Robust design of a multi-echelon dynamic blood supply chain network for disaster relief

Abstract

Purpose- This paper aims to design a robust bi-objective two-stage model for a blood supply chain network in a disaster. The objectives are to minimize total costs and delivery time of blood and its components. The network includes donors, collection facilities, vehicles, blood centers, and demand points. Backup suppliers are utilized to prevent shortages. Uncertainty in supply, demand, costs, and capacities is considered. The model determines the locations of permanent facilities and blood centers, as well as the capacities and locations of temporary and mobile facilities for each scenario.
Methodology- The bi-objective problem is transformed into a single-objective one, and robust optimization is employed to handle uncertainties. A two-phase method is deployed to solve the problem. First, a lower bound is obtained using Lagrangian relaxation, and in the second phase a heuristic based on Lagrangian relaxation is proposed for finding feasible solutions.
Findings- Computational results demonstrate the effectiveness of the proposed heuristic algorithm. The sensitivity of objective functions to fundamental parameters is also examined.
Originality- This study presents a novel blood supply chain network design in disaster that considers various products, echelons, and vehicle types. In order to deal with shortages, it combines backup providers and employs a novel heuristic based on Lagrangian relaxation to find near-optimal solutions.

Keywords- Blood Supply Chain Design, Multi-Product Supply Chain, Robust Optimization, Lagrangian-Based Heuristic
Paper type- Research paper

1. Introduction

Humanitarian logistics (HL) involves managing the flow of goods, services, and information to alleviate suffering during and after disasters. It ensures timely and efficient aid delivery while tackling challenges like unpredictable supply chains, resource shortages, and infrastructure disruptions. Unlike traditional logistics, it requires rapid response, flexibility, and collaboration between stakeholders to succeed (Wassenhove, 2006). Effective HL relies on the seamless integration of technology, coordination, and adaptability to overcome these challenges.

Humanitarian logistics uses mathematical models to optimize disaster relief operations, focusing on facility location, relief distribution, and mass evacuation. These models help determine optimal warehouse locations, efficiently allocate resources, and manage logistics under uncertain conditions. They are essential for real-world applications, improving resource management in large-scale emergencies, such as those handled by organizations like the Red Cross. These models ensure resources quickly reach affected populations, reducing suffering and preventing secondary disasters. Humanitarian logistics models typically aim to minimize costs, optimize resource distribution, and reduce delivery times, with assumptions of limited resources, uncertain demand, and transportation challenges. Equity and sustainability are also considered. Key studies classify models into facility location, relief distribution, and evacuation problems, each addressing specific logistical challenges (Hezam et al., 2021).

Multi-Criteria Decision-Making (MCDM) techniques, particularly Analytic MCDM methods such as AHP, TOPSIS, and DEMATEL, help prioritize actions, optimize resource allocation, and evaluate potential supply chain configurations for greater operational efficiency. AHP helps evaluate factors like cost, delivery time, equity, and environmental impact, aiding decisions such as warehouse location and resource distribution during disaster response, ensuring efficiency and prompt delivery of aid (Paul et al., 2021). Moreover, humanitarian supply chains should be designed with sustainability at the forefront, addressing environmental, social, and economic resilience. This comprehensive approach integrates short-term recovery goals with long-term development objectives, ensuring that communities are better prepared for future disruptions. This not only facilitates rapid recovery during disruptions but also ensures the long-term stability and sustainability of supply chains in the face of continuous challenges (Ülkü et al., 2024). HL includes multiple stages that involve the integration of planning and policies in order to achieve a successful response (Ahmed et al., 2019).

One of the vital components of the healthcare system is the blood supply chain, which plays a crucial role in the system's overall importance. Therefore, any improvement in blood supply chain performance can dramatically improve efficiency and cost savings. Despite progress, there is still no substitute for blood and blood-based treatments. These resources are limited and are transferred from one person to another as needed (Agac et al., 2023). This dependence on voluntary donations underscores the importance of maintaining a robust and well-coordinated blood supply chain to meet urgent demands during crises.

The Natural Disaster Database records 8,378 global disasters since the 21st century, affecting over 4 billion people and resulting in 6 million injuries and nearly 1 million fatalities (EM-DAT, 2020). The Kermanshah earthquake in 2017 serves as a recent example, with a magnitude of 7.3, claiming 630 lives and injuring 7,000 (Mortazavi et al., 2017). This earthquake led to an increased demand for emergency blood supply, exacerbating challenges in the blood supply chain due to infrastructure damage and depleted stocks (Hosseini-Motlagh et al., 2020). The devastating earthquake in Bam in December 2003 illustrates this further, with only one-third of the population surviving from the original 99,000 (Bakhshi et al., 2023). The presence of blood deficiencies during and after a disaster can worsen conditions and increase mortality rates, necessitating immediate action from the health system (Pan American Health Organization, 2002). Addressing these gaps requires a proactive and resilient blood supply system that prioritizes preparedness and rapid response. In times of natural or human-caused calamity, blood is a crucial resource that must be available. Blood supply chain management strives to address this need. (Hosseini et al., 2023). Effective planning requires understanding disaster's effects on critical factors within the blood supply chain (Kuruppu, 2010). Decision-making becomes more complex during disasters due to uncertain supply and demand information (Zhou et al., 2021)

Managing blood effectively is challenging due to factors like expiration, irregularity in donation, and uncertain demand (Beliën and Forcé, 2012). Blood shortages incur high costs and increased mortality rates, while excessive collection leads to inventory costs and product deterioration. Additionally, disaster situations introduce further complexity and uncertainty to the blood supply chain network. Developing advanced forecasting techniques and real-time data systems can significantly enhance the efficiency and reliability of blood supply chains.

In addition to managing whole blood inventory, it is essential to conduct inventory management for blood components such as red blood cells (RBC), platelets, and plasma. Each component has distinct uses and requirements, effectively turning the blood supply chain into a multi-product chain. This diversification allows healthcare providers to tailor transfusions based on specific patient needs, improving outcomes during emergencies.

Designing a dynamic supply chain network plays a significant role in enabling a quick reaction in crisis scenarios (Sheu, 2010). Static models assume that input parameters like demand, costs, and facility capacities remain constant over the planning horizon. On the other hand, dynamic models consider fluctuations in demand and changes in input parameters (Jabbarzadeh et al., 2014). These models divide the planning horizon into multiple periods, allowing for periodic decisions on facility capacity and location (Melo et al., 2009). By integrating real-time data and predictive analytics, dynamic models can better anticipate changes and improve responsiveness during emergencies.

In disaster scenarios like earthquakes, blood centers face critical shortages. Unexpected events significantly impact human life, and numerous such incidents have occurred all over the world in recent years. These occurrences highlight the need for a well-designed and innovative blood supply chain (BSC) program capable of effectively responding to crises (Aliahmadi et al., 2023). Developing blood supply chain systems, particularly in the context of disaster events, has consistently been a critical challenge in the analysis of inflexible supply chains (Aghsami et al., 2023). During the process, there are additional costs, including labor, testing, and fractionation. However, the blood supply chain struggles with the challenge of operating in a cost-efficient manner (Hooshangi-Tabrizi et al., 2022). Due to the uncertainties, it is crucial to control the blood supply system during disasters because the demand for blood frequently rises considerably while the supply is still quite erratic. Blood transfusions may be suddenly more frequently required in emergency situations, to treat injuries and preserve lives. However, estimating the amount, location, and timing of blood that will be required can be challenging. This reinforces the need for advanced decision-support systems and collaborative frameworks to mitigate risks**.**

This study proposes a robust, two-stage method to create a multi-product blood supply chain network. It covers pre-disaster (preparedness) and post-disaster (response) decisions at the supply, processing, and distribution levels. Collected blood is categorized into eight groups for efficient distribution, considering real-world conditions and various vehicles for transportation. Facilities send blood to centers for testing and processing into products. Inventory management is crucial, with immediate backup suppliers addressing any shortages. The objective is to minimize costs and delivery time while meeting demand. The problem is transformed into a single objective using the epsilon constraint method. A high-quality lower bound and a heuristic based on Lagrangian relaxation are developed. Numerical results demonstrate the heuristic's effectiveness, and sensitivity analysis is performed on key parameters. These insights can guide practitioners in enhancing the robustness and adaptability of blood supply chain systems during crises.

The rest of this paper is structured as follows. The literature on the blood supply network in both normal and emergency conditions is reviewed in Section 2. Section 3 presents the problem, introduces the notations, and provides the mathematical programming formulations. Section 4 focuses on the solution approaches, including robust optimization, the epsilon constraint method, Lagrangian relaxation, and the Lagrangian-based heuristic approaches. In Section 5, computational studies are conducted, analyzing the performance of the Lagrangian-based heuristic and performing sensitivity analysis on parameters. Implications for Research, Practice, and Society discussed in section 6. Section 7 concludes and suggests potential areas for future research.

2. Literature review

The efficient management of the blood supply chain plays a critical role in ensuring the availability of safe and adequate blood and its components for medical treatments and emergency situations. This literature review examines key aspects of the blood supply chain, particularly in the context of disaster scenarios, and explores the application of robust optimization techniques in designing resilient blood supply chain networks.

2.1. Blood supply chain in normal conditions

In recent years, there has been growing attention to the blood supply chain and its crucial role in the healthcare system, leading to numerous studies by researchers such as Asadpour *et al.* (2022) and Torrado and Barbosa-Póvoa (2022) in this field. In this section, we will review articles that focus on the blood supply chain, exploring various aspects and advancements in this area. Pierskalla (2006) conducted an extensive review of the blood supply chain management literature, focusing on various aspects such as donor allocation to blood centers, deciding on the right number and location of centers, optimizing inventory levels, and assigning blood centers to hospitals. Building upon this foundation, Beliën and Forcé (2012) further categorized the existing literature on inventory and blood supply chain based on solution methods, planning steps, and product types. Duan and Liao (2014) explored the blood supply chain considering blood groups and the permissible displacements between them in normal conditions at the supply and distribution levels. They introduced a novel Simulation Optimization (SO) framework to effectively manage the inventory in the blood supply chain. Additionally, Dillon *et al.*(2017) proposed a two-stage stochastic programming model, which was solved using off-the-shelf optimization software. This approach minimized costs, shortages, and wastage while addressing perishability and demand uncertainty. Case study results demonstrated that revising target levels and allowing blood substitutions improved efficiency and reduced costs without compromising service quality. Rekabi et al., (2024) proposed a multi-objective model for Green Blood Supply Chain networks, aiming to reduce costs, waiting times, and environmental impact while enhancing resilience. Linear regression was used to forecast blood demand, and the Lagrangian Relaxation (LR) method was employed to solve larger problem instances.

2.2. Blood supply chain in disaster

Researchers have made significant contributions in developing models for designing blood supply chain networks that account for the occurrence of disasters. Natural hazards and other complex emergencies frequently have profound effects on society, the environment, and the economy. For instance, Hurricane Harvey impacted over 13 million people across multiple states and led to economic losses estimated at $180 billion (Entezari *et al.*, 2024). Recent studies, such as those by Farrokhizadeh *et al.*(2022) and Seyfi-Shishavan *et al.* (2021), have specifically focused on earthquakes as the disaster scenario. In order to create an integrated network of blood supply lines in the case of a catastrophe Ghatreh Samani *et al.* (2018) presented a multi-objective mixed-integer linear programming model. The model aimed to minimize total costs and transfer time while maximizing the total met demand. They employed a probabilistic two-stage planning approach to account for random and epistemic uncertainties.

A probabilistic optimization model for a multi-period and sustainable multi-objective blood supply chain with uncertain data originating from unpredictable situations before and after disasters was given by Eskandari-Khanghahi et al. (2018). Their integer linear programming-based model aimed to minimize costs and environmental effects while maximizing social impacts to enhance network efficiency. They utilized the simulated annealing metaheuristic method to solve the problem efficiently on a large scale. Fahimnia et al. (2017) concentrated on developing a stochastic bi-objective blood supply chain model for emergency scenarios. While the second goal sought to shorten the time it took to supply blood, the first target focused on cutting expenses. They used a hybrid strategy that used the ε-constraint technique with Lagrangian relaxation to solve the problem successfully. Liu and Song (2019) proposed a multi-period mixed-integer model that considered different transport modes for managing the blood supply chain in disasters. They utilized a rolling horizon strategy to optimize the blood supply chain, and their model's performance was evaluated using a case study of the 2008 Wenchuan earthquake. Ghahremani-Nahr et al., (2022) developed a two-stage stochastic bi-objective model aimed at improving the efficiency and reliability of the blood supply chain (BSC) during disaster scenarios. To solve their model, they employed a hybrid solution strategy that integrated epsilon-constrained and Lagrangian relaxation methods. Tirkolaee et al., (2023) sought to develop an optimized multi-tier blood supply chain network, addressing uncertainties in demand, capacity, and blood disposal rates. This network encompasses various stakeholders, including blood donors, collection centers, blood banks, regional hospitals, and end-use locations. The authors proposed a novel bi-objective Mixed-Integer Linear Programming (MILP) model aimed at minimizing costs while simultaneously improving employment opportunities, with particular consideration given to challenges posed by pandemics. Abdolazimi *et al.,* (2023) developed a multi-level blood supply chain model to address uncertainties in donation and demand, particularly during crises like COVID-19. The model focused on optimizing location selection and minimizing blood spoilage. They used elastic boundary objectives, modified weighted Chebyshev, and the TOPSIS algorithm to evaluate and select the best solution. The model was validated through a real COVID-19 case study, and sensitivity analyses showed that adding mobile blood facilities helped reduce delivery times. Entezari *et al.*, (2024) developed a bi-objective model to optimize the blood supply chain, aiming to minimize both costs and blood shortages during crises. Their model incorporates donor allocation, blood production, and time-dependent routing decisions. To address uncertainties in supply and demand, they applied scenario-based programming. Through numerical tests and a case study, they validated the model's efficiency, and their sensitivity analysis provided valuable managerial insights.

These studies demonstrate a growing interest in designing resilient blood supply chain networks that can effectively respond to and recover from disasters, providing valuable insights and optimization strategies for the management of blood resources during crisis situations.

2.3. Robust optimization in blood supply chain networks

Robust optimization has been utilized as a common approach for addressing uncertainty while managing the blood supply chain during emergencies. We will review some of these applications in this subsection. In response to disruptions like outbreaks, which delay blood orders and deliveries, leading to significant losses for healthcare organizations, Gilani Larimi *et al.*, (2022) proposed a robust multi-phase optimization approach for blood supply networks. They used real-world data to evaluate the model through two methods: a GIS-based approach for optimizing blood donation center locations and a mathematical model that addressed perishability, supply sources, and demand uncertainties. Their approach underscored the importance of resilient strategies in managing blood supply chains during disasters.
Haghjoo *et al.* (2020) proposed a model for creating a blood supply chain network during a disaster while considering the uncertainty and risks associated with facility disruptions. The model employed a robust approach to handle demand variability and facility disruptions effectively. For large-scale problems, two metaheuristic algorithms, namely the self-adaptive imperialist competitive algorithm and invasive weed optimization, were introduced to solve the model. Jabbarzadeh *et al.* (2014) designed a robust network of blood supply chains for disaster scenarios, encompassing decisions related to the number and location of permanent and non-permanent blood facilities, as well as the allocation of blood facilities to donors. For a multi-period blood supply chain network under catastrophe conditions, Habibi-Kouchaksaraei *et al.* (2018) proposed a robust bi-objective optimization model with a focus on supply, processing, and distribution levels. The model sought to identify the number and location of facilities as well as the best allocation strategy under various scenarios to reduce expenses and blood shortages. The problem was solved using the goal programming approach. Gilani Larimi et al. (2019) developed a multi-objective linear mixed-integer programming model for gathering, testing, producing, banking, and dispensing platelets based on age and product type. The model aimed to minimize costs as the primary objective and maximize the service level as the secondary objective. The authors solved the model under two conditions: certain demand and uncertain demand, using a stochastic robust optimization method to address the uncertainty. Hamdan and Diabat (2020) proposed a blood supply model for disaster scenarios with objectives of cost minimization and delivery time optimization. The model considered the possibility of facility and route disruptions. The effects of disasters on the blood supply system were addressed using robust optimization and two-stage stochastic optimization techniques, and an algorithm based on Lagrangian relaxation was performed to efficiently handle the problem for large-scale examples. Heidari-Fathian and Pasandideh (2018) designed a multi-objective green blood supply chain network considering both cost minimization and environmental impact reduction. Given the uncertain nature of blood demand, they applied robust optimization to handle uncertainty. Additionally, an innovative method based on the Lagrangian relaxation approach was employed to solve the problem. *Ala et al.*, (2024) introduced a multi-objective design problem for blood supply chain networks, which aimed to minimize the costs of establishing both permanent and temporary facilities, transferring blood products, and reducing shortages. To address these challenges and enhance

adaptability amid uncertainties in supply and demand, the paper proposed using lateral freight between hospitals. A novel robust possibilistic mixed-integer linear programming method was developed to handle distribution and location decisions effectively. Sheshkol *et al.*, (2024) explored collaboration between blood centers and hospitals to manage blood platelet supply and demand during normal and emergency conditions. They developed a two-stage robust programming model with two objectives: minimizing network costs (including preparation, transportation, and storage) and optimizing blood type substitution based on compatibility. Their findings showed that the highest performance was achieved when both blood centers and hospitals collaborated as a unified network.

The review of the literature highlights that many studies on blood supply chains tend to focus on specific components rather than taking a comprehensive approach that includes supply, processing, and distribution. There is also a lack of attention to handling uncertainties in supply, demand, and operational costs effectively. Research has rarely explored the integration of mobile facilities, the management of multiple blood products like RBCs, PLTs, and plasma, or the use of diverse transportation options with different capacities. Furthermore, strategies to source blood from backup suppliers during shortages and to adapt to dynamic disaster conditions remain underdeveloped. These gaps point to the need for a more robust and dynamic model that incorporates all these elements, offering a better way to build resilient and efficient blood supply chains in times of crisis. Table 1 summarizes past research on blood supply chain optimization models and identifies research gaps.

Table1 Key findings from previous research and identified gaps in Blood Supply Chain Optimization.

Source: Created by Authors

Study	**Multi-objective**	**Disaster situation**	**Multi-period**	**Multi-echelon**	**Multi-product**	**Multiple Facility Types**	**Multiple Vehicle Types**	**Demand Uncertainty**	**Supply Uncertainty**	**Solution Approach**
Jabbarzadeh *et al.*, (2014)	✓	✓	✓	✓				✓	✓	Robust optimization
Fahimnia *et al.*, (2017)	✓	✓						✓		ε-constraint and Lagrangian relaxation
Dillon *et al.*, (2017)	✓			✓						Cplex
Ghatreh Samani *et al.*, (2018)	✓	✓		✓				✓		Stochastic and possibilistic programming
Eskandari-Khanghahi *et al.*, (2018)	✓	✓	✓	✓				✓		Simulated annealing
Habibi-Kouchaksaraei *et al.*, (2018)	✓	✓	✓	✓				✓	✓	Goal programming
Gilani Larimi *et al.*, (2019)	✓	✓						✓		Lp-metric method
Liu and Song, (2019)	✓	✓	✓	✓			✓			Rolling horizon
Hamdan and Diabat, (2020)	✓	✓						✓	✓	Lagrangian relaxation
Haghjoo *et al.*, (2020)	✓	✓	✓	✓		✓		✓	✓	Imperialist competitive algorithm, Invasive weed optimization
Seyfi-Shishavan *et al.*, (2021)	✓	✓		✓						Fuzzy multi-period mathematical model
Farrokhizadeh *et al.*, (2022)	✓	✓		✓				✓		ε-constraint and Lagrangian relaxation
Ghahremani-Nahr *et al.*, (2022)	✓	✓	✓	✓				✓		ε-constraint and Lagrangian relaxation
Tirkolaee *et al.*, (2023)	✓	✓	✓	✓			✓	✓		Interactive possibilistic programming
Abdolazimi et al., (2023)	✓	✓		✓		✓		✓	✓	Modified weighted Chebyshev
Ala et al., (2024)	✓	✓		✓		✓		✓	✓	Lexicographic and Torabi-Hassini
Rekabi et al., (2024)	✓			✓						Lagrangian Relaxation
Entezari et al., (2024)	✓	✓	✓	✓				✓	✓	Modified augmented ε-constraint 2
Sheshkol et al., (2024)	✓	✓		✓				✓	✓	Robust optimization
Current Study	✓	✓	✓	✓	✓	✓	✓	✓	✓	Robust optimization and Langrangian relaxation heuristic

2.4 Research gap

In this article, some important features in designing blood supply chain in disaster are mentioned as follows:

- Considering three echelons including supply, processing, and distribution.
- Utilizing a strong optimization technique to cope with the uncertainty of the parameters, such as supply and demand, operational expenses, inventory and holding costs, transportation costs, the capacity of collecting sites, and the capacity of blood centers.
- Considering three types of collection facilities, including permanent, temporary and mobile facilities, and blood centers to process the whole blood and making decisions related to their location and allocation in each period.
- Considering the blood supply chain as a multi-product, including whole blood and its components RBC, PLT, and Plasma and separation of collected blood samples into blood groups in the collecting facilities to prevent blood loss and shortage.
- Considering the possibility of using different transportation vehicles with different capacities to carry out transfer operations.
- The ability to supply products from backup suppliers in the event of a shortage.

To the best of our knowledge, this is the first time that all the above-mentioned items are addressed simultaneously in a new stochastic, multi-product, dynamic, robust bi-objective mathematical programming model. Finally, this model is solved by a two phases solution method based on Lagrangian relaxation.

3. Model development

3.1. Problem description

The blood supply chain network under study includes blood donors, permanent facilities (clinics and medical centers), temporary facilities (schools, mosques, and stadiums), mobile facilities (tents and trailers), blood centers, demand points (hospitals), and a backup supplier. Permanent facilities have greater construction costs and capacity compared to temporary and mobile facilities. Temporary facilities can be converted into donation centers during shortages, while mobile facilities enhance efficiency and flexibility by being easily relocated.

Blood is collected from voluntary donors at permanent, temporary, and mobile facilities, allowing flexibility in selecting suitable centers for blood group separation. The collected units are transported to blood centers using different vehicles. At the centers, the units undergo testing, processing, and storage. In the laboratory facilities, the healthy units are separated into Red Blood Cells, Platelets, and Plasma. The supply chain addresses the demand for both whole blood and its components, ensuring the fulfillment of these crucial resources' needs.

Meeting the requirements within the blood supply chain network is essential to satisfy the crucial demand for blood and its components. Failure to do so can result in shortages, requiring the acquisition of additional supplies from backup suppliers at increased costs to address the resulting deficiencies. To adequately prepare for such circumstances, the network considers different scenarios based on the scale and severity of the disaster. These scenarios incorporate factors like demand, supply, facility capacity, and costs, ranging from milder situations to the most severe ones.

Resilience and humanitarian logistics are closely linked as both aim to mitigate disaster impacts and support recovery. HL enhances resilience by ensuring preparedness, adaptive supply chains, and timely responses, reducing vulnerabilities in disaster-prone areas. Effective coordination among stakeholders, sustainable recovery efforts, and robust early warning systems further strengthen resilience. Integrating resilience thinking into HL through data-driven decisions and inclusive strategies ensures communities are better equipped for future disasters (Carnero Quispe *et al.*, 2024). Pre-disaster and post-disaster are two stages of the problem. In the pre-disaster stage, the focus is on constructing and locating permanent facilities and blood centers in preparation for potential disasters. However, decisions regarding temporary and mobile facilities, blood collection volume, processing, transfer, inventory levels, and other relevant factors are made in the post-disaster stage. These decisions are based on the actual occurrence of a crisis, considering the specific circumstances and requirements at that time. The network topology is demonstrated in Figure 1.

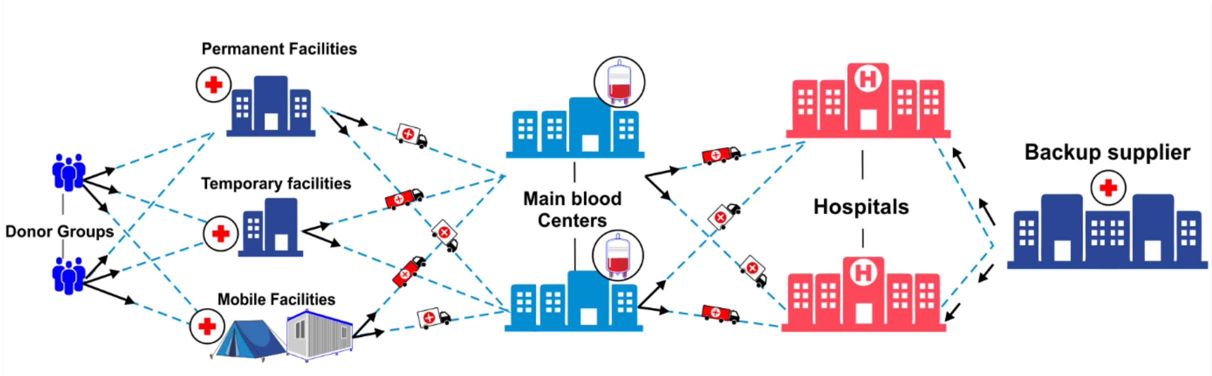

Fig. 1. Supply chain network

Source: Created by Authors

Other assumptions are as follows:

- Considering multiple periods
- Considering multiple blood donor groups to supply the required blood
- The candidate locations of all facilities are known, but the number of located facilities and their locations will be determined after solving the model
- Considering a coverage radius to allocate blood donors to collection facilities
- Vehicles have limited capacity to transport products
- Due to the presence of various blood diseases, including hepatitis, AIDS, and other infectious diseases, after tests in the main blood centers, a percentage of the total volume of collected blood units is considered unusable

3.2. Parameters and decision variables

For the current model's formulation, the following sets, parameters, and decision variables will be utilized:

J	Set of candidate locations for permanent facilities indexed by j
P	Set of candidate locations for mobile facilities indexed by p
Z	Set of types of mobile facilities indexed by z
E	Set of candidate locations for temporary facilities indexed by e
L	Set of candidate locations for main blood centers indexed by l
V	Set of vehicle types indexed by v
G	Set of blood groups indexed by g
K	Set of blood components indexed by k
A	Set of blood donor groups indexed by a
H	Set of hospitals (i.e., demand points) indexed by h
T	Set of time periods indexed by t
S	Set of scenarios indexed by s

Parameters:

CP_j	Cost of establishing permanent facility j
CB_l	Cost of establishing main blood center l

CT_e^s	Cost of establishing temporary facility e under scenario s
CV_v	Cost of using a vehicle of type v per unit distance
Num_v	Number of vehicles of type v
CM_{zpt}^s	Cost of establishing mobile facility of type z in location p in period t under scenario s
CBS^s	Cost of supplying one unit of blood components from backup supplier under scenario s
CBW^s	Cost of supplying one unit of whole blood from backup supplier under scenario s
$CapV_v$	Capacity of a vehicle of type v
$CapM_z^s$	Storage capacity of a mobile facility of type z under scenario s
$CapP_j^s$	Storage capacity of permanent facility j under scenario s
$CapT_e^s$	Storage capacity of temporary facility e under scenario s
$CapB_l^s$	Storage capacity of main blood center l under scenario s
C_{zipt}^s	Displacement cost of a mobile facility of type z from location i to location p in period t under scenario s
$DisM_{ap}$	Distance between donor group a and mobile facility p
$DisT_{ae}$	Distance between donor group a and temporary facility e
$DisP_{aj}$	Distance between donor group a and permanent facility j
DM_{pl}	Distance between mobile facility p and blood center l
DT_{el}	Distance between temporary facility e and blood center l
DP_{jl}	Distance between permanent facility j and blood center l
DH_{lh}	Distance between hospital h and blood center l
OCM_{pzgt}^s	Unit cost for collecting blood group g at mobile facility of type z located in p in period t under scenario s
OCT_{egt}^s	Unit cost for collecting blood group g at temporary facility e in period t under scenario s
OCP_{jgt}^s	Unit cost for collecting blood group g at permanent facility j in period t under scenario s
OCB_{kglt}^s	Unit cost for production of blood component k of blood group g in main blood center l in period t under scenario s
OCW_{glt}^s	Unit cost of processing whole blood with blood group g in main blood center l in period t under scenario s
IW_{glt}^s	Inventory holding cost of whole blood with blood group g in main blood center l in period t under scenario s
IC_{gklt}^s	Inventory holding cost of blood components k with blood group g in main blood center l in period t under scenario s
Max_{at}^s	Maximum blood supply of donor group a in period t under scenario s
$DemC_{gkt}^s$	Demand of blood component k of blood group g in period t under scenario s
Dem_{gt}^s	Demand of whole blood of blood group g in period t under scenario s
TVM_{pl}	Travel time between mobile facility p and main blood center l
TVT_{el}	Travel time between temporary facility e and main blood center l
TVP_{jl}	Travel time between permanent facility j and main blood center l
TVH_{hl}	Travel time between mobile facility p and main blood center l
cd	Blood collection facilities' range of coverage
π_s	Probability of occurrence of scenario s
β_t	Referral rate of blood
α_k	Proportion of blood components k in the whole blood
M	A very large number

Decision variables:

EP_j	A binary variable, equal to 1 if permanent facility is opened at location j; 0 otherwise
EB_l	A binary variable, equal to 1 if main blood center is opened at location l; 0 otherwise

LM_{zpt}^{s}	A binary variable, equal to 1 if mobile facility of type z is placed in location p in period t under scenario s; 0 otherwise
LT_{e}^{s}	A binary variable, equal to 1 if temporary facility is established at location e under scenario s; 0 otherwise
TM_{zipt}^{s}	A binary variable, equal to 1 if mobile facility of type z moves from location i to location p in period t under scenario s; 0 otherwise
W_{apzt}^{s}	A binary variable, equal to 1 if donor group a is assigned to mobile facility of type z located in p in period t under scenario s; 0 otherwise
O_{aet}^{s}	A binary variable, equal to 1 if donor group a is assigned to temporary facility e in period t under scenario s; 0 otherwise
D_{ajt}^{s}	A binary variable, equal to 1 if donor group a is assigned to permanent facility j in period t under scenario s; 0 otherwise
$QM_{agvzplt}^{s}$	Quantity of blood group g collected at mobile facility of type z located in p from donor group a in period t to deliver to main blood center l with vehicle type v under scenario s
QP_{agvjlt}^{s}	Amount of blood group g obtained from donor group a at a permanent facility j in time t to be delivered to the main blood center l with vehicle type v in scenario s
QT_{agvelt}^{s}	Quantity of blood group g taken from donor a at temporary facility e in time t to transport to main blood center l with vehicle type v in scenarios s
QC_{kglt}^{s}	Produced quantity of component k of blood group g in main blood center l in period t under scenario s
Q_{glt}^{s}	Quantity of collected blood of group g decomposed to blood components in blood center l in period t under scenario s
QW_{glt}^{s}	Quantity of collected blood of group g kept as whole blood in blood center l in period t under scenario s
QCH_{kgvlht}^{s}	Quantity of component k of blood group g delivered from main blood center l to hospital h transported with vehicle type v in period t under scenario s
QWH_{glvht}^{s}	Quantity of whole blood group g delivered from main blood center l to hospital h transported with vehicle type v in period t under scenario s
Inv_{glt}^{s}	Inventory level of whole blood group g at main blood center l at the end of period t under scenario s
Inl_{kglt}^{s}	Inventory level of blood component k of blood group g at main blood center l at the end of period t under scenario s
BSC_{gkt}^{s}	Quantity of component k of blood group g supplied by backup supplier in period t under scenario s
BSW_{gt}^{s}	Quantity of whole blood group g supplied by backup supplier in period t under scenario s

The issue is tackled using a two-stage stochastic programming model that includes several scenarios to reflect the problem's uncertain character. The model follows a two-stage planning approach, where the decision variables are divided into two categories. The first-stage decision variables are determined independently of the specific scenario and are quantified prior to the occurrence of the scenario. On the other hand, the second-stage decision variables are contingent upon the realization of the scenario and are measured after the scenario has occurred. This formulation allows for a more robust and flexible decision-making process, as it considers both pre-scenario decisions and post-scenario adjustments in addressing the complexities of the blood supply chain management problem. The variables EP_j and EB_l are the first stage decision variables.

3.3. Objective functions

The first objective function minimizes supply chain network costs. These costs include cost of establishing permanent facilities and blood centers (EC), cost of construction and establishment of temporary and mobile facilities (LC_s), transportation cost (TC_s), operational cost (OC_S), inventory cost (IC_S), and the cost of supplying the shortage from the backup supplier (CB_S). These terms are formulated in Eqs. (1) to (5).

$$EC + LC_S = (\sum_j CP_j\, EP_j + \sum_l CB_l\, EB_l) + \sum_s \pi_s(\sum_z \sum_p \sum_t CM_{zpt}^s\, LM_{zpt}^s + \sum_e CT_e^s LT_e^s\ ) \tag{1}$$

$$\begin{aligned} TC_S = \sum_s \pi_s(& \sum_z \sum_i \sum_p \sum_t C_{zipt}^s TM_{zipt}^s \\ & + \sum_v \sum_t CV_v (\sum_p \sum_z \sum_a \sum_l DM_{pl} \times \left\lceil \frac{\sum_g QM_{agvzplt}^s}{CapV_v} \right\rceil \\ & + \sum_e \sum_l \sum_a DT_{el} \times \left\lceil \frac{\sum_g QT_{agvelt}^s}{CapV_v} \right\rceil + \sum_j \sum_l \sum_a DP_{jl} \times \left\lceil \frac{\sum_g QP_{agvjlt}^s}{CapV_v} \right\rceil \\ & + \sum_l \sum_h \sum_a DH_{lh} \times \left\lceil \frac{\sum_g \sum_k QCH_{kgvlht}^s + \sum_g QWH_{gvlht}^s}{CapV_v} \right\rceil) \end{aligned} \tag{2}$$

$$\begin{aligned} OC_S = \sum_s \pi_s(& \sum_p \sum_z \sum_a \sum_g \sum_l \sum_t \sum_v QM_{agvzplt}^s\, OCM_{pzgt}^s \\ & + \sum_e \sum_g \sum_t \sum_a \sum_l \sum_v QT_{egvalt}^s OCT_{egt}^s + \sum_j \sum_g \sum_t \sum_a \sum_l \sum_v QP_{agvjlt}^s OCP_{jgt}^s \\ & + \sum_k \sum_g \sum_l \sum_t QC_{kglt}^s\, OCB_{kglt}^s + \sum_g \sum_l \sum_t OCW_{glt}^s \left(Q_{glt}^s + QW_{glt}^s\right)) \end{aligned} \tag{3}$$

$$IC_S = \sum_s \pi_s(\sum_l \sum_g \sum_t IW_{lgt}^s Inv_{lgt}^s + \sum_k \sum_g \sum_l \sum_t IC_{kglt}^s\, Inl_{kglt}^s) \tag{4}$$

$$CB_S = \sum_s \pi_s(\sum_g \sum_k \sum_t CBS^s BSC_{gkt}^s + \sum_g \sum_t CBW^s BSW_{gt}^s) \tag{5}$$

Eq. (1) expresses the cost of locating and constructing facilities. Actions related to the opening of permanent facilities and main blood centers are made before the happening of the disaster. In contrast, decisions to locate temporary and mobile facilities depend on the disaster scenario. Eq. (2) calculates the cost of moving mobile facilities, the cost of transferring collected blood units from mobile, temporary, and permanent facilities to blood centers and the cost of transferring whole blood units and blood components from blood centers to demand points (i.e., hospitals). Operating costs for collection facilities and blood centers are formulated in Eq. (3). Further, Eq. (4) shows the cost of inventory of whole blood units and its components in blood centers. The final part of the objective function (i.e., Eq. (5)) is the cost of providing whole blood units and its components from backup suppliers in case of a shortage. The first objective function of the problem (cost function) will be written as Eq. (6) by adding the above five terms.

$$min\, F_1 = EC + LC_S + TC_S + OC_S + IC_S + Cb_S \tag{6}$$

The second objective function of the problem is based on the nature of the perishability of blood. Since blood is a perishable product, the transfer time from the supplier (i.e., donors) to the demand points (i.e., hospitals) should be minimized. The second objective is to reduce the average time it takes to deliver blood from collecting facilities to blood centers (TCB_s) and from blood centers to hospitals (TBH_s). In this regard, the volume of blood transferred is considered as weight.

$$TCB_S = \sum_{s} \pi_s \left(\sum_{a} \sum_{g} \sum_{z} \sum_{p} \sum_{l} \sum_{t} \sum_{v} QM^{s}_{agvzplt}\, TVM_{pl} + \sum_{e} \sum_{g} \sum_{t} \sum_{a} \sum_{l} \sum_{v} QT^{s}_{egvalt} TVT \right.$$
$$\left. + \sum_{j} \sum_{g} \sum_{t} \sum_{a} \sum_{l} \sum_{v} QP^{s}_{agvjlt} TVP_{jl} \right) \tag{7}$$

$$TBH_S = \sum_{s} \pi_s \left(\sum_{k} \sum_{g} \sum_{l} \sum_{h} \sum_{t} \sum_{v} QCH^{s}_{kgvlht}\, TVH_{lh} + \sum_{g} \sum_{l} \sum_{h} \sum_{t} \sum_{v} QWH^{s}_{gvlht} \right) \tag{8}$$

Eq. (7) determines the weighted travel time to deliver whole blood to blood centers from temporary, mobile, and permanent facilities. Eq. (8) displays the weighted time that blood and blood components take to transit from blood banks to hospitals. By adding expressions (7) and (8), the second objective function of the problem is constructed as Eq. (9).

$$Min\ F_2 = TCB_S + TBH_S \tag{9}$$

3.4. Model constraints

The following constraints apply to the objective functions defined in subsection 3. 3.

$$\sum_{i \in P} TM^{s}_{zipt} = LM^{s}_{zpt} \qquad \forall z \in Z, \forall p \in P, \forall t \in T, \forall s \in S \tag{10}$$

$$\sum_{z} LM^{s}_{zpt} \leq 1 \qquad \forall p \in P, \forall t \in T, \forall s \in S \tag{11}$$

$$\sum_{i \in P} TM^{s}_{zpit} \leq \sum_{i \in P} TM^{s}_{zip,t-1} \quad \forall z \in Z, \forall p \in P, \forall t \in T, \forall s \in S \tag{12}$$

$$W^{s}_{apzt} \leq LM^{s}_{zpt} \qquad \forall a \in A, \forall z \in Z, \forall p \in P, \forall t \in T, \forall s \in S \tag{13}$$

$$D^{s}_{ajt} \leq EP_j \qquad \forall a \in A, \forall j \in J, \forall t \in T, \forall s \in S \tag{14}$$

$$O^{s}_{aet} \leq ET^{s}_{e} \qquad \forall a \in A, \forall e \in E, \forall t \in T, \forall s \in S \tag{15}$$

$$QM^{s}_{agvzplt} \leq M \cdot W^{s}_{apzt} \qquad \forall a \in A, \forall g \in G, \forall v \in V, \forall z \in Z, \forall p \in P, \forall l \in L, \forall t \in T, \forall s \in S \tag{16}$$

$$QT^{s}_{agvelt} \leq M \cdot O^{s}_{aet} \qquad \forall a \in A, \forall g \in G, \forall v \in V, \forall e \in E, \forall l \in L, \forall t \in T, \forall s \in S \tag{17}$$

$$QP^{s}_{agvjlt} \leq M \cdot D^{s}_{ajt} \qquad \forall a \in A, \forall g \in G, \forall v \in V, \forall j \in J, \forall l \in L, \forall t \in T, \forall s \in S \tag{18}$$

$$DisM_{ap} \cdot W^{s}_{apzt} \leq cd \qquad \forall a \in A, \forall z \in Z, \forall p \in P, \forall t \in T, \forall s \in S \tag{19}$$

$$DisT_{ae} \cdot O^{s}_{aet} \leq cd \qquad \forall \mathrm{a} \in \mathrm{A}, \forall \mathrm{e} \in \mathrm{E}, \forall \mathrm{t} \in \mathrm{T}, \forall \mathrm{s} \in \mathrm{S} \tag{20}$$

$$DisP_{aj} \cdot D^{s}_{ajt} \leq cd \qquad \forall a \in A, \forall j \in J, \forall t \in T, \forall s \in S \tag{21}$$

$$\sum_{a}\sum_{g} QM_{agvzplt}^{s} \leq M \cdot EB_{l} \qquad \forall v \in V, \forall z \in Z, \forall p \in P, \forall l \in L, \forall t \in T, \forall s \in S \tag{22}$$

$$\sum_{a}\sum_{g} QT_{agvelt}^{s} \leq M \cdot EB_{l} \qquad \forall v \in V, \forall e \in E, \forall l \in L, \forall t \in T, \forall s \in S \tag{23}$$

$$\sum_{a}\sum_{g} QP_{agvjlt}^{s} \leq M \cdot EB_{l} \qquad \forall v \in V, \forall j \in J, \forall l \in L, \forall t \in T, \forall s \in S \tag{24}$$

$$\sum_{a}\sum_{g}\sum_{v} QM_{agvzplt}^{s} \leq CapM_{z}^{s} \cdot LM_{zpt}^{s} \qquad \forall z \in Z, \forall p \in P, \forall l \in L, \forall t \in T, \forall s \in S \tag{25}$$

$$\sum_{a}\sum_{g}\sum_{v} QT_{agvelt}^{s} \leq CapT_{e}^{s} \cdot LT_{e}^{s} \qquad \forall e \in E, \forall l \in L, \forall t \in T, \forall s \in S \tag{26}$$

$$\sum_{a}\sum_{g}\sum_{v} QP_{agvjlt}^{s} \leq CapP_{j}^{s} \cdot EP_{j} \qquad \forall j \in J, \forall l \in L, \forall t \in T, \forall s \in S \tag{27}$$

$$\sum_{g} Inv_{glt}^{s} + \sum_{k}\sum_{g} Inl_{kglt}^{s} \leq CapB_{l} \cdot EB_{l} \qquad \forall l \in L, \forall t \in T, \forall s \in S \tag{28}$$

$$\sum_{p}\sum_{z}\sum_{g}\sum_{l}\sum_{v} QM_{agvzplt}^{s} + \sum_{j}\sum_{g}\sum_{l}\sum_{v} QP_{agvjlt}^{s} + \sum_{e}\sum_{g}\sum_{l}\sum_{v} QT_{agvelt}^{s} \leq max_{at}^{s} \qquad \forall a \in A, \forall t \in T \in S \tag{29}$$

$$Q_{glt}^{s} + QW_{glt}^{s} = (1 - \beta_{t})\left(\sum_{a}\sum_{p}\sum_{z}\sum_{v} QM_{agvzplt}^{s} + \sum_{a}\sum_{e}\sum_{v} QT_{agvelt}^{s} + \sum_{a}\sum_{j}\sum_{v} QP_{agvjlt}^{s}\right) \qquad \forall e \in E, \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \tag{30}$$

$$QC_{kglt}^{s} = \alpha_{k} \cdot Q_{glt}^{s} \qquad \forall k \in K, \forall g \in G, \forall l \in L, \forall t \in T, \forall s \in S \tag{31}$$

$$\left\lceil \frac{\sum_{a}\sum_{g}\sum_{z}\sum_{p}\sum_{l} QM_{agvzplt}^{s}}{CapV_{v}} \right\rceil + \left\lceil \frac{\sum_{a}\sum_{g}\sum_{e}\sum_{l} QT_{agvelt}^{s}}{CapV_{v}} \right\rceil + \left\lceil \frac{\sum_{a}\sum_{g}\sum_{j}\sum_{l} QP_{agvjlt}^{s}}{CapV_{v}} \right\rceil + \left\lceil \frac{\sum_{g}\sum_{l}\sum_{h} Qw_{glht}^{s} + \sum_{k}\sum_{g}\sum_{l}\sum_{h} QT_{kglht}^{s}}{CapV_{v}} \right\rceil \leq num_{v} \quad \forall v \in V, \forall t \in T, \forall s \in S \tag{32}$$

$$Inv_{glt}^{s} = Inv_{gl.t-1}^{s} + QW_{glt}^{s} - \sum_{v}\sum_{h} QWH_{gvlht}^{s} \qquad \forall g \in G, \forall l \in L, \forall t \in T, \forall s \in S \tag{33}$$

$$Inl_{kglt}^{s} = Inl_{kgl.t-1}^{s} + QC_{kglt}^{s} - \sum_{v}\sum_{h} QCH_{kgvlht}^{s} \quad \forall k \in K, \forall g \in G, \forall l \in L, \forall t \in T, \forall s \in S \tag{34}$$

$$Dem_{gt}^{s} - \sum_{v}\sum_{l}\sum_{h} QWH_{gvlht}^{s} = BSW_{gt}^{s} \quad \forall g \in G, t \in T, \forall s \in S \tag{35}$$

$$DemC_{gkt}^{s} - \sum_{v}\sum_{l}\sum_{h} QCH_{kgvlht}^{s} = BSC_{gkt}^{s} \quad \forall k \in K, \forall g \in G, t \in T, \forall s \in S \tag{36}$$

$$EP_j, EB_l, LM_{zpt}^{s}, LT_e^{s}, TM_{zipt}^{s}, W_{apzt}^{s}, O_{aet}^{s}, D_{ajt}^{s} \in \{0.1\} \quad \forall a \in A, \forall g \in G, \forall z \in Z, \forall p \in P, \forall l \in L, \forall t \in T, \forall s \in S \tag{37}$$

$$QM_{agvzplt}^{s}, QT_{agvelt}^{s}, QP_{agvjlt}^{s}, QCH_{kgvlht}^{s}, QWH_{gvlht}^{s}, QC_{kglt}^{s}, Inv_{glt}^{s}, Inl_{kglt}^{s}, Q_{glt}^{s}, QW_{glt}^{s}, BSW_{gt}^{s}, BSC_{gkt}^{s} \geq 0 \quad \forall a \in A, \forall g \in G, \forall v \in V, \forall z \in Z, \forall p \in P, \forall l \in L, \forall t \in T, \forall s \in S, \forall h \in H, \forall k \in K \tag{38}$$

Constraint (10) states that the mobile facility of type z can be moved to location p at the end of period t under scenario s. Constraint (11) states that only a mobile facility is allowed at each candidate point. Constraint (12) ensures that it is impossible to move mobile facilities from a place where they are not located. Constraint (13) states that blood donor groups can be assigned to an open and located mobile facility. Constraint (14) states that blood donor groups can be assigned to an open permanent facility. Constraint (15) states that Blood donor groups can be assigned to an open temporary facility. Constraints (16) - (18) indicate that mobile, temporary, and permanent facilities cannot receive blood from unassigned donor groups. Constraints (19) - (21) state that donor groups may be assigned to mobile, temporary, and permanent facilities within their coverage radius. Constraints (22) to (24) state that the total volume of collected blood in mobile, temporary, and permanent facilities must be transferred to the blood centers. Constraints (25) - (28) indicate limited capacity constraints for mobile, temporary, and permanent collection facilities and blood centers under each scenario. Maximum blood supply is specified by constraint (29) for each donor group in each period and scenario. Constraint (30) states that healthy blood units are considered after testing at the blood centers. Constraint (31) states blood components are present in specific proportions in whole blood units. Constraint (32) states limited and specific number of vehicles for transferring whole blood and blood components between facilities. Constraints (33) and (34) indicate balance equations for the inventory of whole blood and blood components at blood centers. Constraints (35) and (36) state deficiency of whole blood and blood components in the supply chain network provided by the backup supplier. Constraints (37) and (38) state an allowable range of decision variables.

4. Solution methods

4.1. Model linearization

The round-up function causes the transportation costs TC_s in the first objective function to be nonlinear. By defining integer variables ${Y_1}_{azpltv}^{s}$, ${Y_2}_{azpltv}^{s}$, ${Y_3}_{azpltv}^{s}$ & ${Y_4}_{azpltv}^{s}$ the non-linear expression in the first objective function can be changed to a linear expression (44), by adding equations (39) and (43) to the model.

$$\frac{\sum_g QM_{agvzplt}^{s}}{CapV_v} \leq {Y_1}_{azpltv}^{s} \tag{39}$$

$$\frac{\sum_g QT_{agvelt}^{s}}{CapV_v} \leq {Y_2}_{aeltv}^{s} \tag{40}$$

$$\frac{\sum_g QP_{agvjlt}^{s}}{CapV_v} \leq {Y_3}_{ajltv}^{s} \tag{41}$$

$$\frac{\sum_g \sum_k QCH_{kgvlht}^{s} + \sum_g QWH_{gvlht}^{s}}{CapV_v} \leq {Y_4}_{lhtv}^{s} \tag{42}$$

$$Y_{1}{}^{s}_{azpltv}, Y_{2}{}^{s}_{aeltv}, Y_{3}{}^{s}_{ajltv}, Y_{4}{}^{s}_{lhtv} \geq 0 \,\&\, Integer \tag{43}$$

$$\sum_{s} \pi_s (\sum_{v} \sum_{t} CV_v \left(\sum_{p} \sum_{z} \sum_{a} \sum_{l} DM_{pl} \times Y_{1}{}^{s}_{azpltv} + \sum_{e} \sum_{l} \sum_{a} DT_{el} \times Y_{2}{}^{s}_{aeltv} + \sum_{j} \sum_{l} \sum_{a} DP_{jl} \times Y_{3}{}^{s}_{ajltv} + \sum_{l} \sum_{h} \sum_{a} DH_{lh} \times Y_{4}{}^{s}_{lhtv} \right)) \tag{44}$$

Besides, constraint (32) is nonlinear due to the existence of the decision variables in the denominator of the fractions. By defining integer variables $X_{1}{}^{s}_{vt}$, $X_{2}{}^{s}_{vt}$, $X_{3}{}^{s}_{vt}$ & $X_{4}{}^{s}_{vt}$ this constraint can be replaced by set of constraints (45) to (50).

$$\frac{\sum_a \sum_g \sum_z \sum_p \sum_l QM^{s}_{agvzplt}}{CapV_v} \leq X_{1}{}^{s}_{vt} \tag{45}$$

$$\frac{\sum_a \sum_g \sum_e \sum_l QT^{s}_{agvelt}}{CapV_v} \leq X_{2}{}^{s}_{vt} \tag{46}$$

$$\frac{\sum_a \sum_g \sum_j \sum_l QP^{s}_{agvjlt}}{CapV_v} \leq X_{3}{}^{s}_{vt} \tag{47}$$

$$\frac{\sum_g \sum_l \sum_h QWH^{s}_{glht} + \sum_k \sum_g \sum_l \sum_h QCH^{s}_{kglht}}{CapV_v} \leq X_{4}{}^{s}_{vt} \tag{48}$$

$$X_{1}{}^{s}_{vt} + X_{2}{}^{s}_{vt} + X3^{s}_{vt} + X_{4}{}^{s}_{vt} \leq num_v \tag{49}$$

$$X_{1}{}^{s}_{vt}, X_{2}{}^{s}_{vt}\;, X_{3}{}^{s}_{vt}, X_{4}{}^{s}_{vt} \geq 0 \,\&\, Integer \tag{50}$$

4.2. Robust optimization

In real-world problems, uncertainty is common in parameters. Incomplete, erroneous, or missing data in various applications contribute to this uncertainty. The robust optimization strategy is employed to solve this problem, with the goal of producing solutions that are less sensitive to input data uncertainty and continue to be close to the optimal solution (Jabbarzadeh *et al.*, 2014). The robust optimization approach, as proposed by Mulvey *et al.* (1995), introduces two types of stability, which are described as follows:

- Robustness of the solution, or how close it comes to the optimal solution in all scenarios.
- Model robustness, a solution that is ‘almost’ feasible in all scenarios.

According to the contents of the robust optimization method, due to the existence of uncertain parameters such as the demand of the affected area, in this section we will use Mulvey's robust method. The blood supply chain network model's objective functions will be changed as equations (51) and (52). The first two terms of the objective function (Z_1) show solution robustness, and the last two terms show model robustness.

$$min\, Z_1 = \sum_{s \in S} \pi_s F_1^s + \lambda \sum_{s \in S} \pi_s \left(F_1^s - \sum_{s' \in S} \pi_{s'} F_1^{s'} + 2\theta_1^s \right) + \sum_{s} \sum_{t} \sum_{g} \pi_s BSW^{s}_{gt} + \sum_{s} \sum_{t} \sum_{g} \sum_{k} \pi_s BSC^{s}_{gkt} \tag{51}$$

$$min\, Z_2 = \sum_{s \in S} \pi_s F_2^s + \lambda \sum_{s \in S} \pi_s \left(F_2^s - \sum_{s' \in S} \pi_{s'} F_2^{s'} + 2\theta_2^s \right) \tag{52}$$

Constraints (53) to (55) are added to the problem model.

$$F_1^s - \sum_{s' \in S} \pi_{s'} F_1^{s'} + \theta_1^s \geq 0 \tag{53}$$

$$F_2^s - \sum_{s' \in S} \pi_{s'} F_2^{s'} + \theta_2^s \geq 0 \tag{54}$$

$$\theta_1^s, \theta_2^s \geq 0 \tag{55}$$

4.3. Conversion to a single-objective model

The ε-constraint method is a powerful optimization technique used to transform a multi-objective model, as discussed in Section 3, into a single-objective model. This method was first introduced by Haimes (1971) and has since become a well-regarded approach for addressing multi-objective optimization problems. In the ε-constraint method, multiple objective functions are handled by converting all but one into constraints. Specifically, one objective function is selected as the primary objective, while the remaining objectives are incorporated into the constraint set of the model. By doing so, the method aims to find a solution that satisfies the additional objectives within specified bounds, denoted by ε-values. A notable limitation of the ε-constraint method is its inability to guarantee the efficiency of the solutions obtained. This can sometimes lead to what are known as weakly efficient solutions, where the solutions may not be optimal in the context of all objectives (Chankong and Y. Y. Haimes, 1983). Despite this drawback, the method remains widely used due to its simplicity and effectiveness in many practical scenarios.

In the context of this paper, the primary objective function is the total cost of the network, which remains our main objective based on the problem's main goal, while the second objective function, delivery time, is treated as a constraint within the problem formulation. By doing this, we ensure that the solution meets the delivery time requirements while optimizing the main objective. Thus, the bi-objective model is converted into a single-objective model, and the results are represented through a Pareto front, illustrating the trade-offs between the cost and delivery time.

$$min\, Z_1 = (\sum_{s \in S} \pi_s F_1^s + \lambda \sum_{s \in S} p^s \left(F_1^s - \sum_{s' \in S} \pi_{s'} F_1^{s'} + 2\theta_1^s \right) + \sum_s \sum_t \sum_g \pi_s BSW_{gt}^s + \sum_s \sum_t \sum_g \sum_k \pi_s BSC_{gkt}^s) - eps(s_2) \tag{56}$$

$$subject\ to: \quad \sum_{s \in S} \pi_s F_2^s + \lambda \sum_{s \in S} \pi_s \left(F_2^s - \sum_{s' \in S} \pi_{s'} F_2^{s'} + 2\theta_2^s \right) + s_2 = \varepsilon \tag{57}$$

And constraints: (10) - (31), (33) - (38), (39) - (43), (45) - (50) and (53) - (55)

where *eps* is a sufficiently small number (generally between 10^{-3} and 10^{-6}).

4.4. Solving the single-objective model

The final proposed mathematical model is a mixed-integer programming model for designing the blood supply chain network in disaster. Since the supply chain network design problem is NP-hard (Gourdin *et al.*, 2000), the bi-objective problem discussed in this paper is also NP-hard. Therefore, it is impossible to find the optimal solution in huge dimensions in an acceptable amount of time. In the following, we will present a two phases heuristic solution method based on the Lagrangian-relaxation approach to solve the problem.

4.4.1. *Phase 1: A Lagrangian relaxation approach*

One of the most common and efficient techniques for solving models with complex constraints is the Lagrangian relaxation (*LR*) method. Farrokhizadeh *et al.* (2022) and Cui *et al.*, (2016) are among researches who have used the Lagrangian relaxation method in supply chain management.

Relaxing complex constraints method seeks to alleviate the complexity of constraints by incorporating them as penalties within the objective function, thereby eliminating them from the set of constraints (Wolsey, 1998). Lagrangian relaxation method simplifies the problem and make it easier to solve than the original. However, a relaxed solution may be infeasible. Nonetheless, it establishes a lower bound for minimization and an upper bound for maximization, offering insights into the feasible solution space. Choosing which constraints to relax is crucial and affects performance. Utilizing the dual of the corresponding constraints in the linear programming relaxation is a popular method for determining the initial weight of dualized constraints in Lagrangian relaxation. This method is based on the observation that the dual variables in the LP relaxation give an estimate of how sensitive the objective function is to changes in the related constraints. Therefore, it is possible to ensure that the Lagrangian relaxation yields a good lower bound on the ideal solution by employing the dual variables as initial weights. Dual variables are chosen as starting weights under the assumption that the LP relaxation is tight, which is not necessarily the case(Fisher, 1981).

In one specific instance selected to be tested to choose complex constraints, the run time without relaxing any constraints is 9720 seconds. The runtimes and the optimality gaps of various relaxations for this instance are shown in Table 2. To identify which constraints should be relaxed for applying the Lagrangian Relaxation method, a three-step process was followed. First, each constraint was individually relaxed, and the results indicated that only constraints 28, 33, and 34 reduced the runtime by over 50%. These constraints were then selected for further examination as complex constraints.

In the second step, the selected constraints were evaluated with their Lagrangian multiplier dual variables, initially setting these variables to zero. As shown in Table 2, relaxing constraints 33 and 34 simultaneously led to a nearly 98% reduction in runtime, although it resulted in a 59% gap from the optimal solution.

Finally, in the third step, the initial values of the Lagrangian multiplier dual variables were set to the dual values of the relaxed constraints. Table 2 demonstrates that this approach not only reduced the runtime by approximately 90% but also brought the gap close to zero. This confirms that constraints 33 and 34 are the most suitable choices for relaxation.

Table 2

Results of the complex constraint selection approach

Source: Created by Authors

	Lagrangian multiplier dual variable			
Constraint number	Setting initial value to 0		Setting initial value to dual of relaxed constraints	
	Gap%	Run time (S)	Gap%	Run time (S)
28	37	2390	0.06	3900
33	39	1789	0.00	2670
34	41	1187	0.00	2280
28&33	47	657	0.00	1500
28&34	49	732	0.06	3560
33&34	59	201	0.00	960

Since the constraints (33) and (34) are equality equations, the Lagrangian coefficients u_{glt}^{s} and ϑ_{kglt}^{s} are free in the sign. Additionally, if the relaxed model's solution is feasible, it means that the obtained solution is an optimal solution for the original problem (Wolsey, 1998). Otherwise, the obtained solution provides a lower bound for the main problem.

The Lagrangian relaxation algorithm first sets the values of the Lagrangian coefficients to a positive value. These coefficients are updated on each iteration of the algorithm. In this study, the Sub-gradient method (Fisher, 1981) is used to update the Lagrangian coefficients. In this method, Lagrangian coefficients are updated according to the Eqs. (60) and (61).

With the relaxation of these two constraints, the dual Lagrange problem would be as follows.

$$\begin{aligned} min\ \ Z_D\left(u_{glt}^{s}.\vartheta_{kglt}^{s}\right) = Z_1 & \\ + (\sum_{g}\sum_{l}\sum_{t}\sum_{s} u_{glt}^{s}(Inv_{glt-1}^{s} - Inv_{glt}^{s} + QW_{glt}^{s} - \sum_{v}\sum_{h} QWH_{gvlht}^{s})) & \\ + \left(\sum_{k}\sum_{g}\sum_{l}\sum_{t}\sum_{s} \vartheta_{kglt}^{s}\left(Inl_{kglt-1}^{s} - Inl_{kglt}^{s} + QC_{kglt}^{s} \right.\right. & \\ \left.\left. - \sum_{v}\sum_{h} QCH_{kgvlht}^{s}\right)\right) & \end{aligned} \quad (58)$$

Subject to Constraints (10) - (31), (33) - (38), (39) - (43), (45) - (50), (53) - (55) and (57)

The Lagrangian coefficients u_{glt}^{s} and ϑ_{kglt}^{s} for different iterations n will be updated as follows:

$$u_{glt}^{n+1.s} = u_{glt}^{n.s} + stepsize1^{n}(Inv_{glt-1}^{s} - in_{glt}^{s} + QW_{glt}^{s} - \sum_{v}\sum_{h} QWH_{gvlht}^{s}) \quad (59)$$

$$\vartheta_{kglt}^{n+1.s} = \vartheta_{kglt}^{n.s} + stepsize2^{n}(Inl_{kglt-1}^{s} - Inl_{kglt}^{s} + QC_{kglt}^{s} - \sum_{v}\sum_{h} QCH_{kgvlht}^{s}) \quad (60)$$

The superscript n represents the number of iterations. $Stepsize1^{n}$ and $Stepsize2^{n}$ are also calculated through equations (61) and (62).

$$Stepsize1^{n} = \frac{\theta^{n}(Z^{*} - Z_D(u^{n}))}{\sum_{g}\sum_{l}\sum_{t}\sum_{s}(Inv_{glt-1}^{s} - Inv_{glt}^{s} + QW_{glt}^{s} - \sum_{v}\sum_{h} QWH_{gvlht}^{s})^{2}} \quad (61)$$

$$Stepsize2^{n} = \frac{\theta^{n}(Z^{*} - Z_D(u^{n}))}{\sum_{k}\sum_{g}\sum_{l}\sum_{t}\sum_{s}(Inl_{kglt-1}^{s} - Inl_{kglt}^{s} + QC_{kglt}^{s} - \sum_{v}\sum_{h} QCH_{kgvlht}^{s})^{2}} \quad (62)$$

In these equations, Z^{*} is the best upper bound obtained, and $Z_D(u^{n})$ is the lower bound obtained in the n^{th} iteration. If no improvement is made in the value of $Z_D(u^{n})$ after some iterations, the value of θ will be halved.

The best lower bound value will be updated if the lower bound acquired in each iteration is higher than the best lower bound obtained in the prior iterations. When the algorithm encounters one of the following stopping situations, the lower bound generation process will cease:

- The number of iterations reaches a specific number ($Iter$)
- The difference of the lower bound and the known upper bound (if available) reaches a specific gap (δ)
- θ^{j} reaches a specific limit

4.4.2. Phase 2: A heuristic approach based on Lagrangian relaxation

The heuristic method based on Lagrangian relaxation is utilized when the obtained solution is infeasible. It aims to find a feasible solution iteratively by adjusting a subset of variables treated as parameters. Once the relaxed model is solved, all integer and binary variables are determined. In case of infeasibility, the algorithm selectively fixes a subset of variables as known parameters to identify a feasible solution. Two indicators, namely CPU time and gap from the optimal value, are used to determine the most promising subset of fixed variables. These indicators help strike a balance between computational efficiency and solution quality. Table 3 presents the results of this analysis on a numerical example with the optimal objective function 1.791E+15. First, all variables are fixed to determine both solution time and distance from the optimal solution. Since by fixing all the variables, the obtained solution is far from the optimal value, a subset of variables is fixed to find an acceptable combination. The feasible solution obtained by simultaneously fixing the variables LM_{zpt}^{s} and LT_{e}^{s} , which has no gap from the optimal solution and acceptable run time. Hence, these variables are selected to be fixed, and the obtained mixed integer programming problem will be solved.

Table 3
Results of the variable selection approach to be fixed.

Source: Created by Authors

Fixed variables	Value of objective function from fixing variables	%Gap from the optimal value	CPU time (seconds)
By fixing all variables	2.36E15	31.81	0.234
LM_{zpt}^{s}, LT_{e}^{s}, EB_{l}, TM_{zipt}^{s}, W_{apzt}^{s}, o_{aet}^{s}, d_{ajt}^{s}, ${y_1}_{azpvlt}^{s}$, ${y_2}_{aevlt}^{s}$, ${y_3}_{ajvlt}^{s}$, ${y_4}_{hvlt}^{s}$	2.36E15	31.81	0.310
LM_{zpt}^{s}, LT_{e}^{s}, EB_{l}, TM_{zipt}^{s}, W_{apzt}^{s}, o_{aet}^{s}, d_{ajt}^{s}	1.89E15	5.97	0.789
LM_{zpt}^{s}, LT_{e}^{s}, EB_{l}, TM_{zipt}^{s}	1.82E15	1.79	1.934
LM_{zpt}^{s}, LT_{e}^{s}, TM_{zipt}^{s}	1.79E15	0.39	2.356
LM_{zpt}^{s}, LT_{e}^{s}	1.79E15	0.00	2.489

5. Computational studies

In this part, first, a computational study is performed to assess the efficiency of the Lagrangian based heuristic algorithm. The models and algorithms were coded in GAMS 24.1.2 and solved by the *Cplex* solver on a computer with *Intel Core i7*, 4GHz, and 45GB of *RAM*. By changing the number of donor groups, collection facilities, blood centers, vehicles, demand points, periods, and scenarios, different datasets were randomly generated. The dimensions of these datasets are shown in Table 4. Regarding the Lagrangian relaxation approach parameters, by testing various values, the greatest number of iterations ($Iter$) is considered 5 and the initial value of θ is 2. If the best lower bound obtained after one iteration does not improve, the value of this parameter is halved. This process continues until the value of θ reaches 0.5. The initial values of the Lagrangian coefficients u_{glt}^{s} and ϑ_{kglt}^{s} are set to 10^{-3} and δ is equal to 0.

Table 4
Generated datasets.

Source: Created by Authors

Datasets	$\|A\|$	$\|J\|$	$\|E\|$	$\|P\|$	$\|Z\|$	$\|L\|$	$\|V\|$	$\|K\|$	$\|G\|$	$\|H\|$	$\|T\|$	$\|S\|$
1	1	6	6	5	5	1	1	3	8	1	1	1
2	3	7	7	7	7	3	3	3	8	3	1	1
3	3	8	8	8	8	3	4	3	8	3	1	1
4	3	8	8	9	9	3	4	3	8	3	1	1
5	3	9	9	7	7	3	4	3	8	3	1	2
6	4	9	9	9	9	3	4	3	8	4	2	2
7	4	9	9	10	10	3	4	3	8	4	2	2
8	6	10	10	11	11	4	4	3	8	5	2	2
9	7	10	10	10	10	5	4	3	8	6	3	3
10	8	10	10	10	10	4	4	3	8	5	4	3
11	7	10	10	10	10	5	4	3	8	6	4	3
12	10	10	10	10	10	5	4	3	8	10	4	3
13	10	10	12	12	12	8	5	3	8	8	4	3
14	10	15	15	15	15	8	5	3	8	10	4	3
15	15	15	15	15	15	10	5	3	8	10	4	3

The solution values to obtain Pareto front for 15 datasets are given in Table 4. The objective function value that was determined by utilizing the CPLEX solver is displayed in the second column of the following table. LR represents the lower bounds obtained by the Lagrangian relaxation method, and LRH shows the values of the objective function of the heuristic method. Further, $\%GAP_{CPLEX}$ calculates the gap between $CPLEX$ and LR through $\frac{CPLEX-LR}{CPLEX} \times 100$. Similarly, $\%GAP_{LRH}$ computes the gap between LR and LRH through $\frac{LRH-LR}{LRH} \times 100$.

The run times for $CPLEX$ solver, the Lagrangian relaxation algorithm, and the Lagrangian heuristic are represented by $CPUT_{CPLEX}$, $CPUT_{LR}$, and $CPUT_{LRH}$ respectively. These times are the total time taken to obtain 10 Pareto points. It should be noted that none of the lower bound solutions (LR) were feasible. These solutions will be considered as input for the Lagrangian heuristic approach (LRH).

Table 5
The numerical results for all datasets.

Source: Created by Authors

Datasets	$\boldsymbol{Cplex}$	$\boldsymbol{LR}$	$\boldsymbol{LRH}$	$\boldsymbol{\%GAP_{Cplex}}$	$\boldsymbol{\%GAP_{LRH}}$	$\boldsymbol{CPU\,T_{Cplex}}$	$\boldsymbol{CPU\,T_{LR}}$	$\boldsymbol{CPUT_{LRH}}$
1	4.98E15	4.98E15	4.98E15	<0.0001	<0.0001	00:01:04	00:00:11	00:00:06
2	1.78E15	1.78E15	1.78E15	<0.0001	<0.001	00:02:32	00:00:16	00:00:06
3	2.84E15	2.84E15	2.84E15	<0.0001	<0.0001	00:02:45	00:00:15	00:00:08
4	2.67E15	2.67E15	2.68E15	<0.0001	<0.002	00:03:17	00:00:12	00:00:10
5	1.79E15	1.79E15	1.79E15	<0.0001	<0.0001	00:59:49	00:05:19	00:03:20
6	2.92E15	2.92E15	2.92E15	<0.0001	<0.0001	01:20:13	00:07:10	00:04:58
7	2.94E15	2.94E15	2.94E15	<0.0001	<0.0001	03:43:18	00:11:34	00:05:23
8	5.92E15	5.92E15	5.92E15	<0.0001	<0.0001	06:10:51	00:19:02	00:06:31
9	8.18E15	8.18E15	8.18E15	<0.0001	<0.0001	38:19:33	02:47:32	00:17:20
10	8.04E15	8.04E15	8.04E15	<0.0001	<0.0001	84:00:49	03:30:16	01:50:09
11	1.04E16	1.04E16	1.04E16	<0.0001	<0.0001	183:03:39	03:57:19	02:34:45
12	1.06E16	1.06E16	1.06E16	<0.0001	0.114	238:26:20	04:30:09	03:10:40
13	-	7.61E15	7.66E15	-	0.67	-	07:10:02	05:28:23
14	-	7.62E15	7.67E15	-	0.71	-	08:19:26	06:10:18
15	-	1.28E16	1.32E16	-	2.48	-	09:40:16	06:10:25
Average				<0.0001	0.28	46:21:11	02:42:36	01:44:11

As shown in Table 5, the Lagrangian heuristic approach is superior to the $CPLEX$ solver in terms of time. In datasets 1 to 7 (i.e., small and medium sizes), the average gap between the objective function value obtained by the Lagrangian heuristic approach and the solution obtained by solving the problem by the $CPLEX$ solver is less than 0.0001%. Moreover, in these datasets, the average gap between values of objective function that were solved by the heuristic approach and the lower bounds is also less than 0.0001%. By growing the problem size, in dataset twelve, $CPLEX$ created the Pareto front after elapsing 238 hours. This CPU time is not reasonable. In comparison, the Lagrangian heuristic solves the problem more efficiently and reaches $\%GAP_{LRH} = 0.114$ within approximately 7 hours (the time to obtain the lower bounds is included). In addition, in large sizes (i.e., datasets 13 to 15), the $CPLEX$ solver cannot solve problems at a reasonable time. In comparison, the heuristic algorithm can provide the Pareto front with near-optimal solutions in acceptable times.

5.1. Sensitivity analysis

From the problems generated in the previous section, three datasets with different sizes are selected for sensitivity analysis, as shown in Table 6.

Table 6
Features of the three datasets utilized in each experiment.

Source: Created by Authors

Dataset	$\|A\|$	$\|J\|$	$\|E\|$	$\|P\|$	$\|Z\|$	$\|L\|$	$\|V\|$	$\|K\|$	$\|G\|$	$\|H\|$	$\|T\|$	$\|S\|$
1	6	10	10	11	11	4	4	3	8	5	2	2
2	7	10	10	10	10	5	4	3	8	6	3	3
3	8	10	10	10	10	4	4	3	8	5	4	3

Initially, the Pareto front for three problems which were solved by the heuristic method can be seen in Figure 2.

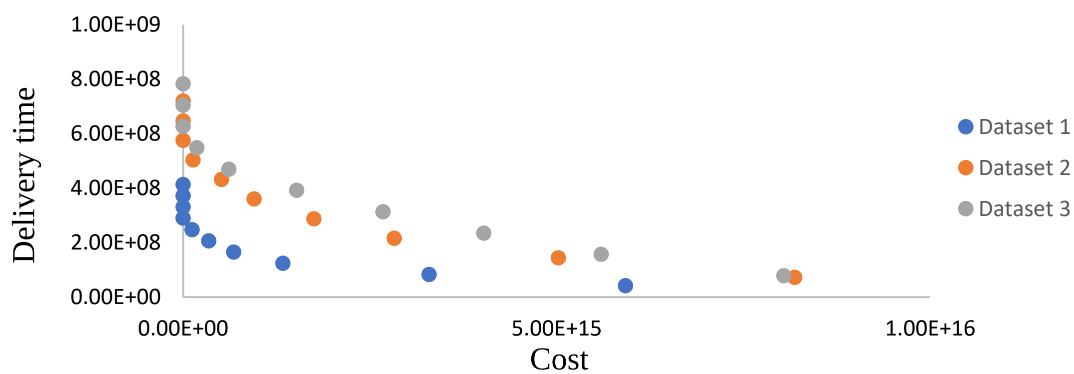

Fig.2. Pareto front of three datasets

Source: Created by Authors

5.1.1. Sensitivity analysis on the referral rate (β_t) by fixing ε

This section examines the effect of changes in referral rates and allowable blood delivery times (ε) on supply chain network costs. The results of this analysis are presented in Table 7 and Fig. 3.

Table 7
Results from the simultaneous effect of referral rate (β_t) and delivery time (ε) on supply chain costs

Source: Created by Authors

dataset	β_t	ε	LR	LRH	$GAP\%$
1	(0.1,0.1)	41286800	5.57E15	5.574E15	0.00
	(0.2,0.2)	82573600	2.95E15	2.95E15	0.00
	(0.3,0.3)	123860400	1.36E15	1.36E15	0.00
	(0.4,0.4)	165147200	9.01E14	9.01E14	0.00
	(0.5,0.5)	206434000	6.93E14	6.93E14	0.00
	(0.6,0.6)	247720800	6.61E14	6.61E14	0.00
	(0.7,0.7)	330294400	5.75E14	5.75E14	0.00
	(0.8,0.8)	371581200	9.01E14	9.01E14	0.00
	(0.9,0.9)	412868000	2.83E15	2.83E15	0.00
2	(0.1,0.1, 0.1)	71899680	5.49E15	5.49E15	0.00
	(0.2,0.2,0.2)	143799360	2.99E15	2.99E15	0.00
	(0.3,0.3,0.3)	215699040	1.61E15	1.61E15	0.00
	(0.4,0.4,0.4)	287598720	7.69E14	7.69E14	0.00
	(0.5,0.5,0.5)	359498400	2.71E14	2.71E14	0.00
	(0.6,0.6,0.6)	431398080	1.31E14	1.31E14	0.00
	(0.7,0.7,0.7)	503297760	4.33E14	4.33E14	0.00
	(0.8,0.8,0.8)	647097120	7.88E14	7.88E14	0.00
	(0.9,0.9,0.9)	718996800	2.94E15	2.94E15	0.00
3	(0.1,0.1, 0.1,0.1)	78297910	7.13E15	7.13E15	0.00
	(0.2,0.2,0.2,0.2)	156595820	4.97E15	4.97E15	0.00
	(0.3,0.3,0.3,0.3)	234893730	3.45E15	3.45E15	0.00
	(0.4,0.4,0.4,0.4)	313191640	1.94E15	1.94E15	0.00
	(0.5,0.5,0.5,0.5)	391489550	1.88E15	1.88E15	0.00
	(0.6,0.6,0.6,0.6)	469787460	1.79E15	1.79E15	0.00
	(0.7,0.7,0.7,0.7)	548085370	2.03E15	2.03E15	0.00
	(0.8,0.8,0.8,0.8)	626383280	3.02E15	3.02E15	0.00
	(0.9,0.9,0.9,0.9)	782979100	4.85E15	4.85E15	0.00

The numerical results indicate that increasing the delivery time (ε) leads to a decrease in supply chain network costs for all three datasets. This means that as the delivery time of blood decreases, network costs increase to meet the demand more quickly and efficiently. The study also examines different referral rates (β_t) during different periods. It is observed that network costs are influenced by the referral rate or the proportion of unhealthy collected blood. Figure 4 demonstrates that initially, network costs decrease with the simultaneous increase of β_t and ε. However, eventually, the effect of β_t becomes dominant, preventing further reductions in network costs. This results in a shift from a decreasing trend to an increasing trend. An increase in β_t signifies challenges in the supply of healthy blood within the network. Consequently, additional facilities need to be established to ensure the supply of healthy blood and eliminate shortages. In some cases, a portion of the demand may have to be met at a higher cost from the backup supplier.

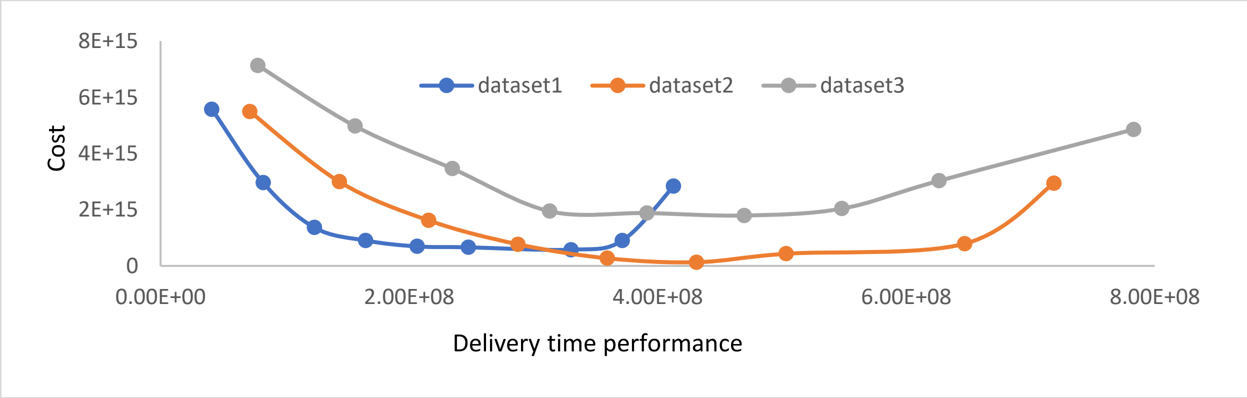

Fig.3. Simultaneous effect of delivery time (ε) and referral rate (β_t) on supply chain cost for datasets1 to 3

Source: Created by Authors

5.1.2. Sensitivity analysis on the referral rate (β_t) by fixing cost

Considering the budget constraint and assuming a fixed value of the total costs of the supply chain (i.e., the first objective function), Table 8 shows the effect of increasing the referral rate on blood delivery performance or delivery time (i.e., the second objective function). It is observed that with increasing the referral rate and decreasing the volume of healthy blood, the delivery time also increases. By increasing the referral rate from 0.1 to 0.9, the delivery times of the first and the second datasets have increased by 421% and in the third dataset by 415%. The reason is that due to budget constraints, fewer facilities can be allocated to donors, and the facilities will be in inappropriate locations. Also, for the transfer of whole blood and blood components, it is necessary to use vehicles with lower cost and consequently less capacity. All these constraints will degrade the delivery time performance.

Table 8
The effect of a variable referral rate (β_t) on delivery time (ε) for a fixed supply chain cost.

Source: Created by Authors

dataset 1			dataset 2			dataset 3		
Referral rate	Delivery time	Time difference	Referral rate	Delivery time	Time difference	Referral rate	Delivery time	Time difference
(0.1,0.1)	41286800	-	(0.1,0.1, 0.1)	71899680	-	(0.1,0.1, 0.1,0.1)	78297910	-
(0.2,0.2)	44003036	6.5	(0.2,0.2,0.2)	77481366	7.7	(0.2,0.2,0.2,0.2)	83200633	6.2
(0.3,0.3)	47495341	15	(0.3,0.3,0.3)	82711661	15	(0.3,0.3,0.3,0.3)	89745680	14
(0.4,0.4)	52151747	26	(0.4,0.4,0.4)	90820648	26	(0.4,0.4,0.4,0.4)	98472409	25
(0.5,0.5)	58670715	42	(0.5,0.5,0.5)	102173229	42	(0.5,0.5,0.5,0.5)	110689829	41
(0.6,0.6)	68449168	65	(0.6,0.6,0.6)	119202101	65	(0.6,0.6,0.6,0.6)	129015960	64
(0.7,0.7)	84746589	105	(0.7,0.7,0.7)	147583553	105	(0.7,0.7,0.7,0.7)	159559511	103
(0.8,0.8)	117341432	184	(0.8,0.8,0.8)	204346459	184	(0.8,0.8,0.8,0.8)	220646614	181
(0.9,0.9)	215125960	421	(0.9,0.9,0.9)	374635176	421	(0.9,0.9,0.9,0.9)	403907922	415

5.1.3. Sensitivity analysis on the number of vehicles

Timely transportation is crucial for perishable blood and components between collection facilities, blood centers, and hospitals. Various vehicle types enhance transportation efficiency. Table 9 shows the impact of vehicle numbers on meeting demand in the supply chain network for the three datasets

Table 9
Total vehicles impact supply chain cost and supplied demand.

Source: Created by Authors

Number of vehicles (Num_v)	dataset 1			dataset 2			dataset 3		
	Cost reduction percentage	Percentage of whole blood supplied in the network	Percentage of blood components supplied in the network	Cost reduction percentage	Percentage of whole blood supplied in the network	Percentage of blood components supplied in the network	Cost reduction percentage	Percentage of whole blood supplied in the network	Percentage of blood components supplied in the network
1	-	6%	0%	-	4%	3%	-	6%	0
5	77.17%	30%	0%	4.5%	28%	8%	8.3%	31%	0
10	90.2%	61%	0%	9.3%	58%	18%	16.4%	53%	10%
15	99.9%	89%	4%	14%	74%	31%	39%	75%	15%
20	99.93%	100%	30%	18.9%	94%	41%	43.5%	96%	19%
25	99.96%	100%	62%	21.75%	100%	59%	44.2%	100%	50%
30	99.96%	100%	74%	23.2%	100%	76%	47.4%	100%	72%
35	99.96%	100%	92%	24.1%	100%	89%	49.9%	100%	81%
40	99.96%	100%	94%	26.6%	100%	95%	51.3%	100%	86%
45	99.96%	100%	96.4%	30.3%	100%	100%	51.8%	100%	92%
50	99.96%	100%	96.8%	30.3%	100%	100%	51.8%	100%	97%
55	99.96%	100%	100%	30.3%	100%	100%	51.8%	100%	100%
60	99.96%	100%	100%	30.3%	100%	100%	51.8%	100%	100%

Insufficient vehicles for transportation can disrupt the transfer of whole blood and its components, necessitating sourcing from backup suppliers at higher costs. Increasing the total number of vehicles improves the proportion of demand met within the network and reduces overall supply chain costs. This trend continues until a certain level is reached, where all demands are fulfilled within the network. For example, in the first data set, increasing the number of vehicles from 1 to 5 results in a 77% cost reduction, and this trend persists up to 25 vehicles per type. Beyond this point, the demand, supply, and costs become independent of the number of vehicles, and further increases have no impact. Figures 4 and 5 illustrate these findings. The best fleet size can be established by considering the fixed costs related to each type of vehicle.

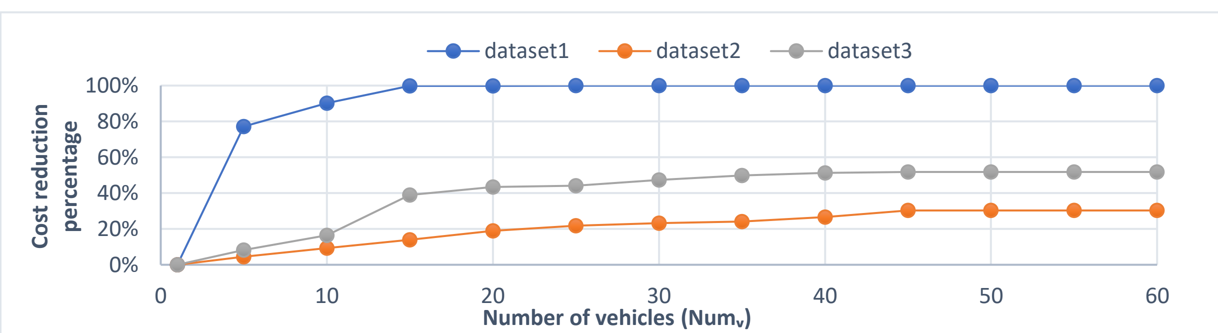

Fig. 4. The effect of the number of vehicles (Num_v) on the supply chain costs

Source: Created by Authors

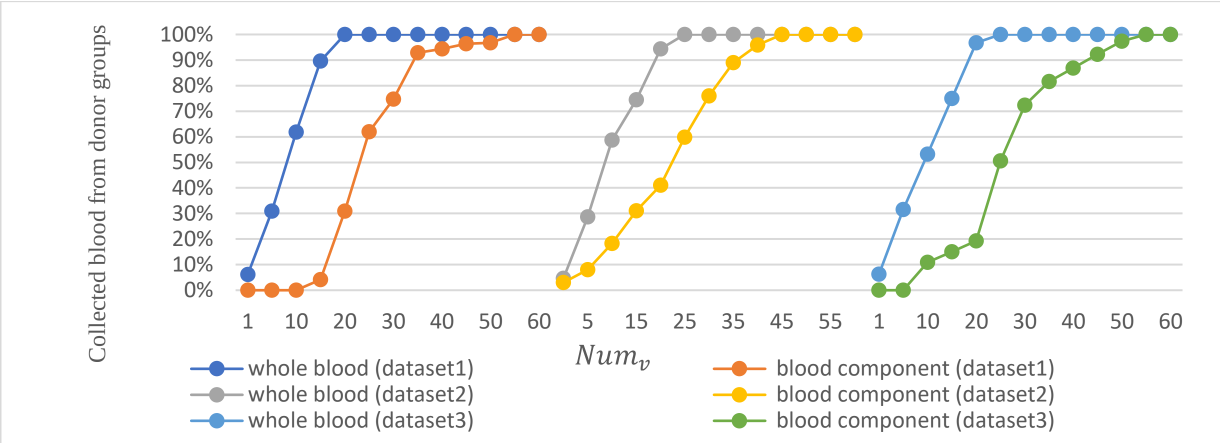

Fig. 5. The impact of the number of vehicles (Num_v) on the percentage of blood supplied in the network

Source: Created by Authors

5.1.4. Conclusion of Sensitivity analysis

The integrated analysis of delivery times, referral rates, and vehicle numbers reveals a complex interplay crucial for optimizing blood supply chains. Increasing delivery times initially reduces network costs, suggesting that extending the time frame for blood delivery can lower operational expenses. However, this benefit diminishes when the demand for faster delivery escalates, leading to higher costs. Concurrently, higher referral rates, indicative of a greater proportion of unhealthy blood, negatively impact network efficiency. This increase in referral rates not only elevates costs but also extends delivery times due to the need for additional facilities and less optimal resource allocation.

The analysis of vehicle numbers further illustrates the interconnectedness of these factors. Increasing the number of vehicles enhances the network's capacity to meet demand and reduces costs, up to an optimal point. Beyond this threshold, additional vehicles no longer affect performance or cost significantly. This optimal fleet size must be balanced against the fixed costs of each vehicle type. Overall, these findings underscore the need for a holistic approach in managing blood supply chains. Effective optimization requires careful consideration of delivery times, referral rates, and transportation resources to maintain cost efficiency while ensuring timely and adequate supply.

6. Implications for Research, Practice, and Society

This study represents a substantial advancement in disaster-oriented blood supply chain management, contributing to the research domain by addressing critical gaps in the literature. Specifically, it introduces a robust, bi-objective, and dynamic optimization model capable of handling multi-product supply chains and incorporating various facility types—permanent, temporary, and mobile—while accounting for uncertainties in supply, demand, costs, and capacities. From a research perspective, the use of robust optimization techniques and the development of heuristic methods, such as the Lagrangian relaxation approach, enhance computational efficiency and allow the model to address complex, large-scale scenarios effectively. These methodological advancements provide a foundation for future studies to explore additional dimensions, including vehicle routing optimization, infrastructure disruptions, and empirical validations through case studies in diverse disaster contexts.

The model also has considerable practical implications. By minimizing both costs and delivery times, it provides a decision-support framework for optimizing resource allocation during disaster response, ensuring that organizations can meet urgent demands efficiently. Its incorporation of dynamic facility planning, reliance on backup suppliers, and robust strategies enhances the adaptability and resilience of the supply chain in the face of unpredictable challenges. Practitioners can utilize the insights from this study to improve operational efficiency, develop contingency plans, and train professionals in advanced humanitarian logistics. Moreover, the findings equip organizations with evidence-based tools to enhance their preparedness for disaster scenarios, ensuring timely and equitable delivery of critical resources.

The societal impact of this research is equally profound, as it emphasizes the equitable distribution of vital resources, particularly to underserved and high-risk regions. By improving the resilience and reliability of blood supply chains, the model contributes to reducing mortality and suffering during crises. It also highlights the necessity of fostering collaboration among key stakeholders, including government agencies, healthcare providers, and humanitarian organizations, to build robust and responsive disaster management systems. This work strengthens societal trust in emergency response mechanisms, reinforcing public confidence in the ability of systems to mitigate the impact of disasters on quality of life.

The findings are also particularly relevant for policymaking, given the role of government as a key stakeholder in humanitarian logistics. The study provides policymakers with a structured framework to guide investments in critical infrastructure, such as mobile collection units and blood centers, and to develop contingency plans involving backup suppliers. By offering robust methods to handle uncertainties and optimize resource allocation, the model aids in prioritizing funding and designing policies that align with broader public health goals. This integration of scientific evidence into decision-making ensures sustainable, resilient, and equitable disaster response systems capable of addressing the demands of complex emergencies.

7. Conclusion

This study offers a significant contribution to disaster-oriented blood supply chain management by introducing a robust, bi-objective, and dynamic model. The model integrates multi-product handling, diverse facility types, and robust optimization to address uncertainties in supply, demand, costs, and capacities. The ε-constraint method is used to effectively balance trade-offs between minimizing costs and reducing delivery times. Additionally, in the solution phase, Lagrangian relaxation techniques are employed to enhance computational efficiency when solving complex problems. This combination helps to optimize the decision-making process while managing bi-objectives within the model. These advancements provide a valuable framework for managers, facilitating optimal resource allocation, enhancing pre- and post-disaster planning, and ensuring timely blood delivery through robust systems that incorporate backup suppliers. The model and solution method presented in the paper offer valuable insights for policymakers and officials managing blood supply chain networks during crisis situations.

The paper proposes potential directions for future research. including the consideration of vehicle routing and accounting for infrastructure disruptions during disasters. Given the computational challenges posed by the large-scale mathematical programming models and the need for substantial processing memory, the authors recommend exploring heuristic methods to address problems in higher dimensions. Addressing these limitations will enhance the model's robustness and practical applicability, further bridging the gap between theoretical frameworks and real-world disaster management needs.

Moreover, to validate the proposed model, conducting a case study involving real-world disaster scenarios could significantly enhance its credibility and practicality. Specifically, improving earthquake impact assessments should involve accounting for fault characteristics and historical data to estimate seismic probabilities accurately. Research should also differentiate between day and night scenarios, as earthquakes at night—when people are less alert—can result in more severe injuries and higher blood demand compared to daytime events.

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