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RESEARCH PAPER

A New Model for Blood Supply Chain Network Design In Disasters Based on Hub Location Approach Considering Intercity Transportation

Mostafa Soltani[1], Rouzbeh Aziz Mohammadi[2], Seyed Mohammad Hassan Hosseini*[3] & Mahdi Mohammadi Zanjani[4]

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ABSTRACT

The blood supply chain network is an especial case of the general supply chain network, which starts with the blood donating and ends with patients. Disasters such as earthquakes, floods, storms, and accidents usually event suddenly. Therefore, designing an efficient network for the blood supply chain network at emergencies is one of the most important challenging decisions for related managers. This paper aims to introduce a new blood supply chain network in disasters using the hub location approach. After introducing the last studies in blood supply chain and hub location separately, a new mixed-integer linear programming model based on hub location is presented for intercity transportation. Due to the complexity of this problem, two new methods are developed based on Particle Swarm Optimization and Differential Evolution algorithms to solve practical-sized problems. Real data related to a case study is used to test the developed mathematical model and to investigate the performance of the proposed algorithms. The result approves the accuracy of the new mathematical model and also the good performance of the proposed algorithms in solving the considered problem in real-sized dimensions. The proposed model is applicable considering new variables and operational constraints to more compatibility with reality. However, we considered the maximum possible demand for blood products in the proposed approach and so, lack of investigation of uncertainty conditions in key parameters is one of the most important limitations of this research.

KEYWORDS: *Blood supply chain; Hub location: Intercity transportation; Particle swarm optimization; Differential evolution.*

1. Introduction

Research in the blood supply chain has largely helped develop effective methods of managing a perishable inventory. Blood is one of the most important needs during and after disasters. Providing this demand has a vital role in saving injures. Therefore, the problem of blood supply chain network design is considerable especially in accident-prone areas and so, this problem has motivated researchers since 1960. A blood supply chain (BSC) network aims to provide blood demands as an important resource for humans during or after disasters. After events that may appear naturally or human-made, a large demand for help and rescue arises[1]. Also, the disaster caused serious infrastructure damage and disrupted land transportation and utility supply systems. In general, the problem of blood supply chain network design consists of three subjects. (I) main centers with proper facilities for blood donating, (II) lab centers with great capacity of storage and technology for required tests, and (III) distribution methods and facilities to cover demands. On the other hand, temporary facilities with more limited levels of capacity are far more cost-effective and flexible to cover the demand and donors.

* **Corresponding author:** ***Seyed Mohammad Hassan Hosseini***
sh.hosseini@shahroodut.ac.ir

1. *Department of Industrial Engineering, Payam-e-Noor University, Tehran, Iran.*
2. *Department of Industrial Engineering, Payam-e-Noor University, Tehran, Iran.*
3. *Department of Industrial Engineering and Management, Shahrood University of Technology, Shahrood, Iran.*
4. *Department of Industrial Engineering, Payam-e-Noor University, Tehran, Iran.*

This issue has been investigated in the literature to some extent because of its importance in the healthcare section. Therefore, many different approaches have been introduced to model and solve this problem. These approaches are mostly based on integer or mixed-integer programming, simulation, dynamic programming, and goal programming. Sometimes heuristics or metaheuristics have been used for the NP-Hard condition of this problem.

To the best of the authors' knowledge, existing studies on relief operations can be categorized into two classes. Some of them are regarding relief supply chain in goods, and the others investigate regarding blood [2]. In the following, some of the papers related to blood supply chain considering blood group types and blood supply management are presented.

Elston et al proposed the first statistical approach to ordering and usage policies for a hospital blood bank in 1963 [3]. They also presented some guidelines to inventory levels for a hospital blood bank determined [4]. Pierskalla et al. in 1980 presented a thorough accurate analysis of the supply chain situation in the United States[5]. In a paper published in the same year by Page [6], the available software at that time was tested to support blood bank processes considering some different factors. These factors include origin, capacity, performance, development status, and cost. A complete review of the work on the blood supply chain to the mid-1980s can be found in Prastacos [7], especially about blood bank management policies and decisions. Besides, Nahmias [1] reviewed perishable inventory theories that had been introduced up to 1982.

In 2004, Pierskalla [8] conducted a comprehensive supply chain design to answer the following questions: (1) where blood banks can be deployed, (2) how to assign donation groups to blood collection centers, (3) blood placement sites (4), and how the collected blood in a blood facility should be transmitted to facilities and blood bank hospitals.

In 2008, Rajagopalan et al. [9] presented a multi-period coverage model to determine the position of the ambulance.

Health research applications have been fully discussed by Papageorgiou in 1978 [10] and Rais and Viana in 2011[11]. An article that focused heavily on the allocation of health facilities relates to Syam, and Côté in 2010[12]. They developed a model for allocating the location of specialized health systems about three critical factors, means, the degree of service focus, the role of patient care as a function of distance to treatment, and the geographic density of the patient population. A common characteristic of the last studies in the BSC section is that all of them conducted this problem with a limited scope of a city or an area. While in many conditions we need to transport blood between cities during and after disasters. So, using hub facilities in form of a network connection of some cities can be useful in cost-saving and reduction of transportation time.

Therefore, in this research, a new approach is developed for the problem of blood supply chain network design based on hub location and hub facilities for intercity transportation.

Hubs are facilities are used as transmission centers in distribution systems. The main purpose of a hub location problem is to make the flow in distribution networks as efficient as possible. In these systems, there are a couple of points as origin and destination with a transportation flow between them. Network designing with direct communication between two points will be very costly; also, a busy and disordered network will be designed. Such a network does not seem reasonable and there will be many problems during transportations. So, using hub facilities will be useful to have a simple network with a minimum cost.

Hub location is almost a new issue in transportation. The first study of using hub location in transportation was done by Toh et al. in 1985 about the use of hubs in airlines and airports [13].

After that, many studies have been done about using hub location in different applications especially in transportation. Zabihi and Gharabkhani published a review paper on hub location studies and their application in the real world from 2013 to 2016 [14]. They also examine some of the new models that have not been addressed in previous review studies. On the other hand, the solution-based classification is divided into three categories, namely exact algorithm, heuristic, and meta-heuristic algorithms, and hybrid algorithm.

In this regard, this paper is going to give appropriate answers to the following main questions:

- ☑ How can the problem of designing the blood supply chain network be modeled with the possibility of intercity transfer based on the hub location approach in disasters?

- ☑ How can we adapt a proper metaheuristic to solve the problem at hand with practical dimensions?
- ☑ What are the key and effective parameters of the problem?
- ☑ What is the impact of changes in the key parameters on the result especially the total cost of the blood supply chain?

To answer the above-mentioned research questions, first, the problem is illustrated carefully and is formulated via developing a new mathematical model. Because this problem is well known as strongly NP-hard, two important population-based algorithms i.e. Differential Evolution and Particle Swarm Optimization are adapted and applied to solve the problem with practical sizes. To the valid performance of the mathematical model and evaluate the optimality of two proposed algorithms, this problem was solved using an exact method with small sizes (16 nodes). Both two proposed solution algorithms are shown suitable performance in solving the problem with a maximum of 0.06% deviation from the exact solution. We also evaluated the performance of these algorithms with data of a real case with medium-sized dimensions. The result of the solution of this problem using two algorithms emphasized the superiority of Particle Swarm Optimization compared to the other algorithm. Furthermore, the number of hubs and the cost discount factor (α)-alpha were identified as the most important parameters affecting the total cost of the blood supply chain. We carried out a sensitivity analysis on these key parameters of a problem to show their influences on the objective function.

It can be considered for relevant managers, to consider pre-defined Hubs for BSC, especially in crisis-prone regions. Moreover, by reducing the cost rate via the Hub networks, which can be supported by the government and the relevant organization, it can be possible to reduce the total cost of the BSC network. To ensure the stability of the proposed algorithms in solving the problem with various sizes, four different problems with large sizes consist of 100, 200, 300, and 400 nodes were generated. Each problem was solved 30 times using these two algorithms and the coefficient of variation (cv) was considered to investigate the performance stability of these algorithms. Solving the result of these four large problems indicated again that the applied Particle Swarm Optimization could present a better solution and introduce a more appropriate network than the Differential Evolution.

This study is organized as follows. Section 2 brings forward a review of the related studies addressed in the literature. In section 3, the problem is described in detail and the assumptions and mathematical model are presented. Section 4 describes the solution approach and proposed algorithms. in section 5 the results are discussed, as well as managerial insights, are extracted. Finally, conclusions and recommendations for future research are described in Section 6.

2. A Review of Relevant Literature

The importance of blood supply chain management has attracted researchers in recent years. In this section, we have a review of the existing literature on planning for blood supply chains. In this section, to more systematically identify the research gap and present our contributions, an extant body of the literature on BSC problems is investigated (see Tab. 1).

Research on the regional and the local management aspects of the blood supply essentially started in the 1960s. Elston et al proposed the first statistical approach to ordering and usage policies for a hospital blood bank in 1963[3]. They also presented some guidelines to inventory levels for a hospital blood bank determined. The most important studies in applications of supply chain management (SCM) in health care up to 1978 have been fully discussed by Papageorgiou [10]. After that, Beliën and Forcé provided a complete literature review on the management of the blood supply chain and claimed that a few types of research have been proposed in this area up to 2012 [15].

Nagurney et al. [16] presented a seven-level bi-objective BSC mathematical model to minimize the total cost and risk. Sha and Huang in 2012 [17] introduced and solved a two-layer BSC network design problem using a new heuristic algorithm. Duan and Liao 2014 [18] introduced a new metaheuristic algorithm named TA-TS to solve a two-layer single-objective model of the BSC network design. Hsieh [19] solved a three-layer bi-objective BSC by NSGA-II. Arvan et al. [20] presented a four-layer multi-objective model to minimize cost and time by an e-constraint method. The same research in 2017 by Fahimnia et al. [21] solve with a hybrid solution. Bellin et al in 2013 have considered the optimization of organ transplant network [22].

Yates et al. in 2017 declared some methods commonly used in commercial supply chain management that can lead to efficiencies in the wastage in the hospital and blood supply chain. They state that an example of this case is to stock sharing or lateral transshipment of blood units close to expiry between hospitals, reducing wastage across the supply chain [23]. Cheraghi et al. [24] in 2016 addressed a mixed-integer linear programming model for blood supply chain network design (BSCND) with the need for making both strategic and tactical decisions throughout multiple planning periods. A robust programming approach was devised to deal with inherent randomness in the parameters of the model. Sibuea et al. in 2017 presented a problem in the management of the blood supply chain at the blood banks with perishability characteristics, especially for the red blood cells and platelets. Their research focuses on minimizing the total cost, shortage, and wastage levels of the blood unit [25]. Zahiri and Pishvaee [26] designed a blood supply chain (SC) network considering blood group compatibility. To this aim, a bi-objective mathematical programming model was developed which minimized the total cost as well as the maximum unsatisfied demand. Due to the uncertain nature of some input parameters, two novel robust possibility programming models were proposed based on credibility measures. The data of a real case study were used to illustrate the applicability and performance of the proposed models as well as validating the proposed robust possibility programming approach. The obtained results show the superiority of the developed models and significant cost savings compared to the current existed blood SC network.

Ramezanian and Behboodi [27] developed a deterministic location-allocation model applying a mixed-integer linear programming (MILP) optimization. Due to the stochastic nature of demand and cost parameters, the aforementioned model has been developed to incorporate uncertainty using a robust optimization approach that can overcome the limitations of scenario-based solution methods, i.e., without excessive changes in the complexity of the underlying base deterministic model.

Ensafian et al. [28] developed a stochastic multi-period mixed-integer model for the collection, production, storage, and distribution of platelet in Blood Transfusion Organizations ranging from blood collection centers to clinical points. In their model, the age of platelet and ABO-Rh priority matching rules are incorporated based on the type of patient to raise the quality and safety of platelet transfusion services. At first, a discrete Markov Chain Process is applied to predict the number of donors. Afterward, the uncertain demand is captured using two-stage stochastic programming. A challenging aspect of applying stochastic programming in a dynamic setting is to construct an appropriate set of discrete scenarios. Therefore, they introduce an improved approach for scenario reduction which well represents multivariate stochastic processes for uncertain parameters. To manage risk, a straightforward approach to reduce the expected value and variance of cost is proposed. Finally, management strategies inspired by a real case study are presented. Mansur et al. developed a mathematical model based on the allocation problem of capacitated planning model. They determined the capacity and the cost of transportation are considered to create an initial capacitated planning model. Then, the inventory holding and shortage costs are added to the model [29]. Osorio et al. in 2018 presented a location-allocation model that considers these factors to support strategic decision-making at different levels of centralization. They illustrated by a case study (Colombia) to redesign the national blood supply chain under a range of realistic travel time limitations [30]. Ozener et al. [31] developed a mathematical model and a column generation approach to tailoring the donations. They also proposed a more practical rule-of-thumb which can be easily implemented by the blood donation organizations. They compared the performances of their proposed approaches against lower bound and the current practice at an apheresis facility. Finally, they showed that the proposed column generation approach can easily be modified to handle realistic aspects of the problem including stock-out and donor eligibility/preferences. Hamdan and Diabat [32] presented a two-stage stochastic mathematical model for red blood cells that accounts for the production, inventory, and location decisions. Their tri-objective model aims to reduce the number of outdates, system costs, and blood delivery time simultaneously. The problem is solved using CPLEX for a real case study from the Hashemite Kingdom of Jordan, and managerial insights were drawn from computational experiments.

Bru Dr et al [33] motivated by a project aimed at reorganizing regional blood management systems in Italy, to reduce total management costs without compromising the self-sufficiency goal, i.e. the goal of satisfying the blood demand coming from the region. In particular, they formulate the problem as a facility location model and they apply it using real data related to a specific regional context. The obtained results are analyzed and discussed and then some conclusions are drawn.

Ghatreh Samani and Hosseini-Motlagh [34] addressed an enhanced perspective incorporating a two-phase preemptive policy considering disruption risk. They proposed a hybrid technique using the fuzzy analytic hierarchy process and grey rational analysis for determining supplementary blood facilities, to cooperate in the production process and decrease interruptions. They examine the validity and practicality of the proposed model and its solution perspective along with the reliability of the network by a real case of Iran. Rahman [35] introduced a robust and reliable model for a dynamic emergency blood network design problem. The proposed approach was applied to control uncertainty and a p-criterion technique was used to protect the solution against the risk of disruptions. Ghatreh Samani et al. [36] proposed a multilateral perspective for blood supply chain network design as an intricate decision-making problem. The proposed approach utilizes a novel multi-objective mathematical model by incorporating both quantitative and qualitative factors to comprehensively model the investigated case study. Ghatreh Samani et al. [37] proposed a bi-objective model for a blood supply chain network design. The first objective function tries to minimize the total network cost, whereas the second objective seeks to maximize the quality factor. Due to the epistemic uncertainty of critical parameters, a fuzzy method, as well as some robust approaches, was tailored. Haeri et al. [38] provided a multi-objective integrated resilient-efficient model to design a blood supply chain network under uncertainty. Khalilpourazari et al. [39] considered a six-echelon blood supply chain that consists of donors, blood collection centers (permanent and temporary), regional blood centers, local blood centers, regional hospitals, and local hospitals. Their study aimed to avoid the worst consequences of a disaster using a neural-learning process to meet new challenges. Hamdan and Diabat [40] presented a bi-objective robust optimization model for the design of blood supply chains that are resilient to disaster scenarios. The proposed two-stage stochastic optimization model aims at minimizing the time and cost of delivering blood to hospitals after the occurrence of a disaster while considering possible disruptions in blood facilities and transportation routes. Hosseini-Motlagh et al. [41] presented a two-stage stochastic programming (SP) approach for planning the supply of blood after disasters that can assist in inventory decisions under hybrid uncertainty, minimizing the shortage and wastages. Karadağ et al. [42] presented a novel multi-objective mixed-integer location-allocation model for the BSC network design problem. Their considered objective was minimizing distances between the blood supply chain elements and the length of the mobile unit routes. The objectives are prioritized by experts using the Analytical Hierarchical Process (AHP). Some new studies in recent years tackle the problem of blood supply chain network design under uncertainty. In this area, we can refer to Haghjoo et al. [43] and Ghatreh Samani et al. [44]. They proposed a dynamic robust location-allocation model for the problem under uncertainty and with disruptions in the operational phase respectively. A summary of the relevant studies to this paper has been presented in Tab. (1) to clear contributions related to the considered problem and solution approaches.

Review the previous related studies indicates that using hub facilities as an effective approach for reducing the total cost of transportation has been not considered in designing a blood supply chain network. Moreover, as the best knowledge of authors, no study has been done on using hub facilities in the blood supply chain considering intercity transportation. When disasters event in a city or an area, the blood bank of that city may not be enough to support all demands. All the above-mentioned features of the BSC network design are investigated in this study for the first time.

Tab. 1. Summary of literature on BSC network design.

Articles	Objective function				Solution method		Features					
	Cost	Unsatisfied demands	Time	Substitutions preferences	Exact	Approximate	# of levels	Intercity transport	Hub Transport	Multi-products	Multi-period	Case study
Nagurney et al. -2012	*				MIP	Variation inequality approach	7					
Sha and Huang -2012	*					Heuristics	3				*	*
Duan and Liao -2014		*		*		Simulation	2				*	
Hsieh -2014	*	*				NSGA-II	3					*
Arvan et al. -2015	*		*		ε-constraint		4			*		
Cheraghi et al. -2016	*				MILP	Robust optimization	4				*	
Fahimnia et al. -2017	*		*		ε-constraint, Lagrangian relaxation		4				*	
Sibuea et al. -2017	*					Stochastic integer programming	2			*	*	*
Zahiri and Pishvaee -2017	*	*		*	MIP	Robust optimization	5	*		*	*	*
Ramezanian and Behboodi-2017	*				MILP	Robust optimization	3	*			*	*
Ensafian et al. -2017	*			*	MIP	Stochastic programming	4				*	*
Mansur et al. -2018	*				MIP		3				*	
Osorio et al. -2018	*				MIP	Heuristic	3			*	*	*
Ozener et al. - 2018	*				MIP	Column generation-based heuristic approach (CG)	2			*	*	
Hamdan and Diabat - 2018	*		*	*	ε-constraint		4				*	*
Bru Dr et al. - 2018	*				MIP		3	*				*
Habibi-kouchaksaraei et al. -2018	*	*				GP method	4				*	*

Ghatreh Samani and Hosseini-Motlagh-2018	*				MIP	Robust-fuzzy	4	*		*	*	*

Tab. 1. (continue): Summary of literature on BSC network design.

Articles	Objective function				Solution method		Features					
	Cost	Unsatisfied demands	Time	Substitutions preferences	Exact	Approximate	# of levels	Intercity transport	Hub Transport	Multi-products	Multi-period	Case study
Rahmani-2018	*				MIP	Robust optimization	3				*	
Ghatreh Samani et al.-2019	*				MILP	Robust optimization	5	*		*	*	*
Khalilpourazari et al.-2019	*	*	*			Lexicographic weighted Tchebycheff method	6	*			*	*
Haeri et al.-2019	*				MILP	Robust stochastic optimization	4	*		*		*
Hosseini-Motlagh et al.-2019	*				MIP	Possibilistic programming	4	*		*		*
Ghatreh Samani et al. – 2019	*					Robust programming	3	*		*	*	*
Hosseini-Motlagh et al.-2020	*					Robust fuzzy stochastic programming	3	*			*	*
Hamdan and Diabat - 2020	*		*			Stochastic programming	4	*		*	*	*
Haghjoo et al. - 2020	*					Robust Optimization & metaheuristics	3				*	*
Ghatreh Samani et al. – 2020	*				MILP	Fuzzy stochastic approach	4	*			*	*
Karadag˘ et al. - 2021	*		*		MIP		4	*				*
This research	*				MIP	PSO & DE algorithm	4	*	*	*		*

3. Problem Description and Mathematical Model Formulation

This section discusses the BSC network design problem and the mathematical programming model for the considered problem. For the considered network, four layers will be investigated as Fig. (1). The network layers are mobile blood facilities, local blood centers, regional blood centers, and demand points including hospitals and medical centers. Blood can be donated at either a mobile blood facility or a blood center within a certain geographical distance, but not at the regional blood centers. The blood collected in mobile blood facilities is shipped to the local blood centers and regional blood centers where the blood transfusion process is completed. These centers will then fulfill the blood demand of hospitals and medical centers. Regional blood centers are capable of providing all transfusion processes and services, but local blood centers may not offer a full range of services. Therefore, we have assumed that blood sent from other cities is sent from regional blood centers.

This study assumes that the disaster (natural or unnatural) is so large that the municipal or provincial supply network was unable to supply the blood needed for the injured. Therefore, we need to get help from different provinces and cities to compensate for the shortage of blood needed. The main purpose of the present study is to design and investigate the desired blood supply chain network assuming blood exchange between different cities and provinces. So that the required blood supply is accomplished using hub facility in the least time and at the least cost (see Fig. (2)).

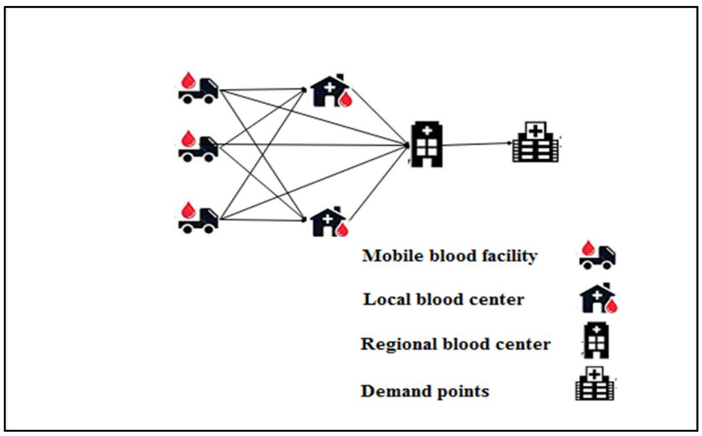


Fig. 1. The layers of the desired blood supply chain.

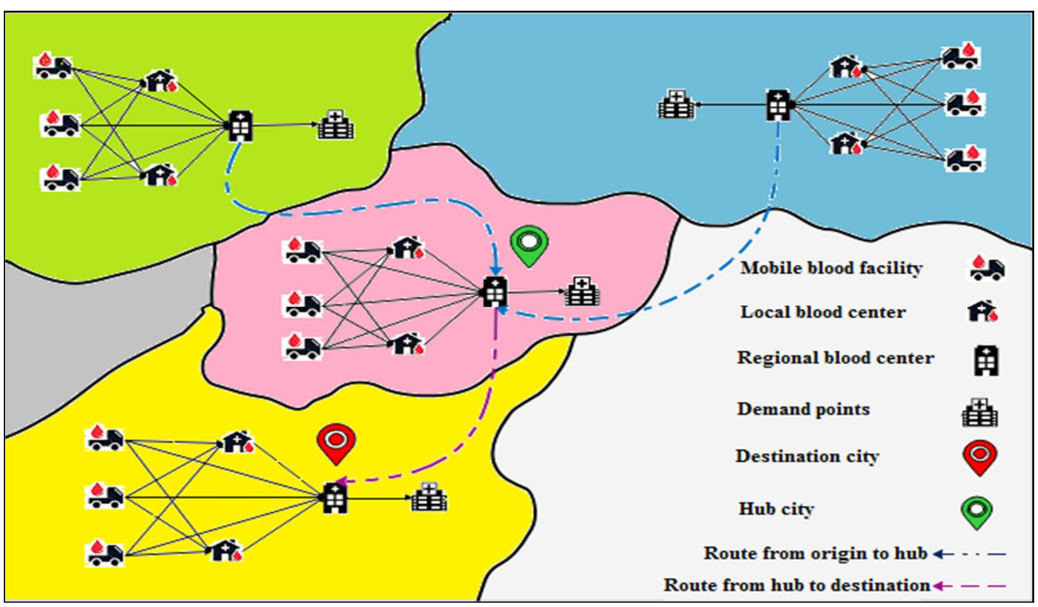


Fig. 2. An overview of the blood supply chain network in this study

In this section, the problem at hand is formulated as a MIP model.

Indices:

$i, m, j, u = 1,2,\dots,I$	indices for nodes
$H \subseteq I$	index of possible locations for hubs
$p \in P$	Index of blood products (platelet & red blood cells)

Parameters:

w_{im}^{p}	The amount of demand blood product p from node i to node m
d_{ij}	The distance from node i to node j
h^{p}	Cost of transportation for product p per kilometer
t_{ij}	The travel time between node i and node j ($t_{ij} = t_{ji}$ for all pair of nodes i and j)
T_{max}^{p}	Maximum transfer time for the product p (expiration date of product p)
Nm_i	The number of mobile blood facilities employed in each city
Nl_i	The number of local blood centers in each city
Nr_i	The number of regional blood centers in each city
P_0	The number of hubs
α_H	Discount factor denoting economies of scale for transferring between hub nodes ($0 \leq \alpha \leq 1$).
α'_H	Discount factor time between hub nodes ($0 \leq \alpha'_H \leq 1$).
F_h	Fixed cost of activating hubs
f	Fixed cost of establishing a mobile blood facility
Om	Unit operational cost at mobile blood facility
Ol	Unit operational cost at local blood centers
Or	Unit operational cost at the regional blood center

Decision variables:

$\boldsymbol{Z_{jj}}$	Binary variable taking value 1 if a hub is located in node $\boldsymbol{j}$ and 0 otherwise
$\boldsymbol{Z_{ij}}$	Binary variable taking value 1 if node $\boldsymbol{i}$ is assigned to hub node $\boldsymbol{j}$ and 0 otherwise
$\boldsymbol{Z_{iu}}$	Binary variable taking value 1 if the origin is assigned to hub node $\boldsymbol{u}$ and 0 otherwise
$\boldsymbol{Z_{mu}}$	Binary variable taking value 1 if the destination is assigned to hub node $\boldsymbol{u}$ and 0 otherwise
$\boldsymbol{dt_{im}^{p}}$	Time is taken to transfer product $\boldsymbol{p}$ between node $\boldsymbol{i}$ to node $\boldsymbol{m}$
$\boldsymbol{Y_{ju}^{ip}}$	The amount of current flowing to commodity $\boldsymbol{p}$ that first passes through the hub $\boldsymbol{j}$ and then through the hub $\boldsymbol{u}$

We can now obtain a nonlinear formulation of the problem as Eq. (1)-(11).

$$
\begin{aligned}
f\colon \min \sum_{i\in I} \sum_{j\in H} \sum_{p\in P} d_{ij} \mathrm{h}^{P} Z_{ij} \left(\sum_{m\in i} W_{im}^{p} + \sum_{m\in i} W_{mi}^{p} \right) \\
+ \sum_{i\in I} \sum_{j\in H} \sum_{u\in H/\{j\}} \sum_{p\in P} \alpha_H d_{ju} h^{P} Y_{ju}^{ip} + \sum_{j\in H} F_j Z_{jj} \\
+ \sum_{i\in I} Nm_i f \\
+ \sum_{i\in I} Nm_i Om + \sum_{i\in I} Nl_i Ol + \sum_{i\in I} Nr_i Or
\end{aligned} \tag{1}
$$

Subject to:

$$\sum_{j\in H} Z_{ij} = 1 \qquad \forall i \in I \tag{2}$$

$$Z_{ij} \leq Z_{jj} \qquad \forall i \in I, j \in H / \{i\} \tag{3}$$

$$\sum_{j\in H} Z_{jj} = P_0 \tag{4}$$

$$\sum_{j\in H} Y_{uj}^{ip} - \sum_{j\in H} Y_{ju}^{ip} = \sum_{m\in I} W_{im}^{p} Z_{iu} - \sum_{m\in I} W_{im}^{p} Z_{mu} \qquad \forall i \in I, u \in H, p \in P \tag{5}$$

$$dt_{im}^{p} = \sum_{j\in H} Z_{ij} Z_{mj}(t_{ij} + t_{jm}) + \sum_{\substack{j,u\in H \\ j\neq u}} Z_{ij} Z_{mu}\left(t_{ij} + \alpha'_H t_{ju} + t_{um} \right) \qquad \forall i,m \in I, i \neq m, p \in P \tag{6}$$

$$dt_{im}^{p} \leq T_{max}^{p} \qquad \forall i,m \in I, i \neq m, p \in P \tag{7}$$

$$dt_{ii}^{p} = 0 \qquad \forall i \in I, p \in P \tag{8}$$

$$dt_{im}^{p} \geq 0 \qquad \forall i,m \in I, i \neq m, p \in P \tag{9}$$

$$Z_{ij}, Z_{jj}, Z_{iu}, Z_{mu} \in \{0,1\} \qquad \forall i,m \in I, j,u \in H \tag{10}$$

$$Y_{ju}^{ip} \geq 0 \qquad \forall i \in I, j,u \in H, j \neq u, p \in P \tag{11}$$

The objective function in Eq. (1) minimizes the total cost (fixed + variable), is equal to the sum of the costs of routine blood product between demand nodes and their hubs, between the hubs, Fixed cost of activating hubs, cost of establishing mobile blood facilities, operational cost at mobile blood facility, local blood centers, and regional blood centers. Constraints in Eq. (2) ensure that each demand node is assigned to a hub. The constraint in Eq. (3) states that if a node is assigned to hub j, then node j should be a hub. The number of hubs to be opened is fixed to P_0, (the number of hub nodes is known (exogenous model)).with Constraint in Eq. (4). Equation (5) is flow balance constraints. Equation (6) Calculate the time that taken to transfer product p between node i to node m. The constraint in Eq. (7) ensures that the time it takes for the blood product p to go from origin to destination should not exceed the expiration date of the products. Platelets are considered highly perishable since they can only be stored up to five days before deteriorating. The second most perishable blood component, Red blood cells, can be kept for up to 42 days on inventory[45]. Equation (8) Ensure that the time it takes for the blood product p from each node to itself is equal to zero. Finally, the constraints (9-11) are positivity and binary constraints.

The constraint in Eq. (6) that calculates time is nonlinear which is linearized as follows, the following decision variables will also be added.

New decision variables to linearize the model

x_{ijm} Binary variable taking value 1 when for $\forall\, i \in I\,, m \in I\,, i \neq m\,, j \in H$ both of variables Z_{ij} and Z_{mj} are equal to 1 and 0 otherwise

This means that if the origin and destination have the same hub, this variable take value 1 and 0 otherwise.

x_{ijum} Binary variable taking value 1 when for $\forall i \in I, m \in I, i \neq m, j,u \in H\,, j \neq u$ both variables $Z_{ij}\ and\ Z_{mu}$ are equal to 1. This means that if the origin and destination have not the same hub, this variable takes values 1 and 0 otherwise.

Linear model

We replace the constraint (6) with nine new constraints as (12) to (20) to linearize the proposed mathematical model.

$$x_{ijm} \geq Z_{ij} + Z_{mj} - 1 \qquad \forall i \in I, m \in I, i \neq m, j \in H \tag{12}$$

$$x_{ijm} \leq Z_{ij} \qquad \forall i \in I, m \in I, i \neq m, j \in H \tag{13}$$

$$x_{ijm} \leq Z_{mj} \qquad \forall i \in I, m \in I, i \neq m, j \in H \tag{14}$$

$$x_{ijum} \geq Z_{ij} + Z_{mu} - 1 \qquad \forall i \in I, m \in I, i \neq m, j,u \in H, j \neq u \tag{15}$$

$$x_{ijum} \leq Z_{ij} \qquad \forall i \in I, m \in I, i \neq m, j,u \in H, j \neq u \tag{16}$$

$x_{ijum} \leq Z_{mu}$	$\forall i \in I, m \in I, i \neq m, j, u \in H, j \neq u$	(17)
$\mathrm{dt}_{im}^{p} = \sum_{j \in H} x_{ijm}(\mathrm{t}_{ij} + \mathrm{t}_{jm}) + \sum_{\substack{j,u \in H \\ j \neq u}} x_{ijum}(\mathrm{t}_{ij} + \alpha'_H \mathrm{t}_{ju} + \mathrm{t}_{um})$	$\forall i, m \in I, i \neq m, p \in P$	(18)
$x_{ijm} \in \{0,1\}$	$\forall i \in I, m \in I, i \neq m, j \in H$	(19)
$x_{ijum} \in \{0,1\}$	$\forall i \in I, m \in I, i \neq m, j, u \in H, j \neq u$	(20)

The correctness of this linearization can be justified by observing that any feasible solution to nonlinear formulation is also a feasible solution to the linear formulation and that any optimal solution to nonlinear formulation is also optimal for linear formulation. The constraints (12-14) ensures that x_{ijm} taking value 1 when for $\forall\, i \in I\,, m \in I\,, i \neq m\,, j \in H$ both of variables Z_{ij} and Z_{mj} are equal to 1 and 0 otherwise. This means that if the origin and destination have the same hub, this variable take value 1 and 0 otherwise. The constraints (15-17) ensures that x_{ijum} taking value 1 when for $\forall i \in I, m \in I, i \neq m, j, u \in H\,, j \neq u$ both variables Z_{ij} *and* Z_{mu} are equal to 1. This means that if the origin and destination have not the same hub, this variable takes values 1 and 0 otherwise. Equation (18) Calculate the time that taken to transfer product p between node i to node m. Finally, Eq. (19-20) are binary constraints [46].

4. Solution Approach

As mentioned before, the hub location problem is well known as strongly NP-hard, hence attainment of exact solutions or solutions via total enumeration is computationally prohibitive for the considered problem. Therefore, the optimal solution based on the mathematical model presented in section 2, can be obtained only for the small-sized scales of the problem and it is necessary to use a heuristic-based algorithm to solve this problem in practical sizes. Particle Swarm Optimization (PSO) and Differential Evolution (DE) are two population-based optimizer algorithms that have shown good performance in solving such NP-hard problems. So, these two algorithms are used in this paper to solve the considered problem with practical-sized scales.

4.1. PSO algorithm

Particle swarm optimization (PSO) is one of the well-known population-based meta-heuristic algorithms that simulate the movements of bird flocks and fish schools in nature and has been first proposed by Kennedy and Eberhart in 1995 [47]. In the context of an optimization problem, a PSO algorithm starts with different points in the solution space to attain a global optimal solution and shares the acquired information to determine good search spaces [48]. In the context of our hub location-allocation problem, each particle is a feasible solution that is represented by two different arrays: selected hubs and allocation array. Installing hubs are randomly selected and all nodes are randomly allocated to hubs.

PSO is initialized with random solutions assigned to the population in which, each solution that is considered as a particle is assigned a randomized velocity [49]. Each particle improves its earlier best solution in the problem space which is achieved so far through previous experiences to stochastically converge towards the best solution in the swarm. This value is called $x_{i(best).G}$. Another best value that is tracked by the global version of the particle swarm optimizer is the overall best value, and its location decisions obtained so far by any particle in the swarm [49]. This is called $x_{best.G}$.

The particle swarm optimization concept consists of, at each time step (iteration), changing the velocity of each particle toward its $x_{i(best).G}$ and $x_{best.G}$ locations. Every particle improves its own earlier position through previous experience to stochastically converge towards the best position of the swarm. Whereas the particle holding the best position in the swarm is entitled as global best; the best position of the particle until the current state is defined as local best. These values are kept in the memory of the algorithm.

For an optimization problem, the decision variable $X = (x_1.x_2.\dots.x_n)$ is an n-dimensional variable, and the variables are called the particles. Assuming the solution space is n-dimensional solution space, each particle has two state descriptions, position $X_i = (x_{i1}.x_{i2}.\dots.x_{in})$, and velocity $V_i = (v_{i1}.v_{i2}.\dots.v_{in})$. The position X_i represents a candidate solution (feasible solution) of the problem. Particles change their positions or states with time (iterations) and navigate in a multidimensional solution space. Each particle moves toward the optimum solution based on its present velocity, its previous experience, and the experience of its neighbors [50].

The particle update rule consists of two equations, one for an update in the velocity vector and the other for a change in the position of the particle due to the movement. The velocity rules are given in Eq. (25) respectively:

$$v_{i.G} = w \times v_{0.G} + c_1 \times rand(i) \times (x_{i(best).G} - x_{i.G}) + c_2 \times rand(i) \times (x_{best.G} - x_{i.G}) \quad (25)$$

In Eq. (25), $w \in (w_{min} - w_{max})$ is the inertia factor. r_1 *and* r_2 are random numbers belonging to the range $[0.1]$. Moreover, c_1 *and* c_2 specify the importance of social moves versus cognitive moves. The c_1 represents the social learning coefficient for each particle and is useful to calculate the local optimum while updating the velocity vector. In other words, c_1 helps each particle to move based on its own previous experiences. In the same manner, c_2 represents the cognitive learning coefficient which identifies the contribution of the global optimum in recalculating velocity vector. The next position of the particle is calculated as shown in Eq. (26).

$$x_{i.G+1} = x_{i.G} + v_{i.G} \quad (26)$$

To prevent a particle from leaving far away out of the search space ,the elements of the velocity vector are restricted in a predetermined minimum and maximum values. If the velocity of a particle would reach w_{max} ,then the velocity is left at w_{max} and could not exceed w_{max} [51].
The above process of the PSO is adopted and need parameters are tuned in this section to solve the considered problem and abstracted in the Tab. (2).

Tab. 2. Parameters of algorithm PSO.

PSO Parameter	Tested values			The best value
w	0.01	0.4	0.8	0.4
c_1	0.1	0.3	0.5	0.3
c_2	0.5	0.9	1.0	0.9
Iteration		200		
N-pop		50		

Solution representation

The performance of meta-heuristic algorithms and the quality of obtained solutions are completely dependent on how the solutions are represented. In this paper, a solution representation is modeled by a matrix. The matrix dimension is $N_p^2 = N_p \times N_p$. At first, this matrix is produced by a random function, so all of the elements are a number between 0 and 1. After some fitting calculations, we alter any number just to 0 or 1.
The matrix that shows a solution has two separate sections. We use the elements of the main diameter to represent hubs location, so for example, if we show the elements of the base diameter of a matrix ($N_p = 10$) with vector Q, then the following statement shows that the 1st, 3rd, 6th, and 10th nodes are hubs:

$$Q = \{1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0\ 1\}$$

We also use other matrix elements to represent each node allocation to a hub. So it can be noticed that by this method, we don't need to use 2 solution representations and solve the problem in 2 phases of locating the hubs and allocating the nodes to the hubs. As a result, the problem-solving speed increases. In this example when the computer code produces an initial solution by N_p=10 and by supposing a Q vector in a random approach, we have a matrix such as a Fig. (2).

	1	2	3	4	5	6	7	8	9	10
1	1	1	0	1	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	1	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	0	1	1	0
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	1	0	0	1

Fig. 3. The schematic structure of the problem solution.

In row 1 of Fig. (3) we have a hub located in node N (1, 1). Nodes 2 and 4 are allocated to hub number 1 because their code is 1 and other nodes will allocate to other hubs because their code is 0. Other rows decoded so.

4.2. DE algorithm

DE algorithm that was introduces in 1995 by Storn and Price inspired by the natural evolution of species [52]. This algorithm has been successfully applied to solve numerous optimization problems in diverse fields. However, the success of the DE algorithm in optimizing a problem depends on appropriately choosing trial vector generation strategies and their associated control parameter values. To adopt this algorithm to the problem in this study, N_p points are considered in our G generation, one of the preset parameters specifies bounds that define the domain from which the N_p vectors in this initial population are chosen. Each vector is indexed with a number from 0 to $N_p - 1$. DE perturbs vectors with the scaled difference of two randomly selected population vectors. DE selects three random vectors and then to produce the trial vector, adds the scaled, random vectors difference to a third randomly selected population vector. In the selection stage, the trial vector competes against the population vector of the same index, in which the vector with the lower objective function value is marked as a member of the next generation. The procedure repeats until all N_p population vectors have competed against a randomly generated trial vector. Once the last trial vector has been tested, the survivors of the N_p competitions become parents for the next generation in the evolutionary cycle.

Unlike the other well-known population-based metaheuristic algorithms, the mutation operator is done before the cross-over in the DE algorithm procedure.

For each target vector $x_{i.G}$ with i = 1, 2 . . . N_p, the vector mutation is created by the Eq. (21).

$$v_{i.G+1} = x_{r1.G} + F(x_{r2.G} - x_{r3.G}) \tag{21}$$

In this equation, the random indices $r1$, $r2$, and $r3$ are chosen using the uniform distribution from the range $1, 2 \ldots, N_p$ in such a way that they must be distinct from each other, as well as different from the current index i. Therefore, N_p should be greater than or equal to four. Factor F is a positive value between 0 to 2 that controls the amplification of $(x_{r2.G} - x_{r3.G})$. A schema of this process can be visualized in Fig. (4).

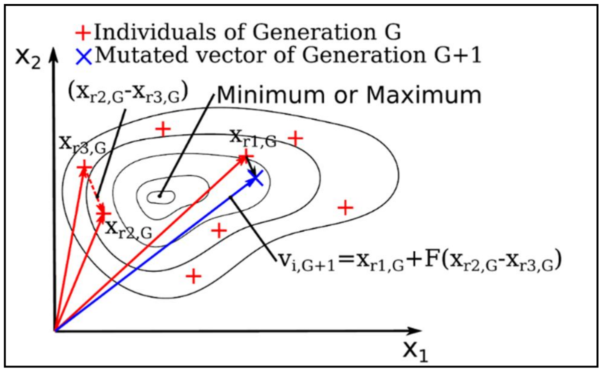


Fig. 4. Schema of differential evolution method (DE).

The purpose of the crossing step is to increase the diversity of the population, disrupting the vector mutation. Thus, the experiment vector $u_{ji.G+1}$ is calculated by Eq. (22).

$$u_{ji.G+1} = \begin{cases} v_{ji.G+1} & if\ (randb\ (j) \leq CR)\ j = rnbr\ (i) \\ x_{ji} & if\ (randb\ (j) > CR)\ j \neq rnbr\ (i) \end{cases} \quad j = 1.2. \dots . D \qquad (22)$$

In Eq. (22), D is the number of optimization variables, $randb\ (j)$ is the jth term in a uniform random number generator between 0 and 1. Parameter CR is the crossover probability chosen by the user between 0 and 1. $rnbr\ (i)$ is used to randomly select the index from the range $1.2. \dots . D$, which ensures that $u_{ji.G+1}$ will receive at least one parameter $v_{i.G+1}$. The selection consists of deciding which individual will become a member of the generation $G + 1$. The experiment vector $u_{i.G+1}$ is compared with the target vector $x_{i.G}$ using the criterion of ambitiousness: if the vector $u_{ji.G+1}$ produces a function value less costly than $x_{i.G}$, then $x_{i.G}$ is equal to $u_{ji.G+1}$, otherwise, the value is kept equal to $x_{i.G}$ [53].

How to implement the proposed DE and the components of the algorithm that are used in this study are described in the following.

Initialization

Population P of generation G contains N_p solution vectors called "individuals" of the population and each vector represents a potential solution for the optimization problem in Eq. (23).

$$P^G = x_{j.i}^G \qquad i = 1.2. \dots . N_p\ ,\ \ j = 1.2. \dots . D\ ,\ \ G = 1.2. \dots . G_{max} \qquad (23)$$

To establish a starting point for optimum seeking, the population must be initialized. Often there is no more knowledge available about the location of a global optimum than the boundaries of the problem variables. In this case, a natural way to initialize the population $P^{(0)}$ (initial population) is to seed it with random values within the given boundary constraints as shown in Eq. (24).

$$P^{(0)} = x_{j.i}^{(0)} = x_j^L + rand_j[0.1] \times \left(x_j^{(U)} - x_j^{(L)}\right) \qquad \begin{matrix} \forall i \in [1.N_p] \\ \forall j \in [1.D] \end{matrix} \qquad (24)$$

Where $rand_j[0.1]$ represents a uniformly distributed random value that ranges from zero to one. In this paper, we used $x_j^{(U)} = 1$ and $x_j^{(L)} = 0$.

Mutation and crossover operators

After initialization, DE employs the mutation operator to produce a mutant vector concerning each individual (target vector), in the current population. For each target vector at the generation, its associated mutant vector can be generated via a certain mutation strategy.

Mallipeddia et al. noted some mutation strategies that can be chosen in [53]. We utilized DE/rand/1/bin strategy which is most widely used.

After the mutation phase, the crossover operator is applied to each pair of the target vector ($x_{i.G}$) and its corresponding mutant vector ($v_{i.G+1}$) generates a trial vector. In the basic version, DE employs the binomial (uniform) crossover.

The crossover rate (CR) controls which and how many components are mutated in each element of the current population [54]. The crossover rate (CR) is a probability $0 \leq CR \leq 1$ of mixing between trial and target vectors. A large CR speeds up convergence and $CR = 0.1$ is a good initial choice while $CR = 0.9$ can be tried to increase the convergence speed [55].

Selection

If the values of some parameters of a newly generated trial vector exceed the corresponding upper and lower bounds, we should reinitialize them within the pre-specified range.

Then the objective function values of all trial vectors are evaluated and a selection operator is performed. The objective function value of each trial vector is compared to that of its corresponding target vector in the current population. If the trial vector has less or equal objective function value (in a minimization problem) than the corresponding target vector, the trial vector will replace the target vector and enter the population of the next generation. Otherwise, the target vector will remain in the population for the next generation. These three steps are repeated generation after generation until a termination criterion is satisfied [56].

Parameters tuning

Choosing suitable values for the needed parameters in DE approaches depends on various factors such as the nature of the problem. The difficulty in using the DE arises when choosing these factors is mainly done based on empirical evidence and practical experience. The F is a scaling factor ,which controls the length of the exploration vector. On the other hand, the CR practically controls the diversity of the population [52].

We talked about CR tuning in the Cross-Over part before, considering different values and references that containing parameters tuning, the most appropriate DE parameters for our problem were selected and are demonstrated in Tab. (3). As shown in this table, the multiplier factor (mutation factor) F was assumed as a uniform probability function between 0.8 and 1.6 ($0.8 \leq F \leq 1.6$). Every optimization calculation was iterated for 200 trials (200 optimization experiments), each one made up of a succession of 50 generations.

Tab. 3. Parameters of algorithm DE.

DE Parameter	Tested values			The best value
CR	0.01	0.1	0.5	0.1
F	Uniform [0.8 , 1.6]			
Iteration	200			
N pop	50			

5. Comparison of Results

This section presents the results of solving test problems using a mathematical model and two proposed algorithms. The mathematical model was run in GAMS and the proposed algorithms were coded in MATLAB (R2018b). The experiments are executed on a PC with an Intel® Core™ i7 6650U – 2.2GHz processor and 16GB of RAM. The test problems were categorized into three classes contain small, medium, and large-sized problems. For the proposed algorithms, each problem has been run 10 times and the best and the average of results have been considered for evaluation.

5.1. Small-sized problems

In this section, we consider the problem with a range of 6 to 16 nodes and determined an appropriate number of hubs for each node number. Each node represents a province center and from this set, we select some cities as a hub from several allowable candidates' hub cities. Then the problem is solved with the mathematical model, DE, and PSO algorithms. The land and time distance between cities are given in Tab. (4) and Tab. (5) respectively. This data extracted from the site: https://www.travelmath.com/distance/.

Also, the demand of each city, number of mobile blood facilities in each city, number of local blood centers in each city, number of regional blood centers in each city, and fixed cost of activating hubs in each potential hubs are needed. The unit cost of establishing a mobile blood facility is 500,000$, operational costs at mobile blood facilities 200,000$, operational costs at local blood centers 2,000,000$, operational costs at regional blood centers 9,000,000$ is considered. We obtained information about the number of blood centers in https://www.ibto.ir/index.jsp?fkeyid=&siteid=1&pageid=128 and summarize them in Tab. (5).

Tab. 4. Distance matrix of small-sized problems.

Distance (KM)	Tehran	Esfahan	Shiraz	Semnan	Qom	Kerman	Ahvaz	Yazd	Zahedan	Tabriz	Khorram Abad	Sanandaj	Ilam	Qazvin	Zanjan	Rasht
Tehran	0	449	932	217	148	1199	813	631	2385	628	486	491	674	174	335	330
Esfahan	449	0	480	615	272	1246	744	322	1176	1003	388	698	639	475	632	644
Shiraz	932	480	0	1056	731	576	752	444	1061	1508	834	1178	980	948	1115	1109
Semnan	217	615	1056	0	344	945	962	577	1281	848	623	827	884	386	555	546
Qom	148	272	731	344	0	854	674	496	1556	768	338	467	597	286	399	467
Kerman	1199	1246	576	945	854	0	1086	359	1098	1600	1073	1299	1324	1083	1221	1307
Ahvaz	813	744	752	962	674	1086	0	776	1582	1078	322	626	451	882	840	980
Yazd	631	322	444	577	496	359	776	0	1456	1239	703	921	1086	1098	863	1041
Zahedan	2385	1176	1061	1281	1556	1098	1582	1456	0	3100	1563	1790	1806	1589	1734	1799
Tabriz	628	1003	1508	848	768	1600	1078	1239	3100	0	799	446	946	472	295	491
Khorram Abad	486	388	834	623	338	1073	322	703	1563	799	0	457	509	521	547	644
Sanandaj	491	698	1178	827	467	1299	626	921	1790	446	457	0	323	404	599	576
Ilam	674	639	980	884	597	1324	451	1086	1806	946	509	323	0	586	580	719
Qazvin	174	475	948	386	286	1083	882	1098	1589	472	521	404	586	0	179	177
Zanjan	335	632	1115	555	399	1221	840	863	1734	295	547	599	580	179	0	198

The small-sized problems were solved with GAMS by running the mathematical model, and also DE and PSO were used in MATLAB. The location of hubs, allocation of the cities to the preferred hubs, and objective function value were specified. Tab. (6) summarizes the result of solving the small-sized problems.

To judge the results we use the deviation factor that calculates the fitness of each method according to the optimum solution found from the exact result, so we use Eq. (25) to find the better algorithm.

$$\%D = \frac{(Algorithm\ solution\ value - optimum\ solution\ value)}{optimum\ solution\ value} \qquad (25)$$

The results abstracted in Tab. (7) show that the deviation factor from the optimum solution is very low. Therefore, we can trust our meta-heuristics DE and PSO to solve the larger problem.

Tab. 5. Time matrix of small-sized problems.

Distance (Hour)	Tehran	Esfahan	Shiraz	Semnan	Qom	Kerman	Ahvaz	Yazd	Zahedan	Tabriz	Khorram Abad	Sanandaj	Ilam	Qazvin	Zanjan	Rasht
Tehran	0	4.78	10.11	2.6	1.8	14.1	9.26	6.63	30.66	6.73	5.58	6.03	7.85	1.98	3.33	4.17
Esfahan	4.78	0	5.61	7	3.21	14.98	9.1	3.8	12.75	11.43	5.05	8.1	8.73	5.41	7.13	7.55
Shiraz	10.11	5.61	0	11.13	8.9	6.83	10.36	5.21	12.28	17.05	10.01	13.36	12.3	10.88	12.76	13.15
Semnan	2.6	7	11.13	0	3.8	10.78	10.91	7.11	14.83	9.13	6.85	9.25	10.2	4.35	6.05	6.95
Qom	1.8	3.21	8.9	3.8	0	8.76	7.88	5.43	18.66	9	4.1	5.61	7.46	3.01	4.76	4.75
Kerman	14.1	14.98	6.83	10.78	8.76	0	13.7	4.25	14.66	16.9	12.18	14.21	15.91	11.5	13.68	12.6

Ahvaz	9.26	9.1	10.36	10.91	7.88	13.7	0	10.38	18.8	13.25	3.77	8.55	5.55	11.26	10.91	12.26
Yazd	6.63	3.8	5.21	7.11	5.43	4.25	10.38	0	18.78	11.63	8.4	11.06	12.56	13.71	9.36	11
Zahedan	30.66	12.75	12.28	14.83	18.66	14.66	18.8	18.78	0	38.11	17.33	19.36	20.86	16.83	18.38	19.03
Tabriz	6.73	11.43	17.05	9.13	9	16.9	13.25	11.63	38.11	0	9.91	5.56	10.85	5.01	3.16	6.5
Khorram Abad	5.58	5.05	10.01	6.85	4.1	12.18	3.77	8.4	17.33	9.91	0	5.61	6.16	5.96	7.25	8.43
Sanandaj	6.03	8.1	13.36	9.25	5.61	14.21	8.55	11.06	19.36	5.56	5.61	0	3.95	5.46	6.98	6.21
Ilam	7.85	8.73	12.3	10.2	7.46	15.91	5.55	12.56	20.86	10.85	6.16	3.95	0	7.7	7.88	9.5
Qazvin	1.98	5.41	10.88	4.35	3.01	11.5	11.26	13.71	16.83	5.01	5.96	5.46	7.7	0	1.78	1.88
Zanjan	3.33	7.13	12.76	6.05	4.76	13.68	10.91	9.36	18.38	3.16	7.25	6.98	7.88	1.78	0	3.43

Tab. 6. Small-sized problems data.

Node	The amount of demand supplied by different cities				Potential Hubs	Number of mobile blood facility	Number of local blood centers	Number of Regional blood centers	Fixed cost of activating hubs
	For PLT		For RBC						
	Kerman	Shiraz	Kerman	Shiraz					
Tehran	10000	20000	10000	20000	*	30	10	1	8e10+10
Esfahan	10000	10000	10000	10000	*	25	9	1	6e10+10
Shiraz	-	-	-	-	*	20	8	1	9e10+10
Semnan	5000	15000	5000	15000	*	17	3	1	2e10+11
Qom	5000	5000	5000	5000	-	17	1	1	-
Kerman	-	-	-	-	*	20	4	1	4e10+11
Ahvaz	5000	7000	5000	7000	-	20	12	1	-
Yazd	10000	10000	10000	10000	-	20	3	1	-
Zahedan	5000	8000	5000	8000	-	17	9	1	-
Tabriz	10000	10000	10000	10000	-	16	5	1	-
Khorram Abad	10000	12000	10000	12000	-	22	3	1	-
Sanandaj	5000	11000	5000	11000	-	21	4	1	-
Ilam	5000	6000	5000	6000	-	20	3	1	-
Qazvin	5000	9000	5000	9000	-	18	8	1	-
Zanjan	5000	6000	5000	6000	-	20	1	1	-
Rasht	5000	11000	5000	11000	-	21	7	1	-

Tab. 7. Solution result of the small-sized problems.

#	n	P_0	Location of hubs			Objective function value			%D	
			GAMS	DE	PSO	GAMS	DE	PSO	DE	PSO
1	6	2	2,3	2,3	2,3	2.95514E+11	2.95514E+11	2.95514E+11	0	0
2	7	2	2,3	2,3	2,3	3.19369E+11	3.19369E+11	3.19369E+11	0	0
3	8	2	2,3	2,3	2,3	3.48678E+11	3.48678E+11	3.48678E+11	0	0
4	9	3	1,2,3	1,2,3	1,2,3	4.50633E+11	4.50843E+11	4.50843E+11	0/05%	0/05%
5	10	3	1,2,3	1,2,3	1,2,3	5.13315E+11	5.13609E+11	5.13609E+11	0/06%	0/06%
6	11	3	1,2,3	1,2,3	1,2,3	5.56722E+11	5.57015E+11	5.57015E+11	0/05%	0/05%
7	12	3	1,2,3	1,2,3	1,2,3	5.95601E+11	5.95895E+11	5.95895E+11	0/05%	0/05%
8	13	4	1,2,3,4	1,2,3,4	1,2,3,4	8.17716E+11	8.17926E+11	8.17926E+11	0/03%	0/03%
9	14	4	1,2,3,4	1,2,3,4	1,2,3,4	8.46222E+11	8.46432E+11	8.46432E+11	0/02%	0/02%
10	15	4	1,2,3,4	1,2,3,4	1,2,3,4	8.73303E+11	8.73513E+11	8.73513E+11	0/02%	0/02%
11	16	4	1,2,3,4	1,2,3,4	1,2,3,4	9.10461E+11	9.10670E+11	9.10670E+11	0/02%	0/02%

5.2.Medium-sized problems

In medium-sized problems, we gathered the information of all the provincial centers of Iran, so we have 31 nodes and specifying 10 cities as hub candidates. However, we have just six nodes allowed to be the hub from 10 candidates. Tab. (8) represents complete data of the problem with 31 nodes as the medium-sized test problems.

Here we solve the problem with two meta-heuristic DE and PSO. Compare the results; we used a deviation factor that calculates the fitness of each method according to the best solution, so we use Eq. (26) to find the better algorithm.

Tab. 8. Medium-sized problems data.

Node	The amount of demand supplied by different cities				Potential Hubs	Number of mobile blood facility	Number of local blood centers	Number of Regional blood centers	Fixed cost of activating hubs
	For PLT		For RBC						
	Kerman	Shiraz	Kerman	Shiraz					
Tehran	10000	20000	10000	20000	*	30	10	1	8e10
Esfahan	10000	10000	10000	10000	*	25	9	1	6e10
Shiraz	-	-	-	-	*	20	8	1	9e10
Semnan	5000	15000	5000	15000	*	17	3	1	2e11
Qom	5000	5000	5000	5000	-	17	1	1	-
Kerman	-	-	-	-	*	20	4	1	4e11
Ahvaz	5000	7000	5000	7000	-	20	12	1	-
Yazd	10000	10000	10000	10000	*	20	3	1	5e11
Zahedan	5000	8000	5000	8000	-	17	9	1	-
Tabriz	10000	10000	10000	10000	-	16	5	1	-
Khorram Abad	10000	12000	10000	12000	-	22	3	1	-
Sanandaj	5000	11000	5000	11000	-	21	4	1	-
Ilam	5000	6000	5000	6000	-	20	3	1	-
Qazvin	5000	9000	5000	9000	-	18	8	1	-
Zanjan	5000	6000	5000	6000	*	20	1	1	1e11
Rasht	5000	11000	5000	11000	-	21	7	1	-
Ardebil	5000	6000	5000	6000	-	11	4	1	-
Arak	10000	8000	10000	8000	*	17	12	1	1.5e11
Bushehr	20000	12000	20000	12000	-	16	3	1	-
Yasooj	5000	4000	5000	4000	-	14	9	1	-
Mashhad	5000	14000	5000	14000	-	17	5	1	-
Bandar Abbas	10000	7000	10000	7000	-	25	3	1	-
Bojnord	5000	4000	5000	4000	-	27	4	1	-
Gorgan	5000	12000	5000	12000	-	13	8	1	-
Birjand	10000	15000	10000	15000	-	11	3	1	-

Karaj	15000	18000	15000	18000	-	18	1	1	-
Sari	10000	20000	10000	20000	-	12	4	1	-
Oromia	5000	12000	5000	12000	-	20	12	1	-
Kermanshah	5000	9000	5000	9000	-	17	3	1	-
Hamedan	5000	10000	5000	10000	*	21	10	1	2e11
Shahrekord	10000	5000	10000	5000	*	14	8	1	8e10

Tab. 9. Performance of two algorithms in solving medium-sized problems.

Algorithm	n	P_0	Location of Hubs	Allocations	objective function	%D
DE	31	6	1,2,3,15,18,31	4,21,23,24,26,27 to 1 5,11,13,14 to 2 6,7,8,9,19,22,25 to 3 10,16,17,28 to 15 30 to 18 12,20,29 to 31	1.65942E+12	%0.7
PSO	31	6	1,2,3,15,18,31	4,21,23,24,26,27 to 1 5,11,13,14 to 2 6,7,8,9,19,20,22,25 to 3 10,16,17,28 to 15 12,29,30 to 31	1.64792E+12	0

We also have a summary result of the solution to the medium-sized problems using two algorithms in Tab. (9). Due to this result, especially considering the deviation factor, PSO shows better performance but this superiority is not significant and so, the two algorithms' performance is similar. We can also see the results of PSO on the map of Iran in Fig. (5).

$$\%D = \frac{(Algorithm\ solution\ value - best\ solution\ value)}{best\ solution\ value} \tag{26}$$

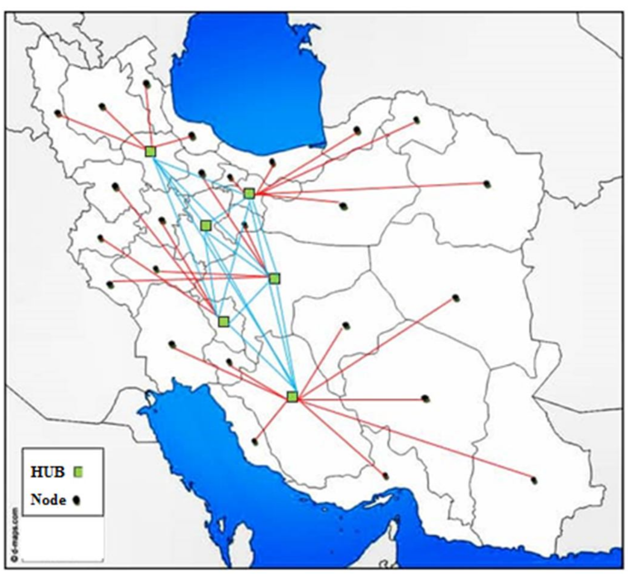


Fig. 5. Result of solving the medium-sized problems.

5.3.Large-sized problems

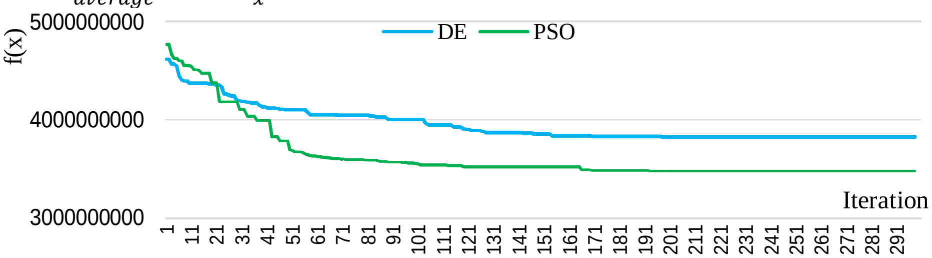
This section shows the result of using two proposed algorithms in solving large-sized problems to find out which one does better. In large-sized problems, we produced the coordinates of four different problems with 100, 200, 300, and 400 nodes randomly. Then the Euclidean Distances (ED) between these nodes were calculated. We do not suppose the time distance between cities and not assign fixed costs to cities and hubs because these quantities strongly depend on inherent properties of cities and is better do not to set randomly. Furthermore, the demand of all cities is a random value between 10 and 50. Finally, we solved these problems with two algorithms DE and PSO and analyzed their performance. At first, the need parameters of this problem and the value of the two algorithms parameters are presented in Tab. (10).

Tab. 10. The large-sized problems parameters.

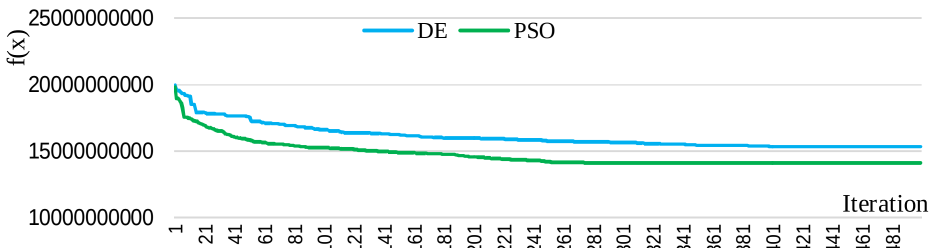
# of nodes	# of hubs	Iteration		# of samples
		DE	PSO	
100	5	300	300	10
200	10	500	500	10
300	15	500	500	10
400	20	500	500	10

The first output of solving these problems by the proposed algorithms is about algorithm convergence in iterations. Fig. (6) shows the convergence of the algorithm in solving four different problems including 100 nodes, 200 nodes, 300 nodes, and 400 nodes via part a to part d respectively. This result shows a faster convergence in solving the problems using PSO in comparison to DE. This superiority of DE is obvious in solving all of these problems.
The result of solving these problems has been presented again as a schematic view in Fig. (7). As this result shows, the PSO algorithm has a more appropriate location for hubs and it is better in allocating the selected hubs to nodes. Based on the solution of the PSO algorithm, the relations between nodes and the hubs are more regular and systematic than the DE algorithm.
To investigate the stability of the two proposed algorithms, we used the coefficient of variation (cv) index. For this, we solved each problem 30 times and calculated this factor as Eq. (27) for each size of the problem.

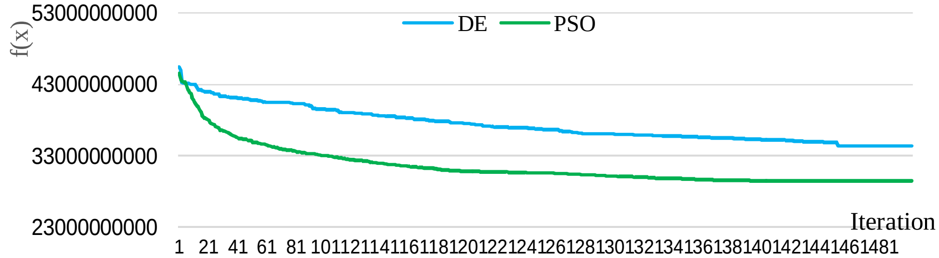
$$cv = \frac{(Standard\ devation)}{average} = \frac{\sigma}{\bar{x}} \tag{27}$$



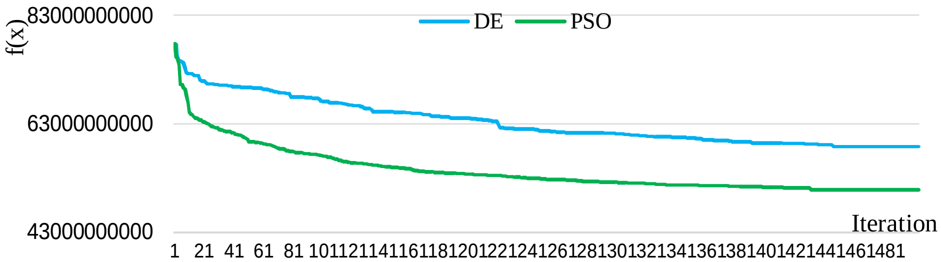
a. **100 nodes**



b. **200 nodes**

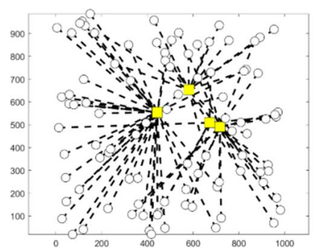


c. **300 nodes**

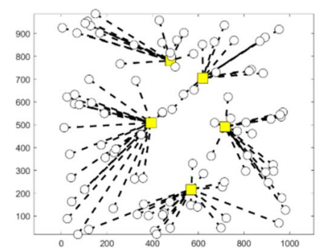


d. **400 nodes**

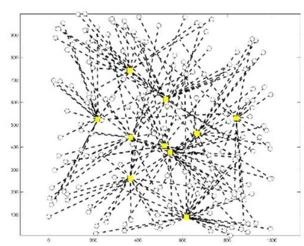
Fig. 6. The convergence of the proposed algorithms.



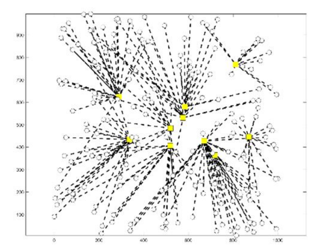
DE – 100 nodes



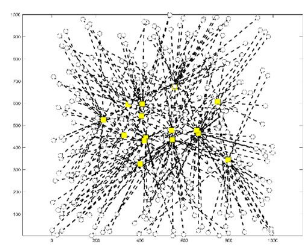
PSO – 100 nodes



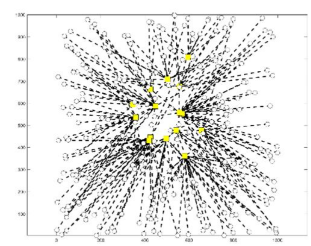
DE – 200 nodes



PSO – 200 nodes



DE – 300 nodes



PSO – 300 nodes

DE – 400 nodes PSO – 400 nodes

Fig. 7. Schematic view of nodes and hubs in large-sized problems.

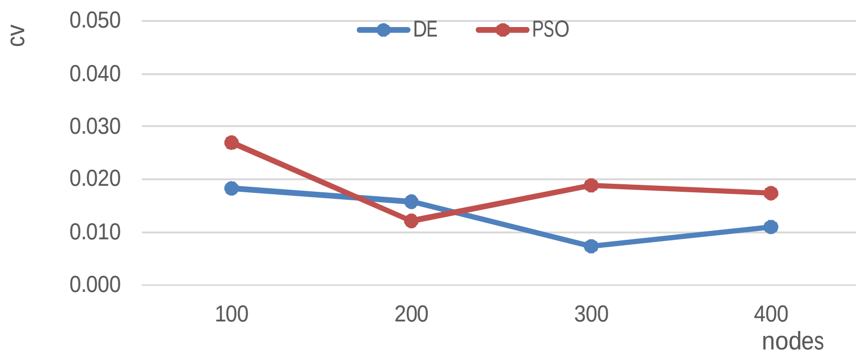


Fig. 8. Changes in cv.

The values of the cv are presented in Fig. (8). According to this factor, both two proposed algorithms have kept their acceptable performance with increasing dimensions of the problem. As we can see in this figure, the amounts of the coefficient of variation are very low for both of the two algorithms without any significant increase for larger problems.

In Tab. (11), we compare two solutions approach based on the objective function values and run times in small, medium, and large scale problems.

Tab. 11. Comparing the result of the two proposed methods.

Size of Problem	# of Nodes	# of Hubs	Objective Function Value (Average) GAMS	DE	PSO	Run Time (Average) GAMS	DE	PSO
	6	2	2.95514E+11	2.95514E+11	2.95514E+11	11.2	4.82	4.82
	7	2	3.19369E+11	3.19369E+11	3.19369E+11	39.7	4.96	4.96
	8	2	3.48678E+11	3.48678E+11	3.48678E+11	61.4	5.43	5.43
	9	3	4.50843E+11	4.50843E+11	4.50843E+11	756.8	5.28	5.28
	10	3	5.13609E+11	5.13639E+11	5.13615E+11	789.8	5.55	5.55
Small	11	3	5.57015E+11	5.57126E+11	5.57092E+11	1002.7	5.60	5.60
	12	3	5.95895E+11	5.96059E+11	5.95917E+11	1367.9	5.74	5.74
	13	4	8.17926E+11	8.18058E+11	8.17942E+11	1890.3	6.15	6.15
	14	4	8.46432E+11	8.46897E+11	8.46478E+11	1958.2	6.19	6.19
	15	4	8.73513E+11	8.74193E+11	8.73793E+11	2060.7	6.30	6.30
	16	4	9.10670E+11	9.11809E+11	9.10948E+11	2309.4	6.74	6.74
Medium	27	6	---	1.59781E+12	1.57908E+12	---	16.80	42.12
	28	6	---	1.60440E+12	1.59218E+12	---	20.81	56.35

	29	6	---	1.62018E+12	1.61890E+12	---	23.09	68.69
	30	6	---	1.63370E+12	1.62439E+12	---	25.54	79.12
	31	6	---	1.65942E+12	1.64792E+12	---	27.23	87.73
	100	5	---	3.79005E+09	3.46891E+09	---	23.74	31.11
	200	10	---	3.82807E+09	3.61047E+09	---	26.85	42.23
Large	300	15	---	1.54994E+10	1.39522E+10	---	174.9	186.3
	400	20	---	3.41000E+10	3.08668E+10	---	288.6	481.7
	500	25	---	5.84899E+10	5.28006E+10	---	1104.9	1702.3

5.4.Sensitivity analysis

We do a sensitivity analysis on two main parameters of the problem; the number of hubs and the value of the alpha coefficient. We do these analyses on a 100 nodes problem with the PSO method. The results have been demonstrated in Fig. (9) and Fig. (10).

As was expected, we can reduce the total cost of the supply chain by adding the number of Hubs. It can be considered for relevant managers, to consider pre-defined Hubs for BSC, especially in crisis-prone regions. Moreover, by reducing the cost rate via the Hub networks, which can be supported by the government and the relevant organization, it can be possible to reduce the total cost of the BSC network.

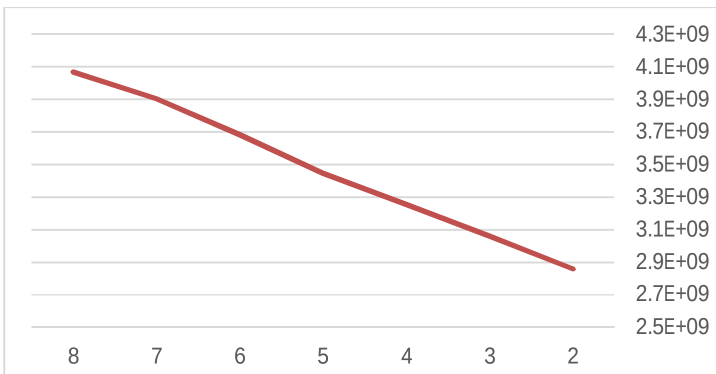


Fig. 9. Objective Function Value vs # of Hubs.

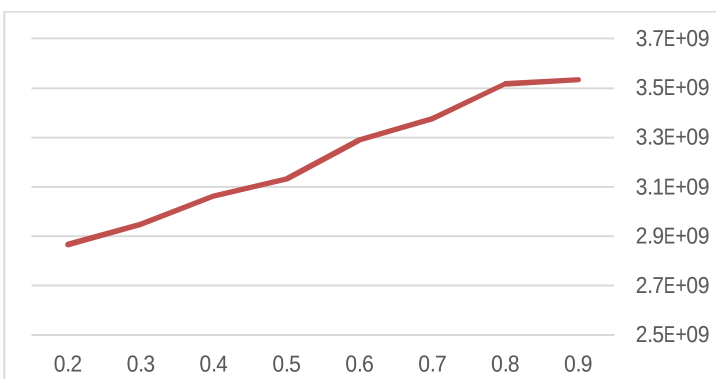


Fig. 10. Objective Function Value vs # Alpha Coefficient.

5.5.Managerial insights

In the event of a disaster, providing an efficient plan for blood distribution is of great significance. However, having good plans alone is not enough, and it is essential to provide insights for managers and planners. Based on the sensitivity analysis and the findings of the paper, some managerial insights are provided to support decision-makers. First, the performance of the model shows that the proposed model can generate a feasible and acceptable solution in designing a network, even if it is used by different managers with different levels of conservatism. The findings show that we can reduce the total cost of the supply chain by tuning the number of Hub nodes. It can be considered for relevant managers, to consider pre-defined Hubs for BSC, especially in crisis-prone regions. Moreover, by reducing the cost rate via the Hub networks, which can be supported by the government and the relevant organization, it can be possible to reduce the total cost of the BSC network. Also In this article, we tried to show the role of using the correct algorithm to solve the problem of the large blood supply chain in critical situations. In the event of a crisis at the level of a country (where the number of transmitting, transporting, and consuming nodes is high) to solve the complex problem of managing the BSC can't use an accurate algorithm, because a lot of time needs to solve this problem. Also, among the high-reliability meta-heuristic algorithms, we can rely on the PSO algorithm and solve the problem at the right time and determine the location of the hubs. This paper suggests that decision-makers and executives use approximate methods to quickly locate hubs in a large-scale BSC problem in critical situations, without making significant errors. With this feature, managers can bring more cities into the relief process as a sender to help crisis areas.

6. Conclusion and Future Directions

Review the last studies in the supply chain sector showed that there are few attempts to solve the problem of blood supply chain network design to reduce total cost using hub network. So, the specifications and advantages of the hub network were considered in this paper as a new approach to design and efficiency BSC during and after disasters. Most of the last studies in the BSC section conducted this problem with a limited scope of a small area, while, in many conditions especially during and after disasters we need to transport blood and its products between cities and even between countries in strict time limits. For this, we first the problem was illustrated carefully via identification and presentation of its parameters and decision variables considering intercity transportation and both of the fixed and mobile blood facilities.

After problem definition, a mixed-linear integer programming (MIP) model was developed to solve it in small-sized dimensions. Because this problem is well known as strongly NP-hard, two important population-based algorithms i.e. DE and PSO were applied to solve the problem with practical sizes. To the valid performance of the mathematical model and evaluate the optimality of two proposed algorithms, this problem was solved using the exact method with small sizes (16 nodes). Both two algorithms presented good performance in solving the problem with a maximum of 0.06% deviation from the exact solution. We also evaluated the performance of the algorithms with data of a real case with medium-sized dimensions. To do this investigation, related data of all the provincial centers of Iran was gathered contains 31 nodes and specifying 10 cities as hub candidates in which just six nodes are needed as hubs. The result of the solution of this problem using two algorithms emphasized the superiority of PSO compared to the other algorithm. To ensure the stability of the proposed algorithms in solving the problem with various sizes, four different problems with large sizes consist of 100, 200, 300, and 400 nodes were generated. Each problem was solved 30 times using these two algorithms and the coefficient of variation (cv) was considered to investigate the performance stability of these algorithms. Solving the result of these four large problems indicated again that the applied PSO could present a better solution and introduce a more appropriate network than the DE.

To future studies, investigation of this problem with a hierarchical hub network can be a new interest field for researchers. Studying this problem under uncertainty especially in the main parameters such as transportation times and demand is another subject that there is no publish about it. The proposed model is applicable considering new variables and operational constraints to more compatibility with reality. Another noteworthy idea for further research is considered a forward-reverse supply chain where the problem of managing blood wastage is also studied.

References

[1] S. Nahmias, "Perishable inventory theory: A review," *Oper. Res.*, Vol. 30, No. 4, (1982), pp. 680-708.

[2] M. Habibi-Kouchaksaraei, M. M. Paydar, and E. Asadi-Gangraj, "Designing a bi-objective multi-echelon robust blood supply chain in a disaster," *Appl. Math.*

Model., Vol. 55, (2018), pp. 583-599. doi: 10.1016/j.apm.2017.11.004.

[3] R. C. Elston and J. C. Pickrel, "A Statistical Approach to Ordering and Usage Policies for a Hospital Blood Bank," *Transfusion*, Vol. 3, No. 1, (1963), pp. 41-47. doi: 10.1111/j.1537-2995.1963.tb04602.x.

[4] R. C. Elston and J. C. Pickrel, "Guides to Inventory Levels for a Hospital Blood Bank Determined by Electronic Computer Simulation," *Transfusion*, Vol. 5, No. 5, (1965), pp. 465-470. doi: 10.1111/j.1537-2995.1965.tb02927.x.

[5] M. G. and V. S. W. Pierskalla, R. Sassetti, M. Cohen, B. Deuermeyer, R. Marritt, J. Consolo, M. Garvey, "*Regionalization of Blood Banking Services. In Executive Summary, Pennsylvania: PA: University of Pennsylvania.*" (1980).

[6] B. Page, "A review of computer systems in blood banks and discussion of the applicability of mathematical decision methods," *Methods Inf. Med.*, Vol. 19, No. 2, (1980), pp. 75-82. doi: 10.1055/s-0038-1635265.

[7] G. P. Prastacos, "Blood Inventory Management: an Overview of Theory and Practice.," *Manage. Sci.*, Vol. 30, No. 7, (1984), pp. 777-800. doi: 10.1287/mnsc.30.7.777.

[8] W. P. Pierskalla, "Supply Chain Management of Blood Banks," *Oper. Res. Heal. Care*, (2006), pp. 103-145. doi: 10.1007/1-4020-8066-2_5.

[9] H. K. Rajagopalan, C. Saydam, and J. Xiao, "A multiperiod set covering location model for dynamic redeployment of ambulances," *Comput. Oper. Res.*, Vol. 35, No. 3, (2008), pp. 814-826. doi: 10.1016/j.cor.2006.04.003.

[10] J. C. Papageorgiou, "Some operations research applications to problems of health care systems (a survey)," *Int. J. Biomed. Comput.*, Vol. 9, No. 2, (1978), pp. 101-114. doi: 10.1016/0020-7101(78)90002-8.

[11] A. Rais and A. Vianaa, "Operations research in healthcare: A survey," *Int. Trans. Oper. Res.*, Vol. 18, No. 1, (2011), pp. 1-31. doi: 10.1111/j.1475-3995.2010.00767.x.

[12] S. S. Syam and M. J. Côté, "A location-allocation model for service providers with application to not-for-profit health care organizations," *Omega*, Vol. 38, No. 3-4, (2010), pp. 157-166. doi: 10.1016/j.omega.2009.08.001.

[13] H. G. TohR. S., "The impact of hub and spoke network centralization and route monopoly on domestic airline profitability," *Transp. Journal, pp. 16-27*, Vol. 11, No. 103, (1985), p. 1984.

[14] A. Zabihi and M. Gharakhani, "A literature survey of HUB location problems and methods with emphasis on the marine transportations," *Uncertain Supply Chain Manag.*, Vol. 6, No. 1, (2018), pp. 91-116. doi: 10.5267/j.uscm.2017.5.003.

[15] J. Belien and H. Forcé, "Supply Chain Management of Blood Products: A Literature Review," *SSRN Electron. J.*, (2012), doi: 10.2139/ssrn.1974803.

[16] A. Nagurney, A. H. Masoumi, and M. Yu, "Supply chain network operations management of a blood banking system with cost and risk minimization," *Comput. Manag. Sci.*, Vol. 9, No. 2, (2012), pp. 205-231. doi: 10.1007/s10287-011-0133-z.

[17] Y. Sha and J. Huang, "The Multi-period Location-allocation Problem of Engineering Emergency Blood Supply Systems," *Syst. Eng. Procedia*, Vol. 5, (2012), pp. 21-28. doi: 10.1016/j.sepro.2012.04.004.

[18] Q. Duan and T. W. Liao, "Optimization of blood supply chain with shortened shelf lives and ABO compatibility," *Int. J. Prod. Econ.*, Vol. 153, (2014), pp. 113-

129. doi: 10.1016/j.ijpe.2014.02.012.

[19] C. L. Hsieh, "An evolutionary-based optimization for a multi-objective blood banking supply chain model," *Lect. Notes Artif. Intell. (Subseries Lect. Notes Comput. Sci.*, Vol. 8481, No. 26, (2014), pp. 511-520. doi: 10.1007/978-3-319-07455-9_53.

[20] M. Arvan, R. Tavakkoli-Moghaddam, and M. Abdollahi, "Designing a bi-objective, multi-product supply chain network for blood supply," *Uncertain Supply Chain Manag.*, Vol. 3, No. 1, (2015), pp. 57-68. doi: 10.5267/j.uscm.2014.8.004.

[21] B. Fahimnia, A. Jabbarzadeh, A. Ghavamifar, and M. Bell, "Supply chain design for efficient and effective blood supply in disasters," *Int. J. Prod. Econ.*, Vol. 183, (2017), pp. 700-709. doi: 10.1016/j.ijpe.2015.11.007.

[22] J. Beliën, L. De Boeck, J. Colpaert, S. Devesse, and F. Van Den Bossche, "Optimizing the facility location design of organ transplant centers," *Decis. Support Syst.*, Vol. 54, No. 4, (2013), pp. 1568-1579. doi: 10.1016/j.dss.2012.05.059.

[23] S. Yates, N., Stanger, S., Wilding, R. and Cotton, "Approaches to assessing and minimizing blood wastage in the hospital and blood supply chain," *ISBT Sci. Ser.*, Vol. 12, No. (2014), p. 2014. doi: 10.1111/voxs.12330.Please.

[24] S. Cheraghi, S.-M. Hosseini-Motlagh, & Mohammadreza, and G. Samani, "A Robust Optimization Model for Blood Supply Chain Network Design," *Int. J. Ind. Eng. Prod. Res.*, Vol. 27, No. 4, (2016), pp. 425-444. doi: 10.22068/ijiepr.27.4.425.

[25] L. Sibuea, H. Saleh, M. Danil, and H. Gamal, "Stochastic Integer Programming Models in the Management of the Blood Supply Chain : A Case Study," *World J. Oper. Res.*, Vol. 1, No. 2, (2017), pp. 41-48. doi: 10.11648/j.wjor.20170102.11.

[26] B. Zahiri and M. S. Pishvaee, "Blood supply chain network design considering blood group compatibility under uncertainty," *Int. J. Prod. Res.*, Vol. 55, No. 7, (2017), pp. 2013-2033. doi: 10.1080/00207543.2016.1262563.

[27] R. Ramezanian and Z. Behboodi, "Blood supply chain network design under uncertainties in supply and demand considering social aspects," *Transp. Res. Part E Logist. Transp. Rev.*, Vol. 104, (2017), pp. 69-82. doi: 10.1016/j.tre.2017.06.004.

[28] H. Ensafian, S. Yaghoubi, and M. Modarres Yazdi, "Raising quality and safety of platelet transfusion services in a patient-based integrated supply chain under uncertainty," *Comput. Chem. Eng.*, Vol. 106, (2017), pp. 355-372. doi: 10.1016/j.compchemeng.2017.06.015.

[29] A. Mansur, I. Vanany, and N. I. Arvitrida, "Modified allocation capacitated planning model in blood supply chain management," *IOP Conf. Ser. Mater. Sci. Eng.*, Vol. 337, No. 1, (2018). doi: 10.1088/1757-899X/337/1/012028.

[30] A. F. Osorio, S. C. Brailsford, H. K. Smith, and J. Blake, "Designing the blood supply chain: how much, how and where?," *Vox Sang.*, Vol. 113, No. 8, (2018), pp. 760-769. doi: 10.1111/vox.12706.

[31] O. Ö. Özener, A. Ekici, and E. Çoban, "Improving blood products supply through donation tailoring," *Comput. Oper. Res.*, Vol. 102, (2019), pp. 10-21. doi: 10.1016/j.cor.2018.09.003.

[32] B. Hamdan and A. Diabat, "A two-stage multi-echelon stochastic blood supply chain problem," *Comput. Oper. Res.*, Vol. 101, (2019), pp. 130-143. doi: 10.1016/j.cor.2018.09.001.

[33] G. Bruno, A. Diglio, C. Piccolo, and L. Cannavacciuolo, "Territorial reorganization of regional blood management systems: Evidences from an

Italian case study," *Omega (United Kingdom)*, Vol. 89, (2019), pp. 54-70. doi: 10.1016/j.omega.2018.09.006.

[34] M. R. G. Samani and S. M. Hosseini-Motlagh, "An enhanced procedure for managing blood supply chain under disruptions and uncertainties," *Ann. Oper. Res.*, Vol. 283, No. 1-2, (2019), pp. 1413-1462, doi: 10.1007/s10479-018-2873-4.

[35] D. Rahmani, "Designing a robust and dynamic network for the emergency blood supply chain with the risk of disruptions," *Ann. Oper. Res.*, Vol. 283, No. 1-2, (2019), pp. 613-641. doi: 10.1007/s10479-018-2960-6.

[36] M. R. G. Samani, S. M. Hosseini-Motlagh, and S. F. Ghannadpour, "A multilateral perspective towards blood network design in an uncertain environment: Methodology and implementation," *Comput. Ind. Eng.*, Vol. 130, No. August 2018, (2019), pp. 450-471. doi: 10.1016/j.cie.2019.02.049.

[37] M. R. G. Samani, S. M. Hosseini-Motlagh, M. I. Sheshkol, and S. N. Shetab-Boushehri, "A bi-objective integrated model for the uncertain blood network design with raising products quality," *Eur. J. Ind. Eng.*, Vol. 13, No. 5, (2019), pp. 553-588. doi: 10.1504/EJIE.2019.102182.

[38] A. Haeri, S. M. Hosseini-Motlagh, M. R. Ghatreh Samani, and M. Rezaei, "A mixed resilient-efficient approach toward blood supply chain network design," *Int. Trans. Oper. Res.*, Vol. 27, No. 4, (2020), pp. 1962-2001. doi: 10.1111/itor.12714.

[39] S. Khalilpourazari, S. Soltanzadeh, G. W. Weber, and S. K. Roy, "Designing an efficient blood supply chain network in crisis: neural learning, optimization and case study," *Ann. Oper. Res.*, Vol. 289, No. 1, (2020), pp. 123-152. doi: 10.1007/s10479-019-03437-2.

[40] B. Hamdan and A. Diabat, "Robust design of blood supply chains under risk of disruptions using Lagrangian relaxation," *Transp. Res. Part E Logist. Transp. Rev.*, Vol. 134, No. August 2019, (2020), p. 101764. doi: 10.1016/j.tre.2019.08.005.

[41] S. M. Hosseini-Motlagh, M. R. G. Samani, and S. Homaei, "Toward a coordination of inventory and distribution schedules for blood in disasters," *Socioecon. Plann. Sci.*, Vol. 72, No. June, (2020), p. 100897. doi: 10.1016/j.seps.2020.100897.

[42] M. E. Keskin and V. Yig, "Re-design of a blood supply chain organization with mobile units," Vol. 3, (2021), doi: 10.1007/s00500-021-05618-3.

[43] N. Haghjoo, R. Tavakkoli-Moghaddam, H. Shahmoradi-Moghadam, and Y. Rahimi, "Reliable blood supply chain network design with facility disruption: A real-world application," *Eng. Appl. Artif. Intell.*, Vol. 90, No. January, (2020), p. 103493. doi: 10.1016/j.engappai.2020.103493.

[44] M. R. G. Samani, S. M. Hosseini-Motlagh, and S. Homaei, "A reactive phase against disruptions for designing a proactive platelet supply network," *Transp. Res. Part E Logist. Transp. Rev.*, Vol. 140, No. December 2019, (2020), p. 102008. doi: 10.1016/j.tre.2020.102008.

[45] S. Gunpinar and G. Centeno, "Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals," *Comput. Oper. Res.*, Vol. 54, (2015), pp. 129-141. doi: 10.1016/j.cor.2014.08.017.

[46] Mahdi Shahin 1; Mohammad Saeed Jabalameli PhD2; Armin Jabbarzadeh PhD3, I. 1Master of Science in Industrial Engineering, Science and Technology University, Tehran, I. 2Prof., Dep. of Industrial Engineering, University of Science and Technology, Tehran, and I. 3Assistant Prof. of Industrial Engineering, University of Science and Technology, Tehran, " Multi-modal and multi-product hierarchical hub location

under uncertainty ," Vol. 8, No. 4, (2017), pp. 625-658. doi: 10.22059/imj.2017.59971.

[47] R. Kennedy, J. and Eberhart, "Particle Swarm Optimization. Proceedings of the IEEE International Conference on Neural Networks."

[48] G. Sen and M. Krishnamoorthy, "Discrete particle swarm optimization algorithms for two variants of the static data segment location problem," *Appl. Intell.*, Vol. 48, No. 3, (2018), pp. 771-790. doi: 10.1007/s10489-017-0995-z.

[49] R.Eberhart and Y.shi, "Particle Swarm Optimization: Developments, Applications and Resources." IEEE, (2001).

[50] Y. Huang, L. Wang, and Q. Wu, "A hybrid PSO-DE algorithm for smart home energy management," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, Vol. 8795, (2014), pp. 292-300. doi: 10.1007/978-3-319-11897-0_35.

[51] Ç. Özgün-Kibiroğlu, M. N. Serarslan, and Y. İ. Topcu, "Particle Swarm Optimization for Uncapacitated Multiple Allocation Hub Location Problem under Congestion," *Expert Syst. Appl.*, Vol. 119, (2019), pp. 1-19. doi: 10.1016/j.eswa.2018.10.019.

[52] S. H. Och, L. M. Moura, V. C. Mariani, L. dos S. Coelho, J. A. Velásquez, and E. Domingues, "Volumetric efficiency optimization of a single-cylinder D.I. diesel engine using differential evolution algorithm," *Appl. Therm. Eng.*, Vol. 108, (2016), pp. 660-669. doi: 10.1016/j.applthermaleng.2016.07.042.

[53] R. Mallipeddi, P. N. Suganthan, Q. K. Pan, and M. F. Tasgetiren, "Differential evolution algorithm with ensemble of parameters and mutation strategies," *Appl. Soft Comput. J.*, Vol. 11, No. 2, (2011), pp. 1679-1696. doi: 10.1016/j.asoc.2010.04.024.

[54] D. Zaharie, "Influence of crossover on the behavior of Differential Evolution Algorithms," *Appl. Soft Comput. J.*, Vol. 9, No. 3, (2009), pp. 1126-1138. doi: 10.1016/j.asoc.2009.02.012.

[55] A. K. Qin, V. L. Huang, and P. N. Suganthan, "Differential evolution algorithm with strategy adaptation for global numerical optimization," *IEEE Trans. Evol. Comput.*, Vol. 13, No. 2, (2009), pp. 398-417. doi: 10.1109/TEVC.2008.927706.

[56] A. Jabbarzadeh, B. Fahimnia, and S. Seuring, "Dynamic supply chain network design for the supply of blood in disasters: A robust model with real world application," *Transp. Res. Part E Logist. Transp. Rev.*, Vol. 70, No. 1, (2014), pp. 225-244. doi: 10.1016/j.tre.2014.06.003.

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