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Reliable blood supply chain network design with facility disruption: A real-world application ☆

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ABSTRACT

The blood supply of hospitals in disasters is a crucial issue in supply chain management. In this paper, a dynamic robust location–allocation model is presented for designing a blood supply chain network under facility disruption risks and uncertainty in a disaster situation. A scenario-based robust approach is adapted to the model to tackle the inherent uncertainty of the problem, such as a great deal of a periodic variation in demands and facilities disruptions. It is considered that the effect of disruption in facilities depends on the initial investment level for opening them, which are affected by the allocated budget. The usage of the model is implemented by a real-world case example that addresses the demand and disruption probability as uncertain parameters. For large-scale problems, two meta-heuristic algorithms, namely the self-adaptive imperialist competitive algorithm and invasive weed optimization, are presented to solve the model. Furthermore, several numerical examples of managerial insights are evaluated.

1. Introduction

Supply chain management (SCM) is often described as a procedure of planning, implementation, and control of supply chain operations based on efficient practices (Melo et al., 2009). The supply chain network design (SCND) has played a dominant role in the performance of the supply chain (SC). It copes with so many prospects of the SC such as information, location of facilities and allocation of material. The SCND is considered as a significant issue in strategic and operational decisions in the SCM scope (Devika et al., 2014; Amin et al., 2017; Fu and Fu, 2015).

Blood supply management and its products are vital issues for humankind. Blood is not a regular commodity since its demand is relatively random, and efficient coordination between supply and demand has not been resolved in various researches yet (Beliën and Forcé, 2012). Human blood is a rare and vital source that is produced only by human beings, and since there is currently no other product that can produce blood and also its uncertainty supply and demand side, keeping an adequate supply level is very important to fulfill demands (Duan and Liao, 2014).

In a supply chain, disaster happens in a situation, which is defined as deactivation of one or more supply chain parts' activities, which results in a crucial disruption to the usual flow of different parts of a supply chain. Some decision-making processes to prevent disasters and reflexive decisions in prevailing over the disaster are named disaster management (Natarajarathinam et al., 2009). Today, supply chains become susceptible to several disruptions. One of the solutions is predicting the disruption and another solution is in knowing which policies will be more suitable in such disrupted conditions (Samvedi and Jain, 2013). Two types of risks can be defined in terms of a supply chain: operational and failure risks. Operational risk is caused by intrinsic disruptions of the chain (e.g., uncertain demand, uncertain capacity and uncertain costs of the chain) while the failure risk is created with natural or abnormal accidents (e.g., earthquake, flood, terrorist attacks and fire). In most cases, the risk of disruption and failure in the supply chain performance has a much greater impact than operational risk (Tang, 2006).

Robust optimization planning provides a risk aversion approach to face uncertainty in optimization issues. Since Ben-Tal and Nemirovski (1998) showed the consequences of not considering uncertainty, every

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person realized that ignoring the uncertainty of the data could even lead to an infeasible answer for the problem when it was executed in reality.

These instances highlight the importance and need for the creative design and planning of blood supply chains, which are robust to such disruptions during and after a disaster condition. Thus, this paper aims to design a network, which proposes a new robust model in a blood supply chain by considering disruption risk and demand uncertainty in a disaster situation in a real-world case study.

The remainder of the paper is classified as follows. The literature on the blood supply chain and concepts of reliability and disaster are reviewed in Section 2. In Section 3, the problem is defined in details with the related assumptions. Section 4 describes a solution method and symbols. Section 5 provides computational and analytic results. Eventually, the managerial insight and conclusion are gathered in Sections 6 and 7, respectively.

2. Literature review

Studies about the location of unreliable facilities were started by introducing the probability of equality of disruption in all facilities in a p-median problem by Drezner (1987). Berman et al. (2009) focused on the location of unreliable facilities based on the assumption that customers have inaccurate information about the location of active facilities. Peng et al. (2011) presented a model based on a scenario approach and considered that each scenario incorporates some facilities that are disrupted at the same time. They reduced the whole cost by reducing the risk of a disruption using p-robust criteria and finally used the genetic algorithm to solve the model. Hong et al. (2012) presented a robust optimization model for the p-median location problem under facility disruption considering the uncertainty of demand and capacity of facilities. Esmaeilikia et al. (2016) introduced an analogous description and classification of hazards in a supply chain scope and considered disruptions in two categories, namely main disruptions and demand or supply disturbances.

Jabbarzadeh et al. (2016) designed a supply chain network based on robust stochastic optimization and Lagrangian relaxation methods. They considered a real-world problem, in which disruption could lead to disability or capacity reduction. Also, they considered a function of the investment level for a disruption probability parameter in the construction of facilities with a budget constraint. Diabat et al. (2019) introduced a bi-objective model for a perishable supply chain considering the robust approach and disaster scenarios. The goal of the model was to minimize the time and cost after a disaster. They developed Lagrangian relaxation and ε-constraint methods to solve the model by considering a real-case study.

Sha and Huang (2012) presented a multi-period model for location-distribution of blood facilities in a disaster condition. They faced with the model by a Lagrangian relaxation method and solved the model for a real-case problem in Beijing. Zahiri et al. (2014) proposed the design and location–allocation model for organ transplantation that aims to minimize the cost of the facility construction, transportation time between centers and relocation of facilities, and based on a robust planning approach to face with uncertainty in some model parameters. Jabbarzadeh et al. (2014) developed a model for the multi-period, single-product blood supply chain network in disaster situations considering the robust approach for the uncertainty of the demand parameter. The proposed model sought to minimize the total cost of the blood supply chain including fixed facility location costs, relocation of temporary facilities, operation costs, shifting and inventory costs.

Zahiri et al. (2015) presented a multi-period location–allocation model in the blood supply chain by considering the collection process, temporary facilities, and blood centers. They solved their model under uncertain conditions of the input parameters (e.g., blood donors and demand) by using a robust optimization approach. Fereiduni and Shahanaghi (2016) proposed a multi-period location–allocation model in a blood supply chain for the Tehran province after the disaster. Ahmadi-Javid et al. (2017) presented a health review paper that reviews related subjects up to 2015. Zahiri and Pishvaee (2017) designed a network for the blood supply chain, whose proposed bi-objective model aimed at minimizing the maximum unsatisfied demand and the entire cost considering the robust approach. Fahimnia et al. (2017) proposed a new stochastic bi-objective model for a blood supply chain in a disaster condition. Their model minimizes the cost and minimizes the time simultaneously. They presented a hybrid solution approach with a combination of Lagrangian relaxation and ε-constraint approaches.

Ramezanian and Behboodi (2017) designed a network for the blood supply chain and developed a mixed-integer linear programming model. They considered two uncertain parameters and some social parameters, such as the distance of donors, advertising budget and donor experience. They utilized a robust optimization approach for evaluating the proposed model and used a real-case study in Tehran.

Zhalechian et al. (2017) considered an uncertain hub location problem and developed a multi-objective model for it by considering responsiveness, social responsibility and economic issue. Habibi-Kouchaksaraei et al. (2018) designed a robust blood supply chain and developed a multi-period model in disaster situations considering the uncertain demand. The objective of the model was to find the location and number of temporary facilities and minimize the total cost and blood shortages. Also, they used a robust approach for uncertainty and solved the model with data taken from the Ghaemshahr city.

Samani et al. (2018) designed a blood supply chain in disaster situations considering the perishable nature of blood and its shortage and uncertain demand. They provided a multi-objective model that simultaneously reduced the most unmet demand and costs.

Eskandari-Khanghahi et al. (2018) developed a sustainable blood supply chain network in disaster situations with uncertain parameters. They considered some objectives as minimizing the costs, environmental effects of blood collection and wasted blood, maximizing the social impacts, such as the number of job opportunities created, and finally minimizing the cost of purchasing, lack of blood, maintenance, etc. The simulated annealing (SA) and harmony search (HS) algorithms were chosen and compared for the large-scale solution.

From what has been discussed above, the effects of a disaster on facilities (e.g., disruption and the budget constraint) are one of the most important issues in most countries, which have not taken managerially into account. Besides, knowing the number of required facilities in such emergency systems is one of the challengeable subjects among managers, which should pay more attention. Besides, it is better to generate the model in a real-world condition to be more practical and even it will be more beneficial study to be generated in a new case study and solved the issues of them. Furthermore, the blood supply chain is an integrated chain, in which all sections influence each other, so considering one city or one region will not be as useful as the whole ones. Moreover, in most real cases when a facility is disrupted, it will not lose the whole capacity, whereas it will lose it, which is affected by disruption partially.

To overcome these shortcomings and fill these gaps, a robust model is developed for a blood supply chain under uncertainty of both demand and disruption probability to investigate the best solutions in a real-world and large-scale supply chain. Furthermore, the budget constraint is considered as a vital issue in making a decision. Besides, two meta-heuristic algorithms are conducted and compared with each other.

In this paper, some gaps in the blood supply chain scope are covered and the following contributions are categorized:

- Considering both types of risks that have not taken into account in the post-disaster blood supply chain literature so far.
- Considering two types of reliable and unreliable facilities and the effect of disruption on them.
- Proposing a new and practical model in an uncertain blood supply chain.

- Solving the model in a real-world case study, which is suffering from insufficient blood in an emergency case.
- Assuming a multi-period model in a post-disaster condition. Most studies in this area consider the models as a single-period one, whereas after a disaster, due to the nature of the uncertainty, the demand should be considered in different periods.
- Considering the available budget for the model. According to the experts, one of the most important issues for blood centers is the considered budget by the government and optimal usage of it in centers and facilities.
- Examining the uncertainty in some parameters of the problem, such as demand and disruption probability of temporary facilities because of a disastrous occurrence.
- Considering the robustness concept to cope with the uncertainty.
- Applying the self-adaptive imperialist competitive algorithm (SAICA) to solve the model and comparing it with the invasive weed optimization (IWO) algorithm.

The features of the proposed supply chain network design models are summarized in Table 1. Besides, for the efficiency of this issue, it is considered a case study in the Mazandaran province located in the north of Iran, which is predisposed to earthquakes and floods disruption, and it is suffered from the lack of blood more than other provinces.

3. Problem definition and the proposed model

The assignment of facilities to centers, donors and the shift of blood between these nodes are shown in Fig. 1. The content of this paper includes locating temporary facilities and blood centers in the blood supply chain network and allocating the facilities and donors in a disaster situation. It should be noted that in the event of a disaster, temporary facilities get disrupted, in which the level of disruption of any facility and center depends on the initial investment for its construction. Also, the disaster will affect the demand for blood needed by hospitals. Furthermore, the planned budget will also have an impact on this issue and the demand which can be met. In the following, the proposed model is solved in deterministic and robust conditions. The reason for choosing this topic is the vitality of blood substance and the fact that countries always face shortages of this supply, especially at the time of the disaster. A robust formulation model is presented according to the uncertainty of some parameters such as demand and disruption probability. Below, we present a brief background of a scenario-based optimization method.

3.1. Background of the robust formulation

Robust optimization planning is a method to handle the uncertainty in problems. Mulvey et al. (1995a) demonstrated a description of scenario-based data and introduced solution robustness and model robustness contexts. The linear optimization model is as follows:

$$\text{Min } c^T x + d^T y \quad \text{s.t.} \tag{1}$$

$$Ax = b, \tag{2}$$

$$Bx + Cy = e \tag{3}$$

$$x, y \geq 0 \tag{4}$$

At this model, x and y define the vectors of decision and control variables, respectively. Control variables are subjected to frame once a specific realization of parameters, while design variables are specified before the realization of the uncertain parameters and are not dependent on the realization of them. A set of scenarios is introduced as $S = \{1, 2, 3, \dots, s\}$. For each scenario $s \epsilon S$, the set $S = \{d_s, B_s, C_s, e_s\}$ of realizations is related to the coefficients. The robust optimization model can be formulated by:

$$\text{Min } \sigma\left(x, y_1, y_2, \dots, y_s\right) + \omega\rho\left(\delta_1, \delta_2, \dots, \delta_s\right) \quad \text{s.t.} \tag{5}$$

$$Ax = b, \tag{6}$$

$$B_s x + C_s y_s + \delta_s = e_s \qquad \forall s \epsilon S \tag{7}$$

$$x \geq 0, y_s \geq 0 \qquad \forall s \epsilon S \tag{8}$$

For modeling with this approach, control variable y_s and error vector δ_s should be introduced to measure the infeasibility allowed in the control constraints under scenario s. With different scenarios, the objective function (1) would become a random variable as $\xi_s = c^T x + {d_s}^T y_s$ with probability p_s, which $\sum_{s=1}^{S} p_s = 1$. Equation $\sigma(.) = \sum_{s\epsilon S} p_s \xi_s$ is used for the first term in the objective function. The second term in the objective function (5) is a measurement of model robustness. Mulvey et al. (1995b) proposed that $\sigma\left(x, y_1, y_2, \dots, y_s\right)$ can be written by:

$$\sigma\left(x, y_1, y_2, \dots, y_s\right) = \sum_{s\epsilon S} p_s \xi_s + \lambda \sum_{s\epsilon S} p_s (\xi_s - p_{s'} \xi_{s'})^2 \tag{9}$$

In the above suggestion, λ is a constant by which the objective function would be less sensitive to change under the scenarios. In brief, the final formulation of the robust optimization model based on the results of Yu and Li (2000) is as follows.

$$\text{Min } Z = \sum_{s\epsilon \text{S}} p_s \xi_s + \lambda \sum_{s\epsilon S} p_s \left[(\xi_s - \sum_{s'\epsilon S} p_{s'} \xi_{s'}) + 2\theta_s \right] + \omega \sum_{s=1}^{S} p_s \delta_t^s \tag{10}$$

s.t.

$$\xi_s - \sum_{s'\epsilon S} p_{s'} \xi_{s'} + \theta_s \geq 0 \qquad \forall s, s' \epsilon S \tag{11}$$

$$\theta_s \geq 0 \qquad \forall s \epsilon S \tag{12}$$

In this model, if a solution remains near to optimal for any realization of each scenario s, the mathematical programming model will be robust with regard to optimality that is defined as "solution robustness" and the solution feasibility is that if the solution remains almost feasible under almost all possible values for any realization of s that is defined as "model robustness". The weighting penalty ω is utilized to represent the trade-off between the two mentioned contents. With various scenarios, the objective function will become a random variable taking the value ξ_s and the θ_s is a variable, which is used to do the linearization of the model

3.2. Assumptions of the model

The assumptions of this model are as follows:

- Two types of facilities are considered in this model: temporary facilities and blood centers. Disruptions occur in temporary facilities, and blood centers are safe against disruptions according to the case study. So, temporary facilities and blood centers are considered as unreliable and reliable facilities, respectively.
- The cost of building a blood center is much higher than a temporary facility.
- Each donor can either donate to blood centers or temporary facilities.
- The probability of disruption in temporary facilities and centers depends on the value of the initial investment for opening them meaning that it is possible to increase the investment to reduce the effects of disruption. For example, in centers due to the high investment, the center will not be disrupted.
- The planned budget has an impact on this problem and the responding demand.
- Disaster affects the blood demand of hospitals.

Table 1
Classification of the related papers.

Articles	Uncertain parameter	Blood supply chain	Disaster	Multi-period	Movement of facilities	Number of required facilities	Investment level	Solution method	Budget	Disruption		Case study
										Partially affected facility	Complete shutdown	
Fereiduni and Shahanaghi (2016)	*	*	*	*	*			*P*-robust				*
Jabbarzadeh et al. (2016)	*				*		*	Robust optimization & Lagrangian relaxation	*	*		*
Jabbarzadeh et al. (2014)	*	*	*	*	*			Robust optimization				*
Diabat et al. (2019)	*	*	*	*	*			Robust optimization & Lagrangian relaxation n			*	*
Ramezanian and Behboodi (2017)	*	*		*	*	*		Robust optimization				*
Habibi-Kouchaksaraei et al. (2018)	*		*	*	*	*		Robust optimization & Goal programming				*
Fahimnia et al. (2017)	*	*	*	*	*			Stochastic programming				
This study	*	*	*	*	*	*	*	Robust optimization & two meta-heuristics	*	*		*

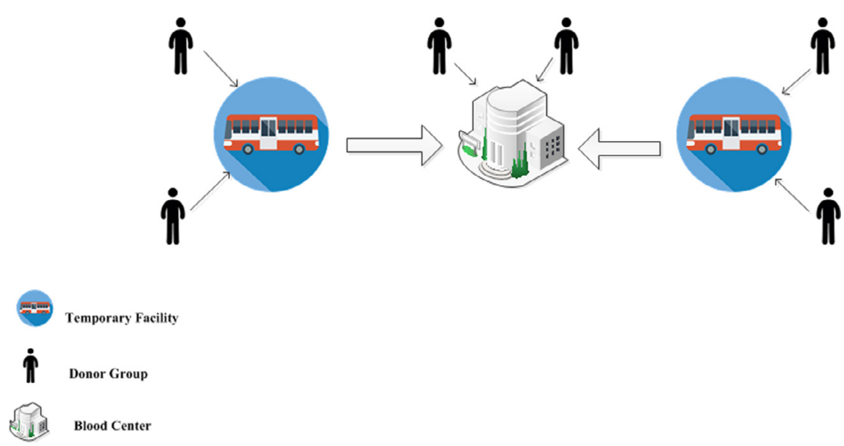

Fig. 1. General view of the problem.

- It is assumed when a disruption occurs on a facility, it is not fully failed. The facility loses some of the capacity to serve in the disruption situation.
- For better controlling the mid-term decisions and fluctuations in demand periods, the model is considered as a multi-period one.

The aim of the presented model is to make an optimal decision about the location of blood centers, location and shift of temporary facilities, the allocation of donors to blood centers or temporary facilities located in the coverage area, blood donation from donors through facility, the number of temporary facilities available to collect and transfer blood to centers at any time period and under any scenarios. In the following sections, the modeling indices, parameters, and variables are described.

3.3. Sets

K Set of blood donors, $k \in K$
I Set of potential locations for blood centers or temporary facilities, $i \in I$
M Set of potential locations for blood centers, $m \in M$
J Set of potential locations for temporary facilities, $j, j_1, j_2 \in J$
N Set of available investment levels, $n \in N$
T Set of periods, $t \in T$
S Set of scenarios, $s_1, s_2, s_3, s_4, s_5, s_6 \in S$

3.4. Parameters

D_t^s Blood demand in period t under scenario s

V_{j_1j} Cost of shifting a temporary facility from location j to j_1
FR_m Fixed cost of constructing a blood center at location m
FU Fixed cost for operating a temporary blood facility
C_{mj} Unit transportation cost of moving blood from the facility at location j to the blood center at location m
Cc_{ik} Unit operational cost of gathering blood at location i from donor group k
Cap Capacity of a temporary facility
a_j Percentage of total capacity in temporary facility j that is affected by the disruption
q_j^s Disruption probability in temporary facility j under scenario s
B Desired budget
r_{ik} Distance between donor k and facility at location i
r Coverage distance of donors and blood facilities
rw_{mj} Distance between temporary facility j and blood center at location m
rw Coverage distance of blood facilities
p_s Probability of scenario s occurrence
d_{kt} Maximum blood donation quantity of group k of donors in period t
Θ Cost of losing blood in the facility capacity that cannot get blood due to disaster
MN A big number

3.5. Variables

$XU_{j_1jt}^s$ A binary variable, equal to 1 if a temporary facility is located at location j in period $t-1$ and moves to Location j_1 in period t under scenario s; 0, otherwise
XR_m 1 if a blood center is opened at location m; 0, otherwise
YU_{jkt}^s 1 if donor group k is assigned to a temporary facility at location j in period t under scenario s; 0, otherwise
R_{mjt}^s 1 if a temporary facility at location j is assigned to a blood center at location m in period t under scenario s; 0, otherwise
YR_{mkt}^s 1 if donor group k is assigned to a blood center at location m in period t under scenario s; 0, otherwise
T_{jt}^s Quantity of blood loss due to a disruption in temporary facility j in period t under scenario s
Q_{jkt}^s Quantity of blood collected at temporary facility j from group k of donors in period t under scenario s
$Q_{mjt}^{\prime s}$ Quantity of blood shifted from a temporary facility at location j to a blood center at location m in period t under scenario s
$Q_{mkt}^{\prime\prime s}$ Quantity of blood gathered at blood center m from group k of donors in period t under scenario s
Pr_t^s Number of the temporary facilities required in period t under scenario s

3.6. Model formulation

The objective function to minimize several cost drivers is as follows:

- Fixed cost of locating facilities:

$$FC^s = \sum_t FU\,Pr_t^s + \sum_m FR_m XR_m \tag{13}$$

- Operational cost: It includes the cost of gathering blood from the donors in the facilities.

$$OC^s = \sum_j \sum_k \sum_t Q_{jkt}^s Cc_{jk} + \sum_k \sum_m \sum_t Q_{mkt}^{\prime\prime s} Cc_{mk} \tag{14}$$

- Transportation cost: It includes the cost of shifting temporary facilities to other locations and to the center to evacuate their collected blood.

$$TC^s = \sum_j \sum_m \sum_t Q_{mjt}^{\prime s} C_{mj} + \sum_j \sum_{j_1} \sum_t V_{j_1j} XU_{j_1jt}^s \tag{15}$$

- Blood loss cost: It includes the cost of losing the capacity of temporary facilities in the event of a disruption.

$$BC^s = \Theta \sum_t \sum_j \sum_{j_1} T_{jt}^s XU_{jj_1t}^s \tag{16}$$

The objective function is formulated based on the approach explained in Section 3.1 for the robust model as follows:

$$\begin{aligned}\text{Min } Z = &\sum_s p_s \left(FC^s + OC^s + TC^s + BC^s\right)\\ &+ \lambda \sum_s p_s \Big[\left(FC^s + OC^s + TC^s + BC^s\right)\\ &- \sum_{s'\epsilon S} p_{s'} \left(FC^{s'} + OC^{s'} + TC^{s'} + BC^{s'}\right) + 2\theta_s\Big] + \omega \sum_{s=1}^{S} p_s \delta_t^s\end{aligned} \tag{17}$$

s.t.

$$\begin{aligned}&(FC^s + OC^s + TC^s + BC^s) - \sum_{s'} p_{s'} (FC^{s'} + OC^{s'} + TC^{s'}\\ &+BC^{s'}) + \theta_s \geq 0\end{aligned} \qquad \forall s \tag{18}$$

$$\sum_j YU_{jkt}^s + \sum_m YR_{mkt}^s \leq 1 \qquad \forall s,k,t \tag{19}$$

$$FU\,Max_t(Pr_t^s) + \sum_m FR_m XR_m \leq B \qquad \forall s \tag{20}$$

$$Q_{jkt}^s \leq MN\,YU_{jkt}^s \qquad \forall k,s,t,j \tag{21}$$

$$Q_{mjt}^{\prime s} \leq MN\,R_{mjt}^s \qquad \forall m,s,t,j \tag{22}$$

$$Q_{mkt}^{\prime\prime s} \leq MN\,YR_{mkt}^s \qquad \forall k,s,t,m \tag{23}$$

$$\sum_m XR_m \geq 1 \tag{24}$$

$$XR_i + \sum_{j_1} XU_{ij_1t}^s \leq 1 \qquad \forall i,t,s \tag{25}$$

$$\sum_{j_1} \sum_j XU_{j_1jt}^s = Pr_t^s \qquad \forall t,s \tag{26}$$

$$\sum_j XU_{j_1jt}^s \leq 1 \qquad \forall j_1,t,s \tag{27}$$

$$\sum_{j_2} XU_{j_2j_1t}^s \leq \sum_j XU_{j_1jt-1}^s \qquad \forall j_1,t,s \tag{28}$$

$$YU_{jkt}^s \leq \sum_{j_1} XU_{jj_1t}^s \qquad \forall j,s,t,k \tag{29}$$

$$YR_{mkt}^s \leq XR_m \qquad \forall k,s,m,t \tag{30}$$

$$R_{mjt}^s \leq XR_m \qquad \forall j,s,m,t \tag{31}$$

$$r_{mk} YR_{mkt}^s \leq r \qquad \forall k,s,t,m \tag{32}$$

$$rw_{mj} R_{mjt}^s \leq rw \qquad \forall j,s,t,m \tag{33}$$

$$r_{jk} YU_{jkt}^s \leq r \qquad \forall j,s,t,k \tag{34}$$

$$q_j^s T_{jt}^s + \left(1 - q_j^s\right)\left(1 - \sum_{j_1} a_j XU_{jj_1t}^s\right) Cap \geq \sum_k Q_{jkt}^s YU_{jkt}^s \qquad \forall s,j,t \tag{35}$$

$$R_{mjt}^s \leq \sum_{j_1} XU_{jj_1t}^s \qquad \forall s,j,m,t \tag{36}$$

$$\sum_j Q_{jkt}^s + \sum_m Q_{mkt}^{\prime\prime s} \leq d_{kt} \qquad \forall s,k,t \tag{37}$$

$$\sum_k Q_{jkt}^s = \sum_m Q_{mjt}^{\prime s} + T_{jt}^s \qquad \forall s,j,t \tag{38}$$

$$\sum_j \sum_m Q_{mjt}^{\prime s} + \sum_k \sum_m Q_{mkt}^{\prime\prime s} + \delta_t^s \geq D_t^s \qquad \forall t,s \tag{39}$$

$$XR_m, XU_{jj_1t}^s, YU_{jkt}^s, YR_{mkt}^s, R_{mjt}^s \in 0,1 \qquad \forall s,j,m,t,k \tag{40}$$

$$T_{jt}^s, \theta_s, Q_{jkt}^s, Q_{mjt}^{\prime s}, Q_{mkt}^{\prime\prime s} \geq 0 \qquad \forall s,t,m,j,k \tag{41}$$

The model is intended to minimize the mentioned costs, including the fixed, operational, transportation, and blood loss cost. Constraint

Table 2
Input parameter values for solving small- and medium-sized problems.

Parameters	Values	Parameters	Values
B	∼ Uniform (25,000, 40,000)	C_{mj}	∼ Uniform (0.00015, 0.0006)
q_j	∼ Uniform (0.25, 0.45)	Cc_{ik}	∼ Uniform (0.05, 0.09)
r	∼ Uniform (4, 10)	Cap	∼ Uniform (80, 140)
rw	∼ Uniform (30, 50)	Cc_{jk}	∼ Uniform (0.0002, 0.0003)
d_{kt}	∼ Uniform (30, 120)	MN	100,000,000
D_t	∼ Uniform (700, 900)	a_j	∼ Uniform (0.3, 0.5)
$V_{j_1 j}$	∼ Uniform (0.0005, 0.0015)	Θ	∼ Uniform (0.01, 0.08)
Fr_m	∼ Uniform (14,000, 35,000)	FU	∼ Uniform (200, 500)

(18) is the auxiliary equation determined in Eq. (11). Constraint (19) shows that only a blood center or a temporary facility can get blood from each group of donors (not both of them). Constraint (20) indicates the budget for construction of the facilities. Constraints (21)–(22) guarantee that donor group k can be donated to a facility or a temporary facility transfer blood units to a center if they are assigned them. Constraint (24) guarantees that at least one blood center should be built because temporary facilities should deliver blood units at the center and this center is responsible for testing and collecting blood units for hospital applications. Constraint (25) ensures that only one facility or center can locate at location i. Constraint (26) indicates the number of required temporary facilities.

Constraint (27) imposes that at most one facility can be shifted to the location j_1 in each period. Constraint (28) ensures that temporary facilities can shift from a location where there has been a facility located there. Constraint (29) makes sure that donor groups can be allocated only to facilities that are facilitated there. Constraint (30) imposes that donors can only be assigned to a blood center that is established there. Constraint (31) guarantees that a temporary facility at location j can allocate to a blood center at location m if the center has been constructed there. Constraints (32)–(34) indicate the radius of coverage of donors with a blood center, temporary facilities with center and donors with temporary facilities. Constraint (35) indicates the capacity of the temporary facilities in consideration of the disruption. Indeed, this constraint reveals that the quantity of blood cannot exceed the capacity, which is not affected by the disruption. Constraint (36) guarantees that a temporary facility at location j can be assigned to a blood center if there has been a temporary facility in there. Constraint (37) limits the number of blood units donated in each period by each donor group. Constraint (38) indicates that some of the blood units donated to a temporary facility are transferred to a blood center, and some of them are also destroyed due to disruption. Constraint (39) is a control constraint indicating that the desirable demand should be fulfilled in each period.

3.7. Linearization

The objective function and formula (35) are nonlinear. However, the nonlinear terms are $T^s_{jt} XU^s_{j_1 jt}$ and $Q^s_{jkt} YU^s_{jkt}$. A new variable is defined by:

$$A^s_{jj_1t} = T^s_{jt} XU^s_{jj_1t} \qquad \forall s \tag{42}$$

$$A^s_{jj_1t} \geq T^s_{jt} + MN(XU^s_{jj_1t} - 1) \qquad \forall j, s, t, j_1 \tag{43}$$

$$A^s_{jj_1t} \leq T^s_{jt} - MN(XU^s_{jj_1t} - 1) \qquad \forall j, s, t, j_1 \tag{44}$$

$$A^s_{jj_1t} \leq MN\, XU^s_{jj_1t} \qquad \forall j, s, t, j_1 \tag{45}$$

$$A^s_{jj_1t} \geq 0 \qquad \forall j, s, t, j_1 \tag{46}$$

The above term can be written in the objective function by:

$$BC^s = \sum_t \Theta \sum_j \sum_{j_1} A^s_{jj_1t} \qquad \forall s \tag{47}$$

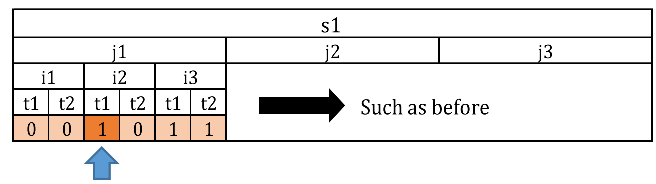

Fig. 2. Solution representation.

Also, the same approach is used to linearize the non-linear term in Eq. (48).

$$Q^s_{jkt} YU^s_{jkt} = QU^s_{jkt} \qquad \forall s \tag{48}$$

The above term in constraint can be written by:

$$q^s_j T^s_{jt} + \left(1 - q^s_j\right)\left(1 - \sum_{j_1} a_j XU^s_{jj_1t}\right) Cap \geq \sum_k QU^s_{jkt} \qquad \forall j, s, t \tag{49}$$

4. Solution methodology

Since solving large-sized location–allocation problems are time-consuming and are NP-hard, meta-heuristic search algorithms are utilized to solve them, because the GAMS solver is unable to solve it. In this paper, we propose a self-adaptive imperialist competitive algorithm (SAICA) to solve the model. Furthermore, an invasive weed optimization (IWO) algorithm is presented to evaluate the efficiency of the proposed SAICA.

4.1. Solution representation

In designing a meta-heuristic algorithm, a solution representation is one of the critical steps to get an appropriate near-optimal solution. For the presented model, a solution representation contains location–allocation parts and some integer variables (e.g., collected and delivered blood). The location part of the proposed solution representation for the centers includes a $(1 \times m)$ matrix, where m is the number of locations, filled with random numbers 0 and 1. In addition, for other parts of location and allocation (e.g., the location part of temporary facilities), we define a $(1 \times s \times t \times i \times j)$ matrix that is filled with random numbers of 0 and 1, and t is the number of periods, s is the number of scenarios, j and i are the number of locations. For instance, in a network with three possible locations, two possible periods and two possible scenarios ($|s| = 2$, $|t| = 2$, $|j| = 3$, $|i| = 3$), a solution representation is displayed in Fig. 2. It illustrates when the third cell is filled with 1, it means that this cell is related to s_1, j_1, i_2, t_1 and it results that $XU^1_{211} = 1$. For integer variables, it is similar to Fig. 2 with a difference that the matrix is filled with random integer numbers.

4.2. Imperialist competitive algorithm

The imperialist competitive algorithm (ICA) is a politically-socio motivated global search algorithm that is utilized to solve a lot of optimization problems (Atashpaz-Gargari and Lucas, 2007; Rahimi et al., 2018). Like Genetic Algorithm, which begins with an initial population named chromosome (Rabbani et al., 2016), the ICA begins with an incipient population is named a country. Then, based on their cost, some of them with the lower cost are chosen to be imperialist (the best solutions in the population) and other ones with more cost are allocated to the imperialists based on their power (Ardalan et al., 2015). Thus, the initial empires are created by the imperialists and their colonies (the solutions, like a generation in the genetic algorithm). Afterwards, such as the assimilation policy, colonies begin to shift toward their related imperialists. Then, a competition starts among all the empires. Notably, the whole power of an empire is decided by two factors, one of which is the power of the imperialist and another is the power of its colonies. An empire will be eliminated if it is not able to increase its power. So, the loser empires will collapse. Finally, just one empire exists based on the competition and the collapse mechanism, and its colonies are other loser countries.

4.2.1. Generating initial empires

In ICA, a country is formed as an array to solve an N-dimensional optimization problem shown below:

$$\mathrm{Country} = [\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots, \mathrm{p}_\mathrm{N}] \tag{50}$$

To start this algorithm, $\mathrm{N}_{\mathrm{pop}}$ is generated as an initial population size and then imperialists are considered as $\mathrm{N}_{\mathrm{imp}}$ that are a number of most powerful countries. In this algorithm, there are two types of countries that are: imperialist and colony. The colonies are distributed among imperialists based on their power, so the normalized cost of an imperialist is needed that is defined by:

$$\mathrm{C}_\mathrm{i} = \max_\mathrm{i}\left\{\mathrm{c}_\mathrm{n}\right\} - \mathrm{c}_\mathrm{i} \tag{51}$$

where c_i is the cost of imperialist i.

The colonies are divided among imperialists due to their power, so the possession probability of each imperialist is as follows:

$$\mathrm{p}_\mathrm{i} = \left|\frac{\mathrm{C}_\mathrm{i}}{\sum_{\mathrm{n}=1}^{\mathrm{N}_{\mathrm{imp}}} \mathrm{C}_\mathrm{n}}\right| \tag{52}$$

It should be noted that in this study, the exponential function is used for this probability.

4.2.2. Power of an empire

The total power of an empire is equivalent to the power of imperialist and a percentage of mean power of the colonies of it which is given as follows:

$$TP_i = C_i + \xi \underset{n\in i}{\mathrm{mean}}\left\{C_n\right\} \tag{53}$$

where TP_i is the total power of the empire i and ξ is a positive and small number, which is better to be less than 1.

4.2.3. Assimilation

The assimilation operator is displayed in Fig. 3. Colonies are moved toward imperialists in another direction by considering a random deviation. where θ is a random number that follows a uniform distribution. Also, d is considered as the distance between the imperialist and the colony.

4.2.4. Crossover

In this step, the information of colonies is shared between themselves by using crossover operators shown by the p-Crossover.

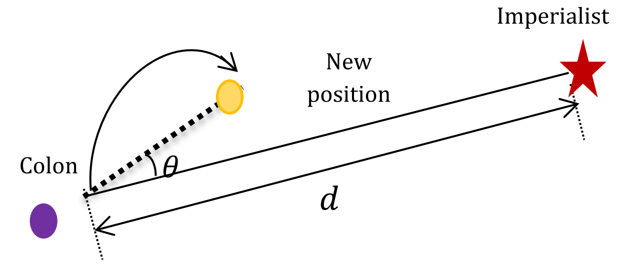

Fig. 3. Assimilation operator.

4.2.5. Revolution

The revolution operator is an action, which selects a number of colonies by using a random selection mechanism and replaces with an equal number of the newly generated ones, also revolution operator decreases the risk of getting trapped in Local searches. three various procedures are performed obtaining: (a) swap, (b) inversion and (c) reversion operators as they are presented in Fig. 4. In the swap operator, places of two randomly chosen bits are exchanged. In the inversion operator, one bit is selected randomly and its value is replaced with a new random value. Finally, In the reversion operator, a random part of a colony is selected and its permutation is reversed. Moreover, for employing the revolution operator on a discrete part of each colony, two various policies are adopted. First, the discrete part stays unchanged. Second, one bit is chosen randomly, and it is replaced with another random number that is not equal to previous ones.

4.2.6. Exchanging positions

The position of a colony and its imperialist might be changed if a colony becomes more powerful than its imperialist.

4.2.7. Eliminating the powerless empires

During the competition process, weak empires will be eliminated.

4.2.8. Stopping criteria

The proposed algorithm will be stopped when the maximum iteration is established or only one empire remains in process.

4.2.9. Self-adaptive ICA

In the ICA, some colonies are influenced by other empires in other countries or maybe empires interchange data with each other. The crossover operator is a practical operator for this concept. There are various methods in the subject literature for the crossover operator, which is utilized before in the genetic algorithm to search the solution space (e.g., one-point crossover, two-point, three-point, uniform, and crossover with three parents), each with its advantages. Since the use of all of them simultaneously rises the algorithm's time, many researchers use only one type of algorithm. In the proposed solution method in this section, it is possible to use most intersection operators without increasing the solving time. To do this, we integrate different operators. For this reason, the proposed algorithm is called SAICA for solving the model. The proposed SAICA has two steps. In the first step, which is called the "Preparation Phase", different crossover operators will compete after a competition. After the competition, the crossover with the higher score has more opportunity to be chosen in the next phase. Two pseudo-codes and flow charts for preparing phases and the ICA are shown in Algorithms 1 and 2, and Figs. 5 and 6.

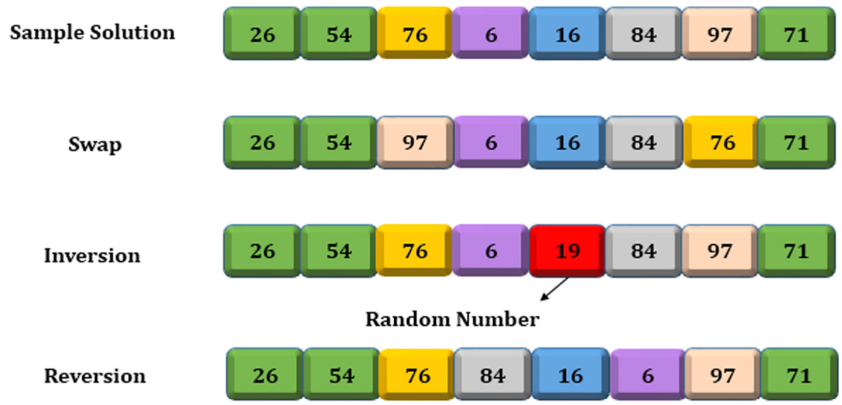

Fig. 4. Three steps revolution.

Algorithm 1 Pseudo code for the Preparation Phase of SAICA

Procedure ($N_{pop} = 200,, Iter_{max} = 250$)
  Number of iterations=0 (SXO(j)=0 (j ∈ All Crossovers-XOs))
  Iter=0
  Generate Initial Population
  Calculate OFV
  While (terminate=**false**) **do**
    Select Parents
    Apply all Crossover Operators
      1.One-point XO (No.1)
      2.Two-point XO (No.2)
      3.Uniform XO (No.3)
      4.Three-point XO (No.4)
    Evaluate Cost of the Obtained Solutions
      If $\min_j\{\text{OFV}_{\text{XO}(j)}\} \cong \text{XO}(j)$ **then**
        SXO(j)=SXO(j)+1
      EndIf
      If Iter ≥ $Iter_{max}$ **then**
        terminate=**True**
      EndIf
        Iter= Iter+1
  EndWhile
  Calculate Selection Probabilty $\left(SP(j) = \dfrac{SXO(j)}{\sum_j SXO(j)}\right)$
EndProcedure

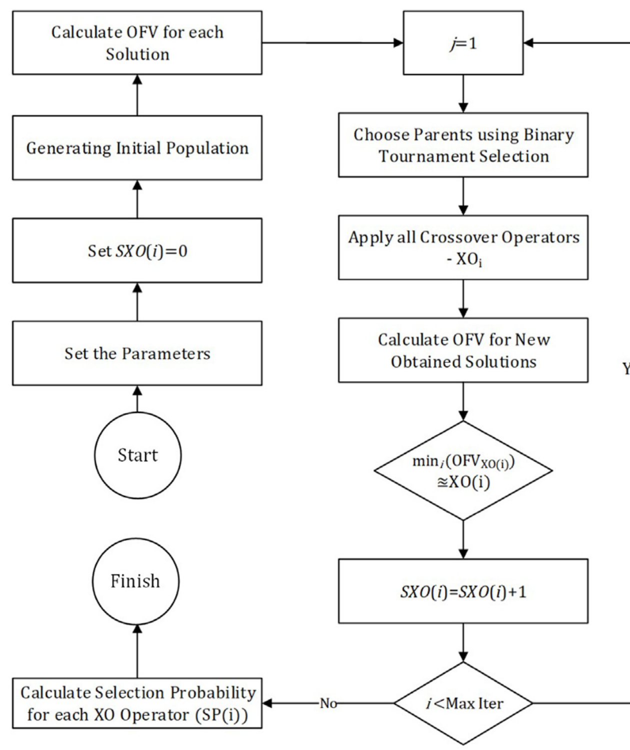

Fig. 5. Flow chart of initial steps in the proposed SAICA.

After the completion of the preparatory phase, the "main phase" of the ICA will be done as mentioned above, with the difference that the response space is searched by all assimilation, crossover, and revolution operators. Notably, the objective function value is shown as OFV in this paper.

4.3. Invasive weed optimization (IWO)

Mehrabian and Lucas (2006) introduced an evolutionary algorithm based on population to optimize problems, which is called IWO. In IWO, the treatment of weeds is simulated in colonizing to discover appropriate sites for breeding and growth. In short, the procedure of the IWO is described below.

In the first step, a generation of the incipient population (i.e., weeds) is done over search space randomly. The next step, a number of seeds ($S \in [S_{min}, S_{max}]$) are created from each weed based on their relative suitability. Afterwards, the distribution of the created seeds is randomly done over the search space. Finally, all seeds are ranked together with their parents as a colony of weed when they have found in the search area.

4.4. Handling the constraints

The considered mathematical model contains several constraints, and the presented algorithms are required to handle them during optimization. The solution representation can guarantee the feasibility of most of the constraints, except for some constraints such as constraint (20). In the literature, there are some approaches to handle these kinds of constraints. In this paper, the penalty function is used based on Yeniay (2005). The penalty is defined based on the amount of deviation from constraints, which is explained as below with assumption of the infeasible constraint ($u(x) \leq c$):

$$P(x) = B \times Max\left\{\left(\frac{u(x)}{c} - 1\right), 0\right\}$$

where $P(x)$ is the penalty value and B is the coefficient for aggression the constraint. Then, the sum of the penalties of all related constraints is added in the objective function. So, the algorithms find the solution with minimum penalties.

Algorithm 2 Pseudo code of the SAICA

Procedure $NFC = 0$
  Set the parameters (N_{Pop}, N_{imp}, ξ, β, α, P_A, P_C, P_R)
  Generate initial Countries containing all distinct five parts ($X_i | i = 1, \ldots, N_{pop}$)
  Evaluate fitness of each country (OFV)
  Form initial empires:
    Choose first N_{imp} countries as the empires min $\{OFV | \; i = 1, \ldots, N_{Pop}\}$
    $N_{Colony} = N_{Pop} - N_{imp}$
    For $i = 1 \colon N_{imp}$
      $P_{empire_i} = e^{\left(-\alpha \frac{OFV_{empire_i}}{\max_k \{OFV_{empire_k}\}}\right)}$
    EndFor
    $NP_{empire_i} = \frac{P_{empire_i}}{\sum_{k=1}^{N_{imp}} P_{empire_k}}$ (NP: Normalized Probability)
    $NC_{empire_k} = NP_{empire_k} \times N_{Colony}$ (NC: Number of Colony)
    Assign colonies to their related empire (pop_1) as:
    For $i = 1 \colon N_{Colony}$
      If $\mathbf{C\_NP}_{\mathbf{P}_{\mathbf{empire}_{k-1}}} \le \mathbf{rand}() \le \mathbf{C\_NP}_{\mathbf{P}_{\mathbf{empire}_{k}}}$ **then** (C_NP: Cumulative Normalized Probability)
        Assign ith Colony to kth Empire
      EndIf
    EndFor
  While (terminate = false) **do**
    at each Imperialist
    Assimilate colonies to their related empire as (pop_2) ⟵ P_A, β
    $X_{colony}^{New} = X_{colony}^{Old} + \beta . rand() . \left| X_{colony}^{Old} - X_{empire} \right|$
    Apply roulette wheel selection to choose a crossover operator
    Apply crossover operator based on **Initialization phase** as (pop_3)⟵ P_C, $SP(i)$
      If $C\_SP_{\mathrm{XO}(i)-1} \le \boldsymbol{rand}() \le C\_SP_{\mathrm{XO}(i)}$ **then**
        Apply $\mathrm{XO}(i)$ on the parents
      EndIf
    Perform Revolution among colonies (pop_4) ⟵ P_R
    Evaluate the fitness of newly created solutions (OFV)
    $Pop_{New} = \{Pop_1 \cup Pop_2 \cup Pop_3 \cup Pop_4\}$
    If ($OFVcolony < OFVempire$) **then**
      $X_{empire}^{New} = X_{colony}^{New}$
      $X_{colony}^{New} = X_{empire}^{Old}$
    EndIf
    Calculate total power of the imperialists (TPI_k) as ⟵ ξ
    $TPI_k = OFVempire + \xi . \frac{\sum_{i=1}^{NC_{empire_k}} OFV_{colony_i}^{empire_k}}{NC_{empire_k}}$
    Perform imperialistic competition
    Eliminate the powerless empires (imperialist with no colony)
    If (NFC = predefined value) **then**
      Terminate = **true**
    EndIf
  EndWhile
EndProcedure

5. Experimental results

In this section, a small-sized problem is solved for validating the proposed model, using data taken from one of the main city in the Mazandaran province located in the north of Iran and according to experts' opinion, which is indicated in Table 2. It should be noted that the unit costs are million Rials (as the Iranian currency).

For this model, there are three scenarios for demand and two scenarios for the disruption probability. All the scenarios are presented in Table 3. Table 4 shows the comparison between deterministic and robust approach for small- and medium-sized problems. The problems in this table are solved by the exact method by GAMS (General Algebraic Modeling System) software (Rosenthal, 2013) using the CPLEX solver.

The computation problems in this paper are solved on a computer with a Core i5 CPU 2.67 GHz and 4 GB RAM. Steps of running the numerical model are depicted in Fig. 7.

As from Table 4, the values of the objective function with the robust approach highly depend on the value of ω. For example, for higher ω the model should decrease the unmet demand and try to fulfill the

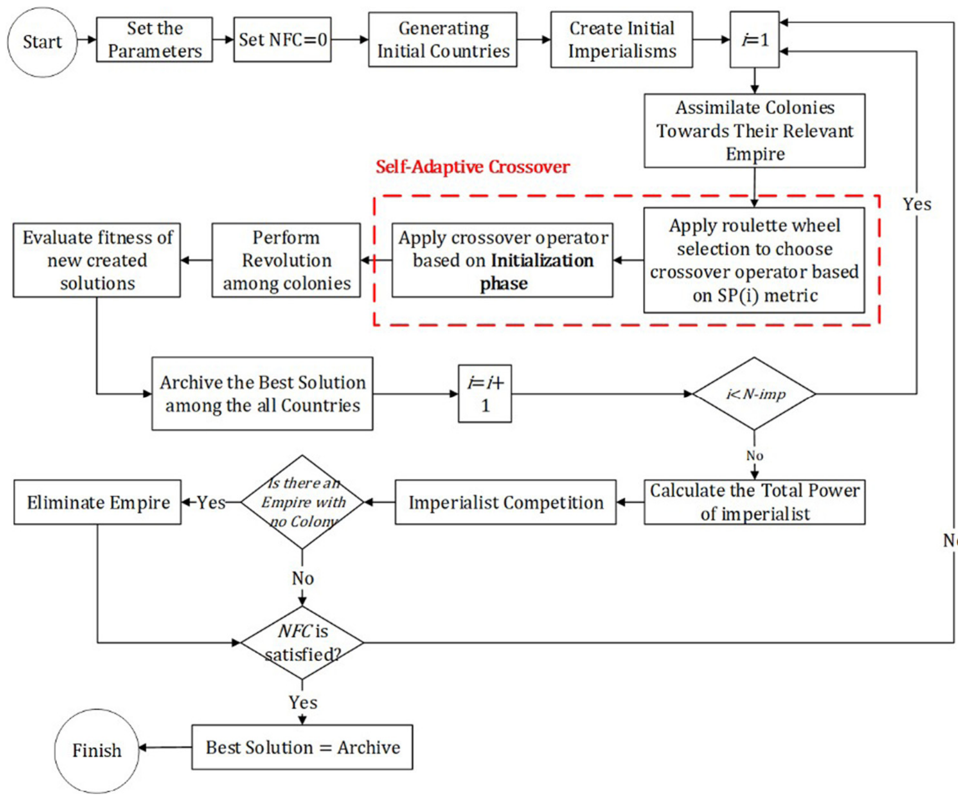

Fig. 6. Flow chart of main steps in the proposed SAICA.

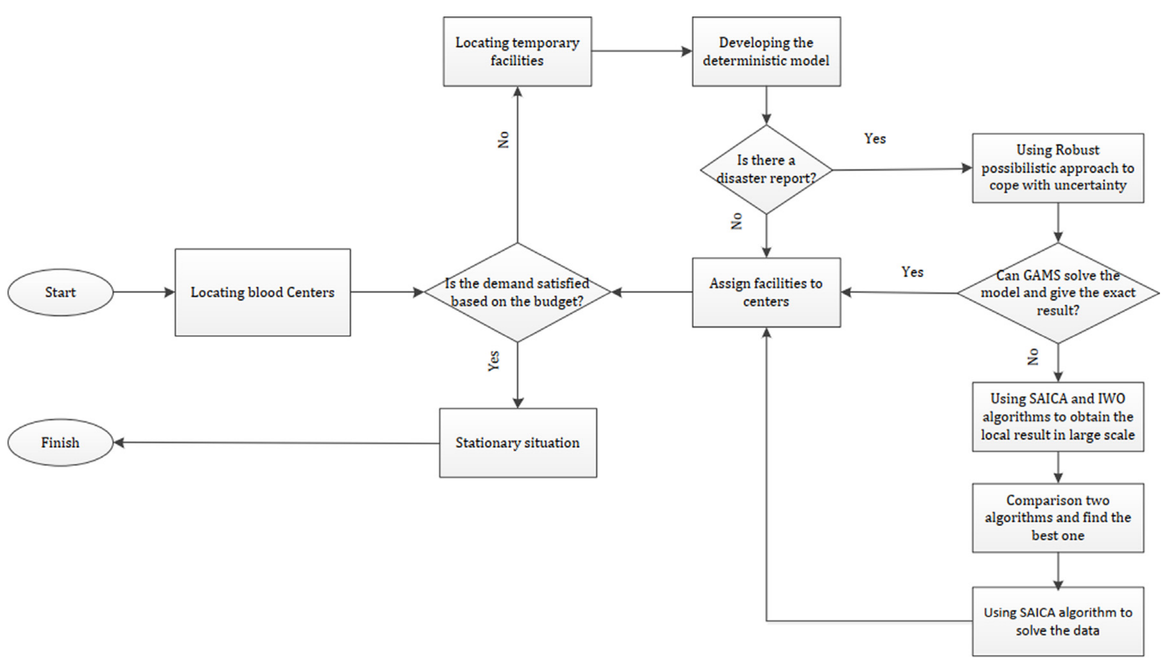

Fig. 7. Flow chart of the solution method.

most quantity of the demand; as a result, the objective function and the solving time increase. Moreover, for a higher value of ω, the model intends to make the solution feasible for almost all the scenarios, that is why the amount of objective function is higher than the deterministic ones. Indeed, this is the price of robustness (Bertsimas and Sim, 2004).

5.1. Model performance assessment

To evaluate the proposed model, a Monte Carlo simulation method is used. This method is an efficient and famous computational algorithm, which runs several simulations according to the random generation of data with a specific statistical distribution (Kalos and Whitlock, 2009).

Table 3
Scenarios of the problem.

Scenarios	Parameter value	p_s	Scenarios	Parameter value	p_s
S_1	$0.5\overline{D_t}\&\overline{q_j}$	0.1	S_4	$0.5\overline{D_t}\&1.3\overline{q_j}$	0.2
S_2	$\overline{D_t}\&\overline{q_j}$	0.2	S_5	$\overline{D_t}\&1.3\overline{q_j}$	0.2
S_3	$1.4\overline{D_t}\&\overline{q_j}$	0.2	S_6	$1.4\overline{D_t}\&1.3\overline{q_j}$	0.1

In this paper, the quantity of the unmet demand is compared in robust and deterministic conditions. The unmet demand in robust is the expected value of variable δ_t^s in different scenarios based on the probability of each scenario. To find the deterministic solution performance in realization under uncertain environment, we applied a Monte Carlo simulation method to find out the quantity of the unmet demand by using a deterministic solution. Indeed, in this simulation, the deterministic model considers the expected value and the robust model considers different scenarios.

As can be seen in Table 4, in conservatism and semi-conservatism solutions of the proposed robust model, the value of the unmet demand, which is shown in the last two columns, is significantly better than the deterministic solution. For example, as it is evident in the last data set, a robust solution with values of $\omega = 80$ yields significantly less the unmet demand in comparison with the deterministic solution by spending just 14% more money on the supply chain. It can be concluded that the proposed model shows better performance because it does not ignore the uncertainty of parameters.

5.2. Parameter setting of meta-heuristic algorithms

The parameters of an algorithm have an effective influence on it, so inappropriate parameters may lead to inappropriate answers. In this paper, the response surface methodology (RSM) is utilized to adjust the appropriate parameters for the proposed algorithm. In this method, first, parameters that influence the algorithm are known and investigated based on input parameters (usually from the objective function value), and by fitting the best regression equation on several levels of the parameters, the desired values are suggested to adjust the parameters. The parameters of SAICA and IWO algorithms are given in Table 5 by considering that the condition for stopping the algorithm is equal to the NFC number of 90,000. Indeed, NFC is the Number of Function Calls used for the stopping criteria. It is defined based on the number of iterations and loops.

5.3. Numerical examples

IWO and SAICA solutions are compared in small- and large-sized problems. For evaluating the gap between each algorithm with the exact solution solved by GAMS, Average Percentage of Relative Gap (APRG) is calculated. It is defined as $\left[100 \times \left(G_{Meta} - G_{Gams}\right)/G_{Meta}\right]$, in which G_{GAMS} is the objective function values (OFV) in GAMS software and G_{Meta} is the OFV for the meta-heuristic algorithm. For each test problem and each algorithm, 30 runs are performed and the results are shown in Table 6. It should be noted that the APRG and Std metric shown in this table are the average and the standard deviation of 30 runs for each test problem. As can be seen, APRG(%) for each test problems of two algorithms are less than 2%. So, both algorithms can result in reasonable solutions.

Table 5
Algorithms' parameters.

Algorithm	Parameters	Settings	Parameters	Settings
IWO	$iter_{\max}$	200	NO	80
	$P_{\max}$	120	$S_{\min}$	2
	N	3	σ_{initial}	0.35
	$S_{\max}$	12	σ_{final}	0.005
SAICA	N_{imp}	3	β	1.8
	ξ	0.7	N_{pop}	181

There are several statistical tests to determine a significant difference between the performance of two algorithms. The Wilcoxon sum-rank test, a non-parametric test, is used to find a meaningful difference between the SAICA and IWO in terms of CPU times (average time solving of 30 independent runs) and quality (average PRG of 30 independent runs) metrics. The Wilcoxon sum-rank is performed in Excel software for small-sized problems. The statistical details of this test are presented in Table 7.

The test is applied to each test problem, and the *p*-value for both metrics of time and quality is less than 0.05 in all test problems. As a result, the null hypothesizes in all test problem are rejected, and there is a considerable difference between the SAICA and IWO in terms of CPU times and quality metrics. Hence, SAICA has less CPU time in all test problems compared to IWO, and it has less gap with the exact solution in all test problems. Therefore, SAICA produces better solutions in terms of both time and gap.

Due to the aforementioned point that the presented mathematical model is an NP-hard, GAMS software is not able to solve the large-sized test problems. In this respect, for large-sized test problems, a gap between SAICA and IWO algorithms is calculated in MATLAB software and is created as $\left[100 \times \left(G_{\text{IWO}} - G_{\text{SAICA}}\right)/G_{\text{SAICA}}\right]$, in which G_{IWO} and G_{SAICA} are the OFV of the SAICA and IWO algorithms. The results are given in Table 8. It also presents the average cost function and time of 30 replications for each test problem. It should be noted that the APRG is the average, and Std is the standard deviation of 30 replications of each test problem. The problem is solved on a computer with a Core i5 CPU 2.67 GHz and 4 GB RAM.

Table 4
Problem-solving with two deterministic and robust modes.

Size problem $\lvert k\rvert \times \lvert i\rvert \times \lvert t\rvert$	Values of ω	OFV		Time (s)		Unmet demand	
		Deterministic	Robust	Deterministic	Robust	Deterministic	Robust
$8 \times 4 \times 3$	5	17001	16,999	120	121	69	92
	20		17,004		122		62
	50		17,013		289		23
$10 \times 5 \times 3$	5	17086	17,009	245	256	75	87
	20		17,115		346		71
	50		17,183		681		33
$14 \times 6 \times 3$	5	17248	17,174	349	423	101	121
	20		18,374		546		96
	50		19,131		825		71
	80		19,854		875		36
$18 \times 8 \times 3$	5	19475	19,379	481	534	112	131
	20		19,485		767		99
	50		21,160		1032		83
	80		22,334		1102		40

Table 6
APRG and STD of the SAICA in comparison with the IWO and computational time for small-sized problems.

Data set	*k*	*i*	SAICA			IWO		
			Std. deviation	APRG(%)	Time (s)	Std. deviation	APRG(%)	Time (s)
1	6	3	0.01	0.07	51	0.04	0.11	83
2	7	3	0.03	0.12	63	0.04	0.17	99
3	8	4	0.04	0.25	77	0.02	0.28	97
4	9	3	0.04	0.24	82	0.03	0.42	123
5	10	5	0.02	0.34	94	0.03	0.73	123
6	12	5	0.01	0.39	94	0.04	0.77	135
7	14	6	0.01	0.45	98	0.03	0.94	137
8	16	6	0.01	0.50	109	0.08	1.13	161
9	17	7	0.02	0.56	119	0.05	1.45	176
10	18	8	0.01	0.65	117	0.04	1.65	185

Table 7
Results of the Wilcoxon test with alpha = 0.05.

Test problem	Time metric			Quality metric		
	p-value	Result of test	Final result	*p*-Value	Result of test	Final result
1	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
2	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
3	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
4	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
5	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
6	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
7	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
8	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
9	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO
10	0.000	Reject null hypothesis	SAICA is better than IWO	0.000	Reject null hypothesis	SAICA is better than IWO

Table 8
APRG and STD of the SAICA in comparison with the IWO and average computational time and average cost function for large-sized problems.

Data set	*k*	*i*	APRG	Std. deviation	Time (s) SAICA	Cost SAICA	Time (s) IWO	Cost IWO
11	26	14	4.82	0.19	368	23,544	480	24,679
12	28	15	5.09	0.12	370	23,887	524	25,102
13	29	16	5.33	0.14	427	23,972	520	25,222
14	30	17	5.71	0.10	521	24,161	625	25,557
15	34	18	6.29	0.06	539	24,355	684	25,928
16	36	17	6.76	0.09	546	24,317	718	25,935
17	38	18	7.21	0.23	586	24,441	789	26,210
18	42	19	7.55	0.07	671	24,543	841	26,389
19	46	19	7.64	0.18	668	24,539	887	26,445
20	50	18	8.27	0.13	598	24,731	931	26,828
21	54	21	8.83	0.42	692	24,866	1023	27,091
22	60	24	9.49	0.06	761	25,180	1274	27,594
23	70	30	11.08	0.22	969	26,655	1353	29,719
24	75	32	12.28	0.33	985	26,744	1366	30,086
25	80	37	13.26	0.43	1012	27,353	1573	31,050
26	86	41	13.91	0.14	1106	27,534	1682	31,411
27	90	46	15.15	0.26	1153	32,464	1754	37,526
28	108	52	16.57	0.48	1234	32,572	1951	38,043
29	120	63	18.47	0.18	1441	33,021	2019	39,125
30	150	70	20.50	0.18	1752	33,149	2160	39,973

The calculation time of meta-heuristic algorithms increases by increasing the size of problems, but in small-sized problems, it has a relative increase. These results show that the approaches of both meta-heuristics can find near-optimal solutions in a reasonable time, while the SAICA is better than the IWO in all the problems in terms of time and APRG. Fig. 8 reveals the comparison between two algorithms in terms of cost function value, which shows that in all sets the cost of SAICA is less than IWO based on the results of Table 8. Meanwhile, Figs. 8 and 9 shows the APRG differences between the two algorithms based on the results of Table 8; it indicates that by increasing the number of problems, not only the GAP between G_{IWO} and G_{Gams} is increased more than the GAP between G_{SAICA} and G_{Gams}, but also the differences between two algorithms in terms of their GAP is growing. Besides, Fig. 9 shows the CPU time of the IWO and SAICA, which the CPU time of the SAICA is less than the IWO. Similar to the explanation mentioned in Fig. 10 by increasing the number of problems, the solving time for IWO grows more than the SAICA. As a result, based on what has been explained above, the performance of the SAICA is better than the IWO in both small- and large-sized problems.

5.4. Case study

The Iranian Blood Transfusion Organization (IBTO) is one of the most important institutions in Iran that has the main responsibility to provide the blood, particularly in disaster and emergencies. One of the most important sub-collections of this institution is the Transfusion Organization of Mazandaran Province. This province is a major province in the north of Iran and is one of the most dangerous provinces

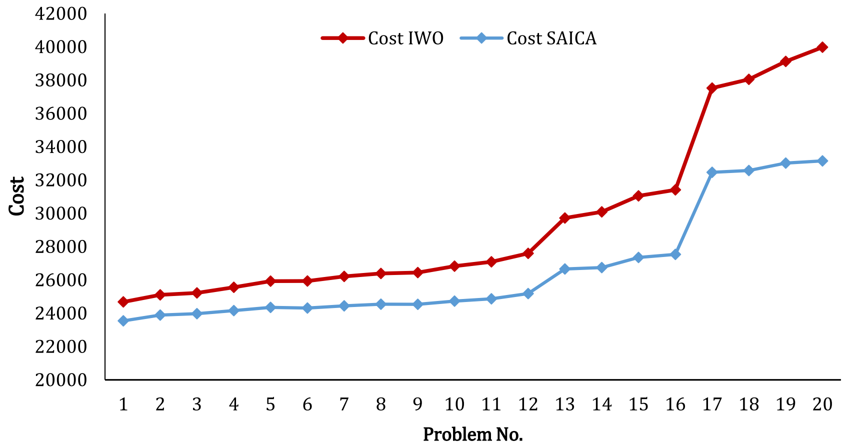

Fig. 8. Average cost objective function value comparison between two algorithms.

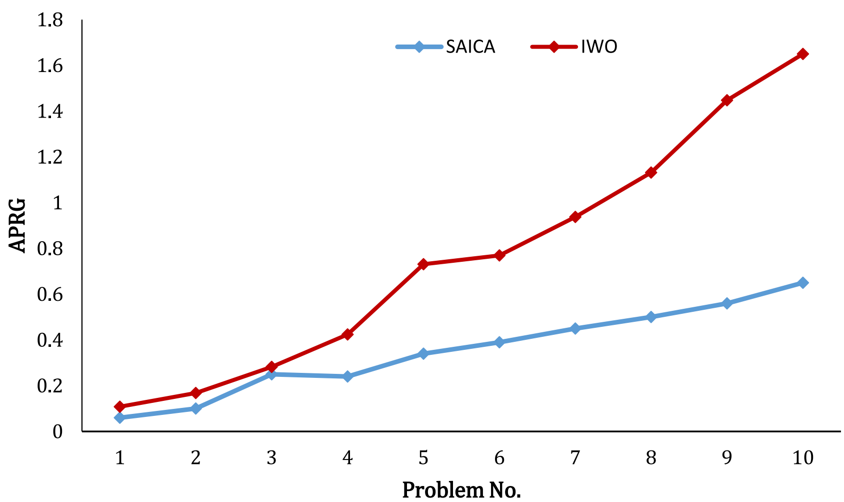

Fig. 9. Average percentage of relative differences between the two algorithms in small size.

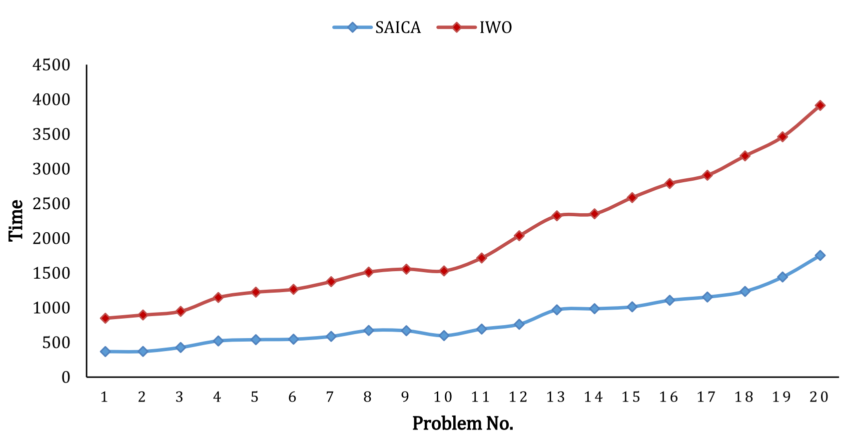

Fig. 10. Average CPU time of the IWO and SAICA.

in terms of natural disasters with a population of over three million. The proposed model aims to develop an efficient blood supply chain network design in Mazandaran.

The collected data is from 73 cities and 150 surrounding villages located in Mazandaran. The cost of shifting temporary facilities is considered to be proportional to the distances between them. Also, the transportation cost of a blood unit is equal to a constant number in the distance between their positions. The quantity of the blood unit, in which each region can donate, is given in Appendix A. It is determined by considering the population of the region. Other information about the data are given in Tables 9 and 10 As it was mentioned before, this province has been exposed to some hazardous disasters (e.g., earthquake and flood). In this study, special attention is paid to this issue and the disruption probability is considered as an important parameter, which is shown in Appendix B. It is determined based on the data during last years and some information about the most likely locations disrupted by disaster.

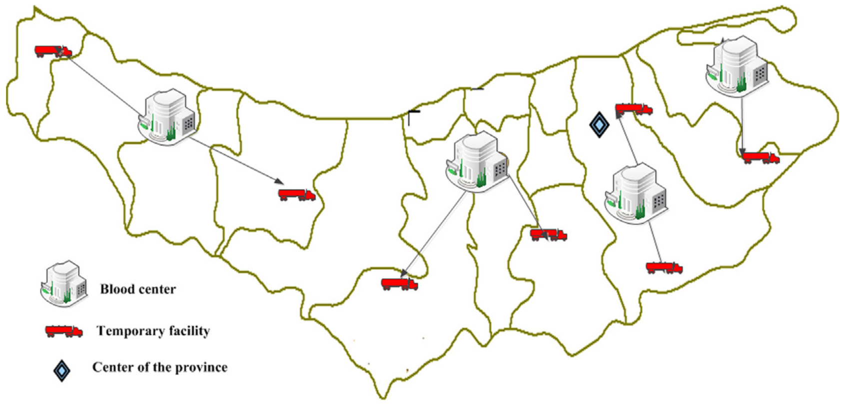

Fig. 11. Aerial map of Mazandaran province and blood facilities.

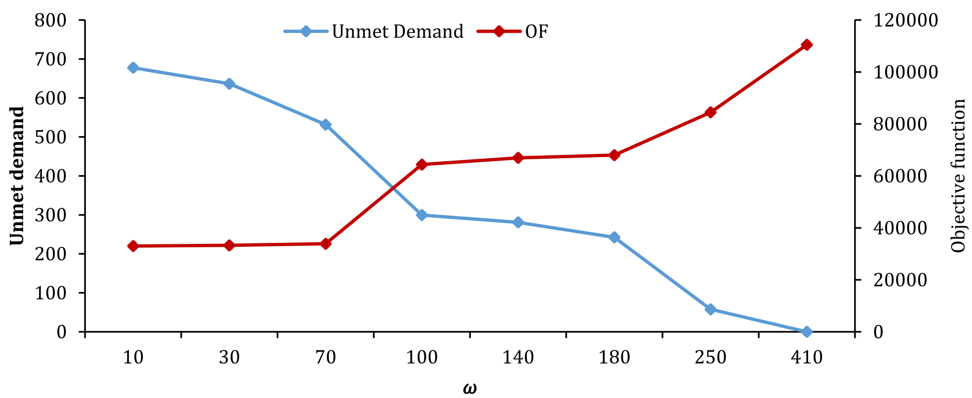

Fig. 12. Trade-off between the objective function and unmet demand without Budget constraint.

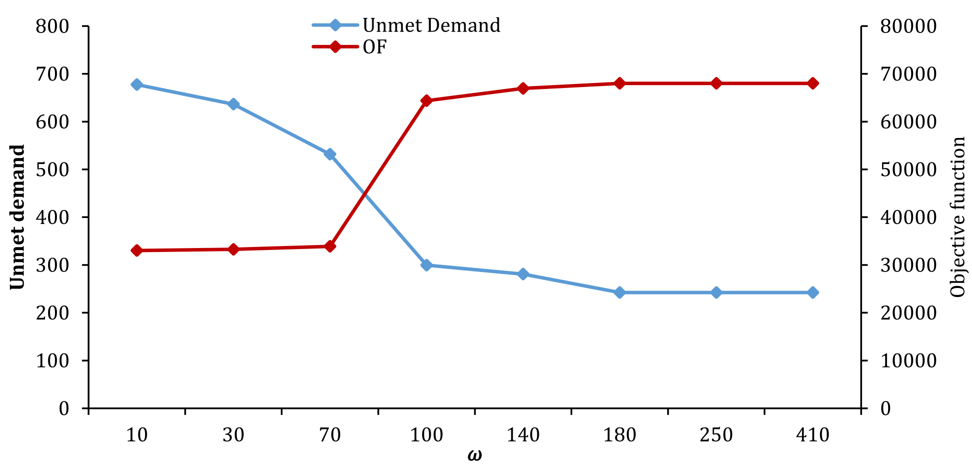

Fig. 13. Trade-off between the objective function and unmet demand with a budget constraint.

Table 9
Parameters of the case study.

Parameters	Values	Parameters	Values
FU	250	rw	50
r	10	Cap	120

Table 10
Associated blood demands in each scenario and period.

Scenarios	$t = 1$	$t = 2$	$t = 3$
S_1, S_4	500	570	474
S_2, S_5	1000	1140	948
S_3, S_6	1400	1596	1327

5.4.1. Model robustness versus solution robustness

Model robustness is defined as being close to a feasible solution while solution robustness means being close to an optimal solution with the least variance between the objective function of scenarios. We examine the trade-off between the objective function value (solution robustness) and the unmet demand (model robustness) which can be assessed by changing a weighting penalty is named ω(*omega*) (the last term in the objective function ((17))). As mentioned before, in the robust optimization problem, the infeasibility in different scenarios is

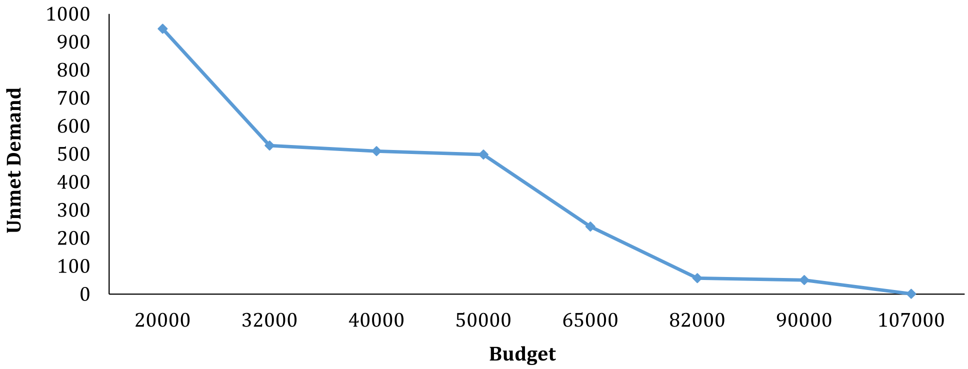

Fig. 14. Trade-off between unmet demand with a budget constraint.

Table 11
Model robustness and solution robustness trade-off solved by SAICA algorithm.

Values of ω	Expected OFV	Unmet demand
10	33,019	677
30	33,267	636
70	33,893	531
100	64,374	299
140	66,943	280
180	68,001	242

Table 12
Optimal number and location of facilities in different omega weights.

Values of ω	Blood center	Temporary facility	Number of temporary facilities
10	44, 69	71, 3, 14, 41	4
30	44, 69	71, 3, 14, 51	4
70	44, 69	71, 51, 16, 4, 36	5
100	44, 69, 5	71, 51, 36, 47, 59, 66, 41	7
140	44, 69, 5, 30	71, 51, 47, 64, 46	5
180	44, 69, 5, 30	71, 51, 47, 57, 49, 36, 20	7
250	44, 69, 5, 30	71, 51, 47, 57, 49, 36, 20	7
300	44, 69, 5, 30	71, 51, 47, 57, 49, 36, 20	7

allowed by using penalty δ_t^s in Constraint (40). As demonstrated in Table 11 that is solved based on the data taken from the mentioned case study, by increasing in the value of ω, the objective function (solution robustness) will increase and the unmet demand (model robustness) will consequently decrease. From this table, at larger risk-aversion weights, there is an inclination toward 'almost' feasible solutions in all the scenarios, at the expense of an increased objective function. This trade-off can help in finding a proper risk-aversion weight. At $\omega = 180$ and more, the problem guarantees the minimum quantity of unmet demand; however, it needs more cost to be feasible and because of the budget constraint, it would be infeasible. Therefore, we choose a smaller risk-aversion weight, which faces the problem with less cost and an acceptable quantity of unmet demand. At $\omega = 180$, the whole cost is 68,001, and simultaneously, the model is robust to most of the scenarios. So, we adjust ω equal to 180 in the rest of solving.

According to the results obtained from solving the developed SAICA for the mentioned case study, some cities of the Mazandaran province are selected for construction of blood centers. It should be noted that in location–allocation issues, location centers are strategic decisions that do not change over the periods, while most allocation decisions are tactical decisions that can be changed as needed in every period. Therefore, the cost of such decisions is considered only once for the entire period, while mid-term decisions often change periodically due to policies (e.g., movement of temporary facilities in periods).

Tables 12 and 13 show the optimal results of solving the model for the case study. Fig. 11 shows the location of candidate blood centers and temporary facilities for one of the periods. As can be seen from Fig. 11 four centers are established in four cities and seven temporary facilities are assigned to them for collecting the blood donated.

Based on the information from Table 12, increasing the ω forces the model to decrease the quantity of the unmet demand and as a result, the number of centers and temporary facilities will increase. It is important to mention that the model equips new facilities and centers until the $\omega = 180$; however, for more than $\omega = 180$, the model cannot build new equipment to fulfill the demand because of the budget constraint.

The value of fundamental variables after solving the problem in each period under each scenario is shown in Table 13.

Table 13
Quantity of blood unit collected, blood unit loss and several temporary facilities required, in each period.

Scenarios	First period				Second period				Third period			
	Q^s_{jk1}	Q'^s_{mj1}	Q''^s_{mk1}	T^s_{j1}	Q^s_{jk2}	Q'^s_{mj2}	Q''^s_{mk2}	T^s_{j2}	Q^s_{jk3}	Q'^s_{mj3}	Q''^s_{mk3}	T^s_{j3}
S_1	0	0	500	0	0	0	500	0	0	0	474	0
S_2	291	266	734	28	627	562	621	65	400	346	602	52
S_3	648	561	839	87	777	684	795	93	660	576	743	84
S_4	0	0	500	0	0	0	500	0	0	0	474	0
S_5	302	246	754	56	616	540	600	78	420	353	596	68
S_6	662	561	839	101	838	728	743	110	672	574	753	97

5.5. Sensitivity analysis of the required parameters

In this part, several sensitivity analyses are conducted to present the management perspective on the basic parameters of the problem. The minimum of the met demand is the parameter that can effectively affect the structure of the model, and the value of ω can affect it as well. As mentioned in Table 11, an increase of this parameter will result in more construction of facilities for more demand coverage, so by increasing in ω, the amount of mean objective function increases and the unmet demand decreases. Fig. 12 shows the sensitivity analysis of the mean objective function values and unmet demand for different values of ω. As can be seen from Fig. 12, by increasing this parameter to 180, more demand is covered by the construction of more facilities and, consequently, by increasing the total cost. As it is mentioned in the prior section, by increasing the ω more than 180 the model needs more cost to fulfill the demand; for comparing the effect of budget constraint, the model is solved with and without considering the budget constraint and the results are shown in Figs. 12 and 13 Based on these figures, without budget constraint the model desires to decrease the unmet demand to zero with increasing the cost function in $\omega = 410$ and the cost 11,0456, which means that if the decision makers want to fulfill the whole quantity of demand, they should cost 11,0456; however, by considering the budget constraint, the best decision is that they accept the quantity of unmet demand which is not high.

Table A.1
Maximum blood supply of each blood donor group.

Donors	First period	Second period	Third period	Donors	First period	Second period	Third period	Donors	First period	Second period	Third period
1	56	27	30	51	176	140	76	101	71	69	46
2	40	43	32	52	74	63	37	102	72	64	48
3	44	46	35	53	74	69	46	103	77	70	63
4	43	25	30	54	74	70	32	104	73	68	56
5	100	90	60	55	78	70	41	105	70	60	47
6	52	35	34	56	70	62	31	106	73	64	52
7	40	43	32	57	72	68	31	107	49	27	31
8	33	44	28	58	68	63	41	108	57	27	40
9	53	39	40	59	70	66	37	109	51	25	34
10	51	33	20	60	71	68	48	110	41	45	33
11	31	31	21	61	106	87	56	111	66	51	45
12	55	42	34	62	64	51	31	112	59	59	33
13	59	41	34	63	61	54	41	113	53	55	50
14	120	100	56	64	62	56	41	114	58	60	54
15	36	25	22	65	59	54	44	115	63	48	30
16	36	37	24	66	59	57	34	116	72	67	65
17	60	36	26	67	110	93	76	117	73	69	50
18	31	35	28	68	60	56	31	118	68	61	47
19	45	48	30	69	64	45	34	119	72	62	51
20	53	50	32	70	110	91	56	120	72	68	44
21	52	50	33	71	58	47	38	121	73	64	38
22	180	130	70	72	61	54	41	122	74	60	38
23	78	61	57	73	57	51	31	123	77	66	48
24	72	60	54	74	35	29	28	124	69	62	46
25	71	62	46	75	40	26	24	125	68	67	46
26	77	60	49	76	55	39	34	126	75	62	54
27	69	64	42	77	39	43	34	127	69	65	32
28	69	67	58	78	53	31	36	128	77	66	36
29	75	60	54	79	38	26	26	129	68	64	40
30	80	65	57	80	49	28	24	130	80	60	30
31	73	67	48	81	41	29	35	131	78	67	44
32	74	70	60	82	52	28	29	132	80	67	36
33	68	67	63	83	54	33	36	133	77	70	44
34	102	89	53	84	49	42	33	134	78	64	36
35	38	53	40	85	46	43	35	135	71	65	37
36	53	46	30	86	51	43	36	136	75	70	42
37	120	103	72	87	36	48	38	137	71	68	45
38	61	57	52	88	46	33	40	138	74	67	42
39	54	52	49	89	51	44	32	139	59	54	44
40	55	49	47	90	51	40	44	140	59	57	34
41	67	59	30	91	57	30	34	141	65	51	39
42	62	55	47	92	42	47	33	142	61	53	45
43	186	110	76	93	72	70	57	143	61	56	44
44	75	70	41	94	70	60	54	144	58	56	32
45	73	69	36	95	69	68	43	145	61	53	35
46	79	61	50	96	78	62	54	146	60	50	31
47	80	65	43	97	72	60	43	147	64	47	35
48	79	65	33	98	70	67	48	148	57	51	33
49	72	63	52	99	75	64	58	149	58	51	39
50	68	67	37	100	75	69	57	150	57	54	45

In Fig. 14, a comparison between the amount of the budget and unmet demand is made. It demonstrates that by increasing the budget, the unmet demand will be decreased; however, there are some important hints in this comparison. With a budget between 32,000 and 50,000, there is no significant reduction in the unmet demand whereas, with more than 65,000, there is a dramatic change in decreasing the unmet demand. As a result, the decision makers should note this matter that if they intend to boost the budget for the system, increasing it between 32,000 and 50,000 does not make difference and when they have less money to allocate, it is better to allocate the 32,000 rather than 50,000. Also, by increasing the budget into 65,000, they will take the opportunity to diminish the unmet demand and fulfill more blood demand in disaster condition. Moreover, if this issue has priority over the cost, by increasing the budget into 82,000 they will fulfill approximately all the demand.

Another remarkable insight can be obtained from Table 12. As can be seen, the location 44 and 69 are the optimal locations for all amount of ω; in other words, these two locations are the proper locations for equipment of blood centers under a variety of budget; Indeed, the decision makers should note that when they face the lack of sufficient budget, these two locations are the best solution for decreasing the whole cost and fulfilling the most quantity of demand. So, they should focus on investing in these two locations. Furthermore, another hint can be obtained from this study is the number of required facilities, which based on the desired budget can be changed and decision makers can utilize the information for making the best decision.

6. Managerial insight

To validate the accuracy of the proposed model, the model is solved on several numerical examples of the case study in prior sections. From another point of view, several problems are solved by changing the parameters to examine and analyze the sensitivity of the model. Managerial insight is an integral part of decision making for each organization. Some of the most important insights given by this paper include:

- Making the best decision in a healthcare system and with a perishable supply.
- Coping with uncertainty in an emergency.

Table B.1
Disruption probability of each location.

Location	Disruption probability	Location	Disruption probability	Location	Disruption probability	Location	Disruption probability	Location	Disruption probability
1	0.23	16	0.42	31	0.28	46	0.24	61	0.32
2	0.24	17	0.27	32	0.27	47	0.25	62	0.36
3	0.25	18	0.43	33	0.23	48	0.21	63	0.21
4	0.26	19	0.34	34	0.25	49	0.25	64	0.27
5	0.25	20	0.35	35	0.19	50	0.19	65	0.32
6	0.28	21	0.25	36	0.18	51	0.42	66	0.34
7	0.26	22	0.22	37	0.24	52	0.32	67	0.35
8	0.25	23	0.28	38	0.21	53	0.34	68	0.31
9	0.18	24	0.34	39	0.21	54	0.21	69	0.29
10	0.23	25	0.31	40	0.23	55	0.23	70	0.36
11	0.25	26	0.29	41	0.45	56	0.25	71	0.40
12	0.23	27	0.23	42	0.40	57	0.23	72	0.42
13	0.27	28	0.24	43	0.24	58	0.19	73	0.19
14	0.41	29	0.24	44	0.32	59	0.28		
15	0.42	30	0.21	45	0.23	60	0.32		

- Coping with both operational and failure risk in the network.
- Making the best decision for evaluating the budget level in the network.
- Making the best decision for equipment of centers and locating facilities in the network in a real case study.

7. Conclusion

Because of increasing attention paid to the health care area in recent years particularly in the emergencies, and since the relocation of facilities will have irreversible effects, this paper has studied location–allocation of facilities in the blood supply chain network. In this paper, we have presented a new mathematical model to make effective decisions in location–allocation of a blood supply chain network in post-disaster periods by considering the budget constraint for the construction of blood facilities and centers. Also, the disruption risk and its effects have been considered for each temporary facility. Due to the existence of disaster conditions, we have developed the model under uncertainty and presented a robust optimization model. A real case study was utilized to evaluate the usage of the presented model. Due to the difficulty of facility location–allocation problems, the self-adaptive imperialist competitive algorithm (SAICA) is considered to solve the proposed model. Furthermore, to evaluate the efficiency of this algorithm, its performance is compared with the invasive weed optimization (IWO) algorithm. Finally, to provide some managerial perspectives for the aforementioned problem, a sensitivity analysis has been performed over the key parameters of the problem. For future studies, we suggest other new and effective methods to face uncertainty (e.g., stochastic programming or fuzzy programming). Also, using other algorithms to solve the developed model is suggested. Moreover, considering the concept of inventory management will be helpful in the case of healthcare systems or even considering another objective function to decrease the computational time will be practical.

CRediT authorship contribution statement

Nazanin Haghjoo: Conceptualization, Writing - original draft. **Reza Tavakkoli-Moghaddam:** Methodology, Writing - review & editing, Validation. **Hani Shahmoradi-Moghadam:** Supervision. **Yaser Rahimi:** Investigation.

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Appendix A

See Table A.1.

Appendix B

See Table B.1.

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