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Robust design of blood supply chains under risk of disruptions using Lagrangian relaxation

Bayan Hamdan[a,b], Ali Diabat[a,c,*]

[a] Division of Engineering, New York University Abu Dhabi, Saadiyat Island, 129188 Abu Dhabi, United Arab Emirates
[b] Department of Industrial & Enterprise Systems Engineering, University of Illinois at Urbana-Champaign, IL 61801, United States
[c] Department of Civil and Urban Engineering, Tandon School of Engineering, New York University, Brooklyn, NY 11201, United States

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ABSTRACT

Emergency supply of blood in disasters is a crucial task for humanitarian aid. In this paper, we present a bi-objective robust optimization model for the design of blood supply chains that are resilient to disaster scenarios. The proposed two-stage stochastic optimization model aims at minimizing the time and cost of delivering blood to hospitals after the occurrence of a disaster, while considering possible disruptions in blood facilities and transportation routes. A Lagrangian relaxation-based algorithm is developed that is capable of solving large-scale instances of the model. We apply this framework to a real case study of blood banks in Jordan.

1. Introduction

Disasters are defined as natural or human-caused events that occur suddenly and cause great damage or loss of life. Examples of disasters include earthquakes, floods, tornadoes, and wars (Kuruppu, 2010). When a disaster occurs, there is usually a significantly elevated demand for blood and shortages in the blood supply. In addition, the expected supply of blood is highly erratic and the demand for blood is uncertain (Beliën and Forcé, 2012). Coupled with its perishability, these circumstances make the collection of blood under disaster conditions difficult (Schmidt et al., 1985).

The blood supply chain starts with the donation of blood when donors volunteer to give blood at collection centers. Collection can occur either at mobile blood centers or at blood donation facilities. The collected blood units are transported to and processed at blood banks. At the blood banks, bacterial and several other mandatory tests are conducted, and additional tests can be requested based on need. Processed blood units are held at blood banks to be distributed to hospitals and healthcare centers, where blood is administered to patients in need (Cohen and Pierskalla, 1975).

Disasters can affect many aspects of the blood supply chain. Blood collection centers can be easily disrupted, making blood products inaccessible; furthermore, blood banks might become inaccessible due to the disruption of roads, traffic, or other reasons. When a facility in the supply chain is out of service, a substitution should be considered or else the entire chain may be affected (Shen et al., 2011; Jabbarzadeh et al., 2016). Therefore, having a robust supply chain design is critical to improving the performance of blood supply chains in cases of disasters (Diabat et al., 2019). As the occurrence of disasters cannot always be predicted, decision makers must take into account possible disaster scenarios in order to determine the optimum number of service facilities before the occurrence of a potential disaster (Kaveh and Ghobadi, 2017).

In this work we formulate a blood supply chain model that uses robust optimization techniques and two-stage stochastic

* Corresponding author.
E-mail address: diabat@nyu.edu (A. Diabat).

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optimization to mitigate the effects of disasters on the blood supply chain. Mitigating the effects of disasters in the context of two-stage stochastic optimization involves both pre-disaster planning (the first stage) and post-disaster planning (the second stage). In pre-disaster planning, based on the geographical location of the area being studied and its vulnerability to certain physical disasters, the probability of occurrence of a specific disaster type at an identified location can be estimated, and this information can then be used to guide decisions such as the location of blood donation centers, the allocation of donors to centers, and the means of collection and transportation of blood to hospitals with the goal of maintaining a reliable supply chain under disaster conditions. Our two-stage stochastic programming approach assumes that a disaster scenario could affect the different echelons of the supply chain as well as the routes, and it allows the model to focus stocks of blood products in certain areas so that they are readily available for disaster-affected areas. The model also takes into account the likelihood of route disruptions under different disaster scenarios, which helps in the placement of inventory in locations that are more likely to be accessible by hospitals and healthcare centers in case of a disaster. After the occurrence of a specific disaster scenario, the model specifies routing decisions based on that disaster scenario. Moreover, in addition to considering the dynamics of the network studied, the model also considers both the social and economic factors involved in requesting blood units from neighboring districts.

The robust optimization aspect appears in the form of a robust counterpart model that allows the user to select the level of robustness required when solving the supply chain prepositioning problem. In addition, a bi-objective framework is assumed in which the objective is to attain a blood supply chain capable of supplying blood at the lowest possible expected delivery time and cost. A Lagrangian relaxation algorithm is presented to solve the proposed model.

The remainder of the paper is structured as follows: Section 2 reviews the related literature; Section 3 states the problem and the mathematical model; Section 4 presents the proposed Lagrangian relaxation algorithm; Section 5 demonstrates the model through a case study and includes a sensitivity analysis of the model; and Section 6 presents conclusions and some insights.

2. Literature review

A review of the relevant literature relating to blood supply chains and robust optimization is presented in this section.

2.1. Blood supply chains

In recent years, blood supply chains have attracted increasing attention from researchers. Several authors presented review papers that provide a comprehensive review of blood supply chain research, including Nahmias (1982), Beliën and Forcé (2012), and Osorio et al. (2015). Beliën and Forcé (2012) classify blood supply chain research by different criteria, including the blood components handled, solution method, and so on. The recent review by Osorio et al. (2015) is structured in such a way that the first four sections review studies on four echelons of the supply chain individually, while the final section reviews studies that consider more than one echelon jointly. Pierskalla (2005) provides a relatively self-contained introduction to blood supply chains, and includes topics such as the cross-matching of blood and the management of different blood components in the supply chain. Karaesmen et al. (2011) review the literature on perishable product supply chains, including supply chains that supply products with different shelf lives. They consider planning decisions as well as routing and storage decisions. In particular, they cover the perishability of blood and consider it an important example for managing perishable systems.

The literature includes several studies that utilize a simulation approach to handling the high uncertainty in the blood supply chain. In some cases, simulation is part of a hybrid solution approach. Examples of such studies include Rytilä and Spens (2006), Haijema et al. (2007), Katsaliaki (2007), Alfonso et al. (2012), and Duan and Liao (2014). Rytilä and Spens (2006) used computer simulation to enhance the efficiency of the blood supply chain. They conclude that simulation could be an appropriate tool for healthcare systems in general, especially in blood supply chains, as it allows the system to perform more efficiently and in a controlled manner. Haijema et al. (2007) applied Markov dynamic programming and simulation approaches to the case of a Dutch blood bank. They focused on costs that are directly related to the production and inventory of platelets. Katsaliaki (2007) used simulation to enhance the cost-effectiveness of the blood supply chain in the UK. The results of her study led to a decrease in outdated units, substitution of blood groups, and a decrease in rare groups of blood being stored in blood centers. Alfonso et al. (2012) addressed the blood collection problem in France, considering both fixed-site and mobile blood collection facilities. They used Petri net models to describe different blood collection processes, donor behaviors, and human resource requirements, and they applied a simulation approach to identify appropriate human resource planning and donor appointment strategies. Duan and Liao (2014) proposed a simulation optimization framework for the management of blood supply chains. They considered a single hospital and a single blood center to assess their framework. They also assumed different maximum shelf lives for red blood cells as well as several scenarios; they then optimized order-up-to policies for red blood cells while accounting for eight different blood groups. One of their main contributions was a new approach for compatible blood substitution that yields a low rate of spoilage.

Delen et al. (2011), Verter and Lapierre (2002), and Hemmelmayr et al. (2010) proposed routing and location models in the blood supply chain context. Delen et al. (2011) used operations research, data mining, and a geographical information system to facilitate decision-making in the blood supply chain. Verter and Lapierre (2002) investigated locations of healthcare facilities; specifically, they focused on preventive facilities. In their study, distance was determined to be the most important factor in a person's choice of a healthcare facility. They proposed a maximum covering location problem for allocating patients to healthcare facilities and assumed that each person would seek the closest facility for services. In addition, they assumed that each opened facility should have a minimum number of clients as a restrictive assumption, and also that demand is deterministic. Hemmelmayr et al. (2010) developed integer programming models to decide which hospitals a vendor should visit each day given that the routes are fixed for each region.

The authors considered recourse actions in order for hospitals to hedge against the uncertainty associated with blood product usage. Both integer programming and variable neighborhood search approaches were used and compared in terms of their efficiencies.

Several models for healthcare optimization assume deterministic supply and demand, such as the work of Hemmelmayr et al. (2009), Arvan et al. (2015), and Sha and Huang (2012). Hemmelmayr et al. (2009) investigated the effect of delivery strategies of blood products on Austrian hospitals. They considered two strategies: the first used a fixed route strategy combined with an integer programming approach to determine the optimal delivery days, while the second combined a more flexible routing strategy with a more regular delivery schedule; the shelf life of blood was also considered in their study. Arvan et al. (2015) proposed a network optimization model for blood supply chains; this network consists of collection sites, laboratory facilities, storage facilities, distribution centers, and demand locations. They considered multiple products and deterministic parameters and solved the model with the GAMS CPLEX solver. Sha and Huang (2012) proposed a dynamic multi-period location-allocation model for the scheduling of emergency blood supply after an earthquake in Beijing, minimizing costs such as transportation costs, inventory costs, and shortage costs over a given planning horizon. They used Lagrangian relaxation to solve their proposed model.

On the other hand, several studies have considered the uncertainty of demand. Sapountzis (1984) proposed an integer programming model that considers orders for fresh blood separately and allocates blood units from regional blood transfusion services to hospitals. The objective is to minimize the total expected number of units that are sent back to the blood transfusion service. Dillon et al. (2017) proposed a two-stage programming model to define periodic review policies for red blood cell inventory management. Their model focuses on minimizing operational costs while taking into account perishability and demand uncertainty. Zhou et al. (2011) analyzed the platelet inventory problem assuming a fixed shelf life of three days and considering stochastic demand. The problem was formulated using a dynamic programming approach in which a dual-sourcing alternative is available and the decision maker has the option of placing an additional order under an order-up-to level policy in addition to the regular order. Hemmelmayr et al. (2010) extended the work of Hemmelmayr et al. (2009) by considering stochastic demand for blood at hospitals. They proposed four alternatives for controlling uncertainty in blood demand and compared an integer programming approach and variable neighborhood search for solving their proposed model. Ghandforoush and Sen (2010) considered platelets instead of whole blood and focused on scheduling mobile units for regional blood centers. They used a decision support system with an embedded non-convex integer model which was then transformed into a linear 0–1 problem, allowing the problem to be solved.

Şahin et al. (2007), Hosseinifard and Abbasi (2018), Ramezanian and Behboodi (2017), Zahiri and Pishvaee (2017) modeled the blood supply chain using both stochastic demand and supply. Şahin et al. (2007) proposed a mathematical model for the regionalization of blood services in Turkey. They assumed that the population of a region determined the demand for blood and used *pq*-median models to solve location-allocation problems for making decisions. Hosseinifard and Abbasi (2018) examined the significance of inventory centralization at the second echelon of a two-echelon blood supply chain. The first echelon includes a single blood bank with uncertain supply, while the second echelon consists of hospitals receiving external demand. They demonstrated that centralization of hospitals' inventory is a key factor in the blood supply chain and can enhance the sustainability and resilience of the blood supply chain. Hamdan and Diabat (2019) also proposed a two-stage stochastic optimization model for the blood supply chain. Their tri-objective model considers the perishability of blood units and considers both prepositioning decisions as well as post-disaster planning. Ramezanian and Behboodi (2017) developed a mixed-integer linear programming model for designing a blood supply chain network. They considered different social factors such as distance, advertising costs, and experience factors that impact donors' decision-making processes. Zahiri and Pishvaee (2017) also considered the design of blood supply chain networks, taking into account blood group compatibility. To this end, a bi-objective mathematical programming model was formulated to minimize the total cost as well as the maximum unsatisfied demand.

Nagurney and Masoumi (2012) developed a sustainable network design for blood supply chains that is process-based rather than location-based, while Nagurney et al. (2012) considered a generalized network optimization model for a blood supply chain, consisting of collection sites, testing and processing facilities, storage facilities, distribution centers, and hospitals. They considered blood as a perishable product and designed a network to determine the optimal allocation to decrease the costs associated with blood wastage.

2.2. Robust optimization

Robust optimization techniques can be used with both single-objective and multi-objective optimization problems. Robust optimization strategies in the single-objective context have been proposed by Bollat and Portillo (2009), Peng et al. (2011), Pishvaee et al. (2011), Azad and Davoudpour (2013), and Jabbarzadeh et al. (2014), among others. Bollat and Portillo (2009) proposed a supply chain model that handles uncertainty using a minimax approach, while Peng et al. (2011) considered an approach to designing reliable supply chain networks that reduces disruption risk using a criterion that bounds the cost in disruption scenarios. Pishvaee et al. (2011) considered a stochastic mixed-integer model based on the robust optimization approach that was introduced by Ben-Tal and Nemirovski (2000). Azad and Davoudpour (2013) developed a robust optimization model that takes into account the risk of disruptions and the multi-echelon structure of the supply chain. Their approach focused on optimally determining resilient location-routing decisions. Jabbarzadeh et al. (2014) considered a robust network design model that can assist in blood facility location and allocation decisions during and after disasters. Lagrangian relaxation was used to solve for the optimal blood supply chain design.

In the bi-objective context, robust optimization strategies have been proposed by Vahdani et al. (2012), Fahimnia et al. (2017), and Diabat et al. (2019), among others. Vahdani et al. (2012) proposed a bi-objective optimization model that uses fuzzy queuing theory and fuzzy programming. Their model is aimed at improving the resilience of the supply chain under disruptions with the goal of minimizing both transportation costs as well as total costs. Fahimnia et al. (2017) developed a stochastic bi-objective supply chain network design model for the efficient and timely supply of blood in disasters. In their proposed two-stage stochastic model, the first objective minimizes the overall supply chain cost while the second objective minimizes blood delivery time. Diabat et al. (2019) proposed a bi-objective robust optimization model for supply chains that considers disruptions in routes as well as blood facilities. They aimed to minimize blood delivery time and total costs and used a Lagrangian relaxation algorithm to solve the model.

The work presented in this paper differentiates itself from the existing literature by presenting a multi-objective, multi-stage, robust optimization model for the blood supply chain under risk of disasters. The model also considers socioeconomic factors when considering the supply of blood in an unstable environment. A Lagrangian relaxation solution algorithm is applied to the model to ensure that the cost of considering realistic constraints is mitigated. These realistic considerations, coupled with a reduced complexity of solving the model, makes it ideal for managing the blood supply chain in a robust environment. The model is presented in the following section.

3. Problem definition

In this section we present our multi-objective blood supply chain model that uses robust optimization techniques and two-stage stochastic optimization to mitigate the effects of disasters, optimizing total costs and delivery time of refined blood to hospitals after a disaster.

We consider a four-echelon blood supply chain that consists of blood donors, blood collection centers, blood banks, and hospitals, where both fixed and mobile blood collection centers are considered. A two-stage stochastic modeling approach is proposed to mitigate the high uncertainty in the occurrence of disasters and their effects on the supply chain. These effects appear in the form of damage to blood banks or damage to the routes leading to blood banks or hospitals. In the first stage, the model determines how many collection centers are to be facilitated, as well as their specific locations. The second stage identifies the locations of mobile collection centers and the allocation of facilitated collection centers and mobile collection centers to blood banks and blood donor centers. The model also determines the quantity of blood and its products that are to be transported among the different levels of the supply chain and the amount of inventory that should be kept in blood banks to offset the effects of disruptions. These disruption scenarios are considered in the model through the second stage decisions, in which a path or entity in the supply chain is not accessible if it is disrupted.

The model uses two main objectives: the total expected delivery time and the total expected system cost. Minimizing the total expected delivery time is extremely important in cases of disasters where there is often urgent demand for blood. The model is structured to prioritize fulfilling the demand for blood from within the same region. However, in the case of insufficient local supply, the model has a maximum demand variable that directs neighboring regions' blood banks to compensate for this shortage (given the assumption that the total available supply is greater than the total demand). The model has a periodic structure and we assume a time period of one day throughout this work.

Fig. 1 illustrates the supply chain structure considered in this work. Arrows representing transportation paths in this figure show existing routes from one echelon to the next. In each of the assumed disruption scenarios, the accessibility of paths is determined, which allows the model to choose only from accessible paths for blood transmission. Our model makes several assumptions:

- Blood products considered include plasma, platelets, and blood cells for each of eight blood groups.
- The capacity for holding blood products is limited.
- The maximum amount of blood that can be donated is estimated based on the population of each zone and the ratio of blood groups to the entire population.
- Only one of the mobile collection centers or fixed collection centers can be located in each area.
- Hospitals' demand is discretized for different scenario occurrences.
- Blood donation is capacitated by the number of personnel and donation stations at each collection facility.

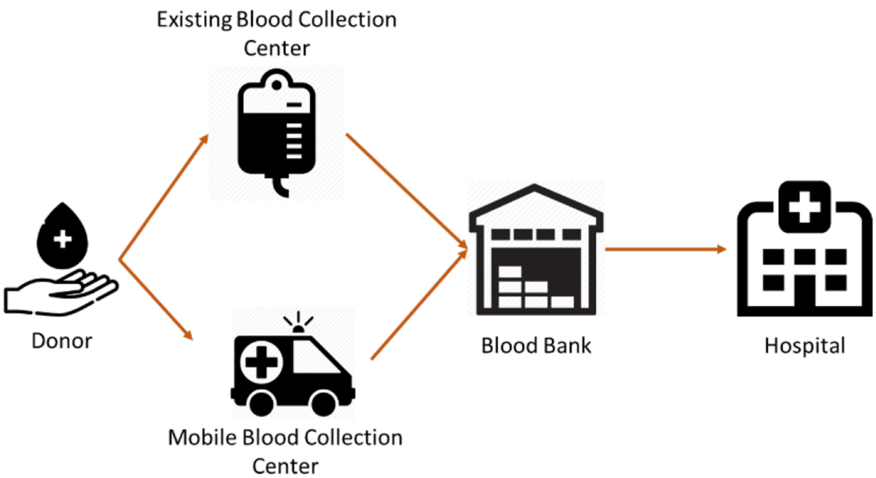

Fig. 1. Blood supply chain network.

- Mobile collection facilities can change their location in each time period.
- If a disruption occurs at a collection center, that center will be out of service; this means the capacity of the collection center will be set to zero.

3.1. Mathematical model

In this section we specify the mathematical model that is to be optimized, including the sets, parameters, decision variables, objective functions, and constraints.

3.1.1. Sets

M	Set of different blood products, indexed by $m \in \{1, 2, ..., \lvert M \rvert\}$
I	Set of blood donor locations, indexed by $i \in \{1, 2, ..., \lvert I \rvert\}$
J'	Set of locations of fixed blood collection centers, indexed by $j \in J' = \{1, 2, ..., n\}$, where n is the number of fixed blood collection centers
J''	Set of candidate locations for mobile blood collection facilities, indexed by $j \in J'' = \{n + 1, ..., N\}$, where N is the total number of fixed and mobile blood collection center locations
J	Set of possible locations of either fixed or mobile blood collection centers, indexed by $j \in J = J' \cup J''$
K	Set of blood banks, indexed by $k \in \{1, 2, ..., \lvert K \rvert\}$
L	Set of hospitals and medical centers, indexed by $\ell \in \{1, 2, ..., \lvert L \rvert\}$
S	Set of disaster scenarios, indexed by $s \in \{1, 2, ..., \lvert S \rvert\}$
T	Set of time periods, indexed by $t \in \{1, 2, ..., \lvert T \rvert\}$, $\rho \in \{1, 2, ..., \lvert P \rvert\}$
R	Set of routes between network nodes, indexed by $r \in \{1, 2, ..., \lvert R \rvert\}$

3.1.2. Parameters

o	Fixed cost of establishing a mobile blood collection center
q	Cost to equip a fixed blood collection center; assumed equal for all fixed centers.
N	Total number of fixed blood collection center locations and candidate locations for mobile collection center facilities. The number of fixed blood collection center locations is n, while the number of candidate locations for mobile collection center facilities is $N - n$.
LT_m	Lifetime of blood product m
e_k	Capacity of blood bank k
c_j	Capacity of blood collected by fixed blood collection center at location j, $j \in J'$
f_j	Capacity of blood collected by mobile blood collection center at location j, $j \in J''$
p_{mit}^s	Maximum blood supply of blood product m at location i in period t under scenario s
$d_{m\ell t}^s$	Blood demand of blood product m at hospital ℓ in period t under scenario s
$ti_{\ell t}$	Travel time from blood banks in other provinces to hospital ℓ in period t
β_{kt}^s	$\begin{cases} 1, & \text{if blood bank } k \text{ is not disrupted in period } t \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$
α_{jt}^s	$\begin{cases} 1, & \text{if fixed blood collection center } j \in J' \text{ is not disrupted in period } t \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$
δ_{jkrt}^s	$\begin{cases} 1, & \text{if route } r \text{ between blood collection center } j \text{ and blood bank } k \text{ is not disrupted in period } t \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$
π^s	Probability of occurrence of scenario s
t'_{jkr}	Travel time from blood collection center j to blood bank k using route r
$t''_{k\ell}$	Travel time from blood bank k to hospital ℓ

3.1.3. Decision variables

V_{mkt}^s	Blood inventory level of product m at blood bank k at the end of period t under scenario s
F_{mjktr}^s	Quantity of blood product m delivered from blood collection center j to blood bank k using route r in period t under scenario s
$U_{mk\ell t}^s$	Quantity of transfused blood product m delivered from blood bank k to hospital ℓ in period t under scenario s
G_{mijt}^s	Quantity of blood product m donated at point i in period t to transport to blood collection center j under scenario s
$H_{m\ell t}^s$	Quantity of transfused blood product m delivered from blood banks in other districts to hospital ℓ in period t under scenario s
O_{mkt}^s	Quantity of outdated blood product m at blood bank k in period t under scenario s
Z_j	$\begin{cases} 1, & \text{if fixed blood collection center } j \ (j \in J') \text{ is equipped} \\ 0, & \text{otherwise} \end{cases}$
Y_{jt}^s	$\begin{cases} 1, & \text{if a mobile blood collection center is opened at location } j \ (j \in J'') \text{ in period } t \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$
X_{jktr}^s	$\begin{cases} 1, & \text{if blood collection center } j \text{ is assigned to blood bank } k \text{ at time period } t \text{ using route } r \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$
W_{ijt}^s	$\begin{cases} 1, & \text{if blood donors at location } i \text{ are assigned to blood collection center } j \text{ in period } t \text{ under scenario } s \\ 0, & \text{otherwise} \end{cases}$

3.1.4. Objective functions

One of the main contributions of this work is the consideration of a multi-objective formulation to design a robust blood supply chain. The two objectives are the supply chain cost and the expected blood delivery time. The blood delivery time objective is vital as it prioritizes the delivery of blood products that are fresher, which has been medically proven to yield benefits to patients, while the cost objective ensures that the system is efficient.

In terms of the mathematical model, the expected delivery time objective F_1 and the supply chain cost objective F_2 are given by:

$$\text{Minimize } F_1 = \sum_{m,j,k,t,r,s} \pi^s F^s_{mjktr} t'_{jkr} + \sum_{m,k,\ell,t,s} \pi^s U^s_{mk\ell t} t''_{k\ell} + \sum_{m,\ell,t,s} \pi^s H^s_{m\ell t} ti_{\ell t} \tag{1}$$

$$\text{Minimize } F_2 = \sum_{s,t} \sum_{j\in J''} o\,\pi^s Y^s_{jt} + \sum_{j\in J'} q\,Z_j. \tag{2}$$

The expected delivery time objective function F_1 is the sum of three terms: the first term corresponds to the transportation time from blood collection centers to blood banks; the second term is the transportation time from blood banks to hospitals; and the third term is the transportation time from blood banks in other provinces to hospitals. The total system cost objective function F_2 reflects the cost of equipping fixed blood collection centers and the cost of establishing new mobile blood collection centers.

3.1.5. Constraints

Eqs. (3)–(21) below summarize the modeling constraints.

$$G^s_{mijt} \leqslant p^s_{mit} W^s_{ijt} \qquad \forall\, m, i, j, t, s \tag{3}$$

$$\sum_j G^s_{mijt} \leqslant p^s_{mit} \qquad \forall\, m, i, t, s \tag{4}$$

$$\sum_i \sum_m G^s_{mijt} \leqslant c_j Z_j + f_j Y^s_{jt} \qquad \forall\, j, t, s \tag{5}$$

$$Z_j + Y^s_{jt} \leqslant 1 \qquad \forall\, j, t, s \tag{6}$$

$$W^s_{ijt} \leqslant \alpha^s_{jt} Z_j + Y^s_{jt} \qquad \forall\, i, j, t, s \tag{7}$$

$$\sum_k \sum_r F^s_{mjktr} \leqslant \sum_i G^s_{mijt} \qquad \forall\, m, j, t, s \tag{8}$$

$$\sum_j \sum_r \sum_m F^s_{mjktr} \leqslant e_k \beta^s_{kt} \qquad \forall\, k, t, s \tag{9}$$

$$X^s_{jktr} \leqslant \alpha^s_{jt} \beta^s_{kt} \delta^s_{jkrt} Z_j \qquad \forall\, j \in J', \forall\, k, t, r, s \tag{10}$$

$$X^s_{jktr} \leqslant Y^s_{jt} \beta^s_{kt} \delta^s_{jkrt} \qquad \forall\, j \in J'', \forall\, k, t, r, s \tag{11}$$

$$\sum_r X^s_{jktr} \leqslant 1 \qquad \forall\, j \in J'', \forall\, k, t, s \tag{12}$$

$$\sum_m F^s_{mjktr} \leqslant c_j X^s_{jktr} \qquad \forall\, j \in J', \forall\, k, t, r, s \tag{13}$$

$$\sum_m F^s_{mjktr} \leqslant f_j X^s_{jktr} \qquad \forall\, j \in J'', \forall\, k, t, r, s \tag{14}$$

$$\sum_m \sum_\ell U^s_{mk\ell t} \leqslant e_k \beta^s_{kt} \qquad \forall\, k, t, s \tag{15}$$

$$d^s_{m\ell t} - \sum_k U^s_{mk\ell t} = H^s_{m\ell t} \qquad \forall\, m, \ell, t, s \tag{16}$$

$$V^s_{mk,t-1} + \sum_j \sum_r F^s_{mjktr} = V^s_{mk,t} + \sum_\ell U^s_{mk\ell t} + O^s_{mkt} \qquad \forall\, t \geqslant 2, \forall\, m, k, s \tag{17}$$

$$O^s_{mkt} = \max\left\{0,\, V^s_{mk,t-LT_m} - \sum_l \sum_{\rho=t-LT_m}^{t} U^s_{mk\ell\rho} - \sum_{\rho=t-LT_m}^{t} O^s_{mk\rho}\right\} \qquad \forall\, t \geqslant 2, \forall\, m, k, s \tag{18}$$

$$\sum_{j\in J'} Y^s_{jt} \leqslant N - n \qquad \forall\, t, s \tag{19}$$

$$\sum_m V^s_{mkt} \leqslant e_k \qquad \forall\, k, t, s \tag{20}$$

$$\begin{cases} V^s_{mkt}, F^s_{mjktr}, U^s_{mk\ell t}, G^s_{mijt}, H^s_{m\ell t}, O^s_{mkt} \geqslant 0 \\ Z_j, Y^s_{jt}, X^s_{jktr}, W^s_{ijt} \in \{0, 1\} \end{cases} \qquad \forall\, m, i, j, k, \ell, t, r, s \tag{21}$$

Constraints (3) and (4) limit the quantity of donated blood from each urban area so as to not exceed the maximum blood supply of donors for each blood product. Constraint (5) ensures that the capacity of blood collection at each facility is not exceeded. Constraint (6) guarantees that at most one of the fixed or mobile blood collection centers is established in each location. Constraint (7) ensures that donors can only be assigned to mobile units that have been allocated to that location or fixed blood collection centers that have been equipped and have not been disrupted. Constraint (8) limits the amount of blood leaving blood collection centers to not exceed the amount of blood collected. Constraint (9) enforces capacity constraints at each blood bank and sets the capacity of disrupted centers to zero. Constraint (10) ensures that fixed blood collection centers are only assigned to blood banks for which the facilities and routes between these centers have not been disrupted. Constraint (11) guarantees that if a mobile blood collection center is assigned to a certain blood bank, then the facility cannot be disrupted. Constraint (12) allocates a route between each blood collection center and blood bank. Constraints (13) and (14) ensure that blood products cannot be transported from a blood collection center or a mobile blood collection facility to a blood bank that is not assigned to it. Constraint (15) ensures that a blood bank can only be assigned to a hospital if it has not been disrupted. Constraint (16) determines the amount of blood products delivered to each hospital from blood banks in other provinces. Constraint (17) represents blood inventory balance constraints at the blood bank. Constraint (18) determines the number of outdated units in each period. Constraint (19) ensures that the number of mobile blood collection facilities in each period does not exceed the number of candidate locations for mobile blood collection facilities. Constraint (20) limits the capacity of blood banks in storing blood. Constraint (21) defines the domains of the decision variables.

Since Constraint (18) is a non-linear "max" function, in order to solve the model as a Mixed Integer Programming model, it must be linearized. This can be achieved by replacing Constraint (18) by the following set of equations.

$$O^s_{mkt} \geqslant V^s_{mk,t-LT_m} - \sum_{l} \sum_{\rho=t-LT_m}^{t} U^s_{mk\ell\rho} - \sum_{\rho=t-LT_m}^{t} O^s_{mk\rho} \qquad \forall\ t \geqslant 2,\ \forall\ m,\ k,\ s \tag{22}$$

$$O^s_{mkt} \leqslant (1 - \Delta_{smkt}) * M \qquad \forall\ t \geqslant 2,\ \forall\ m,\ k,\ s \tag{23}$$

$$O^s_{mkt} \leqslant V^s_{mk,t-LT_m} - \sum_{l} \sum_{\rho=t-LT_m}^{t} U^s_{mk\ell\rho} - \sum_{\rho=t-LT_m}^{t} O^s_{mk\rho} + \Delta_{smkt} M \qquad \forall\ t \geqslant 2,\ \forall\ m,\ k,\ s \tag{24}$$

where Δ_{smkt} is a binary decision variable that is set to 1 if the right hand side of Constraint (24) is negative and 0 otherwise and M is a relatively large number. In the next section, an ε-constraint solution method will be used to convert the proposed multi-objective model into a single-objective model.

3.2. Conversion to a single-objective model

A mathematical program in which multiple objective functions are to be optimized with respect to a set of decision variables is called a Multi-objective Optimization Problem (MOP). Such problems are commonly encountered in engineering, management, and healthcare (Ehrgott and Ruzika, 2008). The literature presents various classes of solution methods aimed at solving MOPs. These methods can broadly be categorized into interactive, decision-aided, meta-heuristic, scalar, and fuzzy methods, amongst others. In this work, we use the *ε-constraint method* to solve the proposed MOP (Liu and Papageorgiou, 2013). In this method, the multi-objective problem is transformed into a single objective model. The advantages of using the ε-constraint method over other methods include:

- In comparison with the weighting method, the ε-constraint method assists in obtaining non-extreme solutions by changing the feasible regions, thereby decreasing the number of runs and obtaining richer, more efficient solutions.
- In the weighting method, the scaling of the objective function has a great impact on the results obtained while in the ε-constraint method scaling is not necessary. An advantage of using the ε-constraint method is that the number of efficient solutions can be easily controlled, as opposed to other methods (Mavrotas, 2009).

Applying the ε-constraint algorithm to our proposed bi-objective model, the delivery time objective function in Eq. (1) is used as the primary objective function while the cost objective function in Eq. (2) is transformed into a modeling constraint with upper bound ε, hereafter called the *cost tolerance*. Thus, the bi-objective model is now converted into the following single-objective model:

$$\text{minimize} \quad F_1 = \sum_{m,k,t,r,s,j} \pi^s F^s_{mjktr} t'_{jkr} + \sum_{m,k,\ell,t,s} \pi^s U^s_{mk\ell t} t''_{k\ell} + \sum_{m,\ell,t,s} \pi^s H^s_{m\ell t} ti_{\ell t} \tag{25}$$

$$\text{s.t.} \quad \sum_{s,t} \sum_{j\in J''} o\, \pi^s Y^s_{jt} + \sum_{j\in J'} q\, Z_j \leqslant \varepsilon \tag{26}$$

Constraints (3)–(21).

3.3. Robust model

Aghezzaf et al. (2010) proposed a robust optimization method in which they use the reliable counterpart model in conjunction with a two-stage stochastic model. To demonstrate the approach, let s be a possible disaster scenario taking values in a set $S = \{1, ..., |S|\}$, and let π^s be the probability that disaster scenario s occurs. Their approach is to solve the optimization model

$$\begin{aligned} \text{minimize}_x \quad & \eta\cdot\max_s(\xi_s-\xi_s^*)+\lambda\cdot\sum_{s\in S}\pi^s\xi_s \\ \text{s.t.} \quad & x\in X \end{aligned} \tag{27}$$

where ξ_s^* is the optimal value that is obtained by solving the deterministic model under scenario s, ξ_s is the optimal cost that results from the occurrence of scenario s, and the weights η and λ are parameters that are set by the decision maker. To increase the robustness of the optimal solution, η should be increased relative to λ, while to lower the expected objective value λ should be increased relative to η (Aghezzaf et al., 2010).

In our model, disruption of the blood banks, blood collection centers, and routes between the blood banks and blood collection centers are assumed to be uncertain, and depend on the scenario s through the parameters β_{kt}^s, α_{jt}^s, and δ_{jkrt}^s, respectively. Applying the robust optimization procedure to our model results in the following optimization problem

$$\begin{aligned} \text{minimize} \quad & \eta\cdot\max_s(\xi_s-\xi_s^*)+\lambda\cdot\sum_{s\in S}\pi^s\xi_s \\ \text{s.t.} \quad & \text{Constraints (3)–(21)},\ (26) \end{aligned} \tag{28}$$

where ξ_s represents the expression

$$\sum_{m,k,t,r,j} F_{mjktr}^s t'_{jkr} + \sum_{m,k,\ell,t} U_{mk\ell t}^s t''_{k\ell} + \sum_{m,\ell,t} H_{m\ell t}^s ti_{\ell t}. \tag{29}$$

The objective function (28) can be linearized by letting $Q=\max_s(\xi_s-\xi_s^*)$, and, incorporating the constraints

$$Q\geqslant\xi_s-\xi_s^* \qquad \forall\ s\in S \tag{30}$$

results in the following optimization problem:

$$\begin{aligned} \text{minimize} \quad & \eta\cdot Q+\lambda\cdot\sum_{s\in S}\pi^s\xi_s \\ \text{s.t.} \quad & \text{Constraints (3)–(21)},\ (26),\ (30). \end{aligned} \tag{31}$$

4. Lagrangian relaxation

As is well known, many large-scale mixed-integer linear programming models have been successfully solved using Lagrangian relaxation. This approach has been applied to many supply chain problems in the literature. Examples include the work of Diabat et al. (2013), Diabat et al. (2014) and Diabat and Richard (2015). Lagrangian relaxation is an iterative procedure that relaxes a set of complicating constraints and finds upper and lower bounds on the optimal solution to the original problem. The optimal solution to the relaxed master problem is a lower bound on the optimal solution to the original problem, while a heuristic provides an upper bound on the optimal objective value. This method iterates until the gap between the upper and lower bounds approaches zero. In each iteration, the values of the Lagrange multipliers, which are penalties on the relaxed constraints, are updated, which updates the values of the upper and lower bounds. We discuss the method in more detail below.

4.1. Finding a lower bound

In order to obtain a lower bound on the optimal solution, a set of complicating constraints is relaxed (Fisher, 2004). In our model, we relax the constraints specified by Eq. (4), as relaxing these constraints results in a model that is easier to solve. By relaxing the aforementioned constraints, the following formulation is obtained:

$$\begin{aligned} \text{minimize} \quad & \eta\cdot Q+\lambda\cdot\sum_{s\in S}\pi^s\xi_s+\sum_{m,i,t,s}\mu_{mit}^s\left(\sum_j G_{mijt}^s-p_{mit}^s\right) \\ \text{s.t.} \quad & \text{Constraints (3)},\ (5)\text{–}(21),\ (26),\ (30) \end{aligned} \tag{32}$$

where as above ξ_s represents the expression given in Eq. (29) and μ_{mit}^s are Lagrange multipliers that result from relaxing the constraints specified by Eq. (4). The solution to the above problem represents a lower bound on the optimal objective function value of the original problem since a set of constraints has been relaxed.

4.2. Finding an upper bound

In each iteration of the Lagrangian solution approach, an upper bound is obtained as follows. If the solution of the Lagrangian dual problem in Eq. (32) is feasible to the original problem, then it provides an upper bound as well. In the case where the value of the upper bound equals the lower bound, then the algorithm terminates as the upper and lower bounds are equal and consequently an optimal solution has been reached. However, if the solution obtained from solving the Lagrangian dual problem is infeasible, a feasible solution is found as follows. The optimal values of Y_{jt}^s from the Lagrangian dual problem are set as constants and Eq. (32) is minimized subject to Constraints (3), (5)–(21), (26) and (30). The solution to this model is feasible and is an upper bound on the original problem. This is referred to as Heuristic1 in Fig. 2. If using the Y_{jt}^{s} values from the relaxed problem is infeasible to the original problem, then a secondary heuristic is used, Heuristic2 in Fig. 2, which sets the optimal values of Z_j as constants and resolves the original problem.

Algorithm 1: Lagrangian Relaxation Code

```
Lagrangian Relax (Data);
Data    : Matrices: p, d, ti, β, α, δ, t', t''
          Vectors: e, c, f, π
          Scalars: o, q
Results: Solution (V, B, F, U, G, H, O, Z, Y, X, W, N) to RMP
begin
    ε ← 2
    λ_smit ← 1 for each s ∈ S, m ∈ M, i ∈ I, t ∈ T
    noimp ← 0
    repeat
        Solve RelaxedMasterProblem using MIP
        Ñ ← N
        Ỹ ← Y
        CLP ← COFV(RelaxedMasterProblem)
        check1 ← 0
        for s ∈ S, m ∈ M, i ∈ I, t ∈ T do
            if ∑_j G_smijt > P_smi then
                check1 ← check1 + 1
            end
            if check1 == 0 then
                PotUB ← COFV(RelaxedMasterProblem)
            else
                Solve Heuristic1 using MIP
                if Heuristic1 is optimal then
                    PotUB ← COFV(Heuristic1)
                else
                    Solve Heuristic2 using MIP
                    if Heuristic2 is optimal then
                        PotUB ← COFV(Heuristic2)
                    end
                end
            end
        end
        if UB > PotUB then
            UB ← PotUB
        else
            noimp ← noimp + 1
        end
        check2 ← 0
        for s ∈ S, m ∈ M, i ∈ I, t ∈ T do
            if ∑_j G_smijt > P_smi then
                Stepsize_smit ← 0
            else
                Stepsize_smit ← ε(UB − CLB)) / sqrt(∑_j G_smijt − P_smi
            end
            if Stepsize_smit ≠ 0 then
                λ_smit ← max {0, λ_smit + Stepsize_smit × (∑_j G_smijt − P_smi)}
                check2 ← check2 + 1
            end
        end
        if CLB > LB then
            LB ← CLB
        end
        if noimp > 5 then
            ε ← ε/2
            noimp ← 0
        end
    until (| UB − LB |< 0.000001) or (ε < 0.005);
end
```

Fig. 2. Lagrangian relaxation algorithm.

4.3. Updating upper and lower bounds

The subgradient method is used to update the algorithm parameters (Fisher, 2004). As the algorithm iterates, the Lagrange multipliers as well as the step sizes are updated, then the upper and lower bounds are determined to calculate the gap. The algorithm parameters are updated through the following equations:

$$\text{Stepsize}^{s}_{mit} = \frac{\theta\cdot(\text{UB} - \text{CLB})}{(\sum_j G^{s}_{mijt} - p^{s}_{mit})^2} \qquad \forall\, m,\, i,\, t,\, s \tag{33}$$

where UB is the best obtained upper bound, CLB is the current lower bound obtained at iteration n, and θ is a parameter that is halved every few iterations that pass without an improvement in the UB and LB. Then the values of the Lagrange multipliers are updated as follows:

$$\mu^{s}_{mit} = \max\left\{0,\, \mu^{s}_{mit} + \text{Stepsize}^{s}_{mit}\cdot\left(\sum_j G^{s}_{mijt} - p^{s}_{mit}\right)\right\} \qquad \forall\, m,\, i,\, t,\, s. \tag{34}$$

As previously mentioned, the parameter θ is set to improve the convergence of the algorithm. Its value is initially set to 2 and is halved after a specified number of consecutive iterations without an improvement in the bounds. The Lagrangian relaxation algorithm is displayed in Fig. 2.

4.4. Extensions to the model

This section presents a number of extensions to the two-stage stochastic programming model formulated above. These extensions take into consideration socioeconomic factors when importing blood from neighboring districts and incorporate reliability metrics. The extensions are as follows:

- The decision variable $H^{s}_{m\ell t}$ is restricted. It is not feasible in reality to have unlimited supply from neighboring districts and therefore $H^{s}_{m\ell t}$ is capped at 10% of the demand in that location.
- A variable $B^{s}_{m\ell t}$ is added to quantify the total unmet demand. $B^{s}_{m\ell t}$ is defined as the quantity of unmet demand of blood product m at hospital ℓ in period t under scenario s. A reliability constraint is also introduced on the total quantity of unmet demand. In particular, the total unmet demand is limited to 5% of the total demand.
- Constraint (6), which prevents mobile blood collection centers from being assigned to locations where a blood collection center is already operating, is relaxed. This allows the model to assign mobile blood facilities to a location even if a blood collection center is already operating in that location. This allows the model to take advantage of excess supply in a specific region.

The updated formulation is presented below:

$$\text{minimize} \quad \eta\cdot Q + \lambda\cdot \sum_{s\in S} \pi^{s}\xi_{s} \tag{35}$$

$$\text{s.t.} \quad \sum_{s,t}\sum_{j\in J''} o\,\pi^{s} Y^{s}_{jt} + \sum_{j\in J'} q\,Z_j \leqslant \varepsilon \tag{36}$$

$$Q \geqslant \xi_s - \xi^{*}_{s} \qquad \forall\, s\in S \tag{37}$$

$$G^{s}_{mijt} \leqslant p^{s}_{mit} W^{s}_{ijt} \qquad \forall\, m,\, i,\, j,\, t,\, s \tag{38}$$

$$\sum_j G^{s}_{mijt} \leqslant p^{s}_{mit} \qquad \forall\, m,\, i,\, t,\, s \tag{39}$$

$$\sum_i\sum_m G^{s}_{mijt} \leqslant c_j Z_j + f_j Y^{s}_{jt} \qquad \forall\, j,\, t,\, s \tag{40}$$

$$W^{s}_{ijt} \leqslant \alpha^{s}_{jt} Z_j + Y^{s}_{jt} \qquad \forall\, i,\, j,\, t,\, s \tag{41}$$

$$\sum_k\sum_r F^{s}_{mjktr} \leqslant \sum_i G^{s}_{mijt} \qquad \forall\, m,\, j,\, t,\, s \tag{42}$$

$$\sum_j\sum_r\sum_m F^{s}_{mjktr} \leqslant e_k \beta^{s}_{kt} \qquad \forall\, k,\, t,\, s \tag{43}$$

$$X^{s}_{jktr} \leqslant \alpha^{s}_{jt}\beta^{s}_{kt}\delta^{s}_{jkrt} Z_j + Y^{s}_{jt}\beta^{s}_{kt} + (1 - Y^{s}_{jt} - Z_j)\delta^{s}_{jkrt} \qquad \forall\, j,\, k,\, t,\, r,\, s \tag{44}$$

$$X^{s}_{jktr} \leqslant 1 \qquad \forall\, j,\, k,\, t,\, r,\, s \tag{45}$$

$$\sum_{r} X_{jktr}^{s} \leqslant 1 \qquad \forall\, j \in J'', \forall\, k, t, s \tag{46}$$

$$\sum_{m} F_{mjktr}^{s} \leqslant c_j X_{jktr}^{s} \qquad \forall\, j \in J', \forall\, k, t, r, s \tag{47}$$

$$\sum_{m} F_{mjktr}^{s} \leqslant f_j X_{jktr}^{s} \qquad \forall\, j \in J'', \forall\, k, t, r, s \tag{48}$$

$$\sum_{m} \sum_{\ell} U_{mk\ell t}^{s} \leqslant e_k \beta_{kt}^{s} \qquad \forall\, k, t, s \tag{49}$$

$$d_{m\ell t}^{s} - \sum_{k} U_{mk\ell t}^{s} = H_{m\ell t}^{s} + B_{m\ell t}^{s} \qquad \forall\, m, \ell, t, s \tag{50}$$

$$H_{m\ell t}^{s} \leqslant 0.1 d_{m\ell t}^{s} \qquad \forall\, m, \ell, t, s \tag{51}$$

$$V_{mk,t-1}^{s} + \sum_{j} \sum_{r} F_{mjktr}^{s} = V_{mk,t}^{s} + \sum_{\ell} U_{mk\ell t}^{s} + O_{mkt}^{s} \qquad \forall\, t \geqslant 2, \forall\, m, k, s \tag{52}$$

$$\sum_{m} \sum_{\ell} \sum_{t} B_{m\ell t}^{s} \leqslant 0.05 \sum_{m} \sum_{\ell} \sum_{t} d_{m\ell t}^{s} \qquad \forall\, s \tag{53}$$

$$O_{mkt}^{s} = \max\left\{0,\, V_{mk,t-LT_m}^{s} - \sum_{l} \sum_{\rho=t-LT_m}^{t} U_{mk\ell\rho}^{s} - \sum_{\rho=t-LT_m}^{t} O_{mk\rho}^{s}\right\} \qquad \forall \geqslant 2, \forall\, m, k, s \tag{54}$$

$$\sum_{j\in J'} Y_{jt}^{s} \leqslant N - n \qquad \forall\, t, s \tag{55}$$

$$\sum_{m} V_{mkt}^{s} \leqslant e_k \qquad \forall\, k, t, s \tag{56}$$

$$\begin{cases} V_{mkt}^{s}, F_{mjktr}^{s}, U_{mk\ell t}^{s}, G_{mijt}^{s}, H_{m\ell t}^{s}, B_{m\ell t}^{s}, O_{mkt}^{s} \geqslant 0 \\ Z_j, Y_{jt}^{s}, X_{jktr}^{s}, W_{ijt}^{s} \in \{0, 1\} \end{cases} \qquad \forall\, m, i, j, k, \ell, t, r, s \tag{57}$$

Constraints (44) and (45) have been modified to account for the possibility of having mobile blood facilities in the same location as a fixed blood facility. Constraint (51) has been modified to account for the case in which the blood supply is less than the demand. This is a very realistic consideration that should be accounted for as it mirrors disaster scenarios in which supply sources are seriously depleted. Constraint (52) has been added to limit the supply of blood from neighboring districts to be less than 10% of the blood available in each location in each time period. Finally, constraint (53) has been added to limit the total unmet demand to at most 5% of the total demand.

5. Computational results

5.1. Case study

In this section, we consider a real case study to demonstrate several aspects of the proposed supply chain modeling approach. We consider the case of Jordan, a country with 13 districts, and the goal is to design a robust blood supply chain that minimizes the effects of disasters for a set of given disruption scenarios. The main city in each district, as well as other locations with high population densities, were considered as candidates for locating mobile blood collection facilities. Specifically, 30 candidate locations were selected in areas where the population density map showed a large congregation of people, as well as in university quads. The former type of location was selected because the more people there are, the higher the chances of donation. The latter type of location was selected because studies have shown that the tendency to donate blood is directly correlated to an individual's educational level (Pule et al., 2014). Fig. 3 shows the 30 selected candidate locations on a map of Jordan. The proposed model was tested using 15 different scenarios, the first of which represented the situation with no disruptions, while the others represented possible disruption scenarios that may occur within the blood supply system. The disaster data was randomly generated based on historical data and documented responses of blood centers (Gschwender and Gillard, 2017). The goal is to find optimal locations for basing mobile blood collection centers under these scenarios.

Following an approach similar to that used by Hamdan and Diabat (2019), the supply of blood is estimated based on the recommendations in the Annual Statistical Book of Jordan's Ministry of Health, 2012. Specifically, supply is estimated based on the assumption of some known estimated percentage of the population donating blood in each area. Each blood unit that is received is broken down into three products: plasma, platelets, and red blood cells. Each of these products is divided into distinct blood groups (A, B, AB, or O), and each of these blood groups is further subdivided into its respective positive or negative groups, for a total of 10 blood products and 24 overall unit types. Depending on the disaster scenario that occurs, values for the overall demand of blood are

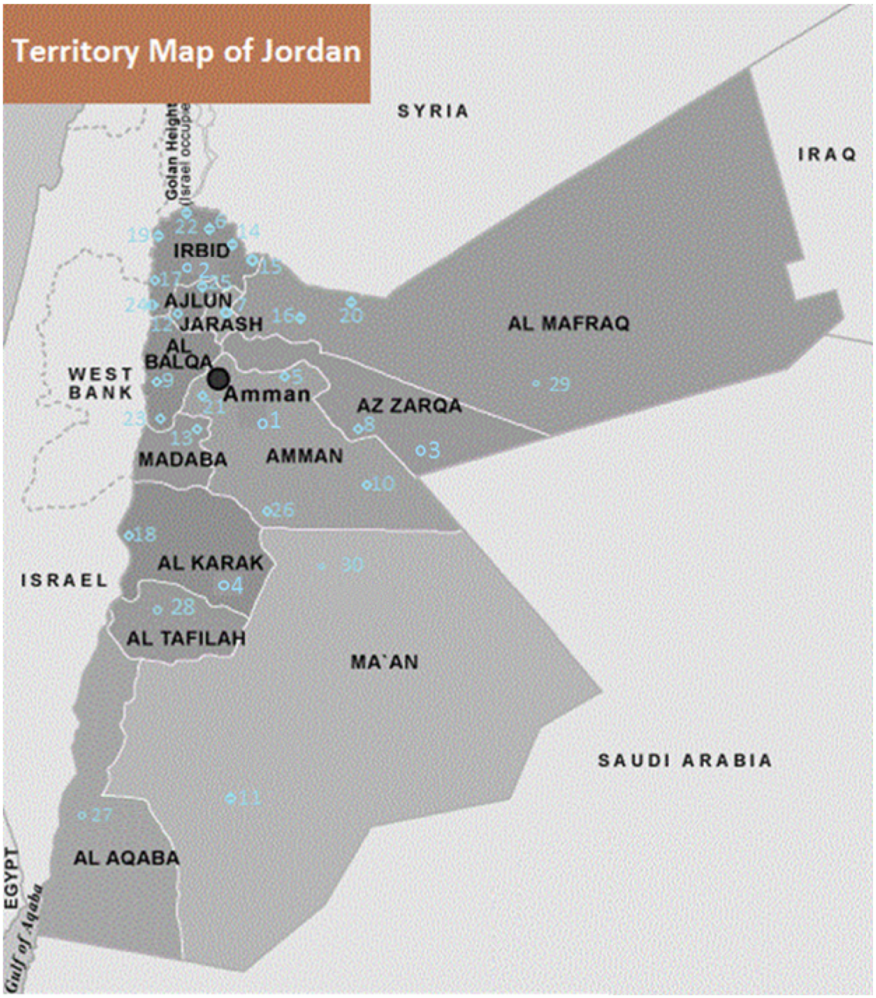

Fig. 3. Candidate locations of the fixed blood centers.

predicted based on the population of the region as well as the disaster severity (high, moderate, or low) (Dillon et al., 2017). Finally, the likelihood of each disaster scenario is roughly estimated based on the history of the region.

The proposed model was solved in GAMS ("General Algebraic Modeling System", Release 24.2.1) using CPLEX on a computer with a Core i5 processor and 4 GB of RAM. The maximum budget was set at $100,000. The robustness parameters η and λ that were introduced to the model were set at 0.75 and 0.25, respectively. Fig. 4 shows the locations of the fixed blood centers obtained by optimizing the model (black dots on the map). We can see that of the 30 candidates, 15 fixed centers were established in the thirteen urban areas of Jordan so that in most urban areas, there is one center and in two of the larger districts (Al Mafraq and Ma'an), there are two, owing to the size of these districts.

5.2. Sensitivity analysis

In the context of supply chain models, a sensitivity analysis is usually performed to determine the effects of modeling parameters on the performance of the supply chain. Here, we examine the effect of increased blood supply on the supply chain delivery time to facilitate decisions on budgeting for blood drives. In blood supply chains, the donation rate is defined as the proportion of people in a given population who are willing to donate blood. The effect of donation rate on the supply chain delivery time is shown in Fig. 5. It should be noted that every time the model is solved, a different location configuration is chosen, and thus the chosen locations of facilities can change. Results in Fig. 5 show an inverse relationship between donation rate and delivery time such that as the donation rate increases, the supply chain delivery time decreases. A higher donation rate means more blood is readily available at different locations in the network, and hence a lower delivery time is needed to transport blood from nearby donation centers to hospitals in need of blood. The donation rate-delivery time relationship shown in Fig. 5 follows an S-like curve indicating a slow decrease in the delivery time at low values of the donation rate, followed by a steeper decrease in the delivery time at higher values of the donation rate, with the curve plateauing again at donation rates greater than 0.25, indicating sufficient supply to fulfill hospitals' demand

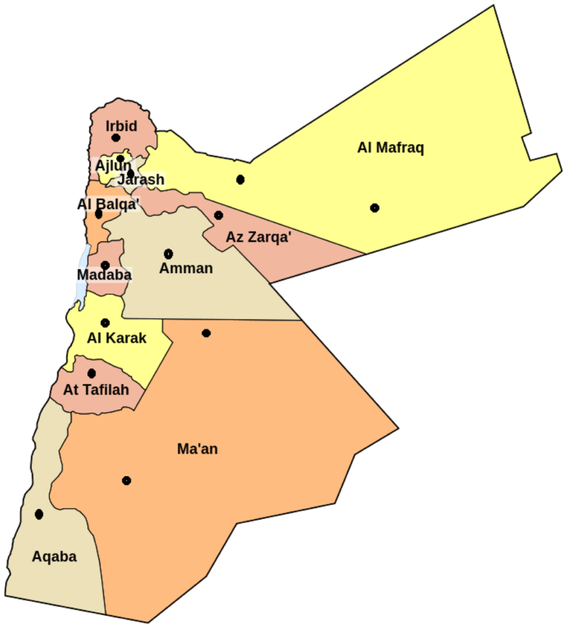

Fig. 4. Chosen locations of the fixed blood centers.

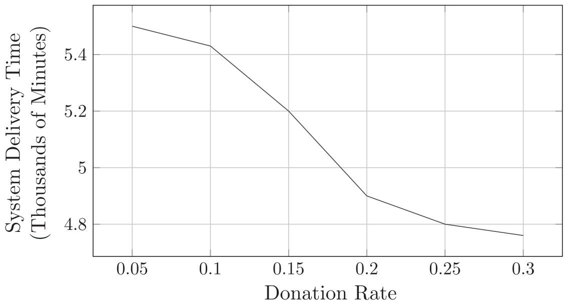

Fig. 5. Impact of increasing the Donation Rate on the System Delivery Time.

through nearby locations. This curve provides insight for decision makers on budgeting for blood drives in order to reach acceptable delivery times.

A comparison of total system delivery times using the proposed stochastic model versus considering the model scenarios as deterministic is illustrated in Fig. 6. Models were compared based on 10 randomly generated model cases with average demand and disruption parameters as shown in Table 1. For model comparison, 10 disruption scenarios were considered, and they were assumed to have equal likelihood of occurrence. Results in Fig. 6 show that in some cases the stochastic model yielded a lower delivery time than the deterministic scenarios, while in the other cases similar delivery times were obtained. The results also show a positive relationship between the average demand and the total system delivery time. As the average demand increases, the average delivery time also increases, which is intuitive since more units need to be transported. This is shown in Fig. 7.

Fig. 8 highlights the benefit of using a robust model over the two-stage stochastic programming model (2SSP) without the robust counterpart model. The benefit is highlighted through the difference between the objective function values in terms of the system delivery time for the 10 model cases shown in Table 1 and the same 10 random scenarios discussed before. Results in Fig. 8 show that the robust model achieves better delivery time than the 2SSP model for almost all model cases used. The gap, defined as the difference between the delivery times of the robust model and the 2SSP model, relative to that of the robust model, is also shown in Fig. 8. The gap curve shows that the robust model yields a delivery time that is 30% to 40% lower on average, and in some cases up to 49% lower. This significant decrease in the system delivery time could improve outcomes for patients requiring blood units, depending on the severity of the injury and how time-sensitive it is.

5.3. Analysis of extensions to the model

This section presents an analysis of the proposed extensions to the model. For simplicity in distinguishing the models, the model presented in Section 2 will be referred to as Model 1 and the extended model presented in Section 4 will be referred to as Model 2. To

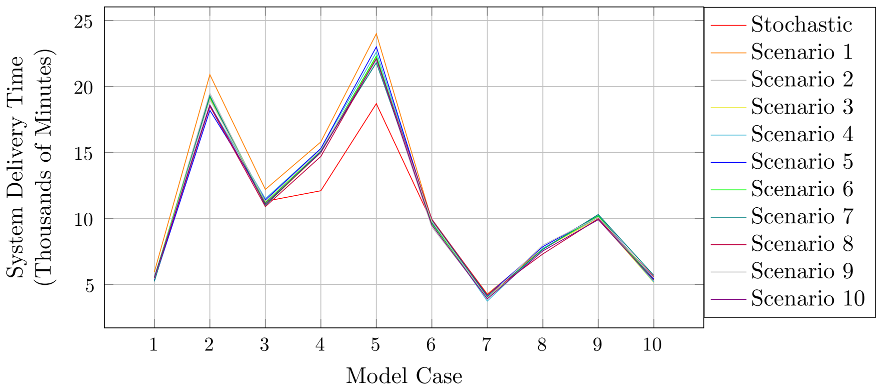

Fig. 6. Difference in the System Delivery Time for the stochastic model and the deterministic cases.

Table 1
Summary of the 10 cases.

Model Case	Average Demand	Blood Bank Disruptions	Collection Center Disruptions	Route Disruptions
1	377549	23	34	1237
2	641543	19	35	1001
3	456651	18	35	804
4	556844	21	33	806
5	764548	1	33	1038
6	465484	19	36	989
7	351215	19	34	1252
8	356484	19	33	798
9	424654	19	33	1012
10	367700	21	30	1336

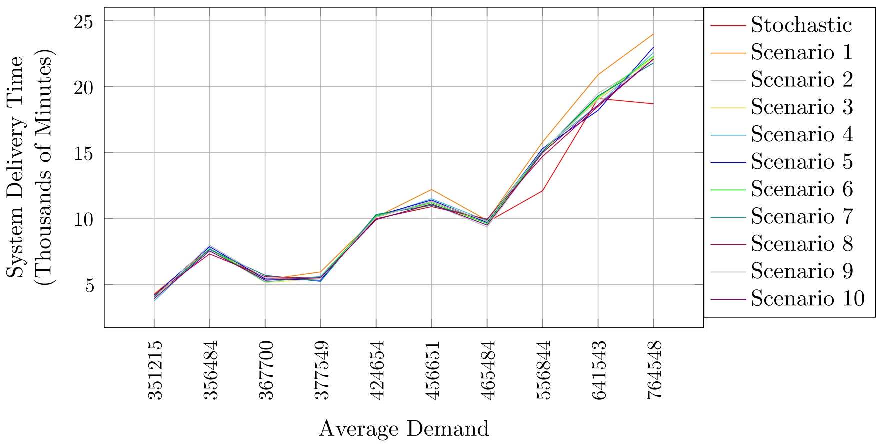

Fig. 7. Relation between System Delivery Time and Average Demand.

evaluate the performance of each model, each model is solved under two circumstances: one where the supply is sufficient and the other where the supply is based on real population data.

Fig. 9 shows the different results for the two supply cases. In the case of sufficient supply, since the model is always able to collect additional supply, the inventory level decreases to zero at the end of the forecast cycle. On the other hand, in the second case, where supply is limited, the model collects supply whenever there is an excess since the availability of supply is highly stochastic.

Fig. 10 demonstrates the different model behavior for the two supply scenarios. In the first scenario, (a), the model does not import any units from neighboring districts since the available supply is adequate to satisfy the demand. Additionally, the number of outdated units is very low since the model does not need to collect inventory beforehand to meet the demand and can collect it during the required time period. This will drastically reduce the number of outdated units since the units can be collected during demand

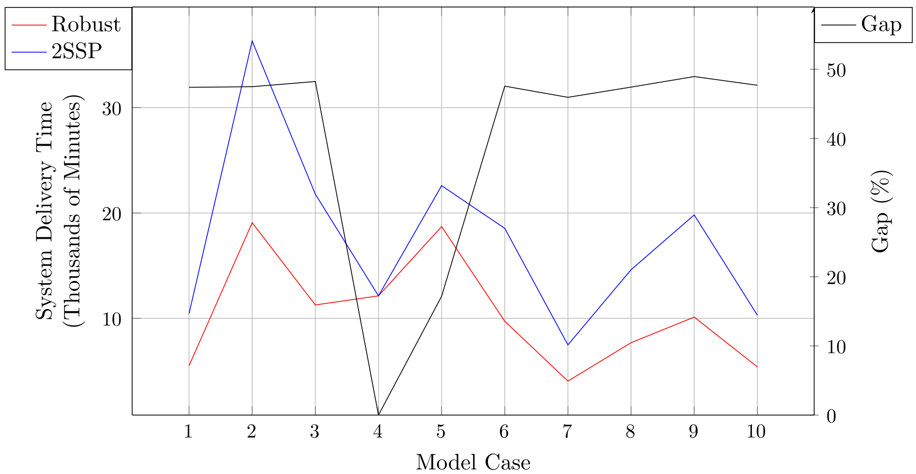

Fig. 8. The difference between the robust model and the two-stage stochastic programming (2SSP) model on System Delivery Time.

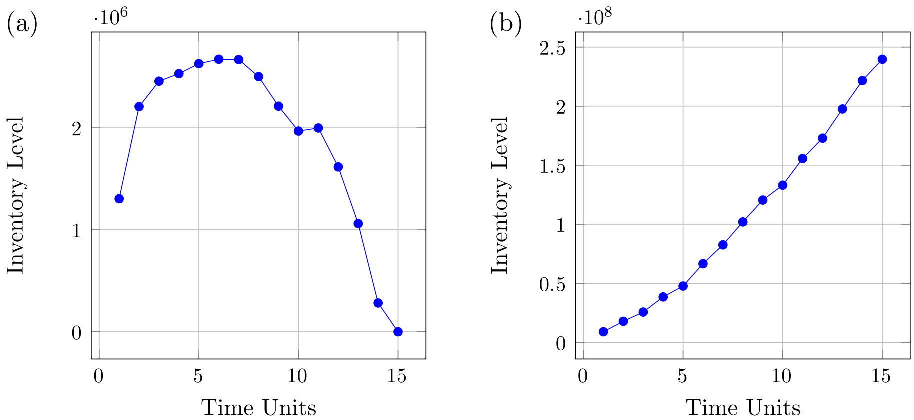

Fig. 9. Inventories levels for the sufficient supply case (left) and the realistic supply case (right). The inventory quantities are summed over the indices and averaged over the scenarios.

realization. It should also be noted that the existence of shortages in the model is a result of different disaster scenarios and limited capacity. The model cannot have a 100% success rate at meeting the demand as demand is not anticipated in advance and the model also aims to reduce the quantity of outdated units. In this case, the model is quite conservative in that it has very low outdate levels and significant shortages. This relationship can be offset through adjusting the epsilon value for the epsilon-constrained objective. In the second scenario, (b), the model imports blood units from neighboring districts since the supply of blood is not generally sufficient. In the figure, it can be seen that the imported quantity follows a similar trend to the quantity of unmet demand. This is logical since as the quantity of unmet demand increases, more units are needed to more closely match the demand. The system shortages also follow a similar pattern to that found in (a) as the demand scenarios remain the same and the only difference between the models is the availability of supply.

6. Conclusions

We presented a blood supply chain model that uses robust optimization techniques and two-stage stochastic optimization to mitigate the effects of disasters on the blood supply chain. A bi-objective framework was used to simultaneously minimize the system cost and delivery time under the risk of disruptions. The model is a multi-echelon supply chain model that considers mobile blood collection facilities, fixed blood collection facilities, blood banks and the demand nodes, hospitals. The proposed model considers realistic constraints on the blood supply chain system including the high perishability rate of blood, the ability to collect blood from neighboring regions and both route and facility disruptions. Moreover, this multi-echelon model is extended to consider socio-economic factors such as accounting for the limited amount of inventory available in neighboring regions, considering the very realistic case in which demand cannot be met due to limited supply and allowing more than one blood collection facility to serve a

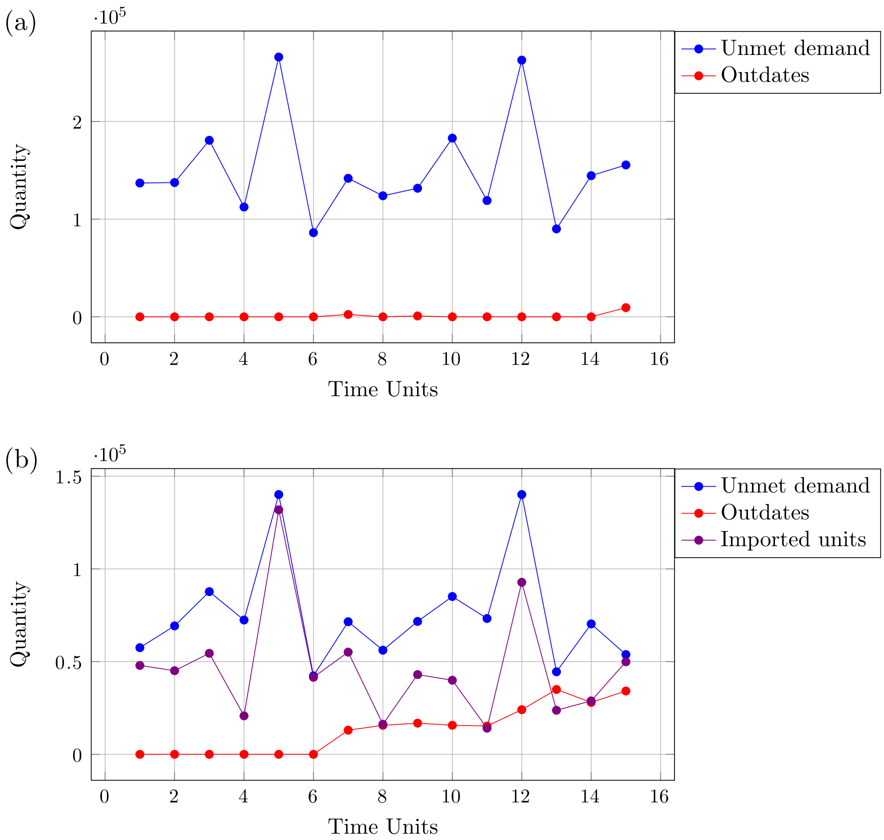

Fig. 10. Comparison between the values of the unmet demand, outdated units and imported units for the two supply cases (a) where there is sufficient supply and (b) where there is limited supply. All quantities are summed over the indices and averaged over the scenarios.

single location if it contains sufficient supply. The system is able to quickly mobilize and distribute blood in times of disaster based on scenario realization. This reduces chaos in the system and further improves response times. The scenario likelihoods and disruption severities can be updated in real time to improve the forecasting ability of the model as data becomes available. Moreover, the model specifically determines the amount of supply that should be imported from neighboring regions. This is an extremely important output, since it allows decision makers to contact the appropriate authorities ahead of time to make the transfer requests.

The proposed blood supply chain model was applied to a real case study of blood banks in Jordan. Thirteen districts were included as potential disaster regions along with 30 candidate locations for blood collection centers. The results showed that fifteen centers are sufficient under the disruption scenarios considered. A few additional scenarios to the case study are then applied to the extended supply chain model to study the effect of capacitated supply on the behavior of the system. The results show the different inventory patterns that can be expected with different supply patterns.

A sensitivity analysis revealed that the donation rate is a significant factor in reducing blood delivery times. This could incentivize entities to increase outreach to possible donors and educate people on the importance of donating blood and the impact it can have on the community. Further insights can be drawn from the results to allow decision makers to structure the supply chain network and locate mobile blood facilities in an optimal allocation to more closely match the demand during disasters. It is hoped that our model will help to mitigate the effects of disasters on blood supply chains, thus helping to ensure the timely delivery of the required blood units at the lowest cost.

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