ISSN: 2783-2678

International journal of Innovation in Management Economics and Social Sciences

Journal homepage: www.ijimes.ir

IJIMES

Int. J. Inn. Man. Eco. Soc. Sci. Vol. 1, No 4, 32-49 (2021)

Designing and Solving Location-Routing-Allocation Problems in a Sustainable Blood Supply Chain Network of Blood Transport in Uncertainty Conditions

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ARTICLE INFO

Received: 13 October 2021

Reviewed: 06 November 2021

Revised:12 November 2021

Accept: 22 November 2021

Keywords:** **Location-Routing-Allocation, Blood Supply Chain Network Design, Perishability in Transport, Meta-heuristic Algorithms, Uncertainty.

ABSTRACT

Purpose: In this paper, a location-routing-allocation problem in a multi-objective blood supply chain network was designed to reduce the total cost of the supply chain network, the maximum unmet demand from distribution of goods, and decline greenhouse gas emissions due to the transport of goods among different levels of the network. The network levels considered for modeling include blood donation clusters, permanent and temporary blood transfusion centers, major laboratory centers and blood supply points. Other objectives 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.

Methodology: Given that the model was NP-hard, the NSGA II and MOPSO algorithms were used to solve the model with a priority-based solution.

Findings: The results of the design of the experiments showed the high efficiency of the NSGA II algorithm in comparison with the MOPSO algorithm in finding efficient solutions.

Originality/Value: This study addresses the issue of blood perishability from blood sampling to distribution to customer demand areas.

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https://doi.org/10.52547/ijimes.1.4.32

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. 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 [1, 2]. 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 [3].

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. 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 [4]. 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 suppliers and consumers, resulting in a lack of exposure to lacking and minimizing the risk of blood products perishability and reducing costs [5, 6]. Therefore, in this paper, a three-objective model of blood supply chain network is proposed with the aim of reducing the total cost of the system, reducing maximum unmet demands and declining the amount of the emissions of greenhouse gases that simultaneously optimizes the number and location of potential facilities, optimizes the flow of blood bags between selected centers and optimizes the appropriate routing of transport and distribution of blood bags to demand centers.

2. Literature Review

The design of a blood supply chain network 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 [4]. Research on the management of the supply chain of perishable products, and in particular on blood products, began specifically by Van Zyl [7]. Sampson et al. [8] 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. Hinojosa et al. [9] considered location of dynamic facilities with the goal of minimizing total network costs. They introduced a mixed integer math model (MIP) for the problem in which the capacity of the suppliers was also considered. In one of the earliest studies in the field of supply chain design with regard to location and inventory, Daskin et al [10] presented a mathematical model for designing a blood supply chain network, taking into account location and inventory costs, including variable and fixed costs. They proposed a Mixed Integer Programming (MIP) for this purpose and used the Lagrange liberation method to solve them. In fact, they presented a mathematical model for the routing-location problem in their paper. In dynamic network design problems, location and capacity of facilities can vary in different periods. This in turn reflects the importance of using dynamic network design in the design of the supply chain network, since it is very important to use a dynamic network design to provide dynamic demand at different rates in each period. In 2003, Shen and colleagues put forward a nonlinear model of single-period integral-inventory model for the supply chain network. The goal was to find the location of the distribution facility and the amount of inventory in each center. Ultimately, they used heuristic methods to solve their model [11]. In 2005, Pereira [12] developed a comprehensive mathematical model for designing a blood supply chain network. 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. Fahimnia et al. [13] 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. To solve the proposed mathematical model, two methods of epsilon constraint and Lagrange coefficient liberation were used. Ghasemi et al., [14] 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. Osorio et al. [15] 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. Ensafian et al. [16] considered a randomized multi-period and integer model for collecting, producing, storing and distributing platelets sent from the blood collection centers to demand points. In this model, the age of platelet and the priority rules for matching ABO-Rh were based on the type of patient in order to increase the quality and safety of services. First, a Markov chain process was used to predict the number of donors; then, the uncertain demand was examined using a two-stage random programming. One of the challenging aspects was the use of random programming in a dynamic environment in which a suitable set of discrete scenarios is considered to make it; therefore, an improved approach is presented to reduce the scenarios which well shows the random processes for uncertain parameters. Zahiri et al. [17] presented a multi-level, 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. Habibi et al. [18] 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. Using the ideal planning method and using the actual data of the case study in Ghaemshahr city, they solved the model.

In previous papers and research, a bulk of studies have been conducted to provide a comprehensive mathematical model for designing a blood supply chain network. Whereas in the real world, considering the blood perishability, the shelf life of the products is considered throughout the network, because corrupted blood products cannot be moved to demand areas. Moreover, there is a dearth of research on routing vehicles in the distribution of blood bags from major laboratories to demand areas and taking into account three opposing objectives (reducing network costs, reducing the maximum demand, and reducing greenhouse gas emissions due to the transfer of products) have not been addressed.

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.

3. Modeling and Definition of the Problem

In this paper, a location-routing-allocation problem in a multi-level blood supply chain network with regard to previous research gaps has been investigated. According to Figure (1), the blood supply chain network levels include blood donation levels, the levels of temporary and permanent blood sampling centers, the levels of the central laboratory and the levels of blood demand centers. In this network, blood donation clusters refer to permanent or temporary blood centers for blood donation. Temporary blood transfusion centers also send blood bags to permanent blood transfusion centers after transfusion from donation clusters. The central laboratory centers also store part of the blood bags 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 bags. In this section, the routing of the vehicle arises. Therefore, the main model of blood supply chain network can be modeled according to the following assumptions:

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

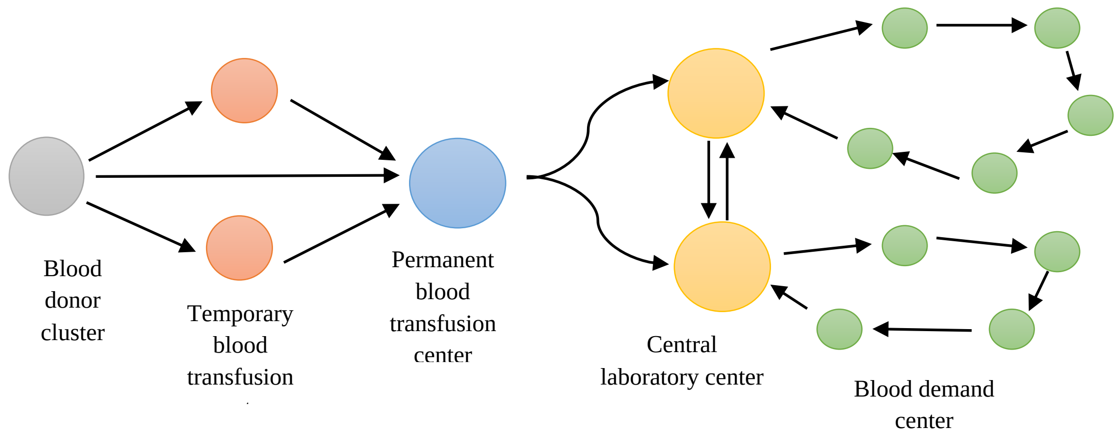

Fig. 1. The proposed blood supply chain network

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 bags to demand centers in such a way that: 1- the total cost of the supply chain network is reduced and 2. The Maximum unmet demands from the delivery of goods to demand centers are minimized, and 3. The greenhouse gas emissions due to the transfer of goods between facilities and demand areas are minimized. Therefore, for modeling, the indices, parameters and decision variables of the 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
$l, l' = \{1, \dots, L\}$	The index of the potential centers of the central laboratory
$m, c = \{1, \dots, C\}$	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
$v = \{1, \dots, V\}$	The index of vehicle

3.2. Parameters

G_j	The cost of establishing the temporary blood tansfusion center j
H_k	The cost of establishing a permanent blood tansfusion center k
U_l	The cost of establishing 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}	Cost of transportation per unit between the temporary blood transfusion center j and the permanent blood transfusion center k
T_{kl}	Cost of transportation per unit between the permanent blood transfusion center k and the central laboratory center l

$T_{ll'}$	The cost of transportation per unit between the central laboratory centers *l* and l'
T_{lc}	The cost of transportation between the central laboratory center *l* and customer *c* $l, c \in L \cup C$
h_{kb}	Maintenance cost per blood bag *b* in the temporary warehouse of the permanent blood transfusion center *k*
h'_{lb}	Maintenance cost per blood bag *b* in the temporary warehouse of the central laboratory center *l*
C_{lb}	Cost of distribution per blood bag *b* by the central laboratory center *l*
tt_{lc}	The time of transportation of goods by the vehicle between the central laboratory center *l* and customer *c* $l, c \in L \cup C$
T_v	Maximum transport time of the vehicle *v* for the delivery of blood to demand centers
D_{cbt}	Demand for a blood center *c* from a blood type *b* in a time period *t*
u_b	The time of perishability of a blood bag *b*
ca_{jb}	The capacity of the temporary blood transfusion center *j* from the blood group *b*
ca_{kb}	Temporary storage capacity of the permanent blood transfusion center *k* from the blood group *b*
ca_{lb}	Temporary warehouse capacity of the central laboratory center *l* of the blood group *b*
ca_v	Vehicle capacity *v*
co_{2ij}	The amount of co_2 gas emission per unit of the donation cluster *i* to the temporary blood transfusion center *j*
co_{2lc}	The amount of co_2 gas emission per unit between the the central laboratory centers *l* and the customer *c* $l, c \in L \cup C$
co_{2ik}	The amount of co_2 gas emission per unit of the donation cluster *i* to the permanent blood transfusion center *k*
co_{2jk}	The amount of co_2 gas emission per unit from the temporary blood transfusion center *j* to the permanent blood transfusion center *k*
co_{2kl}	The amount of co_2 gas emission per unit from the permanent blood transfusion center *k* to to the central laboratory center *l*
$co_{2ll'}$	The amount of co_2 gas emission per unit between the central laboratory centers *l* and l'

3.3. Decision Variables

X_{ikbt}	The amount of blood *b* transported between the donation cluster *i* and the permanent blood transfusion center *k* over time period *t*.
R_{ijbt}	The amount of blood *b* transported between the donation cluster *i* and the temporary blood transfusion center *j* over time period *t*.
Y_{jkbt}	The amount of blood *b* transported between and the temporary blood transfusion center *j* and the permanent blood transfusion center *k* over time period *t*.
W_{klbt}	The amount of blood *b* transported between the permanent blood transfusion center and the central laboratory center *l* over the time period *t*
$S_{ll'bt}$	The amount of blood *b* transported between the central laboratory center *l* and *l'* over the time period *t*
V'_{lbt}	The total amount of blood *b* transmitted to the central laboratory centers *l* in the time period *t*

T_{klbtr}	The amount of blood *b* transfused between the permanent blood transfusion center *k* and the central laboratory center *l* for a time period *t* and blooded transfuted over the period *r*
$A_{l'lbtr}$	The amount of blood *b* transfused between the central laboratory centers *l* and l' in the time period *t* and blood transfuted over the period *r*
B_{lcbtr}	The amount of blood *b* transfused between the central laboratory center *l* and blood demand center *c* at the time period *t* and blood transfuted over the period *r*
Q_{kbtr}	The inventory level of blood group *b* in the p warehouse of the permanent blood transfusion center *k* during the time period *t* and blood donated in the time period *r*
Q'_{lbtr}	Level of inventory of the blood group *b* in the temporary warehouse of the central laboratory center *l* in the time period *t* and blood transfused at time 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 *c* within a time 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 *c*, 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 blood demand center *c* from the blood group *b* during the time period *t*

Regarding the indices, parameters, and decision variables, the locating-routing-allocation problem in a blood supply chain network is modeled as a mixed integer linear mathematical programming model as follows:

$$Min\omega 1 = \sum_{j=1}^{J} G_j Z_j + \sum_{k=1}^{K} H_k Z_k + \sum_{l=1}^{L} U_l Z_L + \sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T}\sum_{r=1}^{t} h_{kb} Q_{kbtr} + \sum_{l=1}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T}\sum_{r=1}^{t} h'_{lb} Q'_{lbtr} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\frac{T_{ij(1)} + 2T_{ij(2)} + T_{ij(3)}}{4}\right) X_{ijbt} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\frac{T_{kl(1)} + 2T_{kl(2)} + T_{kl(3)}}{4}\right) W_{klbt} + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\frac{T_{ik(1)} + 2T_{ik(2)} + T_{ik(3)}}{4}\right) R_{ikbt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\frac{T_{jk(1)} + 2T_{jk(2)} + T_{jk(3)}}{4}\right) Y_{jkbt} + \sum_{l=1}^{L\cup C}\sum_{c=1}^{L\cup C}\sum_{v=1}^{V}\sum_{t=1}^{T}\left(\frac{T_{lc(1)} + 2T_{lc(2)} + T_{lc(3)}}{4}\right) Z_{lcvt} + \sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{t=1}^{T} F_v Z_{lcvt} + \sum_{l=1}^{L}\sum_{\substack{l'=1\\ l'\neq l}}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\frac{T_{ll'(1)} + 2T_{ll'(2)} + T_{ll'(3)}}{4}\right) S_{ll'bt} + \sum_{l=1}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T} C_{lb} V'_{lbt} \tag{1}$$

$$Min\omega 2 = max_{c,b,t}\left(\begin{pmatrix}(1-\alpha)D_{cbt(2)} + \\ \alpha D_{cbt(3)}\end{pmatrix} - \sum_{l=1}^{L} \sigma_{cbt} Z_{lct} \begin{pmatrix}(1-\alpha)D_{cbt(2)} + \\ \alpha D_{cbt(3)}\end{pmatrix}\right) \tag{2}$$

$$Min\omega 3 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T} co_{2_{ij}} X_{ijbt} + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T} co_{2_{ik}} R_{ikbt} + \sum_{l=1}^{L\cup C}\sum_{c=1}^{L\cup C}\sum_{v=1}^{V}\sum_{t=1}^{T} co_{2_{lc}} Z_{lcvt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T} co_{2_{jk}} Y_{jkbt} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T} co_{2_{kl}} W_{klbt} + \sum_{l=1}^{L}\sum_{\substack{l'=1\\ l'\neq l}}^{L}\sum_{b=1}^{B}\sum_{t=1}^{T} co_{2_{ll'}} S_{ll'bt} \tag{3}$$

$s.t.$:

$$\sum_{i=1}^{I} X_{ijbt} = \sum_{k=1}^{K} Y_{jkbt}, \qquad \forall j, b, t \tag{4}$$

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

$$\sum_{r=1}^{t} Q_{kbtr} = \sum_{r=1}^{t-1} Q_{kbt-1r} + \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} - \sum_{l=1}^{L} W_{klbt}, \qquad \forall k, b, 1 < t < u_b \tag{6}$$

$$\sum_{r=t+1-u_b}^{t} Q_{kbtr} = \sum_{r=t+1-u_b}^{t-1} Q_{kbt-1r} + \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} - \sum_{l=1}^{L} W_{klbt}, \qquad \forall k, b, t \geq u_b \tag{7}$$

$$W_{klbt} = \sum_{r=1}^{t} T_{klbtr}, \quad \forall k, l, b, t < u_b \tag{8}$$

$$W_{klbt} = \sum_{r=t+1-u_b}^{t} T_{klbtr}, \qquad \forall k, l, b, t \geq u_b \tag{9}$$

$$Q_{kbtr} = \sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} - \sum_{l=1}^{L} T_{klbtr}, \quad \forall k, b, t = r \tag{10}$$

$$Q_{kbtr} = Q_{kbt-1r} - \sum_{l=1}^{L} T_{klbtr}, \quad \forall k, b, t - r < u_b \tag{11}$$

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

$$\sum_{r=1}^{t} Q'_{lbtr} = \sum_{r=1}^{t-1} Q'_{lbt-1r} + \sum_{k=1}^{K} W_{klbt} - V'_{lbt} + \sum_{\substack{l'=1 \\ l' \neq l}}^{L} S_{l'lbt} - \sum_{\substack{l'=1 \\ l' \neq l}}^{L} S_{ll'bt}, \quad \forall l, b, 1 < t < u_b \tag{13}$$

$$\sum_{r=t-u_b+1}^{t} Q'_{lbtr} = \sum_{r=t-u_b+1}^{t-1} Q'_{lbt-1r} + \sum_{k=1}^{K} W_{klbt} - V'_{lbt} + \sum_{\substack{l'=1 \\ l' \neq l}}^{L} S_{l'lbt} - \sum_{\substack{l'=1 \\ l' \neq l}}^{L} S_{ll'bt}, \quad \forall l, b, t \geq u_b \tag{14}$$

$$V'_{lbt} = \sum_{r=1}^{t} \sum_{c=1}^{C} B_{lcbtr}, \quad \forall l, c, b, t < u_b \tag{15}$$

$$V'_{lbt} = \sum_{r=t-u_b+1}^{t} \sum_{c=1}^{C} B_{lcbtr}, \qquad \forall l, c, b, t \geq u_b \tag{16}$$

$$S_{ll'bt} = \sum_{r=1}^{t} A_{l'lbtr}, \quad \forall l, l', b, t < u_b \tag{17}$$

$$S_{ll'bt} = \sum_{r=t-u_b+1}^{t} A_{l'lbtr}, \quad \forall l, l', b, t \geq u_b \tag{18}$$

$$Q'_{lbtr} = \sum_{k=1}^{K} T_{klbtr} - \sum_{c=1}^{C} B_{lcbtr} + \sum_{\substack{l'=1 \\ l' \neq l}}^{L} A_{l'lbtr} - \sum_{\substack{l'=1 \\ l' \neq l}}^{L} A_{ll'btr}, \qquad \forall l, b, t = r \tag{19}$$

$$Q'_{lbtr} = Q'_{lbt-1r} - \sum_{c=1}^{C} B_{lcbtr} - \sum_{\substack{l'=1 \\ l' \neq l}}^{L} A_{ll'btr}, \quad \forall l, b, t - r < u_b \tag{20}$$

$$\sum_{k=1}^{K} Y_{jkbt} \leq ca_{jb}Z_j, \quad \forall j,b,t \tag{21}$$

$$\sum_{k=1}^{K} W_{klbt} + \sum_{\substack{l'=1 \\ l'\neq l}}^{L} S_{l'lbt} \leq ca_{lb}Z_l, \quad \forall l,b,t \tag{22}$$

$$\sum_{j=1}^{J} Y_{jkbt} + \sum_{i=1}^{I} R_{ikbt} \leq ca_{kb}Z_k, \quad \forall k,b,t \tag{23}$$

$$V'_{lbt} = \sum_{c=1}^{C} \sigma_{cbt}Z_{lct}\left((1-\alpha)D_{cbt(2)} + \alpha D_{cbt(3)}\right), \quad \forall l,b,t \tag{24}$$

$$\sum_{v=1}^{V}\sum_{l=1}^{C\cup L} Z_{lcvt} = 1, \quad \forall c,t \tag{25}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{C\cup L}\sum_{b=1}^{B} \sigma_{cbt}Z_{lcvt}\left((1-\alpha)D_{cbt(2)} + \alpha D_{cbt(3)}\right) \leq ca_v, \quad \forall v,t \tag{26}$$

$$U_{mvt} - U_{cvt} + CZ_{mcvt} \leq C-1, \quad \forall m,c \in C,v,t \tag{27}$$

$$\sum_{c=1}^{C\cup L} Z_{lcvt} = \sum_{c=1}^{C\cup L} Z_{clvt}, \quad \forall v,t,l \in C\cup L \tag{28}$$

$$\sum_{l=1}^{L}\sum_{c=1}^{C} Z_{lcvt} \leq 1, \quad \forall v,t \tag{29}$$

$$\sum_{b=1}^{B} V'_{lbt} \leq \sum_{b=1}^{B} ca_{lb}\,Z_l, \quad \forall l,t \tag{30}$$

$$-Z_{lct} + \sum_{u=1}^{C\cup L}(Z_{luvt} + Z_{ucvt}) \leq 1, \quad \forall l,c,v,t \tag{31}$$

$$\sum_{c=1}^{C\cup L}\sum_{l=1}^{C\cup L}\left((1-\alpha)tt_{lc(1)} + \alpha tt_{lc(2)}\right)Z_{lcvt} \leq T_v, \quad \forall v,t \tag{32}$$

$$Q_{kbtr} = 0, \quad \forall k,b,t < r \tag{33}$$

$$Q'_{lbtr} = 0, \quad \forall l,b,t < r \tag{34}$$

$$X_{ijbt}, R_{ikbt}, Y_{jkbt}, W_{klbt}, S_{l'lbt}, U_{lvt}, \sigma_{cbt} \geq 0, \quad \forall i,j,k,c,l,l',b,v,t \tag{35}$$

$$B_{lcbtr}, A_{ll'btr}, T_{klbtr}, Q'_{lbtr}, Q_{kbtr} \geq 0, \quad \forall l,l',c,k,b,t,r \tag{36}$$

$$Z_j, Z_l, Z_k, Z_{lct}, Z_{lcvt} \in \{0,1\}, \quad \forall i,k,l,v,t,c,b \tag{37}$$

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 bags between centers). Equation (2) shows the second objective function including minimizing the maximum unmet demand from the distribution of blood bags to demand centers. Equation (3) represents the third objective function, and includes minimizing the amount of Co_2 gas emission by the transport of blood bags between centers and facilities. Constraint (4) shows the equilibrium relation in the transport of blood bags from blood donation clusters to main blood transfusion centers. Constraints (5) to (7) are related to the amount of blood bags 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 bag and at any time period. Constraints (8) and (9) show the transport of blood bags from the main blood transfusion centers to the central laboratory centers with regard to the perishability of the blood bags. Constraints (10) and (11) indicate the level of inventory of each blood group in the temporary storage of primary blood donation centers and constraints (12) to (14) reflect the level of inventory of each type of blood group in temporary warehouses of the primary laboratory. Constraints (15) and (16) show the amount of the transport of blood bags from the central laboratory centers to all demand points in each time period. Constraints (17) and (18) indicate the transfer of blood bags between the central laboratory centers according to the demand of the customer centers and the perishability time. Constraints (19) and (20) show the equilibrium relationship at the central laboratory centers and ensures that the blood bags are transferred to demand points before the period of blood corruptions. Constraints (21) to (23) 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 cannot be used until the center has been established. Equation (24) shows the total flow of products (demand) in the central laboratory centers for transfer to demand centers. Constraint (25) ensures that each central laboratory center can only be allocated to a blood supply center. Constraint (26) shows the maximum carrying capacity of blood bags by the available vehicle. Constraint (27) is the restriction related to the removal of the sub-tour. Constraint (28) ensures that the vehicle can only enter and exit from any demand center once. Constraints (29) to (31) ensures that the start and end routing points of vehicle in the distribution of blood bags to the demand centers are the central laboratory centers. Constraint (32) shows the time limit for the transport of blood bags to customer demand centers. Constraints (33) and (34) show the rational relationships in the inventory of blood bags in the temporary warehouses of the primary blood transfusion centers and the central laboratory. Constraints (35) to (37) show the type and gender of the decision variables.

4. Solution Method

Multi-objective optimization is one of the most active and highly applied research areas among optimization issues. Often, multi-objective optimization is also known as multi-criteria optimization and vector optimization. The purpose of multi-objective optimization is to find a set of Pareto answers is a problem that creates the right balance between different objectives. So far, several methods have been proposed to solve multi-objective optimization problems, among which intelligent optimization methods (evolutionary algorithms) have a special place because, unlike the classical methods in applied mathematics, they often solve the multi-objective optimization problems as they are, and do not use Geometric transformations and the like. Among the evolutionary and intelligent algorithms presented for solving multi-objective optimization problems, we continue to examine the NSGA II and MOPSO algorithms and generate the initial solution to solve the problem in this paper.

4.1. NSGA II Algorithm

The genetic algorithm begins by randomly generating a primitive population of chromosomes, while satisfying the boundaries or limits of the problem. In other words, chromosomes are strings of the proposed values for solution variables of the problem, each representing a probable answer to the problem. The chromosomes are deduced from successive repetitions called generations. Throughout each generation, these chromosomes are evaluated according to the optimization objective, and chromosomes that are considered to be a better response to the problem are more likely to reproduce problem solving. It is very important to formulate the chromosome assessment function in order to help accelerate the convergence of computations towards the optimal public response. Because in the genetic algorithm, for each chromosome, the amount of the evaluation function must be calculated and since in many cases with a significant number of chromosomes, in general, the timing of the calculation of the evaluation function can actually make it impossible to use the genetic algorithm on some problems, based on the values obtained by the objective function in the population of strings, each string is assigned a fitness number. This fitness number will determine the probability of selction for each string. Based on this probability, a set of strings is first selected. For generation of the next generation, new chromosomes that are called offsprings are created through the transplantation of two chromosomes from the current generation using the combinator or by chromosome modification using the mutation operator. Then new strings replace strings from the initial population so that the number of strings in the repetitive computations is constant. Random mechanisms that act on the selection and removal of strings are such that strings that are more agile are more likely to combine and produce new strings and are more resistant to the other strings during the replacement phase. In this regard, the population of sequences in a competition based on the objective function over different generations is completed and increased by the value of the objective function in the population of strings, so that after several years, the algorithm converges to the best chromosome, which hopefully represents an optimal or sub-optimal solution for the problem. In general, in this algorithm, while in each computational repetition, genetic operators search for new points of the search space, the search mechanism explores the search for areas of the space whose mean of the statistical function of the target is greater. Usually a new population which substitutes the previous one enjoys more fitness than the previous population. This means that it will improve from generation to generation. When the search is done, it will be possible to reach the maximum possible generation, either the convergence has been achieved or the stop criteria have been met, and thus the best chromosome obtained from the last generation is chosen as an estimated optimal solution or optimal solution for the problem.

4.2. MOPSO Algorithm

Kennedy and Eberhart, with the modeling of the movement of birds in the air, and the discovery of a logical relationship between the direction and speed of birds, and using the physics knowledge, proposed a method called particle mostion. The scientists later realized in their own research of the dependence of these movements, and found that the movement of a bird was due to information from birds around them. Therefore, they completed the proposed method and called it a swarm motion. In general, the particle swarm algorithm has many similarities to algorithms such as ant, or genetics algorithms, but there are also serious differences with them, which makes the algorithm more distinct and simpler. As an example, this algorithm does not use operators such as intersection and mutation. Consequently, this algorithm does not require the use of numeric strings and the decoding step, which is much simpler than algorithms such as genetics algorithm. This algorithm divides the solution space using a pseudo-probabilistic function to multi-path paths, which are formed by the motion of individual particles in space. The movement of a group of particles consists of two main components (definite and probable). Each particle is interested in the direction of the best current answer x^* or the best answer g^* obtained so far.

4.3. Initial Chromosome

In this paper, due to the high complexities of the proposed model, a new decoding based on priority, introduced by Ghahremani et al. [19], has been used. This encoding is based on a permutation of natural numbers to the length of the number of nodes in each level. Figure (2) shows the modified priority-based decoding for one of the network levels with 3 potential donor centers and 4 fixed demand centers. In Figure (2), encoding is shown in one of the levels of the supply chain network with three potential donor centers and four fixed demand centers. Encoding is based on a permutation of the number of nodes, which is shown in Figure (2) as (3-4-7-1-2-5-6) where priorities (1-2-5-6) are related to fixed demand centers and priorities (3-4-7) are related to the potential donor center. To decode, the following two steps must be taken:

Step 1: First, the highest priority is selected among the potential selected donation centers (priority 7 for the third supplier), and if this donor can respond to all customer demand, the priority of the remaining donation centers will be reduced to zero. In the example of Figure (2), the capacity of the donation center 3 equals to 1,400, whereas the total demand for customer of fixed centers is 1600. In this case, the next donation center will be selected with the next highest priority (priority 4 for the second donation center). The total capacity of the two donation centers (2900) is larger than the total demand of customer centers (1600). In this case, the priority of the first donation center will be reduced to zero.

Step 2: After determining the number and location of potential donation centers, an optimal allocation between the selected donation centers and demand centers takes place. At this step, the highest priority (priority 7 for the third supplier center) is selected and the lowest transportation cost per customer is identified with the donation center selected from the first step (fourth demand center at a cost of 26) and the minimum amount of capacity of the donation center selected and the designated customer as the optimal allocation value is determined. After updating the remaining capacity or unsuccessful demand, the priority value is reduced to zero. As long as all the priorities are not reduced to zero, the second step is repeated.

Node	Capacity	Demand
1	1200	400
2	1500	450
3	1400	350
4	-	400

Cost-transportation

Node	1	2	3	4
1	22	38	34	36
2	32	28	36	30
3	30	32	38	26

$v(K+J)$

Node	1	2	3	1	2	3	4
Priority	3	4	7	1	2	5	6

⇩

$v(K+J)$

Node	1	2	3	1	2	3	4
Priority	0	4	7	1	2	5	6

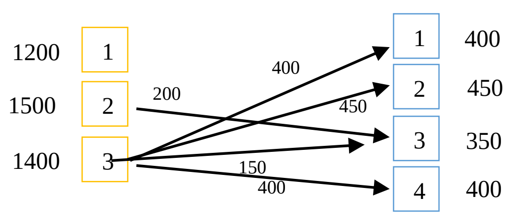

Fig. 2. Encoding and decoding based on modified priority [20]

5. Computational results

In this section, in order to solve the sample problems, 15 sample problems according to Table (1) 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 (2). 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.

Table 1. The size of the designed Sample problems

Sample problem	i	j	k	l, l'	m, c	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 boundaries of the parameters produced on the basis of uniform distribution

Deterministic parameter	Interval boundaries	Deterministic parameter	Interval boundaries
G_j	~U (10000‹20000)	$co2_{ij}$	~U (50‹200)
H_k	~U (20000‹30000)	$co2_{lc}$	~U (50‹200)
U_l	~U (50000‹60000)	$co2_{ik}$	~U (50‹200)
F_v	~U (200‹300)	$co2_{jk}$	~U (50‹200)
h_{kb}	~U (1‹2)	$co2_{kl}$	~U (50‹200)
h'_{lb}	~U (1‹2)	$co2_{ll'}$	~U (50‹200)
C_{lb}	~U (10‹20)	ca_{jb}	~U (300‹500)
T_v	~U (500‹1000)	ca_{kb}	~U (300‹500)
u_b	~U (1‹3)	ca_{lb}	~U (300‹400)
		ca_v	~U (500‹800)
Non-deterministic parameter		**Interval boundaries**	
D_{cbt}		~U ((150‹180)‹(120‹150)‹(120‹100))	
tt_{lc}		~U ((20‹30)‹(15‹20)‹(10‹15))	
$T_{ij}, T_{ik}, T_{jk}, T_{kl}, T_{ll'}, T_{lc}$		~U ((20‹30)‹(10‹20)‹(10‹5))	

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 (38). Given that the criteria do not have the same importance, the weight coefficients used for them are determined according to Table (3).

Table 3. Weight of assessment criteria for calculating the response variable

Criteria	NPF	MSI	SM	SI	CPU Time
Weights	1	2	2	2	1

$$R_i = \frac{w_1\overline{RPD_1} + w_2\overline{RPD_2} + \cdots + w_n\overline{RPD_n}}{w_1 + w_2 + \cdots + w_n} \tag{38}$$

The factors and operating levels used for the NSGA-II and MOPSI algorithms are defined according to Table (4):

Table 4. The optimal levels of the factor used for the NSGA-II algorithm

Algorithm	Parameter	Level of factor 1	Level of factor 2	Level of factor 3	Level of optimal factor
NSGA II	nPop	50	**70**	100	70
	pc	**0.2**	0.5	0.8	0.2
	pm	**0.2**	0.3	0.4	0.2
MOPSO	nParticle	50	75	**100**	100
	nRep	**70**	100	150	70
	W	0.5	0.6	**0.7**	0.7
	C1	**1**	1.25	1.5	1
	C2	**1**	1.25	1.5	1

After determining the optimal parameters of the meta-heuristic algorithms and their adjustment, the sample problems are solved by the meta-heuristic algorithms and the average results are selected as the basis of the comparison. Table (5) and (6) show the average of 5 problems designed for each sample problem in different sizes. This table contains the mean of the first, second, and third objective functions as well as the mean of multi-objective meta-analysis algorithms (number of effective responses, maximum exponent, metric distance index, and computational time).

Table 5. The mean of objective functions and comparison indices in solving with NSGA II algorithm

Sample problem	Objective function 1 (Dollar)	Objective function 2 (Number)	Objective function 3 (Kg)	NPF	MSI	SM	CPU time
1	533806.72	67.21	626021.7	9	270273.91	0.37	36.46
2	778692.87	70.65	1183581.5	19	585593.25	0.77	108
3	881581.31	71.63	1254446.7	20	479316.63	0.7	170.3
4	1033814.6	69.74	1500880.8	14	850298.87	0.57	242.53
5	1674913.5	73.77	2738382.1	14	1129077.8	0.41	335.5
6	2369557.6	75.81	3742531.8	22	1508175.5	0.55	434.4
7	2500890.6	75.05	4255514.3	23	1797128	0.53	545.77
8	3416474.1	76.62	5820890.5	18	2739770.1	0.57	669.07
9	4301936	76.63	7502772.8	21	2529228.6	0.4	819.6
10	4860023.4	75.96	8698211.2	23	3529017.4	0.75	959.67
11	5040590.1	76.69	8939161	23	3087180.7	0.74	1040.13
12	8540218.4	77.88	15083483	23	4883033.1	0.69	1326
13	8887924.2	77.42	15628763	30	3839628.2	0.66	1528.37
14	10361986	77.46	19331574	21	4564822.6	0.77	1802.27
15	12608666	78.02	23272981	24	5383709.7	0.87	2640

Table 6. The mean of objective functions and comparison indices in solving with MOPSO algorithm

Sample problem	Objective function 1 (Dollar)	Objective function 2 (Number)	Objective function 3 (Kg)	NPF	MSI	SM	CPU time
1	495858.69	70.1	605637.22	8	109850.13	0.46	34.4
2	776699.89	68.99	1110774.6	14	329845.53	0.62	39.07
3	871134.25	68.48	1296974	8	370471.43	0.23	51.66
4	1046187.5	69.15	1444397	16	463108.57	0.59	95.93
5	1653146.4	74.62	2780052.9	18	817523.73	0.35	131.2
6	2353344.2	74.41	3954175.9	23	1526123.7	0.49	280.5
7	2450251.7	75.41	4339170.4	16	2008648.7	0.55	349.16
8	3434001.9	76.71	6063469.1	31	2559860.1	0.75	494.7
9	4334688.4	76.19	7482226	28	3694417.3	0.64	723.16
10	4817592.1	76.79	8017340.4	19	2215230.1	0.59	980.4
11	5020566.3	75.34	8757922.6	12	2437807.9	0.76	1328.75
12	8500502.4	78.06	14956724	25	3887334.5	0.44	1834.56
13	8759033.2	77.5	15871173	12	3757576.1	0.72	2337.3
14	10251099	77.66	19121379	12	4593286.9	0.66	2983.04
15	12554017	77.53	22872852	17	5138916	0.51	3957.9

Tables (5) and (6) show the average of the results obtained from solving the sample problems with meta-heuristic algorithms. According to results, it can be concluded that the MOPSO algorithm has better results than the NSGA II algorithm for the sample problems (12) to (15). This shows that in the very large dimensions, the efficiency of the MOPSO algorithm will be greater in achieving the results of the first objective function. Also, the result illustrates the comparison of the means of the second objective function in different sample problems. Therefore, we cannot easily comment on the efficiency of the algorithm in obtaining the results of the second objective function. At the end, according to Table (5) and (6), the means of the third objective function obtained by the proposed algorithms are close to each other in different sample problems. It can only be seen that in sample problems (14) and (15), NSGA II algorithm has gained better solutions that the NSGA II algorithm. The NSGA II algorithm is expected to have higher efficiency in achieving the results of the third objective function than in the MOPSO algorithm. Given Tables (5) and (6), it can be seen that computational time increases exponentially with increasing sample size, which is the reason for the NP-Hard problem. However, the MOPSO algorithm for medium sized problems is better than the computational time of the NSGA II algorithm, but with increasing size, the computational time gained by this algorithm has been greatly increased.

A sample of the Pareto front obtained by solving the sample problem 1 using meta-heuristic algorithms NSGA II and MOPSO shown in Figure (3). These efficient solutions of the objective functions are presented in pairs alongside each other

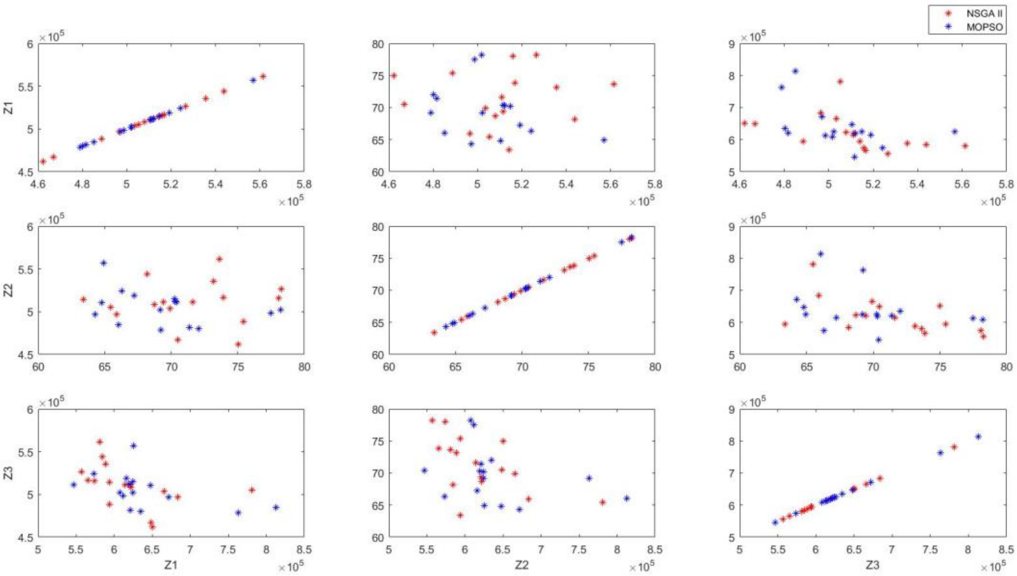

Fig. 3. Pareto Front obtained from solving the sample problem 1 using NSGA II and MOPSO Algorithms

According to the results obtained from the t-test on the mean of objective functions and 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 NSGA II and MOPSO. Given the P-value of other indices, there is no significant difference between their means. Therefore, for determining the most efficient algorithm, a multi-criteria decision making method is used as a comprehensive criterion. In this way, the means of all indices are determined from all sample problems and the basis for a general comparison of algorithms is selected. If the value of objective functions, the metric distance index and algorithm computing time is less and the indicator of the metric distance and the number of responses are efficient, then the algorithm will be efficient.

6. Conclusions and suggestions

In this paper, a location-routing-allocation problem in a blood supply chain network was designed and modeled in terms of uncertainty and considering the perishability nature of blood. Three opposing objective functions considered for this model were to minimize the cost of the entire supply chain network, minimize the maximum unmet demand and minimize greenhouse gas emissions. At first, a non-deterministic model of the problem was designed and demand parameters, transport costs, and the time of blood transport were considered uncertain and a robust optimization model was presented for controlling non-deterministic parameters. Then, 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 functions, and the meta-heuristic algorithm comparisons (the number of efficient responses, the most exponential index, the metric distance index, 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 first objective function obtained from solving sample problems using NSGA II and MOPSO algorithms. Then, in order to determine the most efficient algorithm, the TOPSIS multi-criteria decision-making method was used and the most efficient algorithm was determined. The output result indicated the efficiency of the NSGA II algorithm with a weight gain of 0.6905 as opposed to the MOPSO algorithm with a weight of 0.3095. So, in general, considering all the indices, the NSGA II algorithm was more efficient than the MOPSO algorithm in solving the location-routing-allocation problem in a blood supply chain network. Suggestions for future research are listed below:

1. Using other multi-objective meta-heuristic algorithms such as multi-objective 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 blood supply chain network designed in a case study
5. Using the DEA method to select the optimal solutions among from the efficient solutions

References

[1] Nahr, J. G., Bathaee, M., Mazloumzadeh, A., & Nozari, H. (2021). Cell Production System Design: A Literature Review. *International Journal of Innovation in Management, Economics and Social Sciences*, *1*(1), 16-44. https://doi.org/10.52547/ijimes.1.1.16

[2] Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2021). The Ideas of Sustainable and Green Marketing Based on the Internet of Everything—The Case of the Dairy Industry. *Future Internet*, *13*(10), 266. https://doi.org/10.3390/fi13100266

[3] Nory, F., & Ghahremani Nahr, J. (2019). Robust-possibilistic optimization method at design of a pharmaceutical supply chain network under uncertainty and discount on purchase the raw material. *Journal of Modeling in Engineering*, *17*(58), 249-266. DOI: 10.22075/jme.2019.13798.1358

[4] Jabbarzadeh, A., Fahimnia, B., & Seuring, S. (2014). Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. Transportation Research Part E: Logistics and Transportation Review, 70, 225-244 .https://doi.org/10.1016/j.tre.2014.06.003

[5] Ghahremani Nahr, J., Ghodratnama, A., IzadBakhah, H. R., & Tavakkoli Moghaddam, R. (2019). Design of multi-objective multi-product multi period green supply chain network with considering discount under uncertainty. *Journal of Industrial Engineering Research in Production Systems*, *6*(13), 119-137. DOI: 10.22084/ier.2017.8877.1421

[6] Nahr, J. G., Nozari, H., & Sadeghi, M. E. (2021). Green supply chain based on artificial intelligence of things (AIoT). *International Journal of Innovation in Management, Economics and Social Sciences*, *1*(2), 56-63. https://doi.org/10.52547/ijimes.1.2.56

[7] Van Zyl, G. J. (1963). Inventory control for perishable commodities. North Carolina State University. Dept. of Statistics .

[8] Sampson, M., Kong, C., Patel, A., Unwin, R., & Jacobs, H. S. (1996). Ambulatory blood pressure profiles and plasminogen activator inhibitor (PAI-1) activity in lean women with and without the polycystic ovary syndrome. Clinical endocrinology, 45(5), 623-629 .

[9] Hinojosa, Y., Puerto, J., & Fernández, F. R. (2000). A multiperiod two-echelon multicommodity capacitated plant location problem. European Journal of Operational Research, 123(2), 271-291 . https://doi.org/10.1016/S0377-2217(99)00256-8

[10] Daskin, M. S., Coullard, C. R., & Shen, Z. J. M. (2002). An inventory-location model: Formulation, solution algorithm and computational results. Annals of operations research, 110(1), 83-106 . https://doi.org/10.1023/A:1020763400324

[11] Shen, Z. J. M., Coullard, C., & Daskin, M. S. (2003). A joint location-inventory model. Transportation science, 37(1), 40-55 .

[12] Pereira, A. (2005). Blood inventory management in the type and screen era. Vox sanguinis, 89(4), 245-250 . https://doi.org/10.1111/j.1423-0410.2005.00700.x

[13] Fahimnia, B., Jabbarzadeh, A., Ghavamifar, A., & Bell, M. (2015). Supply chain design for efficient and effective blood supply in disasters. International Journal of Production Economics . https://doi.org/10.1016/j.ijpe.2015.11.007

[14] Ghasemi, S. E., Hatami, M., Hatami, J., Sahebi, S. A. R., & Ganji, D. D. (2016). An efficient approach to study the pulsatile blood flow in femoral and coronary arteries by Differential Quadrature Method. Physica A: Statistical Mechanics and its Applications, 443, 406-414 .https://doi.org/10.1016/j.physa.2015.09.039

[15] Osorio, A. F., Brailsford, S. C., Smith, H. K., Forero-Matiz, S. P., & Camacho-Rodríguez, B. A. (2017). Simulation-optimization model for production planning in the blood supply chain. Health care management science, 20(4), 548-564 .https://doi.org/10.1007/s10729-016-9370-6

[16] Ensafian, H., Yaghoubi, S., & Yazdi, M. M. (2017). Raising quality and safety of platelet transfusion services in a patient-based integrated supply chain under uncertainty. Computers & Chemical Engineering, 106, 355-372 . https://doi.org/10.1016/j.compchemeng.2017.06.015

[17] Zahiri, B., & Pishvaee, M. S. (2017). Blood supply chain network design considering blood group compatibility under uncertainty. International Journal of Production Research, 55(7), 2013-2033 . https://doi.org/10.1080/00207543.2016.1262563

[18] Habibi-Kouchaksaraei, M., Paydar, M. M., & Asadi-Gangraj, E. (2018). Designing a bi-objective multi-echelon robust blood supply chain in a disaster. Applied Mathematical Modelling, 55, 583-599 . https://doi.org/10.1016/j.apm.2017.11.004

[19] Ghahremani Nahr, J., Kian, R., & Rezazadeh, H. (2018). A modified priority-based encoding for design of a closed-loop supply chain network using a discrete league championship algorithm. *Mathematical problems in engineering*, *2018*. https://doi.org/10.1155/2018/8163927

[20] Ghahremani-Nahr, J., Kian, R., & Sabet, E. (2019). A robust fuzzy mathematical programming model for the closed-loop supply chain network design and a whale optimization solution algorithm. *Expert systems with applications*, *116*, 454-471. https://doi.org/10.1016/j.eswa.2018.09.027