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Multi-objective location-distribution optimization in blood supply chain: an application in Turkiye

Burcu Altunoglu[1*†] and Gül Didem Batur Sir[2†]

Abstract

Purpose Blood donors are crucial in maintaining the blood supply chain. This study aims to improve the location and distribution of blood donation centers by focusing on two main objectives: minimizing costs and maximizing quality. Minimizing costs includes setting up and transporting blood efficiently while maximizing quality to ensure that blood products are delivered to hospitals promptly and in the right quantities.

Methods A multi-objective mathematical model is proposed to address the placement of both fixed and mobile blood donation centers. The first objective focuses on minimizing the costs of setting up centers and transporting blood. The second objective aims to maximize quality by ensuring timely deliveries and meeting hospitals' blood demand. The model utilizes real-world traffic and blood donation data from urban settings to simulate its effectiveness and applicability in practice. The model uses the ε constraint method to optimize both objectives simultaneously.

Results The model was tested in various scenarios, optimizing cost and quality separately. The algorithm determined the ideal locations for blood donation centers to meet demand by exploring different options. It also accounted for factors that reduce quality, such as delayed deliveries and product returns, and showed that these issues could be minimized.

Conclusion This study highlights the need to balance cost and quality when determining the locations of blood donation centers. Using the ε constraint method, the model successfully optimized both objectives, offering valuable insights for improving the efficiency and effectiveness of blood donation operations.

Keywords Health systems, Blood donation, Multi-objective mathematical model, ε constraint method, Location problem, Distribution problem

Introduction

Human blood sources, collectively known as "blood products", cannot be produced artificially and require a regular whole blood donation system to replenish stocks. There should be an effective blood supply chain (BSC) design so that blood products are always accessible. To increase the efficiency of the supply chain, it is important to ensure the availability of blood products and to keep whole blood donations at adequate levels.

Access to blood banks is important in healthcare systems. The primary challenge faced by blood banks arises

†Burcu Altunoglu and Gül Didem Batur Sir contributed equally to this work.

*Correspondence:
Burcu Altunoglu
baltunoglu@thk.edu.tr
[1] Department of Industrial Engineering, The University of Turkish Aeronautical Association, Ankara 06790, Turkey
[2] Department of Industrial Engineering, Gazi University, Ankara 06570, Turkey

from the limited shelf-life of donated blood, which spans a mere duration of 21 days. Since blood products are such important and perishable products, blood donation is one of the critical points of human life [1].

The blood demand patterns in hospitals exhibit irregularity. A study examining the behavior of university students as blood donors found significant differences in blood donation rates between students in different regions, suggesting the need for specific interventions [2]. Thus, blood donation centers (BDC), blood banks and the BSC structure within urban areas are very important. The BSC consists of donors, mobile blood donation centers (MBC), fixed blood donation centers (FBC) and hospitals representing the demand points.

The connection between quality and the blood supply chain is essential, especially in facilitating the timely and secure delivery of blood products to hospitals. Given that blood is a perishable commodity with a finite shelf life, any delays in its transportation or management can significantly jeopardize its quality, diminishing its effectiveness or potentially making it unsuitable for use. Prompt delivery of blood components is essential in ensuring their safety and efficacy since hospitals rely on these products for critical interventions, including surgical operations, emergency trauma care, and management of chronic illnesses. Any delay has the propensity to lead to deterioration, which may jeopardize patient health outcomes. On the other hand, early delivery of blood products can compromise their quality due to improper storage conditions, increased contamination risks, and disruptions in hospital inventory management, making timely delivery essential for maintaining their effectiveness and safety. As a result, a smooth flow and organized blood supply chain is crucial to maintaining product integrity and ensuring that hospitals can meet pressing medical needs.

Its central motivation lies in the need to address the important question of ensuring an adequate and consistent supply of blood products, essential in the health frameworks. Poor accessibilities to blood products are often a consequence of insufficient numbers and lack of access to BDCs, therefore hindering hospitals from meeting their blood product needs. The motivation of this research is based on enhancing the operational efficiency of BDCs in such a way that cost and quality are optimized throughout the process. The model considers not only the location and capacity decisions of FBCs and MBCs but also develops an integrated model that would better address the variable and, at times, unpredictable demand for blood products in highly populated urban regions, such as Ankara.

The paper provides several new contributions to existing literature. Among them, the most important contribution is the development of a multi-objective mathematical model that can address simultaneously the two main problems of the blood supply chain: cost reduction and quality improvement. Traditional models consider only one objective function, most of the time cost reduction, and may fail to consider this vital aspect of service quality, particularly in fields involving human lives. This paper departs from that tradition by using a two-objective approach. While on one hand, the model is trying to minimize costs by optimizing the location of BDCs and transportation routes to deliver blood products, on the other hand, it maximizes quality by considering variables such as compliance with delivery times and reducing product returns due to degraded quality or delays in delivery.

One of the developments in this study is the application of the ε constraint methodology to achieve a compromise between the inherent conflicting objectives. Unlike other methods, the ε constraint methodology allows the decision-maker more flexibility in choosing the objective on which to anchor, given shifting needs and circumstances. The methodology allows for dynamism, allowing the decision-makers to adjust the balance between cost and quality, following prevailing needs. For instance, in times of emergencies when the demand for blood soars, it can switch to an optimum quality, such as delivery time, rather than cost. In routine operations, there would be the possibility to minimize the cost without sacrificing any key quality metric. This could be very important in the blood supply chain, where demand is usually highly unpredictable.

Another improvement proposed in this study is the integration of stationary and mobile blood collection facilities within the model. Most of the existing models focus more on stationary centers, which can limit access to blood collection services, especially in areas that are either under-served or hard to reach. The inclusion of mobile centers increases the flexibility of the model, thereby enabling it to respond efficiently to localized demand fluctuations, occasions, or seasonal blood donation rates. The primary distinction between fixed and mobile blood donation centers lies in cost, operational flexibility, accessibility, and service scope, with fixed centers offering stability and comprehensive services, while mobile units enhance outreach but incur higher operational costs. Mobile centers offer the flexibility required to operate in areas marked by high demand or where permanent facilities are inappropriate for financial reasons or geographic location. Such a twofold strategy enhances the overall robustness and responsiveness of the blood supply chain.

Moreover, the emphasis of the research on practical applicability serves as a significant motivational element.

Blood supply chains play a vital role in healthcare systems, and any inefficiencies could lead to severe repercussions. Consequently, the proposed model is intended to be both functional and capable of adjustment to actual conditions. This study demonstrates the utility of the model in locating optimum sites for BDCs, both stationary and mobile, while considering the two objectives of cost efficiency and quality improvement, through its application in Ankara. The ability to change priorities based on changing circumstances-e.g., emergencies or changes in demand- reflects the model's particularly useful position in dynamic urban environments.

In summary, the impetus for this research is rooted in addressing a significant challenge within the healthcare supply chain: guaranteeing a dependable and efficient supply of blood. The novel elements consist of formulating a dual-objective optimization model, employing the ε constraint method to achieve a balance between cost and quality, and incorporating both stationary and mobile blood centers into the issues of location and distribution. These are the innovations that provide an adaptive, flexible solution for the challenges of blood supply chains and have considerable potential for a markedly improved availability and quality of blood products in towns and cities.

The rest of this article is structured as follows. Literature review section examines the studies conducted in the related literature for BSC. In Model description and assumptions section defined the problem in detail and present the proposed model. Case study description section describes the case study, Results and Discussion section is given in Results and discussion section. Conclusions and suggestions for future work are collected in Conclusion and future recommendations section.

Literature review

With the rising life expectancy of the global population, managers are increasingly required to allocate greater budgets and resources to address the health needs of individuals. Consequently, they must optimize to efficiently utilize these limited financial and material resources [3]. Challenges related to delays in supply and operational logistics, are counted to be one of the main challenges identified in the medicines and vaccines supply chains [4]. Managing supply chain has a vital importance, especially for products like blood or vaccines, and weaknesses of cold chain management are often observed during transportation and storage of such products [5]. Problems related to supply chain management under uncertain conditions -like disasters, pandemics, etc.- are also commonly studied in the literature [6, 7]. Parameters like the available budget, production capacity, demand for each product in each period, minimum order quantity, purchase price, the impact of supply risk, and supply chain visibility are some of the criteria considered in the supply chain management problems [8]. The primary objectives of studies focused on the optimal design of BSCs are to ensure the cost-effective delivery of blood products to hospitals while minimizing shortages. These efforts aim to enhance blood supply chains' effectiveness, efficiency, and sustainability BSC.

Studies [9–15] have been carried out on different modeling and optimization approaches to enhance the blood supply chain's efficiency, sustainability, and reliability across various contexts. Alfonso et al. (2014) proposed the approach for the blood transport collection plan while trying to ensure that the blood donations made in each region are sufficient in their respective regions [9]. Zahiri et al. (2015) proposed a mathematical model determining the number and location of blood banks. In the multi-period planning horizon, they focused on minimizing the transportation of temporary blood centers and package delivery costs for each period [10]. Fereiduni et al. (2016) studied a BSC design to reduce the uncertainty that occurs during and after catastrophes. A dynamic optimization model has been developed aimed at determining the number of blood facilities, distribution decisions, and the level of stock in hospitals [11]. Osorio et al. (2017) aimed to improve the performance of the supply chain in different complex scenarios [12]. Ucal et al. (2017) conducted a study at a company operating in health systems to measure the sustainability performances for the selection of suppliers [13]. Imamoglu et al. (2023) conducted a comprehensive review of the blood supply chain using bibliometric analysis. They highlighted that there is increasing attention on optimizing the entire supply chain using various decision models [14]. Alghamdi (2023) reviewed the sustainability of blood delivery systems, particularly in urban areas [15].

Studies [16–28] aimed at minimizing costs in the blood supply chain (BSC) with different mathematical models. They highlight different optimization models proposed by researchers to reduce expenses related to transportation, facility construction, and operations in the BSC. Chaiwuttisak et al. (2016) proposed a binary integer programming model aimed at minimizing transportation and construction costs [16]. Ramezanian and Behboodi (2017) proposed the BSC model, which minimizes the transportation costs of fixed and temporary facilities [17]. Mohamed et al. (2019) proposed a BSC aiming at the minimum cost for the Marmara region [18]. Samani et al. (2019) proposed a model to minimize the overall network cost, maintain blood freshness, and search for blood collection facility locations [19]. Fazli-Khalaf et al. (2019) proposed a mathematical model with multi-objective functions for BSC network design in emergencies while aiming to minimize total cost [20]. Haghjoo et al. (2020) proposed a location-allocation model to minimize fixed, operational, and blood loss costs [21]. Araujo et al. (2020) constructed an integer linear programming (ILP) model for planning the BSC and they tried to minimize the total cost [22]. Khalilpourazari et al. (2020) proposed a BSC to avoid the worst consequences in a crisis and minimize unfulfilled demand, transportation time, and cost [23]. Karadağ et al. (2021) focused on a BSC problem with the multi-objective mixed integer location model and designed to minimize the distance between the units, and hospitals [24]. Seyfi-Shishavan et al. (2023) proposed a supply chain model with fixed and mobile blood centers that minimize costs and blood shortages in uncertain hospital demands [25]. Nahofti Kohneh et al. (2023) developed a model for the BSC aiming at maximizing donated blood and minimizing the total cost of the BSC [26]. Satır and Yolcu (2023) developed a model that aims at minimal cost and time, including different stages for the BSC [27]. Entezari et al. (2024) aim to minimize the operational cost in the blood supply chain, including collection, production, transportation, and inventories, while alleviating blood shortage problems in healthcare facilities. This model allows hospitals to meet the demand of patients during an emergency by developing a bi-objective model [28].

With the immediate need for blood products, there is the need to consider the temporal restrictions of its supply chain activities, particularly the routing of vehicles. In that regard, current studies have focused not just on vehicle routing but also on vehicle routing with a time window to address such considerations. Studies [29–32] focus on the temporal restrictions and vehicle routing challenges within the blood supply chain (BSC). Özener et al. (2018) proposed a routing model in which the platelet processing time is considered and aimed at the maximum number of donations [29]. Zhou et al. (2021) dealt with a BSC, considering the shelf lives of blood products, and created a discrete event system simulation (DESS) in uncertain supply and demand [30]. Ay et al. (2022) proposed a two-stage location-routing for Covid-19 vaccines with time constraints and difficult storage conditions and it has been successfully stated that vaccines are consumed before their shelf life expires [31]. Zheng et al. (2023) explored vehicle routing problems (VRP) with fairness and timeliness constraints, particularly in public health emergencies [32].

Optimization studies [33–37] in healthcare and blood supply chain management have focused on multi-objective optimization models. More critical objectives such as cost minimization, increased response time, and reliability are pursued simultaneously to be effective during emergencies and high-demand events. Heidari-Fathian and Pasandideh (2018) proposed a BSC network covering temporary and stationary blood collection units, aiming to minimize the total environmental impact and the total cost [33]. Arani et al. (2021) developed a multi-objective mathematical model that considers the shelf life of blood products and aims to minimize the environmental impact and costs [34]. Hosseini et al. (2023) adapted their model to minimize costs due to blood shortages substitute products in disaster situations and guarantee responsive and reliable supply chains during crises. Together, these studies have highlighted the growing importance of multi-objective optimization in building resilient, sustainable, and cost-effective healthcare supply networks [35]. Fariman et al. (2024) presented a robust optimization method for blood supply chains that balances cost-effectiveness and response capabilities under uncertain conditions [36]. Ala et al. (2024) focused on integrating sustainability into healthcare logistics through the design of a fuzzy multi-objective model that allows accommodating environmental, economic, and social objectives by providing a framework to address variable demands and resource availability [37].

Despite significant progress in optimizing blood supply chains (BSCs) through diverse mathematical and modeling approaches, there remains a critical gap in addressing the integrated optimization of both fixed and mobile blood donation centers. Existing literature has primarily focused on individual aspects of BSC optimization, such as cost reduction, environmental impact mitigation, or operational efficiency, often treating fixed and mobile units separately or concentrating on a single objective. This fragmented approach overlooks the complexity of simultaneously optimizing the spatial and operational dimensions of blood donation centers. Specifically, there is a lack of comprehensive multi-objective models that account for both the location and distribution of blood donation centers while balancing factors such as cost, quality, and sustainability. Addressing this gap requires the development of a unified mathematical model that integrates these elements, thereby enhancing the effectiveness and responsiveness of blood supply chains. Such a model would offer a holistic solution to the challenges of optimizing both fixed and mobile blood donation centers, improving overall system performance and service delivery. Table 1 presents an overview of some research studies in the literature.

Model description and assumptions

In this study, the blood supply chain process starts with donors who can donate at fixed or mobile blood donation centers. The collected blood is sent directly from the donation center to the hospitals where it is distributed after the necessary tests have been carried out. There is

Table 1 Summary of some studies in the literature

Studies	Objective of Study	Methodology
Sahoo (2024) [7]	To optimize the transportation of relief supplies from supply points to destination points under uncertainties following a disaster.	Genetic Algorithm, Particle Swarm Optimization
Sahoo et al. (2023) [8]	To minimize cost and to maximize service level by taking into account the existing uncertainties.	Chance Constrained Model
Mohamed et al. (2019) [18]	To minimize transportation and opening costs	MILP
Samani et al. (2019) [19]	To minimize the overall network cost, maintain blood freshness, and search for blood collection facilities	MOO & Fuzzy Solution Approach
Fazli-Khalaf et al. (2019) [20]	To maximize the test reliability of donated blood, to minimize blood transportation time together with the total costs	MOO & Chance Constraint Programming
Haghjoo et al. (2020) [21]	To minimize the total costs	Self-Adaptive Imperialist Competitive Algorithm
Araujo et al. (2020) [22]	To minimize the cost by reducing the waste of purchasing blood.	ILP
Khalilpourazari et al. (2020) [23]	To minimize unfulfilled demand, to minimize transportation time and cost	MOO & Neural Learning
Karadag et al. (2021) [24]	To minimize the distance between units, and the length of the moving unit paths	MOO & MILP
Seyfi-Shishavan et al. (2023) [25]	To minimize the total cost satisfying hospital demands under uncertainty	Fuzzy Programming
Nahofti Kohneh et al. (2023) [26]	To minimize the total cost and to maximize the amount of donated blood	MOO & Lagrangian Relaxation Method
Satır & Yolcu (2023) [27]	To minimize the total cost, and the total time lost in the blood supply chain.	Goal Programming
Entezari et al. (2024) [28]	To reduce the overall operational costs associated and to minimize the shortage of blood components	Augmented ε Constraint Method
Zhou et al. (2021) [30]	The determine blood allocation and blood transshipment.	DESS
Zheng et al. (2023) [32]	To make the demand satisfaction rates and to reduce the total delivery time of medical supplies.	Differential Evolution Algorithm
Arani et al. (2021) [34]	To minimize the environmental impacts, to maximize the social impacts and to minimize the variable and fixed costs	MOO & Multi-Choice Goal Programming
Hosseini et al. (2023) [35]	To minimize the total cost of the network and the transportation time between facilities and the total unsatisfied demand for blood products, and to maximize the total reliability of the tested blood in the laboratory.	NSGA-II Algorithm
Fariman et al. (2024) [36]	To reduce the deficit of blood flow during various times and to minimize the overall costs associated with the blood supply chain	Weighted Sum Method
Ala et al. (2024) [37]	To reduce the overall costs associated with the healthcare supply chain and to minimize the ecological footprint of healthcare operations.	Multi-objective Gray Wolf Optimizer, Non-dominated Sorting Genetic Algorithm II (NSGA-II)
The Proposed Model	To minimize the sum of the distribution costs between centers and hospitals, and opening cost of BDC; and to minimize transportation costs, and the penalties for early and late delivery	MOO & ε Constraint Method

no blood transfer between fixed and mobile blood donation centers, but blood can be transferred between hospitals to manage supply and demand efficiently. A location and distribution model is proposed for this process.

The location and distribution model for blood donation centers is presented in this section. Decisions included in the model are determining the locations of MBCs to be opened, the amount of blood to be transported from opened BDCs to hospitals, and the arrival times to hospitals.

The model assumptions are as follows:

- All blood collected from any donor will be regarded as whole blood; no processing is done before it arrives at the BDCs.
- The blood testing and processing take at least two days, meaning that the blood components are at least two days old before they are shipped from the BDCs to their respective requesting facilities, in most cases hospitals.
- Each hospital should be assigned to exactly one delivery route, which implies that from the BDCs, blood is delivered through a single, consistent path.

- All delivery routes must commence from the blood donation centers, thereby ensuring a centralized distribution system for the management of logistics and transportation.
- The aggregate demand for blood from all the hospitals serviced by a particular route cannot exceed the storage and transportation capacity of the mobile blood donation centers.
- The transportation time between nodes (i.e., between BDCs and hospitals) is directly related to the physical distance separating them, ensuring realistic time calculations for delivery schedules.
- The total volume of blood collected from donors at any one time should not exceed the capacity for storage or processing capacity of the donation centers.
- All donations are compulsorily tested and processed at the blood donation center to ensure safety and quality before distribution.
- The vehicles assigned to deliver the blood are assumed to be homogeneous and move with constant speed, to simplify the logistics calculations for homogeneity in the different sets of routes.
- It assumes that the operational costs are computed yearly, and an assessment is done on the proposed system for one year of operational cycles to account for seasonal variations in demand for blood and donations.
- It is expected that all blood donation centers with a fixed location continue to operate all year round, thus providing a stable platform in terms of location and distribution.

Notation

The objective of the developed model is to create a BSC that provides the blood demand values specified in the fastest and least costly way. In the problem of choosing the best location among the FBC and MBC, the distribution model that allows the blood to reach hospitals in the desired time intervals is also proposed, as well as the location model in which the center installation and operation costs and the transportation costs are included.

The sets, parameters, and decision variables related to the proposed mathematical problem are the following:

Sets

N	Set of nodes, $n \in N, N_I \cup N_D = N$
N_I	Set of hospital,$i \in N_I$
N_D	Set of blood donation centers , $d \in N_D$
M_O	Set of blood donation centers that are open ,$o \in M_O, M_O \subset N_D$

Parameters

g_d	The annual cost of blood donation centers
p_d	Annual capacity of blood donation centers (units of blood)
D^+	The upper limit of the number of blood donation centers
h_i	Annual demand of hospitals (units of blood)
$[e_i, b_i]$	Delivery time intervals of hospitals (minute)
$t_{n,n'}$	Traveling time between nodes by vehicle (minute)
μ	Transport cost for one unit of blood per minute
Q	Capacity of vehicle (units of blood)
s	Total number of nodes
$BigM$	A large positive value

Decision Variables

$x_{n,n'}$	1,if vehicle travels between nodes,$n, n' \in N$; 0,otherwise
y_d	1, if a donation center is located on node d; 0,otherwise
$z_{n,n'}$	The amount of blood transported between the nodes, $n, n' \in N$
u_i	The position of hospital i, $i \in N_I, \lvert N_I \rvert = s$
v_i	Arrival time to node $i \in N_I$
EE_i	The earliness value of a vehicle at node i, $i \in N_I$
GG_i	The tardiness value of a vehicle at node i, $i \in N_I$

Mathematical model

The MILP is as follows:

$$Min \sum_{d \in N_d} g_d * y_d + \sum_{n \in N} \sum_{n' \in N} \mu * t_{n,n'} * (z_{n,n'}/Q) \quad (1)$$

$$Min \sum_{i \in N_I} EE_i + \sum_{i \in N_I} GG_i \quad (2)$$

Subject to:

$$\sum_{d \in N_D} x_{d,j} + \sum_{i \in N_I} x_{i,j} = 1 \ , \forall j \in N_I, \ i \neq j \quad (3)$$

$$u_i - u_j + s * x_{i,j} + (s-2) * x_{j,i} \leq s - 1 \ , \forall i, j \ \in N_I, \ i \neq j \quad (4)$$

$$\sum_{j \in N_I} x_{i,j} \leq |N_I| * u_i \ , \forall i, \in N_I, \ i \neq j \quad (5)$$

$$\sum_{i \in N_I} z_{d,i} \ = \sum_{i \in N_I} h_i * x_{d,i} \ , \forall d \in N_D \quad (6)$$

$$\sum_{i\in N_I} z_{d,i} \le p_d * y_d \ , \forall d \in N_D \quad (7)$$

$$\sum_{d\in N_D} z_{d,i} + \sum_{j\in N_I} z_{j,i} \ge h_i \ , \forall i \in N_I, \ i \neq j \quad (8)$$

$$z_{i,j} \le h_j * x_{i,j} \ , \forall i,j \in N_I, \ i \neq j \quad (9)$$

$$z_{d,i} \le h_i * x_{d,i} \ , \forall d \in N_D, \ \forall i \in N_I \quad (10)$$

$$\sum_{d\in N_D} z_{d,i} \ge \sum_{j\in N_I} z_{i,j} \ , \forall i \in N_I, \ i \neq j \quad (11)$$

$$y_o = 1 \ , \forall o \in M_O \quad (12)$$

$$v_i = \sum_{d\in N_D} t_{d,i} * x_{d,i} \ , \forall i \in N_I \quad (13)$$

$$v_j \le \sum_{i\in N_I} t_{i,j} * x_{i,j} + v_i \ , \forall j \in N_I, \ i \neq j \quad (14)$$

$$GG_i \ge v_i - b_i \ , \forall i \in N_I \quad (15)$$

$$EE_i \ge e_i - v_i \ , \forall i \in N_I \quad (16)$$

$$x_{n,n'} \in 0,1 \ , \forall n,n' \in N \quad (17)$$

$$y_d \in 0,1 \ , \forall d \in N_D \quad (18)$$

$$z_{n,n'} \ge 0 \ , \forall n,n' \in N \quad (19)$$

$$u_i, v_i, EE_i, GG_i \ge 0 \ , \forall i \in N_I \quad (20)$$

Constraint (1) aims to minimize the sum of the annual costs of blood donation centers and the cost of transporting blood, while Constraint (2) minimizes the sum of earliness and tardiness (E/T) in the acceptable time window. The unit of the model covering the first objective function is annual, while the unit of the second objective function is minute. Constraint (3) indicates that every hospital is visited exactly once. Constraints (4) and (5) are the subtour elimination constraints. Constraint (6) guarantees that the total amount of blood sent from each blood donation center meets the needs of hospitals. Constraint (7) shows that the amounts of blood sent from blood donation centers do not exceed the capacity of related center. Constraint (8) ensures that every hospital should receive as many blood products as demand. Constraints (9) and (10) are used to link the assignment variables with the routing variables. are used to link the assignment variables with the routing variables. The fact that the total amount of blood coming from blood donation centers should be equal to or greater than the total amount of blood transported between hospitals, is guaranteed by Constraint (11). Constraint (12) shows the stationary blood donation centers that are opened.Constraints (13) and (14) allow calculating the arrival times to the hospitals.These constraints calculate the exact time a vehicle reaches each hospital, thus ensuring that the arrival times are properly incorporated into the scheduling and routing model.Constraint (15) calculates tardiness, which refers to the number of minutes a vehicle arrives after the end of the allowable time window at the hospital. It is essentially the positive difference between the actual arrival time at the hospital and the latest permissible time for that delivery. Constraint (16) calculates the earliness, representing the number of minutes a vehicle arrives before the start of the acceptable time window at the hospital. It shows the positive deviation between the actual arrival time at the hospital and the earliest acceptable time scheduled for the delivery. Finally, Constraints (17) - (18) and Constraints (19) - (20) are (0-1) and nonnegativity constraints, respectively.

The application of ε constraint method to the problem

In the literature, there are several methodologies used to solve MOOPs. Along with this, in a recent study, Poonia et al. (2024) assessed the efficacy of three prevalent multi-objective optimization methodologies for electronic waste management within the context of the circular economy, specifically ε constraint, LP-metric, and the Weighted Sum Method (WSM) [38]. They introduced a mixed integer linear programming (MILP) model designed to enhance economic, environmental, and social goals, including the maximization of profit, reduction of costs, and minimization of pollution. Then they compared these methods via the TOPSIS technique and showed that the ε constraint method is the most efficient for generating Pareto-optimal solutions that can achieve a better tradeoff between non-cooperative objectives. According to their analysis, LP metric achieved average results, while WSM was identified as relatively less efficient because it cannot handle disproportionate priorities among certain objectives [38]. That study showed that the ε constraint method successfully resolves complex tradeoffs present in multi-objective optimization and thus, we apply the method with the aim of achieving efficient solutions in our problem.

The ε constraint method is a widely used technique for solving MOOPs. It allows for a systematic analysis of the trades among different objectives by transforming multi-objective optimization problems defined with multiple competing objectives into a single-objective optimization problem. In this method, one of the objectives is considered the actual objective, while all other objectives are handled as constraints, taking the form of upper bound limits, known as epsilon values. It will give different optimal solutions and converge to the Pareto frontier by altering the values of ε [39].

While the ε constraint method has shown flexibility and efficiency in exploring the Pareto frontier, it also suffers from difficulties related to appropriate epsilon value selection and scalability for an increasing number of objectives.

Objective 1 focuses on reducing annual operational costs for BDCs, while Objective 2 emphasizes minimizing penalties from delayed blood deliveries, measured in minutes to ensure timely, effective service, with both objectives highlighting the need for financial efficiency and delivery speed.

In this study, the first objective function of the location and distribution model, which aims at minimum cost, is selected as the objective, while the second objective function, which aims at the appropriate delivery time interval, is added as a constraint and is given below.

$$Min \sum_{d \in N_d} g_d * y_d + \sum_{n \in N} \sum_{n' \in N} \mu * t_{n,n'} * z_{n,n'}/Q$$

$$\sum_{i \in N_I} EE_i + \sum_{i \in N_I} GG_i \leq \varepsilon \quad \varepsilon \in [obj2^-, obj2^+] \tag{21}$$

subject to

Constraints (3) – (20)

According to the ε constraint method used in the solution of the problem, the first objective function is minimized by taking the second objective as one of the constraints. The value of ε is run between the lower bound and the optimal value of the second objective function. The value of ε is updated in percentage increments between the limits of the second objective function. The calculation of the rate of increase for ε is given:

$$\varepsilon^+ = obj_2^- + (obj_2^+ - obj_2^-) * increment(\%) \tag{22}$$

The mathematical model is run until it reaches the upper value of the second objective function. At the end of each run, the total cost and total E/T time are recorded and compared to analyze the scenarios with the minimum total cost.

Case study description

According to the report presented by Turkish Red Crescent, it is allowed for any individual to be a blood donor, if he/she is a healthy person between the ages of 18-65 [40]. Looking at the population distribution of Ankara province by districts, the regions with an excess of eligible individuals for blood donation are considered and 10 most populous districts of Ankara province are selected to be used in this study. Figure 1 shows the populations of these 10 districts. They are also listed in Table 2, as the candidate locations for mobile donation centers.

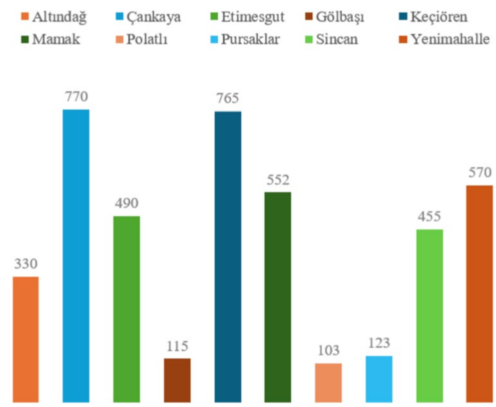

Fig. 1 Population of 10 districts (thousands)

Table 2 Mobile blood donation centers

	Candidate MBC		Candidate MBC
1	Altindag MBC	6	Mamak MBC
2	Cankaya MBC	7	Polatli MBC
3	Etimesgut MBC	8	Pursaklar MBC
4	Golbasi MBC	9	Sincan MBC
5	Kecioren MBC	10	Yenimahalle MBC

The two fixed blood donation centers located in Ankara and 10 mobile blood donation centers selected as the candidates are shown in Fig. 2.

The hospitals of which the demands for blood supplies are dealt with, are selected among the state hospitals located in the candidate districts. Related hospital list is given in Table 3.

The data of distances between the hospitals and candidate blood donation centers are determined via Google Maps. Selected hospitals are shown in Fig. 3.

According to the report of the Turkish Red Crescent in 2019, 2 million 809 thousand 237 units of blood were donated throughout Turkiye. 293,883 units of blood were donated to Ankara Regional Blood Center, which constitutes 2% of the total donated blood in Turkiye [41]. Taking advantage of these information, we determine the capacities of the donation centers assuming that up to 2% of the population of selected districts donate blood.

The department where the most blood is spent in a hospital varies depending on the type of hospital, the

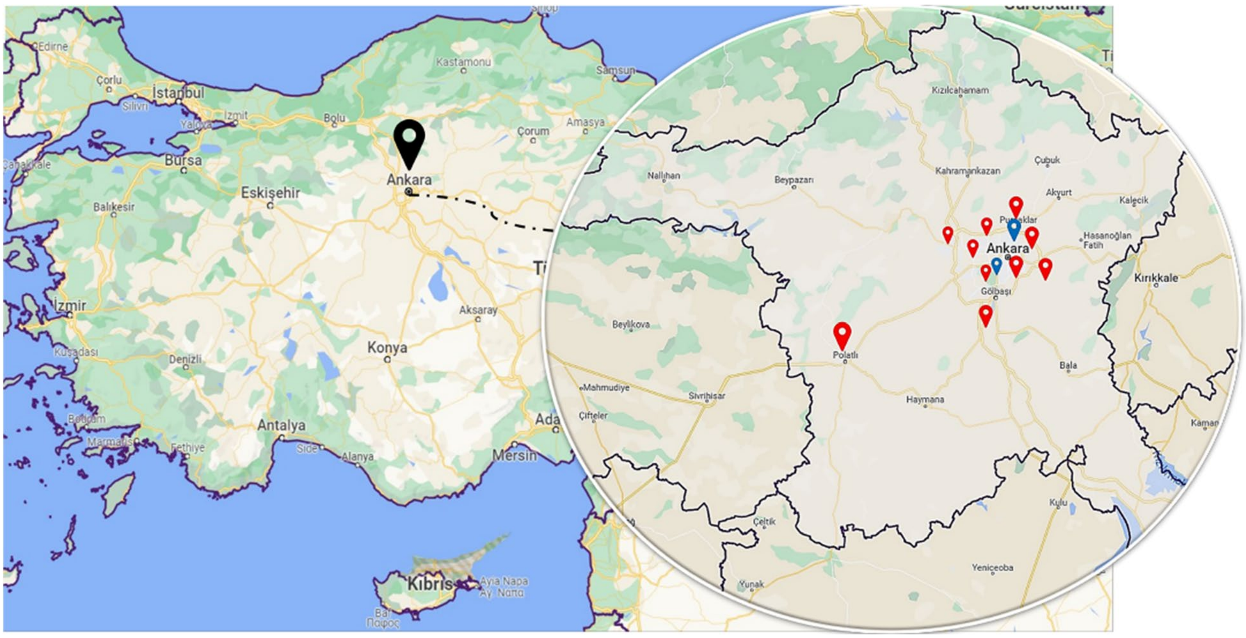

Fig. 2 Fixed and mobile blood donation centers

Table 3 Selected hospitals for proposed model

	Hospital
1	Dışkapı Yıldırım Beyazıt Training and Research Hospital
2	Dr. Sami Ulus Obstetrics and Gynecology, Child Health and Diseases Training and Research Hospital
3	Ankara 29 Mayıs State Hospital
4	Ankara Atatürk Training and Research Hospital
5	Gazi University Hospital
6	Hacettepe University Hospital
7	Ufuk University Dr. Ridvan Ege Health Research and Application Hospital
8	Etimesgut State Hospital
9	Gölbasi Şehit Ahmet Özsoy State Hospital
10	Gülhane Training and Research Hospital
11	Ataturk Sanatorium Training and Research Hospital
12	Etlik Zübeyde Hanım Gynecology Training and Research Hospital
13	Mamak State Hospital
14	Polatlı Duatepe District State Hospital
15	Ankara Pursaklar State Hospital
16	Ankara Dr. Nafiz Körez Sincan State Hospital
17	Yildirim Beyazit University Yenimahalle Training and Research Hospital

size of the hospital, the specialties, and the needs of patients. Usually, emergency departments rank high among the departments with intensive blood needs. Since emergency service data could not be accessed throughout Turkiye, traffic accident data is used.

The study by [42] emphasises the high demand for type O blood, especially due to traffic accidents and injuries. TSI (Turkish Statistical Institute) reports that the number of traffic accidents with fatal injuries for Ankara province was determined as 5.5 per thousand vehicles [43]. Figure 4 shows the number of accidents per specified district according to the TUIK data. Transfusion needs of a patient with severe internal bleeding or extensive injury where multiple trauma sites are involved require the administration of 4 to 6 units of RBCs or more. In this present study, one blood request for a single patient is considered to involve the transfusion of 6 units of RBCs (Red Blood Cells) [44, 45]. Taking the number of accidents into account, annual demands for each district are calculated and shown in Fig. 5.

Parameters related with the BDCs, cost, and capacity; and with hospitals' delivery times are presented in Tables 4 and 5, respectively. Delivery time intervals of hospitals refer to designated time windows crucial for optimizing BDCs and ensuring timely delivery of urgent or perishable medical supplies. The delivery time intervals given in Table 5 are based on the geographical location of the hospitals relative to the city center, assuming a scenario without traffic. Early delivery times were estimated using Google Maps to reflect the time required to reach the hospitals under these conditions. Late delivery times were set as twice the time taken for early delivery.

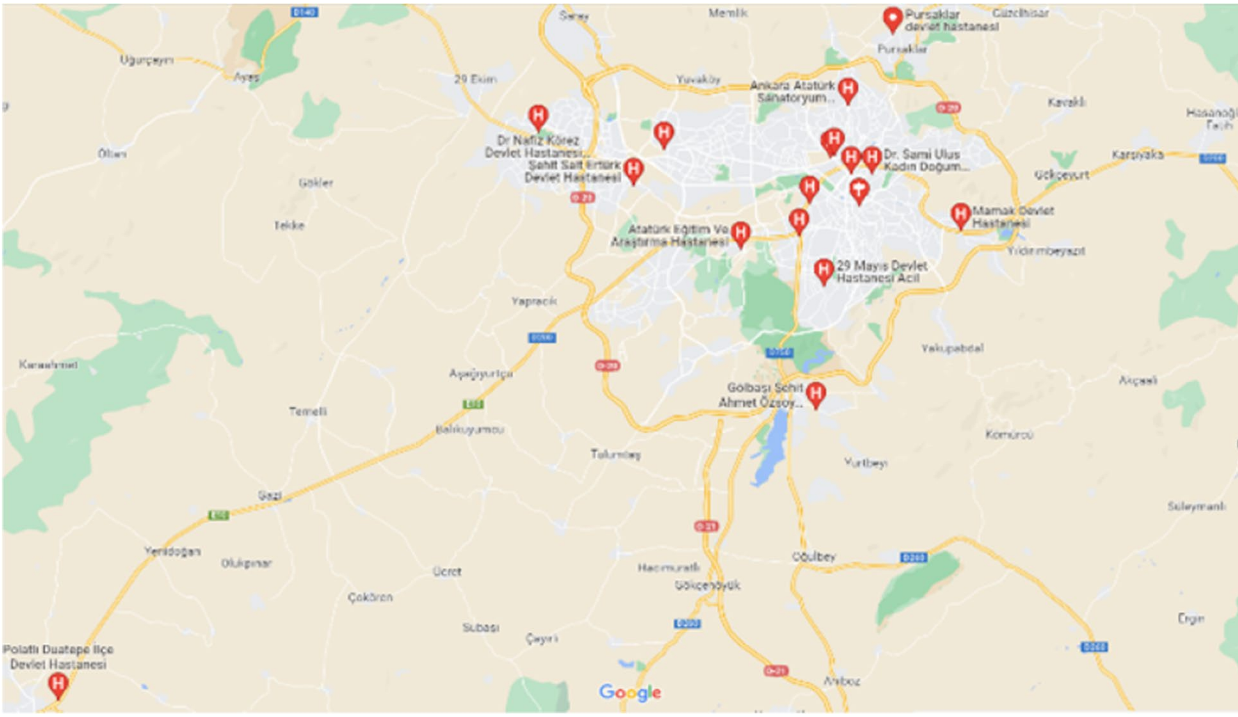

Fig. 3 Selected hospitals

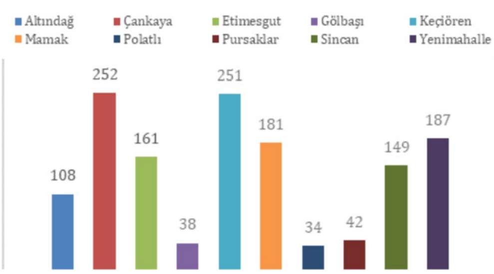

Fig. 4 Number of fatal accidents in selected districts

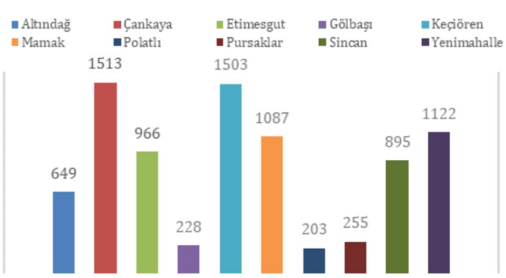

Fig. 5 Annual demands of selected districts

The blood transfer vehicle has a carrying capacity of a maximum of 100 units of blood per trip. This feature influences the overall logistics and distribution efficiency in terms of the number of trips that have to be done to deliver blood supplies to different destinations [34]. There is currently no available information regarding the cost of transporting blood in Turkey. The cost of transporting one unit of blood per unit of time, denoted as μ, is assumed to be 500 TL/minute. This cost encompasses all expenses related to transporting one unit of blood by vehicle, including fuel, vehicle maintenance, staff, and driver labor costs.

Table 4 Cost and capacity of BDCs [34, 46]

d BDCs	g_d Cost of BDCs (TL/year)	p_d Capacity of BDCs (unit)
Cankaya FBC	100000	500
Yenimahalle FBC	100000	500
Altindag MBC	360000	900
Cankaya MBC	360000	800
Etimesgut MBC	360000	110
Golbasi MBC	360000	400
Kecioren MBC	360000	1400
Mamak MBC	360000	700
Polatli MBC	360000	100
Pursaklar MBC	360000	100
Sincan MBC	360000	700
Yenimahalle MBC	360000	2000

Table 5 Delivery time intervals of hospitals (minute)

i Hospitals	e_i Early Time	b_i Late Time	*i* Hospitals	e_i Early Time	b_i Late Time
1	5	10	10	12	24
2	6	12	11	20	40
3	7	14	12	15	30
4	8	16	13	15	30
5	6	12	14	25	50
6	10	20	15	35	70
7	10	20	16	40	80
8	12	24	17	30	60
9	10	20			

Table 6 Objective function values when the model is run for first objective

Obj_1	Obj_2
1747750 TL	204 min.

Table 7 Opened blood donation centers for the first objective

	Blood donation centers
1	Cankaya FBC
2	Yenimahalle FBC
3	Altindag MBC
4	Kecioren MBC
5	Yenimahalle MBC

Results and discussion

The model is run twice for the two objective functions of the proposed approach. In this section, the result of the proposed mathematical model is shown.

The problem is solved by the GAMS CPLEX solver. Firstly, the program is run for the objective function, which aims to minimize the route cost, and the installation and operational costs of donation centers. The first objective function value and the second objective function value aiming at the appropriate delivery times are shown in Table 6.

The list of blood donation centers opened when the first objective function is optimized in Table 7, and the routes created are shown in Table 8 and Fig. 6.

The number of BDC that are opened when the first objective function is ran is limited as the total number of BDC that will be opened for the second objective function.

$$\sum_{d} y_d = D^+ \tag{23}$$

Table 8 Routes for the first objective

	Routes
1	Cankaya FBC - 5 - 6
2	Yenimahalle FBC - 12 - 1
3	Altindag MBC - 2 - 15
4	Altindag MBC - 10 - 11
5	Kecioren MBC - 17 - 13
6	Yenimahalle MBC - 4 - 14
7	Yenimahalle MBC - 7 - 3
8	Yenimahalle MBC - 8 - 16
9	Yenimahalle MBC - 9

For the second objective function, Constraint (23), which limits the number of hospitals to be opened, is added. Thus, the second objective function and its constraints are given below.

$$Min \sum_{i \in N_i} EE_i + \sum_{i \in N_i} GG_i$$

subject to

Constraints (3) - (20)

Constraint (23)

Then, the program is run for the second objective function, which aims to provide the appropriate delivery time. Related objective function values are shown in Table 9.

The list of blood donation centers opened when the second objective function is optimized in Table 10, and the routes created are shown in Table 11 and Fig. 7.

So far, both two objective functions are optimized separately, and the results are presented. The first objective function is based on the location and distribution problem. The second objective function, which aims at the appropriate delivery time interval, includes the installation and operational costs of donation centers, the cost of the route, and the penalties for early and late delivery.

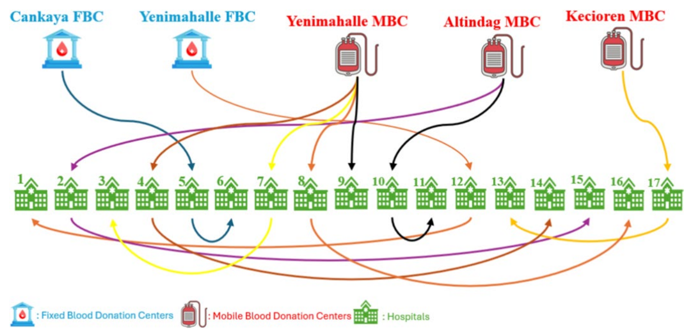

Fig. 6 Distribution of blood donation centers to hospitals for the first objective

Table 9 Objective function values when the model is run for second objective

Obj_1	Obj_2
2183250 TL	166 min.

Table 10 Opened blood donation centers for the second objective

	Blood Donation Centers
1	Cankaya FBC
2	Yenimahalle FBC
3	Kecioren MBC
4	Sincan MBC
5	Yenimahalle MBC

Table 11 Routes for the second objective

	Routes
1	Cankaya FBC - 9 - 3
2	Yenimahalle FBC - 12 - 1
3	Kecioren MBC - 17 - 2 - 7 - 11
4	Sincan MBC - 6 - 5
5	Sincan MBC - 15 - 14
6	Yenimahalle MBC - 13 - 8
7	Yenimahalle MBC - 16 - 4 - 10

Optimizing the objective functions separately, a 24.92 % change is observed in the value of the first objective function, while an 18.63% change is observed in the value of the second objective function. The ε constraint method is applied to the proposed multi-objective mathematical model to deal with two objectives simultaneously.

For the ε constraint application to be applied to the model, the second objective function was added as a constraint and the range of values to be taken was determined as (166; 204). The values of ε , the percentage of change, the objective function providing the minimum total cost, and the total E/T time values taken in line with the ε constraint method are given in Table 12.

Running the model with the ε constraint method 9 times, the minimum cost was obtained in the ninth run at an ε value of "200.2". In the ninth run, the value of the objective function for the first time reached its minimum compared to all values obtained using the ε constraint method. The assembly of the blood donation centers opened can be seen in Table 13 and the routes developed by the model using the ε constraint method in Table 14 and Fig. 8.

In the multi-objective mathematical framework addressed by the ε constraint approach, a marginal increase of 0.06% in the value of the minimum cost objective function concerning the location and distribution dilemma has been identified. Simultaneously, there has been a 3.43% decrease in the value of the second objective function, which aims at refining the optimal delivery time window. These results show that while there has been a moderate rise in costs, the reduction of maximum total delivery time is significantly improved. This outcome indicates the capability of the ε constraint method to deal with the trade-off between cost minimization and optimization of delivery efficiency.

These results from the multi-objective mathematical framework indicate important findings for the logistics and distribution management decision-makers. This was a marginal increase in cost, made against the backdrop of the significant reduction in delivery times very important trade-off for managers. An application of the ε constraint approach enables the manager to find a proper balance between the minimization

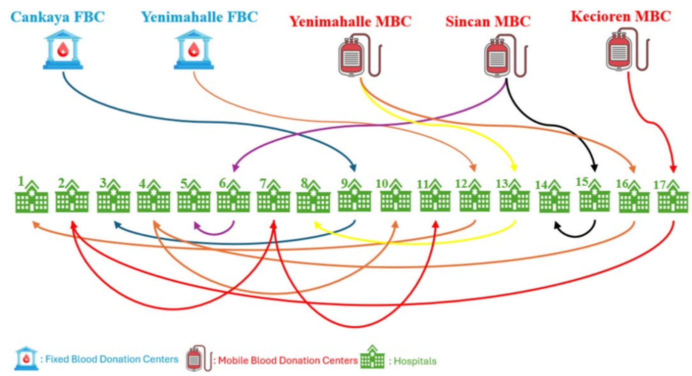

Fig. 7 Distribution of blood donation centers to hospitals for the second objective

Table 12 Results of ε constraint method

	ε **value (min.)**	ε **increment value (%)**	**Total cost (TL)**	**Total E/T time (min.)**
1	169.8	%10	1977750	169
2	173.6	%10	1936750	173
3	177.4	%10	1917750	177
4	181.2	%10	1774250	181
5	185	%10	1769750	185
6	188.8	%10	1766750	186
7	192.6	%10	1756250	192
8	196.4	%10	1751750	196
9	200.2	%10	1748750	197

Table 13 Opened blood donation centers

	Blood Donation Centers
1	Cankaya FBC
2	Yenimahalle FBC
3	Altindag MBC
4	Kecioren MBC
5	Yenimahalle MBC

Table 14 Routes

	Routes
1	Cankaya FBC - 9
2	Yenimahalle FBC - 12 - 1
3	Altindag MBC - 2 - 15
4	Altindag MBC - 10 - 11
5	Kecioren MBC - 17 - 13
6	Yenimahalle MBC - 4 - 14
7	Yenimahalle MBC - 5 - 6
8	Yenimahalle MBC - 7 - 3
9	Yenimahalle MBC - 8 - 16

of operational costs and the improvement of service quality, represented by delivery time reductions. This added capability is particularly valuable for industries in which timely deliveries are critical, such as health-care and emergency response; that is, areas where minor increases in cost are offset by dramatic gains in service performance. These findings serve as a good basis through which resource allocation, scheduling, and operational strategies could now be optimized to achieve improvements in financial and operational performance.

Conclusion and future recommendations

The blood supply chain (BSC) constitutes a fundamental aspect of healthcare, with cost and quality representing the two most significant factors in guaranteeing its efficiency. Within the framework of this study, the minimization of costs entails the reduction of installation and operational expenses, alongside the optimization of transportation routes. Simultaneously, the attainment of high quality necessitates the assurance of timely deliveries of blood products to hospitals, the minimization of stock holding times, and the prevention of delays or premature arrivals. The study addresses location and distribution challenges by developing a multi-objective mathematical model that integrates both fixed and mobile blood centers (FBCs and MBCs), aiming to optimize the balance between cost efficiency and operational quality within the blood supply network.

The proposed multi-objective model involves two major objectives. The first objective aims to minimize two types of costs: the setup and routing cost of blood collection centers and paths. The second objective is concerned with minimizing penalties for deliveries that arrive too early or too late to hospitals, crucial to maintaining the quality of blood products. The ε constraint method allowed for the optimization of both objectives by designating the primary objective as the

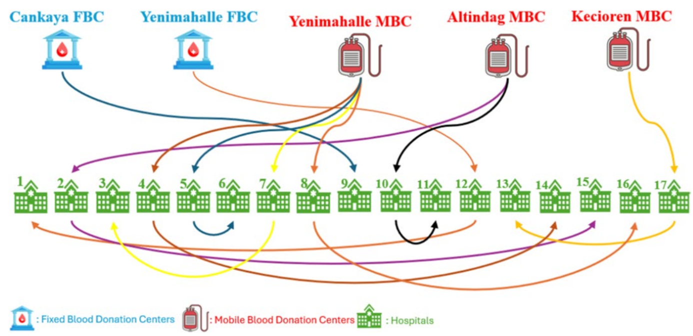

Fig. 8 Distribution of blood donation centers to hospitals for the ε constraint method

focal aim and the secondary objective as a constraint. In contrast to optimizing each objective independently, it was found that the aggregate cost had only a marginal increase of 0.06%, while the assessment of early and late deliveries recorded an improvement of 3.43%. This outcome implies a significant development in general efficiency within the system. Therefore, the Pareto optimal solutions prove that the multi-objective approach can successfully handle cost and quality problems, while this might be a more balanced and practical solution for BSC management.

The result obtained from multi-objective mathematical model represents important findings for logistics and distribution managers, raising costs by a small amount that was offset by the substantial reduction in delivery times worthwhile trade-off for managers. The ε constraint method enables the manager to obtain the proper balance between the reduction of operational costs and the increase in service quality, represented by decreased delivery times. This capability is valuable enough for sectors where timely deliveries may play a key role, such as in health care or emergency services. These are domains wherein even minor cost increments are justified by the substantial improvement in service efficiency. Such results provide a sound basis for enhancements in resource allocation, scheduling, and operational strategies that result in financial and operational improvements.

There are several avenues for further research apparent in the future. Future studies could incorporate daily demand data and take into consideration stock holding costs, hence providing a more dynamic and responsive framework for managing the blood supply. In addition, diversification of blood products and taking into consideration the different capacities of blood transport vehicles would further add realism to this model. Another promising avenue might be the integration testing and stock-holding period, something that is inherently part of any blood supply chain. In this respect, and given the increasing worldwide concern for environmental sustainability, another avenue for future research may involve vehicle routing models to reduce CO_2 emissions given the wider aim of greening logistics operations. Besides, a major limitation of the study is the difficulty in accessing real or test data related to the problem. At this point, it is anticipated that more effective observations and comparisons can be made if appropriate data becomes available.

Authors' contributions
Both authors contributed equally to this study. B.A. and G.D.B.S. jointly conceived the research idea, analysed the data and wrote the paper. Both authors read and approved the final manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Materials availability
Available from the corresponding author on reasonable request.

Code availability
Available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This research does not involve human subjects, human material, or human data.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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