

Optimal Blood Transportation in Disaster Relief Considering Facility Disruption and Route Reliability under Uncertainty

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Abstract

The blood supply chain as a part of a healthcare system plays a substantial role in improving health within societies and supplying blood for daily needs. Specifically in disaster condition, blood supply is the challenge requiring more attention. This paper presents a fuzzy-stochastic mixed integer linear programming model to design blood supply chain network for disaster relief. To deal with uncertainty in the model parameters, a fuzzy programming approach is considered, and the combination of the expected value and the chance constrained programming is applied to solve the proposed model. Besides, a real case study in Iran is implemented to illustrate the applicability of the model. The results imply that an appropriate adjustment in the capacity and coverage radius of blood facilities, a decrease in the disruption probability of facilities and transportation routes as well as referral rate, can be applied as strategies to improve the supply chain costs.

Keywords: Blood supply chain; disaster; fuzzy-credibility; chance-constrained programming

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1. Introduction

Rapidly increasing healthcare costs, especially in developing countries, have impeded health systems to improve their performance. Since blood supply chains (BSCs) as parts of healthcare systems play a key role in contributing to health improvement within societies, improving service quality besides reducing costs of the BSC is of great significance [Cheraghi, Hosseini-Motlagh and Ghatreh-Samani, 2017; Riahi, Hosseini-Motlagh and Teimourpour, 2013]. Blood is one of the most critical products in healthcare, for which no alternatives have been found so far despite medicines development. Although blood availability in both regular healthcare treatment and emergency cases is so critical, blood donation rate varies in each country. In the US, for instance, only 10% of the qualified people donate blood. However, the rate is even less in developing and low-income countries according to WHO¹. As a result, blood supply and demand conformity requires the infrastructure development in collection, production and distribution of blood. Moreover, satisfying demand and minimizing costs and wastages are regarded as the chain preferable targets.

BSC and disaster management have become the two popular research fields in recent decades due to the increasing number of disasters. According to the related studies by IFRCⁱⁱ, around 71,800 disasters occurred in the world from 2000 to 2010 by which around a million were killed, and over 2,550 million were injured [Chester, 1995]. A part of this loss is directly owing to the disaster itself, while the rest concerns the deficiency of management as well as the supply of blood and other relief items. Thus, the necessity of an appropriate BSC network is perceived more than ever.

After the disasters happen (i.e., post-disaster phase), the affected people will demand food, shelters, healthcare equipment and other critical requirements that the most significant one is blood, which is considered as a scarce and vital commodity in healthcare. Accordingly, the proper supply of blood is regarded as the challenge that governments' healthcare systems

always face with [Beliën and Forcé, 2012]. Blood donation has no specific pattern and usually occurs in an irregular basis. In addition, the imprecise demand of blood besides the diversity of blood products with limited and different shelf lives; e.g., platelets, as the most perishable blood component and plasma as almost non-perishable one, imposes more complexity on BSCs [Rytila and Spens, 2006]. Moreover, any shortages are too costly, and may even lead to death. Blood donation takes place while referring to either mobile or permanent blood facilities. All blood quantities, drawn from the donors, are then temporarily transferred to regional facilities which account for testing and delivering blood products to hospitals and healthcare centers as soon as they are in need.

Generally, a BSC, which is composed of blood collection and production as well as inventory control and distribution processes, requires to make strategic, tactical and operational decisions, respectively for facility location, needed before the disaster occurrence, and inventory management besides blood distribution in post-disaster phase. Therefore, an efficient comprehensive BSC design especially in disaster condition, is of an importance to the chain improvement.

Papers on BSCs are mostly presented while accounting for deterministic condition, and only a few papers have studied the chain in disaster condition. Accordingly, we aim to investigate a BSC model in disasters considering uncertainty in model parameters to make the situation more realistic.

The inevitable uncertainty of critical data is a significant issue while designing a BSC network in disasters through optimization models. In large-scale real problems such as disasters or emergency cases, not enough data may be available or easy to access. In such occasions, parameters including demand amount, costs, and travel times are involved with uncertainty. Thus, it is of specific importance to consider these uncertain parameters in our model. Randomness and fuzziness are the two main types of uncertainty. Randomness is originated from

random (chance) nature of data. In such case, probability distributions (either discrete or continuous) can be estimated by using available sufficient historical data. Moreover, this type of uncertainty can be modeled through stochastic or robust programming approaches whether the random distributional information is available or not. Besides, stochastic programming approach is preferred only if an action is repeated several times over the planning horizon [Tofighi, Torabi and Mansouri, 2016]. However, these conditions do not hold in some cases like disasters in which the shortage of historical data and no repetition of a disaster occurrence during the planning horizon withhold us from modeling uncertain parameters as random data. In such occasions, we encounter imprecise parameters in the sense that we have no knowledge about their precise values. Indeed, it implies the epistemic uncertainty (an inherent impreciseness) in these parameters [Kabak and Ülengin, 2011] for which it is almost impossible to guess the probability distributions. In this situation, using fuzzy concept, reasonable estimations for these epistemic uncertain parameters will be provided based on the field experts' professional opinions. Thus, as a complement to the probability theory, we can formulate these parameters via the possibility theory. To this end, we first adopt a possibility distribution (i.e. trapezoidal or triangular fuzzy numbers) for each imprecise parameter, then an appropriate fuzzy-stochastic programming approach is applied to cope with the parameters epistemic uncertainty [Torabi and Hassini, 2008].

In this paper, we devise a hybrid uncertainty programming approach based on two-stage stochastic programming and fuzzy programming to handle inherent random and epistemic uncertainties in critical input data while designing a BSC network for disaster relief.

The reminder of the paper is classified into 7 sections. The related literature to disaster management and BSCs as well as BSC in disasters is reviewed in Section 2. Section 3 is dedicated to problem definition and model formulation. The combination of the expected value and the chance constrained programming is developed in Section 4 to solve the proposed

model. In Section 5, we apply a real case study to evaluate the efficiency and applicability of the proposed model, and the corresponding results are reported in Section 6. Finally, the conclusion remarks and possible future research directions comprise Section 7.

2. A Review of Related Literature

In this section, we first briefly review the related papers to blood supply chain network design. Furthermore, Papers on disaster management are then reviewed and BSC in disasters is investigated by the relevant papers at the end.

The study of BSC management started in 1960s. According to the related surveys, one developed by Beliën, and Forcé [Beliën and Forcé, 2012] and another by Osorio, Brailsford and Smith [Osorio, Brailsford and Smith, 2015], papers on this field of interest can be classified into diverse ranges based on different criteria such as type of blood products, type of problems and the decision levels, solution methods and practical implementation. In an effort, an optimization model for donors' allocation to blood centers was proposed by Pierskalla and Roach [Pierskalla and Roach, 1972] by which the optimal numbers and location of blood centers as well as the coordination between supply and demand points are determined. In another effort, a bi-objective integer mathematical model for blood bank location-allocation problem in the Turkish Red Crescent Society was outlined by Şahin, Süral and Meral [Şahin, Süral and Meral, 2007]. The objective functions aim at minimizing the weighted traveled distance and the number of blood terminals as well as maximizing the covered population. Nagurney and Masoumi [Nagurney and Masoumi, 2012] presented an optimization bi-objective mathematical model including the location of collection facilities, laboratories and distribution centers to obtain the optimal allocation while minimizing the total supply risk and costs including operating cost as well as depot penalty and shortage costs over a single-period planning horizon. Arvan, Tavakkoli-Moghaddam and Abdollahi [Arvan, Tavakkoli-Moghaddam and Abdollahi, 2015] worked on a bi-objective model to design the

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BSC network considering laboratories, blood bank centers, hospitals and donation zones. The objectives were considered as minimizing operating and transportation costs as well as blood products expiration. They applied ε -constraint approach to solve the proposed model in which all parameters are considered to be deterministic. In another work, Zahiri et al. [Zahiri et al., 2015] developed an integer programming model for blood collection management under uncertainty. They applied a fuzzy-robust approach, and implemented a case study of Babol. The required decisions were made in two phases, such that the location of mobile and permanent blood facilities was determined in strategic phase, and the allocation of donors was then decided in tactical phase.

Disaster management totally consists of four stages including mitigation, preparedness, response and recovery [Sheu, 2007]. Some papers have considered the problem as a two-stage model due to uncertainty in demand. Decisions are normally made deterministically at the first stage and the results are transferred to the next one. Huang, Smilowitz and Balcik [Huang, Smilowitz and Balcik, 2012] studied a two-stage network design mathematical model for disaster preparedness and response phases. Demand and vehicles capacities are taken into account as stochastic parameters. At the first stage, the capacity and location of each facility besides relief items supplies are determined, and the quantity of satisfied demand at each demand zone as well as shortage level in each facility is then specified at the second stage. The problem has been formulated as a single-objective model while minimizing the establishment cost of facilities, relief items supply and shortage costs. A mathematical model was analyzed by Noyan [Noyan, 2012] to specify the location and inventory level of relief distribution centers in mitigation phase. Demand and supply of relief items as well as the capacity of facilities are considered as imprecise parameters. Besides, the network costs are to be minimized through the single-objective model. A robust optimization model for earthquake response phase was presented by Najafi, Eshghi and Dullaert [Najafi,

Eshghi and Dullaert, 2013]. They worked on a multi-objective model to minimize unsatisfied demand, the number of disregarded injured and vehicles used, in which demand and supply of relief items besides the number of injured are inexplicit parameters. They also applied a related case study to the problem in Iran to illustrate the applicability of their model. Chakravarty [Chakravarty, 2014] proposed a two-stage model for preparedness and response phases to decide on time and quality of relief distribution in disasters. In this model, response time and excess demands are to be minimized as the objectives, in which the disaster severity, cost structure and demand of relief resources are regarded stochastic. The inventory level in each supply point is specified at the first stage, and the quantity of supply and response time are then determined at the second stage. Tofighi, Torabi and Mansouri [Tofighi, Torabi and Mansouri, 2016] worked on a two-echelon humanitarian logistics network design for earthquake preparation in Tehran while dealing with both pre- and post-disaster logistical problems. They proposed a novel mixed possibilistic two-stage scenario-based stochastic programming approach to cope with the epistemic uncertainty of the problem. The locations of facilities including central warehouses and local distribution centers besides the amount of inventory prepositioned for relief supplies are specified in the first stage with respect to the uncertainty in supply and demand data along with the transportation routes availability while an earthquake occurs. Planning for relief distribution is provided during the second stage under different disaster scenarios to minimize total delivery time, total cost of inventory surplus, the maximum delivery time for critical relief items and shortage cost resulting from unsatisfied demand. They applied the weighted augmented ε -constraint method to solve the proposed multi-objective model and developed a tailored differential evolution (DE) algorithm to obtain efficient solutions within a reasonable length of time.

In an effort, a dynamic multi-period model was developed by Sha and Huang [Sha and Huang, 2012] for blood supply in Beijing after earthquake

occurrence. The model was applied to optimize the location-allocation of temporary blood facilities by minimizing the total costs of facilities establishment and repositioning besides operating and shortage costs over the planning horizon, regardless to uncertainty in blood supply. In another work, an MILP stochastic model for BSC in emergency condition was proposed by Jokar and Hosseini-Motlagh [Jokar and Hosseini-Motlagh, 2015]. Their model aimed to optimize the network total cost including blood wastage and shortage costs. They considered the capacity of mobile blood facilities as a variable, and determined the optimal service area and number of blood facilities with respect to different disaster scenarios. Their results proved that changes in the capacity of mobile blood facilities can affect the optimal number of mobile as well as permanent facilities. A bi-objective model was proposed by Fahimnia et al. [Fahimnia et al., 2015] to determine the optimal way of blood distribution to hospitals and minimize the average delivery time from local and regional blood centers to hospitals. They applied ε -constraint method to formulate the proposed model, and solved it using Lagrangian relaxation. Table 1 classifies the reviewed papers according to their special features.

Since only a few papers have studied blood supply chain network design in disasters, we intend to investigate the mentioned network under uncertainty by taking the imprecise parameters into account.

This paper contributes to the area by: 1) Employing a fuzzy two-stage stochastic programming approach to formulate the model in disaster condition and a credibility-based chance-constrained programming method to solve the proposed fuzzy-stochastic model. 2) Considering disruption probability feature for local and regional blood facilities and each route between facilities. 3) Developing a BSC network that synthesizes blood donors and mobile blood facilities as well as local and regional blood centers and demand zones. 4) Applying a real case study to evaluate the performance and efficiency of the proposed model.

3. Problem Description and Model Formulation

The considered supply chain consists of blood donors, mobile and local blood facilities and regional blood centers as well as demand zones such as healthcare centers and hospitals. Blood can be donated at either a mobile or a local blood facility except for the regional blood centers. Each mobile blood facility might move from one location to another in each period. The blood units collected by mobile facilities is transferred to either local or regional blood centers. All transfusion services are provided by regional blood centers, but not by local ones. In this regard, φ percent of the processes of a local center must be referred to a pre-determined regional blood center defined as the referral rate. Finally, the local blood facilities along with the regional blood centers account for delivering blood to the specified demand zones. Additionally, each route has certain reliability to be working, and the disruption probability of each facility has been taken into account. A schematic plan of the concerned BSC is depicted in Figure 1.

The problem is formulated as a two-stage fuzzy-stochastic model applying a number of disaster scenarios to design a BSC network in disasters in which all parameters are considered to be imprecise.

In a two-stage programming approach, two categories of decision variables could be defined [Birge and Louveaux, 2011]. The first category belongs to the first-stage decision variables and the second one is associated with the second-stage decision variables. The first category variables do not rely on the disaster scenarios and can be determined before a scenario realization, while the second-stage decision variables are scenario-dependent and thus are made after a scenario is realized. In the considered model, the value of decision variable Y , which represents the number of mobile blood facilities, would be taken in the first stage since it is a scenario-independent variable. On the other hand, the rest of decision variables are specified in the second stage as their values are reliant on the disaster scenarios.

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Table 1. Classification of the reviewed papers

Reference	Hierarchical level		Disaster condition	Modelling approach	Uncertainty		Solution method		Time period		Case study
	Supply chain level	Collection echelon			Fuzzy	Stochastic/Robust	exact	(Meta) heuristic	Single-period	Multi-period	
Şahin, Süral and Meral (2007)	✓		No	Mixed integer linear programming			✓		✓		No
Nagurney and Masoumi (2012)	✓		No	Linear programming			✓		✓		No
Huang, Smilowitz and Balcik, (2012)	✓		Yes	Mixed integer linear programming				✓	✓		No
Noyan (2012)			Yes	Risk-averse two-stage stochastic programming		✓	✓		✓		Yes
Sha and Huang (2012)		✓	Yes	Mixed integer non-linear programming			✓			✓	Yes
Najafi, Eshghi and Dullaert (2013)	✓		Yes	Robust programming		✓		✓		✓	Yes
Chakravarty (2014)			Yes	Two-stage stochastic programming		✓	✓		✓		No
Jokar and Hosseini-Motlagh (2015)	✓			Mixed integer linear stochastic programming		✓	✓		✓		No
Arvan, Tavakkoli-Moghaddam and Abdollahi, (2015)	✓		No	Mixed integer non-linear programming			✓		✓		No
Zahiri et al. (2015)		✓	No	Mixed integer non-linear programming / Robust possibilistic	✓	✓	✓			✓	Yes
Fahimnia et al. (2015)	✓		Yes	Two-stage stochastic programming		✓	✓			✓	No
Tofghi, Torabi and Mansouri, (2016)	✓		Yes	Mixed possibilistic two-stage scenario-based stochastic programming	✓		✓			✓	No
Our paper	✓		Yes	Mixed integer linear programming	✓		✓			✓	Yes

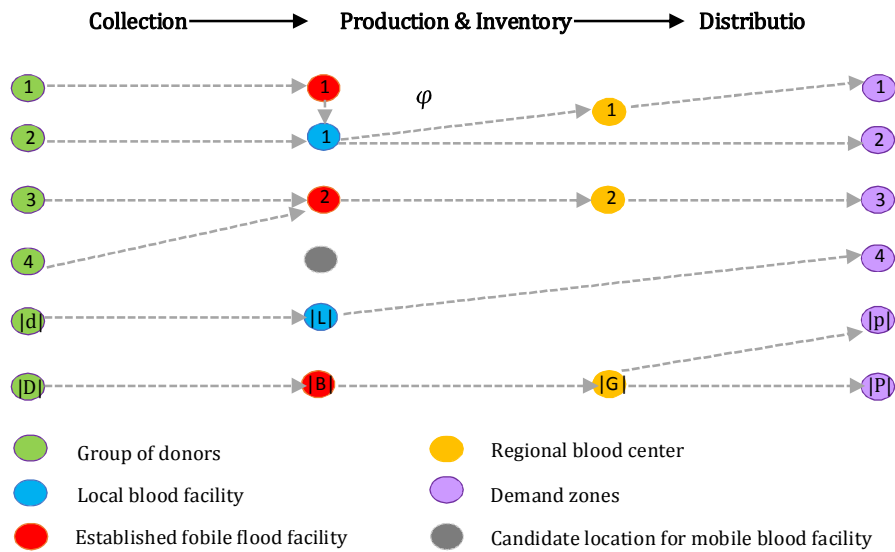


Figure 1. An overview of the concerned blood

The objective function aims to minimize the total cost of supply chain including establishing and moving costs of each mobile blood facility and operating cost at both local blood facilities and regional blood centers as well as inventory holding cost and transportation cost. The following values are obtained through solving the proposed model:

1. The optimal number and location of mobile blood facilities based on different scenarios.
2. The number of blood units collected by each facility under each scenario in each period.

3. The number of blood units transported from mobile facilities to local and regional blood centers based on each scenario in each period.

4. The number of blood units shipped from local blood centers to regional blood centers based on each scenario in each period.

5. The level of blood inventory at both local and regional blood centers based on each scenario at the end of each period.

6. The amount of blood shipped from local and regional blood centers to healthcare centers and hospitals based on each scenario in each period.

3.1. Model Sets, Parameters and Decision Variables

The following components are applied to formulate the proposed fuzzy-stochastic model.

Indices:

D	The set, assigned to the d^{th} donor group
B	The set, assigned to candidate locations for b^{th} mobile blood facility
L	The set, assigned to l^{th} local blood center
G	The set, assigned to g^{th} regional blood center
P	The set, assigned to p^{th} hospital or healthcare center
S	The set, assigned to s^{th} disaster scenario
T	The set, assigned to t^{th} time period

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Technical parameters:

de_{pts}	Demand of blood at p^{th} hospital in period t under s^{th} scenario
V	Capacity of each mobile blood facility
v'_l	Storage capacity of l^{th} local blood center
v''_g	Storage capacity of g^{th} regional blood center
d_{ds}	Maximum quantity of blood donated by d^{th} group of donors under s^{th} scenario
r_{db}	Distance between d^{th} donor group and b^{th} mobile blood facility
r'_{dl}	Distance between d^{th} donor group and l^{th} local blood center
R	Coverage radius for each blood facility
p_s	Probability of s^{th} scenario occurrence
α_{bl}	Disruption probability of each route from b^{th} mobile blood facility to l^{th} local blood center
γ_{lg}	Disruption probability of each route from l^{th} local blood center to g^{th} regional blood center
μ_{bg}	Disruption probability of each route from b^{th} location to g^{th} regional blood center
γ'_{gp}	Disruption probability of each route from g^{th} regional blood center to p^{th} hospital
α'_{lp}	Disruption probability of each route from l^{th} local blood center to p^{th} hospital
ρ_l	Disruption probability of l^{th} local blood center
ρ'_g	Disruption probability of g^{th} regional blood center
φ	The rate at which services of local blood centers are directed to regional blood centers (called referral rate)
M	An arbitrary large value

Cost parameters:

fc	Establishment fixed cost of each mobile blood facility
mv^s_{jbt}	Cost of each mobile blood facility moving from location j to location b in period t under s^{th} scenario
oc^s_{bat}	Operating cost per blood unit at b^{th} mobile blood facility from d^{th} group of donors in period t under s^{th} scenario
oc'^s_{lt}	Operating cost per blood unit at l^{th} local blood center in period t under s^{th} scenario
oc''^s_{gt}	Operating cost per blood unit at g^{th} regional blood center in period t under s^{th} scenario
tc^s_{blt}	Transportation cost per blood unit from b^{th} mobile blood facility to l^{th} local blood center in period t under s^{th} scenario
tb^s_{bgt}	Transportation cost per blood unit from b^{th} mobile blood facility to g^{th} regional blood center in period t under s^{th} scenario

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td_{lgt}^s	Transportation cost per blood unit from l^{th} local blood center to g^{th} regional blood center in period t under s^{th} scenario
te_{lpt}^s	Transportation cost per blood unit from l^{th} local blood center to p^{th} hospital in period t under s^{th} scenario
tf_{gpt}^s	Transportation cost per blood unit from g^{th} regional blood center to p^{th} hospital in period t under s^{th} scenario
hc_{lt}	Holding cost per blood unit at l^{th} local blood center in period t
hc'_{gt}	Holding cost per blood unit at g^{th} regional blood center in period t

Integer decision variables:

Y	The number of mobile blood facilities
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Continuous decision variables:

qc_{bdl}^{ts}	The amount of blood collected at b^{th} mobile blood facility from d^{th} donor in period t to be delivered to l^{th} local blood center under s^{th} scenario
qb_{bag}^{ts}	The amount of blood collected at b^{th} mobile blood facility from d^{th} donor in period t to be delivered to g^{th} regional blood center under s^{th} scenario
qd_{lat}^s	The amount of blood collected at l^{th} local blood center from d^{th} donor in period t under s^{th} scenario
qe_{lgt}^s	The amount of blood delivered from l^{th} local blood center to g^{th} regional blood center in period t under s^{th} scenario
qa_{lpt}^s	The amount of blood delivered from l^{th} local blood center to hospital p in period t under s^{th} scenario
qf_{gpt}^s	The amount of blood delivered from g^{th} regional blood center to hospital p in period t under s^{th} scenario
I_{lts}	The amount of blood inventory in l^{th} local blood center at the end of period t under s^{th} scenario
I'_{gts}	The amount of blood inventory in g^{th} regional blood center at the end of period t under s^{th} scenario

Binary decision variables:

X_{jbt}^s	Is equal to 1 if a blood facility is located at j^{th} site in period $t-1$, and moves to site b^{th} in period t under s^{th} scenario; 0, otherwise
W_{abt}^s	Is equal to 1 if d^{th} group of donors is assigned to b^{th} mobile blood facility in period t under s^{th} scenario; 0, otherwise
U_{dlt}^s	Is equal to 1 if d^{th} group of donors is assigned to l^{th} local blood center in period t under s^{th} scenario; 0, otherwise
U'_{lgt}^s	Is equal to 1 if l^{th} local blood center is allocated to g^{th} regional blood center in period t under s^{th} scenario; 0 otherwise

3.2. Objective function:

$$\begin{aligned}
 \text{Minimize } Z = & fc * Y + \sum_s p_s \sum_b \sum_j \sum_t m v_{jbt}^s X_{jbt}^s \\
 & + \sum_s p_s \sum_d \sum_b \sum_l \sum_t \rho_l \alpha_{bl} oc_{bdt}^s qc_{bdl}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_g \sum_t \rho'_g \mu_{bg} oc_{bdt}^s qb_{bdg}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_l \sum_t \rho_l \alpha_{bl} oc'_{lt}{}^s qc_{bdl}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_l \sum_t \rho_l \alpha_{bl} oc_{bdt}^s qc_{bdl}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_g \sum_t \rho'_g \gamma_{lg} oc''_{gt}{}^s qb_{bdg}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_l \sum_t \rho_l oc'_{lt}{}^s \alpha_{bl} qc_{bdl}^{ts} \\
 & + \sum_s p_s \sum_d \sum_j \sum_l \sum_t \rho_l oc'_{lt}{}^s qd_{ldt}^s + \sum_s p_s \sum_d \sum_b \sum_g \sum_t \rho'_g \mu_{bg} oc''_{gt}{}^s qb_{bdg}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_g \sum_t \rho_l \rho'_g \gamma_{lg} oc''_{gt}{}^s qe_{lgt}^s \\
 & + \sum_s p_s \sum_d \sum_b \sum_l \sum_t \rho_l \alpha_{bl} tc_{blt}^s qc_{bdl}^{ts} \\
 & + \sum_s p_s \sum_d \sum_b \sum_g \sum_t \rho'_g \mu_{bg} tb_{bgt}^s qb_{bdg}^{ts} \\
 & + \sum_s p_s \sum_l \sum_g \sum_t \rho_l \rho'_g \gamma_{lg} td_{lgt}^s qe_{lgt}^s \\
 & + \sum_s p_s \sum_l \sum_p \sum_t \rho_l \alpha'_{lp} te_{lpt}^s qa_{lpt}^s \\
 & + \sum_s p_s \sum_g \sum_p \sum_t \rho'_g \gamma'_{gp} tf_{gpt}^s qf_{gpt}^s + \sum_s p_s \sum_l \sum_t hc_{lt} I_{lts} \\
 & + \sum_s p_s \sum_p \sum_t hc'_{gt} I'_{gts}
 \end{aligned}
 \tag{1}$$

The present objective function minimizes the total cost of system, which comprises establishment cost of mobile facilities, total moving cost of mobile blood facilities, total operating cost of blood facilities considering the

rate of facilities disruption, total transportation cost between blood facilities and demand zones regarding relevant routes reliability and total inventory cost at local blood facilities as well as demand zones.

3.3. Model constraints:

$$\sum_b \sum_j X_{jbt}^s \leq Y \quad \forall t \in T, \forall s \in S \quad (2)$$

$$\sum_j X_{jbt}^s \leq 1 \quad \forall b \in B, \forall t \in T, \forall s \in S \quad (3)$$

$$\sum_j X_{jbt}^s \leq \sum_j X_{bjt-1}^s \quad \forall b \in B, \forall t \in T, \forall s \in S \quad (4)$$

$$W_{abt}^s \leq \sum_j X_{jbt}^s \quad \forall d \in D, \forall b \in B, \forall t \in T, \forall s \in S \quad (5)$$

$$\sum_b \sum_l \sum_t qc_{bdl}^{ts} + \sum_b \sum_g \sum_t qb_{bdg}^{ts} + \sum_l \sum_t qd_{ldt}^s \leq do_{ds} \quad \forall d \in D, \forall s \in S \quad (6)$$

$$\sum_d \sum_l qc_{bdl}^{ts} + \sum_d \sum_g qb_{bdg}^{ts} \leq V \quad \forall b \in B, \forall t \in T, \forall s \in S \quad (7)$$

$$qc_{bdl}^{ts} \leq M W_{abt}^s \quad \forall d \in D, \forall b \in B, \forall l \in L, \forall t \in T, \forall s \in S \quad (8)$$

$$qb_{bdg}^{ts} \leq M W_{abt}^s \quad \forall d \in D, \forall b \in B, \forall g \in G, \forall t \in T, \forall s \in S \quad (9)$$

$$qd_{ldt}^s \leq M U_{dlt}^s \quad \forall d \in D, \forall l \in L, \forall t \in T, \forall s \in S \quad (10)$$

$$r_{db} W_{abt}^s \leq R \quad \forall d \in D, \forall b \in B, \forall t \in T, \forall s \in S \quad (11)$$

$$r'_{dl} U_{dlt}^s \leq R \quad \forall d \in D, \forall l \in L, \forall t \in T, \forall s \in S \quad (12)$$

$$\sum_g U_{lgt}^s \leq 1 \quad \forall l \in L, \forall t \in T, \forall s \in S \quad (13)$$

$$qe_{lgt}^s \leq M U_{lgt}^s \quad \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \quad (14)$$

$$qe_{lgt}^s \leq \varphi \left(\sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{ldt}^s \right) \quad \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \quad (15)$$

$$I_{l,t-1,s} + (1 - \varphi) \left(\sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{ldt}^s \right) - \sum_p qa_{lpt}^s = I_{lts} \quad \forall l \in L, \forall t \in T, \forall s \in S \quad (16)$$

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$$I'_{g,t-1,s} + \left(\sum_d \sum_b qb_{bdg}^{ts} + \sum_l qe_{lgt}^s \right) - \sum_p qf_{gpt}^s = I'_{gts} \quad \forall g \in G, \forall t \in T, \forall s \in S \quad (17)$$

$$\sum_l te_{lpt}^s + \sum_g ta_{gpt}^s = de_{pts} \quad \forall p \in P, \forall t \in T, \forall s \in S \quad (18)$$

$$I_{lts} \leq v_l' \quad \forall l \in L, \forall t \in T, \forall s \in S \quad (19)$$

$$I'_{gts} \leq v_g'' \quad \forall g \in G, \forall t \in T, \forall s \in S \quad (20)$$

$$W_{dbt}^s, U_{dlt}^s, U'_{lgt}^s \in \{0,1\} \quad \forall d \in D, \forall b \in B, \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \quad (21)$$

$$qc_{bal}^{ts}, qb_{bdg}^{ts}, qd_{dlt}^s, qe_{lgt}^s, qa_{lpt}^s, qf_{gpt}^s, I_{lts}, I'_{gts} \geq 0 \quad \forall b \in B, \forall d \in D, \forall l \in L, \forall g \in G, \forall p \in P, \forall t \in T, \forall s \in S \quad (22)$$

The total number of mobile facilities in each period must be at most equal to or less than the number of established blood facilities, represented by constraint (2). No more than one mobile facility will be established at each location, ensured by constraint (3). Constraint (4) guarantees that no mobile facility can move to another location in which any facilities have been established before. The donors must merely be assigned to open facilities, stated by constraint (5). Constraint (6) denotes the maximum allowable amount of blood, collected from each group of donors. Constraint (7) indicates the total amount of blood, collected by mobile facilities, must not exceed their capacities. Constraints (8) and (9) guarantee that no mobile facility can transport the donated blood if it is not assigned to the corresponding group of donors. Constraint (10) ensures that blood cannot be collected by local blood facilities from donors' groups not assigned to those facilities. Constraints (11) and (12) denote that donors would be only served by mobile blood facilities and local blood centers within their service area. Each local blood facility can only be assigned to one regional blood center, ensured by constraint (13). Constraint (14) makes sure that blood cannot be transported from a local blood facility to a regional blood center to which it is not assigned.

Constraint (15) expresses that a φ -percent rate of blood transfusion services is directed from a local blood facility to a regional blood center. Constraints (16) and (17) are known as blood inventory balance constraints at local blood facilities and regional blood centers, respectively. Blood demand in hospitals must be satisfied under each scenario s , ensured by constraint (18). The storage capacities of local blood facilities and regional blood centers are denoted by constraints (19) and (20), respectively. Constraints (21) and (22) define the type of decision variables.

4. Fuzzy Chance - Constrained Programming Model Based on the Credibility Theory

The chance of fuzzy events was introduced in the form of possibility measure by Zadeh [Zadeh, 1978]. Later on, the dual part of possibility measure called necessity measure was defined. However, neither possibility measure nor necessity measure is self-dual. Thus, Liu and Liu [Liu and Liu, 2002] presented a new self-dual measure in the context of credibility measure, which is the average value of the two previous measures; i.e., possibility and necessity measures [Li and Ralescu, 2009].

Since chance constrained programming method enables the decision maker satisfy the chance constraints in at least the confidence level α , and is applicable for different types of fuzzy numbers including triangular as well as trapezoidal ones, the problem is then dealt with by applying a credibility-based chance constrained programming method as an efficient fuzzy approach using the credibility measure regarding its self-duality feature and the expected value of fuzzy numbers [Nadizadeh and Hosseini Nasab, 2014; Majidi, et al. 2017]. According to the self-duality property, a fuzzy event would hold if its credibility is 1, however, it fails if its credibility is 0.

Consider $\tilde{\varepsilon}$ as a fuzzy variable and assume r is a real number. The credibility measure is then defined as equation (23) [Liu and Liu, 2002].

Additionally, constraint (23) is equal to the relationship (24) because $Pos\{\tilde{\varepsilon} \leq r\} = sup \mu(x)_{x \leq r}$ and $Nec\{\tilde{\varepsilon} \leq r\} = 1 - sup \mu(x)_{x > r}$.

Furthermore, the expected value of $\tilde{\varepsilon}$ could be defined as equation (25) according to the credibility measure [Liu and Liu, 2002].

$$Cr\{\tilde{\varepsilon} \leq r\} = \frac{1}{2} (sup \mu(x)_{x \leq r} + 1 - sup \mu(x)_{x > r}) \quad (23)$$

$$Cr\{\tilde{\varepsilon} \leq r\} = \frac{1}{2} (pos\{\tilde{\varepsilon} \leq r\} + nec\{\tilde{\varepsilon} \leq r\}) \quad (24)$$

$$E[\tilde{\varepsilon}] = \int_0^\infty cr\{\tilde{\varepsilon} \geq r\} dr - \int_{-\infty}^0 cr\{\tilde{\varepsilon} \leq r\} dr \quad (25)$$

Let $\tilde{\varepsilon}$ be a trapezoidal fuzzy number such that $\tilde{\varepsilon} = (\varepsilon_{(1)}, \varepsilon_{(2)}, \varepsilon_{(3)}, \varepsilon_{(4)})$. Thus, the corresponding credibility measures and the expected value of $\tilde{\varepsilon}$ are determined by the following relationships:

$$Cr\{\tilde{\varepsilon} \leq r\} \geq \alpha \iff r \geq (2 - 2\alpha)\varepsilon_{(3)} + (2\alpha - 1)\varepsilon_{(4)} \quad \alpha > 0.5 \quad (28.1)$$

$$Cr\{\tilde{\varepsilon} \geq r\} \geq \alpha \iff r \leq (2\alpha - 1)\varepsilon_{(1)} + (2 - 2\alpha)\varepsilon_{(2)} \quad \alpha > 0.5 \quad (28.2)$$

$$Cr\{\tilde{\varepsilon} \leq r\} = \begin{cases} 0 & r \in (-\infty, \varepsilon_{(1)}) \\ \frac{r - \varepsilon_{(1)}}{2(\varepsilon_{(2)} - \varepsilon_{(1)})} & r \in (\varepsilon_{(1)}, \varepsilon_{(2)}) \\ \frac{1}{2} & r \in (\varepsilon_{(2)}, \varepsilon_{(3)}) \\ \frac{r - 2\varepsilon_{(3)} + \varepsilon_{(4)}}{2(\varepsilon_{(4)} - \varepsilon_{(3)})} & r \in (\varepsilon_{(3)}, \varepsilon_{(4)}) \\ 1 & r \in (\varepsilon_{(4)}, +\infty) \end{cases} \quad (26.1)$$

$$Cr\{\tilde{\varepsilon} \geq r\} = \begin{cases} 1 & r \in (-\infty, \varepsilon_{(1)}) \\ \frac{2\varepsilon_{(2)} - \varepsilon_{(1)} - r}{2(\varepsilon_{(2)} - \varepsilon_{(1)})} & r \in (\varepsilon_{(1)}, \varepsilon_{(2)}) \\ \frac{1}{2} & r \in (\varepsilon_{(2)}, \varepsilon_{(3)}) \\ \frac{\varepsilon_{(4)} - r}{2(\varepsilon_{(4)} - \varepsilon_{(3)})} & r \in (\varepsilon_{(3)}, \varepsilon_{(4)}) \\ 0 & r \in (\varepsilon_{(4)}, +\infty) \end{cases} \quad (26.2)$$

$$EV(\tilde{\varepsilon}) = \frac{\varepsilon_{(1)} + \varepsilon_{(2)} + \varepsilon_{(3)} + \varepsilon_{(4)}}{4} \quad (27)$$

According to above-mentioned relationships, the credibility measure of $\tilde{\varepsilon}$ as a trapezoidal fuzzy number could be defined as follows [Zhu and Zhang, 2009]:

To solve the proposed fuzzy model, we have applied the combination of the expected value and the chance constrained programming. The first method is used to formulate the objective function, while the second one is applied to model the chance constraints including imprecise parameters. The hybrid method (i.e., EV and CCP) benefits from the advantages such as simplicity by not increasing the number of constraints. It also does not require confidence level for objective functions nor the ideal solution.

4.1. The Equivalent Auxiliary Crisp Model

Considering the relationships (26.1), (26.2) and (27), the above model can be transformed to the equivalent crisp one as below if the chance

constraints are satisfied with minimum confidence level 0.5 (i.e., $\alpha > 0.5$).

$$\begin{aligned}
 & \text{Minimize } E[Z] \\
 & = \left(\frac{fC_{(1)} + fC_{(2)} + fC_{(3)} + fC_{(4)}}{4} \right) Y \\
 & + \sum_j \sum_b \sum_t \sum_s p_s \left(\frac{mv_{jbt(1)}^s + mv_{jbt(2)}^s + mv_{jbt(3)}^s + mv_{jbt(4)}^s}{4} \right) X_{jbt}^s \\
 & + \sum_d \sum_b \sum_l \sum_t \sum_s p_s \left(\frac{oc_{bdt(1)}^s + oc_{bdt(2)}^s + oc_{bdt(3)}^s + oc_{bdt(4)}^s}{4} \right) \left(\frac{\alpha_{bl(1)} + \alpha_{bl(2)} + \alpha_{bl(3)} + \alpha_{bl(4)}}{4} \right) \\
 & * \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) qc_{bdal}^{ts} \\
 & + \sum_d \sum_b \sum_g \sum_t \sum_s p_s \left(\frac{oc_{bdt(1)}^s + oc_{bdt(2)}^s + oc_{bdt(3)}^s + oc_{bdt(4)}^s}{4} \right) \left(\frac{\mu_{bg(1)} + \mu_{bg(2)} + \mu_{bg(3)} + \mu_{bg(4)}}{4} \right) \\
 & * \left(\frac{\rho'_{g(1)} + \rho'_{g(2)} + \rho'_{g(3)} + \rho'_{g(4)}}{4} \right) qb_{bdg}^{ts} \\
 & + \sum_d \sum_b \sum_l \sum_t \sum_s p_s \left(\frac{oc'_{lt(1)}^s + oc'_{lt(2)}^s + oc'_{lt(3)}^s + oc'_{lt(4)}^s}{4} \right) \left(\frac{\alpha_{bl(1)} + \alpha_{bl(2)} + \alpha_{bl(3)} + \alpha_{bl(4)}}{4} \right) \\
 & * \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) qc_{bdal}^{ts} \\
 & + \sum_j \sum_l \sum_t \sum_s p_s \left(\frac{oc'_{lt(1)}^s + oc'_{lt(2)}^s + oc'_{lt(3)}^s + oc'_{lt(4)}^s}{4} \right) \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) qd_{idt}^s \\
 & + \sum_d \sum_b \sum_g \sum_t \sum_s p_s \left(\frac{oc''_{gt(1)}^s + oc''_{gt(2)}^s + oc''_{gt(3)}^s + oc''_{gt(4)}^s}{4} \right) \left(\frac{\mu_{bg(1)} + \mu_{bg(2)} + \mu_{bg(3)} + \mu_{bg(4)}}{4} \right) \\
 & * \left(\frac{\rho'_{g(1)} + \rho'_{g(2)} + \rho'_{g(3)} + \rho'_{g(4)}}{4} \right) qb_{bdg}^{ts} \\
 & + \sum_d \sum_b \sum_l \sum_t \sum_s p_s \left(\frac{tc_{blt(1)}^s + tc_{blt(2)}^s + tc_{blt(3)}^s + tc_{blt(4)}^s}{4} \right) \left(\frac{\alpha_{bl(1)} + \alpha_{bl(2)} + \alpha_{bl(3)} + \alpha_{bl(4)}}{4} \right) \\
 & * \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) qc_{bdal}^{ts} \\
 & + \sum_d \sum_b \sum_g \sum_t \sum_s p_s \left(\frac{tb_{bgt(1)}^s + tb_{bgt(2)}^s + tb_{bgt(3)}^s + tb_{bgt(4)}^s}{4} \right) \left(\frac{\mu_{bg(1)} + \mu_{bg(2)} + \mu_{bg(3)} + \mu_{bg(4)}}{4} \right) \\
 & * \left(\frac{\rho'_{g(1)} + \rho'_{g(2)} + \rho'_{g(3)} + \rho'_{g(4)}}{4} \right) qb_{bdg}^{ts}
 \end{aligned}$$

$$\begin{aligned}
 & + \sum_l \sum_g \sum_t \sum_s p_s \left(\frac{td_{lgt(1)}^s + td_{lgt(2)}^s + td_{lgt(3)}^s + td_{lgt(4)}^s}{4} \right) \left(\frac{\gamma_{lg(1)} + \gamma_{lg(2)} + \gamma_{lg(3)} + \gamma_{lg(4)}}{4} \right) \\
 & * \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) \left(\frac{\rho'_{g(1)} + \rho'_{g(2)} + \rho'_{g(3)} + \rho'_{g(4)}}{4} \right) qe_{lgt}^s \\
 & + \sum_l \sum_p \sum_t \sum_s p_s \left(\frac{te_{lpts(1)} + te_{lpts(2)} + te_{lpts(3)} + te_{lpts(4)}}{4} \right) \left(\frac{\alpha'_{lp(1)} + \alpha'_{lp(2)} + \alpha'_{lp(3)} + \alpha'_{lp(4)}}{4} \right) \\
 & * \left(\frac{\rho_{l(1)} + \rho_{l(2)} + \rho_{l(3)} + \rho_{l(4)}}{4} \right) qe_{lgt}^s \\
 & + \sum_g \sum_p \sum_t \sum_s p_s \left(\frac{tf_{gpt(1)}^s + tf_{gpt(2)}^s + tf_{gpt(3)}^s + tf_{gpt(4)}^s}{4} \right) * \left(\frac{\gamma'_{gp(1)} + \gamma'_{gp(2)} + \gamma'_{gp(3)} + \gamma'_{gp(4)}}{4} \right) \\
 & * \left(\frac{\rho'_{g(1)} + \rho'_{g(2)} + \rho'_{g(3)} + \rho'_{g(4)}}{4} \right) qf_{gpt}^s \\
 & + \sum_l \sum_t \sum_s p_s \left(\frac{hc_{lt(1)} + hc_{lt(2)} + hc_{lt(3)} + hc_{lt(4)}}{4} \right) I_{lts} \\
 & + \sum_p \sum_t \sum_s p_s \left(\frac{hc'_{gt(1)} + hc'_{gt(2)} + hc'_{gt(3)} + hc'_{gt(4)}}{4} \right) I'_{gts}
 \end{aligned} \tag{29}$$

Subject to:

$$\sum_b \sum_j X_{jbt}^s \leq Y \quad \forall t \in T, \forall s \in S \tag{30}$$

$$\sum_j X_{jbt}^s \leq 1 \quad \forall b \in B, \forall t \in T, \forall s \in S \tag{31}$$

$$\sum_j X_{jbt}^s \leq \sum_j X_{bjt-1}^s \quad \forall b \in B, \forall t \in T, \forall s \in S \tag{32}$$

$$W_{dbt}^s \leq \sum_j X_{jbt}^s \quad \forall d \in D, \forall b \in B, \forall t \in T, \forall s \in S \tag{33}$$

$$\sum_b \sum_l \sum_t qc_{bdl}^{ts} + \sum_b \sum_g \sum_t qb_{bdg}^{ts} + \sum_l \sum_t qe_{lat}^s \leq (2\alpha - 1)do_{ds(1)} + (2 - 2\alpha)do_{ds(2)} \tag{34}$$

) $\forall d \in D, \forall s \in S$

$$\sum_d \sum_l qc_{bdl}^{ts} + \sum_d \sum_g qb_{bdg}^{ts} \leq (2\alpha - 1)V_{(1)} + (2 - 2\alpha)V_{(2)} \tag{35}$$

) $\forall b \in B, \forall t \in T, \forall s \in S$

$$qc_{bdl}^{ts} \leq M W_{dbt}^s \quad \forall d \in D, \forall b \in B, \forall l \in L, \forall t \in T, \quad \forall s \in S \tag{36}$$

)

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$$qb_{bdg}^{ts} \leq M W_{dgt}^s \quad \forall d \in D, \forall b \in B, \forall g \in G, \forall t \in T, \quad \forall s \in S \quad (37)$$

$$qe_{idt}^s \leq M U_{dit}^s \quad \forall d \in D, \forall l \in L, \forall t \in T, \quad \forall s \in S \quad (38)$$

$$[(2 - 2\alpha)r_{ab(3)} + (2\alpha - 1)r_{ab(4)}] W_{dgt}^s \leq [(2\alpha - 1)R_{(1)} + (2 - 2\alpha)R_{(2)}] \\ \forall d \in D, \forall b \in B, \forall t \in T, \quad \forall s \in S \quad (39)$$

$$[(2 - 2\alpha)r'_{dl(3)} + (2\alpha - 1)r'_{dl(4)}] U_{dit}^s \leq [(2\alpha - 1)R_{(1)} + (2 - 2\alpha)R_{(2)}] \\ \forall d \in D, \forall l \in L, \forall t \in T, \quad \forall s \in S \quad (40)$$

$$\sum_g U_{lgt}^s \leq 1 \quad \forall l \in L, \forall t \in T, \quad \forall s \in S \quad (41)$$

$$qe_{lgt}^s \leq M U_{lgt}^s \quad \forall l \in L, \forall g \in G, \forall t \in T, \quad \forall s \in S \quad (42)$$

$$qe_{lgt}^s \leq [(2\alpha - 1)\varphi_{(1)} + (2 - 2\alpha)\varphi_{(2)}] \left(\sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{idt}^s \right) \\ \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \quad (43)$$

$$\varphi_{(3)} \left(\sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{idt}^s \right) \leq I_{l,t-1,s} - I_{lts} + \sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{idt}^s - \sum_p qa_{lpt}^s \\ \leq \varphi_{(2)} \left(\sum_d \sum_b qc_{bdl}^{ts} + \sum_d qd_{idt}^s \right) \\ \forall l \in L, \forall t \in T, \quad \forall s \in S \quad (44)$$

$$I'_{g,t-1,s} + \left(\sum_d \sum_b qb_{bdg}^{ts} + \sum_l qe_{lgt}^s \right) - \sum_p qf_{gpt}^s = I'_{gts} \quad \forall g \in G, \forall t \in T, \quad \forall s \in S \quad (45)$$

$$\sum_l qa_{lpt}^s + \sum_g qf_{gpt}^s \geq (2 - 2\alpha)de_{pts(3)} + (2\alpha - 1)de_{pts(4)}$$

$$\forall p \in P, \forall t \in T, \quad \forall s \in S \quad (46)$$

$$I_{lts} \leq (2\alpha - 1)v'_{l(1)} + (2 - 2\alpha)v'_{l(2)} \quad \forall l \in L, \forall t \in T, \quad \forall s \in S \quad (47)$$

$$I'_{gts} \leq (2\alpha - 1)v''_{g(1)} + (2 - 2\alpha)v''_{g(2)} \quad \forall g \in G, \forall t \in T, \quad \forall s \in S \quad (48)$$

$$W_{dbs}^s, U_{dts}^s, U_{lgt}^s \in \{0,1\} \quad \forall d \in D, \forall b \in B, \forall l \in L, \forall g \in G, \forall t \in T, \forall s \in S \quad (49)$$

$$\begin{aligned} q_{bdl}^{ts}, q_{bdg}^{ts}, q_{lpt}^s, \\ q_{gpt}^s, q_{lgt}^s, I_{lts}, I'_{gts}, q_{ldt}^s \geq 0 \end{aligned} \quad \forall l \in L, \quad \forall g \in G, \forall t \in T, \quad \forall s \in S \quad (50)$$

5. Case Study

Numerous natural disasters such as earthquakes occur in the world each year, which cause loss of life and leave some economic damage in its wake. Iran is among top 10 countries with natural disasters, situated on one of the most seismic earthquake belts in the world. According to the official statistics, around 18 percent of the world's destructive earthquakes belong to Iran, and populous provinces such as Tehran, the capital of Iran, will have a greater share of losses caused by earthquakes. The present case study is considered

for earthquake occurrence in district 1 of Tehran, and the geographic position of the district is depicted in Figure 2.

Many years ago, JICAⁱⁱⁱ investigated the vulnerable areas of Tehran at the request of Iran to estimate the damage and losses caused by earthquakes. According to the studies done by this group on 22 districts of Tehran and its main active faults, a brief explanation of the most likely dangerous faults and their properties is presented and the related scenario models are then outlined in Table 2.

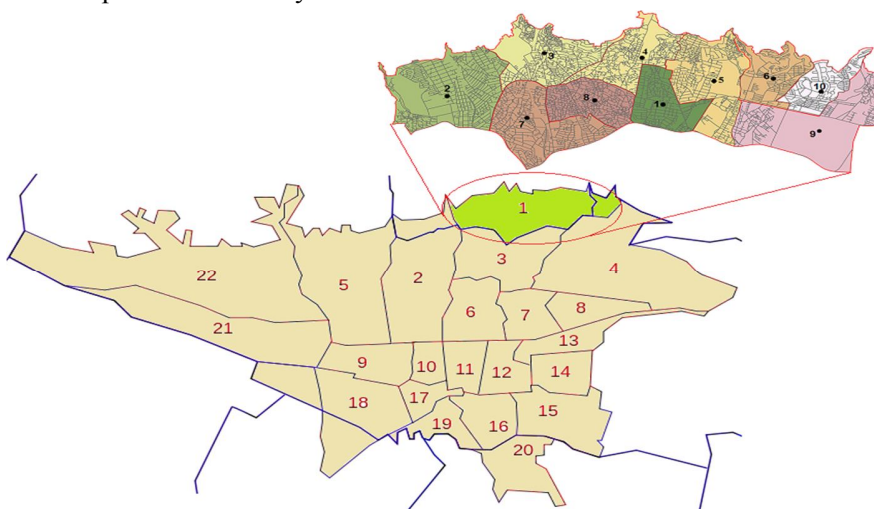


Figure 2. Geographic dispersion of 22 districts of Tehran metropolis

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Mosha Fault (MF), which is more than 200 km long, is one of the major active faults in Tehran in terms of the length and danger. The largest historical earthquake by magnitude occurred in 958 with a distance of 50 km from the center of Tehran. The earthquake corresponded to the activity of the western part of the fault.

North Tehran Fault (NTF) is a 90 km-long fault, located in the northern margin of Tehran. The damage caused by the earthquakes originated from this fault will be even worse than one occurred in 958. So, we consider the North

Tehran Fault instead of Mosha Fault for the earthquake scenario.

South Ray Fault (SRF), which is about 20 km long, is located in south of Tehran. This fault is considered for the sake of its better geological surface trace and micro-seismic activities.

Besides, The Modified Mercalli Intensity (MMI) scale of earthquakes occurred in each region of district 1 is estimated in Table 3. In continue, north Tehran fault and the vulnerable areas of district 1 based on this fault are mapped in Figures 3 and 4, respectively.

Table 2. The properties of earthquake scenario models

Properties	MF Model	NTF Model	SRF Model	Floating fault model
length	68	58	26	13
width	30	27	16	10
location	North eastern	North	South	--
magnitude	7/2	7/2	6/7	6/4

Table 3. The Modified Mercalli Intensity (MMI) scale of earthquakes in each region

Region	MF	NTF	SRF	Floating fault model
1	8/3	9/3	7/3	8/7
2	7/6	8/8	6/9	8/18
3	7/8	8/9	6/8	8/2
4	8/2	9/3	7/1	8/6
5	8/1	9	7	8/3
6	8/1	9	7	8/3
7	7/7	9	7	8/3
8	8/1	9/3	7/3	8/6
9	8/1	9/1	7/1	8/3
10	8	8/5	6/7	7/9

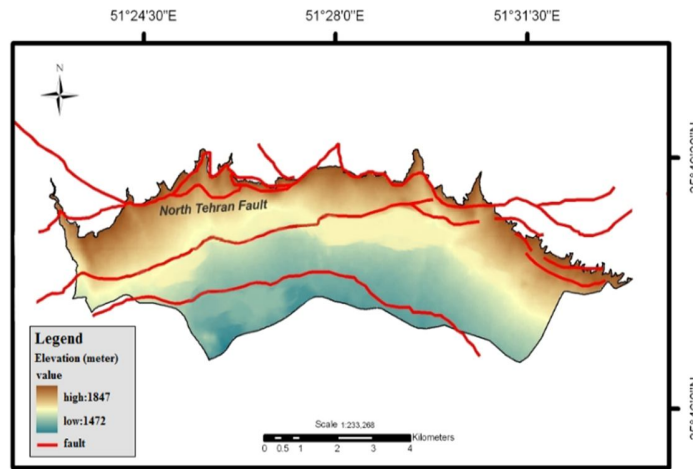


Figure 3. The north Tehran fault

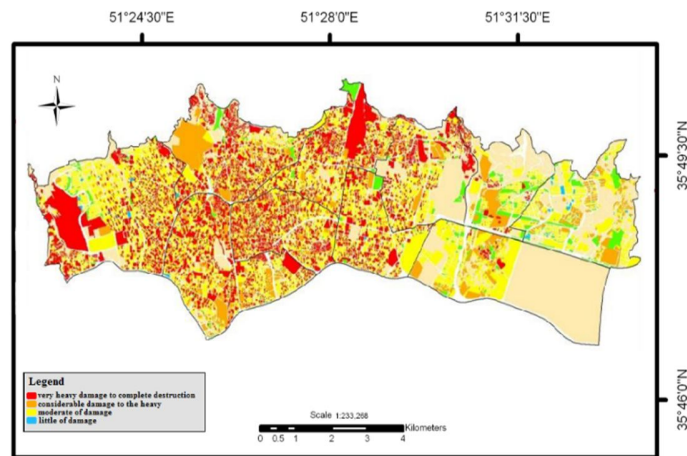


Figure 4. The vulnerable areas of district one according to the north Tehran fault

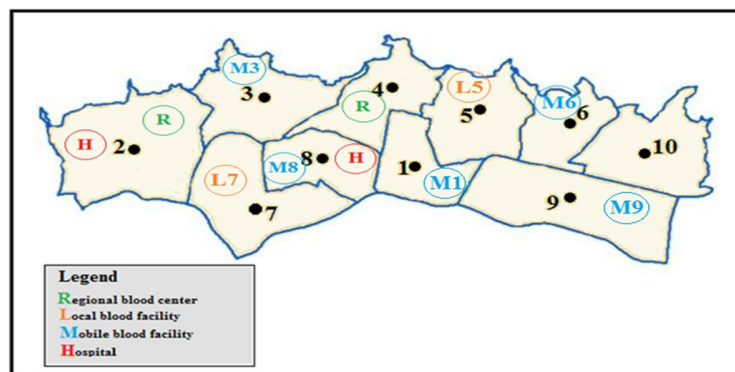


Figure 5. The candidate location of mobile blood facilities and existing local blood facilities, regional blood centers and hospitals

Table 4. The geographic coordinates of donor points and hospitals

Points	Longitude	Latitude
D_1	35.810363	51.523087
D_2	35.794213	51.433588
D_3	35.791915	51.442772
D_4	35.809736	51.451183
D_5	35.804725	51.461569
D_6	35.815444	51.475559
D_7	35.797554	51.483198
D_8	35.799782	51.483971
D_9	35.805699	51.509806
D_{10}	35.815931	51.504484
H_1	35.790687	51.414276
H_2	35.791648	51.422644

As stated before, district 1 with a population over 350,000, includes 10 regions. To supply blood when facing disasters, all 10 regions of district 1 are assumed to contribute to blood distribution to the affected areas. In this paper, the center of each region represents a donor point; the locations of blood facilities and hospitals as demand zones are depicted in Figure 5. Besides, the geographic coordinates of donor points and hospitals are estimated in Table 4, and the distance between two arbitrary points can be obtained by the following equation:

$$d_{ij} = 6371.1 \times \arccos[\sin(LAT_i) \times \sin(LAT_j) + \cos(LAT_i) \times \cos(LAT_j) \times \cos(LONG_j - LONG_i)] \quad (73)$$

6. Results

In this section, we report the corresponding results to evaluate the proposed model and the solution approach. The proposed model is solved using CPLEX solver encoded in GAMS software

– version 24.1 - on a laptop computer with features of Intel Core i5 CPU, 2.5 GHz and 6GB of RAM. The model is implemented considering different confidence levels α , provided in Table 5, then the sensitivity analysis is presented.

What is evident is that the model is solved within a reasonable length of time ended up with no gap and no need to mathematical solution methods. In addition, the increased value of α results in the increased number of mobile blood facilities and thus the increased supply chain costs, as shown in Figure 6. In the meantime, no changes can be observed in the number of mobile blood facilities when α is increased from 0.6 to 0.7 and from 0.9 to 1. Therefore, the increase of objective function value could be owing to the increase of transportation cost and operating cost caused by the increase of service level for fuzzy parameters. Since blood supply is so critical especially in disasters, decision makers need to determine conditions, in which the demand is satisfied at higher reliability degree α although it imposes higher costs on the chain. In fact, the decision

maker has to make a tradeoff between cost and demand satisfaction to decide on the confidence level of demand satisfaction besides the number and location of mobile blood facilities.

The model is solved for 5 mobile blood facilities, and the allocation of donors to mobile and local blood facilities is shown in Table 6 considering the 1st time period and the confidence level $\alpha = 0.7$. An overall observation is that, mobile blood facilities are frequently assigned to the regions with higher destruction risk regarding the disaster intensity based on each scenario. As can be observed in Figures 7, 3 mobile blood facilities are chosen from 5 candidate locations.

This section analyzes the changes in the supply chain costs as the capacity of mobile facilities is increased. Figures 8 and 9 show supply chain costs over different capacity levels at confidence levels $\alpha = 0.7$ and $\alpha = 0.9$, respectively. As can be seen in the corresponding diagrams, the increased capacity of mobile facilities results in decreased supply chain costs. The amount of cost savings (i.e. curve steepness) is a function of “inventory cost over transportation cost” ratio. Accordingly, a higher ratio is obtained by adopting a greater inventory cost and smaller transportation cost, which lets the supply chain network take advantage of increased capacity of facilities in order to reduce the times of transportation between nodes.

Table 5. The value of objective function and the number of mobile blood facilities based on different α levels

α	Y	Z	Run time (S)
0.5	2	6148	0:17:34
0.6	3	7024	0:22:21
0.7	3	7313	0:16:58
0.8	4	8142	0:20:09
0.9	5	8963	0:24:33
1	5	9074	0:20:41

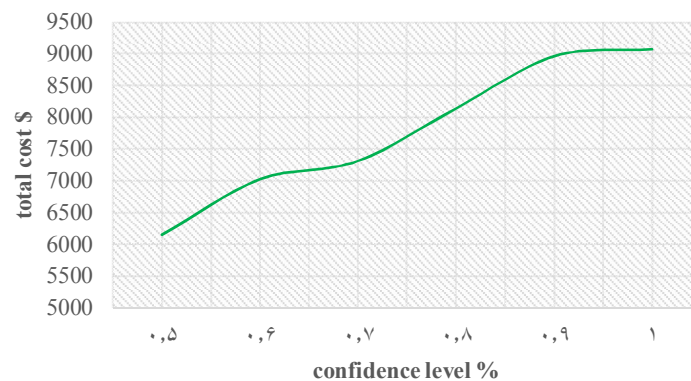


Figure 6. The impact of confidence level changes on the supply chain cost

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Table 6. Donors assignment to mobile and local blood facilities based on each scenario model considering $t=1$

Regions	MF scenario	NTF scenario	SRF scenario	Floating fault scenario
1	L5	M8	M8	L5
2	M3	M3	M3	M3
3	M3	M3	M3	M3
4	L5	L5	L5	M8
5	L5	L5	L5	L5
6	M6	M6	M6	M6
7	L7	M8	L7	L7
8	M8	M8	L7	L7
9	M6	M6	M6	M6
10	M6	M6	M6	M6

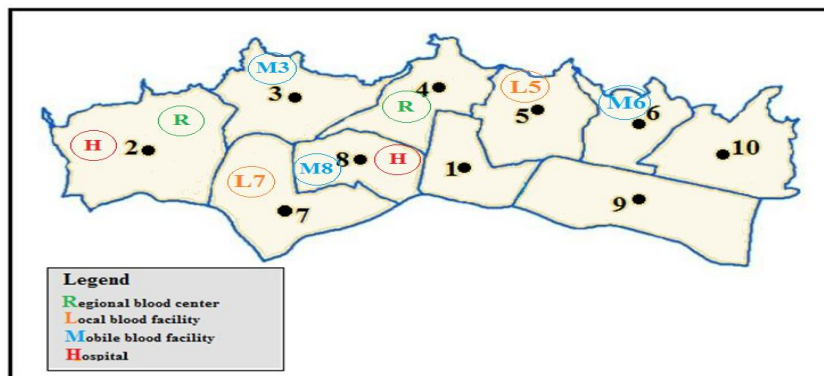


Figure 7. The established mobile blood facilities considering $t=1$ and $\alpha = 0.7$

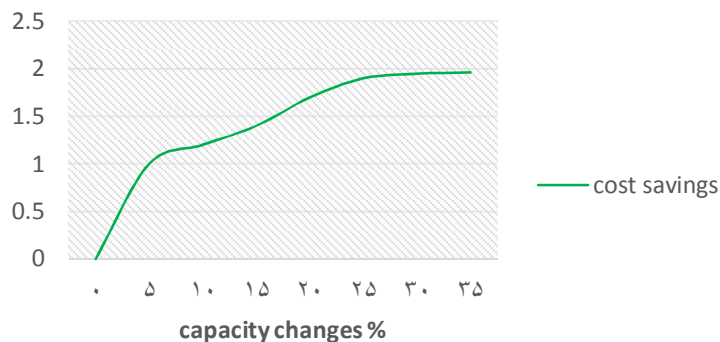


Figure 8. The impact of capacity changes on the total supply chain cost; $\alpha = 0.7$

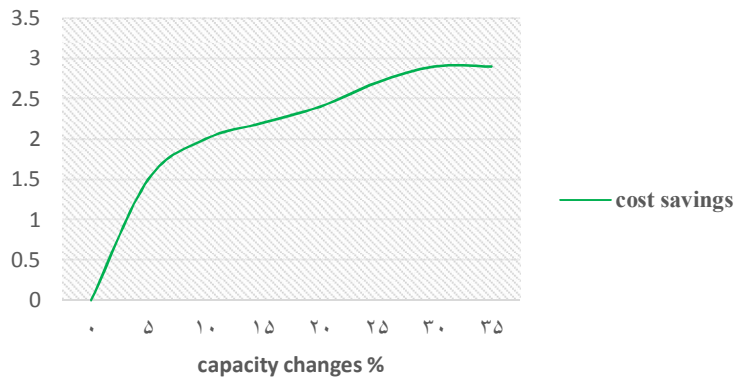


Figure 9. The impact of capacity changes on the total supply chain cost; $\alpha = 0.9$

6.1 Sensitivity Analysis on the Capacity of Mobile Facilities

In some parts, as shown in Figures 8 and 9, the curve is steeper which indicates reduced supply chain costs and thus increased cost savings resulting from the reduced transportation cost in total since the transportation duration decrease by increasing the capacity of mobile blood facilities. For instance, as the increase in capacity level reaches 5%, the amount of cost savings will become 1% while this amount of saving will be 1.95% when the capacity increases to 30%, if possible. Thus, these levels could be regarded as appropriate points for making a remarkable

reduction in supply chain costs even though choosing the level of capacity increase is reliant on the decision makers' policies. However, the slope of the curve will reduce gradually until it comes to zero in some parts and no changes would be observed as the capacity of facility is increased, which means that no capacity shortage has occurred. In other words, the current capacity of facility can satisfy the respective demand. Besides, the amount of cost savings will decrease due to the increase in supply chain costs as the service level increases from 0.7 to 0.9.

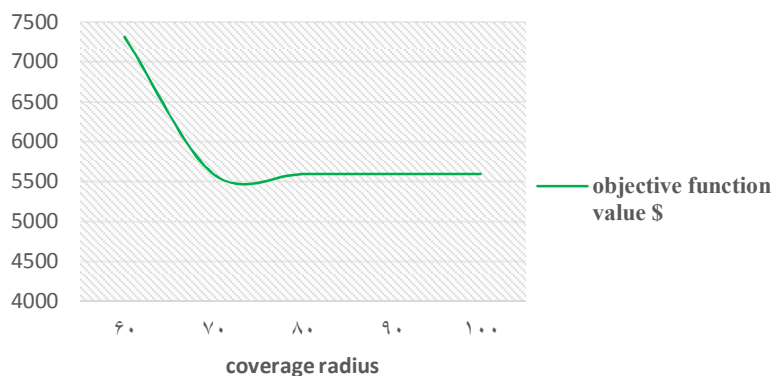


Figure 10. The impact of increasing coverage radius on the total supply chain cost; $\alpha = 0.7$

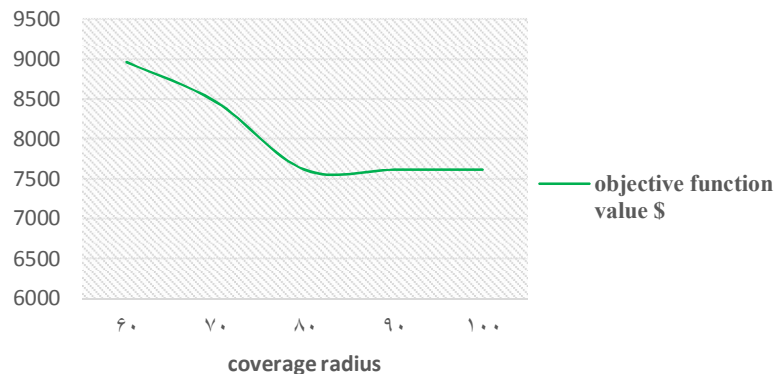


Figure 11. The impact of increasing coverage radius on the total supply chain cost; $\alpha = 0.9$

6.2. Sensitivity Analysis on the Coverage Radius of Blood Facilities

In this section, the impact of an increase in coverage radius of blood facilities on total network cost is examined. To do so, the value of this parameter is varied, as shown in Figures 10 and 11. A general observation is that increasing the coverage radius of facilities leads to an increase in the capability of each facility to cover more donors, and thus, the total required number of blood facilities reduces. This reduction provides cost savings for the supply chain. This pattern will carry on until the total volume of blood to be collected by each blood facility does not exceed the capacity of that facility. To be more specific, in Figure 10, total cost of the network will reduce dramatically by increasing the coverage radius to 70. From this point on, further increases in the value of this parameter have no impact on reducing the objective function value. Almost the same pattern can be observed in Figure 11, but the difference is that more cost will be imposed on the supply chain as the service level increases from 0.7 to 0.9 and the network cost will decrease with slighter slope.

6.3. Sensitivity Analysis on the Reliability of Routes

We now aim to examine whether changes in the reliability of routes between facilities affect the supply chain costs. To this end, the model is solved for different reliability levels of routes

with respect to $\alpha = 0.7$ and $\alpha = 0.9$. As can be observed in the following figures, the increased reliability of routes, or in other words, decreased disruption probability of routes leads to reduced supply chain costs. Comparing the two Figures 10 and 11, it can be inferred that supply chain cost savings would decrease owing to the increased confidence level of services from 0.7 to 0.9, which leads to the increased supply chain costs. Furthermore, for some disruption levels (that part of the route reliability axis with negative numbers), cost savings reduce almost dramatically which possibly implies substituting another route with the current one, which may be out of order, so as to transfer required blood units from one facility to another or to a demand zone. On the other hand, decreases in the probability of route failure (that part of the route reliability axis with positive numbers), will enhance the amount of cost savings. For instance for Figure 10, if the reliability of route increases to 5%, the slope of the curve will reach 0.52 which shows 2.6% increase in cost savings while the slope reduces for greater route reliability. For example, the increase of 10% in route reliability results in the slope of 0.38 and 3.8% increase in cost savings and this amount is about 5% if we have 15% decrease in the route failure

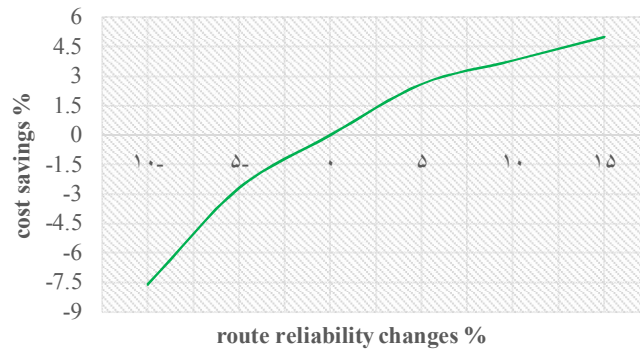


Figure 12. The impact of route reliability changes on the total supply chain cost; $\alpha = 0.7$

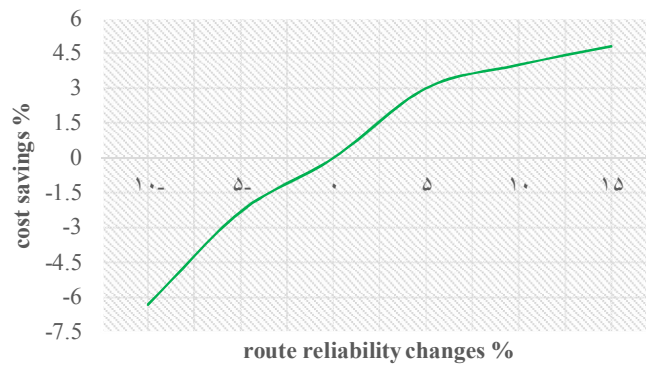


Figure 13. The impact of route reliability changes on the total supply chain cost; $\alpha = 0.9$

6.4. Sensitivity Analysis on the Disruption Probability of Local and Regional Facilities

This section is supposed to investigate the impact of changes in the disruption probability of facilities on the supply chain costs. According to Figures 12 and 13, a general observation is that the supply chain cost is affected by the changes in the facilities disruption. It means that the decreased probability of facilities disruption ends in supply chain cost improvement, in the meantime, the increased percentage of facilities disruption leads to cost increase. Noteworthy, those parts of the curve with steeper slope and thus the greater cost savings indicate that the same facilities are going to be used as did before. So, no extra costs will be imposed on the supply

chain while the lower-slope parts (those for the positive numbers on the facility disruption axis) represent reduced cost savings because higher costs are imposed on the supply chain. It may be due to replacing new facilities with the previous ones as they are out of work or badly disrupted. For instance for Figure 12, if the facility disruption decreases to 5%, the slope of the curve will reach 0.12, which indicates 0.6% increase in cost savings while the slope thus the amount of cost savings increases as the percentage of facility disruption reduces more. On the other hand, the slope of 0.06 will be obtained when the facility disruption increases to 5%, which causes a cost increase of 0.3% and this amount will be even more if the disruption of facilities grows until it comes to 3.8% at disruption rate of 0.2.

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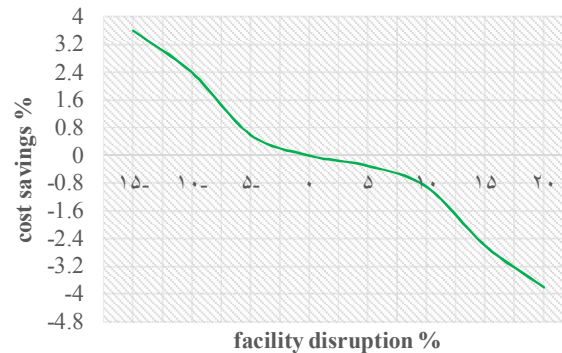


Figure 14. The impact of facilities disruption changes on the total supply chain cost; $\alpha = 0.7$

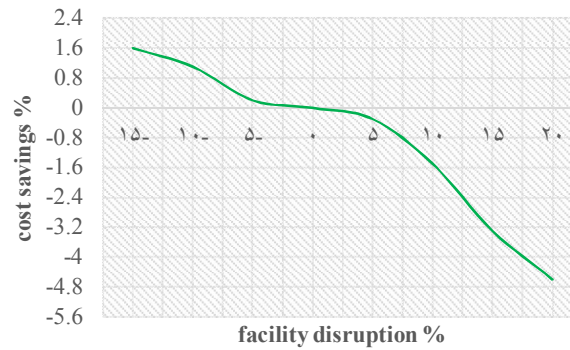


Figure 15. The impact of facilities disruption changes on the total supply chain cost; $\alpha = 0.9$

6.5.Sensitivity Analysis on the Referral Rate

In this section, we examine if changes in the referral rate can be employed as a strategy to improve supply chain costs. Notably, more transfusion services would be conducted in regional blood centers as referral rates become larger. For instance, a referral rate of 0.4 indicates that 40% of transfusion operations are to be referred to regional blood centers and the rest of them would be done in local blood centers. As can be observed from Figures 16 and 17, the greater referral rates eventuate in increased supply chain

costs and more facilities are required to be opened in order to maintain the same service level. Consequently, it would be more cost-effective to facilitate local blood centers and enhance their independency from regional blood centers with the aim of decreasing the referral rate and thus the supply chain costs. What is evident in all figures, represented earlier, is that the amount of cost savings would reduce as the service level grows. The increase of service level would result in larger supply chain costs by enhancing either the number of facilities or any other probable changes in the supply chain characteristics so as to meet demand as much as possible.

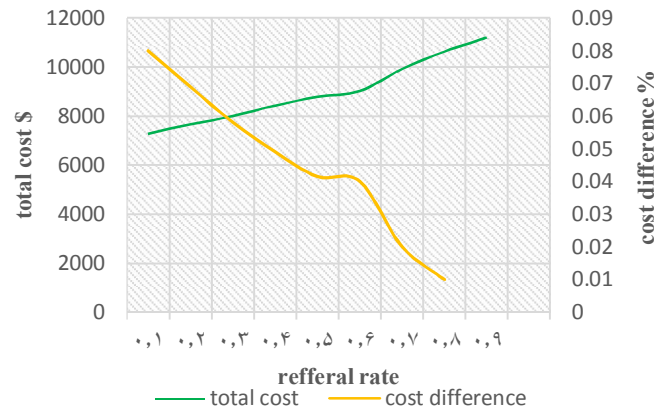


Figure 16. The impact of facilities disruption changes on the total supply chain cost; $\alpha = 0.7$

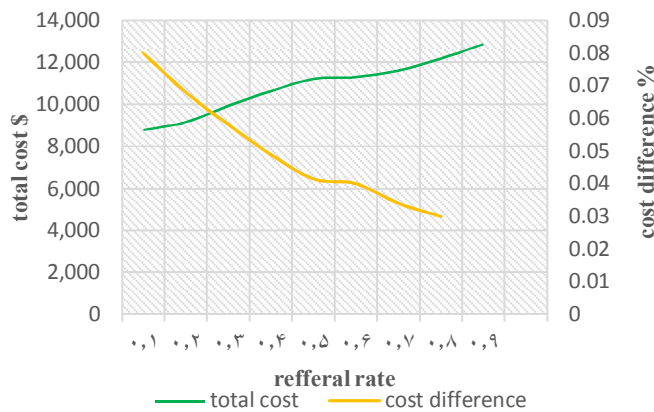


Figure 17. The impact of facilities disruption changes on the total supply chain cost; $\alpha = 0.9$

6.6. Model Performance (Fuzzy-Stochastic Approach Versus Deterministic Approach)

Finally, this section provides a comparable analysis for the performance of the proposed model under fuzzy-stochastic and deterministic approaches. To do so, we evaluate the model by particularly considering the impact of increasing the capacity of mobile blood facilities. Figure 18 depicts how the proposed model performs under aforementioned approaches while $\alpha = 0.7$. The figure implies that the network total cost under

both approaches decreases as the capacity of mobile blood facilities is enhanced. For instance, if we have an increase of 5% in the capacity of facilities, we will observe that total cost of fuzzy-stochastic model will come near to \$7203 with a reduction of 1.5%. This pattern will continue with a slight slope until it reaches \$7101 while we have a 35-percent increase in the capacity of facilities. The cost difference between the two approaches comes from the fact that fuzzy approach estimates the value of uncertain parameters more realistic than that of the deterministic approach.

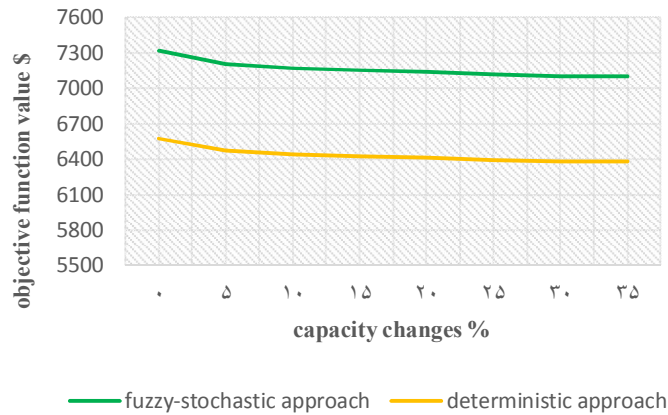


Figure 18. Total supply chain cost under fuzzy-stochastic and deterministic approaches; $\alpha = 0.7$

7. Conclusions

Since the natural disasters are increasingly happening all over the world, blood supply in such emergency situations is of a great challenge considering the disasters direct impacts on humans and their emergency needs thereafter. This paper presents a fuzzy-stochastic programming model to design a BSC network for the efficient blood supply in disasters. The objective function aims to minimize the total supply chain costs regarding as the efficiency factor. In the proposed two-stage fuzzy-stochastic programming model, the number of blood facilities to be opened is decided at the first stage as there is no knowledge available of disasters, and blood collection and the frequency of transportation besides the level of inventory at the end of each period are specified at the second stage as the disaster scenarios are realized.

To formulate the proposed model, a fuzzy programming approach is considered to cope with the uncertainty in model parameters. A credibility-based chance-constrained programming method is then applied to convert the proposed model into an auxiliary crisp one. The following valuable insights are provided through solving the proposed model. (1) the hybrid solution method (i.e., EV and CCP) benefits from the advantages such as simplicity

by not increasing the number of constraints. It also does not require confidence level for objective functions. (2) an increase in credibility level would lead to a decrease in the system's cost savings. (3) if the capacity of blood facilities is enhanced from %5 to %30, if possible, cost savings will increase from %1 to %1.9. (4) a %10 decrease in route reliability results in %3.8 increase in the network total cost. (5) having a %5 increase in facility disruption, we witness % 0.3 decrease in cost savings. (6) as the referral rate increases, more facilities must be provided to respond the demand at the same service level. So, we will have an increase in the network cost.

At the end, a real case study in Iran was conducted to evaluate the applicability of the proposed model.

Future research could investigate other solution methods including heuristic or metaheuristic methods in the case the one presented in this paper would not be able to solve the problem of larger sizes. Other stochastic approaches could be also applied to the problem in order to compare the corresponding results with those of the proposed solution approach. Moreover, the routing problem could be simultaneously considered for the present model to improve the network costs.

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9. Endnotes

¹ World Health Organization (WHO)

² International Federation of Red Cross and Red Crescent Societies (IFRC)

³ Japan International Cooperation Agency (JICA)