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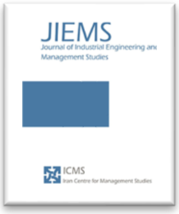

Optimizing Blood Supply Chains in Crisis Conditions: A UAV-Based Transportation System with a Real-World Case Study

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Abstract

This study proposes a four-stage blood supply chain network for crisis conditions, integrating donor groups, permanent/temporary blood collection centers, regional blood centers, and hospitals. A multi-objective, multi-period integer linear programming model optimizes blood distribution using unmanned aerial vehicles (UAVs), ambulances, and vehicles to minimize total supply chain costs and maximum travel times. Computational experiments and a real-world case study in Kurdistan province, Iran, demonstrate that UAVs with higher speeds (150 km/h) reduce travel times by up to 35% and costs by 22% compared to baseline (100 km/h), while increasing UAV capacity from 1.6 kg to 2.2 kg decreases Pareto optimal solutions by 16%, indicating improved efficiency. Deploying 150 UAVs (vs. 110) shifts the Pareto front, lowering costs by 18% and maximum travel times by 1.2 hours. Sensitivity analyses reveal UAV specifications critically impact performance, with optimal blood allocation achieved when donor groups supply centralized processing. The epsilon-constraint method solves problems of varying scales, with CPLEX achieving solutions for medium instances in under 40 minutes, highlighting UAVs' role in enhancing crisis-response blood supply chains.

Keywords: Blood supply chain, Crisis conditions, Unmanned aerial vehicles (UAVs), Resource allocation.

Paper Type: Original Research

1. Introduction

Crisis events create immediate, life-or-death demands for blood products, where delays in distribution can mean the difference between survival and preventable mortality. In disaster scenarios—especially in geographically isolated or infrastructure-poor regions—traditional blood supply chains collapse precisely when they are needed most. UAVs emerge not merely as an alternative but as a paradigm shift to overcome systemic vulnerabilities in last-mile blood delivery. Crisis events, whether natural or human-induced—such as earthquakes, floods, terrorist attacks, and pandemics—occur suddenly and often result in devastating consequences, necessitating immediate and effective responses to mitigate their impacts. Disaster relief operations (DROs) play a pivotal role in the response phase, providing essential humanitarian assistance to affected regions. Among the critical components of DROs, the establishment of a reliable and responsive network for delivering relief items, particularly blood, is of paramount importance. Blood is a lifesaving resource that must be delivered promptly to injured individuals, especially in the aftermath of disasters, which are often accompanied by an unprecedented surge in demand for blood products. Despite significant advancements in medical science, no viable substitutes for human blood have been developed, making blood donation the sole source of supply. This reliance on human donors underscores the strategic importance of effective blood supply chain management. Countries must maintain sufficient blood reserves to address escalated demands during crises, including natural disasters and other life-threatening incidents. However, the fortuitous nature of blood donation and the logistical challenges associated with its distribution make the optimization of the blood supply chain a critical area of study. A key component of the blood supply chain is the distribution network, which has garnered increasing attention in recent years, particularly in crisis scenarios. In the aftermath of a disaster, traditional ground-based transportation methods often face significant disruptions due to damaged infrastructure, blocked roads, and other logistical challenges. These obstacles can delay the delivery of blood products, jeopardizing the lives of those in need. To address these challenges, alternative transportation methods, such as UAVs, commonly known as drones, have emerged as a viable solution. UAVs offer the potential to overcome logistical barriers, ensuring the timely and efficient delivery of blood to affected areas. Delayed blood delivery during disasters often leads to devastating consequences, significantly increasing

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mortality rates and exacerbating health crises. In many disaster-stricken regions, the inability to transport blood and medical supplies quickly and efficiently results in preventable deaths, particularly among those suffering from severe injuries or hemorrhagic shock. For example, during major earthquakes and floods, the destruction of infrastructure severely hinders ground-based transportation, leaving remote and inaccessible areas critically underserved. In low-resource settings, where healthcare systems are already fragile, these delays further strain medical facilities and dramatically reduce the chances of survival for patients in need of urgent blood transfusions. These challenges highlight the urgent necessity for innovative solutions, such as UAV-based transportation systems, to effectively address logistical barriers and ensure timely delivery of blood products during emergencies. This research focuses on the utilization of UAV technology, which has seen significant advancements and widespread adoption in various fields, including logistics and disaster response. By integrating UAVs into the blood supply chain, this study aims to optimize the distribution network, ensuring that blood products reach their destinations quickly and cost-effectively, even in the most challenging conditions. The proposed approach not only enhances the efficiency of blood distribution but also improves resource allocation, ultimately saving lives and reducing the suffering of those affected by crises. This research addresses a critical gap in crisis management and healthcare logistics. During disasters, the timely delivery of blood products is essential for saving lives and mitigating the adverse impacts on affected populations. Traditional transportation methods are often inadequate in such scenarios, highlighting the need for innovative solutions. UAVs offer a promising alternative, capable of bypassing damaged infrastructure and reaching remote or inaccessible areas. By leveraging UAV technology, this study introduces a novel approach to blood supply chain management, enhancing the resilience and responsiveness of disaster relief operations. The primary objectives of this study are:

- To design a four-stage blood supply chain network tailored for crisis conditions, integrating donor groups, blood collection centers, regional blood centers, and hospitals.

- To develop a multi-objective, multi-period integer linear programming model that minimizes supply chain costs and total travel times.

- To evaluate the effectiveness of UAVs in optimizing blood distribution, particularly in scenarios where traditional transportation methods are compromised.

- To conduct a sensitivity analysis on key parameters, such as UAV capacity and speed, to assess their impact on the overall efficiency of the blood supply chain.

This research contributes to the advancement of healthcare logistics and crisis management in several ways:

- It introduces a novel framework for blood supply chain optimization in crisis conditions, leveraging UAV technology to overcome logistical challenges.

- Propose a four-stage UAV-integrated network that dynamically adapts to crisis volatility, replacing static "brick-and-mortar" systems with mobile collection and airborne distribution.

- Develop a multi-period optimization model that jointly minimizes cost and time while accounting for UAV payload constraints and real-world demand surges.

- It provides a real-world case study of Kurdistan province, Iran, demonstrating the practical applicability of the proposed model.

- Validate in a conflict-zone case study, demonstrating how UAVs outperform ground transport where roads are impassable. It offers insights into the integration of UAVs, into disaster response operations, enhancing the preparedness and resilience of healthcare systems. The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the literature on blood supply chain management and UAV applications in logistics. Section 3 including the development of the mathematical model. Section 4 presents the results and discusses their implications. Finally, Section 5 concludes the paper with recommendations for future research.

2. Literature Review

The literature surrounding the utilization of drones in supply chain management has witnessed significant advancements in recent years. Researchers and practitioners have recognized the potential of drones to revolutionize the delivery of various products, including food, time-sensitive items, and life-saving blood products, particularly in inaccessible or disaster-stricken areas.

2.1. Supply Chain

A supply chain is a network of processes aimed at providing goods and services. This network encompasses suppliers, manufacturers, and distributors who collaborate to minimize system costs and meet service needs, ensuring that goods are produced and distributed in the right quantities and at the right times. Supply chain management is considered a critical activity in many organizations (Pasandideh et al., 2015). A literature review on multi-objective optimization (MOO) for supply chain management (SCM) highlights the importance of using MOO techniques to address the complex challenges in supply chains. Supply chain optimization often involves balancing competing objectives, such as minimizing costs, maximizing service levels, and reducing environmental impacts. MOO helps decision-makers find optimal or near-optimal solutions by considering multiple objectives simultaneously (Trisna et al., 2016). The paper by Baharmand et al. (2019) emphasizes two main components of network flexibility: structural flexibility (which refers to the design and structure of the supply chain network) and operational flexibility (which focuses on the responsiveness and adaptability of supply chain operations). It discusses methods for measuring flexibility in humanitarian supply chains, including performance metrics and tools that assess how quickly and effectively the supply chain can respond to new challenges. Recent advances in closed-loop supply chain (CLSC) optimization highlight the integration of sustainability with operational decisions. Khorshidvand et al. (2021a) propose a two-stage CLSC model that jointly optimizes pricing, green quality, and advertising through fuzzy multi-objective programming, demonstrating significant improvements in profit and CO_2 reduction. Their work is complemented by Khorshidvand et al. (2021b), who develop a hybrid CLSC framework combining network design with coordination tools (price, advertising, greening) under demand uncertainty, solved via robust optimization and Lagrangian relaxation. These studies collectively underscore the critical role of multi-objective trade-offs (economic-environmental-social) in supply chain design and the need to coordinate strategic (network design) and tactical (pricing/advertising) decisions—insights that inform our UAV-integrated blood supply chain model's structure. The paper "Advancements in Sustainable Manufacturing Supply Chain Modelling: A Review" examines the progress made in modeling sustainable supply chains within the manufacturing sector (Wofuru-Nyenke et al., 2023).

2.2. Blood Supply Chain

Several processes are involved in making a unit of whole blood available to a patient in need. First, blood donors visit blood centers to donate blood. The collected blood is then sent to blood banks, where it is tested and processed into blood products. These products are subsequently shipped to points of demand (Brandeau et al., 2004). All these activities are part of blood supply chain management. The study of blood in the field of blood supply chain management differs from traditional supply chains in the following ways (Gunpinar & Centeno, 2015):

- Scarcity and Human Dependency: Blood is a scarce resource that can only be supplied by human donors, with no alternative means of production.
- Multiple Products from a Single Unit: Different blood products, including red blood cells, platelets, and plasma, are derived from a single unit of whole blood. The blood is placed in centrifuge machines, which separate it into three components: red blood cells, platelets, and plasma. Red blood cells are used to treat patients with anemia or those undergoing surgery. Platelets play a crucial role in preventing bleeding by coagulating blood. Plasma, a yellow liquid component obtained by removing red blood cells from whole blood, is vital for emergency operations. Unlike most production sectors in the supply chain, where one type of final product is produced from multiple materials, the blood supply chain network produces various blood products from a single material (whole blood).
- Urgent Demand: The customers of the blood supply chain are patients with an urgent need for blood products. Failure to meet their needs can lead to irreparable harm.
- Perishability: Most blood products have a limited shelf life and become unusable after their expiration date.

Appropriate solutions for collecting blood from donors are essential. There are two main types of facilities for this purpose: permanent and temporary collection units. Temporary collection units include mobile facilities, such as buses, which do not have fixed locations and can relocate to collect blood more effectively. Permanent collection units, on the other hand, are located in fixed places. Although their establishment costs are higher than temporary units, they offer greater equipment capacity (Mohammadi Bidhandi & Mohd Yusuff, 2011). The blood collected by both permanent and temporary units is sent to blood centers, which are responsible for testing, processing, and distributing blood products to hospitals. Decisions in supply chain management can be classified into three main categories: strategic planning, tactical planning, and operational planning. Decisions related to permanent collection centers fall under strategic planning, while decisions about the location of temporary collection centers in each planning period are tactical (Yilmaz, 2025). This review emphasizes the importance of inventory pooling, stating that when applied effectively, it can lead to cost savings, better inventory turnover, and increased customer satisfaction.

2.3. Blood Supply Chain in Crisis Conditions

According to the reviewed literature, few researchers have proposed mathematical models for the blood supply chain. One of the earliest studies is by Brandeau et al. (2004), who developed a location-allocation model for designing a blood supply chain in 1979. Their goal was to estimate blood demand in hospitals using regional blood banks. Şahin et al. (2007) proposed location-allocation problems to design an efficient blood supply chain for a network of fixed and mobile blood centers. They extended the blood level classification in each center and considered distance measurement as the objective in their proposed model, using data envelopment analysis to solve it. Sha & Huang (2012) proposed a multi-period deterministic allocation problem for blood supply in emergency conditions. Their single-objective model minimized total operational costs and was solved using a Lagrangian relaxation-based metaheuristic algorithm. They applied their model to a real case study of a seismic situation in China. Hsieh (2014) presented a two-stage blood supply chain model, focusing on an allocation problem that minimized costs and maximized demand satisfaction using a genetic algorithm. Arvan et al. (2015) proposed a blood supply chain model that considered the location of blood banks. In addition to location and allocation decisions, the model incorporated delivery times and total supply chain costs. A sensitivity analysis was performed using the epsilon constraint method on the deterministic model. Kohneh et al. (2016) used a bi-objective model to design a supply chain for natural disasters, focusing on minimizing overall costs and maximizing donor satisfaction. Zahiri & Pishvaee (2017) proposed a new model to minimize costs and maximize unmet demand satisfaction, incorporating blood compatibility into the mathematical model. Samani et al. (2018) developed a mixed-integer linear programming model to design an integrated blood supply chain network for disaster relief, applying it to a real case study in Mashhad, Iran. Habibi-Kouchaksaraei et al. (2018) investigated the blood supply chain network with the goal of timely and appropriate provision, processing, and distribution of blood. They proposed a bi-objective mathematical model to minimize costs and shortages, solving it using the ε-constraint method. Khalilpourazari et al. (2020) proposed a new model for blood supply chain network design, considering a six-tier network. For the first time, they used helicopters to transport blood from regional hospitals to local hospitals, optimizing the network to prevent shortages. They also transferred injured patients who could not be treated in local hospitals due to limited capacity to regional hospitals. The goal was to minimize transportation costs and unmet demands. Khalilpourazari & Arshadi Khamseh (2019) extended the model proposed by Jabbarzadeh et al. (2014), incorporating various transportation methods and investigating disruptions in the blood supply chain. Ghorashi et al. (2020) proposed a multi-objective model for managing emergency blood supply chains, considering blood compatibility, routing, and location-allocation decisions. Their three-objective mathematical model minimized supply chain costs and time while maximizing reliability. They used a Grey Multi-Objective Algorithm to solve the model. Razavi et al. (2021) proposed a model for allocating blood types, considering blood shelf life, to respond to field hospitals during natural disasters. Their goal was to cover the demand for blood types and distribute blood evenly among hospitals with optimal routing at the lowest cost. Dehghani et al. (2021) proposed a stochastic programming method for blood supply chain network design, incorporating realistic assumptions such as uncertainty and perishability to minimize waste and shortages. Tavana et al. (2018) proposed a multi-level humanitarian logistics network that considered the location of central warehouses, inventory management of perishable products in the pre-disaster phase, and routing of relief vehicles in the post-disaster phase. They used a non-dominated sorting genetic algorithm (NSGA-II) to solve the mixed-integer linear programming problem. Oksuz & Satoglu (2020) proposed a two-stage stochastic model for the location planning of temporary medical centers for natural disaster response. Their model minimized total system setup costs and expected transportation costs by considering damage types, demand, road and hospital damage probabilities, and distances between disaster areas and medical centers. Ghasemi et al. (2023) proposed a multi-stage mixed-integer programming model for logistics distribution and evacuation planning during earthquakes, addressing cost issues through three objective functions. Their model was solved using the NSGA-II algorithm. García-Alviz et al. (2021) discussed road network reconstruction and relief distribution under heterogeneous road disruptions. They proposed a mathematical model for scheduling and routing vehicles and relief operations, prioritizing road reconstruction to support relief efforts. Their approach was applied to a realistic case study based on floods in the Mojana region of northern Colombia. Kyriakakis et al. (2022) solved the humanitarian vehicle routing problem with time windows using a hybrid metaheuristic search algorithm called Tabu Search - Variable Neighborhood Descent (HTS-VND). This algorithm was also used to solve the capacitated cumulative vehicle routing problem (CCVRP). Recent work by Babazadeh Rafiei et al. (2024) advances pandemic-responsive blood supply chain modeling through a scenario-based multi-level approach. Their study addresses COVID-19-specific demand uncertainty via robust optimization, aligning with our focus on crisis adaptability. However, while their model optimizes fixed facilities and ground logistics, it does not account for aerial delivery methods—a gap our UAV-integrated framework directly addresses. This contrast highlights the need for hybrid ground-air solutions in extreme disruptions. Tirkolaee et al. (2023) provided an innovative model for optimizing the blood supply chain, demonstrating how socio-economic factors and advanced programming techniques can improve blood distribution efficiency, especially during health crises like the COVID-19 pandemic. Mansur et al. (2025) proposed a comprehensive model for managing the blood supply chain, focusing on minimizing waste and ensuring the efficient availability of fresh products to meet demand.

2.4. Blood Supply Chain and Drone-Based Transportation

Amukele et al. (2015) used drones to transport clinical laboratory samples daily, demonstrating that drone flights had no statistically significant effect on the samples' integrity. Nedjati et al. (2016) introduced a relief distribution system using unmanned helicopters in Tehran to cope with emergency responses after earthquakes. Their system showed good capability for high-population-density urban areas, meeting large demands in a short time. Haidari et al. (2016) proposed a simulation model to analyze the effects of using UAVs for vaccine distribution, finding that drones were cheaper than traditional ground transportation systems. Wen et al. (2016) investigated the vehicle routing problem for drones in emergencies, proposing a multi-objective optimization problem that considered blood temperature, drone scheduling, and route planning. Ling & Draghic (2019) highlighted the potential of drones to improve healthcare delivery in remote environments, reducing transportation costs. Lawrence et al. (2023) discussed the challenges and limitations of using drones for medical purposes, emphasizing the need for further research in areas such as battery life, airspace regulations, and weather conditions. Thibbotuwawa et al. (2020) provided a comprehensive overview of UAV routing problems, focusing on challenges like battery limitations and airspace restrictions. Rejeb et al. (2021) analyzed the potential applications of UAVs in humanitarian fields, proposing a research agenda to guide future studies. Torrado & Barbosa-Póvoa (2022) reviewed the optimization and sustainability of blood supply chains under uncertainty, focusing on perishability, fluctuating demand, and rapid response requirements. Alghamdi (2023) conducted a comparative study of blood delivery systems in crowded cities, identifying the most effective solutions based on cost, time, and emergency severity. Jahani et al. (2024) analyzed 5,364 papers from Scopus (1978–2023) using the Latent Dirichlet Allocation (LDA) model, identifying ten research topics and proposing future directions, including sustainable drone-based solutions and pandemic control applications. Yucesoy et al. (2025) examined the role of drones in disaster response, highlighting their effectiveness in various stages of disaster management. While significant progress has been made in the field of blood supply chain management, several limitations persist in existing studies, particularly in the context of crisis conditions. First, many studies focus on traditional ground-based transportation methods, which are often inadequate during disasters due to damaged infrastructure and impassable routes (Brandeau et al., 2004; Şahin et al., 2007). These approaches fail to address the urgent need for rapid and reliable delivery of blood products in emergency scenarios. Second, while some research has explored the use of UAVs in logistics, their application in blood supply chains remains underexplored, especially in resource-constrained settings (Amukele et al., 2015; Haidari et al., 2016). Third, existing models often rely on deterministic assumptions, ignoring the inherent uncertainty in blood supply and demand during crises (Zahiri & Pishvaee, 2017; Dehghani et al., 2021). This limits their applicability in real-world scenarios where variability and unpredictability are prevalent. This research addresses some of these gaps by proposing a comprehensive and innovative framework for blood supply chain optimization in crisis conditions. Unlike traditional studies, the model integrates UAV technology to overcome logistical challenges, ensuring timely delivery of blood products even in inaccessible or disaster-affected areas. Additionally, our approach incorporates a multi-objective, multi-period integer linear programming model, which balances cost efficiency and delivery timeliness, providing a more holistic solution. While the current study operates under deterministic conditions, it lays the groundwork for future research to incorporate uncertainty and probabilistic approaches, such as fuzzy programming or stochastic optimization. By addressing these limitations, our research not only enhances the efficiency of blood supply chains but also contributes to the broader field of healthcare logistics and disaster response.

3. Problem Description and Mathematical Formulation

3.1. Problem Description

The blood supply chain network proposed in this study operates under crisis conditions and involves four key stages: donor groups, blood collection centers (both permanent and mobile), regional blood banks, and hospitals (regional and rural). The process begins with blood donors traveling to the nearest permanent or mobile collection centers to donate blood. Once collected, the blood is transported to regional blood banks for processing. At these facilities, centrifuge machines separate the whole blood into its components: red blood cells, plasma, and platelets. Additional tests are conducted to determine blood types and ensure the quality of the collected blood. In the affected regions, hospitals communicate their blood product requirements to regional hospitals via text messages or messaging applications. Regional hospitals assign two operators: one to receive and process messages, and the other to prepare and package the shipments. Each order is carefully packed into single-use boxes, protected with bubble wrap, and equipped with a parachute system for safe delivery. A unique QR code is assigned to each package to designate its destination. These packages are then loaded into the refrigerated compartments of drones. Before launch, the drones are transported to designated launch sites, where fully charged batteries are installed, and visual inspections are conducted to ensure operational readiness. Modern drone models, such as those developed by Zipline, are capable of covering approximately 160 kilometers on a single battery charge, achieving speeds of up to 130 kilometers per hour. Each drone has a payload capacity of up to 1.8 kilograms. During flight, the drones maintain communication with the requesting hospitals, providing real-time updates on their progress. As the drones approach their destinations, they release the packages, which descend safely using parachutes. Hospital personnel retrieve the packages at the specified delivery points, ensuring timely delivery within 30 to 40 minutes. Figure1.illustrates the structure of the blood supply chain and the role of drones in delivering blood products efficiently.

Figure 1. Structure of the Proposed Blood Supply Chain Network

The following assumptions are considered in this study:

1. Collection Capacity: Blood collection facilities have limited capacities, with permanent centers having higher capacities compared to mobile facilities.
2. Donor Groups: Individual planning for each donor is impractical; therefore, donors are grouped for logistical purposes.
3. Deterministic Parameters: All parameters are examined under deterministic conditions.
4. Facility Locations: The candidate location set can accommodate both permanent and temporary collection centers, as determined by the model.
5. Drone Launch Sites: Launch sites for drones are established near blood banks to minimize transportation costs.
6. Station Capacities: Specific capacities are defined for all stations in the network.
7. Cooling Systems: Drones are equipped with cooling systems to prevent blood spoilage during transportation.
8. Drone Capacity: Drones are subject to capacity constraints based on their payload and battery life.
9. Time Periods: The planning horizon is divided into quarterly periods, each consisting of three consecutive months.

The sets, parameters, and decision variables used in the mathematical model are described in Table 1.

Table 1. Definitions of Sets, Parameters, and Decision Variables.

Sets	
I	Set of blood donor groups, indexed by i
J	Set of candidate locations for establishing permanent and temporary blood collection centers, indexed by j , l
K	Set of blood centers, indexed by k
M	Set of regional hospitals, indexed by m
N	Set of rural hospitals, indexed by n
T	Set of time periods, indexed by t
V	Set of transportation modes, indexed by v
Parameters	
f_j	Cost of establishing a permanent blood collection center at candidate location j
VC_{jl}	Cost of transferring temporary blood collection facilities from location l to location j
O_{ijt}	Cost of collecting blood from donor group i at collection center j in time period t
h_k	Cost of blood storage at blood center k
ct_{jkv}	Cost of transporting blood from collection center j to blood center k using transportation mode v
dis_{km}^1	Distance between blood center k and regional hospital m
dis_{kn}^2	Distance between blood center k and rural hospital n
tjk_{jkv}	Blood transportation time from blood collection center j to blood center k using transportation mode v
ca_{jkv}	Capacity of transportation mode v for transferring collected blood from collection center j to blood center k
$number_{jtv}$	Number of available vehicles of type v at collection center j in time period t
UV	Drone speed
St	Time required for charging a drone
θ	Conversion factor for time to cost (for travel time by drone)
q	Conversion factor for time to cost (for charging time by drone)
Nav_{kt}	Number of drones available at blood center k in time period t
mbs_i	Maximum blood supply from donor group i
b_{jt}	Capacity of temporary blood collection center j in time period t
c_{jt}	Capacity of permanent blood collection center j in time period t
$capk_k$	Capacity of blood center k
d_{mt}^1	Blood demand at regional hospital m in time period t
d_{nt}^2	Blood demand at rural hospital n in time period t
w	Drone capacity
$\bar{M}$	A sufficiently large number
Decision variables	
X_j	1 if a permanent blood collection center is established at location j; 0 otherwise
Z_{jlt}	1 if temporary blood collection facilities are transferred from location l to location j in time period t; 0 otherwise
y_{ijt}^1	1 if blood donor group i is allocated to collection center j in time period t; 0 otherwise
y_{jkt}^2	1 if blood collection center j is allocated to blood center k in time period t; 0 otherwise
$*y_{kmt}^3$	1 if blood center k is allocated to regional hospital m in time period t; 0 otherwise
y_{knt}^4	1 if blood center k is allocated to rural hospital n in time period t; 0 otherwise
Q_{ijt}	Quantity of blood collected from donor group i at collection center j in time period t
Qa_{jktv}	Quantity of blood transferred from collection center j to blood center k in time period t using transportation mode v
P_{kmt}^1	Quantity of blood transferred from blood center k to regional hospital m in time period t using drones
P_{knt}^2	Quantity of blood transferred from blood center k to rural hospital n in time period t using drones
num_{jktv}	Number of required transportation vehicles of type v at collection center j in time period t for transferring blood to blood center k
Inv_{kt}	Blood inventory level at blood center k in time period t
nf_{kmt}^1	Number of drones required for transferring blood from blood center k to regional hospital m in time period t
nf_{knt}^2	Number of drones required for transferring blood from blood center k to rural hospital n in time period t
μ_{kt}	Maximum travel time from collection centers to blood center k in time period t
β_t	Maximum travel time in the supply chain in time period t

Below is the mathematical model proposed for the given problem:

$$\begin{aligned}\min Obj_1 = {} & \sum_{j\in J} f_j X_j + \sum_{j\in J}\sum_{l\in J}\sum_{t\in T} VC_{jl} Z_{jlt} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} O_{ijt} Q_{ijt} + \sum_{j\in J}\sum_{k\in K}\sum_{t\in T}\sum_{v\in V} ct_{jkv} Qa_{jktv} \\ & + \sum_{k\in K}\sum_{t\in T} h_k Inv_{kt} + \sum_{k\in K}\sum_{m\in M}\sum_{t\in T}\left(q.St + \theta\frac{dis^1_{km}}{UV}\right) nf^1_{kmt} \\ & + \sum_{k\in K}\sum_{n\in N}\sum_{t\in T}\left(q.St + \theta\frac{dis^2_{kn}}{UV}\right) nf^2_{knt}\end{aligned} \tag{1}$$

$$\min Obj_2 = \sum_{t\in T} \beta_t \tag{2}$$

$$X_j + \sum_{l\in J,l\neq j} Z_{jlt} \leq 1 \qquad \forall\, j\in J, t\in T \tag{3}$$

$$\sum_{l\in J.\ l\neq j} Z_{jlt} \leq \sum_{l\in J,l\neq j} Z_{jl.t-1} \qquad \forall\, j\in J, t\in T \tag{4}$$

$$y^1_{ijt} \leq X_j + \sum_{l\in J,l\neq j} Z_{jlt} \qquad \forall\, i\in I, j\in J, t\in T \tag{5}$$

$$y^2_{jkt} \leq X_j + \sum_{l\in J.\ l\neq j} Z_{jlt} \qquad \forall\, j\in J, k\in K, t\in T \tag{6}$$

$$Q_{ijt} \leq \bar{M} y^1_{ijt} \qquad \forall\, i\in I, j\in J, t\in T \tag{7}$$

$$Qa_{jktv} \leq \bar{M} y^2_{jkt} \qquad \forall\, j\in J, k\in K, t\in T, v\in V \tag{8}$$

$$P^1_{kmt} \leq \bar{M} y^3_{kmt} \qquad \forall\, k\in K, m\in M, t\in T \tag{9}$$

$$P^2_{knt} \leq \bar{M} y^4_{knt} \qquad \forall\, k\in K, n\in N, t\in T \tag{10}$$

$$\sum_{j\in J}\sum_{t\in T} Q_{ijt} \leq m_i \qquad \forall\, i\in I \tag{11}$$

$$\sum_{i\in I} Q_{ijt} \leq c_{jt} X_j + b_{jt} \sum_{l\in J.\ l\neq j} Z_{jlt} \qquad \forall\, j\in J, t\in T \tag{12}$$

$$\sum_{k\in K} num_{jktv} \leq number_{jtv} \qquad \forall\, j\in J, t\in T, v\in V \tag{13}$$

$$num_{jktv} \geq \frac{Qa_{jktv}}{Ca_{jkv}} \qquad \forall\, j\in J, k\in K, t\in T, v\in V \tag{14}$$

$$Inv_{kt} \leq capk_k \qquad \forall\, k\in K, t\in T \tag{15}$$

$$\sum_{k\in K}\sum_{v\in V} Qa_{jktv} = \sum_{i\in I} Q_{ijt} \qquad \forall\, j\in J, t\in T \tag{16}$$

$$Inv_{k.t-1} + \sum_{j\in J}\sum_{v\in V} Qa_{jktv} - Inv_{kt} = \sum_{m\in M} P^1_{kmt} + \sum_{n\in N} P^2_{knt} \qquad \forall\, k\in K, t\in T \tag{17}$$

$$nf^1_{kmt} \geq \frac{P^1_{kmt}}{w} \qquad \forall\, k \in K, m \in M, t \in T \tag{18}$$

$$nf^2_{knt} \geq \frac{P^2_{knt}}{w} \qquad \forall\, k \in K, n \in N, t \in T \tag{19}$$

$$\sum_{k \in K} P^1_{kmt} = d^1_{mt} \qquad \forall\, m \in M, t \in T \tag{20}$$

$$\sum_{k \in K} P^2_{knt} = d^2_{nt} \qquad \forall\, n \in N, t \in T \tag{21}$$

$$\sum_{m \in M} nf^1_{kmt} + \sum_{n \in N} nf^2_{knt} \leq Nav_{kt} \qquad \forall\, k \in K, t \in T \tag{22}$$

$$\mu_{kt} \geq tjk_{jkv} y^2_{jkt} \qquad \forall\, j \in J, k \in K, v \in V, t \in T \tag{23}$$

$$\beta_t \geq \mu_{kt} + \left(St + \frac{dis^1_{km}}{UV} \right) y^3_{kmt} \qquad \forall\, k \in K, m \in M, t \in T \tag{24}$$

$$\beta_t \geq \mu_{kt} + \left(St + \frac{dis^2_{kn}}{UV} \right) y^4_{knt} \qquad \forall\, k \in K, n \in N, t \in T \tag{25}$$

$$X_j . Z_{jlt} . y^1_{ijt} . y^2_{jkt} . y^3_{kmt} . y^4_{knt} \in \{0,1\} \tag{26}$$

$$num_{jktv} . nf^1_{kmt} . nf^2_{knt} \in \mathbb{Z}^+ \tag{27}$$

$$Q_{ijt} . Qa_{jktv} . P^1_{kmt} . P^2_{knt} . Inv_{kt} . \mu_{kt} . \beta_t \geq 0 \tag{28}$$

The proposed mathematical model addresses the blood supply chain problem under crisis conditions, focusing on two primary objectives: minimizing costs and minimizing maximum travel times. Below is a detailed description of the model, including its objective functions, constraints, and their implications.

Objective Functions:

Minimizing Total Cost (Equation 1):
The first objective function aims to minimize the overall cost of the blood supply chain. This includes:

- The cost of establishing permanent blood collection centers.
- The cost of transferring temporary blood collection facilities from location l to location j.
- The cost of collecting blood from donor groups i at collection centers j.
- Transportation costs from collection centers j to blood centers k using ambulances and cars.
- Maintenance costs of blood centers k.
- Transportation costs to regional hospitals m and rural hospitals n using drones.

By minimizing these costs, the model seeks to optimize the financial efficiency of the supply chain while ensuring the availability of blood products.

Minimizing Maximum Travel Time (Equation 2):
The second objective function minimizes the sum of maximum travel times across all periods. This ensures that blood products are delivered as quickly as possible, enhancing the responsiveness of the supply chain during crises.

Constraints:

The model incorporates several constraints to ensure feasibility and operational efficiency:

Facility Type Constraint (Constraint 3):
Ensures that each candidate location j can host only one type of blood collection facility (permanent or temporary).

Temporary Facility Routing (Constraint 4):
Determines the optimal routes for transferring temporary blood collection facilities between locations.

Donor Group Allocation (Constraint 5):
Assigns each donor group i to only one blood collection facility j in each time period t.

Blood Center Allocation (Constraint 6):
Assigns blood collected at center j to blood center k for processing.

Flow Feasibility (Constraints 7-8):
Ensure that blood can only be transported if the corresponding assignments (donor groups to collection centers and collection centers to blood centers) are made.

Drone Transportation Feasibility (Constraints 9-10):
Prevent blood from being transported from blood centers k to hospitals m and n using drones unless the assignments are made.

Donor Supply and Collection Capacity (Constraints 11-12):

Constraint (11) limits the maximum blood supply from donor groups i.

Constraint (12) enforces the capacity limitations of blood collection centers.

Vehicle Availability (Constraints 13-15):
Specify the maximum number of vehicles required and available for transporting blood from collection centers j to blood centers k.

Blood Inventory and Demand (Constraints 16-21):

Constraint (16) determines the amount of blood transferred using each transportation mode.

Constraint (17) evaluates the blood inventory levels at blood centers k.

Constraints (18-19) calculate the number of drones round trips required to meet demand at hospitals m and n.

Constraints (20-21) ensure that the demand at regional and rural hospitals is met.

Travel Time Constraints (Constraints 23-25):

Constraint (23) ensures that the maximum travel time equals the transportation time from collection centers j to blood centers k using transportation mode v.

Constraints (24-25) calculate the maximum travel time across the supply chain.

Decision Variable Definitions (Constraints 26-28):
Define the nature of the decision variables, including binary, continuous, and integer variables.

Balancing Objectives:

The model's dual objectives—minimizing costs and minimizing maximum travel time—are inherently interconnected but may conflict in practice. For instance:

- **Cost Minimization:** May involve consolidating transportation routes or using fewer resources, potentially increasing delivery times.
- **Travel Time Minimization:** May require deploying additional resources, such as drones, to ensure rapid delivery, thereby increasing costs.

Finding an optimal balance between these objectives is critical. The model aims to achieve a solution that:

- Ensures cost **efficiency** by minimizing operational expenses.
- Enhances **responsiveness** by reducing delivery times, ensuring timely access to blood products during crises.

This balance is essential for maintaining the quality and effectiveness of blood transfusions and medical treatments, ultimately benefiting both healthcare systems and patients in need.

4. Computational Results

This section presents the computational analysis of the proposed model, utilizing both generated instances and a real-world case study from Kurdistan province, Iran. The analysis provides valuable insights into the model's performance and its applicability in real-world scenarios. Additionally, generated instances were used to further explore the problem's characteristics and validate the model's robustness. Given the complexity of multi-objective optimization problems, the augmented epsilon-constraint algorithm was employed to solve the model. This algorithm, an extension of the traditional epsilon-constraint method, is well-suited for generating Pareto optimal solutions. The computational experiments were conducted using the CPLEX solver on a computer system with a 64-bit architecture, 8GB of RAM, and a Core i7 CPU operating at 2.60 GHz.

4.1. Case Study: Kurdistan Province, Iran

Iran is one of the world's most disaster-prone countries, frequently experiencing natural disasters such as earthquakes, floods, and wildfires. Kurdistan province, in particular, is at high risk due to the presence of active faults and a history of devastating earthquakes. Although Sanandaj, the provincial capital, has relatively lower seismicity, its proximity to earthquake-prone regions makes it a strategic location for emergency blood supply operations. This case study focuses on designing a blood supply chain network for Kurdistan province to address the challenges of blood collection and distribution during crises. Currently, Kurdistan province has two established blood transfusion centers located in Sanandaj and Saqqez, which serve the population (see Figure 2). However, other cities in the province face significant challenges due to the lack of adequate infrastructure for blood collection and storage. Many potential donors are willing to contribute but are discouraged by the absence of nearby facilities and transportation difficulties. To address these issues, a comprehensive blood supply chain network was proposed, incorporating:

- **Fixed Blood Donation Centers:** Located in Sanandaj and Saqqez.
- **Central Blood Bank:** Situated in Sanandaj.
- **Mobile Blood Centers:** To reach underserved areas.
- **Drone Stations:** Equipped for rapid blood delivery during crises (see Figure 3).

This case study validates the accuracy and effectiveness of the proposed model, demonstrating its potential to improve blood supply chain operations in disaster-prone regions.

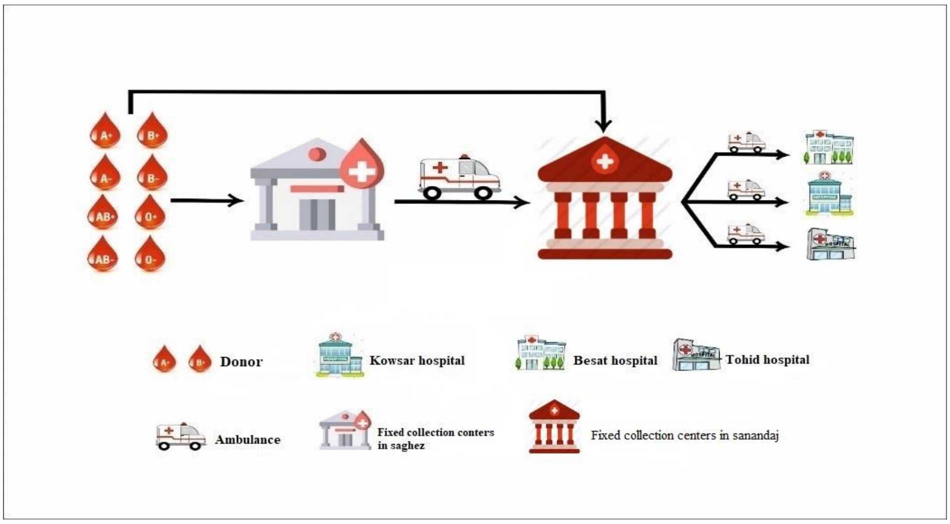


Figure 2. Current Blood Supply Chain Network in Kurdistan Province

In the proposed design, the ten cities of Kurdistan province were considered as blood donor groups and potential locations for establishing permanent or temporary blood collection centers. After solving the model using real-world data, four centers were identified as optimal locations for blood collection facilities:

- Fixed Centers: One in Sanandaj and one in Saqqez.
- Mobile Centers: Two mobile units to serve other areas.

A central blood bank, located in Sanandaj, was designated for blood purification, storage, and maintenance. Additionally, four hospitals were strategically placed in disaster-prone areas, comprising two regional hospitals and two rural hospitals. This optimized structure significantly enhances the efficiency and responsiveness of the blood supply chain in Kurdistan province. The initial layer of the blood supply chain involves assigning donor groups to blood collection centers. This allocation process is critical, as it minimizes both transportation costs and delivery times, contributing to a more efficient and reliable blood supply chain network. A geographical representation of this allocation is provided in Figure 4, which illustrates the locations of donor groups, collection centers, and hospitals across Kurdistan province.

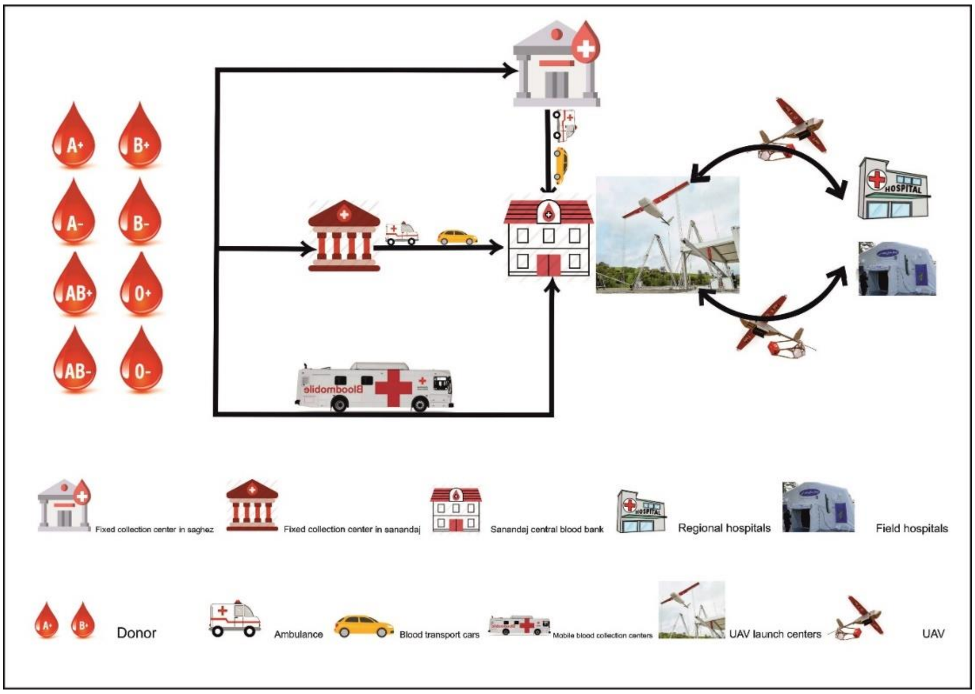


Figure 3. Proposed Blood Supply Chain Network with Drone Integration in Kurdistan Province

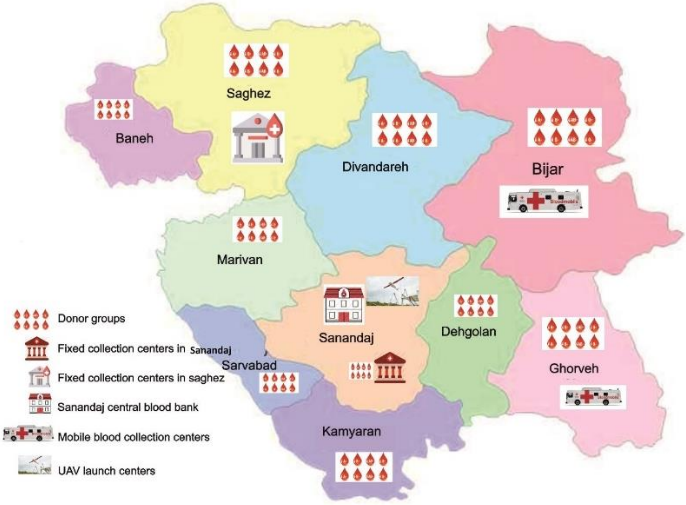
Based on the proposed supply chain design for Kurdistan province, ten cities were selected as blood donor groups: Saqqez, Bijar, Baneh, Marivan, Sarvabad, Sanandaj, Qorveh, Dehgolan, and Kamyaran. Among these, Sanandaj and Saqqez were designated as fixed blood collection centers, while Bijar and Qorveh were identified as mobile collection centers. These locations were chosen based on population density and accessibility to ensure efficient blood collection and distribution.

Results for the First Objective Function (Cost Minimization)

The structure of the blood supply chain network, optimized for cost minimization, is illustrated in Figure 5. The results for all three planning periods are summarized below:

Blood Collection Centers:

- Sanandaj was consistently selected as the primary blood collection center across all periods.
- In the first period, four cities—Sanandaj, Qorveh, Dehgolan, and Kamyaran—were identified as blood donor groups. The blood quantities collected from these cities were:
  - Sanandaj: 41.046 kg
  - Qorveh: 58.707 kg
  - Dehgolan: 57.194 kg
  - Kamyaran: 48.052 kg



Figures 4. Geographical Allocation of Donor Groups and Collection Centers in Kurdistan Province

Blood Processing and Distribution:

- All collected blood was transported to the central blood bank in Sanandaj, where the total inventory reached 205 kg.
- After processing (e.g., centrifugation and testing), the blood was distributed to regional and rural hospitals.
- To minimize costs, the blood inventory at the central bank was reduced to zero by the end of each period.

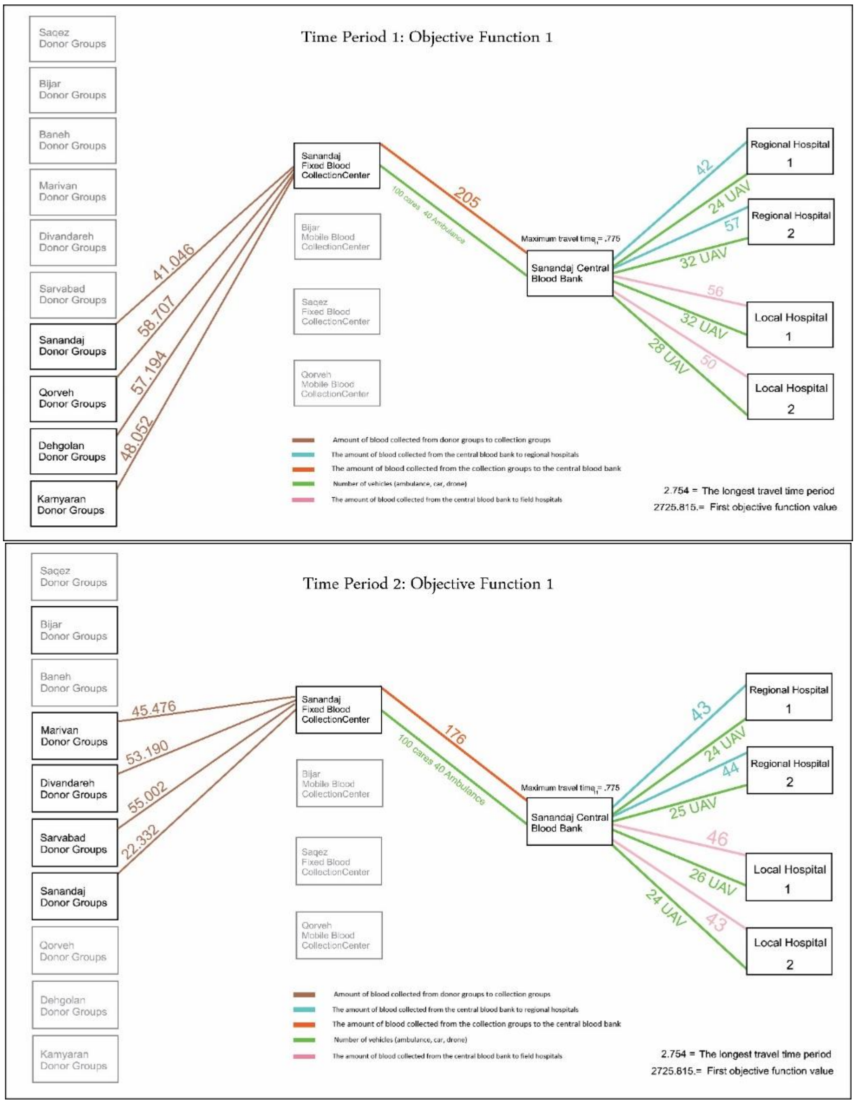
Travel Times:

- The maximum travel time from donor groups to the central blood bank in Sanandaj was 0.775 hours across all three periods.
- The maximum travel time across the entire supply chain was 2.754 hours for all periods.

Objective Function Value:

- The total cost for the first objective function was calculated as **2725.815**.

The allocation and distribution of blood are represented in Figure 5 using colored lines, while inactive centers are depicted in gray. This visualization highlights the efficiency of the proposed network in minimizing costs while ensuring timely blood delivery.



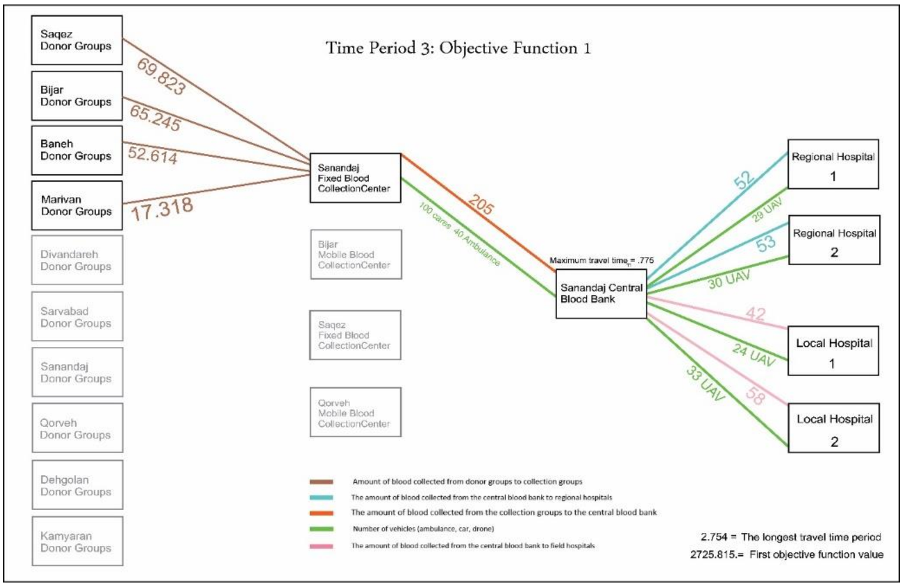


Figure 5. Optimized Network Structure for Cost Minimization (First Objective Function).

Results for the Second Objective Function (Minimizing Maximum Travel Time)

Based on the results obtained from the second objective function, ten cities in Kurdistan province were designated as blood donor groups, with Sanandaj and Saqqez selected as fixed blood collection centers. The amount of blood donated by each city is as follows:

- Divandareh: 17.666 kg
- Sarvabad: 41.046 kg
- Sanandaj: 58.707 kg
- Qorveh: 57.194 kg
- Dehgolan: 48.052 kg
- Kamyaran: 77.335 kg
- Saqqez: 69.822 kg
- Bijar: 65.245 kg
- Baneh: 52.614 kg
- Marivan: 62.794 kg

The collected blood was transported directly to the two blood collection centers in Sanandaj and Saqqez. From these centers, 300 kg of blood from Sanandaj and 286 kg from Saqqez were transferred to the Central Blood Bank in Sanandaj, increasing the total blood inventory to 586 kg. Since the second objective function aims to minimize travel time, the blood from the Central Blood Bank was distributed to regional and rural hospitals based on their demand. This process ensures optimized blood distribution and timely delivery to meet patient needs.

Key Metrics:

- **Maximum Travel Time:**
  - From donor groups to the Central Blood Bank in Sanandaj: **1.123 hours** (first period).
  - Across the entire supply chain: **1.979 hours** (first period).
- **Objective Function Value:** The total value of the second objective function was calculated as **7.061**.

The network structure for the second objective function is illustrated in Figure 6, with colored graphs representing the allocation and distribution of blood. This visualization highlights the efficiency of the proposed network in minimizing travel time while ensuring effective blood delivery.

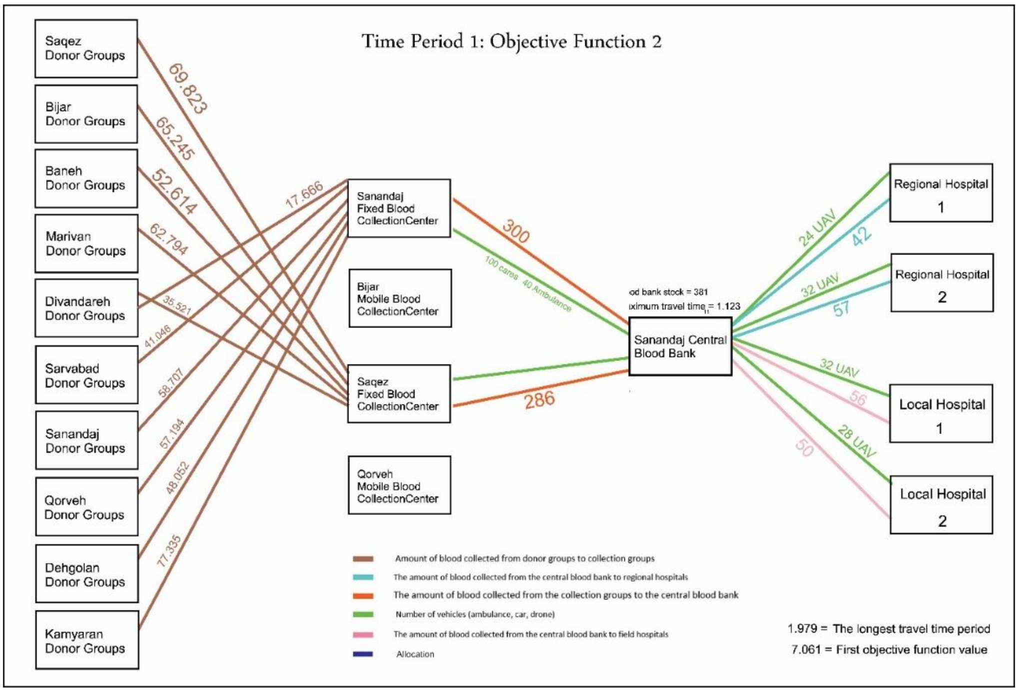


Figure 6. Optimized Network Structure for Minimizing Maximum Travel Time (Second Objective Function).

4.2. Experimental Instances

To thoroughly evaluate the model's capabilities and analyze its performance, we conducted a further study involving the solution of various problem instances across multiple design dimensions. A total of eight problem instances were meticulously designed, each representing different aspects of the design space, as outlined in Table 2. Each instance was solved using the proposed model and its corresponding dataset. The model's performance was assessed by analyzing the results for each objective function individually. Key findings include:

- **First Objective Function (Cost Minimization):**
  Sample problems 1 to 7 were solved efficiently, with each instance requiring less than five minutes. Sample problem 8, being more complex, took slightly longer, with a solution time of under 40 minutes.
- **Second Objective Function (Minimizing Maximum Travel Time):**
  Due to the min-max formulation, solving the problem instances under the second objective function required a longer computational time. However, the results demonstrated that the problem, across all design dimensions, can be optimally solved using the CPLEX solver.

Table 2. Dimensions of Generated Problem Instances.

Instances	|I|	|J|	|k|	|M|	|N|	|T|	|V|
1	3	5	2	2	2	3	2
2	6	10	4	4	4	3	2
3	9	15	6	6	6	3	2
4	12	20	8	8	8	3	2
5	15	25	10	10	10	3	2
6	18	30	12	12	12	3	2
7	21	35	14	14	14	3	2
8	24	40	16	16	16	3	2

To achieve the primary research objective of utilizing drones for the transportation of critical blood supplies in emergency situations, a sensitivity analysis was conducted on the key parameters associated with the UAVs in the model. For this analysis, **Instance 1** was selected, and the parameters examined included:

- **UAV Speed:** Initial speed set at 130 km/h.
- **UAV Capacity:** Initial capacity set at 1.8 kg.
- **Number of UAVs:** Initial number set at 120.

To evaluate the model's sensitivity, these parameters were varied, and their impact on the objective functions was analyzed.

Impact of UAV Speed

The problem was solved at varying UAV speeds: 100, 110, 120, 130, 140, and 150 km/h. The results, presented in Table 3, include the ideal and nadir points for both objective functions, as well as the number of optimal Pareto solutions for each scenario. Key observations include:

- **Improved Objective Functions:** As the UAV speed increased, both objective functions (cost minimization and travel time minimization) showed improvement.
- **Model Sensitivity:** The results confirm that the model is highly sensitive to changes in UAV speed, aligning with our expectations.

Table 3. Sensitivity Analysis Results for UAV Speed (Instance 1).

UAV speed	Ideal point of the first objective function	Nadir point of the second objective function	Ideal point of the second objective function	Nadir point of the first objective function	Number of pareto solutions
100	4859.91	11.59	7.12	10860.78	40
110	4836.33	11.20	6.83	10836.78	39
120	4816.67	10.88	6.59	10816.78	37
130	4800.04	10.60	6.39	10799.86	60
140	4785.79	10.37	6.21	10785.36	59
150	4773.43	10.17	6.06	10772.79	60

The results of the sensitivity analysis were visualized using a Pareto diagram, as shown in Figure 7. The analysis revealed that as the speed of the drone increases, the optimal values of both the first and second objective functions decrease. Specifically:

- The Pareto front shifts toward lower values for both objective functions, indicating improved performance.
- Higher UAV speeds lead to more favorable outcomes, reducing both costs and travel times.

This finding underscores the significant impact of UAV speed on the overall performance of the blood supply chain system. It highlights the importance of selecting an appropriate drone speed to optimize blood transportation during crisis situations, ensuring timely and cost-effective delivery.

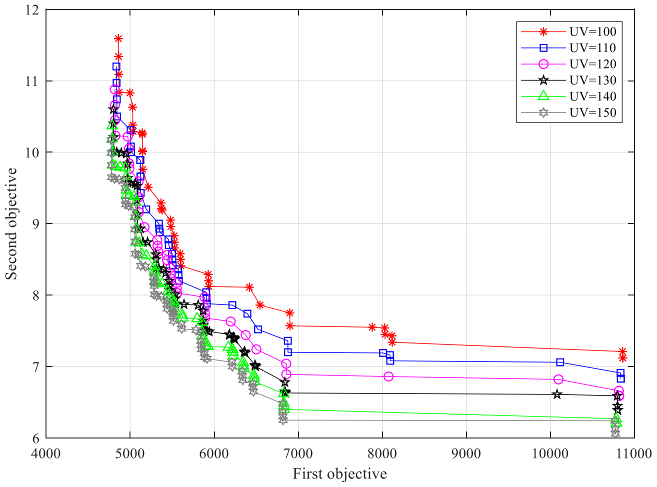


Figure 7. Pareto Front Analysis: Impact of UAV Speed on Objective Functions.

Impact of UAV Capacity

In a separate investigation, the UAV capacity was analyzed across different values: 1.6, 1.8, 2.0, and 2.2 kg. After solving the model and analyzing the results (Table 4), a Pareto diagram was constructed, as shown in Figure 8. Key observations include:

- **Reduction in Pareto Optimal Solutions:** As the UAV capacity increased from 1.6 kg to 2.2 kg, the number of Pareto optimal solutions decreased from 67 to 56.

- **Improved Objective Functions:** The Pareto front shifted toward lower values for both the first and second objective functions, indicating improved performance.

These findings demonstrate that increasing the UAV capacity enhances the efficiency of the blood supply chain, leading to better outcomes in terms of cost and travel time. This highlights the importance of selecting an appropriate drone capacity to optimize blood transportation during crisis situations.

Table 4. Sensitivity Analysis Results for UAV Capacity (Instance 1)

UAV capacity	Ideal point of the first objective function	Nadir point of the second objective function	Ideal point of the second objective function	Nadir point of the first objective function	Number of pareto solutions
1.6	4926.03	10.60	10846.55	6.39	67
1.8	4800.04	10.60	10799.86	6.39	60
2	4678.63	10.60	10773.60	6.39	55
2.2	4564.00	10.60	10754.85	6.39	45
2.4	4451.46	10.60	10737.89	6.39	56

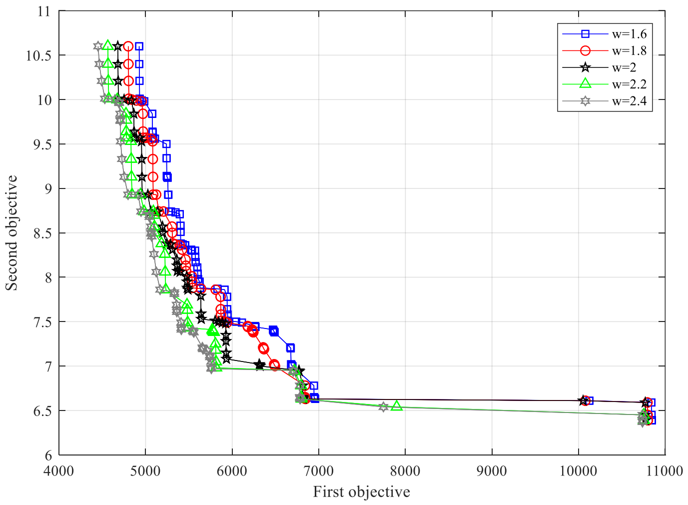


Figure 8. Pareto Front Analysis: Impact of UAV Capacity on Objective Functions.

Impact of the Number of UAVs

The model was also evaluated for different numbers of UAVs: 110, 120, 130, 140, and 150. After solving the model, the following observations were made:

- **First Objective Function (Cost Minimization):**
  The optimal value of the first objective function decreases as the number of drones increases. However, the value of the second objective function remains constant at the ideal point of the first objective function.
- **Second Objective Function (Minimizing Maximum Travel Time):**
  The value of the first objective function at the ideal point of the second objective function decreases, and the ideal value of the second objective function also shows a decreasing trend.
- **Range of Objective Functions:**
  - The range of the first objective function in the balance table increases with the number of drones.
  - The range of the second objective function remains constant up to 140 drones and then increases.

As illustrated in Figure 9, the optimal Pareto front shifts toward lower values for both the first and second objective functions as the number of drones increases. This indicates that a higher number of drones improves the overall performance of the blood supply chain, enhancing both cost efficiency and delivery timeliness.

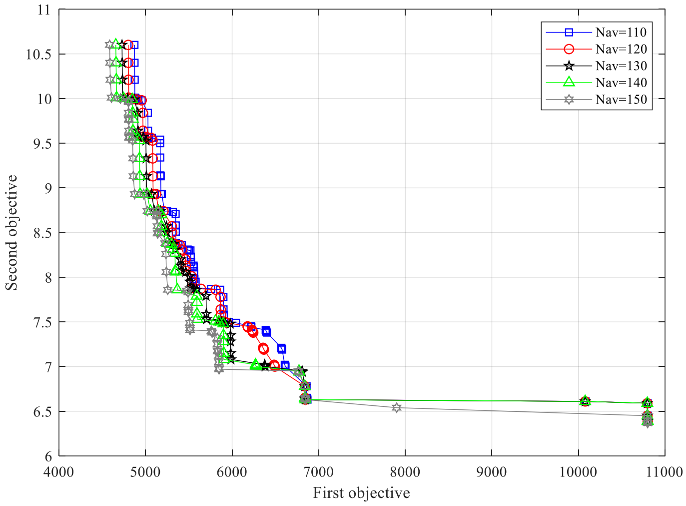


Figure 9. Pareto Front Analysis: Impact of the Number of UAVs on Objective Functions.

4.3. Implications of Sensitivity Analysis and Managerial Insights

The sensitivity analysis demonstrated that higher technical specifications of drones—such as increased speed, capacity, and quantity—lead to improved service delivery and greater operational efficiency in crisis situations. These findings provide valuable **managerial insights** for decision-makers and policymakers involved in emergency response and healthcare logistics:

- **Investment in Advanced Drone Technology:** The results underscore the importance of investing in drones with higher speeds and larger payload capacities. Such advancements can significantly reduce delivery times and operational costs, ensuring timely access to critical blood supplies during emergencies.
- **Strategic Resource Allocation:** Managers should prioritize the allocation of resources to procure and maintain a sufficient number of drones. The analysis shows that increasing the number of drones improves the Pareto front, enhancing both cost efficiency and delivery timeliness.
- **Scalability and Flexibility:** The model's sensitivity to drone parameters highlights the need for scalable and flexible supply chain solutions. Managers should design systems that can adapt to varying crisis scenarios by adjusting drone specifications and deployment strategies.
- **Cost-Benefit Analysis:** While advanced drones may involve higher upfront costs, the long-term benefits—such as reduced transportation costs, minimized travel times, and improved patient outcomes—justify the investment. Managers should conduct detailed cost-benefit analyses to evaluate the tradeoffs.
- **Collaboration with Technology Providers:** Partnerships with drone manufacturers and technology providers can facilitate access to cutting-edge solutions. Collaborative efforts can also drive innovation, leading to drones specifically designed for medical supply transportation.
- **Training and Preparedness:** Effective utilization of drones requires trained personnel and well-defined protocols. Managers should invest in training programs and simulation exercises to ensure seamless integration of drones into emergency response systems.

As drone technology continues to evolve, its integration into emergency response systems will further enhance the timeliness, reliability, and effectiveness of blood transportation. These advancements, coupled with strategic managerial decisions, will ultimately save more lives during crises and strengthen the resilience of healthcare supply chains.

5. Conclusions

This study proposed a comprehensive mathematical model for optimizing the blood supply chain network in crisis conditions, with a focus on integrating unmanned aerial vehicles (UAVs) for efficient blood transportation. The model was designed to minimize both supply chain costs and maximum travel times, ensuring timely and cost-effective delivery of blood products during emergencies. Through extensive computational experiments, sensitivity analyses, and a real-world case study in Kurdistan province, Iran, the model demonstrated its effectiveness in improving the efficiency and responsiveness of blood supply chains. The sensitivity analysis revealed that higher technical specifications of drones—such as increased speed, capacity, and quantity—significantly enhance the performance of the system. These findings provide valuable managerial insights, emphasizing the importance of investing in advanced drone technology, strategic resource allocation, and scalable solutions for emergency response. Collaboration with technology providers, training programs, and cost-benefit analyses were also highlighted as critical steps for successful implementation. Future research can build on this study by addressing its limitations and exploring new opportunities. For instance, the model could be extended to incorporate uncertainty in blood supply and demand using stochastic or fuzzy programming approaches. Additionally, the use of drones could be expanded to transport blood between collection centers and central blood banks, further enhancing the supply chain's efficiency. Finally, developing advanced solution algorithms to solve large-scale instances of the problem in shorter computational times would improve the model's scalability and applicability to real-world scenarios.

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