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RESEARCH ARTICLE

A robust fuzzy framework for designing a sustainable blood supply chain network under disruption

Mohammad Amin Khosravi, Hassan Khademi Zare*, Hassan Hosseini Nasab, Davood Shishebori

Department of Industrial Engineering, Faculty of Engineering, Yazd University, Yazd, Iran

Abstract – Blood supply chain network is impacted by multiple uncertainties including demand, short shelf life of blood products, and disruption of normal operations. This paper proposes an integrated data-driven framework that includes Long Short-Term Memory (LSTM) demand forecasting, fuzzy scenario modeling, and robust multi-objective optimization to support the design of a sustainable blood supply chain network. Historical demand data is first predicted with an LSTM model under three conditions: optimistic, base and pessimistic. The forecasts are expressed as asymmetric triangular fuzzy numbers and then defuzzified before being input to the optimization model. The model is structured to minimize three objectives concurrently: total cost, blood shortage and environmental impacts. The optimization solutions are obtained by the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the results are verified by CPLEX. The LSTM model showed good forecast performance with Root Mean Squared Error (RMSE) values between 1.28 and 3.65 and Mean Absolute Percentage Error (MAPE) values between 4.12% and 8.90%. Among the three scenarios, the base scenario generated the least prediction errors. The deviations of NSGA-II from the exact CPLEX solutions were 1.97% for total cost and 4.76% for environmental impact, while the blood shortage deviation was 0%. The results indicate that NSGA-II can provide solutions close to the exact optimization results with substantially less computational effort. Sensitivity analysis on demand growth, budgets for temporary facilities and disruption severity also showed the framework can adapt to changes in operating conditions. Overall, the proposed framework provides a practical decision-support approach for planning sustainable and more disruption-resilient blood supply chain networks.

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1. Introduction

The blood supply chain (BSC) is a vital part of the healthcare system; it must ensure an uninterrupted supply of safe blood products for emergencies, surgery, trauma care and patients with chronic conditions. But BSCs are different from normal supply chains in several ways. Blood products spoil and have a short shelf life, donor turnout varies, blood group compatibility must be taken into account, and demand can vary widely over time. These problems are exacerbated by natural disasters, pandemics, epidemics, and transportation breakdowns, which may disrupt blood collection and distribution and, in severe cases, threaten patient safety and the health system's ability to respond. In recent years, healthcare logistics and operations management have put more emphasis on designing resilient and sustainable blood supply chain networks [1]-[3]. Good demand forecasting is an important component of planning for collection, inventory and distribution. Conventional statistical techniques such as Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing work fairly well in cases where demand follows reasonably stable patterns but tend to underperform when demand exhibits nonlinear behavior or abrupt shifts due to seasonality, disease outbreaks or unanticipated disruptions. Deep learning has been developed and widely used for demand forecasting, with Long Short-Term Memory (LSTM) networks able to learn temporal patterns from historical data. Most forecasting approaches still yield a single deterministic number. Such an estimate does not adequately capture the typical uncertainty in healthcare demand, limiting its usefulness when the forecast is used as an input for disruption-aware network planning [4], [5].

A number of studies have considered uncertainty in blood supply chain planning using fuzzy approaches, robust optimization and scenario-based methods. Habibi Kouchaksaraei et al. [1] proposed a resilient multi-echelon blood supply chain model for disaster situations. Hosseini Motlagh et al. [2] designed a robust optimization model considering the disruption risk and blood compatibility constraints to enhance the network resilience. Later, Fariman et al. [3] proposed a multi-objective robust optimization model by scenario analysis for the blood supply chain network design under uncertainty, highlighting the significance of uncertainty in strategic planning. More recently, forecasting research has suggested that the use of advanced prediction methods combined with optimization models can lead to improved decisions about blood inventory and resource allocation [4]. These contributions notwithstanding, there are still gaps. For one, demand forecasting and network optimization are often considered as separate stages with little attention to

***CORRESPONDING AUTHOR | Hassan Khademizare** | ✉ hkhademiz@yazd.ac.ir

how the uncertainty of the forecast propagates to strategic decisions. Second, only few studies have combined deep learning-based forecasting, fuzzy representation of uncertainty and robust multi-objective optimization in a single decision-support framework. Third, previous work has usually been more concentrated on economic considerations. The existing literature offers relatively little information on an integrated approach that considers cost, blood shortages, environmental impact, disruption resilience, and the roles of fixed and mobile blood collection facilities [1]-[3].

To fill these gaps, this study proposes an integrated framework of sustainable BSC network design by linking LSTM-based demand forecasting, fuzzy scenario generation, and robust multi-objective optimization. The historical demand data in optimistic, base and pessimistic cases is forecasted by LSTM model, and the forecasts are represented as asymmetric triangular fuzzy numbers. The resulting fuzzy forecasts are defuzzified and input into a robust location-allocation model which determines how to configure fixed and mobile blood collection facilities while minimizing three objectives simultaneously: total operational cost, blood shortages, and environmental impact. The resulting optimization problem is solved with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The solutions obtained are validated using IBM CPLEX. Then the framework is applied to a real-world case study of the blood supply chain network of Fars Province, Iran.

2. Method and Materials

2.1. Literature Review

Recent blood supply chain (BSC) management studies can be broadly categorized into three: artificial intelligence and deep learning for demand forecasting; fuzzy and robust optimization for uncertainty management; and predictive models and optimization for decision support. However, the complexity of healthcare logistics has increased, particularly during pandemics, natural disasters, and other disruptions, as has the need for decision-making approaches that account for uncertainty while ensuring the efficiency of BSC operations [6]-[8].

Machine learning (ML) and deep learning methods have drawn more attention in forecasting, as they can capture nonlinear relationships and temporal changes that conventional statistical techniques often miss. Edalat Sarvestani et al. [9] proved the superiority of hybrid forecasting methods in comparison to the conventional ARIMA models in predicting blood demand. Miri Moghaddam et al. [10] used Long Short-Term Memory (LSTM) networks to predict the demand for blood products with promising results on nationwide Iranian data. Then, Zebari et al. [5] proposed a hybrid Long Short-Term Memory–Extreme Gradient Boosting (LSTM-XGBoost) model and reported further gains in accuracy over individual deep learning models. Their results suggest that combining learning methods can help improve demand prediction in healthcare settings more broadly.

Also, robust and fuzzy optimization approaches have been widely explored for BSC network planning. A strong possibilistic programming approach to sustainable supply chains was proposed by Pishvaee et al. [11] and since then it has been used as the basis for dealing with uncertainty in a number of supply chain problems. In particular, Habibi Kouchaksaraei et al. [1] proposed a bi-objective robust model for disaster management in BSC, and Hosseini Motlagh et al. [2] incorporated disruption risk and blood compatibility constraints into the network design problem. [3] used scenario-based robust optimization for the uncertainty in BSC network design, and Shishebori et al. [12] proposed a hybrid robust optimization model for a multi-echelon blood products supply chain under pandemic conditions.

Currently, researchers have begun to connect demand forecasting with optimization rather than treat them as separate problems. Niakan et al. [13] presented a hybrid model integrating demand forecasting and blood distribution optimization. Qing et al. [14] proposed a two-stage adaptive robust model that accounts for uncertainty in demand, supply, and disruption under disaster conditions. These studies demonstrate the benefits of integrating forecasting and optimization. However, many existing methods still rely on deterministic demand forecasts or keep a clear separation between forecasting and optimization. This opens up possibilities for further work on frameworks where forecasting uncertainty is directly incorporated in BSC network planning.

Hence, despite the considerable progress in forecasting accuracy and optimization methodologies, there remains an important research gap in developing a unified framework for directly translating fuzzy deep learning forecasts into robust optimization inputs, while simultaneously accounting for economic, social and environmental sustainability objectives. As summarized in Table 1, prior research has primarily addressed individual components of blood supply chain management, with limited work on combining these components into a holistic framework. Furthermore, only a few studies have evaluated such integrated frameworks on real-world blood supply networks with permanent and mobile collection facilities under multiple disruption scenarios. The objective of this study is to fill these gaps with an integrated fuzzy demand forecasting based on LSTM and robust multi-objective optimization in a unified decision-support framework.

2.2. Method

In this section, the proposed framework for designing a sustainable and disruption-resilient blood supply chain (BSC) network under uncertainty is presented. The framework combines LSTM based demand forecasting, fuzzy scenario modeling and robust multi-objective optimization in one decision support approach. The historical demand for blood is forecasted in three scenarios: optimistic, base and pessimistic. The forecasts are then expressed as asymmetric triangular fuzzy numbers and defuzzified before they are used in the optimization model. Figure 1 shows the methodology. The methodology follows a top-down sequence starting with data acquisition and preprocessing, followed by demand forecasting, fuzzy scenario generation, robust optimization, and model validation through sensitivity analysis. The optimization model simultaneously considers three objectives: minimizing total cost, minimizing blood shortages, and minimizing environmental impact. The objective of this framework is to help design a sustainable BSC network.

2.2.1. Data Source and Study Area

The framework is architected using operational data of the Iranian Blood Transfusion Organization (IBTO), particularly the Fars Provincial Blood Transfusion Center in Iran (Figure 1). The data set includes daily blood demands from five permanent blood centers, Shiraz, Marvdasht, Jahrom, Fasa and Lar, which are the major blood collection and distribution centers in Fars Province.

Table 1. Summary of recent literature and research gaps

Reference	Forecasting	Optimization	Uncertainty	Sustainability	Real Case	Research Gap
Habibi Kouchaksaraei et al. (2018)[1]	✗	Robust optimization	✓	Economic	✓	No AI forecasting
Hosseini Motlagh et al. (2020) [2]	✗	Robust optimization	✓	Economic	✓	No predictive module
Edalat Sarvestani et al. (2022) [9]	Hybrid ML	✗	✗	✗	✓	No optimization
Miri Moghaddam et al. (2024) [10]	LSTM	✗	✗	✗	✓	Deterministic forecasting
Fariman et al. (2024) [3]	✗	Multi-objective robust	✓	Partial	✓	No deep learning integration
Niakan et al. (2024) [13]	Prediction	Optimization	Partial	Partial	✓	Limited fuzzy modeling
Qing et al. (2025) [14]	✗	Adaptive robust	✓	Partial	✓	No fuzzy-LSTM integration
Zebari et al. (2025) [5]	LSTM-XGBoost	✗	✗	✗	✓	No optimization framework
This Study	Fuzzy-LSTM	Robust multi-objective	✓	Economics + Social + Environmental	✓	Integrated forecasting–optimization framework

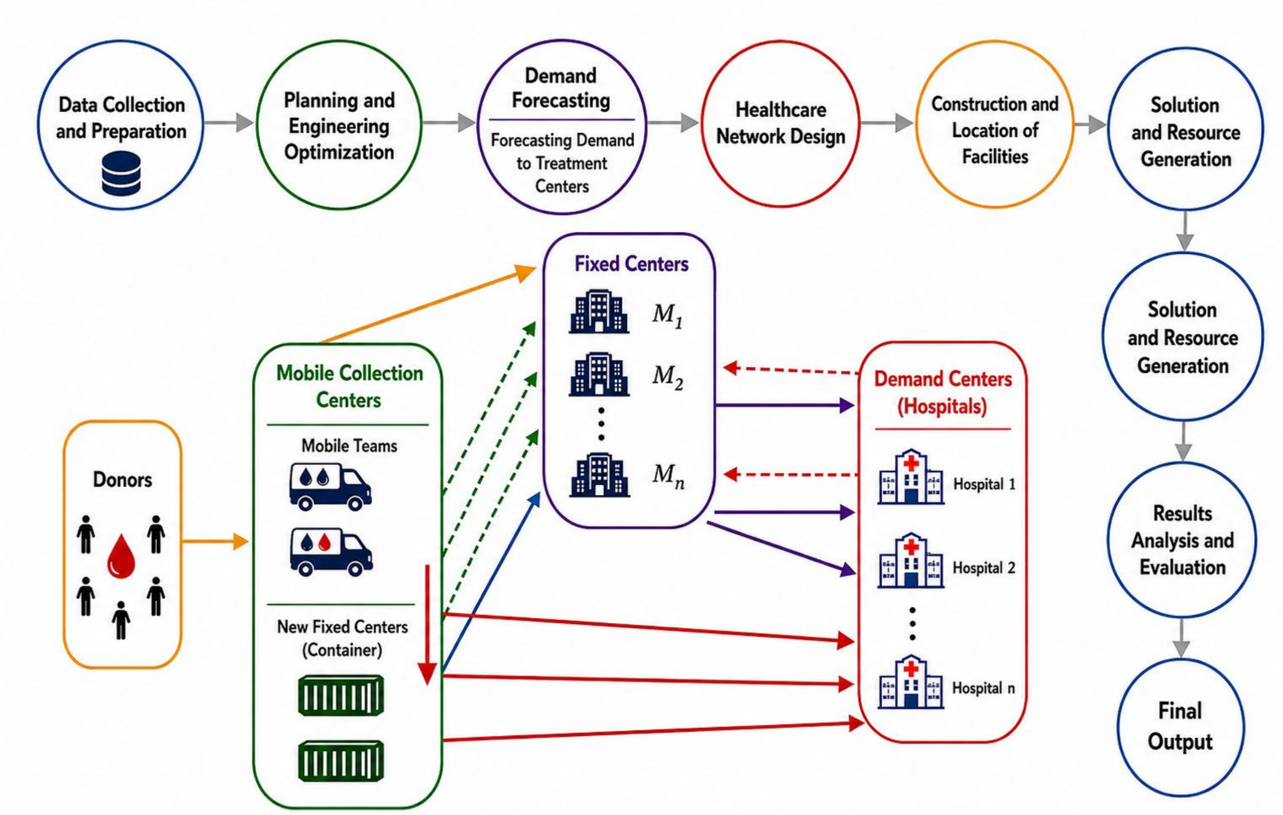

Figure 1. Architecture of the blood supply chain decision support framework

Historical demand records for different blood groups were retrieved from the provincial operational database and preprocessed before being used in model development. Operational data such as potential locations of permanent and temporary blood collection centers, transportation distances, capacities, operating costs, and parameters on possible disruptions were gathered from official planning documents and internal data provided by the provincial blood transfusion authority. The proposed framework is tested with real operational data under realistic healthcare logistics conditions, while the source data is confidential.

2.2.2. Data Preprocessing

Before model development, the data collected were checked for missing, incomplete and inconsistent entries and missing observations were estimated by interpolation where appropriate. Then, the numerical variables were scaled using Min-Max normalization, which scales the values in a consistent range and speeds up the training of the deep learning model. Demand forecasting was based on a rolling-window scheme, i.e., demand over the previous 15 days was used to forecast demand over the next 15 days. The model can then learn to respond to demand changes over time, in a way able to capture both short-term variations as well as longer time-based patterns.

2.2.3. Overview of the Fuzzy-LSTM Forecasting Framework

The proposed forecasting module combines an LSTM neural network with fuzzy logic to account for uncertainty in future blood demand, and it works through five successive stages:

i. Input Layer: The input layer is composed of the historical daily blood demand and time-related variables as input sequences to the model.

ii. Data Preprocessing: The time-series data are rearranged into supervised learning samples after normalization by the above rolling-window approach.

iii. LSTM Network: The prediction model contains two LSTM layers with 64 and 32 hidden neurons, respectively and a fully connected layer to generate the prediction. The network is trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function for 100 epochs with a batch size of 16, following the settings reported in recent healthcare demand forecasting research [15].

iv. Fuzzy Logic Module: Instead of a single point forecast, three asymmetric triangular fuzzy scenarios, optimistic, base, and pessimistic, are created with LSTM predictions. The scenarios represent the variability in future blood demand in the face of, in particular, supply chain disruptions.

v. Defuzzification: The triangular fuzzy numbers are converted into crisp demand values using an asymmetric weighted averaging method, and the resulting values feed into the robust optimization model as demand parameters.

2.2.4. Model Validation and Case Study

The proposed framework was tested on two levels: forecast performance and optimization performance. The LSTM model for forecasting was evaluated by the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. These metrics are commonly used to measure the accuracy of demand forecasting in healthcare applications [4]. The model was trained on historical demand data and tested with a rolling forecasting procedure to evaluate its performance for subsequent observations.

In the optimization stage, the NSGA-II algorithm solutions were compared with the exact solutions obtained by the IBM ILOG CPLEX for smaller problem instances to determine the closeness of the metaheuristic results to the exact solutions and to evaluate the computational performance of the NSGA-II [16], [17].

Then, the entire framework was tested on the real operational data of blood supply network in Fars Province, Iran. The case study includes the five current permanent blood centers, potential new permanent facilities and a number of mobile blood collection units under various disruption scenarios. We carried out sensitivity analyses by varying the levels of demand, severity of disruptions and the investment budgets to observe the response of the framework to the different operating conditions and to observe the suitability of the framework for practical decision-making in the planning of blood supply chains.

2.2.5. Mathematical Modeling Framework

The mathematical model formulates robust multi-objective location-allocation problem under uncertain demand to design sustainable and disruption resilient BSC networks. It links the fuzzy demand forecasts to strategic network planning and identifies which facilities to open, how donors are allocated, and how blood flows in the network. The LSTM model captures the demand uncertainty to generate optimistic, base, and pessimistic scenarios. The defuzzified values are inputted into the optimization model.

The model aims to simultaneously minimize the total operational cost, blood shortage, and environmental impact, subject to practical constraints such as capacities of facilities, available budget, geographic coverage, allocation of donors, and limited shelf life of blood products. The disruption events are modeled as the decrease in the capacity of the blood collection facilities, which is to examine the network performance under various emergency conditions. The Appendix contains a full mathematical model including sets, indices, parameters, decision variables, objective functions, and constraints.

3. Results and Discussion

In this section, we show the results of the proposed framework following the workflow presented in Figure 1. The results are divided into six steps: (1) data source, (2) demand forecasting based on LSTM, (3) defuzzification, (4) fuzzy-robust optimization, (5) model validation and sensitivity analysis for decision support, and (6) evaluation of the whole supply chain system. The methodology with the same sequence enables the direct linkage of each computational outcome to the respective step in the framework.

The framework was tested using real operational data from five main blood centers in Fars Province, Iran. In the first phase, the LSTM model predicted blood demand for a 15-day planning horizon in optimistic, base and pessimistic scenarios. These forecasts were represented in terms of triangular fuzzy values and then defuzzified before being input to the robust optimization model. The multi-objective optimization problem was solved using NSGA-II and the obtained Pareto solutions were analysed to evaluate the trade-offs between total cost, blood shortages and environmental impact. Then, these solutions were compared with results obtained by IBM ILOG CPLEX on reduced-size instances. Sensitivity analyses were also performed to improve the changing demand levels, severity of disruption and investment budgets to see the response of the framework under different operating conditions.

3.1. Case Study Description

The proposed framework was applied to the blood supply network of the Fars Province of Iran. The network consists of five permanent blood donation centers in Shiraz, Marvdasht, Jahrom, Fasa and Lar and candidate mobile blood collection units to serve different donor areas and transfusion centers. The demand forecasts obtained from the LSTM model in the optimistic, base, and pessimistic scenarios were used in the optimization model to reflect different possible demand conditions.

Disruptions were represented by reducing the capacity of blood collection facilities, from normal operation to more severe disruption levels. Other operational inputs such as facility capacities, transportation costs and planning constraints were taken from information obtained from the Iranian Blood Transfusion Organization (IBTO) and the Fars Provincial Blood Transfusion Center. This real-world network enables investigation of the proposed framework's performance under practical operating conditions.

3.2. LSTM-based Demand Forecasting

In the first stage of analysis, the LSTM model was applied to the historical daily demand data from the five blood centers. The model generated three asymmetric triangular fuzzy scenarios for each center, which represent optimistic, base and pessimistic demand for the 15-day planning horizon. These scenarios together represent the uncertainty of future blood demand before the optimization phase.

Figure 2 shows the predicted demand for the three fuzzy scenarios, where lower, middle and upper values are optimistic, base and pessimistic estimates respectively. The differences between these values indicate the range of demand considered in the model and directly represent the uncertainty carried into the optimization stage. The forecasting performance was evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The MAPE and RMSE were computed using defuzzified demand values for the five blood centers across the 15-day forecasting horizon.

Table 2 presents the comparison of the proposed Fuzzy-LSTM model with the benchmark ARIMA model in terms of the RMSE and MAPE. The LSTM model resulted in RMSE and MAPE values of 1.28-2.26 and 4.12-4.78%, respectively. All MAPE values were less than 5%, which implies a high level of forecasting accuracy for the demand data in this case study. The results also show that the LSTM model was better at capturing variations in blood demand than the traditional statistical model. In contrast, for the five centers the RMSE values of ARIMA ranged from 2.37 to 3.47 and MAPE values ranged from 5.65% to 6.91%. Overall, the LSTM model reduced RMSE by about 38% and MAPE by about 26% compared to ARIMA, which suggests that the proposed LSTM-based approach yielded more accurate demand predictions for the blood centers in this study. These results support the use of the fuzzy demand estimates generated by the LSTM as inputs to the subsequent optimization stage.

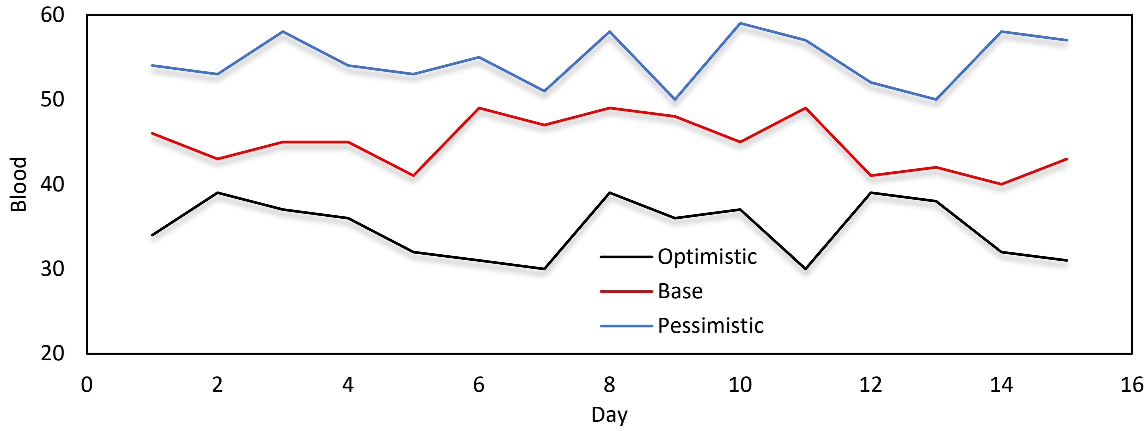

Figure 2. Fuzzy blood demand forecast under three scenarios

3.3. Fuzzy Demand Modeling and Defuzzification

To include forecast uncertainty in the optimization model, the blood demand predicted by the LSTM model is represented using asymmetric triangular fuzzy numbers. The three values correspond to optimistic, base, and pessimistic demand conditions. This allows the forecast to be expressed as a range rather than as a single value. Each fuzzy demand value $\widetilde{D}_{its}$ is defined as shown in Equation (1).

$$\widetilde{D}_{its} = (L_{its}, M_{its}, U_{its}) \tag{1}$$

where L_{its}, M_{its}, and U_{its} denote the lower, central, and upper demand values, respectively. In this study, L_{its} represents the demand under favorable or optimistic conditions, M_{its} is the most likely or base-case forecast, and U_{its} corresponds to the higher demand expected under pessimistic disruption conditions.

An asymmetric fuzzy representation is used because the effect of disruptions may not be the same in both directions. For example, an adverse event may lead to a larger increase in blood demand than the reduction associated with a favorable change in operating conditions. The fuzzy demand is therefore converted into a single value before it is included in the optimization model. The defuzzified value $D_{its}^{\text{defuzzified}}$ is calculated using Equation (2).

$$D_{its}^{\text{defuzzified}} = \frac{w_1 \cdot L_{its} + w_2 \cdot M_{its} + w_3 \cdot U_{its}}{w_1 + w_2 + w_3} \tag{2}$$

The weights used in this study are $w_1 = 1$, $w_2 = 3$, $w_3 = 2$. The higher weight assigned to the central value gives greater importance to the base forecast, while the lower and upper values are still retained to account for uncertainty on either side of the expected demand.

This weighted defuzzification method offers a practical way to retain information from the fuzzy demand range without adding much computational complexity to the optimization model. The resulting crisp demand values feed directly into the robust multi-objective model while still reflecting the variation tied to different disruption conditions [18], [19].

3.4. NSGA-II Optimization Results and Pareto Analysis

The fuzzy multi-objective optimization model was solved using NSGA-II, as it is capable of dealing with multiple conflicting objectives and producing a set of non-dominated solutions. The implementation was in Python using the DEAP library with parameters set as in Table 3. Optimization produced a set of non-dominated solutions for various combinations of total cost, blood shortages and environmental impact. The resulting Pareto front is shown in Figure 3. The solutions to the left side have lower operational costs, mainly due to fewer facility activations and less transportation activity, but result in higher blood shortages. By contrast, right-side solutions target reducing shortages and improving environmental performance, requiring wider facility coverage and heavier use of mobile blood collection units and increasing cost. Solutions in the middle of the Pareto front represent a trade-off between the three objectives, i.e., balancing the economic, social, and environmental outcomes without strongly favoring any of them. The spectrum of solutions generated by NSGA-II offers several possible network configurations for decision makers to consider against available resources and operational priorities.

Table 2. Comparison of forecast performance between LSTM and ARIMA

Blood Center	Model	RMSE	MAPE (%)
Shiraz	LSTM	2.26	4.78
	ARIMA	3.47	6.91
Marvdasht	LSTM	1.91	4.63
	ARIMA	2.98	6.12
Jahrom	LSTM	1.64	4.26
	ARIMA	2.73	5.88
Fasa	LSTM	1.42	4.31
	ARIMA	2.56	5.73
Lar	LSTM	1.28	4.12
	ARIMA	2.37	5.65

Table 3. Parameter settings for NSGA-II execution

Parameter	Value
Population size	100
Generations	300
Crossover rate	0.9
Mutation rate	0.1
Selection method	Tournament
Elitism strategy	Enabled (non-dominated sorting)

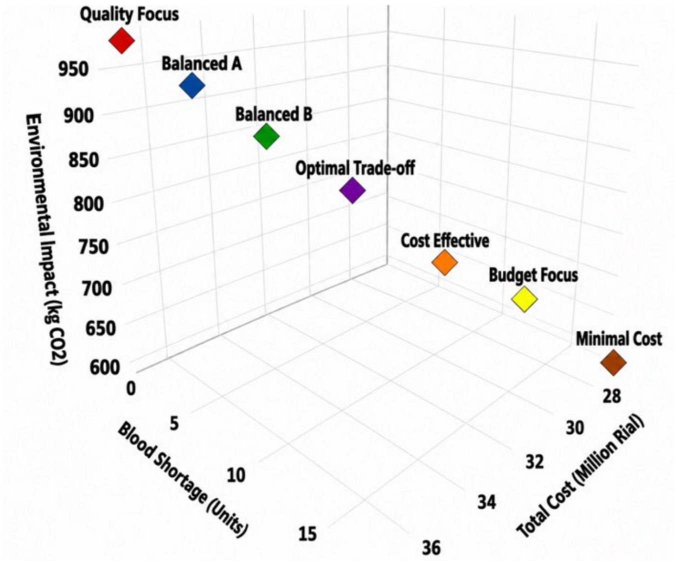

Figure 3. Pareto front: Trade-offs among cost, shortage volume, and environmental impact

Table 4. Comparison of NSGA-II vs. CPLEX on small-scale instance

Metric	CPLEX (Exact)	NSGA-II (Best Solution)	% Deviation
Total Cost	12,700	12,950	+1.97%
Blood Shortage (units)	1	1	0.00%
Environmental Impact	210	220	+4.76%

3.5. CPLEX Validation and Benchmarking

The performance of the proposed NSGA-II algorithm was evaluated by solving the same optimization model with CPLEX for a small-sized problem instance. The CPLEX solution was used as a benchmark for exact computation to judge the quality of the NSGA-II results. The reduced instance had fewer facilities, donor regions and planning periods so that the exact optimization problem could be solved in a reasonable computation time.

Table 4 presents the results of the comparison. The best solution found by NSGA-II was within 1.97% of the CPLEX solution in total cost. At the same blood shortage level, the two methods had a difference of environmental impact of 4.76%. These small differences indicate that NSGA-II was able to find solutions close to the exact CPLEX results, with similar performance in the three objectives. CPLEX is quite good at finding exact solutions for relatively small problem instances. However, the computational burden can blow up significantly as the size of the optimization problem grows. In contrast, NSGA-II can produce a set of non-dominated solutions without an exact search of the whole solution space. This makes it a practical option for larger and complex BSC network design problems with multiple objectives and uncertain operating conditions.

3.6. Sensitivity Analysis of Critical Parameters

Sensitivity analysis is an important part of checking the robustness of an optimization model, especially when input parameters are uncertain [20]. By modifying the selected input values, the response of the outputs can be observed to find out which parameters have the greatest effect on the solutions and the feasibility of the proposed network. This is crucial for a sustainable, resilient disruption blood supply chain, as the demand, infrastructure availability, and financial resources could be different during real operations. These changes can be used to evaluate the robustness of the proposed solutions under different demand, disruption, and budget conditions [21].

3.6.1. Sensitivity Analysis: Demand Volatility

The most significant source of uncertainty in blood supply chains is the variation in blood demand, which can be due to seasonal trends, public holidays, or emergency events. To observe the reaction of the proposed model to such changes, we tested three scenarios with increased demand. The demand increase is applied uniformly to all blood centers and planning periods.

Table 5 shows that all objectives, total cost in Million Iranian Rials (M IRR), blood shortage, and emissions, increase as demand increases. The shortages are not growing linearly, meaning that as demand increases, the existing network capacity is increasingly strained. The total cost goes up by 14.3% from Scenario A to Scenario C. This is largely due to the increased demand, which requires more resources. Emissions are also up – but not by much. Blood shortages seem to be especially sensitive to demand peaks, and the results suggest the need for measures including greater temporary collection capacity, flexible transportation routes and pre-positioning stock during high demand periods. The changes in cost, shortage, and emissions across the three scenarios are shown in Figure 4, and the trade-offs with increasing demand are demonstrated.

Table 5. Sensitivity Analysis: Demand Volatility

Scenario	Demand Increase	Total Cost (M IRR)	Shortage (Units)	Emissions (kg CO_2)
A	+10%	32,100	8	800
B	+20%	34,300	12	845
C	+30%	36,700	17	900

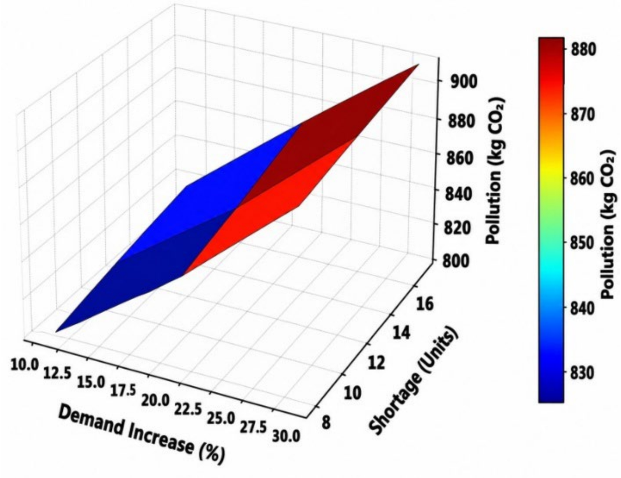

Figure 4. Sensitivity analysis: Demand volatility

Table 6. Sensitivity analysis: Temporary facility budget

Scenario	Budget Level	Total Cost (M IRR)	Shortage (Units)	Emissions (kg CO_2)
A	80% of base budget	33,800	11	840
B	100% (baseline scenario)	31,400	6	790
C	120% of base budget	30,100	3	765

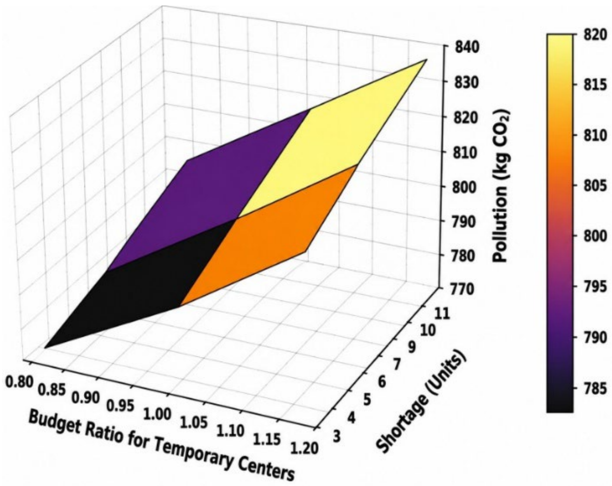

Figure 5. Sensitivity analysis: Temporary facility budget

3.6.2. Sensitivity Analysis: Temporary Facility Budget

Temporary blood collection sites may increase capacity in an emergency, but how much they are used depends on the funding available. Three scenarios were developed that varied the budget for temporary facilities by different percentages to study the impact of changes in funding.

The results in Table 6 show that this budget has a big impact on network performance. In Scenario A, the smaller budget constrains the number of temporary centers that can be opened, which limits the effectiveness of the blood distribution and results in a shortage that is nearly twice the baseline level. With a bigger budget, Scenario C can operate more temporary centers, increasing access for donors, reducing emissions and cutting the blood shortage by 50%. Total costs change only slightly, while supply availability and environmental performance improve more markedly. Figure 5 shows the relationship between temporary facility budget, blood shortage, and emission in a 3D surface plot. The surface shows that network performance improves with budget, but the rate of improvement slows at higher budget levels. This implies that additional funding for temporary blood collection facilities can be an effective way to enhance network capacity and improve performance in emergencies.

3.6.3. Sensitivity Analysis: Localized Disruption in Facility Capacity (Parameter δ)

In the proposed fuzzy robust model, δ denotes the share of operational capacity a facility loses during a disruption. To examine a localized disruption, three scenarios reduced the capacity of the Shiraz center, an important facility in the network, while the remaining centers continued operating normally.

The results in Table 7 show that a capacity reduction at Shiraz has a noticeable effect on overall network performance. As δ increases, total cost rises by more than 10%, and the blood shortage more than doubles from its initial level. This ties back to Shiraz's role in the network's geographic coverage and distribution activities: disruption at a strategically important facility can drag down performance across the wider network even while other centers keep operating normally. Backup capacity, alternative transportation routes, and priority resource allocation at key facilities could help soften the effects of such disruptions. Figure 6 shows how network performance changes as δ increases and illustrates the impact of the capacity reduction at Shiraz.

3.6.4. Managerial Interpretation of Sensitivity Results

According to the sensitivity analysis, the proposed decision-support framework can address shifts in demand and disruption levels and in investment conditions. As these factors change, the model adjusts donor assignments, mobile blood collection operations, and blood supply flow to maintain service levels while keeping any decrease in network performance within an acceptable range.

A further worse-case stress test was performed to test the framework in more severe conditions. This test was conducted by combining the pessimistic demand scenario, the 50% reduction in the capacity of the critical mobile collection unit in Shiraz as well as the 20% increase in the construction cost of permanent facilities. However, the fuzzy-robust model managed to achieve a 99.3% rate of demand fulfillment, with the maximum cumulative shortage over the 15-day planning period being limited to 24 units and the daily shortage standard deviation being limited to 1.4 units. It demonstrates that the proposed network can maintain a fairly stable level of service in the face of a considerable degree of uncertainty and disruption. Furthermore, it offers decision-makers alternative solutions to balance cost, blood availability, and environmental impact when planning a resilient blood supply network.

4. Conclusions

This study presented an integrated decision-support framework for sustainable blood supply chain (BSC) network design under disruption, combining LSTM-based demand forecasting, fuzzy scenario generation, and robust multi-objective optimization. Following the six-stage process in Figure 1, real operational data from the blood supply network in Fars Province, Iran, were collected and preprocessed before training the forecasting model. The proposed Fuzzy-LSTM model generated optimistic, base, and pessimistic demand scenarios, which were then defuzzified and fed into the optimization model. Forecasting accuracy was good, with RMSE ranging from 1.28 to 2.26 and MAPE from 4.12% to 4.78%, and the comparison against the ARIMA benchmark confirmed that the LSTM-based approach produced more accurate forecasts.

Table 7. Sensitivity analysis: Localized disruption in facility capacity

Scenario	Disruption Level (δ at Shiraz)	Total Cost (M IRR)	Shortage (Units)	Emissions (kg CO_2)
A	0.1 (Mild, 10% capacity loss)	31,600	7	795
B	0.3 (Moderate, 30% capacity loss)	32,800	10	810
C	0.5 (Severe, 50% capacity loss)	34,900	15	850

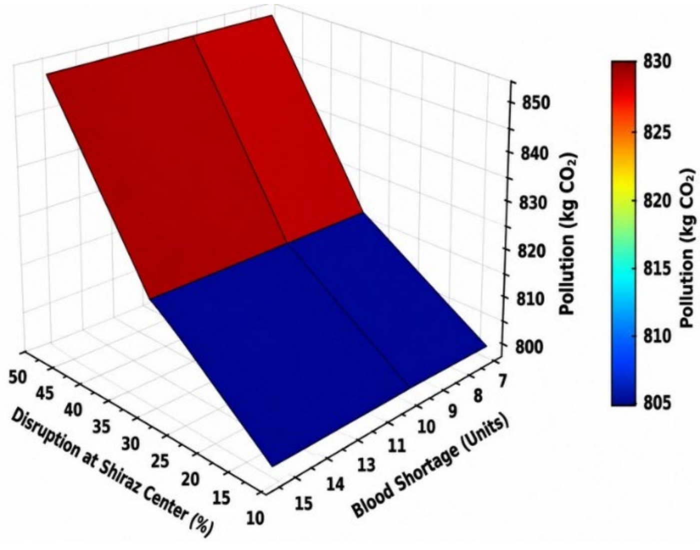

Figure 6. Sensitivity analysis: Localized disruption in facility capacity

The defuzzified demand values then went into the fuzzy-robust multi-objective optimization model, solved using NSGA-II, which generated a range of Pareto-optimal solutions with different trade-offs among economic, social, and environmental objectives. These results were validated against CPLEX solutions: the best NSGA-II solution differed from the exact solution by only 1.97% in total cost and matched it on blood shortage level. Sensitivity analysis and the worst-case stress test showed that the framework held up reasonably well even when demand, facility capacity, and investment costs changed at the same time, achieving a 99.3% demand fulfillment rate under the extreme conditions tested. Overall, these results suggest that linking demand forecasting with fuzzy uncertainty representation and multi-objective optimization can offer real support for blood supply chain planning under uncertain, disruptive conditions. Rather than relying on a single deterministic demand estimate, the proposed framework lets planners account for different demand conditions and weigh alternative network configurations before committing to strategic decisions.

Despite its promising results, this study has several limitations. First, the proposed framework was evaluated using data from a single regional blood supply network, which may limit the generalizability of the findings to other healthcare systems. Second, disruption scenarios were represented through predefined parameter variations and did not explicitly model dynamic disruption propagation over time. Finally, donor behavioral factors and real-time operational information were not incorporated into the forecasting and optimization processes. Future studies may extend the proposed framework by incorporating multi-regional blood supply networks, dynamic disruption propagation, and real-time decision-making mechanisms. Integrating donor behavior prediction, reinforcement learning, and digital health data with the proposed fuzzy-robust optimization framework could further improve adaptability and operational resilience in healthcare supply chain management.

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Declaration of Competing Interest

The authors declare no conflict of interest.

CRediT Authorship Contribution Statement

Mohammad Amin Khosravi (Conceptualization; Methodology; Software; Formal analysis; Visualisation; Writing - original draft)
Hassan Khademi Zare (Supervision; Methodology; Validation; Writing - review & editing)
Hassan Hosseini Nasab (Conceptualization; Validation; Writing - review & editing)
Davood Shishebori (Methodology; Supervision; Writing - review & editing)

Availability of the Data and Materials

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to the data-sharing policies of the Fars Province Blood Transfusion Organization.

Ethical Declaration

This research did not involve any human participants, animals, or sensitive personal data. Therefore, ethical approval was not required. All data used in this study were obtained from publicly available sources and used in accordance with relevant guidelines and regulations.

Generative Artificial Intelligence Declarations

AI-based tools were used solely for language editing and grammar refinement. No AI content generation, data interpretation, or analysis was performed. All intellectual contributions are original and solely attributable to the authors.

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Appendix

Mathematical Modeling Framework

The mathematical model developed in this study provides a framework for designing and operating a blood supply chain under uncertain demand and disruption, by combining three main elements: the network structure, the demand forecasting module and the multi-objective optimization model. The network structure represents the various facilities involved in blood collection, processing and distribution. The forecasting module predicts future demand requirements based on historical demand information and captures the uncertainty involved. The forecasts are then used in the optimization model to determine facility operations, resource allocation and transportation. The model considers three significant performance measures, operational cost, blood shortage and environmental impact, and it also considers the perishable nature of blood products and the need to maintain service during disruption.

The network has both permanent and mobile facilities to add flexibility to blood collection. The LSTM model predicts future demand and generates fuzzy demand scenarios that are input to the optimization model to determine the necessary facility configurations, allocation of blood collection activities and blood movement across the network. The mathematical formulation is built to include disruption conditions so that the model can examine alternative operating decisions when part of the collection capacity is unavailable.

Modeling Assumptions, Network Configuration, and Theoretical Structure

The model is based on a set of assumptions to reflect the main operating features of a blood supply chain while keeping the optimization problem tractable. The proposed network will consist of existing permanent facilities, new fixed collection centers and mobile blood collection units. Blood is collected in the mobile units and the newly established fixed centers, which have limited processing and storage capacity. Permanent centers such as established hospitals and blood banks are downstream facilities for blood processing, storage and patient demand fulfillment.

The disruption scenarios consider only the loss of capacity for the mobile blood collection units, given their greater vulnerability to problems with staff availability, equipment, transportation, and adverse environmental conditions. Permanent facilities and newly established fixed centers are assumed to continue their operation. Blood collected at mobile units and new fixed centers is transported to permanent facilities or, where the network structure requires, to newly established fixed centers for further processing and distribution. This arrangement is to study the effect of partial loss of capacity on mobile units without removing the permanent facilities which anchor the network.

Demand is uncertain because blood needs change with time and may increase unexpectedly in emergencies. Three fuzzy demand conditions are generated by the forecasting module: optimistic, base, and pessimistic, meant to describe a range of possible demand levels rather than three equally likely outcomes. These forecasts are used to evaluate the performance of the network in case of deviations of actual demand from the central forecast. Disruptions are modeled as degrees of reduction of the capacity, and not as a binary state of fully-operational-or-unavailable, thus allowing for partial disruptions. The model also incorporates constraints on blood-type compatibility, blood shelf life, transportation capacity, travel limits, and availability of operational resources, with the corresponding parameters being customizable to the blood supply system under consideration.

The theoretical contribution of the proposed formulation is the unification of demand forecasting and network optimization in the same decision framework. The LSTM model provides fuzzy demand estimates which are included in the optimization constraints, so that planning decisions take into account changes in expected demand, rather than using a fixed demand value or separating forecasting and optimization stages. The model also includes resilience-oriented capacity, coverage and disruption constraints in a single multi-objective formulation, and its three-objective structure simultaneously balances economic efficiency, shortage reduction and environmental impact, creating a Pareto-efficient picture of resilience trade-offs. Together, these contributions extend the existing deterministic or crisp-scenario BSC formulations and offer a novel optimization setup, in which predictive analytics is tightly integrated with the prescriptive decision-making process in healthcare logistics.

Sets and Indices

$\mathcal{K}$: Set of candidate locations for new permanent blood collection centers.
$\mathcal{J}$: Set of potential locations for temporary facilities.
$\mathcal{L}$: Set of blood donor groups.
$\mathcal{T}$: Set of time periods ($t = 1,2,\dots,T$).
$\mathcal{S}$: Set of demand scenarios ($s \in \{\text{pessimistic}, \text{base}, \text{optimistic}\}$).
$\mathcal{M}$: Set of existing permanent centers and hospitals.

Parameters

C_k^{fix}: Fixed cost to build a permanent center at k.
C_j^{temp}: Operational cost for temporary facility j.
C_j^{move}: Relocation cost for temporary facility j.
c_{jm}^{trans}: Transportation cost per unit blood from j to m.
c_{km}^{trans}: Transportation cost per unit blood from k to m.
C_{jm}^{route}: Maximum amount of blood that can be transported along route m from facility j.
c_{jl}^{coll}: Cost to collect blood from donor group l at j.
c_{kl}^{coll}: Cost to collect blood from donor group l at k.
π_j^t: Penalty cost for unmet demand at j in period t.
η_j^t: Capacity of temporary facility j in period t.
δ_{js}^t: Capacity disruption rate at j under scenario s.
ρ_{js}^t: Probability of disruption at j under scenario s.
d_{jl}: Distance between donor group l and temporary facility j.
d_{jm}: Distance between j and permanent center/hospital m.
d_{jk}: Distance between j and permanent center k.
d_{km}: Distance between k and permanent center/hospital m.
R_l: Maximum coverage radius for donor group l.
S_{min}: Minimum coverage distance between facilities.

R_{min}: Minimum amount of blood that must always be available in the system
N_{max}: Maximum number of donor groups that can be assigned to a single center.
B_{main}: Total budget allocated for maintaining permanent blood centers.
D_{ms}^{t}: Forecasted blood demand at m under scenario s.
D_{ks}^{t}: Forecasted blood demand at k under scenario s.
E_{l}^{t}: Maximum donation from donor group l.
θ_s: Probability of scenario s.
α: Emission coefficient per unit distance of blood transportation.
B: Total budget.
M_k: Maintenance cost of permanent center k per period.
γ: Maximum relocations per period.
τ^t: Minimum temporary facilities required in t.
r_k^t: Inventory level of blood at permanent center k in period t.
S_{ms}^{t}: Blood shortage at center or hospital m in period t under scenario s.
$\mathscr{M}$: A sufficiently large positive number.

Decision Variables
$y_k \in \{0,1\}$: 1 if permanent center k is built.
$w_j^t \in \{0,1\}$: 1 if temporary facility j is active in t.
$z_{jl}^t \in \{0,1\}$: 1 if donor group l is assigned to j in t.
$v_{jj'}^t \in \{0,1\}$: 1 if temporary facility j is relocated to j' in t.
$x_{jm}^t \geq 0$: Blood transported from j to m in t.
$x_{jk}^t \geq 0$: Blood transported from j to k in t.
$x_{km}^t \geq 0$: Blood transported from k to m in t.
$q_k^t \geq 0$: Blood collected at k in t.
$q_j^t \geq 0$: Blood collected at j in t.

Objective Functions and Constraints

$$min\, Z_1 = \sum_{k} C_k^{fix}\, y_k + \sum_{j,t}\left(C_j^{temp} w_j^t + C_j^{move} v_{jj'}^t\right) + \sum_{j,m,t} c_{jm}^{trans}\, x_{jm}^t + \sum_{j,k,t} c_{jk}^{trans}\, x_{jk}^t + \sum_{k,m,t} c_{km}^{trans}\, x_{km}^t + \sum_{j,l,t} c_{jl}^{coll}\, z_{jl}^t + \sum_{k,l,t} c_{kl}^{coll}\, z_{kl}^t + \sum_{j,t,s} \pi_j^t\, U_{js}^t q_j^t$$

$$min\, Z_2 = \sum_{m,t,s} \theta_s \cdot S_{ms}^t + \sum_{k,t,s} \theta_s \cdot T_{ks}^t$$

$$min\;\; Z_3 = \alpha\left(\sum_{j,m,t} d_{jm} x_{jm}^t + \sum_{k,m,t} d_{km} x_{km}^t + \sum_{j,k,t} d_{jk} x_{jk}^t\right)$$

$$\sum_{j} x_{jm}^t + \sum_{k} x_{km}^t \geq D_{ms}^t \quad \forall m,t,s$$

$$q_k^t + \sum_{j} x_{jk}^t \geq D_{ks}^t + \sum_{m} x_{km}^t \quad \forall k,t,s$$

$$S_{ms}^t \geq D_{ms}^t - \left(\sum_{j} x_{jm}^t + \sum_{k} x_{km}^t\right) \forall m,t,s$$

$$T_{ks}^t \geq D_{ks}^t - \left(q_k^t + \sum_{j} x_{jk}^t\right) \quad \forall k,t,s$$

$$q_j^t \leq \left(1 - U_{js}^{t}\right)\eta_j^t \quad \forall j,t,s$$

$$q_k^t \leq \eta_k^t \cdot y_k \quad \forall k,t$$

$$q_j^t = \sum_{l} z_{jl}^t E_l^t \quad \forall j,t$$

$$q_k^t = \sum_l z_{kl}^t E_l^t \quad \forall k, t$$
$$x_{jm}^t \leq C_{jm}^{route} \quad \forall j, m, t$$
$$x_{jk}^t \leq C_{jk}^{route} \quad \forall j, k, t$$
$$x_{km}^t \leq C_{km}^{route} \quad \forall k, m, t$$
$$\sum_m x_{jm}^t + \sum_k x_{jk}^t \geq \nu \eta_j^t \quad \forall j, t$$
$$\sum_j w_j^t \geq \tau^t \quad \forall t$$
$$x_{jm}^t \leq (1 - \lambda_j^t) q_j^t \quad \forall j, m, t$$
$$\sum_j z_{jl}^t + \sum_k z_{kl}^t \leq 1 \quad \forall l, t$$
$$d_{jl} z_{jl}^t \leq R_l \quad \forall j, l, t$$
$$d_{kl} z_{kl}^t \leq R_l \quad \forall k, l, t$$
$$\sum_k y_k \geq 1$$
$$d_{jm} w_j^t \geq S_{min}$$
$$\sum_l z_{jl}^t \leq N_{max}$$
$$\sum_l z_{kl}^t \leq N_{max}$$
$$\sum_{j'} v_{jj'}^t \leq \gamma \quad \forall j, t$$
$$v_{jj'}^t \leq w_j^{t-1} \quad \forall j, j', t$$
$$t_{jm} \leq t_{max}$$
$$t_{jk} \leq t_{max}$$
$$t_{km} \leq t_{max}$$
$$w_j^t \leq w_j^{t-1} + \sum_{j'} v_{j'j}^t \quad \forall j, t$$
$$x_{jk}^t \leq \mathcal{M} \cdot w_j^t \quad \forall j, k, t$$
$$x_{jm}^t \leq \mathcal{M} \cdot w_j^t \quad \forall j, m, t$$
$$\sum_k C_k^{fix} y_k + \sum_{j,t} \left(C_j^{temp} w_j^t + C_j^{move} \sum_{j'} v_{jj'}^t \right) \leq B$$
$$\sum_k M_k y_k \leq B_{main}$$
$$\sum_k r_k^t \geq R_{min}$$
$$x_{jm}^t, x_{jk}^t, x_{km}^t, q_j^t, q_k^t, S_{ms}^t, T_{ks}^t \geq 0 \quad \forall j, k, m, t, s$$
$$y_k, w_j^t, z_{jl}^t, z_{kl}^t, v_{jj'}^t \in \{0,1\} \quad \forall j, k, l, m, t$$

Accordingly, the fuzzy disruption rate of temporary center *j* in period *t* under scenario *s*, denoted by the triangular fuzzy number $\tilde{\delta}_{js}^t = (L_{js}^t, M_{js}^t, U_{js}^t)$ is robustified using a worst-case approach, and its upper bound $\delta_{js}^{t,} = U_{js}^t$ is adopted as a conservative deterministic disruption rate in the mathematical formulation.

Overview of Objective Functions and Constraints

The proposed multi-objective optimization model uses a holistic strategy to simultaneously consider the three essential dimensions of sustainability; economic, social and environmental; in the design of a blood supply chain network under disruption scenarios. The objective functions and the constraints have been carefully designed to reflect the real-world operational conditions and strategic organizational goals accurately.

The first objective function minimizes the total cost of the system, which includes the fixed costs of establishing new permanent centers, the operating costs of mobile and fixed collection facilities, the transportation costs between network nodes, the relocation costs of mobile units, and the penalty costs of unmet blood demand. The first objective is to support the economic sustainability of the blood supply network by considering investment requirements versus operating costs under different disruption scenarios. The second one is to decrease the blood shortages in permanent centers and hospitals over the planning horizon and demand scenarios; reducing the unmet demand not only increases the service reliability and healthcare coverage but also reduces the risk of insufficient blood supply in emergencies and high-demand periods and therefore covers the social and humanitarian aspects of the blood supply chain. Third, the environmental impact of transportation and reducing carbon emissions due to movement of blood between mobile collection units, newly set up fixed centers and permanent facilities based on shipment sizes, transportation routes and distances travelled.

The model incorporates constraints from five main areas, to ensure the feasibility and operation of the blood supply network in different operational conditions.

i. Demand Satisfaction Constraints: These constraints ensure that the demand at each healthcare center is satisfied in each planning period and in each demand scenario, including optimistic, base and pessimistic cases. The model also establishes a minimum level of blood reserves for emergency use, a minimum share of the collected blood that should reach the relevant centers and minimum utilization of resources requirements to reduce unused capacity.

ii. Operational Capacity Constraints: Each facility's maximum blood collection capacity, given the potential disruptions. The amount collected has to equal the amount allocated to donor groups. Limits are put on how much blood can move between facilities. Spoilage rates are part of the usable amount of blood collected. The model also restricts the minimum number of facilities to be active and avoids overloading of individual centers.

iii. Resource Allocation Constraints: Every donor group can be assigned to only one collection center, and donor locations must be within the permissible service radius of that collection center. The model is characterized by the minimum number of permanent facilities and the geographic dispersion requirements to avoid the facilities being clustered in one area. The sequential activation rules are used for the activation and the reactivation of the temporary facilities.

iv. Logistical Limitations: The model limits the number of times temporary facilities can be relocated and facilities that are already active can only be relocated. Maximum transportation times are maintained to preserve blood quality in transit. The formulation ensures that the reactivation decisions are not invalid and that blood is transferred only between active facilities.

v. Financial and Managerial Constraints: The total amount spent on facility investment, routine operations, and relocation cannot exceed the available budget, and spending on maintenance for permanent facilities is limited by its own budget allocation. The model connects investment with a lower risk of disruption and restricts facility reinforcement spending. All decision variables such as blood flow and amount of collection must be non-negative.

These objectives and constraints allow the model to balance trade-offs among economic performance, blood availability, and environmental impact while satisfying the operational requirements of a disrupted blood supply network.