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Multi-objective Design of a Blood Supply Chain Based on Sustainability Approach and Demand Prediction Using Deep Learning Algorithm

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ABSTRACT

One of the most important components of a healthcare system is the blood supply chain, which accounts for a significant proportion of the system's expenditure. Therefore, any improvement in the blood supply chain's performance can significantly increase healthcare systems' efficiency and cost-effectiveness. The main challenge in managing blood products lies in supply and demand uncertainty, leading to a trade-off between scarcity and waste, especially in developing countries. In addition, the predictive power of deep learning models for estimating and forecasting the demand for blood products has not been sufficiently explored. This paper proposes a multi-objective model to optimize the blood supply chain network. The objectives include minimizing blood delivery times, reducing economic costs in the supply chain, reducing carbon dioxide emissions, and finally maximizing demand satisfaction as an aspect of social sustainability. Given the uncertainty of blood supply and demand, a deep learning model based on the CNN method is used to predict blood demand. The LP-Metric algorithm is used to solve the model in the GAMS software, and the SA simulation algorithm is used to validate the results. The calculation results show that the SA algorithm performs better in optimizing the first objective function, resulting in a shorter product delivery time, and the third objective function. However, the LP-Metric method performs better for the second objective function.

1. Introduction

Despite remarkable advancements in medical technologies, no substitute has been found for blood and its products to date. In all societies, there is a constant demand for blood products, and although a large number of individuals donate blood, in some instances, these demands are not fully met. To prevent such issues, an effective and well-planned blood supply chain must be designed. Blood supply chain management is of vital importance, as the unavailability of

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blood can lead to the death and complications of patients. Conversely, blood wastage incurs significant costs for governments. Optimal decision-making in the blood product supply chain is necessary to minimize shortages and wastage levels.

In general, the worldwide blood donation rate is low, with approximately 1 to 3 percent of the global population engaging in blood donation. On the other hand, blood demand is variable, exacerbated by factors such as crises and demand fluctuations. Therefore, for the establishment of a balance between supply and demand, appropriate planning in the blood supply chain and predicting the demand levels in this chain are essential (Hosseini-Motlagh et al., 2020).

In recent years, researchers have focused on developing efficient and sustainable blood supply chain models. Traditional approaches often rely on deterministic models that may not adequately capture the inherent uncertainties in blood demand and supply. To address this limitation, this paper proposes a multi-objective optimization model for blood supply chain design that incorporates a deep learning algorithm for demand prediction. The proposed model aims to balance multiple objectives such as minimizing costs, maximizing blood product availability, and ensuring sustainability. By leveraging the power of deep learning, the model can more accurately forecast blood demand, leading to improved decision-making and resource allocation. The findings of this research can help policymakers and healthcare organizations make informed decisions to enhance the efficiency and effectiveness of blood supply systems. 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 for predicting demand levels using a deep learning algorithm. Section 4 analyzes the performance of the proposed mathematical model through a numerical example. 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

Today, the management of blood products is a challenging issue in the healthcare domain (Attari and Jami, 2018; Özener et al., 2019). The blood supply chain must be efficient and sustainable to ensure blood-related needs. Such systems involve the collection of blood from various individuals, known as donors, to the collection, transportation, and delivery of blood to patients and healthcare facilities (Osorio et al., 2018). The goal of blood supply chains is to meet the demand for blood with minimal cost, and waste, and ensure the availability of blood to respond the patient demands in different conditions (Guan et al., 2017). Blood contains perishable products such as platelets, red blood cells, and plasma, with different lifespans: platelets last 5 days after collection, red blood cells last 42 days, and plasma lasts 36 months (Pirabán et al., 2019). The perishability of blood products increases the complexity of the supply chain, making the optimization of optimal blood quantities for medical treatments (e.g., cancer, anemia), organ transplants, and surgeries (e.g., open-heart surgery) challenging (Zahiri et al., 2015).

The limited and decreasing number of donors (e.g., due to aging) compels blood donation organizations to effectively manage available donors (Özener et al., 2019). Limited financial resources have negative impacts, requiring effective management of the blood supply chain for two main reasons. Firstly, blood is not easily producible or replaceable by other products and can only be supplied by eligible individuals (Eskandari-Khanghahi et al., 2018; Katsaliaki, 2008; Rabbani et al., 2017). Secondly, eligible donors must wait for a period before engaging in a new donation. If perishable blood components are not managed well or used promptly, the costs of disposal, storage, and donation increase. Insufficient availability of blood may lead to blood shortages, resulting in the cancellation and rescheduling of surgeries due to blood supply issues (Masoumi et al., 2017), and in crises, it may result in the loss of lives (Hamdan and Diabat, 2019).

As mentioned, various challenges exist in the management of the blood supply chain network. Consequently, many operations researchers in recent years have sought to enhance each layer or the entire chain through the development of new models and approaches. The concept of a closed-loop supply chain design is an important one in the traditional supply chain literature. Tonanont et al., (2009**)** defined a closed-loop supply chain as a network that simultaneously includes reverse and forward flows. Blood is needed for various medical activities, including patient treatment, cancer treatment, surgeries, organ transplants, etc., supplied through the blood supply chain network. Natural disasters such as earthquakes, tsunamis, and volcanic eruptions bring about damages that also affect human lives. In such cases, considering the large number of casualties being admitted to hospitals, the demand for blood products is likely to significantly increase. Local and regional blood centers also face emergency blood supply demands from hospitals (Shokouhifar et al., 2022).

Designing an effective and efficient supply chain network is challenging due to the complex decisions encountered throughout this chain. This factor has led researchers in recent years to focus more on the design and management of the blood supply chain as a lifesaving substance.

On the other hand, given the uncertainty in blood demand and supply, coupled with the limited and perishable nature of blood products, inventory management of blood poses a significant challenge (Stanger et al., 2012). The main challenge in managing blood products lies in the uncertainty of demand and supply, accompanied by the trade-off between scarcity and wastage. The demand for blood in developed countries is rapidly increasing, with approximately 10 out of every 100 hospital patients requiring some blood products (Lancet, 2005). Among developing countries, an annual estimate of about 100,000 deaths due to blood shortages and transfusion-transmitted infections are reported from untested and unscreened blood (Lancet, 2005). Therefore, reliable demand forecasting can be essential for planning blood donation campaigns and improving blood availability.

Demand forecasting methods in the supply chain are divided into two categories: traditional and modern. Traditional methods typically rely on text-based forecasting of future demand based on previous periods using algebraic methods. In contrast, modern methods utilize machine learning techniques, particularly artificial intelligence algorithms and data mining, to predict future demand. Machine learning algorithms for predicting blood demand time series have recently been developed, and their performance has been examined against classical models in previous studies (Bontempi et al., 2013; Papacharalampous et al., 2018; Shih and Rajendran, 2019). However, in the field of blood supply management, no recognized study has investigated the performance of deep learning algorithms in predicting blood demand, considering a mathematical modeling approach for optimizing the blood supply chain. Machine learning and deep learning models, such as Support Vector Machines, Neural Networks, and Recurrent Neural Networks, are among the many prediction models that have gained popularity among researchers and experts due to their ability to overcome challenges. Therefore, in this research, the optimization of a multi-objective blood supply chain model is addressed, and the blood demand is considered with the incorporation of a deep learning algorithm for demand prediction.

In recent years, various studies have been conducted on mathematical modeling and optimization of the blood supply chain. Fahiminia et al., (2017) addressed the design of an efficient and effective supply chain network under crisis conditions, examining two objective functions: cost and time. They utilized a combined approach for solving the model, simultaneously employing the epsilon-constraint method and Lagrangian relaxation. Ramezanian & Behboodi (2017) researched the design of the blood supply chain network under uncertainty in supply and demand, considering social aspects. Among the influential factors in blood donation, they emphasized the distance of blood donors from blood centers, the experiences of blood donors in healthcare facilities (staff behavior and technical staff skill level), and incentives (advertising budget in blood centers). In this study, blood donation is a voluntary activity, and motivating individuals to donate blood is a challenging task.

Disasters, especially earthquakes, have adverse effects such as destruction, loss of life, and the weakening of the effectiveness of healthcare services. Research conducted by Khalilpourazari et al. (2020) considers a six-tier blood supply chain, including donors, blood collection centers (permanent and temporary), regional blood centers, local blood centers, regional hospitals, and local hospitals. It was proposed for the first time that helicopters could transport blood from regional hospitals to local hospitals and return patients who cannot be treated in local hospitals due to the limited capacity of regional hospitals. In addition to the above, various transportation modes with limited capacities have been considered, and the optimal number of transportation equipment is determined after the resolution process.

The importance of blood in disasters is heightened due to its vital role in saving human lives. The study conducted by Rahmani (2019) presented a robust and reliable model for a dynamic emergency blood network design problem. A strong approach was used to control uncertainty. The p-metric technique was employed to protect the solution against disturbances. Additionally, a numerical example was extensively provided to demonstrate the effect of considering disturbance scenarios. The performance of the proposed model was evaluated using a series of test problems of various sizes. The results indicate that the model's performance is entirely satisfactory.

In a study by Mousavi et al. (2021), a two-objective and sustainable blood supply chain network, considering social and environmental factors, is introduced. In addition, some aspects of uncertainty are addressed, both in terms of the amount of blood collected from blood transfer centers and the breakdown ratio at the blood separation center. By considering bi-objective planning in the developed network, the problem simultaneously optimizes carbon dioxide emissions, balances the flow of all used vehicles, penalizes unvisited centers, total costs of using all vehicles, and most importantly, social and environmental factors. The findings of this study show that social factors transfer higher costs in most cases.

In another study, a closed-loop blood supply chain of blood products, considering transportation equipment and related quality features, is formulated in the research conducted by Fallahi et al. (2021). Subsequently, a differential evolution algorithm, enhanced with the expansion of two new DE versions, is used to solve the problem. Finally, some sensitivity analyses on the model parameters are performed to report some managerial insights.

The paper by Matin et al. (2022) introduces an Advanced Network Data Envelopment Analysis (NDEA) method for evaluating the sustainability and flexibility of Balanced Scorecards (BSCs). Their proposed model can handle various types of data, including integers, undesirable outputs, negative, zero, and positive outputs. Undesirable outputs are outputs that negatively impact the performance of Decision-Making Units (DMUs). Additionally, the developed method addresses the sustainability and flexibility of BSCs.

In the study conducted by Xu & Szmerekovsky (2022), a multi-period, multi-product stochastic program is presented for an integrated blood supply chain that considers red blood cells and platelets, as well as interactions between multiple products, demand uncertainty, blood age information, blood group substitution, and three types of patients. The objective is to minimize the total incurred costs throughout the collection, production, inventory, and distribution stages under centralized control. The results show that cost savings in the multi-product model are primarily due to changes in the number of blood donors. Khalilpourazari and Doulabi (2023) proposed a new multi-objective Transportation-Location-Inventory-Routing (TLIR) model for the emergency design of a blood supply chain network. They suggest two flexible non-deterministic models to provide robust and risk-averse solutions for the problem.

In the paper conducted by Eslamipoor and Nobari (2023), a multi-objective model is presented for establishing a sustainable blood supply chain, including multiple donors, collection centers, distribution centers, and hospitals at various levels. Considering the potential for blood shortages, the proposed model considers the supply chain capacity as a reliable means to meet the blood needs of hospitals as a trusted tool for achieving social goals. To solve the proposed multi-objective model, an improved ε-constrained approach is first used to construct a single-objective model. Additionally, a competitive imperialist competitive algorithm is developed to solve the single-objective model.

In recent years, there has been a special focus on demand forecasting approaches in the blood supply chain.

The uncertainty in the supply and short shelf life of blood products has led to a significant aging of donated blood. On the other hand, hospitals and blood centers face severe blood shortages due to the limited donor population. Therefore, the need to predict the blood supply to minimize aging and scarcity is essential. The study conducted by Shih and Rajendran (2019) aimed to predict the effective supply of blood components in blood centers. In this research, two different types of prediction techniques, time series, and machine learning algorithms, were developed, and the best-performing method for a specific case study was determined. The results showed that time series prediction methods outperformed machine learning algorithms. More precisely, the minimum error was observed in ESM seasonal and ARIMA models.

In another study, Abbasi et al. (2020) investigated how Big Data Analytics (BDA) enhances the accuracy of predictions. In this study, a conceptual framework based on the design science paradigm was applied to create a categorization for BDA. The results indicate that integrating various data sources is possible for demand prediction in the blood supply chain.

The COVID-19 pandemic has negatively impacted blood supply chain management due to uncertain supply/demand and logistical disruptions. In the early weeks of the COVID-19 outbreak, a 20 to 30 percent reduction in blood donation was observed, negatively affecting the entire blood supply chain. Therefore, in the study conducted by Shokouhifar and Ranjbarimesan (2022) a deep learning model for multi-variable time series based on short-term memory was proposed for predicting blood donation/demand. The research, aiming at achieving flexible blood inventory management, was able to handle uncertainties during the COVID-19 pandemic [37-47]. The obtained results demonstrate the effectiveness of the proposed model, achieving an error rate of 6.1 percent and 6.5 percent between actual and predicted values for the number of donations and demands, respectively. The application of the proposed model for platelet blood inventory management shows a 32.1 percent reduction in shortage and a 26.6 percent reduction in wastage compared to uncertainty control models.

The study conducted by Twumasi & Twumasi (2022) aimed to compare the performance of K-Nearest Neighbors regression (KNN), Generalized Regression Neural Network (GRNN), Neural Network Autoregressive (NNAR), Multi-Layer Perceptron (MLP), and Extreme Learning Machine (ELM) in predicting and forecasting blood demand data with missing and outlier values from a government hospital in Ghana. The KNN method demonstrated effective blood demand prediction with a low error rate of 12.55%.

In the research carried out by Ben Elmir and colleagues (2023), a smart platform-based approach was proposed to establish a robust blood supply and demand chain capable of achieving objectives such as reducing uncertainty in blood demand through predicting blood collection/demand, minimizing waste, and addressing blood shortages by balancing blood collection. They utilized machine learning and time series prediction models to develop an AI/ML decision support system. As a result, the level of invalid blood before and after preparation decreased, leading to an improvement in the system's ability to reduce blood shortages and wastage. Their proposed solution provided strong and accurate predictions, increasing the integrated volume of collected blood by 11% and reducing inventory wastage by up to 20%.

2.2. Research Gap

Due to the necessity of blood demand prediction and three aspects of sustainability in the blood supply chain**,** the main innovations of the present research are as follows:

i. Presenting a combined approach for optimizing the mathematical model of the blood supply chain and predicting demand based on machine learning.

ii. Demand prediction in the blood supply chain using a deep learning algorithm.

iii. Optimization of the multi-objective model of the blood supply chain with the objectives of minimizing blood delivery time and optimizing economic costs, considering sustainability in three aspects: economic, social, and environmental.

In light of the findings, a summary of the conducted studies in the studied domain is presented in Table 1.

Table 1. A review of studies in the related areas

Authors	Publication year	Blood supply chain	Optimization model		Sustainability			Demand prediction algorithm	TS	RF	DT	LR	SVM	DL	KNN	NN
			Single-Objective	Multi-Objective	Economic	Social	Ecological									
Fahimnia et al	2017	✓		✓												
Ramezanian & Behboodi	2017	✓	✓			✓										
Hamdan & Diabat	2020	✓		✓												
Khalilpourazari et al	2020	✓		✓												
Rahmani	2019	✓	✓		✓											
Mousavi et al	2021	✓		✓	✓	✓	✓									
Fallahi et al	2021	✓	✓													
Matin et al	2022	✓	✓		✓	✓										
Eslamipoor & Nobari	2023	✓		✓	✓	✓	✓									
Xu & Szmerekovsky	2022	✓		✓	✓											
Shih & Rajendran	2019	✓						✓	✓							
Abbasi et al	2020	✓														
Shokouhifar & Ranjbarimesan	2022	✓			✓			✓	✓					✓		
Twumasi & Twumasi	2022	✓						✓							✓	✓
Ben Elmir et al	2023	✓						✓	✓							✓
current study		✓		✓	✓	✓	✓	✓						✓		

TS: Time Series (TS) Forecasting; RF: Random Forest (RF) Algorithm; DT: Decision Trees (DT); LR: Linear Regression (LR); SVM: Support Vector Machine (SVM); DL: Deep Learning (DL); KNN: K-Nearest Neighbor Algorithm (KNN); NN: Neural Network

3. Problem statement

Unforeseen demand in a blood supply chain poses a significant challenge to healthcare systems, as it can lead to critical shortages during emergencies or unexpected medical events. This unpredictability often results from factors such as natural disasters, sudden outbreaks of diseases, or unanticipated surgical procedures, which can rapidly deplete available blood reserves. The inability to accurately forecast and manage blood inventory not only jeopardizes patient care but also strains the operational efficiency of blood banks and hospitals. Consequently, addressing this issue requires the implementation of robust demand forecasting models and agile supply chain strategies to ensure a steady and reliable blood supply, ultimately safeguarding public health during crises. Given the uncertainty in blood demand and donation levels and the importance of all aspects of sustainability, the research considers a deep-learning algorithm. The Convolutional Neural Network (CNN) algorithm is effective for predicting demand in supply chains due to its ability to analyze complex patterns in large datasets. The CNN algorithm excels at identifying trends and anomalies in historical demand data influenced by various factors. By automatically extracting relevant features through multiple layers, CNN enhances demand forecasting accuracy.

3.1. Proposed Model

In the present research, a multi-objective blood supply chain model based on a sustainability approach that considers three aspects of sustainability will be addressed. The objective functions of the proposed supply chain model consist of 1) minimizing the total costs of the blood supply chain, 2) minimizing blood delivery time, 3) minimizing environmental transportation costs for blood transportation, and 4) maximizing demand satisfaction created in the proposed supply chain.

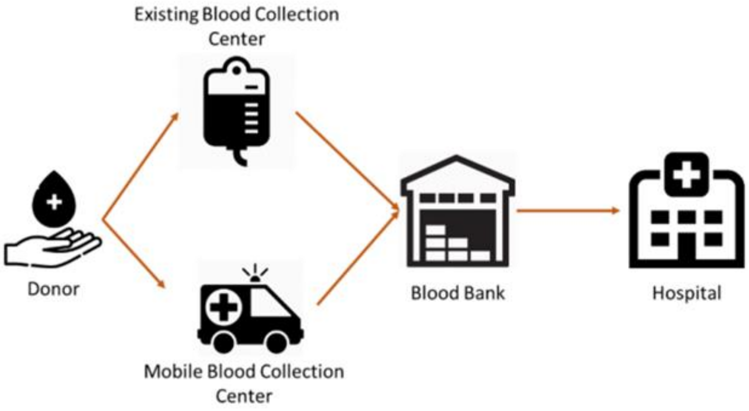

Figure1. Blood Supply Chain Sections

Assumptions:

The assumptions of the proposed model are as follows:

I. The storage capacity for blood products is constrained.
II. Each region can accommodate either a single mobile or fixed collection center.
III. Hospitals' blood product requirements are segmented for various scenarios.
IV. In the proposed model, demand is considered under uncertainty.
V. The model is developed in a multi-product condition.
VI. Each mobile blood collection center is equipped with only one Specialized Collection Vehicle (SCV) responsible for mobile blood collection.

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 CO2 emission caused by each mobile blood collection facility (SCV)
LT_{PC}	Maximum carbon budget
LTC_{m}	The minimum amount of blood product *m*
dco	Blood fractionation ratio

Variables:

Nco_{m}	Total number of blood products *m* for demanding patients
V_{mkt}^{s}	The inventory level of blood product *m* at blood bank *k* at the end of period *t* for scenario *s*
F_{mjktr}^{s}	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*
$U_{mk\vartheta t}^{s}$	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_{mijt}^{s}	The amount of blood product *m* donated at point *i* at period *t* to transport to blood collection center *j* for scenario *s*
$H_{m\vartheta t}^{s}$	The amount of blood product *m* transfused from blood banks in other regions to hospital ϑ at period t for scenario *s*
O_{mkt}^{s}	The amount of expired blood product *m* at blood bank *k* at period *t* for scenario *s*

Binary Variables:

Z_j	It equals 1 if the permanent blood collection center *j* is well-equipped, otherwise, it is 0
Y_{jt}^{s}	It equals 1 if the mobile blood collection center opens at site *j* at period *t* for scenario *s*, otherwise, it is 0
X_{jktr}^{s}	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_{ijt}^{s}	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

$$Minimize\ F_1 = \sum_{m,j,k,t,r,s} \pi^s F_{mjktr}^{s} t'_{jkr} + \sum_{m,k,\vartheta,t,s} \pi^s U_{mk\vartheta t}^{s} t''_{k\vartheta} + \sum_{m,\vartheta,t,s} \pi^s H_{m\vartheta t}^{s}\, ti_{\vartheta t} \tag{1}$$

$$Minimize\ F_2 = \sum_{s,t} \sum_{j\in J''} o\ \pi^s Y_{jt}^{s} + \sum_{j\in J'} q\, Z_j + \sum_{j,k,t,r,s} PC_{J''} \,.\, \delta_{jkrt}^{s}.\, \beta_{kt}^{s}.\, Y_{jt}^{s}.\, X_{jktr}^{s} \tag{2}$$

$$Maximize\ F_3 = \sum_{m,j,k,t,r,s} dco.\, F_{mjktr}^{s}.\, Nco_m \tag{3}$$

subject to:

$$\sum_{k,t,r,s} PC_{J''} \,.\, \delta_{jkrt}^{s}.\, \beta_{kt}^{s}.\, Y_{jt}^{s}.\, X_{jktr}^{s} \le LT_{PC} \qquad \forall j \in J'' \tag{4}$$

$$\sum_{j,k,t,r,s} dco.\, F_{mjktr}^{s}.\, Nco_m \ge LTC_m \qquad \forall m \tag{5}$$

$$G_{mijt}^{s} \le p_{mit}^{s}.\, W_{ijt}^{s} \qquad \forall\ m, i, j, t, s \tag{6}$$

$$\sum_{j} G_{mijt}^{s} \le p_{mit}^{s} \qquad \forall\ m, i, t, s \tag{7}$$

$$\sum_{i}\sum_{m} G^{s}_{mijt} \leq c_j.Z_j + f_j.Y^{s}_{jt} \qquad \forall j,t,s \tag{8}$$

$$Z_j + Y^{s}_{jt} \leq 1 \qquad \forall j,t,s \tag{9}$$

$$W^{s}_{ijt} \leq \alpha^{s}_{jt}.Z_j + Y^{s}_{jt} \qquad \forall i,j,t,s \tag{10}$$

$$\sum_{k}\sum_{r} F^{s}_{mjktr} \leq \sum_{i} G^{s}_{mijt} \qquad \forall m,j,t,s \tag{11}$$

$$\sum_{j}\sum_{r}\sum_{m} F^{s}_{mjktr} \leq e_k.\beta^{s}_{kt} \qquad \forall k,t,s \tag{12}$$

$$X^{s}_{jktr} \leq \alpha^{s}_{jt}.\beta^{s}_{kt}.\delta^{s}_{jkrt}.Z_j \qquad \forall k,t,r,s\ ,\forall j \in J' \tag{13}$$

$$X^{s}_{jktr} \leq Y^{s}_{jt}.\beta^{s}_{kt}.\delta^{s}_{jkrt} \qquad \forall k,t,r,s\ ,\forall j \in J'' \tag{14}$$

$$\sum_{r} X^{s}_{jktr} \leq 1 \qquad \forall k,t,r,s\ ,\forall j \in J'' \tag{15}$$

$$\sum_{m} F^{s}_{mjktr} \leq c_j.X^{s}_{jktr} \qquad \forall j \in J', \forall k,t,r,s \tag{16}$$

$$\sum_{m} F^{s}_{mjktr} \leq f_j.X^{s}_{jktr} \qquad \forall j \in J'', \forall k,t,r,s \tag{17}$$

$$\sum_{m}\sum_{\vartheta} U^{s}_{mk\vartheta t} \leq e_k.\beta^{s}_{kt} \qquad \forall k,t,s \tag{18}$$

$$d^{s}_{m\vartheta t} - \sum_{k} U^{s}_{mk\vartheta t} = H^{s}_{m\vartheta t} \qquad \forall m,\vartheta,t,s \tag{19}$$

$$V^{s}_{mkt-1} + \sum_{j}\sum_{r} F^{s}_{mjktr} = V^{s}_{mkt} + \sum_{\vartheta} U^{s}_{mk\vartheta t} + O^{s}_{mkt} \qquad \forall t \geq 2, m,k,s \tag{20}$$

$$O_{mkt}^{s} = \max\left\{0, V_{mkt-LT_m}^{s} - \sum_{\vartheta}\sum_{p=t-LT_m} U_{mk\vartheta p}^{s} - \sum_{p=t-LT_m} O_{mkp}^{s}\right\} \quad \forall t \geq 2, m, k, s \tag{21}$$

$$\sum_{j\epsilon j'} Y_{jt}^{s} \leq N - n \qquad \forall t, s \tag{22}$$

$$\sum_{m} V_{mkt}^{s} \leq e_k \qquad \forall\, k, t, s \tag{23}$$

$$V_{mkt}^{s}, F_{mjktr}^{s}, U_{mk\vartheta t}^{s}, G_{mijt}^{s}, H_{m\vartheta t}^{s}, O_{mkt}^{s} \geq 0 \qquad \forall m, i, j, k, t, r, s, \vartheta \tag{24}$$

$$Z_j, Y_{jt}^{s}, X_{jktr}^{s}, W_{ijt}^{s} \in \{0,1\}$$

The developed mathematical model consists of three 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. Finally, the third objective function addresses the social sustainability aspect, maximizing the overall social impact by maximizing the collection of total blood and its products for individuals in need of these products.

In the proposed model, Constraint (4) limits the maximum amount of carbon dioxide (CO_2) emissions. Constraint (5) ensures that the amount of blood products produced for each product should not be less than a specified value. Constraints (6) and (7) restrict the amount of blood donation from each urban area to prevent exceeding the maximum blood supply of donors for each blood product. Constraint (8) ensures that the blood collection capacity at each center is not exceeded. Constraint (9) ensures that at most one fixed or mobile blood collection center is established at any given location. Constraint (10) ensures that donors can only be assigned to designated mobile units or fixed blood collection centers that are equipped and operational. Constraint (11) limits the output of blood from blood collection centers to avoid exceeding the collected blood amount. Constraint (12) enforces capacity constraints on each blood bank and sets the capacity of unstable centers to zero. Constraint (13) ensures that fixed blood collection centers are only assigned to blood banks with unobstructed facilities and routes between these centers. Constraint (14) ensures that if a mobile blood collection center is assigned to a specific blood bank, facilities cannot be obstructed. Constraint (15) allocates a route between each blood collection center and blood bank. Constraints (16) and (17) 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 (18) ensures that a blood bank can only be assigned to a hospital that is unobstructed. Constraint (19) determines the amount of blood products delivered to each hospital from blood banks in other provinces. Constraint (20) represents inventory balance constraints in blood banks. Constraint (21) determines the number of outdated units in each period. Constraint (22) 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 (23) restricts the capacity of blood banks for blood storage. Finally, Constraint (24) defines the range of decision variables.

3.2. Solution Method

3.2.1 Blood Transfer Routing Considering Problem Conditions and CNN Algorithm

In this research, the optimal number and suitable routes for mobile blood collection facilities are determined with the goal of maximizing donor coverage. Various blood products, including red blood cells, plasma, and platelets, are produced in laboratories and stored in blood banks at blood centers. They are then sent to demand centers based on the existing demand. Given that many routes for transporting blood products to treatment centers are damaged and unusable, appropriate routing should be performed for the transportation fleet in the distribution phase. Establishing treatment centers should be done in suitable areas to maximize coverage of the affected population.

Considering the different storage temperatures for blood products, different refrigerators are used for their storage, and the capacity for each blood product is taken into account based on the various storage capacities in different hospitals. This is represented in a fuzzy numerical form according to expert opinions, as shown in Table 2.

Table 2. Fuzzy Capacity of Blood Products

Product	Capacity	Product	capacity	Product	capacity
Red blood cell	(1000, 1400,1850)	platelet	(750, 1125,1500)	plasma	(1000, 1375, 1700)

3.2.2. Secure Mobile and Fixed Points (Supply Points)

In times of crisis, in addition to the loss of life and financial damage, there are also significant social damages. Therefore, to reduce social and psychological damages in providing shelter and temporary housing for the affected population, the routing of these centers should take into account a series of considerations.

3.2.3. Calculating the Suitability of Routing

The suitability of a secure route refers to the inherent desirability of a given site based on compatibility and incompatibility criteria. In this study, a multi-criteria evaluation method is employed to calculate the suitability of routing. First, the values for each criterion are calculated for each route. After standardization and determining the weight for each criterion, the final suitability is obtained using a weighted linear combination method.

The higher the values for incompatibility criteria, the more desirable a secure route will be. To achieve this, Equation 25 is used to standardize the values for each criterion in ascending order.

$$D_{new} = \frac{d_{near} - \min(d)}{\max(d) - \min(d)} \tag{25}$$

On the other hand, a shorter distance in compatibility criteria will result in higher desirability for a route. In this case, using the following equation, the criterion values will be standardized in descending order.

$$D_{new} = \frac{\max(d) - d_{near}}{\max(d) - \min(d)} \tag{26}$$

The weight of each criterion represents its level of importance and value relative to other criteria. To calculate the weights, tables were prepared based on the deep learning method with the CNN architecture.

Table 3 - Final Weights of Criteria and Sub-criteria

Criterion	Weight	Sub-Criterion	Weight
Compatible	0.5	Cost	0.445
		Time	0.262
		CO2	0.152
		Economic	0.089

		Job	0.052
Incompatible	0.5	Transportation	0.5
		Crisis	0.25
		Unemployment	0.25

As mentioned at the beginning of this section, the method of linear weighted combination has been used to integrate compatibility and incompatibility criteria. Given the final table of weights for criteria and sub-criteria, the suitability of a route is calculated for each path. These suitability values are used as specific information in the stage of selecting safe routes for the research.

$$SS = \sum W_i \,.\, C_i + \sum W_j \,.\, I_j \tag{27}$$

In the above formula, SS refers to the identification of the compatibility of a path. W_i and W_j represent the weights of each criterion, and C_i and I_j correspond to the compatibility and incompatibility criteria, respectively.

3.2.4. Implementation of Routing and Allocation Steps

Considering that the CNN algorithm can be adapted to the research problem conditions, modifications have been applied to the solution method of the routing and allocation model designed according to its specific criteria. To optimize the process, the determination of optimal secure paths, determination of optimal paths, and population allocation in target locations are performed in three phases for planetary points and transfers.

Figure 2 illustrates the evaluation of the objective function for each agent. An agent that satisfies all three constraint values can proceed to the next stage, which involves updating the proposed network. Before updating, its value is compared with the value of the objective function of other agents, and an agent with the minimum value can perform the CNN update. Otherwise, the solution is deemed unacceptable. This stage should be examined for other agents, and eligible agents can proceed to the update stage.

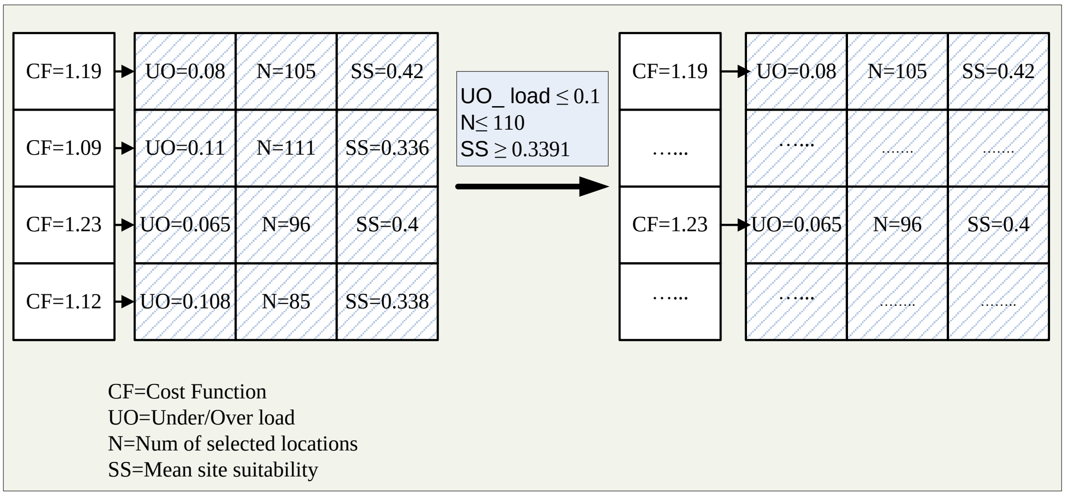

Figure 2. Evaluation of Objective Function Values for Agents in a Single Iteration Update:

The purpose of optimization is to find the best combination of N paths in such a way that, in addition to having the minimum cost (maximum desirability), it satisfies the constraints of the problem. In the first to third steps, the goal is to construct the solution and assess its quality based on the objective function. In the last stage, which is the most crucial part of the CNN algorithm, the aim is to record these solutions for subsequent stages and assist in improving problem-solving by other agents in subsequent iterations. By performing these operations, the optimization process is completed. At the beginning of solving the model, an equal amount is assigned to all secure paths. The only difference in secure paths in the selection stage in the first step is their heuristic value. As mentioned, the combination of secure paths is evaluated by the objective function; therefore, agents, based on their search-like properties, tend to choose paths that have the highest desirability. Consequently, with consecutive selections of better paths by agents, more pheromone is placed on them.

Considering that the CNN algorithm can be adapted to the research problem conditions, modifications have been applied to the solution method of the routing and allocation model designed according to its specific criteria. To optimize the process, the determination of optimal secure paths, determination of optimal paths, and population allocation in target locations are performed in three phases for planetary points and transfers.

Figure 2. Evaluation of Objective Function Values for Agents in a Single Iteration Update:

Considering the recent discussion, the value of the objective function for an agent is acceptable only if the agent satisfies all three constraints. In this case, its value is recorded, and if another agent has also reached this stage, it is compared with that agent. Finally, the proposed algorithm, named the Chain-Based CNN Optimization Algorithm for Supply Chain, is suggested for solving the problem, and its pseudocode is provided in Appendix 1.

In Figure 3, in part "A," both alpha (α) and beta (β) have equal values, resulting in a uniform impact on the generated solutions. This leads to created costs being within a certain range with little dispersion. As the value of beta increases, in parts "B," "C," and "D," the dispersion of solutions becomes more apparent. In this scenario, the identified minimum solutions are created purely based on randomness. On the other hand, an increase in the value of beta implies giving greater importance to the spatial proportion of fixed and mobile transfer points compared to the CNN parameter.

Therefore, by keeping the alpha coefficient constant and increasing the beta coefficient, the probability of selecting paths with higher spatial proportions increases. In this case, the model, regardless of its previous history in path selection and without considering the costs associated with them, chooses transfer points and blood supply locations. Lower values of the alpha parameter ensure that previous solutions are not given much importance in each iteration. This results in each agent randomly selecting a combination of secure locations in each iteration.

As the beta coefficient increases, the spatial proportionality of the selected paths will be higher. These changes are illustrated in Figure 3, representing four different scenarios with varying beta values.

The alpha coefficient is intended to preserve the obtained satisfactory results in each iteration for use by agents in subsequent iterations. In this section, the beta coefficient is set to 0.5, and by changing the value of alpha, the results are examined. As the alpha value increases, it prevents the dispersion of solutions in terms of cost. This issue is depicted in Figure 4.

However, some of these solutions, occasionally due to the increase in the number of selected paths, may fail to satisfy the quantity constraint and, therefore, are not chosen. Another effect that an increase in the alpha coefficient creates in the solutions of each iteration is that, due to the increased power of CNN in selecting a path, the paths chosen in the initial iterations see an increase in their values. This causes the probability of their selection by subsequent agents to increase, leading to the convergence of costs for each agent in each iteration and preventing their dispersion.

Based on the above discussions, it is evident that in both cases, high values for either alpha or beta can prevent the model from reaching a suitable solution. The model has been executed five times for each set of alpha and beta values, and the results are presented in Tables 4 and 5. In this research, the minimum final value of each combination of paths is considered as a criterion for its evaluation. However, due to the inclination to explore more problem space, the combination of two parameters, alpha and beta, has been considered as 0.5 and 1, respectively.

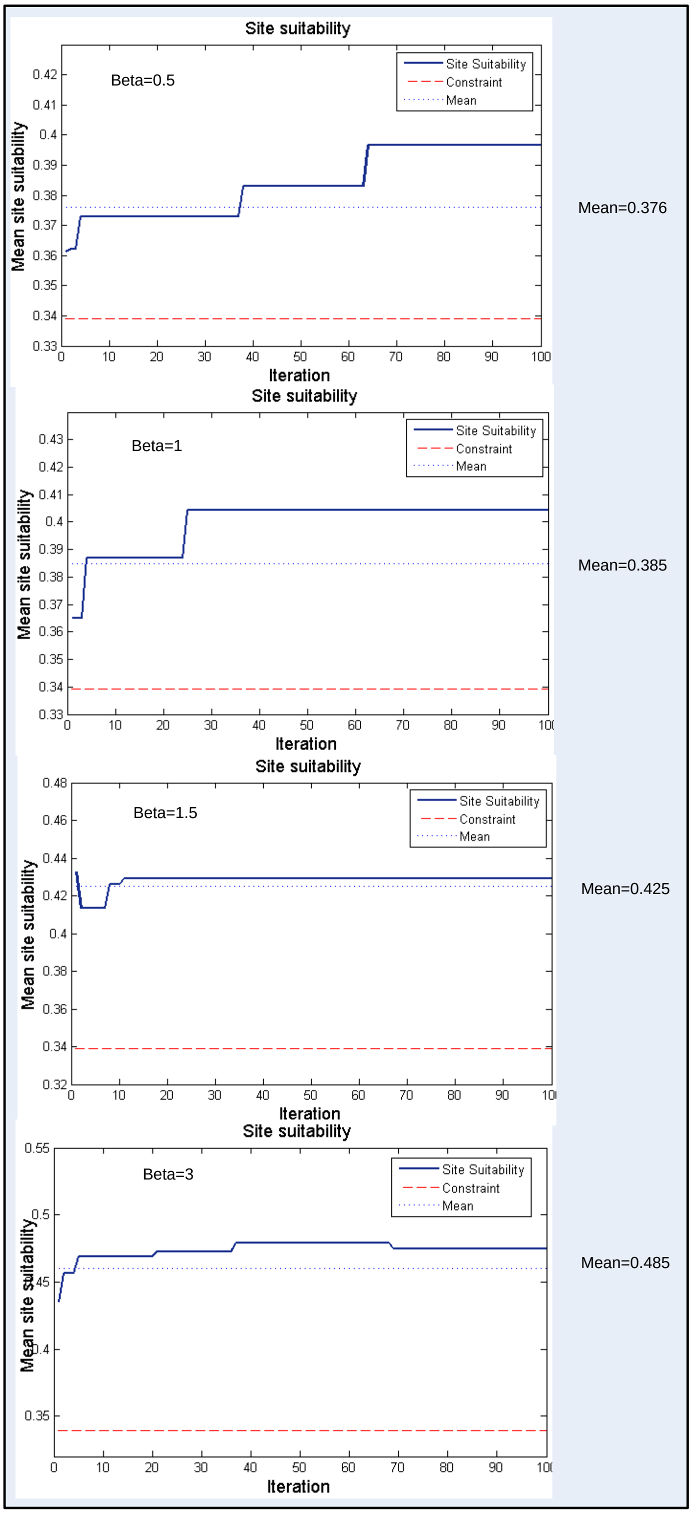

Figure 3. Average Spatial Proportion and Beta Coefficient

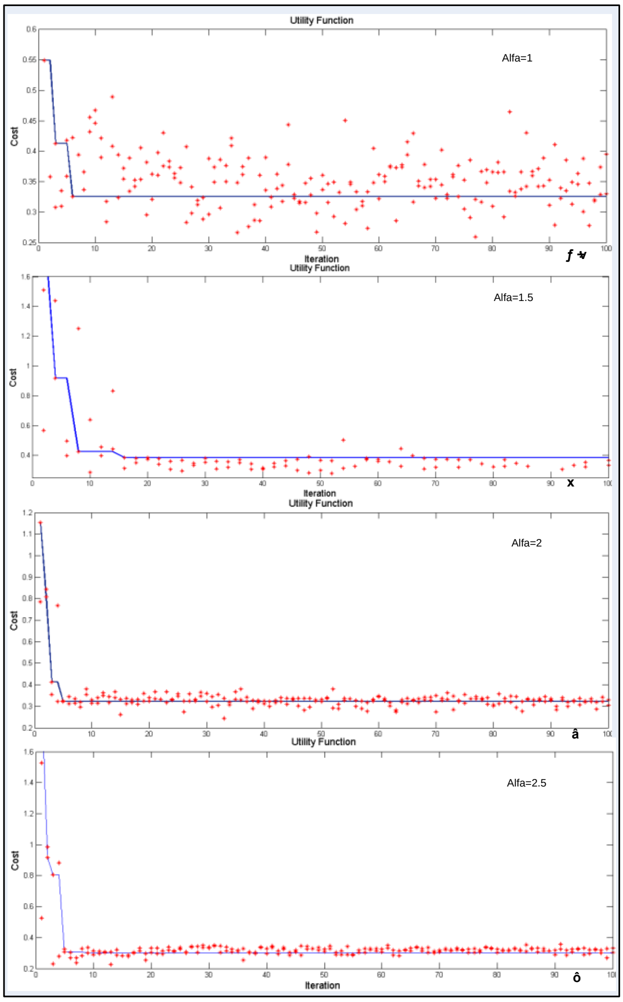

Figure 4 - Objective Function and Alpha Coefficient with Constant Beta

Table 4. Changes in the Cost Objective Function with Varying Alpha Values.

Execution number	Alpha	overflow	Spatial suitability	Convergence amount	Number of places
1	0.5	0.069	0.372	0.2988	94
2	1	0.071	0.342	0.2914	105
3	1.5	0.073	0.355	0.395	96
4	2	0.0745	0.359	0.33	109
5	2.5	0.068	0.348	0.356	110

Table 5. Changes in the Cost Objective Function with Beta

Execution number	Beta	overflow	Spatial suitability	Convergence amount	Number of places
1	0.5	0.069	0.372	0.298	94
2	1	0.066	0.382	0.3670	104
3	1.5	0.075	0.421	0.3937	95

Execution number	Beta	overflow	Spatial suitability	Convergence amount	Number of places
4	2	0.071	0.442	0.4328	103
5	2.5	0.0704	0.452	0.4606	107

Table 6. Blood Transfer Cost Based on Demand

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F1	F1	F1	F1	F1	F1	F1	F1	F1	F1	F2	F2	F2
F1	٠	٩	١٠	١١	٩	١٢	١٤	١٥	٢٠	٢٢	٢١	٢٣	١٨	١٩	٢١	٢٠	١٨	١٩	٢٣	٢٢	٢٢	٢٣
F2	١٠	٠	١٥	١٤	١٢	٨	٩	١٠	١٥	١٧	١٣	١٢	١٠	١٤	١١	١٢	١٥	١٣	١٢	١٠	٩	١٤
F3	٥	٧	٠	٤	٨	١١	١٢	١٥	١٠	١١	١٢	١٤	١٥	١٣	١٥	١٢	٨	٩	٧	١٦	١٩	٢٢
F4	٨	١٢	٢	٠	٥	٨	٩	١٤	٤	٧	٧	١٨	٤	٢	١٢	١٤	١٢	١٥	١٠	١١	١٢	١٤
F5	١٠	٨	١٢	١٠	٠		٩	١٢	١٥	١٧	١٣	١٢	٨	١٤	١١	١٢	١٥	١٣	١٤	١١	١٠	١٥
F6	١١	٤	٢٠	١٨	٩	٠	١٢	١٢	١٢	٥	١٤	٤	٧	٧	١٨	٤	٢	١٢	١٤	١٦	٢١	١٤
F7	٦	١٠	٥	٤	٨	١٥	٠	١٢	١٠	١٤	١١	١٢	١٥	١٣	١٢	١٠	٩	٨	٢٢	١١	١٠	١٥
F8	٤	٧	١٨	٤	٢	٥	٣	٠	١٨	٢٠	١٢	١٥	١٧	١٣	١٢	١٠	١٠	١١	١٢	١٤	١٨	١٨
F9	٣	٧	٧	١٨	٤	٢	١٢	١٧	٠	١٥	١٧	١٣	١٢	١٠	٧	٧	١٨	٤	٢	١٢	١٦	٢٠
F1	١٢	٨	١٤	١١	١٢	١٥	٤	١٥	١٨	٠	٢٠	٢١	٨	٩	١٠	١٢	١٥	١٠	١٥	١٢	١٤	١٢
F1	١٩	٢٠	٢١	١٢	١٥	١٠	١١	١٢	١٤	٢٠	٠	١٧	١١	١٨	١٢	١٥	١٠	١١	١٢	١٤	١٢	١٤
F1	٢١	١٧	١٨	١٤	١١	١٢	١٤	١٢	١٥	١٠	١٤	٠	٧	١٨	١٤	٢	١٢	١٤	١٢	١٥	٢٢	١٦
F1	١٢	١٣	١٥	١٩	١٢	١٥	١٠	١١	١٢	٩	٢٠	٦	٠	٧	١٨	٤	٢	١٢	١٤	١٢	١٥	٢٠
F1	٧	١٨	٤	٢	١٢	١٤	١٢	١٥	١٠	١٥	١١	١٢	١٥	٠	١٢	٢٣	١٢	١٥	٢١	١١	١٢	١٤
F1	٩	١٨	٤	٢	١٢	١٤	١٢	١٥	١٠	١٤	٩	١٢	١٠	٥	٠	٦	٨	١٤	١١	١٢	١٥	٦
F1	٢٠	٢٢	١٩	٧	١٨	٤	٢	١٢	١٤	١٢	١٥	١٠	١٢	١٤	٢٤	٠	١٨	٢٢	٢٣	٢٠	٨	٧
F1	٤	٩	١٤	١٢	١٢	١٥	١٠	١١	١٢	١٤	١٢	١٥	١٠	١١	١٢	١٤	٠	٨	١٤	١١	١٢	١٥
F1	١٢	١٥	١٠	١١	١٢	١٤	١٥	١٠	١١	١٢	١٤	١٢	١٤	٢٣	٢٠	١٥		٠	١٩	٢٥	١٤	١١
F1	١٠	١١	١٢	١٥	١٠	١١	١٢	١٤	١٢	١٤	١٤	١٢	١٥	١٠	١١	١٢	١٤	١١	٠	٧	٢١	٢٢
F2	١٥	١٧	١٢	١٥	١٠	١١	١٢	١٤	١٢	١٤	١٠	١١	١٢	١٤	١١	١٢	١٤	١٢	٩	٠	١٩	٢٠
F2	٥	٩	١٢	٨	١٤	١١	١٢	١٥		١٢	١٥	١٠	١١	١٢	١٤	١٤	٨	١٩	١٩	٢٠	٠	١٨
F2	١١	١٠	١٦	١٧	١٨	٨	١٤	١١	١٢	١٥	١٥	١٠	١١	١٢	١٤	١٥	١٠	١١	١٢	١٤	١٢	٠

Table 7 presents the results of solving the problem using the proposed method. The solution obtained by the proposed method is competitively optimal in terms of the values of the first and second objective functions.

Table 7. Percentage of Error of the Proposed Method in Blood Supply Problem

Method	Platelet	RBC	Plasma	Blood type
CNN	0.04	0.02	0.03	0.02
Supply chain optimization with deep learning-based supply chain optimization algorithm	0.001	0.001	0.001	0.001
Pareto	0.05	0.04	0.03	0.04
Global Programming	0.03	0.02	0.02	0.02

Considering the above table, Figure 5 illustrates the values of the objective functions. Optimal Pareto solutions assist the decision-maker in selecting the most suitable solution. For example, if the first objective function is a priority, the decision-maker can choose the Min-Max or LP-metric method. Conversely, if the second objective function is a priority, the decision-maker can opt for the goal programming method to solve the problem.

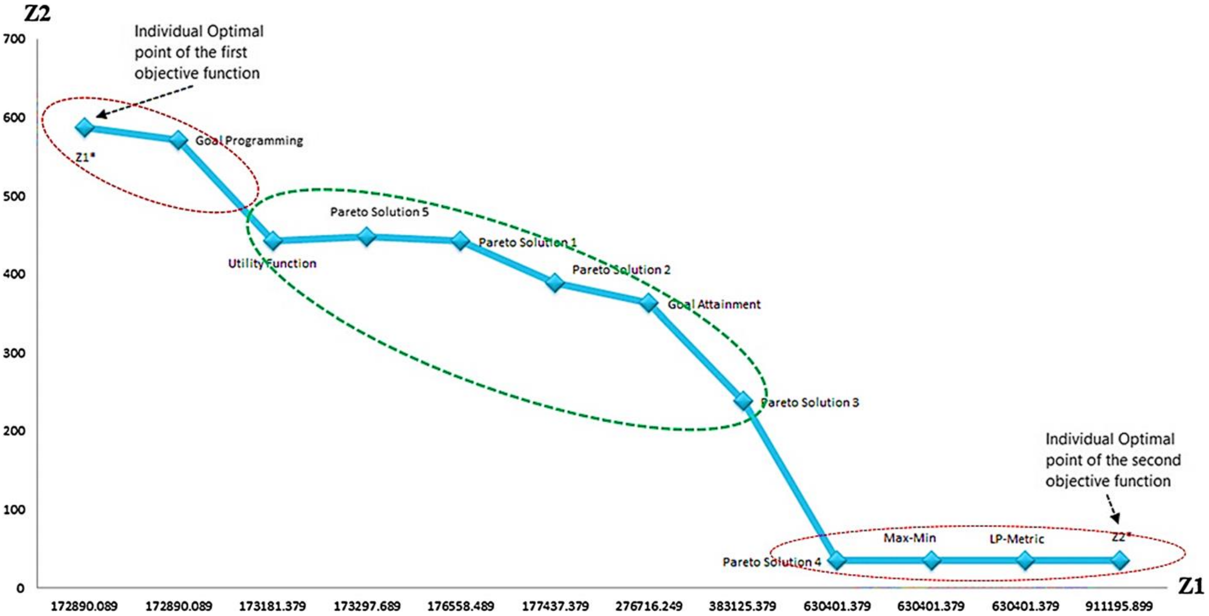

Figure 5. Values of the Functions

Figure 6 depicts the computation time of the lexicographic weighted Tchebycheff method and the proposed methods. The lexicographic weighted Tchebycheff method requires less computation time compared to the MODM method. The third Pareto optimal solution obtained using the lexicographic weighted Tchebycheff method represents the best solution in terms of computational time.

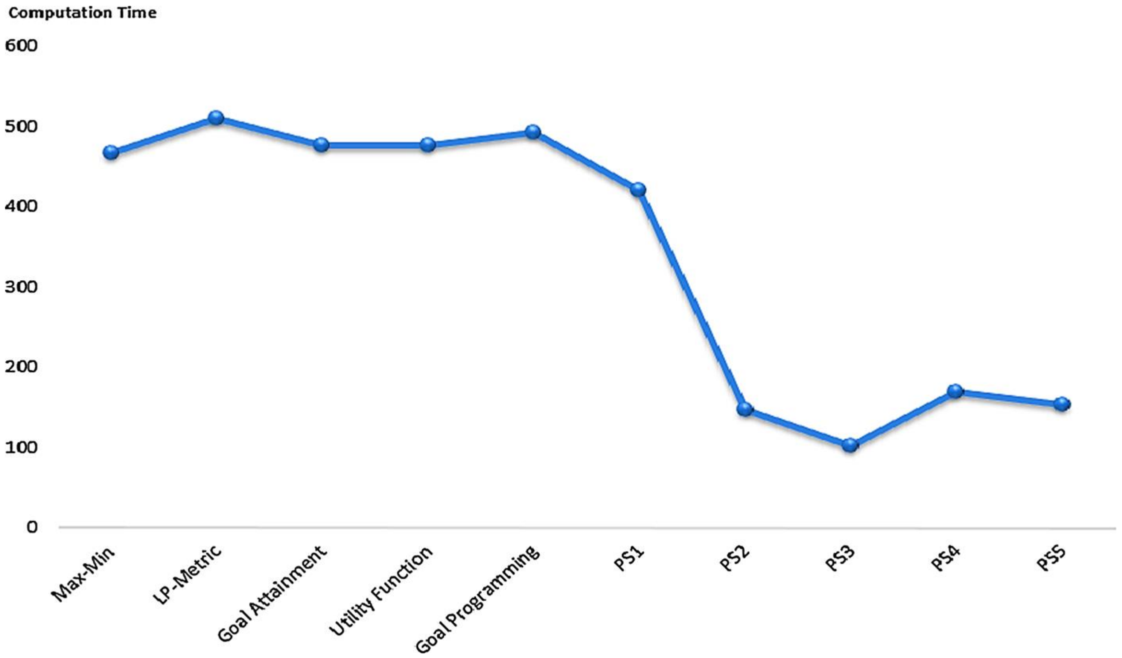

Figure 6. Computation Time

An increase in demand leads to an increase in both objective functions, and a 50%+ increase renders the problem impractical. Additionally, small changes in demand result in changes in both objective function values. An increase in mi leads to a reduction in the objective function values, and a 50% decrease makes the problem impractical. Increasing EM increases both objective function values, as stronger earthquakes cause more casualties and greater destruction, leading to the loss of more permanent collection centers. This result leads to a significant increase in supply chain costs and the time required to transport collected blood to blood centers.

An increase in coverage reduces both objective function values, indicating that more donor groups are covered, and there is no need to establish new permanent collection centers to collect blood from donor groups. The results show that increasing the capacity and coverage radius parameters significantly reduces the objective function values. Therefore, the decision-maker can reduce both the total supply chain costs and the total transportation time.

4. Simulation Results

4.1. Description

After predicting the demand level in the blood supply chain model using the CNN method in the previous section, the presented model based on the LP-metric method has been coded in the GAMS software and solved in this section. This method is introduced to address the multi-objective optimization problem, where different coefficients are assigned to the objective functions, and the model is solved. Additionally, the validation of the proposed model's accuracy is performed by solving the model in larger dimensions using the SA simulation algorithm in MATLAB, and the model's performance is examined.

4.2. Computational Results and Sensitivity Analysis

For validation and solving the proposed model, 10 different approaches or scenarios are considered, taking into account the number of fixed and mobile blood collection centers. The model has three objective functions, with the first objective representing the minimization of expected delivery time. The second objective minimizes the total supply chain costs, and the third objective reflects the social sustainability aspect, maximizing the overall societal impact by maximizing the total collected blood and its derivatives for individuals in need of these products. The data and parameters used are based on a numerical example in the model.

The results related to solving the model in small dimensions indicate that the SA algorithm performs better in the first objective function, a shorter product delivery time, and the third objective function. However, for the second objective function, the LP-Metric method performs better. In medium and large dimensions, the GAMS software is unable to solve the model, but results for the SA algorithm are obtained in medium and large dimensions.

Table 8 illustrates the performance of the developed model based on the number of fixed and mobile blood collection centers.

Table 8. Performance of the developed model based on the number of fixed and mobile blood collection centers

Scenario		$\|J'\|$	$\|J''\|$	GAMS			SA Algorithm		
				Obj1	**Obj2**	**Obj3**	**Obj1**	**Obj2**	**Obj3**
Small Scale	TP1	3	2	12.328	27543	96.457	11.689	28653	102.715
	TP2	5	4	11.671	29358	112.307	10.354	30412	117.623
	TP3	7	6	7.395	29589	149.652	8.365	32216	167.206
	TP4	9	8	5.364	31579	135.284	7.154	34895	142.635
Medium Scale	TP5	9	11	-	-	-	6.325	35623	148.634
	TP6	10	12	-	-	-	5.649	37649	176.321
	TP7	12	13	-	-	-	5.154	38662	183.164
Large Scale	TP8	14	12	-	-	-	3.657	40378	194.637
	TP9	16	15	-	-	-	3.142	43652	234.521
	TP10	17	18	-	-	-	2.967	44239	221.836

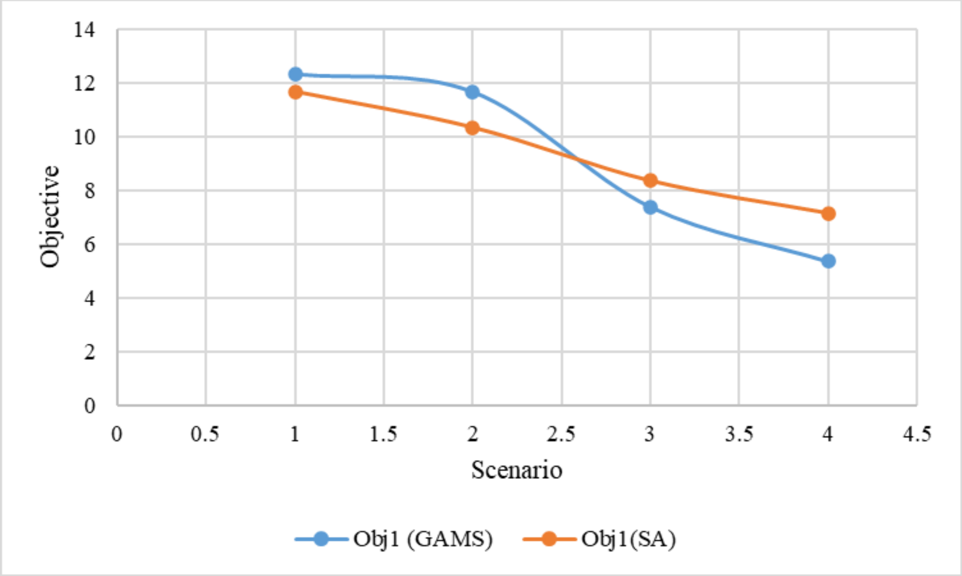

Figure 7. Changes in the first objective function based on the number of fixed and mobile blood collection centers

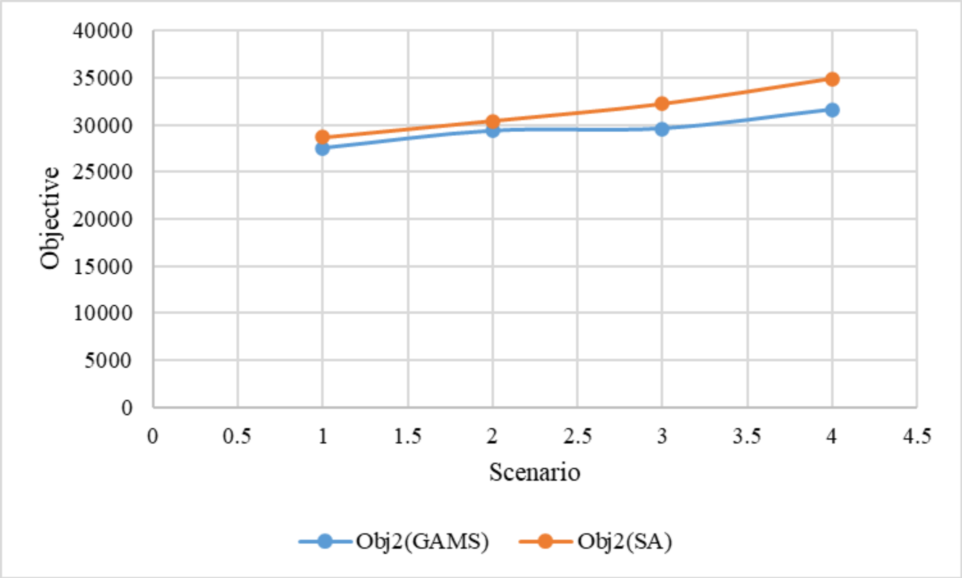

Figure 8. Changes in the second objective function based on the number of fixed and mobile blood collection centers

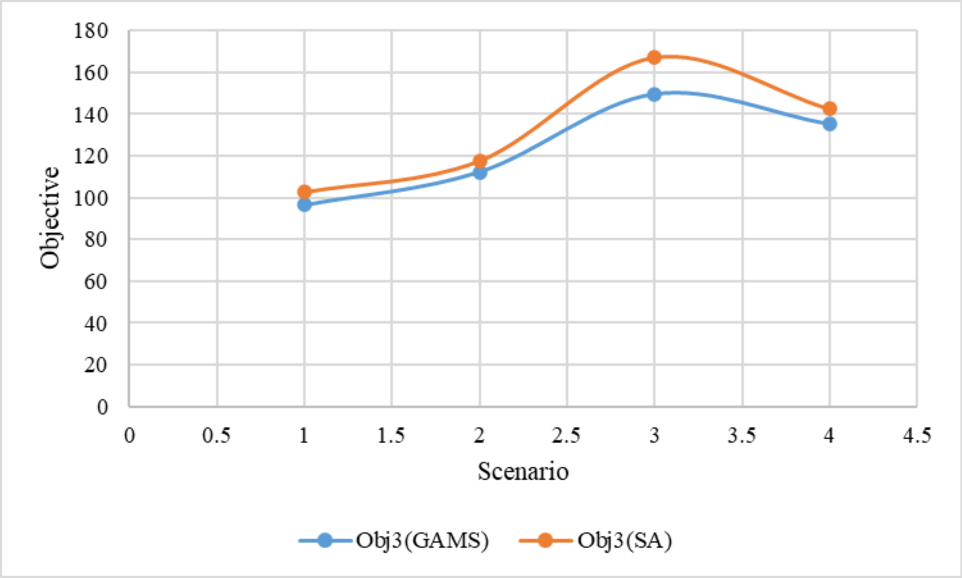

Figure 9. Changes in the third objective function based on the number of fixed and mobile blood collection centers

According to Figures 7, 8, and 9, 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, the expected delivery time, in both proposed methods has a downward trend. Also, the results related to the changes of 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 takes on an upward trend and increases, which in the Lp-Metric method first with a low slope and then it happens with a steeper slope. It is noteworthy that due to the increase of fixed and mobile blood collection centers (dimensions of the problem), the costs of the blood supply chain as a whole have an upward trend, which shows the logical trend of the proposed model in both methods of solving the problem on a small scale. The changes of the third objective function based on the values of the number of fixed and mobile blood collection centers in Figure 9 shows that with the increase in the scale of the problem, the figure has a sinusoidal trend and at first the value of the third objective function increases and then decreases. Therefore, it fluctuates depending on the scale of the problem. Also, considering Figures 10, 11, and 12, which depict solving the model based on all scenarios, it can be understood that with an increase in the number of fixed and mobile blood collection centers (in other words, with an increase in problem size), the value of the first objective function decreases. The results also show that with changes in the second objective function, as problem dimensions' increase, the cost of the blood supply chain increases, following an ascending trend. It is noteworthy that with the increase in fixed and mobile blood collection centers (problem dimensions), the overall cost of the blood supply chain follows an ascending trend, indicating the logical trend of the proposed model in solving the problem on a small scale. Changes in the third objective function based on the number of fixed and mobile blood collection centers in Figure 12 show that with an increase in problem dimensions, the graph exhibits a sinusoidal trend. Therefore, it oscillates depending on the problem dimensions. Changes in the first, second, and third objective functions based on the simulated annealing algorithm in all dimensions are illustrated in Figures 10, 11, and 12.

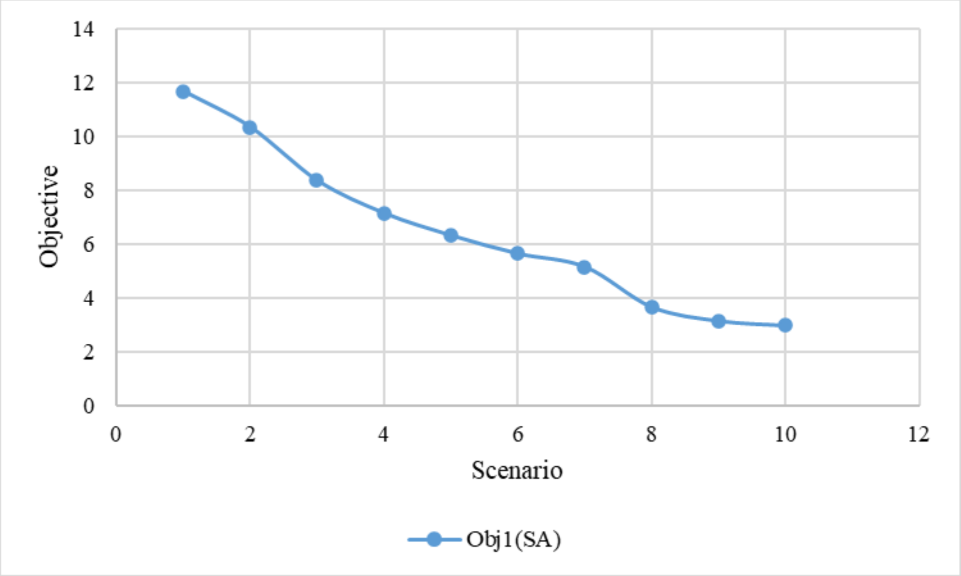

Figure 10. **C**hanges in the first objective function based on the values of the number of fixed and mobile blood collection centers for all scenarios.

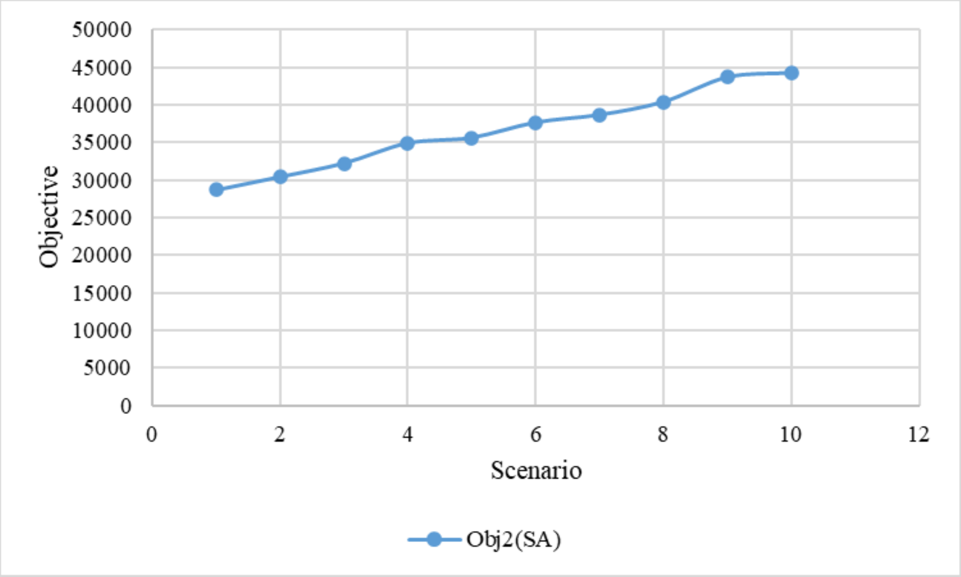

Figure 11. Changes in the second objective function based on the values of the number of fixed and mobile blood collection centers for all scenarios

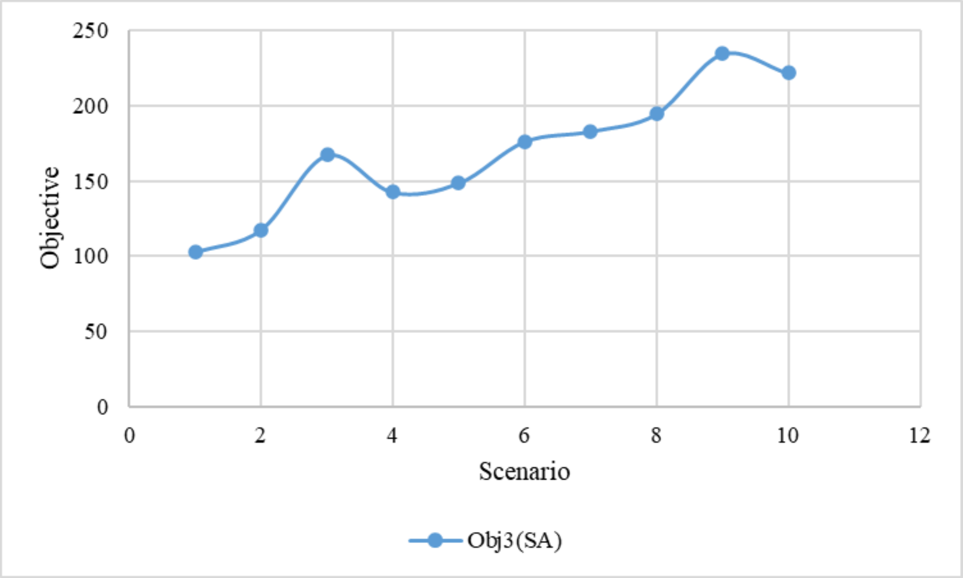

Figure 12. **C**hanges in the third objective function based on the values of the number of fixed and mobile blood collection centers for all scenarios

5. Conclusion and Outlook

In the present research, a multi-objective and multi-period mathematical model for the blood supply chain was introduced. In the first step, considering the uncertainty in blood supply and demand, a deep learning algorithm based on the CNN method was used to predict the amount of blood demand in the proposed model. After predicting the demand, the LP-Metric method in the GAMS software was utilized to solve the proposed model in this study. Additionally, for model validation, the simulated annealing algorithm was employed, and its results were compared with the LP-metric method. The results of the proposed model in small dimensions were compared for the LP-metric method and the SA algorithm. The SA algorithm performs better in optimizing the first objective function, resulting in a shorter product delivery time, and the third objective function. However, the LP-Metric method performs better for the second objective function. For small-scale problems, the LP-metric method can be used, but considering its limitations in medium and large dimensions, metaheuristic methods should be employed.

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