutionary algorithms in terms of quality and computation time [41, 42]. To improve the performance of the algorithm due to the number of objectives and the complexity of the proposed mathematical BSC, some modifications were made to the classic NSGA-II (see Fig. 2). According to these modifications, the top 5% of the ranked solutions are duplicated to provide the more crowding distance value. This mechanism significantly improves the quality of the final solution on the provided Pareto front.

TABLE 4. Tested and final values of parameters provided by the Taguchi method.

Algorithm parameter	Level 1	Level 2	Level 3	Final values
Iteration	100	200	300	100
Number of population	100	200	300	300
Crossover	0.7	0.8	0.9	0.8
Mutation	0.02	0.05	0.1	0.02

Moreover, additional steps have been defined that help increasing the population. The crossover operator has twice the chance of choosing a better solution (the solution with better value at the crowding distance) in each generation. First, the decision maker could select the percentage of the population with appropriate answers that rank first and proceed to the duplication step. In the duplication step, the solutions are duplicated based on the ranking function and DM preference percentage. This step increases the population going to the genetic algorithm equal to the initial population plus the percentage of DM preference. This improvement increases the chance of crossover and mutation of the best solution.

Parameters tuning is another factor, which has a significant impact on the performance of approximation methods. We used the Taguchi method to set up the algorithm parameters. In this way, three different levels for each parameter were defined to evaluate the influence of relevant parameters on performance metrics. Therefore, a 27-factorial design was tested, and the result is presented in Appendix A. The defined test values of the main factors and the results of the Taguchi method for each factor are shown in Table 4.

General steps of NSGA-II developed and improved to solve the considered problem according to the mentioned difficulties in BSC problems are as follows:

(I) **[Start]** Generate a random population of $N(300)$ chromosomes which contain 20 genes (number of decision variables) as the required initial solutions.

(II) **[Fitness]** Evaluate the fitness *f(x)* of each chromosome x in the population. This evaluation is performed based on the non-dominance levels rule. Therefore, after generating the initial population, all population members are evaluated based on their level of dominant front from the first level to the end.

(III) **[Sorting]** Sort the initial population for further run of the algorithm considering the non-dominated rule and the crowding distance value. A better rank in the solution has a greater chance of being selected. If the non-dominated solution is smaller than the population, the solution with the greater value of the crowding distance in the second front is chosen.

(IV) **[New population]** Create a new population by repeating the following steps until the new population is complete.
- **[Duplication]** Duplicate the first 5% of the population with a better rank (5% of better solution of the population after sorting). This step could increase the better solutions in the population, and the population number will be increased to $P_t + Q_t + 0.05 * N$.
- **[Selection]** Select two parent chromosomes from a population randomly.
- **[Crossover]** Cross the parents with a certain crossover probability to produce new offspring (children). If no crossover has been performed, the offspring is an exact copy of the parents. In this mode, we use single point crossover.
- **[Mutation]** Mutate new offspring at each locus (position in chromosome) with a given mutation probability.

  Types of Mutation:

  (i) Insert Mutation: it is used in permutation encoding. First, pick two allele values at random. Then move the second allele to follow the first, shifting the rest along to accommodate. Note that this preserves most of the order and the adjacency information [43].

(ii) Swap Mutation: it is also used in permutation encoding. To perform swap mutation, select two alleles at random and swap their positions. It preserves most of the adjacency information, but links broken disrupt order more [43].

(iii) Reversing Mutation: in this kind of mutation for binary-encoded chromosomes, a random position is chosen, and then bits next to that position are reversed, and the child chromosome is produced [43].

In this research, we combine three types of mutation (insert, inversion, and swap) randomly to enhance the algorithm's performance.

- [**Accepting**] Place new offspring in a new population.
- [**Sorting**] Sort the combination of the newly generated population for a further run of the algorithm by ranking. Non-dominated solution and crowding distance value, better rank in solution have bigger chance to be selected if the non-dominated solution is less than population and the solution with the bigger value of crowding distance in the second front is to be chosen.
- [**Truncate**] Withdraw the $N + 1$ chromosome.

(V) [**Stop condition**] If the end condition is satisfied, stop and return the best solution in the current population.

(VI) [**Loop**] Go to step II.

3.2. Performance metrics

Having established the key parameters of the proposed algorithm and having solved the problem at hand, we need to evaluate the efficiency of the algorithm. In this way, the optimality metrics are applied to evaluate the performance of the algorithm compared to the result obtained by the *ε-constraint* when solving the small instances. Therefore, Generational Distance (GD) and Inverse Generational Distance (IGD) would be included as performance metrics in the first problem. The GD reports how far, on average, the final Pareto front obtained by the proposed algorithm ($\mathrm{PF}_{\mathrm{known}}$) is from the optimal Pareto front ($\mathrm{PF}_{\mathrm{true}}$) [44]. IGD is known as another reliable performance indicator to simultaneously quantify the convergence and diversity of evolutionary algorithms with multi and many objectives [45].

These two metrics can be explained as the following:

Suppose P^* is a set of uniformly distributed points along with the Pareto front (PF). Also, assume that A is approximately equal to the PF. The metrics GD and IGD of set A are defined mathematically as follows (Eq. (37)) and (Eq. (38)), respectively:

$$\mathrm{GD}(A, P^*) = \frac{1}{|A|}\sqrt{\sum_{i=1}^{|A|} d_i^2} \tag{37}$$

$$\mathrm{IGD}(A, P^*) = \frac{1}{|P^*|}\sqrt{\sum_{i=1}^{|P^*|} \tilde{d}_i^2} \tag{38}$$

where $d_i^2(\tilde{d}_i^2)$ is the Euclidean distance between the ith member in set A (P^*) and the next member in set $P^*(A)$. The GD can only reflect the convergence of the algorithm, while the IGD could measure convergence and diversity in a sense. For both of the above two metrics, a smaller value means better quality. The GD typically evaluates the convergence of a set of solutions generated by a multi-objective evolutionary algorithm. It measures the distance between the solutions obtained by the algorithm and the true Pareto front. If a GD equals 0, all points of the approximate solutions belong to the true Pareto front [46]. On the other hand, the IGD emphasizes the diversity of the solutions obtained, while the solutions preserve convergence. When IGD equals 0, this shows that solution points are distributed over the true Pareto front [46]. However, for IGD > 0, we may have good convergence but poor diversity. Therefore, it is better to use both GD and IGD together as the most popular performance metrics in multi-objective optimization field [47].

To evaluate the performance of the proposed NSGA-II, some metrics are used to compare the result obtained with the classic NSGA-II. These metrics consist of *Diversity (D)*, *Spacing (S)*, *CPU time*, and MOCV, which are defined below.

Diversity is the metric presented by Zeitler in 1998 [47] and for the model of this study is equal to the Euclidean distance between the two boundary solution in objective space. This criterion is defined as follows (Eq. (39)):

$$Diversity = \sqrt{\sum_{j=1}^{4}\left(\max_i f_i^j - \min_i f_i^j\right)^2}. \tag{39}$$

The higher the value of this metric, the better the solution set.

The *Spacing* metric presented by Scott [47] measures the deviation of the distances between the solutions belonging to the Pareto front. This calculation is done as follows (Eq. (40)):

$$Spacing = \sqrt{\frac{1}{|n-1|}\sum_{i=1}^{4}\left(d_i - \overline{d}\right)^2} \tag{40}$$

where:

$$\overline{d} = \sum_{i=1}^{4}\frac{d_i}{|n|} \quad \text{and} \quad d_i = \min_{k\in n, k\neq 1}\sum_{m=1}^{4}\left|f_m^i - f_m^k\right|.$$

In principle, this metric calculates the sum of the lowest values between the obtained solutions in pairs. It is noticeable that the lower value of this metric is desirable. The zero number for this measure indicates the same spreading of solutions in the optimal Pareto front.

CPU time is another performance metric that calculates the running time of the algorithm.

The Multi-Objective Coefficient of Variation (MOCV) metric is defined as the ratio between the Mean Ideal Distance (MID) and the*Diversity* metric [48]. The MOCV metrics are then defined as follows (Eq. (41)):

$$\text{MOCV} = \frac{\text{MID}}{Diversity} \tag{41}$$

which (MID) metric is calculated as follows (Eq. (42)).

$$\text{MID} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\sum_{g=1}^{m} f_{ig}^2}. \tag{42}$$

In equation (42), f_{ig} shows the value of objective function g in solution i. The greater value of the measure for *diversity* and smaller value for MID provide better solution so that the ideal value for MOCV metrics is the one with the lowest value.

4. Case study description

Iran is known to be one of the most earthquake-prone countries in the world. This area is crossed by several major faults covering at least 90% of the country. As a result, earthquakes in Iran are frequent and destructive (United States Geological Survey report). As the country's capital and largest city, Tehran has suffered some historic earthquakes. Recent seismic tectonic studies indicate that this city is located in a zone of high seismic activity. Based on the probabilistic and deterministic evaluations, seismologists assume that a strong earthquake is to be expected in or around Tehran soon.

In addition, the vulnerability of structures and urban areas in Tehran is significant. Weak buildings, old urban structures, vulnerable lifelines, insufficient emergency infrastructure and roads, lack of evacuation places

TABLE 5. Indices value of model implementation.

i	22 districts of Tehran
$j\&l$	22 districts of Tehran
k	Tehran North Blood Center, Tehran Central Blood Center
t	2 periods
h	Emam Khomeini hospital, Kasra hospital
n	Central IBTO Lab, Masoud Lab, Emadi Lab
v	2 vehicles
g	Blood group A, B, AB, ...
p	RBC, Plasma
a	2 technology blood test

TABLE 6. Demand of blood products in each health center in different period.

Demand of blood products	Emam Khomeini hospital.1	Emam Khomeini hospital.2	Kasra hospital.1	Kasra hospital.2
A^+.RBC	200	100	200	180
A^+ .Plasma	240	104	204	148
B^+.RBC	190	90	190	988
B^+.Plasma	470	307	4	378
AB^+.RBC	210	110	210	118
AB^+.Plasma	100	500	310	588
O^+.RBC	230	130	230	103
O^+.Plasma	190	900	109	955
A^-.RBC	310	210	310	251
A^-.Plasma	590	490	590	495
B^-.RBC	660	560	660	565
B^-.Plasma	410	310	410	315
AB^-.RBC	230	130	230	135
AB^-.Plasma	450	350	450	355
O^-.RBC	220	120	220	125
O^-.Plasma	110	200	110	255

in several districts, etc. are some of the critical parameters of the city for earthquake vulnerability. In addition, Tehran is located in a high-risk area, and with a population of about 20 million people is one of the largest cities in Asia. Therefore, this city needs more attention and planning for prevention activities. After every disaster, including an earthquake, there will be a high demand for emergency blood supply due to enormous injuries. Therefore, to implement the proposed mathematical model proposed in this research on Tehran city, 22 donor groups are considered for each district (Tab. 5). Also, the maximum blood supply of each donor group (each district) is estimated by assuming 13% of the deferral rate (inspired by Fazli-Khalaf *et al.* [31], Jabbarzadeh *et al.* [39], and Khalilpourazari and Khamseh [40]). Additional data can be accessed *via* the link `https://link.springer.com/article/10.1007%2Fs10479-017-2729-3`.

We also simulate blood demand products in health care centers in the proportion of real data presented in Table 6.

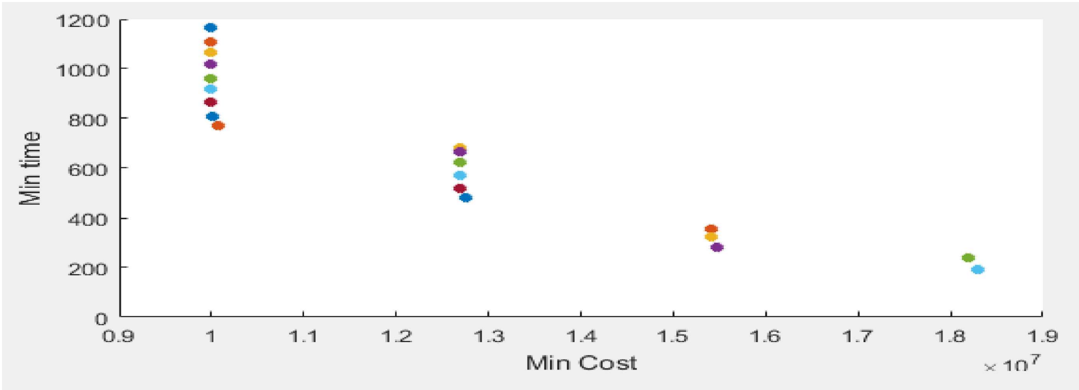


FIGURE 3. Pareto front of bi-objective optimization model – Minimizing time and cost.

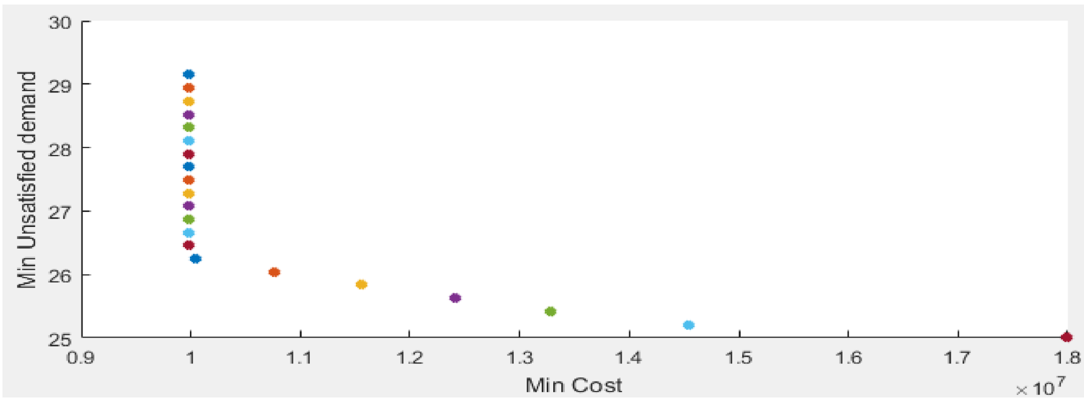


FIGURE 4. Pareto front of bi-objective optimization model – Minimizing unsatisfied demand and cost.

5. Computational result

The mathematical model presented in this research was used to solve the above case study by the improved ε-*constraint* method with a solver of CPLEX in GAMS23.0. In addition, the proposed NSGA-II was coded in MATLAB (R2019b). Then experiments are performed on a PC with a 2.0 GHz Intel Core 2 Duo processor and 4 GB RAM. First, the problem was solved in bi-objective condition to investigate the paired conflict of objectives. The bi-objective Pareto-front is presented in Figures 3–7. Based on these results, all four objectives are in conflict with each other; pairwise exception two functions unsatisfied demands and reliability not expected to conflict.

Based on some of these results, conflicting objectives have several critical cut points. For example, in order to minimize the total costs and the transportation time at the same time, four critical cut points are seen. This means that for a given cost amount, we can save time without increasing costs. The improvement that continues to the first critical cut point, after which another objective function shifts up with a slight reduction in time. There is a similar condition for the cost function *versus* unsatisfied demand, transportation time *versus* reliability, and transportation time under unsatisfied demand.

Some other conflicts cause the objective functions to change linearly. Because our mathematical model is an integrated model, we incorporated a new compatibility statement for disaster situations into objective functions

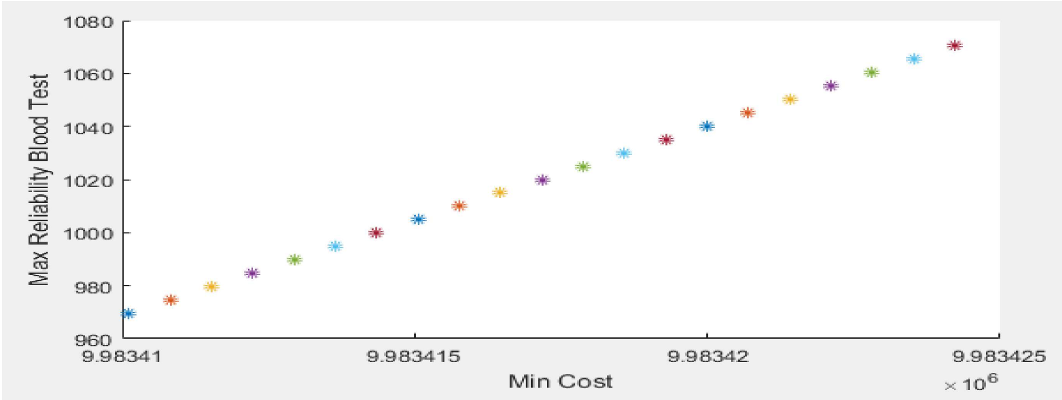


FIGURE 5. Pareto front of bi-objective optimization model – Minimizing cost and maximizing reliability blood test.

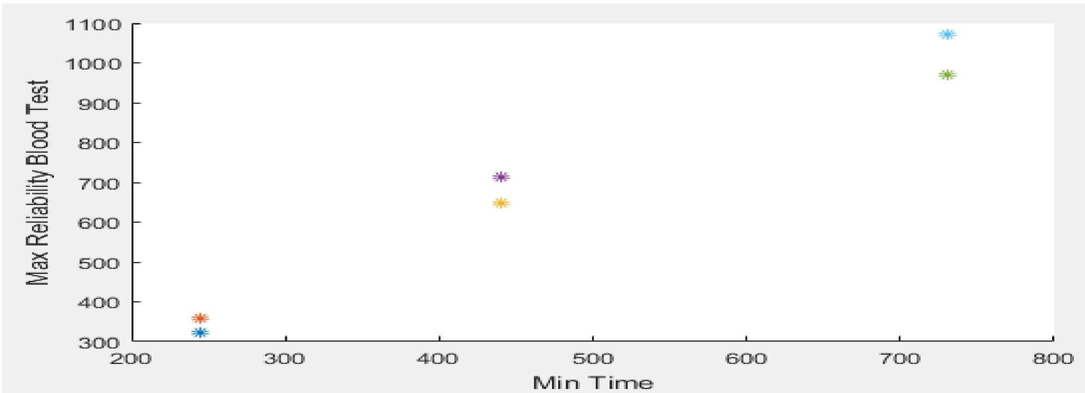


FIGURE 6. Pareto front of bi-objective optimization model – Minimizing time and maximizing reliability blood test.

of cost and unmet demand, bringing the total cost of the blood supply chain down to 93.49%. To show the impact of this compatibility, we compare these two conditions by solving mathematical models considering blood compatibility and not. As shown in Figure 8, the value of the cost function has been significantly reduced in the proposed model. Therefore, if DM knew in advance the cost of BSC in a disaster operational situation, they could plan better and make a more efficient decision in that situation.

Figure 9 shows the result of the proposed model compared to the model by Fazli-Khalaf *et al.* [31] in the cost function. Accordingly, this new model has a more efficient compared to the model by Fazli-Khalaf *et al.* due to the more operational situation in the mathematical model. To this end, Fazli-Khalaf *et al.* given the quantities required, the proposed model can be executed and the result recorded. As can be seen, the proposed model showed a cost reduction of 76.87% with the same demand and equipment.

After testing the mathematical model and running it under bi-objective conditions for study pairs, we solved it while considering four objectives simultaneously. The solution setup presented 690 points in 4-dimensional space within 19 294 s of CPU computing time (Fig. 11). Alternating objective functions within these 690 points were examined to show the conflict between all four objectives. To this end, Figure 10 shows changing each objective function along with changing the other objective functions. Due to space limitations, these results

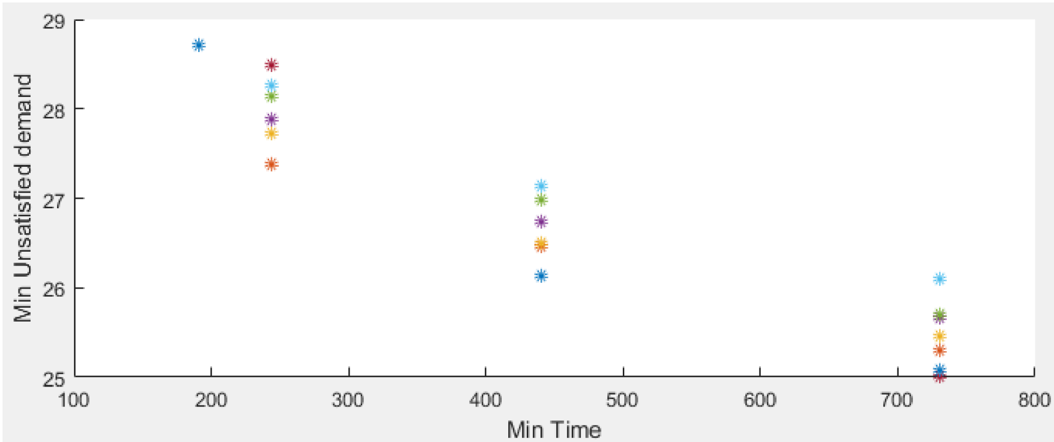


FIGURE 7. Pareto front of bi-objective optimization model – Minimizing time and unsatisfied demand.

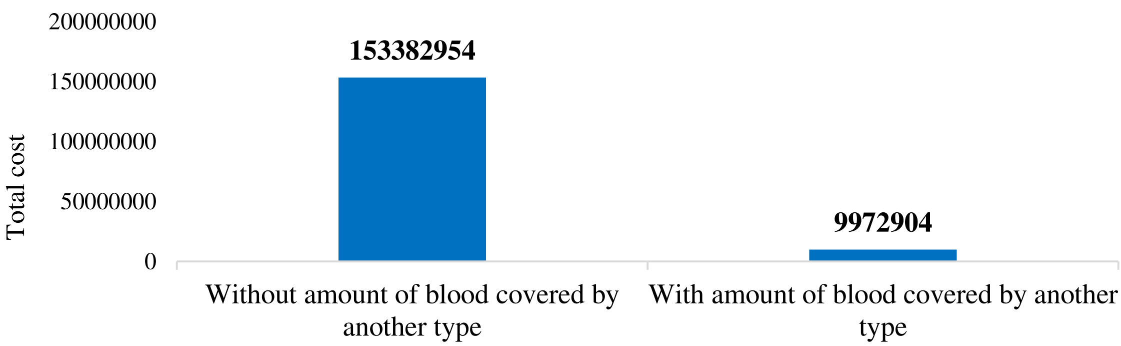


FIGURE 8. The influence of blood compatibility on cost function.

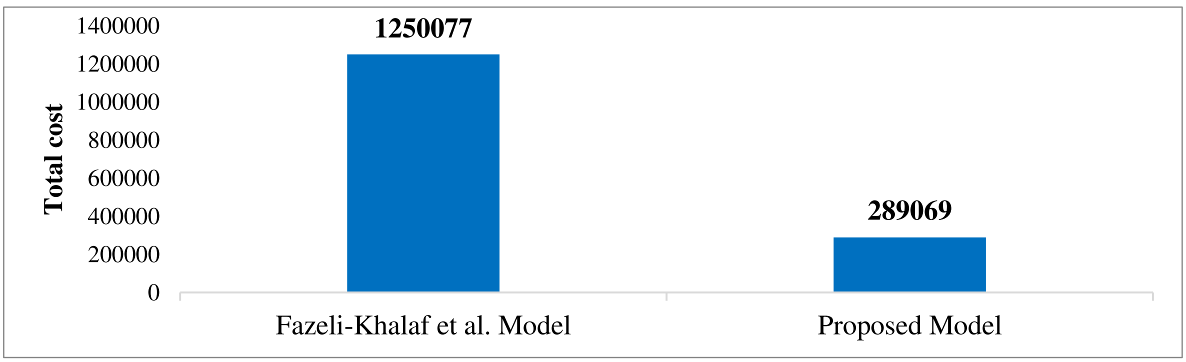


FIGURE 9. Cost objective comparison between proposed model and Fazli-Khalaf *et al.* model.

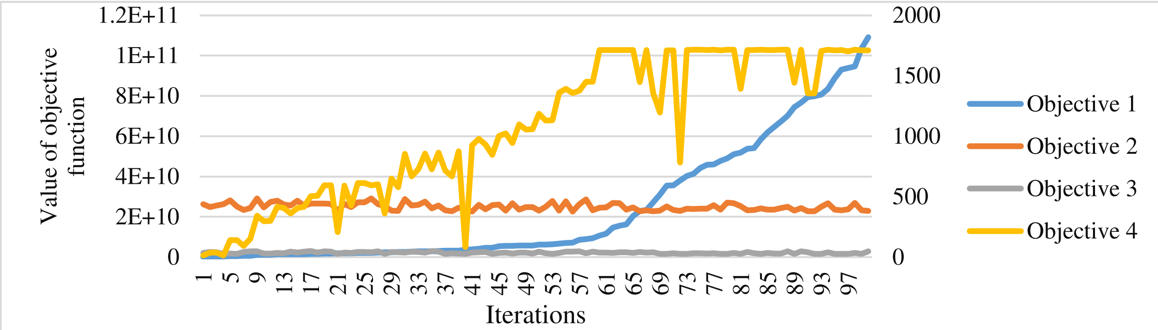


FIGURE 10. Variation of objective function in different solution.

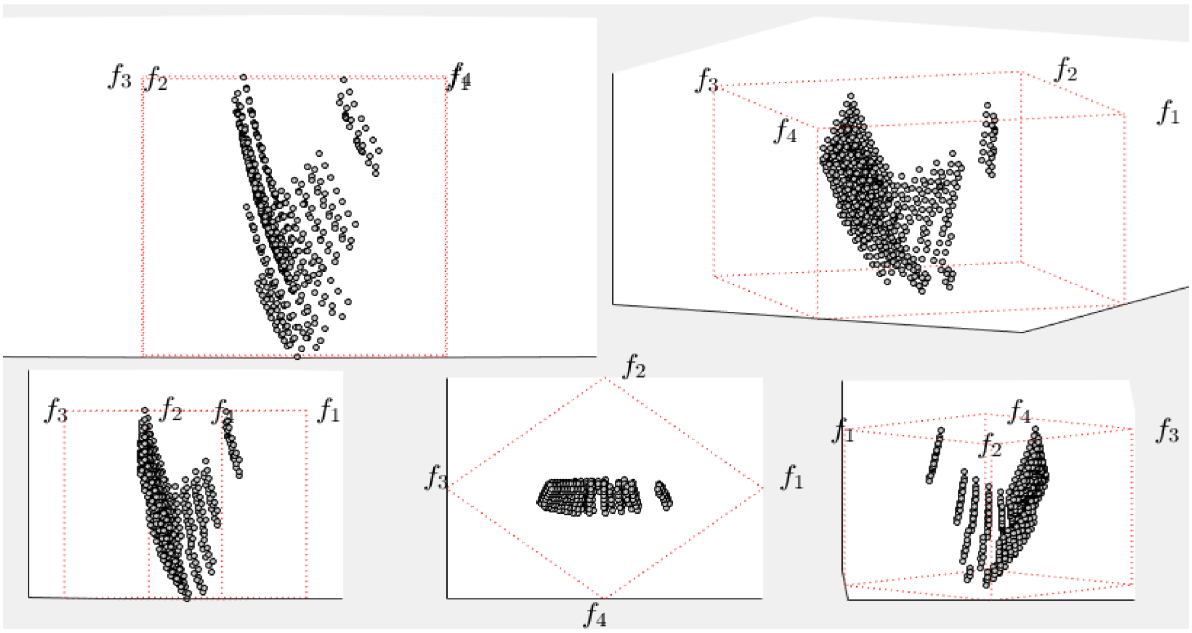


FIGURE 11. Pareto-optimal space in 3D-RadVis figure.

are only given for the first 100 points. The minimum or maximum amounts of these graphs represent the best and optimal value of each objective obtained by solving the problem in a single objective condition. This figure indicates that all objectives are in conflict with each other.

In Figure 11, due to the impossibility of representing the Pareto front in a popular three-dimensional figure (because we should have four dimensions in our objective space), we use the 3D RadVis figure to represent the Pareto optimum. As shown in Figure 11, the Pareto front spreads closer to the first and third functions, which means the model could offer a solution to the higher costs by providing more demand in different modes. However, transport and reliability functions do not have distinct choices. By increasing the costs, the transport time and reliability could change to a lesser extent due to its constraints. In the next section, the influence of the sensitivity analysis of the deterministic model is considered.

We also tried to find the parameters that have more impact on our objective functions. To deal with this, we had to do the sensitivity analysis for objective functions separately. Therefore, we changed the number of

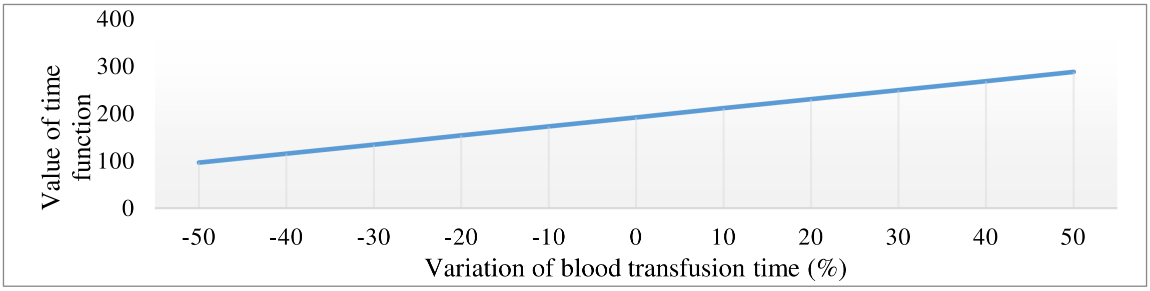


FIGURE 12. Sensitivity of time function to variable blood transfusion time.

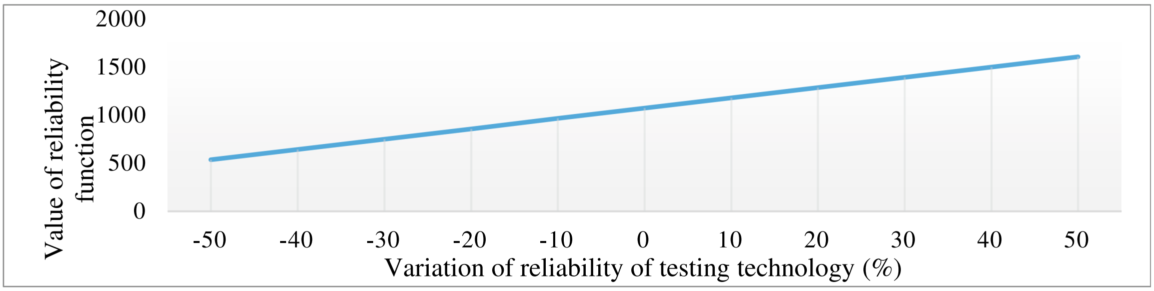


FIGURE 13. Sensitivity of reliability function to reliability of testing technology.

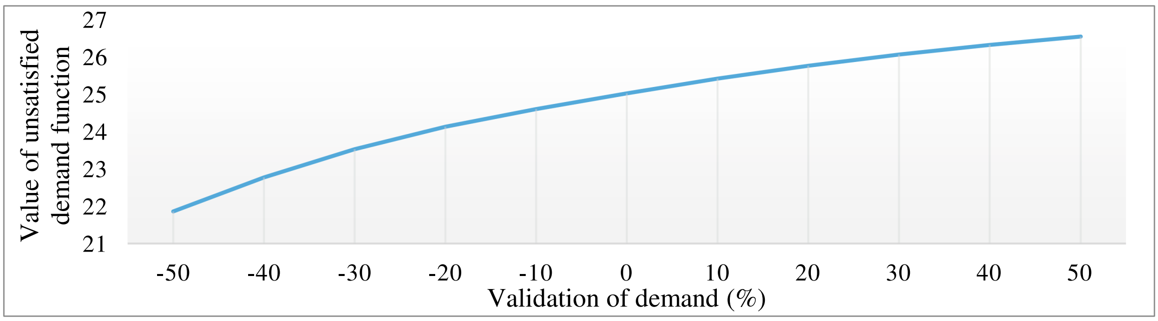


FIGURE 14. Sensitivity of unsatisfied demand function to variable demand.

parameters to analyze the result. After enough testing, most of the objective changes were detected based on the effective parameters. As shown in Figure 12, the duration of the blood transfusion has a linear effect on the second objective (time). According to Figure 13, the fourth objective of our mathematical model followed the technology of testing.

Figures 14 and 15 demonstrate the impact of demand on total costs and unsatisfied demand. These results show that a change in demand causes a gradual increase in total costs and unsatisfied demand.

Due to the duration of solving the model with the improved ε-*constraint* method, this research proposed a newly developed NSGA-II algorithm in the previous section to better solve the proposed BSCM model. The proposed mathematical BSCM model is solved by classical NSGA-II and proposed NSGA-II. The algorithm is repeated ten times, the average performance is evaluated and the results are presented in Figure 16. As shown in Figure 16, all selected metrics to evaluate the proposed NSGA-II for our BSCM model are better than

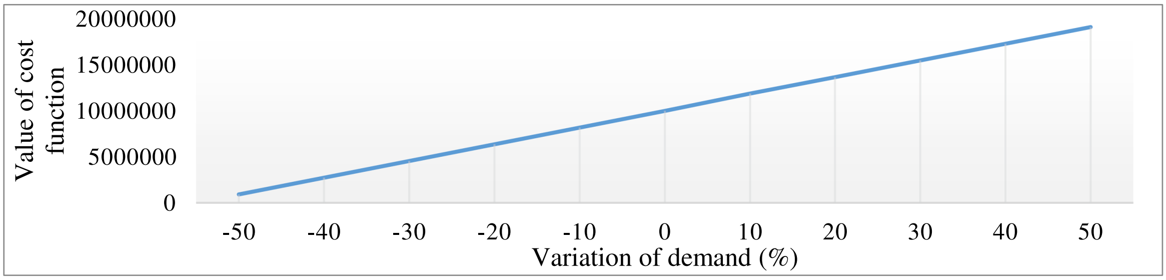


FIGURE 15. Sensitivity of cost function to variable demand.

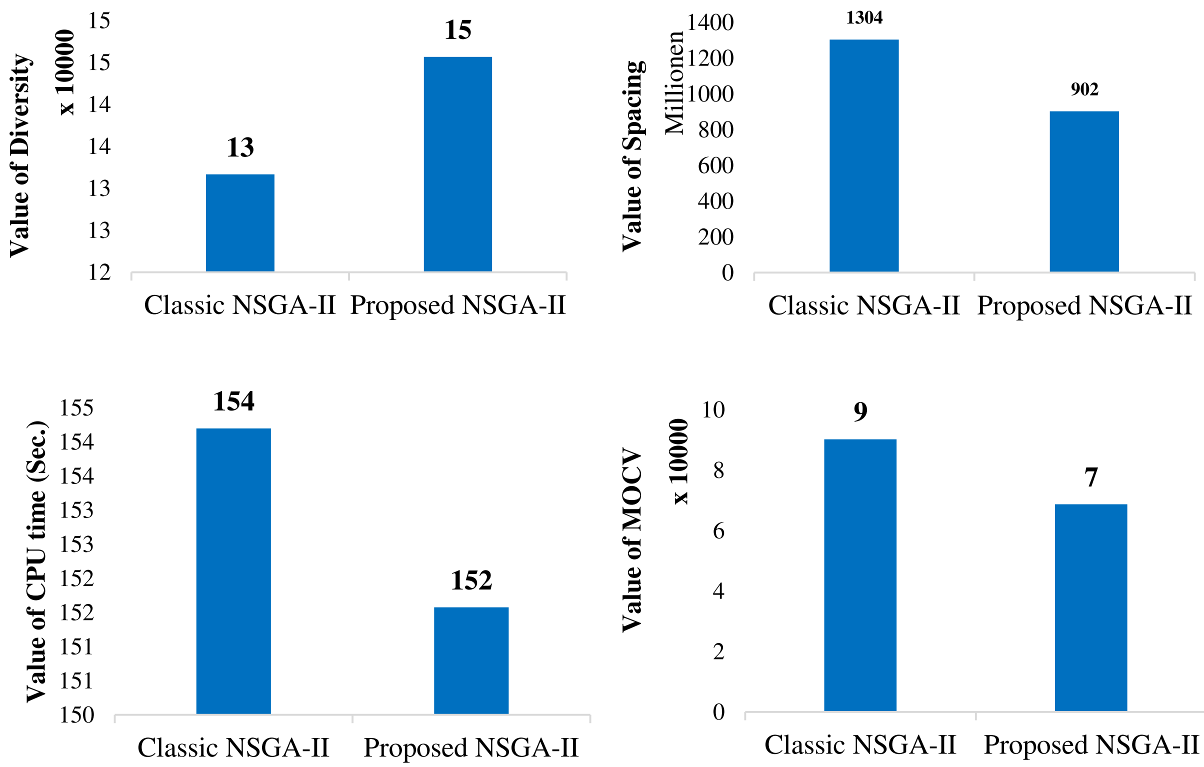


FIGURE 16. Performance metrics comparison in classic NSGA-II and proposed NSGA-II.

the classical NSGA-II. The improvement rate of the proposed algorithm to achieve a better solution is 1.7%, 30.78%, 10.65%, and 23.88% in terms of CPU time, distance, diversity, and MOCV, respectively. These results show that the proposed NSGA-II algorithm represents an improvement step and effectively solves the proposed BSCM mathematical model.

Figure 17 shows the Pareto front obtained by the proposed NSGA-II algorithm after 100 iterations. According to this result, this algorithm has a good performance in minimizing the total cost (the first objective). In addition, it optimizes the other objectives relatively.

Figures 18 and 19 present changes in the indices: IGD and GD during the 100 iterations of the algorithm. These numbers indicate that the proposed NSGA-II algorithm shows a trend of improvement over the 100 iterations and its fluctuation tends to be less as more iterations are run. By duplicating 5% in the first-place

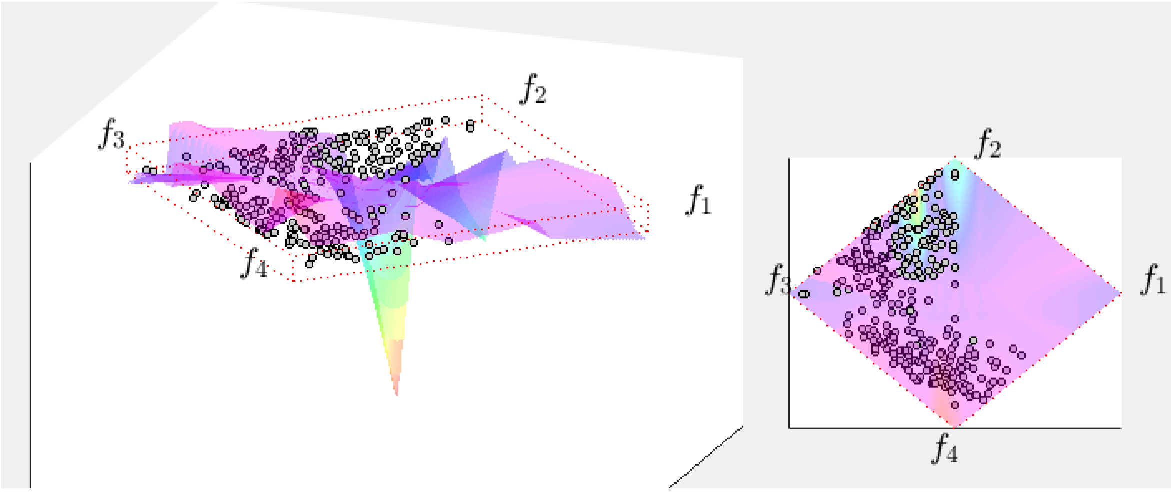


FIGURE 17. Graphical demonstration of true Pareto front and NSGA-II solutions in 3D-RadVis.

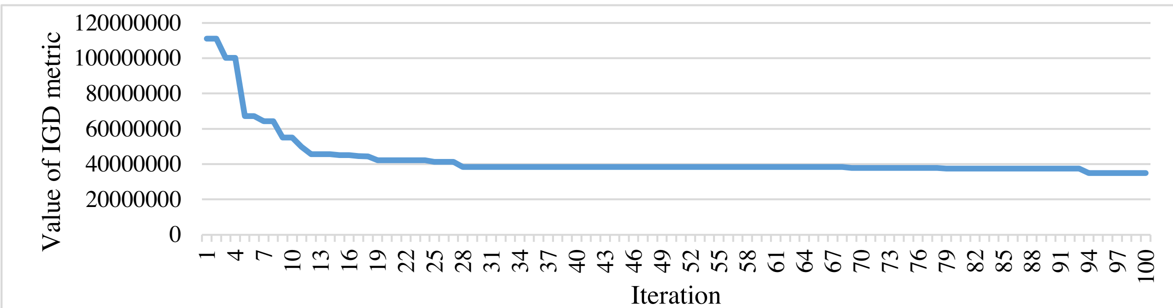


FIGURE 18. Variety of IGD metric value in iterations.

solution in each iteration, the proposed algorithm gradually leads solutions to a permanent Pareto optimal space. The result also shows that the proposed algorithm has good convergence and diversity in solving the problem.

6. Conclusion

This research proposes a new mathematical model with a four-objective approach to designing a blood supply chain network, considering minimizing the cost of shortage and replacement in a disaster as a new objective function. Although the issue of blood compatibility according to the ABO matrix has been explored in some previous research, none of the risky attitudes have been embraced and the penalty has not been considered. This model was presented to cover more aspects and needs of DM in different areas: cost, time, reliability of blood testing technology, and unmet demand. These functions close the problem to real-world conditions and provide stakeholders with more options. After defining this problem, a new mathematical model was developed that considers a new approach to the total cost of BSCM to calculate the penalty cost of compliance.

A real case study was applied to run the proposed model and the simulation defined new demand parameters and added them to the data. Then the mathematical model was run to solve this problem with four objectives and this data to ensure the conflict of objective functions. For this purpose, the improved ε-*constraint* method

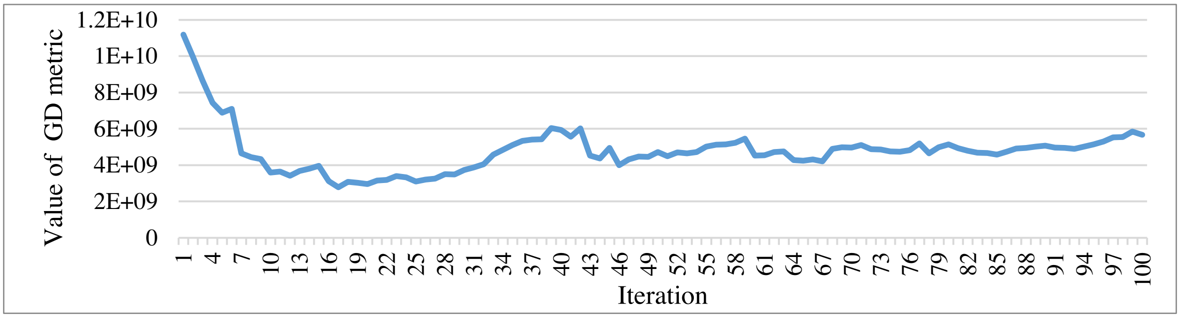


FIGURE 19. Variety of GD metric value during iterations.

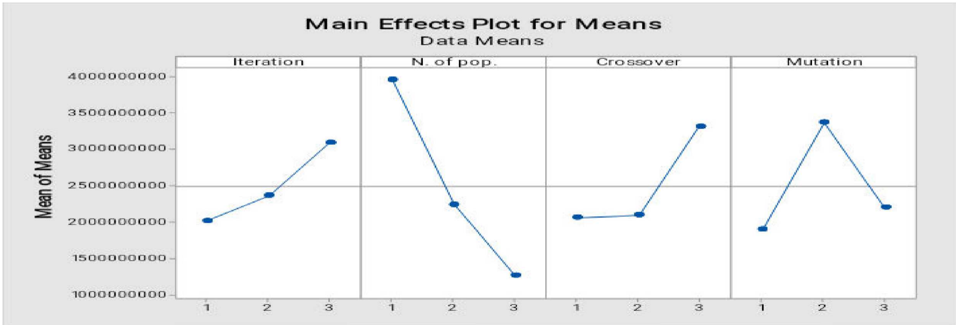
with the CPLEX solver was applied. Finally, 690 solution points were obtained along the Pareto front during 19 294 s. The analysis of the results successfully proved the new proposed model and its superiority compared to the previous studies as more real conditions were considered.

Due to the high-dimensional mathematical model and its complexity, a suitable algorithm based on the NSGA-II approach was also introduced to solve the considered problem in a reasonable time. The proposed intelligent algorithm duplicates the first 5% of the high-ranking solutions twice to lead the remained solutions to Pareto Optimal faster. The algorithm parameters were tuned by the Taguchi method in the DOE within a 27-factorial design. These results were obtained by evaluating the proposed algorithm performance within the Pareto front in 4-dimensional space and some many-objective indices such as diversity, spacing, CPU time and MOCV. The improvement rate of the solution in the proposed algorithm is 1.7%, 30.78%, 10.65%, and 23.88% in terms of CPU time, distance, diversity, and MOCV, respectively. These last indices show that this algorithm shows reasonable convergence and diversity while solving the considered problem.

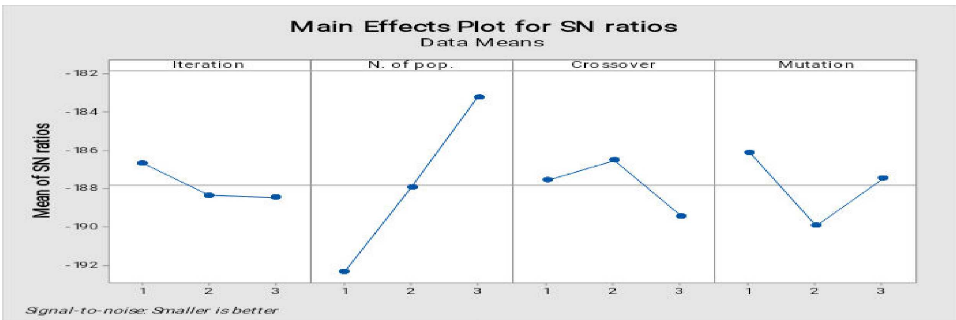
In addition, some sensitivity analyzes were also performed and the effect of the main parameters on their relative functions was assessed. As these results show, changing two parameters, blood transfusion time and testing technology level, has the most effective punctuality target function or chain reliability. The demand parameter is most effective in both the objective functions of total cost and unsatisfied demand.

In this research, the metrics of performance evaluation of metaheuristic algorithms based on dominance for multi-objective problems were used. These metrics become more complicated as the number of objective functions increases. Designing other performance evaluation metrics for many-objective problems in the real world can be improved in real-world application modeling. The development and application of new algorithms to increase the accuracy of many-objective blood supply chain networks can help improve the solutions. The consideration of some parameters such as demand or transport time (*e.g.* due to urban traffic changes) under stochastic conditions can also be interesting for research.

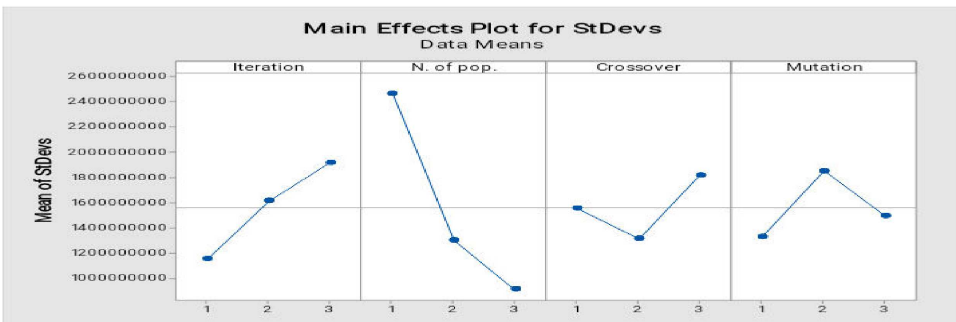
Appendix A. Test result of parameters tuning



a)



b)



c)

Figure A.1. (a) Main effects plot for means in variable factors. (b) Main effects plot for SN ratios for variable factors. (c) Main effects plot for standard deviations.

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Ethical approval. This article does not contain any studies with human participants or animals performed by any of the authors.

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