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Presenting a Mathematical Model for a Sustainable Blood Supply Chain Considering Demand Uncertainty in Disasters

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ABSTRACT

A blood supply chain is one of the most important parts of a healthcare system. Any improvement in the performance of the blood supply chain can significantly increase its efficiency. In the present study, a multi-objective optimization model was used to design a blood supply chain network that minimizes the blood delivery time and the total supply chain cost. This model considered the penalty for CO_2 emission considering the environmental aspect of the blood supply chain. Due to uncertainty in supply and demand, the uncertainty model was changed into a deterministic model using a robust possibilistic programming method. Then, the multi-objective model was converted into a single-objective model using the ε-constraint method and was solved in GAMS software. The SA metaheuristic algorithm was used to validate the model. Comparing the results on a small scale showed that the SA algorithm performed better in the first objective function and the product delivery time was less. However, in the second objective function, the performance of the epsilon constraint method was better.

1.Introduction

In the realm of healthcare logistics, especially within the intricate network of blood supply chains, the uncertainty surrounding blood demand presents a significant challenge. The dynamic and unpredictable nature of blood requirements can result in inefficiencies, stockouts, and potential wastage if not effectively managed. Such shortages can severely affect society, healthcare systems, and individuals. Delays in critical medical procedures, surgeries, and treatments that necessitate blood transfusions can expose patients to high-risk treatment processes. To tackle this issue, various methodologies have been developed to enhance the resilience and responsiveness of blood supply chains in light of fluctuating demand patterns.

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This paper focuses on the application of a specific mathematical method to mitigate the inherent uncertainty in blood supply chains. By exploring and implementing strategies that address this variability, the goal is to improve the overall effectiveness and efficiency of blood distribution management. This approach aims to ensure a reliable and sustainable supply chain of blood products, minimize the overall cost of the supply chain while considering environmental sustainability aspects, and meet the needs of patients promptly.

The structure of the current research is as follows. In Section 3, the developed model is presented. This section includes a description of the problem, a presentation of the proposed mathematical model, and the research methodology to cope with demand uncertainty. Section 4 analyzes the performance of the proposed mathematical model through numerical examples and validates the results using a meta-heuristic algorithm (Simulated Annealing). Sensitivity analysis is conducted to examine the model's performance using a sensitivity analysis approach. Finally, Section 5 presents the research results.

2. literature Review

2.1. Review and classify literature review

Blood is a scarce and precious resource all over the world. Similar to any perishable goods, blood is vital. Therefore, blood inventories should be managed well to minimize wastage since the wastage of each blood unit might not only lead to economic issues but also waste donors' time and energy (Yates et al., 2017). Balancing blood supply and demand efficiently poses a significant challenge. Blood and its derivatives, being perishable commodities, further complicate this delicate equilibrium. The repercussions of blood shortages extend far beyond logistics, with society bearing a heavy burden in the form of increased mortality rates. Consequently, the development of a well-structured blood supply chain emerges as a crucial imperative. This intricate network encompasses a multitude of tasks—ranging from collection and transportation to testing and distribution. By meticulously orchestrating a comprehensive blood donation program, ensuring stringent safety protocols, and streamlining blood transportation to designated facilities such as hospitals and medical centers, organizations not only curtail operational expenses but also elevate service standards and satisfaction levels for recipient centers.

In addition to that, the blood supply chain is a key section in the healthcare system which accounts for a large share of the healthcare costs; Therefore, any improvement in the performance of the blood supply chain can lead to significantly improved efficiency and reduced healthcare costs. The blood supply chain includes the whole process of blood collection, processing, and transportation to hospitals to meet patient demands. The blood units collected in different locations are sent to blood centers 4-6 hours after blood collection. Blood is then separated into its components and screened for infections and various diseases. After this stage, which lasts for about two days, healthy blood units are transported to hospitals and surgical centers for health purposes (Hamdan and Diabat, 2020).

Another key aspect to consider in the supply chain is sustainability. A sustainable supply chain emphasizes both profitability and the long-term impacts of supply chain operations, ensuring the sustainability of resources for the future. Such a supply chain integrates social and environmental considerations into all processes. Within the blood supply chain, these processes encompass the entire lifecycle from blood collection through storage, distribution, and delivery. A sustainable blood supply chain represents a business strategy that adapts the logistics network based on environmental factors, risks, and waste management. Notably, there has been significant progress in enhancing environmental integrity through the management of sustainable blood supply chains, marking a new approach that has reshaped operations management in recent years.

Various studies have been conducted on the blood supply chain in recent years. Cetin and Sarul (2009) used a joint mathematical programming model which is a combination of the center of gravity continuous location model and the set covering discrete location model. The objective function was formulated using the non-linear goal programming technique and aimed to reduce the distance between blood banks and hospitals and also the fixed costs of blood bank location allocation. An inequality index was also used in this study. Fahimnia et al. (2017) designed an efficient and effective supply chain network for disasters to study the two objective functions of cost and time. They used a hybrid approach and combined the epsilon constraint and Lagrangian relaxation methods to solve the model. Ramezanian & Behboodi (2017) studied designing a blood supply chain network under uncertain supply and demand and based on social aspects. This study considers the distance between blood donors and blood centers, the experiences of blood donors in medical centers (the behavior and skill level of the technical staff), and incentives (marketing budget of blood centers) as effective factors in blood donation. Since blood donation is a voluntary activity, it is difficult to encourage people to donate blood. There has been a significant focus on a blood supply chain for natural disasters in recent years. Natural disasters, such as earthquakes might have undesirable consequences like damage and casualties, and reduce the effectiveness of healthcare services. The study conducted by Khalilpourazari et al. (2020) presented a six-echelon blood supply chain that consists of blood donors, blood collection centers (mobile and permanent), regional blood centers, local blood centers, regional hospitals, and local hospitals. It was the first study to propose that helicopters could transport blood from regional to local hospitals. In addition to that, the injured people who could not be treated in local hospitals due to limited capacity could be sent back to regional hospitals. Furthermore, different transportation modes were considered with limited capacity, and the optimal number of required transportation equipment was determined following the problem solution. The importance of blood is further understood during natural disasters due to its vital role in saving lives. Rahmani (2019) presented a robust and reliable model for designing a dynamic emergency blood supply chain network. A p-criterion technique was used to protect the solution against disruption risks. Moreover, a numerical example was used extensively to show the effect of disruption scenarios. The functionality of the proposed model was analyzed using a series of test problems of various sizes. The results indicated that the model had a satisfactory function.

2.2. Research Gap

The present study aims to design a multi-objective and sustainable blood supply chain under uncertainty. The contributions of the proposed method are as follows:

1. Designing a blood supply chain model based on a sustainability approach
2. Considering demand uncertainty based on the robust possibilistic programming approach
3. Validating the research results using a meta-heuristic algorithm (Simulated Annealing)

Table 1. A review of studies in the related areas

Authors	Year of Publication	Mathematical Model		Blood Supply Chain	Multi-period	Sustainability			Uncertainty			Case Study
		Single-objective	Multi-objective			Economic	Social	Environmental	Robust	Possibilistic	Fuzzy	
Cetin & Sarul	2009	✓		✓								✓
Fahimnia et al.	2017		✓	✓	✓							
Ramezanian & Behboodi	2017	✓		✓			✓		✓			
Hamdan & Diabat	2020		✓	✓					✓			
Khalilpourazari et al.	2020		✓	✓	✓							✓
Rahmani	2019	✓		✓		✓			✓			
The Present Study			✓	✓	✓	✓		✓			✓	

3. Problem statement

3.1. Proposed Model

The present study aims to design a multi-objective and sustainable blood supply chain model under uncertainty. Due to the uncertainty in supply and demand, a robust possibilistic programming approach was considered to deal with blood demand uncertainty. The sustainability concept was also considered in the objective functions of the proposed model. The objective functions of the proposed supply chain model are: 1) Minimizing the total costs of the blood supply chain, 2) minimizing the blood delivery time, and 3) minimizing the environmental costs of transporting blood by vehicles.

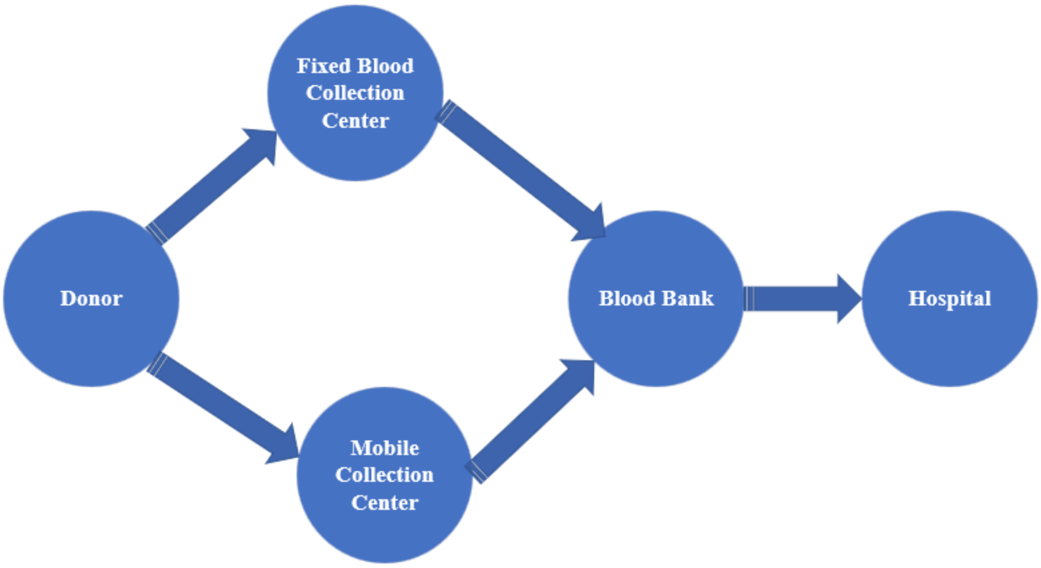

Figure1. Blood Supply Chain Network

Assumptions:

The assumptions of the proposed model are as follows:

I. The capacity for holding blood products is limited.
II. Only one of the mobile collection centers or fixed collection centers can be located in each area.
III. Hospitals' demand is discretized for different scenarios.
IV. In the proposed model, demand is considered under uncertainty.
V. The model is developed in a multi-product condition.

Indices:

M	The set of blood derivatives (products) m
I	The set of blood donation sites i
J'	The set of permanent blood collection sites j'
J''	The set of candidate sites for mobile blood collection facilities (SCV) j''
J	The set of possible sites for mobile or permanent blood collection centers j
K	The set of blood banks k
L	The set of hospitals and healthcare centers ϑ

S	The set of disruption scenarios *s*
T	The set of time periods *t*
R	The set of routes between network nodes *r*

Parameters:

O	Fixed cost of establishing mobile blood collection centers
q	Equipment cost of permanent blood collection centers: equal cost for all permanent centers
N	The total number of permanent blood collection sites and candidate sites for mobile blood collection centers. The number of permanent blood collection sites is indicated with *n*, whereas the number of candidate sites for blood collection facilities is indicated with $N - n$
LT_m	The shelf life of blood product *m*
e_k	The capacity of blood bank *k*
c_j	The capacity of blood collected by the permanent blood collection centers at point *j*
f_j	The capacity of blood collected by the mobile blood collection centers at point *j*
p_{mit}^s	The maximum supply of blood product *m* at point *i* at period *t* for scenario *s*
$d_{m\vartheta t}^s$	Demand for blood product *m* at hospital ϑ at period *t* for scenario *s*
$ti_{\vartheta t}$	Blood transportation time from blood banks in all provinces to hospital ϑ at period *t*
β_{kt}^s	It equals 1 if the blood bank *k* is not disrupted at period *t* for scenario *s*, otherwise, it equals 0
α_{jt}^s	It equals 1 if the permanent blood collection center *j* is not disrupted at period *t* for scenario *s*, otherwise, it equals 0
δ_{jkrt}^s	It equals 1 if there is no disruption at route *r* between blood collection center *j* and blood bank *k* at period *t* for scenario *s*, otherwise, it is 0
π^s	Probability of scenario *s*
t'_{jkr}	Travel time from blood collection center *j* to blood bank *k* using route *r*
$t''_{k\vartheta}$	Travel time from blood bank *k* to hospital ϑ
$PC_{J''}$	Penalty rate for CO_2 emission caused by each mobile blood collection facility (SCV)

LT_{PC}	Maximum carbon budget

Variables:

V^s_{mkt}	The inventory level of blood product *m* at blood bank *k* at the end of period *t* for scenario *s*
F^s_{mjktr}	The amount of blood product *m* delivered from blood collection center *j* to blood bank *k* using route *r* at period t for scenario *s*
$U^s_{mk\vartheta t}$	The amount of blood product *m* transfused to the hospital ϑ at period *t* for scenario *s* after being delivered from blood bank *k*
G^s_{mijt}	The amount of blood product *m* donated at point *i* at period *t* to transport to blood collection center *j* for scenario *s*
$H^s_{m\vartheta t}$	The amount of blood product *m* transfused from blood banks in other regions to hospital ϑ at period t for scenario *s*
O^s_{mkt}	The amount of expired blood product *m* at blood bank *k* at period *t* for scenario *s*
Z_j	It equals 1 if the permanent blood collection center *j* is well-equipped, otherwise, it is 0
Y^s_{jt}	It equals 1 if the mobile blood collection center opens at site *j* at period *t* for scenario *s*, otherwise, it is 0
X^s_{jktr}	It equals 1 if the blood collection center *j* is allocated to blood bank *k* at period *t* for scenario s using route *r*, otherwise, it is 0
W^s_{ijt}	It equals 1 if blood donors at location *i* are assigned to blood collection center *j* at period *t* for scenario *s*, otherwise, it equals 0

$$Minimize\ F_1 = \sum_{m,j,k,t,r,s} \pi^s F^s_{mjktr} t'_{jkr} + \sum_{m,k,\vartheta,t,s} \pi^s U^s_{mk\vartheta t} t''_{k\vartheta} + \sum_{m,\vartheta,t,s} \pi^s H^s_{m\vartheta t}\, ti_{\vartheta t} \quad (1)$$

$$Minimize\ F_2 = \sum_{s,t} \sum_{j\in J''} o\ \pi^s Y^s_{jt} + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''}\ \delta^s_{jkrt}\, \beta^s_{kt}\, Y^s_{jt}\, X^s_{jktr} \quad (2)$$

subject to:

$$\sum_{k,t,r,s} PC_{J''}\ \delta^s_{jkrt}\, \beta^s_{kt}\, Y^s_{jt}\, X^s_{jktr} \le LT_{PC} \qquad \forall j \in J'' \quad (3)$$

$$G^s_{mijt} \le p^s_{mit}\, W^s_{ijt} \qquad \forall\ m, i, j, t, s \quad (4)$$

$$\sum_{j} G^{s}_{mijt} \leq p^{s}_{mit} \qquad \forall\, m, i, t, s \tag{5}$$

$$\sum_{i}\sum_{m} G^{s}_{mijt} \leq c_j\, Z_j + f_j\, Y^{s}_{jt} \qquad \forall j, t, s \tag{6}$$

$$Z_j + Y^{s}_{jt} \leq 1 \qquad \forall j, t, s \tag{7}$$

$$W^{s}_{ijt} \leq \alpha^{s}_{jt}\, Z_j + Y^{s}_{jt} \qquad \forall i, j, t, s \tag{8}$$

$$\sum_{k}\sum_{r} F^{s}_{mjktr} \leq \sum_{i} G^{s}_{mijt} \qquad \forall m, j, t, s \tag{9}$$

$$\sum_{j}\sum_{r}\sum_{m} F^{s}_{mjktr} \leq e_k\, \beta^{s}_{kt} \qquad \forall k, t, s \tag{10}$$

$$X^{s}_{jktr} \leq \alpha^{s}_{jt}\, \beta^{s}_{kt}\, \delta^{s}_{jkrt}\, Z_j \qquad \forall k, t, r, s\,, \forall j \in J' \tag{11}$$

$$X^{s}_{jktr} \leq Y^{s}_{jt}\, \beta^{s}_{kt}\, \delta^{s}_{jkrt} \qquad \forall k, t, r, s\,, \forall j \in J'' \tag{12}$$

$$\sum_{r} X^{s}_{jktr} \leq 1 \qquad \forall k, t, r, s\,, \forall j \in J'' \tag{13}$$

$$\sum_{m} F^{s}_{mjktr} \leq c_j\, X^{s}_{jktr} \qquad \forall j \in J', \forall k, t, r, s \tag{14}$$

$$\sum_{m} F^{s}_{mjktr} \leq f_j\, X^{s}_{jktr} \qquad \forall j \in J'', \forall k, t, r, s \tag{15}$$

$$\sum_{m}\sum_{\vartheta} U^{s}_{mk\vartheta t} \leq e_k\, \beta^{s}_{kt} \qquad \forall k, t, s \tag{16}$$

$$d^{s}_{m\vartheta t} - \sum_{k} U^{s}_{mk\vartheta t} = H^{s}_{m\vartheta t} \qquad \forall m, \vartheta, t, s \tag{17}$$

$$V^{s}_{mkt-1} + \sum_{j}\sum_{r} F^{s}_{mjktr} = V^{s}_{mkt} + \sum_{\vartheta} U^{s}_{mk\vartheta t} + O^{s}_{mkt} \qquad \forall t \geq 2, m, k, s \tag{18}$$

$$O^{s}_{mkt} = \max\left\{0, V^{s}_{mkt-LT_m} - \sum_{\vartheta}\sum_{p=t-LT_m} U^{s}_{mk\vartheta p} - \sum_{p=t-LT_m} O^{s}_{mkp}\right\} \qquad \forall \geq 2, m, k, s \tag{19}$$

$$\sum_{j\epsilon j'} Y^{s}_{jt} \leq N - n \qquad \forall t, s \tag{20}$$

$$\sum_{m} V_{mkt}^{s} \leq e_k \qquad \forall\, k,t,s \tag{21}$$

$$V_{mkt}^{s}, F_{mjktr}^{s}, U_{mk\vartheta t}^{s}, G_{mijt}^{s}, H_{m\vartheta t}^{s}, O_{mkt}^{s} \geq 0 \qquad \forall m,i,j,k,t,r,s,\vartheta \tag{22}$$

$$Z_j, Y_{jt}^{s}, X_{jktr}^{s}, W_{ijt}^{s} \in \{0,1\} \qquad \forall m,i,j,k,t,r,s,\vartheta \tag{23}$$

The developed mathematical model consists of two objective functions. The first objective function represents the minimization of expected delivery time, which is composed of three components. The first term corresponds to the transfer time from blood collection centers to blood banks. The second term represents the transportation time from the blood bank to hospitals, and the third term represents the transportation time from blood banks in other provinces to hospitals. The second objective function minimizes the overall costs of the blood supply chain, including the fixed equipment costs for blood collection centers, the cost of establishing new mobile blood collection centers, and the cost of carbon dioxide emissions. In other words, this objective function addresses the economic and environmental sustainability aspect, minimizing the total costs associated with the supply chain and carbon emissions.

In the proposed model, Constraint (3) limits the maximum amount of carbon dioxide (CO_2) emissions. Constraints (4) and (5) restrict the amount of blood donation from each urban area to prevent exceeding the maximum blood supply of donors for each blood product. Constraint (6) ensures that the blood collection capacity at each center is not exceeded. Constraint (7) ensures that at most one fixed or mobile blood collection center is established at any given location. Constraint (8) ensures that donors can only be assigned to designated mobile units or fixed blood collection centers that are equipped and operational. Constraint (9) limits the output of blood from blood collection centers to avoid exceeding the collected blood amount. Constraint (10) enforces capacity constraints on each blood bank and sets the capacity of unstable centers to zero. Constraint (11) ensures that fixed blood collection centers are only assigned to blood banks with unobstructed facilities and routes between these centers. Constraint (12) ensures that if a mobile blood collection center is assigned to a specific blood bank, facilities cannot be obstructed. Constraint (13) allocates a route between each blood collection center and blood bank. Constraints (14) and (15) ensure that blood products cannot be transferred from a blood collection center or a mobile blood collection center to a blood bank not assigned to it. Constraint (16) ensures that a blood bank can only be assigned to a hospital that is unobstructed. Constraint (17) determines the amount of blood products delivered to each hospital from blood banks in other provinces. Constraint (18) represents inventory balance constraints in blood banks. Constraint (19) determines the number of outdated units in each period. Constraint (20) ensures that the number of mobile blood collection facilities in each period does not exceed the number of candidate locations for mobile blood collection facilities. Constraint (21) restricts the capacity of blood banks for blood storage. Finally, Constraints (22) and (23) define the range of decision variables.

3.2. Solution Method

3.2.1 Uncertainty Based on Robust Possibilistic Programming Approach

One of the most important issues in responding to a crisis is satisfying demands for the required items. The demand uncertainty leads to a lot of problems in this area. In the present research, a robust possibilistic programming model is considered to cope with demand uncertainty. In the proposed model, objective functions will be considered for trapezoidal fuzzy numbers and a robust possibilistic programming approach will be used to model the uncertainty parameter ($d^s_{m\vartheta t}$) and constraint (17):

$$Minimize\ \ E(Z_i) = E(c)x + E(\widetilde{B})y \tag{24}$$

$$Nec(\tilde{A}_1 x \leq B_1) \geq \alpha_1 \tag{25}$$

$$Nec(A_2 x \leq \tilde{B}_2) \geq \alpha_2 \tag{26}$$

$$Nec(\tilde{A}_3 x + R_1 y \leq \tilde{B}_3) \geq \alpha_3 \tag{27}$$

$$Nec(\tilde{R}_2 y = \tilde{B}_4) \geq \alpha_4 \tag{28}$$

$$y \in \{0,1\}\ , x \geq 0 \tag{29}$$

Based on the relation above, the basic robust possibilistic programming approach used to solve the proposed model based on the uncertainty of constraint (17) has been shown below. In this section, constraint (17) is converted into two constraints:

$$Minimize\ F_2 = \sum_{s,t} \sum_{j \in J''} o\ \pi^s\ Y^s_{jt} + \sum_{j \in J'} q\ Z_j + \sum_{j,k,t,r,s} PC_{J''}\ \delta^s_{jkrt}\ \beta^s_{kt}\ Y^s_{jt}\ X^s_{jktr} \tag{30}$$

$$\frac{\alpha_1}{2} d^s_{m\vartheta t(2)} + \left(1 - \frac{\alpha_1}{2}\right) d^s_{m\vartheta t(1)} - \sum_k U^s_{mk\vartheta t} \leq H^s_{m\vartheta t} \qquad \forall m, \vartheta, t, s \tag{31}$$

$$\frac{\alpha_1}{2} d^s_{m\vartheta t(3)} + \left(1 - \frac{\alpha_1}{2}\right) d^s_{m\vartheta t(4)} - \sum_k U^s_{mk\vartheta t} \geq H^s_{m\vartheta t} \qquad \forall m, \vartheta, t, s \tag{32}$$

In the presented model, the parameter $d^s_{m\vartheta t}$ is considered a trapezoidal fuzzy number. In other words, $\tilde{d}_m = (d^s_{m\vartheta t(1)}, d^s_{m\vartheta t(2)}, d^s_{m\vartheta t(3)}, d^s_{m\vartheta t(4)})$. Therefore, the standard form of the robust possibilistic programming approach is used to rewrite equations and $E(Z)$, Z_{max}, and Z_{max} as follows. In the equation below, β and γ values are set as cost coefficients and are considered due to uncertainty in the model. Additionally, β′ and β values are applied as penalty values for constraints involving uncertainty.

$$Minimize\ Z = E(Z) + \gamma\left(Z_{max} - Z_{min}\right) + \beta\left[d^{s}_{m\vartheta t(2)} - \left(1 - \frac{\alpha_1}{2}\right) d^{s}_{m\vartheta t(1)} - \frac{\alpha_1}{2} d^{s}_{m\vartheta t(2)}\right] + \beta'\left[\frac{\alpha_1}{2} d^{s}_{m\vartheta t(3)} + \left(1 - \frac{\alpha_1}{2}\right) d^{s}_{m\vartheta t(4)} - d^{s}_{m\vartheta t(3)}\right] \tag{33}$$

$$E(z) = \sum_{s,t}\sum_{j\in J''} o\ \pi^{s}\, Y^{s}_{jt} + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''}\, \delta^{s}_{jkrt}\, \beta^{s}_{kt}\, Y^{s}_{jt}\, X^{s}_{jktr} - \left(\frac{d^{s}_{m\vartheta t(1)} + d^{s}_{m\vartheta t(2)} + d^{s}_{m\vartheta t(3)} + d^{s}_{m\vartheta t(4)}}{4} - \sum_{k} U^{s}_{mk\vartheta t} - H^{s}_{m\vartheta t}\right)\beta' + \left(H^{s}_{m\vartheta t} - \frac{d^{s}_{m\vartheta t(1)} + d^{s}_{m\vartheta t(2)} + d^{s}_{m\vartheta t(3)} + d^{s}_{m\vartheta t(4)}}{4} + \sum_{k} U^{s}_{mk\vartheta t}\right)\beta \tag{34}$$

$$Z_{max} = \sum_{s,t}\sum_{j\in J''} o\ \pi^{s}\, Y^{s}_{jt} + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''}\, \delta^{s}_{jkrt}\, \beta^{s}_{kt}\, Y^{s}_{jt}\, X^{s}_{jktr} - \left(d^{s}_{m\vartheta t(4)} - \Sigma_k U^{s}_{mk\vartheta t} - H^{s}_{m\vartheta t}\right)\beta' + \left(H^{s}_{m\vartheta t} - d^{s}_{m\vartheta t(4)} + \Sigma_k U^{s}_{mk\vartheta t}\right)\beta \tag{35}$$

$$Z_{min} = Minimize\ F_2 = \sum_{s,t}\sum_{j\in J''} o\ \pi^{s}\, Y^{s}_{jt} + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''}\, \delta^{s}_{jkrt}\, \beta^{s}_{kt}\, Y^{s}_{jt}\, X^{s}_{jktr} - \left(d^{s}_{m\vartheta t(1)} - \Sigma_k U^{s}_{mk\vartheta t} - H^{s}_{m\vartheta t}\right)\beta' + \left(H^{s}_{m\vartheta t} - d^{s}_{m\vartheta t(1)} \Sigma_k U^{s}_{mk\vartheta t}\right)\beta \tag{36}$$

subject to:

$$\frac{\alpha_1}{2} d^{s}_{m\vartheta t(2)} + \left(1 - \frac{\alpha_1}{2}\right) d^{s}_{m\vartheta t(1)} - \sum_{k} U^{s}_{mk\vartheta t} \le H^{s}_{m\vartheta t} \qquad \forall m, \vartheta, t, s \tag{37}$$

$$\frac{\alpha_1}{2} d^{s}_{m\vartheta t(3)} + \left(1 - \frac{\alpha_1}{2}\right) d^{s}_{m\vartheta t(4)} - \sum_{k} U^{s}_{mk\vartheta t} \ge H^{s}_{m\vartheta t} \qquad \forall m, \vartheta, t, s \tag{38}$$

3.2.2. An Epsilon Constraint Method (Ɛ-constraint)

This method was presented to solve multi-objective optimization problems. In this method, one of the objective functions was selected as the main objective function and was used to transform other objective functions into constraints with certain conditions. The stages of the Ɛ-constraint method are as follows:

Considering the multi-objective programming approach for the developed model, the main model used to solve the proposed method is as follows:

$$P_1(\varepsilon_1)\ \text{or}\ P_2(\varepsilon_2) \tag{39}$$

$$Minimize\ f_1(\vec{x}) \tag{40}$$

subject to:

$$f_2(\vec{x}) \leq \varepsilon_2 \tag{41}$$

$$\vec{x} \in \aleph \tag{42}$$

Below are the steps for solving the multi-objective optimization problem using an exact version of the Ɛ-constraint approach:

1. Set $i = 1$ and $j = 2$
2. Solve the initial model and obtain (z_i, z_j) using epsilon values $\varepsilon_j = z_j - \Delta$ ($\Delta = 0.1$)
3. Calculate $P(\varepsilon_j)$ values using (z_i, z_j) values obtained in the previous step
4. Calculate $\varepsilon_j = z_j - \Delta$ and obtain the optimal solution

In this method, ε_j denotes the positive and negative deviation variables for goal j. $P(\varepsilon_j)$ is the main objective function used to calculate the maximum value of other objective functions in each step based on positive and negative deviations. Δ is the constant used to calculate the steps of the model solution and z_j is the optimal value of the objective function in step j. Finally, the developed model is solved using the second objective function as the main objective function and the first objective function as the constraint. The objective functions based on the Ɛ-constraint method are as follows:

$$Minimize\ F_2 = \sum_{s,t}\sum_{j\in J''} o\ \pi^s\, Y_{jt}^s + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''}\, \delta_{jkrt}^s\, \beta_{kt}^s\, Y_{jt}^s . X_{jktr}^s \tag{43}$$

subject to:

$$F_1 = \sum_{m,j,k,t,r,s} \pi^s\, F_{mjktr}^s t'_{jkr} + \sum_{m,k,\vartheta,t,s} \pi^s\, U_{mk\vartheta t}^s t''_{k\vartheta} + \sum_{m,\vartheta,t,s} \pi^s H_{m\vartheta t}^s\, ti_{\vartheta t} \leq \varepsilon_1 \tag{44}$$

Constraints (3)-(23) (45)

3.2.3. Metaheuristic Algorithm Based on SA

In the SA algorithm, a probabilistic method is used to solve the optimization problem. In the SA algorithm, point s is considered a state of the physical system, and the function E(S) is similar to the internal energy of the system in state *s*. Its goal is to reach a state in which the function E(S) is minimum by starting the system from an arbitrary initial state. Starting from an arbitrary state of the physical system, a state is reached where the internal energy of the system is minimum (the system will have the lowest energy in that state). To do this, the algorithm starts from an arbitrary point and then selects a neighboring state. After that, it probabilistically decides to stay in the current state or move to the neighboring state. The sum of these possible displacements leads the system to a state with lower internal energy. This is done until the system reaches a rational state or the number of calculations exceeds a certain threshold. The probability of transition from a current state, for example, s, to a new candidate state, such as s', is determined by an acceptance probability function P, where the function E in the state space represents the internal energy of the system and the temperature value is expressed by T. The temperature T changes with time. If the temperature T decreases and tends to zero, the probability of P should also decrease and either tend to zero or a positive number. The temperature decreases gradually in the simulation. Therefore, the algorithm starts from a very large temperature T and the temperature decreases at each step according to a predetermined cooling schedule. In this research, the presented model was solved using Matlab R2019b software, and the written program was executed by a computer with 2.3 GHZ, core i7 processor with 4GB RAM memory, and the execution time in all executions was less than 44.225 minutes. Validation of the desired model was done through sensitivity analysis of some effective parameters in the model and the efficiency of the model was also checked. To solve the model developed by the refrigeration method, the parameters of the problem were determined in MATLAB software. In this simulation, the value of the initial temperature ($T=1200$) was considered according to the literature, which started to decrease in order to reach the optimal solution.

4. Simulation Results

4.1. Description

In the present research, a multi-objective and multi-period mathematical model was considered to study a sustainable blood supply chain design under uncertainty and disruption risk. The research tools used to solve the problem include mathematical programming models, programming approaches to cope with uncertainty and disruption risk, etc. The proposed model was formulated and solved using GAMS software. A meta-heuristic algorithm based on the Simulated Annealing (SA) algorithm was used to validate the model and the results were compared to the results of GAMS. The multi-objective or multi-criteria optimization is the simultaneous optimization of two or more conflicting objective functions with constraints. Due to the conflicting and incomparable nature of the objectives in the multi-objective optimization approach, reaching a solution where all objectives are simultaneously optimized is not possible.

4.2. Computational Results and Sensitivity Analysis

The presented model based on the exact epsilon constraint method has been coded and solved in GAMS software. Also, validation of the desired model was done by solving the model with the SA algorithm in MATLAB software in 10 different scenarios according to the number of fixed and mobile blood collection centers.

The model has two objective functions; the first objective function represents the minimization of the expected delivery time. The second objective function minimizes the set of supply chain costs. To compare the efficiency of the SA algorithm, several examples in different categories and sizes including small, medium, and large have been designed so that the algorithm can be evaluated. Table 2 shows the performance of the developed model based on the number of fixed and mobile blood collection centers, which calculates the results of GAMS software based on the values of the first and second objective functions of the model and compared with the SA method.

Table 2. Performance of the developed model based on the number of fixed and mobile blood collection centers

Scenario		$\|J'\|$	$\|J''\|$	GAMS		SA Algorithm	
				Obj1	**Obj2**	**Obj1**	**Obj2**
Small scale	TP1	4	3	12.048	28,993	11.489	30,753
	TP2	6	5	11.231	30,808	10.154	32,412
	TP3	8	7	9.795	31,039	8.165	34,326
	TP4	10	9	8.723	33,029	6.954	37,240
Medium scale	TP5	10	12	-	-	6.125	37,623
	TP6	11	13	-	-	5.449	39,649
	TP7	13	14	-	-	4.954	40,662
Large scale	TP8	15	13	-	-	3.457	42,378
	TP9	17	16	-	-	2.942	45,652
	TP10	18	19	-	-	2.767	46,239

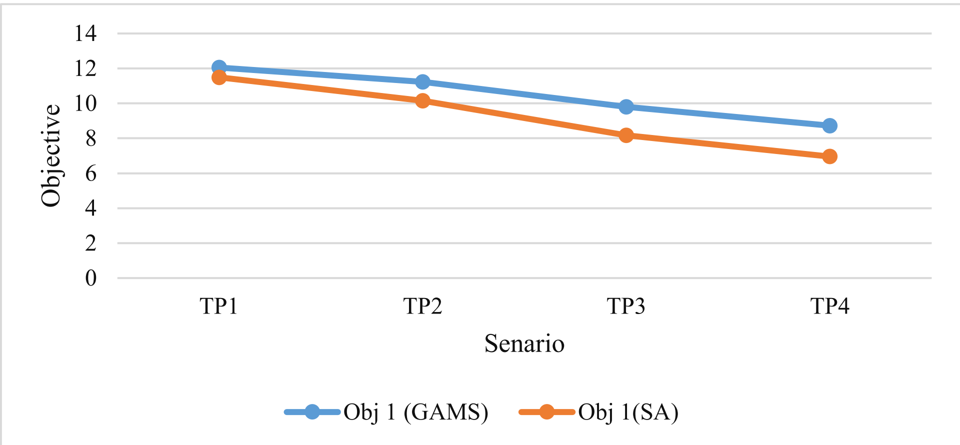

Figure 2. Changes in the first objective function based on the values of the number of fixed and mobile blood collection centers

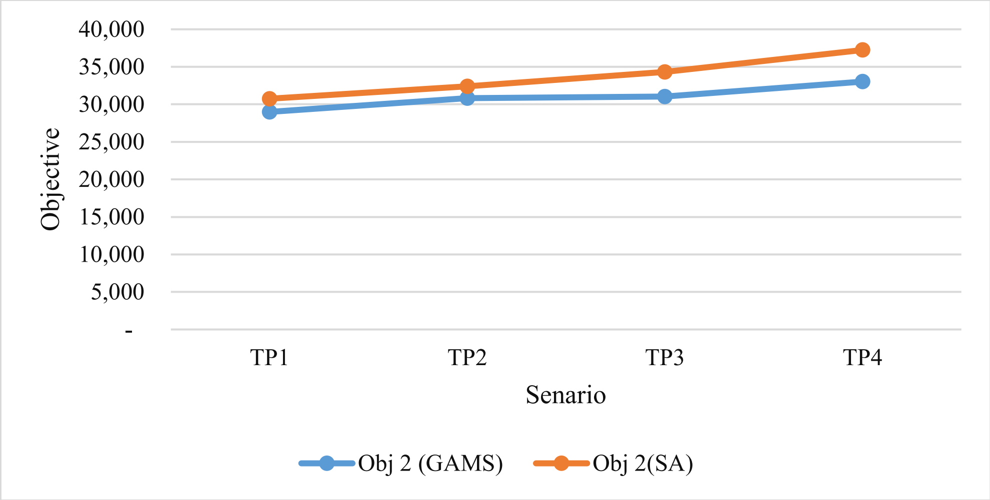

Figure 3. Changes in the second objective function based on the number of fixed and mobile blood collection centers

The model's results on a small-scale show that the SA algorithm has performed better in the first objective function and the amount of product delivery time is less. However, regarding the second function, the performance of the exact epsilon constraint method is better. In medium and large scales, the GAMS software was not able to solve the model using the epsilon constraint method, and the results of the SA algorithm were obtained in medium and large scales.

Finally, according to Figures 2 and 3, it can be understood that by increasing the number of fixed and mobile blood collection centers (in other words, by increasing the size of the problem), the value of the first objective function, i.e., the expected delivery time, in both proposed methods have a downward trend. Also, the results related to the changes in the second objective function show that with the increase in the dimensions of the problem, the value of blood supply chain costs for both proposed methods take on an upward trend and increases.

The changes in the solution time of the proposed model for both methods were obtained in Table 3 and Figure 4.

Table 3. The solution time of the developed model

Scenario		$\|J'\|$	$\|J''\|$	Time	
				GAMS	SA Algorithm
Small scale	TP1	4	3	3.328	4.659
	TP2	6	5	4.965	6.214
	TP3	8	7	6.319	8.249
	TP4	10	9	6.826	11.325
	TP5	10	12	-	12.328

Scenario		$\|J'\|$	$\|J''\|$	Time	
				GAMS	SA Algorithm
Medium scale	TP6	11	13	-	17.671
	TP7	13	14	-	24.638
Large scale	TP8	15	13	-	28.546
	TP9	17	16	-	35.637
	TP10	18	19	-	44.225

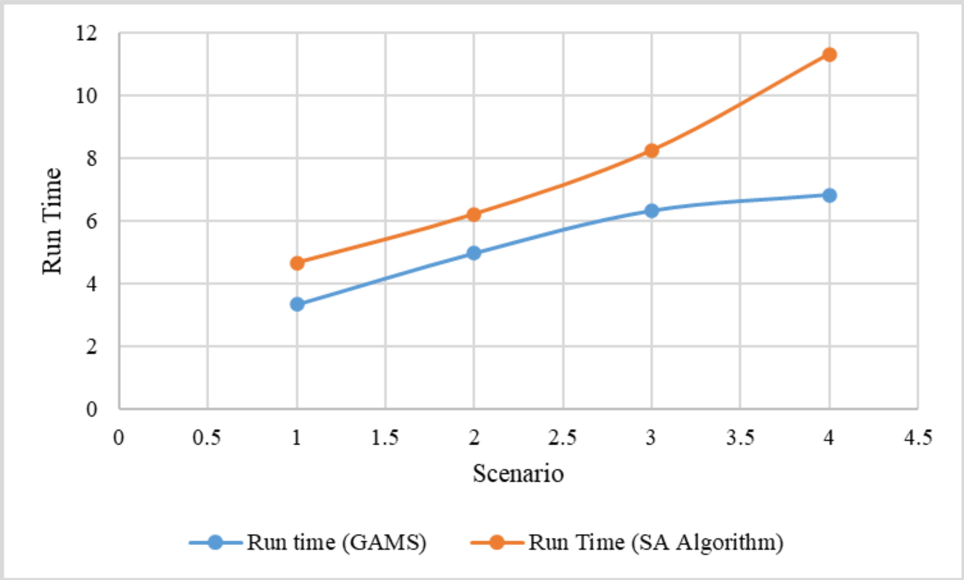

Figure 4. Changes in the solution time of the proposed model for small dimensions

The comparison of the results related to the amount of model execution time for small dimensions of the problem in the two approaches showed that the epsilon constraint method has a better performance in solving the model than the SA method. The noteworthy point in Table 3 is the trend of simulation model execution time for small and medium scales compared to the large scale of the problem. In small and medium scales of the problem, the amount of model execution time in the SA method increases with a relatively constant trend. However, in medium dimensions, the model execution time takes a much steeper slope and increases, indicating that in larger dimensions, the model execution time increases more steeply. In this section, to compare the performance of the proposed model under uncertainty for the demand parameter, the objective function values were compared in both deterministic and uncertain scenarios. For this purpose, the values of both objective functions for the deterministic and uncertain scenarios in the defined scenarios were calculated. This comparison can be seen in Table 4.

Table 4. Performance of the developed model based on the uncertainty and certainty approach

Scenario		$\lvert J'\rvert$	$\lvert J''\rvert$	Uncertainty Approach		Certainty Approach	
				Obj1	**Obj2**	**Obj1**	**Obj2**
Small scale	TP1	4	3	11.689	28653	12.957	23658
	TP2	6	5	10.354	30412	12.637	24368
	TP3	8	7	8.365	32216	9.743	31655
Medium scale	TP4	10	9	7.154	34895	9.476	32569
	TP5	10	12	6.325	35623	8.972	33498
	TP6	11	13	5.649	37649	8.545	35749
	TP7	13	14	5.154	38662	7.126	35964
Large scale	TP8	15	13	3.657	40378	6.729	39548
	TP9	17	16	3.142	43652	5.486	40548
	TP10	18	19	2.967	44239	5.122	41637

The results of Table 4 show that the values of the first objective function (blood product delivery time) in the case where the model uncertainty is considered using a robust optimization method have a lower value compared to the model in the deterministic case, indicating a better performance of the robust optimization model compared to the deterministic case. On the other hand, the results of the second objective function (economic costs and carbon dioxide emissions) demonstrate that the performance of the model in the deterministic case is better than the robust optimization approach because considering uncertainty increases the overall costs of the blood supply chain. This is due to the uncertainty and fluctuations in demand and the establishment of new centers to meet the demand.

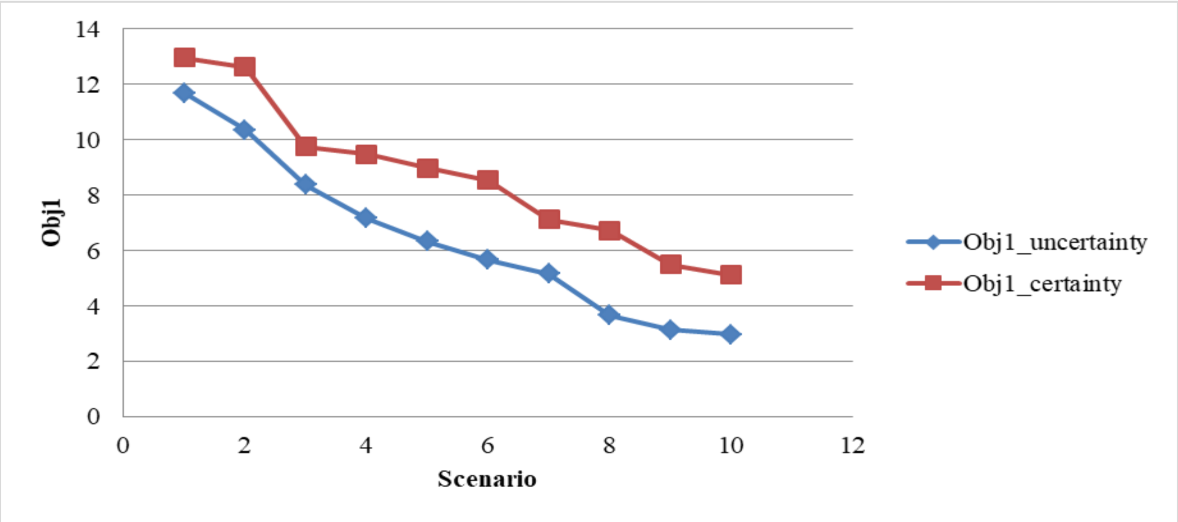

Figure 5. Comparison of the performance of the first objective function based on the uncertainty approach

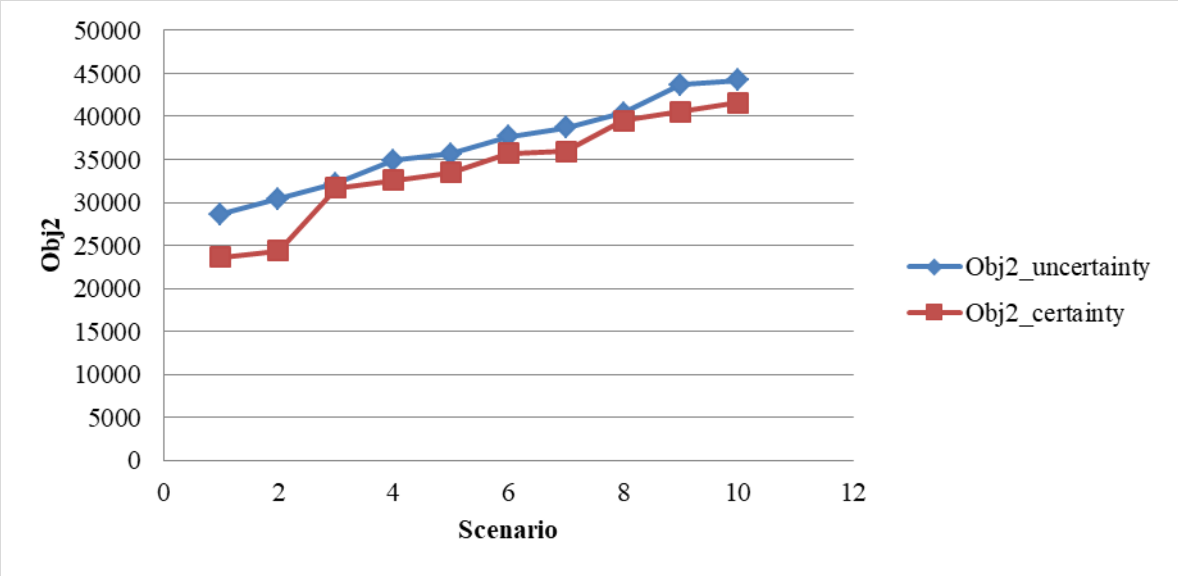

Figure 6. Comparison of the performance of the second objective function based on the uncertainty approach

5. Conclusion and Outlook

In the current research, a multi-objective and multi-period mathematical model was presented for the blood supply chain under conditions of sustainability and demand uncertainty. To solve the proposed model in this research, an approach based on the epsilon constraint method was used. Also, in this paper, the SA metaheuristic algorithm was used to validate the model and its results were compared with the exact epsilon constraint method. The results of the proposed model were compared in small, medium, and large scales for the epsilon constraint method and the SA algorithm. The results showed that the SA algorithm performed better in the first objective function and the product delivery time was less. However, regarding the second objective function the performance of the exact epsilon constraint method is better. In medium and large dimensions, the GAMS software was not able to solve the model using the epsilon constraint method, and the results of the SA algorithm were obtained in medium and large scales. Also, the results related to medium and large scales for the SA algorithm showed that the first objective function for different scales of the problem has a downward trend and the second objective function has an upward trend. Therefore, for small scales of the problem, the exact epsilon method can be used, but due to the limitation of this method in medium and large scales, meta-heuristic methods should be used in larger scales. Regarding future research, it can be said that due to the uncertainty in the demand values in the blood supply chain, it is suggested to use the demand forecasting approach using machine learning methods to estimate the demand.

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