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Research Paper

Robust Box Approach for Blood Supply Chain Network Design under Uncertainty: Hybrid Moth-Flame Optimization and Genetic Algorithm

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In this paper, a blood supply chain network (BSCN) is designed to reduce the total cost of the supply chain network under demand and transportation costs. The network levels considered for modeling include blood donation clusters, permanent and temporary blood transfusion centers, major laboratory centers and blood supply points. Other goals included determining the optimal number and location of potential facilities, optimal allocation of the flow of goods between the selected facilities and determining the most suitable transport route to distribute the goods to customer areas in uncertainty conditions. This study addresses the issue of blood prishability from blood sampling to distribution to customer demand areas. Given that the model was NP-hard, the MFGO algorithm were used to solve the model with a priority-based solution. The results of the design of the experiments showed the high efficiency of the MFGO algorithm in comparison with the PSO algorithm in finding efficient solutions. Also, the mean of the objective function in robust approach is more than the one in the deterministic approach, while the standard deviation of the first objective function in the robust approach is less than the one in the deterministic approach at all levels of the uncertainty factor.

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1. Introduction

Supply Chain is a set of organizations which are linked together by material, information, and financial flows. Such organizations include enterprises that produce raw materials and components of products and provide services such as distribution, storage, wholesale, and retail. In this set, final customers are considered the last level of the chain and one of the members of these organizations (Ghahremani Nahr et al., 2020). In general, supply chain includes facilities such as raw material suppliers, manufacturing centers, warehouses, wholesalers and retailers, distribution centers, and customers in which material and information flows exist within and between them (Nozari et al., 2019). In other words, supply chain consists of various components involved in a network that begins with the production of the raw material, and ends with its transport to warehouses, distribution centers, and customer satisfaction (Ghanbarzadeh et al., 2021).

In the meantime, one of the most important types of supply chain network is blood supply chain. Blood supply chain has been the focus of attention in recent years due to the importance of this vital and rare product in health systems. Healthy and adequate blood supply as well as its management are of particular concern to the human race. Hence, the collection and management of blood distribution which is raised in the form of blood supply chain management, requires comprehensive and accurate management and planning because blood supply chain has complexities that differentiate it from the supply chain of ordinary goods. Blood is one of the most critical perishable substances in nature, which is closely related to the lives of humans (Sadeghi et al., 2021). One of the most significant reasons for the importance of blood and blood products is its human origin and that it cannot be artificially produced. In addition, blood products such as red blood cells, platelets and plasma have a different life span and require special storage conditions. On the other hand, blood supply chain, which involves processes for collecting, producing, storing and distributing blood and blood products from donors to blood recipients, is associated with uncertainty. This uncertainty is obvious in both supply and demand because blood supply from donors is relatively unplanned and uncertain, and demand for this product does not enjoy a constant rate. Therefore, matching supply and demand in blood supply chain requires designing a proper supply chain network to supply blood and blood derivatives (Jabbarzadeh et al., 2014). Therefore, since blood is one of the most important needs of each patient in various critical situations and that one of the concerns of health centers is the phenomenon of deficiency or bloody perishability, blood supply chain management attempts to bridge the gap between blood supplyers and consumers, resulting in a lack of exposure to lacking and minimizing the risk of blood products perishability and reducing costs. Therefore, in this paper, a BSCN is designed with the objective of reducing the total cost of the network that simultaneously optimizes the number and location of potential facilities, optimizes the flow of blood groups between selected centers and optimizes the appropriate routing of transport and distribution of blood groups to demand centers.

2. Literature Review

The design of a BSCN requires a number of strategic and operational decisions, including decisions on the location of blood collection centers and how blood donors are allocated to blood collection centers, the number and location of donation points, and so on. Because the demand for blood after a quake is different in different periods (in the first 24 hours of the earthquake, demand is much higher), the design of a blood supply chain is part of a dynamic network design (Jabbarzadeh et al., 2014). Research on the management of the supply chain of perishable products, and in particular on blood products, began specifically by Van Zyl (Van Zyl, 1963). From the first articles published in the field of dynamic supply chain design, one can refer to the Ballo article in 1968, in which a mathematical model was presented for the dynamic location problem with different periods (Ballo, 1968). Given the importance of perishability, authors categorized perishable goods into fixed and variable types according to their shelf life in their articles. Sampson et al., examined the problem of relocation of blood donation bases in Norfolk, Virginia, and provided conclusions on the timing of information collection and blood distribution products (Sampson et al., 1996). Pereira

developed a comprehensive mathematical model for designing a BSCN. He aimed at answering the questions such as: 1. Where to establish blood centers? 2. Allocation of donors to blood centers and 3. Place of construction of blood collection centers (Pereira, 2005). Hijema et al., in order to minimize shortage and waste, presented a Markov dynamic process (MDP) and a simulation approach in which two types of demand were proposed in accordance with different types of patients. In his proposed model, he considered the young platelets used to meet the needs of patients with oncological and hematological disorders, while for general surgery, the use of platelets of any age (up to the maximum shelf life) is permissible (Hijema et al., 2007). Ghandforoush and Sen, in order to assist regional blood transfusion centers to generate and collect platelets on a daily basis, developed a non-convex integer program to create a DSS system. The goal was to minimize the total daily cost, which included collection, production and costs of shortages. Although collection and production constraints were taken into consideration, the inventory variable was not added to the model. He concluded that the rate of supply and production should be proportionate in demand (Ghandforoush and Sen, 2010). Fahimnia and colleagues presented a two-objective randomized mathematical model for designing an efficient and effective blood supply network. In addition to minimizing the total cost of the chain, including the costs of moving temporary blood donation sites, operating costs in blood centers, the cost of transporting and keeping inventory, and the costs of temporary blood donations, they also minimized overall transport time. They considered a supply chain including blood donors, blood collection centers, local and regional blood donation centers and demand points, including hospitals and medical centers. (Fahimnia et al., 2015). Gunpinar and centeno addressed the single-level inventory (distribution) for perishable items (blood) in hospitals. Their proposed optimization model for blood supply chain included donors, blood banks, mobile centers and patients, as well as internal factors such as capacity, demand and delivery time to minimize total cost (Gunpinar and centeno, 2015). Ghasemi et al., strived to consider the problems mentioned by installing appropriate and suitable new bases for blood and building backup bases and using available equipment, including available mobile bases and buses for receiving blood in the east of Mazandaran province so as to minimize these problems to a desirable extent. Therefore, a three-objective mathematic planning model was considered based on minimizing deficiencies, costs, and maximizing the timely receipt of blood using GAMS software and Pareto solutions (Ghasemi et al., 2017). Osorio et al., presented a simulation-optimization model for production planning in the blood supply chain. They showed that the mathematical model provided by them can largely prevent the occurrence of shortages (Osorio et al., 2017). Zahiri et al., presented a multilevel, bi-objective supply chain network, taking into consideration reducing network design costs and reducing the maximum unmet demand. They considered uncertain parameters such as demand and transport costs and used a robust planning method to control the parameters (Zahiri et al., 2017). Khalilpour and Arshadi Khamseh, presented a multi-objective mathematical model for designing an efficient BSCN in earthquake through a comprehensive study of the real world. A three-step supply chain including blood donors, blood collection sites (permanent and temporary) and blood centers that were essential for the design of the supply chain network were considered. (Khalilpour and Arshadi Khamseh, 2017). Habibi et al. presented a multi-objective linear programming model for the design of a post-crisis blood supply chain. A three-level model consisting of donors, blood collection centers (permanent and temporary) and blood centers were considered. Their aim was to determine the number and location of facilities, the allocation of blood to various facilities, and minimization of the costs and shortcomings that were in conflict with each other (Habibi et al., 2018).

Arani et al. considered a new mixed-integer programming model to design a BSCN with a sustainable ancillary supply. They developed a scenario-based stochastic optimization model and a modified multiechelon programming approach to solve it by examining a blood supply routing problem with supply and demand uncertainties (Arani et al., 2021). Fazli-Khalaf et al. presented a new three-objective mathematical model for designing an emergency BSCN. In this model, they consider five categories including blood donor groups, blood collection facilities, laboratories, blood centers and hospitals. And two robust potential resilience probability (RPFCCP) programming programs and a potential resilience resilience programming model to provide robust and robust solutions for decision makers (Fazli-Khalaf et al., 2019). Salehi et al. presented a robust multi-echelon stochastic model for the design of the blood supply network considering a possible natural disaster, which consists of three layers; the donation areas are blood collection centers and a blood transfusion center. The mathematical model was implemented and evaluated using a simulation method (Salehi et al., 2019). Samani et al. proposed a multi-objective mixed integer linear programming model to design an integrated BSCN for disaster relief. Numerical experiments were performed to validate the proposed model and its solution method, and also, a real case study was presented to show the application of the proposed model (Samani et al., 2019). Rahmani provided a robust and reliable model for a dynamic emergency blood network design problem. They used a robust approach to control uncertainty. A numerical example was widely used to illustrate the effect of considering disruption scenarios. The performance of the proposed model was evaluated using a series of test problems in different sizes. The results showed that the performance of the model was quite satisfactory (Rahmani, 2019). Samani et al. approached an advanced perspective involving a two-phase prevention policy in which the risk of disruption is reduced through a combined method using a fuzzy hierarchical process and gray logic analysis to determine the possibilities of excess blood. They developed a robust formula for controlling network reliability under low-cost disruption scenarios and developed an integrated fuzzy measurement-based approach to protect the network from uncertainty (Samani et al., 2019). Asadpour et al. designed a multiobjective BSCN model considering blood corruption. They used the method of achieving the ideal to solve their two-objective model. The model presented by them leads to a reduction in covid transfer rate (Asadpour et al., 2021). Abbasi et al. developed a new way to solve large size problems based on machine learning. They used this method to solve the problem of BSCN (Abbasi et al., 2020). Shokouhifar et al. presented an inventory management model for age-distinct platelets in supply / demand uncertainties for lateral transport blood supply chains. They solved the problem using the supra-innovative Wall optimization algorithm (Shokouhifar et al., 2021). Samani et al. used a robust optimization method to control uncertain parameters in the BSCN. The results show that relevant managers should be aware of the behavior of blood donors, people affected by the disaster and the effect of disruption in the design of the BSCN (Samani et al., 2020). Araújo et al. proposed a new integer linear programming model for tactical and operational blood supply chain planning. In this model, several products, several periods and corruption are considered in a wide planning horizon (Araújo et al., 2020).

Accordingly, in this paper, we will work on the development of previous work, taking into account the shelf life of products across the network and routing vehicles in the distribution of goods, to fill this research gap. Table (1) compares some of the most important articles published on blood supply chain.

		Objective function								Nur c proc	nber of lucts	levels	riod	ıdy	malysis	ort	amage	om other	dition
Research	Cost Distance	Distance	Risk	Time	Safety	Reliability	Coverage	Shortage	Gas emission	Single-	Multi-	Number of	Multi-pe	Case stu	Sensitivity a	Transpo	Earthquake] Radius	Transport fr	Crisis cone
Şahin et al. 2007	-	*	-	-	-	-	-	-	-	*	-	3	-	*	-	-	-	-	-
Nagurney et al 2012	*	-	*	-	-	-	-	-	-	*	-	7	-	-	-	-	-	-	-
Li & Liao 2012	*	-	-	-	*	-	-	-	-	*	-	1	*	-	-	-	-	-	-
Sha & Huang 2012	*	-	-	-	-	-	-	-	-	*	-	2	*	-	-	-	-	-	-
Bozorgi et al 2014	*	-	-	-	-	-	-	-	-	*	-	3	-	-	-	-	-	-	-
Jabbarzadeh. 2014	*	1	-	-	1	-	-	1	-	*	-	3	*	*	-	-	-	-	*
Arvan et al. 2015	*	1	-	*	1	*	-	1	-	-	*	4	-	-	-	-	-	-	-
Fahimnia al. 2015	*	1	-	*	1	*	-	1	-	*	-	4	*	-	-	-	-	-	*
Ghasemi et al 2016	*	1	-	-	1	-	*	*	-	*	-	4	-	*	*	-	-	-	-
Kohneh et al. 2016	*	1	-	-	1	-	*	1	-	-	*	5	*	*	-	-	-	*	*
Salehi et al 2017	*	1	-	-	1	-	-	1	-	-	*	3	*	*	-	-	-	-	*
khalilpourazari 2017	*	1	-	*	1	*	-	-	-	*	-	3	*	*	*	*	*	-	*
Zahiri et al 2017	*	-	-	-	-	-	-	-	-	-	*	5	*	*	-	-	-	-	-
Heydari et al 2018	*	-	-	-	-	-	-	*	-	-	*	3	-	*	*	-	-	-	-
Fazli-Khalaf et al 2019	*	-	-	-	-	*	*	-	-	-	*	3	*	-	*	-	-	-	*
Khalilpour et al 2020	*	1	1	*	1	1	-	*	-	*	-	6	*	*	-	-	*	-	*
Samani et al 2020	*	-	-	-	-	-	*	-	-	*	*	4	*	-	-	*	*	-	*
Araújo et al 2020	*	-	-	-	-	-	-	-	*	*	*	3	*	*	-	-	-	*	*
Asadpour et al 2021	*	-	-	-	-	-	-	-	*	*	-	3	-	*	-	-	*	-	*
Shokuhifar et al 2021	*	-	-	-	-	-	-	*	-	-	*	3	-	*	-	-	*	-	*
Soltani et al 2021	*	-	-	*	-	-	-	-	*	*	*	3	*	-	-	-	*	*	-
Dehghani et al., 2021	*	*	-	-	-	-	*	-	*	*	*	4	*	-	-	*	-	-	-
Present study	*	-	-	-	-	-	-	-	-	-	*	5	*	-	-	*	-	-	*

Table (1): Comparison of some of the most important articles on BSCN

3. Mathematical Model

In this paper, a robust multi echelon BSCN has been designed. According to Figure (1), the BSCN echelons include blood donation centers, temporary and permanent blood sampling centers, laboratory and blood demand centers (Hospitals). In this network, blood donation clusters refer to permanent or temporary blood centers for blood donation. Temporary blood transfusion centers also send blood groups to permanent blood transfusion centers after transfusion from donation clusters. The central laboratory centers also store part of the blood groups in their temporary storage, taking into account the perishability time of blood and the time of blood donation, and send the other part to the demand centers according to the customer's request. In this section, each primary laboratory center, taking into account the closest demand centers, uses the available vehicles to distribute blood groups. In this section, the routing of the vehicle arises. Therefore, the main model of BSCN can be modeled according to the following assumptions:

- The problem is multi-period and its planning horizon is mid-term.
- The location of the permant and primary blood transfusion centers and the main potential lab centers and the number of them are unknown.
- The demand and transportation costs are considered as uncertain.
- The capacity of potential facilities is already known.
- Shortage is not allowed and all customer demand for all products must be provided.



Figure (1): The proposed BSCN

According to the assumptions stated, the main objective of this paper is to determine the optimal number and location of potential facilities, allocation of the flow of goods between selected locations and routing vehicles in the transport of blood groups to demand centers in such a way that the total cost of the supply chain network is minimized. Therefore, for modeling, the indices, parameters and decision variables of the blood supply chain network problem are defined as follows:

3.1 Indices

$i = \{1, \dots, I\}$	The index of blood donation clusters
$j = \{1, \dots, J\}$	The index of temporary blood transfusion centers
$k = \{1, \dots, K\}$	The index of permanent blood transfusion centers
$l,l'=\{1,\ldots,L\}$	The index of the potential centers of the central laboratory
$m,c=\{1,\ldots,C\}$	The index of blood demand centers
$b = \{1, \dots, B\}$	The index of type of blood group and blood derivatives
$t = \{1, \dots, T\}$	The index of time period
$r = \{1, \dots, T\}$	The index of blood transfusion time
$v = \{1,, V\}$	The index of vehicle

3.2 Parameters

- G_j The establishing cost the temporary blood tansfusion center *j*
- H_k The establishing cost a permanent blood tansfusion center k

- U_l The establishing cost the central laboratory center l
- F_v The fixed cost of using the vehicle v
- T_{ij} Cost per unit for blood donation cluster *i* and temporary blood tansfusion center *j*
- T_{ik} Cost per unit transport between blood donation cluster *i* and permanent blood donation center *k*
- T_{jk} The transportation cost per unit between the temporary blood transfusion center *j* and the permanent blood transfusion center *k*
- T_{kl} The transportation cost per unit between the permanent blood transfusion center k and the central laboratory center l
- $T_{ll'}$ The transportation cost per unit between the central laboratory centers l and l'
- T_{lc} The transportation cost between the central laboratory center l and customer $c \ l, c \in L \cup C$
- h_{kb} Maintenance cost per blood group b in the temporary warehouse of the permanent blood transfusion center k
- h'_{lb} Maintenance cost per blood group b in the temporary warehouse of the central laboratory center l
- C_{lb} The distribution cost per blood group b by the central laboratory center l
- D_{cbt} Demand for a blood center c from a blood group b at period t
- u_b The perishability time of a blood group b
- ca_{ib} The capacity of the temporary blood transfusion center j from the blood group b
- $\begin{array}{l} \text{Temporary storage capacity of the permanent blood transfusion center } k \text{ from the blood group} \\ b \end{array}$
- ca_{lb} Temporary warehouse capacity of the central laboratory center l of the blood group b
- ca_v Vehicle capacity v
- π_{cbt} Penalty cost of unmet demand for a blood center c from a blood group b at period t

3.3 Decision variables

v	The amount of blood group b transported between the donation cluster i and the permanent
Aikbt	blood transfusion center k at period t.
R	The amount of blood group b transported between the donation cluster i and the temporary
Nijbt	blood transfusion center <i>j</i> at period <i>t</i> .
V	The amount of blood group b transported between and the temporary blood transfusion center
¹ jkbt	j and the permanent blood transfusion center k at period t .
147	The amount of blood group b transported between the permanent blood transfusion center and
<i>vv</i> klbt	the central laboratory center <i>l</i> at period <i>t</i>
ς,	The amount of blood group b transported between the central laboratory center l and l' at
Jll'bt	period t
V' _{lbt}	The total amount of blood group b transmitted to the central laboratory centers l at period t
<i>T</i>	The amount of blood group b transfused between the permanent blood transfusion center k
¹ klbtr	and the central laboratory center l for a time period t and blood donated at period r
A	The amount of blood group b transfused between the central laboratory centers l and l' at
Πl'lbtr	period t and blood donated at period r
P	The amount of blood group b transfused between the central laboratory center l and blood
Dlcbtr	demand center c at period t and blood donated at period r
0	The inventory level of blood group b in the p warehouse of the permanent blood transfusion
V kbtr	center k at period t and blood donated at period r

- Q'_{lbtr} Level of inventory of the blood group b in the temporary warehouse of the central laboratory center l at period t and blood donated at period r
- Z_j If a temporary blood transfusion center *j* is established, it is 1 and otherwise 0.
- Z_k If the Permanent Blood transfusion center k is established, it will be 1 and otherwise 0.
- Z_l If the central laboratory center *l* is established, it will be 1 and otherwise 0.
- Z_{lct} If the blood demand center *c* is allocated to the the central laboratory center *l* at period *t*, it will be 1 and otherwise 0.

 Z_{lcvt} If the blood center *c* is visited by the vehicle *v* after the central laboratory center *l* at period *t*, it will be 1 and otherwise 0. $l, c \in L \cup C$

- U_{cvt} Auxiliary variable for the elimination constraint
- σ_{cbt} Percentage of unmet demand center c from the blood group b at period t
- A_{vt} If the vehicle v period t is used, it will be 1 and otherwise 0.

Regarding the indices, parameters, and decision variables, the robust multi echelon BSCN is modeled as a mixed integer non linear mathematical programming model as follows:

$$\sum_{i=1}^{L} X_{ijbt} = \sum_{k=1}^{L} Y_{jkbt}, \quad \forall j, b, t$$
(2)

$$\sum_{r=1}^{L} Q_{kbtr} = \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{L} R_{ikbt} - \sum_{l=1}^{L} W_{klbt}, \quad \forall k, b, t = 1 < u_b$$
(3)

$$\sum_{r=1}^{t} Q_{kbtr} = \sum_{r=1}^{t-1} Q_{kbt-1r} + \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{l} R_{ikbt} - \sum_{l=1}^{L} W_{klbt}, \quad \forall k, b, 1 < t < u_b$$
(4)

$$\sum_{r=t+1-u_b}^{t} Q_{kbtr} = \sum_{r=t+1-u_b}^{t-1} Q_{kbt-1r} + \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} - \sum_{l=1}^{L} W_{klbt}, \quad \forall k, b, t \ge u_b$$
(5)

$$W_{klbt} = \sum_{r=1}^{\infty} T_{klbtr}, \quad \forall k, l, b, t < u_b$$
(6)

$$W_{klbt} = \sum_{r=t+1-u_b}^{l} T_{klbtr} , \qquad \forall k, l, b, t \ge u_b$$
(7)

$$Q_{kbtr} = \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} - \sum_{l=1}^{L} T_{klbtr}, \quad \forall k, b, t = r$$
(8)

$$Q_{kbtr} = Q_{kbt-1r} - \sum_{l=1} T_{klbtr}, \quad \forall k, b, t-r < u_b$$
(9)

$$\sum_{r=1}^{t} Q'_{lbtr} = \sum_{k=1}^{K} W_{klbt} - V'_{lbt} + \sum_{\substack{l'=1\\l' \neq l}}^{L} S_{l'lbt} - \sum_{\substack{l'=1\\l' \neq l}}^{L} S_{ll'bt}, \quad \forall l, b, t = 1 < u_b$$
(10)

$$\sum_{r=1}^{t} Q_{lbtr}' = \sum_{r=1}^{t-1} Q_{lbt-1r}' + \sum_{k=1}^{K} W_{klbt} - V_{lbt}' + \sum_{\substack{l'=1\\l' \neq l}}^{L} S_{l'lbt} - \sum_{\substack{l'=1\\l' \neq l}}^{L} S_{ll'bt}, \quad \forall l, b, 1 < t < u_b$$
(11)

$$\sum_{\substack{r=t-u_b\\+1}}^{t} Q'_{lbtr} = \sum_{\substack{r=t-\\u_b+1}}^{t-1} Q'_{lbt-1r} + \sum_{k=1}^{K} W_{klbt} - V'_{lbt} + \sum_{\substack{l'=1\\l'\neq l}}^{L} S_{l'lbt} - \sum_{\substack{l'=1\\l'\neq l}}^{L} S_{ll'bt}, \quad \forall l, b, t \ge u_b$$
(12)

$$V'_{lbt} = \sum_{r=1}^{c} \sum_{\substack{c=1\\t}}^{c} B_{lcbtr}, \quad \forall l, c, b, t < u_{b}$$
(13)

$$V'_{lbt} = \sum_{\substack{r=t-u_b+1 \ c=1}}^{t} \sum_{c=1}^{c} B_{lcbtr}, \quad \forall l, c, b, t \ge u_b$$
(14)

$$S_{ll'bt} = \sum_{r=1}^{t} A_{l'lbtr}, \quad \forall l, l', b, t < u_b$$
(15)

$$S_{ll'bt} = \sum_{\substack{r=t-u_b+1\\K}} A_{l'lbtr}, \quad \forall l, l', b, t \ge u_b$$
(16)

$$Q_{lbtr}' = \sum_{k=1}^{K} T_{klbtr} - \sum_{c=1}^{C} B_{lcbtr} + \sum_{\substack{l'=1\\l'\neq l}}^{L} A_{l'lbtr} - \sum_{\substack{l'=1\\l'\neq l}}^{L} A_{ll'btr}, \quad \forall l, b, t = r$$
(17)

$$Q'_{lbtr} = Q'_{lbt-1r} - \sum_{c=1}^{C} B_{lcbtr} - \sum_{\substack{l'=1\\l' \neq l}}^{L} A_{ll'btr}, \quad \forall l, b, t-r < u_b$$
(18)

$$\sum_{k=1}^{N} Y_{jkbt} \le ca_{jb}Z_j, \quad \forall j, b, t$$
(19)

$$\sum_{k=1}^{K} W_{klbt} + \sum_{\substack{l'=1\\l'\neq l\\I}}^{L} S_{l'lbt} \le ca_{lb}Z_l, \quad \forall l, b, t$$

$$(20)$$

$$\sum_{j=1}^{r} Y_{jkbt} + \sum_{i=1}^{r} R_{ikbt} \le ca_{kb}Z_k, \quad \forall k, b, t$$

$$(21)$$

$$V'_{lbt} = \sum_{\substack{c=1\\c \in UL}}^{\infty} \sigma_{cbt} \widetilde{D}_{cbt} Z_{lct}, \quad \forall l, b, t$$
(22)

$$\sum_{c=1}^{c} \sum_{l=1}^{col} \sum_{b=1}^{b} \sigma_{cbt} \widetilde{D}_{cbt} Z_{lcvt} \le ca_{v} A_{vt}, \quad \forall v, t$$
(23)

$$\sum_{\nu=1}^{V} \sum_{l=1}^{C \cup L} Z_{lc\nu t} = 1, \quad \forall c, t$$

$$(24)$$

$$U_{mvt} - U_{cvt} + CZ_{mcvt} \le C - 1, \quad \forall m, c \in C, v, t$$

$$(25)$$

$$\sum_{c=1}^{COL} Z_{lcvt} = \sum_{c=1}^{COL} Z_{clvt}, \quad \forall v, t, l \in C \cup L$$
(26)

$$\sum_{l=1}^{L} \sum_{c=1}^{C} Z_{lcvt} \le 1, \quad \forall v, t$$

$$(27)$$

$$\sum_{h=1}^{l=1} V'_{lbt} \le \sum_{h=1}^{B} ca_{lb} Z_{l}, \quad \forall l, t$$
(28)

$$-Z_{lct} + \sum_{\nu=1}^{C \cup L} (Z_{lu\nu t} + Z_{uc\nu t}) \le 1, \quad \forall l, c, \nu, t$$

$$(29)$$

$$Q_{kbtr} = 0, \quad \forall k, b, t < r \tag{30}$$

$$Q'_{lbtr} = 0, \quad \forall l, b, t < r \tag{31}$$

$$X_{ijbt}, R_{ikbt}, Y_{jkbt}, W_{klbt}, S_{l'lbt}, U_{lvt}, \sigma_{cbt} \ge 0, \quad \forall i, j, k, c, l, l', b, v, t$$

$$B_{lcbtr}, A_{ll'btr}, T_{klbtr}, O'_{lbtr}, 0_{kbtr} > 0, \quad \forall l, l', c, k, b, t, r$$

$$(32)$$

$$Z_{j}, Z_{l}, Z_{k}, Z_{lct}, Z_{lcvt} \in \{0,1\}, \quad \forall i, k, l, v, t, c, b$$
(34)

Equation (1) shows the first objective function and includes minimizing the costs of the entire supply chain network (construction costs, maintenance costs, and transport costs of blood group between centers). Constraint (2) shows the equilibrium relation in the transport of blood groups from blood donation clusters to main blood transfusion centers. Constraints (3) to (5) are related to the amount of blood groups stored in the temporary stores of the primary blood transfusion centers at the time of blood donation, with regard to the time of perishability of each blood group and at any time period. Constraints (6) and (7) show the transport of blood groups from the main blood transfusion centers to the central laboratory centers with regard to the perishability of the blood groups. Constraints (8) and (9) indicate the level of inventory of each blood group in the temporary storage of primary blood donation centers and constraints (10) to (12) reflect the level of inventory of each type of blood group in temporary warehouses of the primary laboratory. Constraints (13) and (14) show the amount of the transport of blood groups from the central laboratory centers to all demand points in each time period. Constraints (15) and (16) indicate the transfer of blood groups between the central laboratory centers according to the demand of the customer centers and the perishability time. Constraints (17) and (18) show the equilibrium relationship at the central laboratory centers and ensures that the blood groups are transferred to demand points before the period of blood corruptions. Constraints (19) to (21) are related to the capacity constraints of the temporary blood transfusion centers, the central laboratory centers and permanent blood transfusion centers, and ensure that the center can not be used until the center has been established. Constraint (22) ensures that each central laboratory center can only be allocated to a blood supply center. Constraint (23) shows the total flow of products (demand) in the central labratory centers for transfer to demand centers. Constraint (24) shows the maximum carrying capacity of blood groups by the available vehicle. Constraint (25) is the restriction related to the removal of the sub-tour. Constraint (26) ensures that the vehicle can only enter and exit from any demand center once. Constraints (27) to (29) ensures that the start and end routing points of vehicle in the distribution of blood groups to the demand centers are the central laboratory centers. Constraints (30) and (31) show the rational relationships in the inventory of blood groups in the temporary warehouses of the primary blood transfusion centers and the central laboratory. Constraints (32) to (34) show the type and gender of the decision variables.

3.4 The deterministic model of BSCN

CUI

CUI

The proposed model presented in the previous section is related to the model in an uncertain state. This model has been developed based on the robust optimization model provided by Ben Tal and Nemirovski (1999). Ben Tal et al. (1999) showed that in a limited framework, a robust model can be transformed into an equilibrium problem from a semi-immutable problem where the set u_{box} is replaced by the boundary set u_{ext} . In this problem, u_{ext} includes the maximum values in the set u_{box} . Regarding the index, the parameter and decision variables of the proposed non-linear math programming model are the integer as follows:

$$\begin{aligned} &\text{Minol} = Zcost \end{aligned} \tag{35} \\ &\text{s.t.:} \end{aligned}$$

$$\begin{aligned} &\sum_{j=1}^{l} G_{j}Z_{j} + \sum_{k=1}^{\kappa} H_{k}Z_{k} + \sum_{l=1}^{L} U_{l}Z_{l} + \sum_{k=1}^{\kappa} \sum_{b=1}^{B} \sum_{l=1}^{T} \sum_{r=1}^{t} h_{kb}Q_{kbtr} + \\ &\sum_{l=1}^{L} \sum_{b=1}^{B} \sum_{t=1}^{T} \sum_{r=1}^{t} h_{lb}'Q_{lbtr}' + \sum_{l=1}^{l} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{ij}X_{ijbt} + \eta_{ijbt}^{ij}) + \\ &\sum_{l=1}^{l} \sum_{k=1}^{K} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{ik}R_{ikbt} + \eta_{ikbt}^{ik}) + \sum_{l=1}^{J} \sum_{b=1}^{K} \sum_{l=1}^{K} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{ik}R_{ikbt} + \eta_{ikbt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{L} \sum_{l=1}^{B} \sum_{t=1}^{T} (T_{kl}W_{klbt} + \eta_{klbt}^{il}) + \sum_{l=1}^{L} \sum_{c=1}^{L} \sum_{\nu=1}^{T} \sum_{t=1}^{T} (T_{ic}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{k=1}^{L} \sum_{l=1}^{L} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{kl}W_{klbt} + \eta_{klbt}^{il}) + \sum_{l=1}^{L} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{ic}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{L} \sum_{t=1}^{B} \sum_{l=1}^{T} (T_{kl}W_{klbt} + \eta_{klbt}^{il}) + \sum_{l=1}^{L} \sum_{b=1}^{B} \sum_{t=1}^{T} (T_{ic}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{L} \sum_{t=1}^{L} \sum_{l=1}^{L} \sum_{l=1}^{L} (T_{il}W_{klbt} + \eta_{klbt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{T} T_{l}(T_{kl}W_{klbt} + \eta_{klbt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{T} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{T} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{T} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{R} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{t=1}^{R} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{b=1}^{R} \sum_{l=1}^{R} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_{l=1}^{L} \sum_{l=1}^{R} \sum_{l=1}^{R} T_{l}(T_{lc}Z_{lcvt} + \eta_{lcvt}^{il}) + \\ &\sum_$$

$$\sum_{c=1}^{N} \sum_{l=1}^{N} \sum_{b=1}^{r} \sigma_{cbt} [\rho \overline{D}_{cbt} + (1-\rho) \overline{D}_{cbt}] Z_{lcvt} \le c a_v A_{vt}, \quad \forall v, t$$
(50)

Eqs. (2-21) and Eqs. (24-35) (51)

Eqs. (2-21) and Eqs. (24-35)

4. Solution method

The outcome of the proposed model is an MINLP one. The SCN design problem's NP-hardness has been demonstrated in several studies (Ghahremani et al., 2020). The developed model includes three various problems which are location, routing and allocation problems. So, this model can be reduced to the facility location problem that shown this problem is NP-hard. That is why the mentioned BSCN problem is introduced as NP-Hard in this study. Accurate review of this problem by exact solutions is time-consuming and often impractical. So, in order to reach to near-optimal solutions many meta-heuristic algorithms with various representations have been proposed, but they are not efficient. In the next section, an FMGO algorithm was described.

4.1. Hybrid Moth-Flame Optimization and Genetic Algorithm

Moths as a group of insects are very similar to butterflies. One of the most interesting behaviour of moths is their unique navigation approach. To travel long distances in straight path, they fly by keeping a fixed angle with respect to the moon. This effective approach is called transverse orientation (Mirjalili, 2015). The effectiveness of the transverse orientation strongly depends on the distance of the light source. For example, when the light source is close to the moth, the moth starts flying in a spiral path around the light. This spiral fly path eventually converges the moth to the light. Using this behaviour and mathematical modelling, the Moth-Flame Optimization algorithm is proposed by Mirjalili (2015) and genetic operators is proposed.

In the MFO algorithm, the moths are considered as the candidate solutions and their position is considered as a vector of decision variables. Therefore, each moth can fly in the solution space of the problem freely.

$$MO = \begin{bmatrix} mo_{1,1} & \dots & mo_{1,n} \\ \vdots & \ddots & \vdots \\ mo_{npop,1} & \dots & mo_{npop,n} \end{bmatrix}$$
(52)

where npop is the number of moths in initial population and n presents the number of decision variables. Another basic concept of the MFGOA algorithm is the flame matrix. Since each moth flies around its corresponding flame, therefore, the flame matrix is in the same size as the moth's matrix.

$$Fx = \begin{bmatrix} Fl_{1,1} & \dots & Fl_{1,n} \\ \vdots & \ddots & \vdots \\ Fl_{npop,1} & \dots & Fl_{npop,n} \end{bmatrix}$$
(53)

where *npop* and *n* are the number of moths and number of decision variables, respectively. The difference between moth and flame is that the moth flies around its corresponding flame to find better solutions, while the flame is the best solution obtained so far by the moth. Since, the flying path of the moths is spiral around their corresponding flame, therefore, a logarithmic spiral function is defined to set a spiral fly path for the moths (Mirjalili, 2015).

$$Mo_i^{X+1} = |Mo_i^X - Fl_i| \cdot e^{bt} \cdot \cos(2\pi t) + Fl_i$$
(54)

The parameter t is b random uniform number between -1 and 1 which defines the closeness of the next position of the moth to its corresponding flame. To explore the solution space more effectively in the first iterations and exploitation of the solution space in last iterations, an adaptive procedure is proposed to reduce the values of the parameter t over the iterations.

$$b = -1 + Current it \left(\frac{-1}{\max it}\right)$$

$$t = (b-1), rand() + 1$$
(55)
(56)

where *Maxit* is the maximum number of iterations. Mirjalili (2015) defined as convergence constant which decreases linearly from
$$-1$$
 to -2 over the course of iterations.

In addition to the above-mentioned solution search method, the crossover and mutation operators have been used to achieve near-optimal solutions. In Figure (2), the operator with two-point crossover is illustrated.



Figure (2): Two-point crossover operator

Two crossover points in the two-point crossover, are chosen randomly, from the parent chromosomes. The genes between the two points in parent's chromosome are swapped. Figure (3) shows the performance of the mutation operator.





This operator replaces the selected gene with a random amount. According to the presented contents and moving the ant-lions for search the near-optimal solution, the crossover and mutation operators of the genetic algorithm have been used. In the following, an chromosome to solve the BSCN design is discussed.

4.2. Designing the chromosome BSCN

As it is shown in Figure (4), consider a layer of SCN with (|K|) sources, (|J|) depots and (|G|) products at (|T|) periods. This chromosome's length is (|K| + |J|) * [|G|, |T|] and each cell's location represents the priorities of each node (Ghahremani et al., 2019). For example, Fig 5 shows an chromosome with 3 sources, 4 depots, 2 products and 3 periods. Also, in this Fig, the demand of each product for depots, potential capacities for sources and transportation costs between nodes are shown.

S	ources		Depots		Sourc	es	D	epots	
250 (300 (280			$ \begin{array}{c} 1\\ \hline 2\\ \hline 3\\ \hline 4 \end{array} $	120 100 150 100	$300 \qquad 1$ $280 \qquad 2$ $320 \qquad 3$))	$ \begin{array}{cccc} 1 & 100 \\ \hline 2 & 150 \\ \hline 3 & 180 \\ \hline 4 & 120 \\ \end{array} $		
	Transportation Cost = Sources $ \begin{bmatrix} 2 & 5 & 1 & 4 \\ 4 & 3 & 2 & 6 \\ 5 & 2 & 7 & 3 \end{bmatrix} $ Depots								
			chromoson	the $\{(K + J)\}$) * [<i>P</i> . <i>T</i>]}				
Period	Nodes	Source-1	Source-2	Source-3	Depot-1	Depot-2	Depot-3	Depot-4	
Period	Product 1	2	7	6	1	3	5	4	
1	Product 2	1	5	3	2	6	4	7	
Period 2	Product 1	7	6	1	3	4	2	5	
2	Product 2	2	4	6	7	2	3	1	
Period 3	Product 1	3	2	4	7	1	6	5	
5	Product 2	4	1	7	2	6	3	5	

Figure (4): A sample of BSCN chromosome

The following two steps are considered to decode the chromosome:

Step 1. For any period, the first product, select the position of the highest priority between sources. If the chosen sources potential capacity is greater than the all warehouse ' demand sum, non-selected sources' priority is reduced to zero. Else, select the highest priority between non-selected sources. Continue this step until the sum of all selected sources' capacity becomes greater than the sum of all depots' demand.

At this step, the location of resources to be selected is specified.

Step 2. Select the position of the highest priority between Nodes. If the node position is between sources, refer to (A), else (B).

- **A.** Select the minimum transportation cost between the selected source and all depots. The optimal flow between selected nodes is the minimum of the (depot demand and source capacity). If the value of depot demand or source capacity becomes zero, reduce the node's priority to zero.
- **B.** Select the minimum transportation cost between the selected depot and all sources. The optimal flow between selected nodes is the minimum of the (depot demand and source capacity). If the value of depot demand or source capacity becomes zero, reduce the node's priority to zero.

Step 3. Repeat this process in order to make all priorities equal to zero.

At the end, do the same for all products.

The decoding of the presented example in Figure (4) for period 1 is shown in Figure (5).

Product 1				Pro	duct 2					
S	ources		Depots		Sour	ces	Ι	Depots		
250 ((1)			120	300 1	120	*(1	100	
300	2^{120}		₹ 2	100	280 (2			2	150	
300	$\begin{array}{c} 2 \\ \hline 150 \\ \hline 100 \\ \hline \end{array}$		3	150		100	(3	180	
280	$(3)_{100}$		4	100	320	150		4	120	
	$Transportation \ Cost = Sources \begin{bmatrix} 2 & 5 & 1 & 4 \\ 4 & 3 & 2 & 6 \\ 5 & 2 & 7 & 3 \end{bmatrix}$ Depots									
			chromosom	$e \{ (K + J) \}$	* (<i>P</i> . <i>T</i>)}					
period	Nodes	Source-1	Source-2	Source-3	Depot-1	Depot-2	Depot-3	Depot	-4	
period 1	Product 1	0	7	6	1	3	5	4		
	Product 2	0	5	3	2	6	4	7		

Figure (5): Decoding the sample chromosome for period 1

As it is mentioned, this is a multi-echelon, multiproduct, BSCN design, problem and the initial presented solution must include these items. Figure (6) is shown the encoding which is priority-based is presented by a matrix, where B, T, I, J, K, L, C, and V estpectively gives the number of blood grups, time periods, donation clusters, temporary blood transfusion centers, permanent blood transfusion centers, central laboratory, demand centers and vehicles in the BSCN.

Ι	J	Ι	K	J	K	K	L	L	L	L	С
(<i>I</i> +	· J)	(<i>I</i> +	- K)	(<i>J</i> +	- K)	(K -	+ L)	(L -	⊦ L)	(L +	+ C)
* (<i>P</i>	. T)	* (<i>P</i>	. T)	* (<i>P</i>	. T)	* (P	. T)	* (P	. T)	* (V	. T)

Figure (6): The final solution of the BSCN

5. Computational results

In this section, in order to solve the sample problems, 15 sample problems according to Table (2) were randomly generated in MATLAB software. Because of the lack of access to real data, random data was used based on uniform distribution in accordance with Table (3). Also, for better analysis of algorithms, from each sample problem, 5 replicates were performed in the same range within the defined data set. Finally, the means of each of the indicators were evaluated and compared as the basis for comparison.

Sample problem	i	j	k	l, l'	т, с	b	t	r	v
1	5	4	4	6	8	2	4	4	4
2	6	6	4	6	9	3	4	4	4
3	6	6	4	7	10	3	4	4	4
4	8	10	5	8	12	3	4	4	5
5	12	12	10	9	16	3	5	5	5
6	13	15	12	11	17	4	5	5	6
7	14	15	14	12	18	4	5	5	6
8	17	15	15	12	20	5	5	5	6
9	17	16	16	13	21	5	6	6	7
10	19	16	16	14	24	5	6	6	7
11	19	17	16	15	25	5	6	6	7
12	20	18	17	15	26	7	7	7	7
13	20	19	17	16	27	7	7	7	8
14	20	19	17	16	28	7	8	8	8
15	20	20	20	20	30	8	8	8	8

Table (2): The size of the designed Sample problems

Table (3): The boundaries of the parameters produced on the basis of uniform distribution

Deterministic	Interval boundaries	Deterministic parameter	Interval boundaries
parameter	interval boundaries	Deterministic parameter	interval boundaries
G_j	~U(10000,20000)	π_{cbt}	~ <i>U</i> (1000,2000)
H_k	~U(20000,30000)	ca_{jb} , ca_{kb} , ca_{lb}	~ <i>U</i> (3000,5000)
U_l	~ <i>U</i> (50000,60000)	ca_v	~ <i>U</i> (500,800)
F_{v}	~ <i>U</i> (200,300)	D_{cbt}	$\sim U(120, 150)$
h_{kb}	~ <i>U</i> (1,2)	$T_{ij}, T_{ik}, T_{jk}, T_{kl}, T_{ll'}, T_{lc}$	~ <i>U</i> (10,20)
h_{lb}^{\prime}	~ <i>U</i> (1,2)	u_b	~ <i>U</i> (1,3)
C_{lb}	~ <i>U</i> (10,20)		

Before solving sample problems by meta-heuristic algorithms, the initial parameters of each of the algorithms must be adjusted to increase their efficiency in finding effective solutions. Therefore, in this section, the parameter of meta-heuristic algorithms is first set by Taguchi method. To adjust the parameter, response variable is used. This variable is a combination of the five criteria provided and its value is calculated using equation (57).

$$RPD = \frac{\text{Alg}_{\text{sol}} - \text{Min}_{\text{sol}}}{\text{Min}_{\text{sol}}}$$
(57)

In this relation, Alg_{sol} and Min_{sol} are respectively the values of R_i for each replication of the test and the best solution. After converting the value of R_i to RPD, according to the structure of the Taguchi parameter design, the S/N ratio is calculated based on RPD. Then, the average S/N ratio of experiments is calculated for each parameter level. The best value of each parameter has the least amount of mean averages, in fact, the levels of the optimal factors that result in at least the average averages. After performing the Taguchi test, the results, mean averages and average S/N ratio for each level of factors in the FMGO and PSO algorithms for the presented model are given in Figure (7).



Figure (7): The mean averages and S/N Ratio for the FMGO and PSO Algorithms

According to the graphs obtained from Figure (7), the optimal level of factors of the FMGO and PSO algorithms is:

Algorithm	Doromotor	Level of factor	Level of factor	Level of factor	Level of optimal
Algorithm	Faranieter	1	2	3	factor
	nPop	50	70	100	70
FMGO	pc	0.2	0.5	0.8	0.2
	pm	0.2	0.3	0.4	0.2
	nParticle	50	75	100	100
	nRep	70	100	150	70
PSO	W	0.5	0.6	0.7	0.7
	<i>C1</i>	1	1.25	1.5	1
	<i>C</i> 2	1	1.25	1.5	1

Table (4): The optimal levels of the factor used for the algorithms

After determining the optimal parameters of the meta-heuristics algorithms and their parameter tuning, the sample problems are solved by the meta-heuristic algorithms and the average results are selected as the basis of the comparison. Table (5) show the average of 5 problems designed for each sample problem in different sizes. This table contains the mean of the objective function and the computational time.

Sample	FMG	0	PS	O
problem	Objective function	CPU time	Objective function	CPU time
1	495858.69	36.46	533806.72	34.4
2	776699.89	108	778692.87	39.07
3	871134.25	170.3	881581.31	51.66
4	1046187.5	242.53	1033814.6	95.93
5	1653146.4	335.5	1674913.5	131.2
6	2353344.2	434.4	2369557.6	280.5
7	2450251.7	545.77	2500890.6	349.16
8	3434001.9	669.07	3416474.1	494.7
9	4334688.4	819.6	4301936	723.16
10	4817592.1	959.67	4860023.4	980.4
11	5020566.3	1040.13	5040590.1	1328.75
12	8500502.4	1326	8540218.4	1834.56
13	8759033.2	1528.37	8887924.2	2337.3
14	10251099	1802.27	10361986	2983.04
15	12554017	2640	12608666	3957.9

 Table (5): The mean of objective function and the CPU-time in large scale sample problems

Tables (5) show the average of the results obtained from solving the sample problems with metaheuristic algorithms. Figure (8) and (9) show the average variations of the objective functionand the computational time in different sample problems with the FMGO and PSO algorithms.



Figure (8): Comparing the means of the first objective function in sample problems with meta-heuristic algorithms

According to Figure (8), it can be concluded that the FMGO algorithm has better results than the PSO algorithm for the sample problems (12) to (15). This shows that in the very large dimensions, the efficiency of the FMGO algorithm will be greater in achieving the results of the first objective function



Figure (9): Comparison of computational time averages in sample problems with meta-heuristic algorithms

Given Figure (9), it can be seen that computational time increases exponentially with increasing sample size, which is the reason for the NP-Hard problem. However, the PSO algorithm for medium sized problems is better than the computational time of the FMGO algorithm, but with increasing size, the computational time gained by this algorithm has been greatly increased.

In order to analyze the results, t-test was used at 95% confidence level to compare the mean values of each index. Therefore, if the P-value test statistic for each index was less than 0.05, the null hypothesis is rejected and shows that there is a significant difference between the mean of that index and if the P-value test statistic is greater than 0.95; the assumption is rejected and indicative that there is no significant difference in the mean of that index. Table (6) shows the output results of the t-test at a confidence level of 95% for the difference in the mean of objective function and CPU-time indices.

Algorithm	Index	Number of sample	Mean	SD	95% confidence level	T-value	P-value	
FMGO	Objective	75	4487875	3831512		0.77	0.015	
PSO	function	75	4519405	3859336	(/144 * 5591/)	2.77	0.015	
FMGO	CPU-	75	844	730	(() • • • • • • • • • • • • • • • • •	1 /8	0.16	
PSO	time	75	1041	1220	(-483 * 88)	1.70	0.10	

Table (6): The output results of t-test on the means of the objective function and the CPU-time indices

According to the results obtained from the t-test on the mean of objective function and CPU-time indices, it can be concluded that because of the lower value of the P-value test on the objective function than 0.05, only between the mean of the first objective function derived from, there is a significant difference in the problem solving with the meta-heuristic algorithms FMGO and PSO. Given the P-value of other indices, there is no significant difference between their means. Therefore, by considering the means of the objective function and CPU-time the FMGO algorithm is more efficient than the PSO algorithm in solving the BSCN problem.

After verifying and validating the proposed model, to analyze the model's sensitivity, uncertainty rate is selected, and changes of the OBFV for the first sample problem in this analysis are shown in Table (7).

Uncertainty rates (ρ)	OBFV	
0.1	527883.3	
0.2	534265.5	
0.3	543648.4	
0.4	564793.3	
0.5	589577.9	
0.6	627543.2	
0.7	663654.2	
0.8	694678.5	
0.9	724876.8	

Table (7): Changings of the OBFV by applying changes to the uncertainty rates

According to Table (7), with increasing the uncertainty rate, the demands are increased and the OBFV are increased. Figure (10) shows the trend of changes to OBFV in different uncertainty rates.



Figure (10): Changes in the OBFV by changing the uncertainty rates

According to (11), the mean of the objective function in robust approach is more than the one in the deterministic approach, while the standard deviation of the first objective function in the robust approach is less than the one in the deterministic approach at all levels of the uncertainty factor.



Figure (11): Comparison of objective function based on deterministic and robust approach

6. Conclusions

In this paper, a BSCN was designed and modeled in terms of uncertainty and considering the perishability nature of blood. The objective function considered for this model were to minimize the cost of the entire supply chain network. At first, a non-deterministic model of the problem was designed and demand and transportion costs were considered uncertain. Then a robust optimization model was presented for controlling non-deterministic parameters. In order to solve the model, 15 sample problems were randomly generated and in order to generate more realistic answers, 5 problems were designed in the same size and the means of the objective function and computational time were analyzed as the basis for evaluation and comparison. Firstly, using statistical tests including t-test, the significant difference of the indices was evaluated. It was observed that there was only a significant difference between the means of the objective function in robust approach is more than the one in the deterministic approach, while the standard deviation of the first objective function in the robust approach is less than the one in the deterministic approach at all levels of the uncertainty factor. Suggestions for future research are listed below:

- 1. Using other meta-heuristic algorithms such as ant lion algorithm
- 2. Considering more non-deterministic parameters with regard to environment uncertainty
- 3. Considering vehicle routing between the other levels of the supply chain network
- 4. Implementing the model of BSCN designed in a case study
- 5. Using the DEA method to select the optimal solutions among from the efficient solutions

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