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A fuzzy stochastic bi-objective model for blood provision in disastrous time

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Abstract

Emergency blood distribution seeks to employ different means in order to optimize the amount of blood transported while timely provision. This paper addresses the concept of blood distribution management in disastrous conditions and develops a fuzzy scenario-based bi-objective model whereas blood compatibility concept is incorporated in the model, and the aim is to minimize the level of unsatisfied demand of Affected Areas (AAs) while minimizing the cost of the supply chain. The blood supply chain network under investigation consists of blood suppliers (hospitals or blood centers), Blood Distribution Centers (BDCs), and AAs. Demand and capacity, as well as cost, are the sources of uncertainty and in accordance with the nature of the problem, the fuzzy-stochastic programming method is applied to deal with these uncertainties. After removing nonlinear terms, Ɛ-constraint solves the bi-objective model as a single objective one. Finally, we apply a case from Iran to show the applicability of the model, results prove the role of blood distribution management in decreasing the unsatisfied demand about 38%.

Keywords: Blood supply chain, disaster, fuzzy programming, stochastic programming, Ɛ-constraint, case study.

1-Introduction

Since the beginning of creation, human being have faced natural incidents leaving fatal injuries, deaths and losses, such that hundreds of 200 million people that annually involve natural disaster, die and disaster-prone countries endure losses about 3% of their GDP per year (Green et al., 2003) Thus, healthcare operation management and disaster management have recently received a deal of attention from researchers. Human losses can be reduced by an efficient and effective supply chain planning and management of healthcare-related activities under disastrous situations (Ghatreh Samani et al., 2018).

Planning for supplying blood during and after the disaster while there exist a sudden boost in blood demand is one of the common fields seeking to reduce the negative consequence of such conditions (Schultz et al., 1996; Hess and Thomas, 2003). Providing timely and adequate blood during and after earthquakes has been a major concern (Abolghasemi et al., 2008).

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Recent disasters have proved considerable challenges in the effective operation of blood systems in case of external disruptions, for instance, the blood supply on the Pacific coast of Tahoka was disrupted as a result of the Great East Japan Earthquake in 2011 and the subsequent tsunami (Nollet et al., 2013). On the 2008 Sichuan earthquake, Chinese blood management system faced the concerns associated with wastage and the quality of the blood units (Sha and Huang, 2012). National Blood Transfusion Service in 2004 tsunami of Sri Lanka had difficulty to avoid its blood supply chain from excessive blood due to a huge influx of donation (Kuruppu, 2010). The other example depicting the ineffective blood supply chain planning is about Bam earthquake in Iran in 2003, where only 23% of the whole blood units denoted was actually supplied to the affected residents (Abolghasemi et al., 2008), on the other hand, Supply shortage is one of the major problems having various consequences in disasters (Knott 1987; Ingram 1987) especially blood shortage which can be the leading cause of an increased mortality rate (Beliën and Forcé, 2012).

In light of such examples, it is difficult to ignore the importance of designing a blood supply chain which is resilient to respond to the complex and unpredictable nature of blood demand on disasters. Thus, it is necessary to design strategies for timely supply of adequate and safe blood required for injured people in AAs. In this regard, the present paper aims to design an efficient blood supply system in a disastrous time by using the concept of blood compatibility possibility.

Different blood groups are determined according to the presence or absence of specific antigens on the surface of red blood cells (Lowarlekar and Ravichandran, 2015). The ABO and Rh blood group systems are the most important blood group systems which the compatibility of these two antigen systems are required to human blood transfusion (Holland, 2006). The blood demand of patients is usually transfused by the same ABO/ Rh blood type, but in case of shortage of the specific blood type, its demand can be satisfied with a different type provided that it matches the patient's blood (Lang, 2010). Table 1 shows the compatibility of different blood groups. we use this concept to design a proper blood network in disasters. Therefore, this paper provides a blood network based on the compatibility of different blood groups in order to reduce the risk of shortages and wastages. The designed blood supply chain involves the collection of the blood group with the higher rate of compatibility especially O- (as the blood group with the highest rate of compatibility) and transfusion of blood units based on compatibility priority.

Table 1. Red blood cell compatibility

Recipient	Donor							
	O−	**O+**	**A−**	**A+**	**B−**	**B+**	**AB−**	**AB+**
O−	OK	NO	NO	NO	NO	NO	NO	NO
O+	OK	OK	NO	NO	NO	NO	NO	NO
A−	OK	NO	OK	NO	NO	NO	NO	NO
A+	OK	OK	OK	OK	NO	NO	NO	NO
B−	OK	NO	NO	NO	OK	NO	NO	NO
B+	OK	OK	NO	NO	OK	OK	NO	NO
AB−	OK	NO	OK	NO	OK	NO	OK	NO
AB+	OK	OK	OK	OK	OK	OK	OK	OK

It should be noted that the concept of blood has recently been called into question by academic studies demonstrating the importance of this controversial subject within the field of public health. Despite research successes, blood management has a number of problems in practice which highlight the need for investigating this context in various fields of knowledge such as data mining, analytical methods, optimization approaches, and etc. in continue, we mention a number of these studies applied in other areas which can be adopted and customized to solve blood problems.

Koksal et al. (2011) provided an extensive review covering the literature from 1997 to 2007 to data mining applications for quality improvement in manufacturing industry and proposed several analyses on selected quality tasks were suggested to DM applications in the manufacturing industry including product/ process quality description, predicting quality, classification of quality, and parameter optimization.

Batmaz et al. (2017) employed data mining methods to determine deposit pricing by using proprietary data provided by a commercial bank. Their findings demonstrated that depositors with a multi-faceted and long-term relationship with the same bank seem to benefit from higher deposit rates as a reward for being a core depositor and a limited effect of the location of the customer on the deposit rates.

Akyüz and Weber (2010) adapted semi-infinite programming to their infinite kernel learning model and analyzed the existence of solutions and convergence for the given algorithms and introduced" infinite" kernel learning (IKL) on heterogeneous data sets by using exchange method and conceptual reduction method. They proved the applicability of their proposed model in improving the classification accuracy on heterogeneous data compared to classical one-kernel approaches.

Taylan and Weber (2008) Considered stochastic differential equations and proposed an approximation by discretization and additive models based on splines. Afterward, they constructed a penalized residual sum of square (PRSS) for their proposed model.

Royuela-del-Va et al. (2019) presented a feasibility study on the use of multi-layer neural networks to determine air flow in filtration from thermographs in order to evaluate the intake air flow through an opening in the building's envelope. They benefited from several neural network topologies to explore the generalization capability of this method.

This paper will focus on mathematical modeling in blood concept. In continue, we review some of the more recent and related articles.

The earliest study directed at blood supply chain was by Van Zyl in the 1960s; who noticed perishability of the blood. Afterward, Nahmias (1982) provided a review of blood bank management with respect to the perishability, and Brandeau et al. (2004) published a book in the context of blood supply chain. Belien and Force (2012) presented a comprehensive review for blood concept, classifying conducted studies into different categories based on the type of blood products, solution method, the main type of problem categories, exact and heuristic approaches and etc.

The related academic literature in this context falls into four main streams: location-allocation, inventory, distribution, production planning, and supply problems.

Sahin et al. (2007) developed regionalization plans for blood Turkish Red Crescent Society that combined all the information in connection with location-allocation roles to restructure the blood services, presenting several mix integer models. Sha and Huang (2012) considered decision support, required for scheduling of an emergency blood supply chain in their proposed multi-period location-allocation model. Jabarzadeh et al. (2014) proposed a dynamic robust facility location-allocation model to supply the blood to demand points during and after disasters by considering the cost. Ramezanian and Behboodi (2017) presented a location-allocation model in order to increase utility and the number of donors.

Research on inventory management focuses on determining blood quantities required at various facilities along the blood chain, especially at the hospitals.

Duan and Liao (2013) developed a simulation-optimization inventory control model with ABO blood group compatibility that could be used for the minimization of the expected system wastages. Dillon et al. (2017) formulated a stochastic inventory model that determined the optimal periodic review policy for a hospital in order to minimize cost and shortages and wastages number, simultaneously. Ahmady and Najafi (2017) presented a bi-objective inventory model to determine critical decisions such as blood ordering and blood issuing. The problem was to hold enough stock at the hospital in a way that ensured a high level of supply while minimizing the risk of expiration rate. They considered blood transshipment in the model, as well. Hossienifard and Abbasi (2018) focused on inventory centralization at the second echelon of a two-echelon supply chain with perishable items. Gunpinar and Centeno (2015) modeled inventory planning of red blood and platelet at a hospital using two-stage stochastic programming models, their models could serve as a decision-making tool for the hospital to minimize cost as well as shortages and wastages rate.

Ensafian and Yaghoubi (2017) developed several robust optimization models for planning the distribution of platelet (one of the blood components) based on FIFO and LIFO issuing policies. The purpose of the proposed models was to minimize total cost while maximizing the freshness of platelets. Ensafian et al. (2017) introduced a two-stage stochastic optimization model in order to assist in deciding on the collection, production, storage, and distribution of platelet. After predicting the number of donors by Markov, they offered an interesting method that is potentially useful in reducing the number of scenarios.

Ghandforosh and Sen (2010) developed a non-convex integer model (DSS method) that planned the platelet production and blood mobile scheduling and solved it as a linear problem using a two-step conversion process. Osorio et al (2017) focused on production planning in a blood center regarding simulation-optimization model, blood flows of the blood center were determined by simulation and daily decisions by the optimization model. Fahimnia et al. (2017) studied the problem of blood supply after a disaster. They developed a stochastic bi-objective model and applied ε-constraint and Lagrangian relaxation as the solution method.

Hemmelmayr et al. (2010) also faced the problem of planning delivery routes in the context of supplying blood products to hospitals. The authors proposed a stochastic mixed-integer model that used the concept of variable neighborhood search in solving the model.

Puranam et al. (2017) offered a dynamic multi-period model for a blood supply chain in order to keep cost level at the minimum. In addition to the typical standing order process, the hospitals that randomly transferred blood to healthcare centers were considered the sources of supply.

Finally, Osorio et al. (2017) suggested a multi-objective stochastic model. The objectives of their proposed model were the minimization of total cost and maximization of the number of donors and solved it by Average Approximation and the augmented ε-constraint algorithm.

Observing the literature review although the vast area of concepts considered in the different studies associated with blood supply chain, but to the best of our knowledge, before the present work, there was no consideration about blood compatibility concept to blood distribution management. Therefore, this paper lies among the first to consider this issue in the form of a mathematical model in disastrous condition. Furthermore, table 2 classifies the aforementioned papers based on the way to deal with uncertainty. It is obvious from table 2 that the papers applied stochastic approach outnumbered to the papers applied deterministic approach, the stochastic nature of supply in addition to having uncertain demand in the context of blood is the motivation of paying more attention to stochastic approaches. However, stochastic approach has proved an important genre in the applied methods to cope with uncertainties, inability of conventional stochastic models to handle risk aversion or decision makers' preferences has led to exclude many important domains of application (Azaron et al. 2008), this defection is a motivation to employ new methods. This study is an attempt to address the issue of blood distribution management applying fuzzy programming and stochastic programming to handle existing uncertainties in disastrous time. It is worth mentioning that searching for more functional and efficient methods to handle uncertainty is still an open issue. Ozem et al. (2013) applied an advanced optimization method namely robust conic GPLM method in order to predict credit default. Their methodology contained a combination of two predictive regression models, logistic regression and robust conic multivariate adaptive regression splines (RCMARS), as linear and nonlinear parts of a generalized partial linear model.

Baltas et al. (2018) addressed the robust control problems of parabolic stochastic partial differential equations under model uncertainty which was expressed as a stochastic differential game in a real separable infinite dimensional Hilbert space. Then, they proved that the elliptic partial differential equation associated with the problem admitted a unique solution as the value function of the game.

Savku and Weber (2018) studied a stochastic optimal control problem for a delayed Markov regime-switching jump-diffusion model and established necessary and sufficient maximum principles under full and partial information for such a system. They proved their results by a problem of optimal consumption problem from cash flow with delay and regimes.

Table 2. Classification of the papers on blood supply chain in case of uncertainty

Conducted studies	**Applied approach to cope with uncertainty**			
Conducted studies	Deterministic	Fuzzy Programming	Stochastic programming	Robust programming
Sahin et al. (2007)	✓			
Hemmelmayr et al. (2010)			✓	
Grandforoush and Sen (2010)	✓			
Sha and Huang (2011)	✓			
Jabarzadeh et al. (2014)				✓
Duan and Liao (2014)	✓			
Gunpinar and Centeno (2015)			✓	
Fahimnia et al. (2015)			✓	
Civelek et al. (2015)	✓			
Ramezanian and Behboodi (2017)				✓
Dillon et al. (2017)			✓	
Ahmady and Najafi (2017)		✓		
Ensafian et al. (2017)			✓	
Ensafian and Yaghoubi (2017)				✓
Osorio et al. (2017)			✓	
Hossienifard and Abbasi (2018)			✓	

This paper aims to present a fuzzy-stochastic bi-objective model for blood distribution management in disasters. The incremental contributions are as follows:

1) The blood compatibility concept as one of the factors that strongly affect blood management decisions is considered and importance rank for blood types is set.

2) Importance rank for AAs is defined according to devastation rate and the number of injured.

3) To cope with the intrinsic uncertainty of the model parameters, fuzzy programming and stochastic programming are simultaneously applied, discrete scenarios are incorporated in the model in the form of stochastic programming where demand, capacity, and cost are fuzzy parameters.

4) A real case study is applied to show practically the present application of the proposed model.

2-Research methodology

This study develops a mixed integer bi-objective mathematical model for the blood supply problem in the disastrous conditions considering different importance ranks for AAs using devastation rate and different importance ranks for different blood groups by means of the concept of blood compatibility, so that, the first objective function minimizes the maximum amount of weighted unsatisfied blood demand in AAs, and the second objective function minimizes total costs in the presented supply chain. In addition to fuzzy numbers, discrete scenarios are defined and fuzzy-stochastic programming approach is applied to cope with the inherent uncertainty of the input parameters, after removing the non-linear terms by means of mathematical approximations, ε-constraint solves the proposed bi-objective model as a single objective one. Finally, a real case study is employed to demonstrate the applicability of the model.

3-Problem description

The supply chain under investigation is comprised of the set of blood suppliers (either blood centers or hospitals), the set of blood distribution centers (BDCs), and the set of affected areas (AAs) (see figure 1). by occurring a disaster, BDCs are located near the demand points to satisfy the blood demand of the AAs, the location of these centers are associated with the site of the demand points that occur in a scenario. With respect to the different number of injured people on different AAs and the concept of blood compatibility, the importance rank of different AAs and different blood types are respectively determined and incorporated in the model.

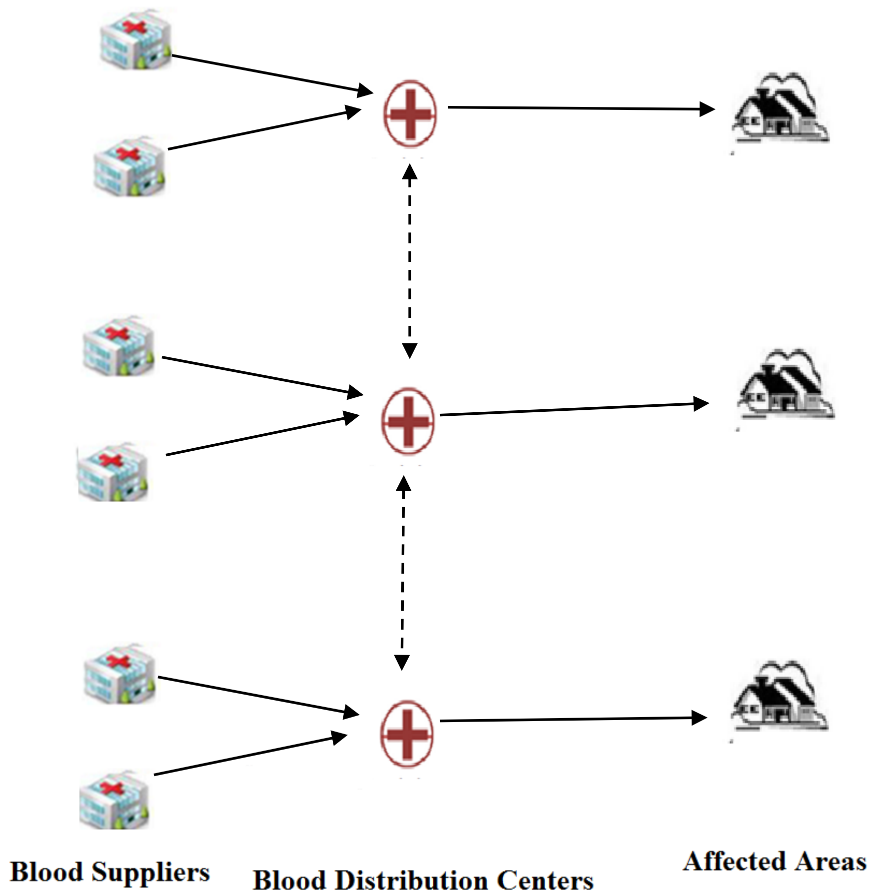

Fig 1. General schema of the blood supply chain

In this research, the following assumptions are considered:

1. The importance of different blood types and different AAs is different.
2. The blood demand of AAs, the cost parameter, and the capacity of the blood distribution centers are uncertain.
3. Blood units younger than three days cannot be available at the distribution centers due to the necessity of testing blood units for two days at the blood center.
4. A distribution center can be located only in one of the candidate locations.
5. The capacity of the distribution centers is limited.
6. The age of blood units is known in advance and varies over time.
7. The lifetime of blood cells includes forty-two days incorporating two days of testing (Kopach et al., 2008).
8. If demand is not met due to unavailability, a shortage is incurred.

9. If a blood unit expires, an outdating or wastage incurred

Sets:

I:	Set of candidate locations for blood distribution centers indexed by i
J:	Set of affected areas indexed by j
h:	Set of sporadic suppliers for blood (blood centers, and hospitals,) indexed by h
B:	Set of blood types indexed by b
A:	Set of the age of blood units indexed by a
T:	Set of time periods indexed by t
S:	Set of scenarios indexed by s

Parameters:

p_s:	The occurrence probability of scenario s
α_b:	Weight factor for blood type b
γ_{jts}:	Weight factor for AA j in time period t under scenario s
$\tilde{f}_{its}$:	The fuzzy parameter of fixed cost for opening a blood distribution center at location i in time period t under scenario s
$\tilde{\theta}_{bi}$:	The fuzzy parameter of procuring cost of a unit blood type b in blood distribution center i
$\tilde{\varphi}_{bi}$:	The fuzzy parameter of the penalty for a unit blood type b that haven't consumed in the end time period t at distribution center i
$c\tilde{a}p_{is}$:	The fuzzy parameter of capacity of distribution center i under scenario s
$\tilde{d}_{bjts}$:	The fuzzy parameter of demand for blood type b at AA j in time period t under scenario s
r_i:	Coverage distance of distribution center i
l_{ij}:	Distance between distribution center i and AA j
l_{hi}:	Distance between blood supplier h and blood distribution center i
$\tilde{\varpi}_{bi}$:	The fuzzy parameter of penalty cost for a unit blood type b outdated at distribution center i
$\tilde{\eta}_{bi}$:	The fuzzy parameter of penalty cost of a unit blood shortages type b at distribution center i
$\tilde{\zeta}_{bi}$:	Economical saving from transporting excessive blood units type b from distribution center i to other blood distribution centers
A:	Lifetime of the blood units ($A = 42$)
M:	A big number

Variables:

Z_i:	1 if distribution center is located at candidate location i; 0 otherwise
λ_{hi}:	1 if blood supplier h is assigned to distribution center i; 0 otherwise
Q_{bahits}:	The blood flow type b and a days old transported from blood supplier h to distribution center i in time period t under scenario s
I_{baits}:	Amount of inventory level of blood type b and a days old at distribution center i in time period t under scenario s

π_{bjts} : Amount of shortage blood type b at AA j in time period t under scenario s

Y_{ij} : 1 if AA j is allocated to distribution center i ; 0 otherwise

N_{bits} : Amount of blood type b haven't consumed at distribution center i in time period t under scenario s

W_{bits} : Amount of outdated blood type b at distribution center i in time period t under scenario s

π_{bits} : Amount of shortage blood type b at distribution center i in time period t under scenario s

X_{bijts} : The blood flow type b transported from distribution center i to AA j in time period t under scenario s

3-1-Mathematical model

$$MinZ_1 = \sum_s p_s \sum_b \sum_t \underset{j}{Max}\left\{\alpha_b \gamma_{jts} \pi_{bjts}\right\} \tag{1}$$

$$MinZ_2 = \sum_s p_s \left(\sum_h \sum_i \sum_b \sum_a \sum_t (\tilde{f}_{its} Z_i + \tilde{\theta}_{bi} Q_{bahits}) + \sum_b \sum_i \sum_t \tilde{\varpi}_{bi} W_{bits} + \tilde{\eta}_{bi} \pi_{bits} + \left(\tilde{\varphi}_{bi} - \tilde{\zeta}_{bi}\right) N_{bits} \right) \tag{2}$$

$$Z_i \le 1 \qquad \forall i \tag{3}$$

$$Z_i \le \sum_j \sum_b \tilde{d}_{bjts} Y_{ij} \qquad \forall i, t, s \tag{4}$$

$$I_{baits} = I_{bai(t-1)s} + \sum_h Q_{bahits} - \sum_j X_{bijts} Y_{ij} - W_{bits} \qquad \forall b, a \ge 3, i, t, s \tag{5}$$

$$\pi_{bits} - N_{bits} = \sum_j \left(\tilde{d}_{bjts} Y_{ij} - I_{baits} \right) \qquad \forall a \ge 3, b, i, t, s \tag{6}$$

$$Y_{ij} = Z_i \qquad \forall i = j \tag{7}$$

$$l_{ij} Y_{ij} \le r_i Z_i \qquad \forall i \ne j \tag{8}$$

$$l_{hi} \lambda_{hi} \le r_i Z_i \qquad \forall h, i \tag{9}$$

$$\sum_b \sum_{a=3} Q_{bahits} \le M \lambda_{hi} \qquad \forall h, i, t, s \tag{10}$$

$$\sum_i \sum_{a=1}^{3} Q_{bahits} = 0 \qquad \forall b, h, t, s \tag{11}$$

$$\sum_h \sum_b \sum_a Q_{baits} \le C\tilde{a}p_{is} Z_i \qquad \forall i, t, s \tag{12}$$

$$\sum_{b} X_{bijts} \leq MY_{ij} \qquad \forall i, j, t, s \tag{13}$$

$$\sum_{j \neq i} X_{bijts} \leq N_{bits} \qquad \forall b, i, t, s \tag{14}$$

$$\pi_{bjts} \leq \sum_{i} \pi_{bits} Y_{ij} \qquad \forall b, j, t, s \tag{15}$$

$$I_{baits} = W_{bits} \qquad \forall a \geq A, i, b, t, s \tag{16}$$

$$z_{ic}, y_{ij} \in \{0,1\} \tag{17}$$

$$Q_{bits}, I_{baits}, \pi_{bjts}, \pi_{bits}, N_{bits}, W_{bits} \geq 0 \tag{18}$$

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The maximum amount of weighted unsatisfied blood demand in AAs is minimized in the first objective function. The second objective function minimizes the total cost. This cost includes procurement cost (cost of opening distribution centers and cost of Procuring blood units) and the penalty costs (penalty cost of outdating, shortages and not consuming). Constraints (3) and (4) ensure that only one BDC can be located at each of nodes and it is opened in a location when at least the blood demand of one AA is allocated to it. Constraint (5) updates the inventory level of each BDC. Constraint (6) is a control balance equation for each BDC determining the number of shortages or not consuming units. Constraints (7) and (8) specify that an AA is allocated to the BDC when the AA and the BDC are located on the same nodes (the same city) and AAs on different nodes are allocated to the BDC when they are located on its coverage area. Constraint (9) shows that blood suppliers are allocated to the BDC when they are located on its coverage area, constraints (10) and (11) respectively make sure that blood units are shipped from suppliers to a BDC when the suppliers are allocated to BDC and the age of blood flow cannot be younger than 3 days old, because two days are required for processing and testing of blood units before transfusion. Constraint (12) restricts the amount of blood procurement by each BDC. Constraints (13) and (14) respectively indicate that there exists blood flow between a BDC and an AA when the BDC is assigned to the AA and this flow is between the BDC and AAs located on different nodes when the BDC has the excessive blood units. Constraint (15) designates incurring shortages in AAs in case of shortages in their assigned BDC. Constraint (16) identifies the number of blood wastages at BDC. Constraint (17) and (18) describes the type of variables.

4-Solution approach

4-1- Linearization

Clearly, due to the existence of the terms $\underset{j}{Max}\{\alpha_b \gamma_{jts} \pi_{bjts}\}$ in the first objective function, $X_{bijts} Y_{ij}$ in constraint (5), and $\pi_{bits} Y_{ij}$ in constraint (15) the proposed model is a nonlinear program.

We benefit the auxiliary variable $\kappa_{bst} \geq 0$ to rewrite the linear equivalent equations for the first objective function as follows:

$$Min' Z_1 = \sum_{s} p_s \sum_{b} \sum_{t} \kappa_{bts} \tag{19}$$

$$\kappa_{bts} \geq \alpha_b \gamma_{jts} \pi_{bjts} \qquad \forall b, j, t, s \tag{20}$$

$$\kappa_{bts} \ge 0 \qquad \forall b,t,s \tag{21}$$

To linearize constraint (5), the term $X_{bijts}Y_{ij}$ is replaced by ε^1_{bijts} and constraints (22)-(25) are added to the model, as follows:

$$\varepsilon^1_{bijts} \le MY_{ij} \qquad \forall b,i,j,t,s \tag{22}$$

$$\varepsilon^1_{bijts} \le X_{bijts} \qquad \forall b,i,j,t,s \tag{23}$$

$$\varepsilon^1_{bijts} \ge X_{bijts} - M(1-Y_{ij}) \qquad \forall b,i,j,t,s \tag{24}$$

$$\varepsilon^1_{bijts} \ge 0 \qquad \forall b,i,j,t,s \tag{25}$$

The term $\pi_{bits}Y_{ij}$ in constraint (15) is also nonlinear, $\pi_{bits}Y_{ij}$ is replaced by ε^3_{bijts} and the following constraints are added to the model:

$$\varepsilon^3_{bijts} \le MY_{ij} \qquad \forall b,i,j,t,s \tag{26}$$

$$\varepsilon^3_{bijts} \le \pi_{bits} \qquad \forall b,i,j,t,s \tag{27}$$

$$\varepsilon^3_{bits} \ge \pi_{bits} - M(1-Y_{ij}) \qquad \forall b,i,j,t,s \tag{28}$$

$$\varepsilon^3_{bijts} \ge 0 \qquad \forall i,j,t,s \tag{29}$$

4-2-Defuzzification

In this section, we employ fuzzy programming in order to convert the proposed model to an equivalent auxiliary crisp model based on the fuzzy numbers. Several methods have been developed in the literature to solve fuzzy problems (Pishvaee et al., 2012). One of the commonly used methods is introduced by Jime´nez et al. (2007). Since this method can be applied to different membership while preserving the linearity of the model without increasing the number of objective functions or inequality constraints, it is computationally efficient to solve fuzzy linear problems (Pishvaee 2010, and Shiraz 2015).

Given equations (30)-(33) as a linear programming model including fuzzy parameters:

$$Min \quad \tilde{h}X \tag{30}$$

$$s.t: \tilde{a}_i X \ge \tilde{b}_i \qquad \forall i = 1,2,...,l \tag{31}$$

$$\tilde{a}_i X = \tilde{b}_i \qquad \forall i = l+1,...,m \tag{32}$$

$$X \ge 0 \tag{33}$$

Assume $\tilde{h} = \left(h^{p}, h^{m}, h^{o}\right)$ as a triangular fuzzy parameter. Equations (34) and (35) respectively represent the expected value and the expected interval of the triangular fuzzy number $\tilde{h}$, as follows:

$$EV\left(\tilde{h}\right) = \frac{E_1^h + E_2^h}{2} = \frac{h^p + 2h^m + h^o}{4} \tag{34}$$

$$EI\left(\tilde{h}\right) = \left[E_1^h, E_2^h\right] = \left[\frac{1}{2}\left(h^p + h^m\right), \frac{1}{2}\left(h^m + h^o\right)\right] \tag{35}$$

With respect to Jimenez method and the study of Pishvaee and Torabi (2010), the above model can be replaced by equations (36) – (39):

$$MinEV(\tilde{h})X \tag{36}$$

$$s.t: \left[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}\right]X \geq \left[\alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}\right] \tag{37}$$

$$\left[\left(\frac{\alpha}{2}\right)E_2^{a_i} + \left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]X \leq \left[\left(1-\frac{\alpha}{2}\right)E_2^{b_i} + \left(\frac{\alpha}{2}\right)E_1^{b_i}\right] \tag{38}$$

$$\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i} + \left(\frac{\alpha}{2}\right)E_1^{a_i}\right]X \geq \left[\left(\frac{\alpha}{2}\right)E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i}\right] \tag{39}$$

α is the minimum confidence level which is determined by the decision maker (DM). In light of the above explanations, the objective function (2), constraints (4), (6) and (12) are reformulated as follows:

$$\begin{aligned} MinZ_2 = \sum_s p_s \Bigg(& \sum_h \sum_i \sum_b \sum_a \sum_t \left(\frac{f_{its}^{(1)} + 2f_{its}^{(2)} + f_{its}^{(3)}}{4}\right) Z_i + \left(\frac{\theta_{bi}^{(1)} + 2\theta_{bi}^{(2)} + \theta_{bi}^{(3)}}{4}\right) Q_{bahits} \\ & + \sum_b \sum_i \sum_t \left(\frac{\varpi_{bi}^{(1)} + 2\varpi_{bi}^{(2)} + \varpi_{bi}^{(3)}}{4}\right) W_{bits} + \left(\frac{\eta_{bi}^{(1)} + 2\eta_{bi}^{(2)} + \eta_{bi}^{(3)}}{4}\right) \pi_{bits} \\ & + \left(\left(\frac{\varphi_{bi}^{(1)} + 2\varphi_{bi}^{(2)} + \varphi_{bi}^{(3)}}{4}\right) - \left(\frac{\zeta_{bi}^{(1)} + 2\zeta_{bi}^{(2)} + \zeta_{bi}^{(3)}}{4}\right)\right) N_{bits} \Bigg) \end{aligned} \tag{40}$$

$$Z_i \leq \sum_j \sum_b \left(\alpha\left(\frac{d_{bjts}^{(2)} + d_{bjts}^{(3)}}{2}\right) + (1-\alpha)\left(\frac{d_{bjts}^{(1)} + d_{bjts}^{(2)}}{2}\right)\right) Y_{ij} \qquad \forall i, t, s \tag{41}$$

$$\pi_{bits} - N_{bits} \geq \sum_j \left(\left(\left(\frac{\alpha}{2}\right)\left(\frac{d_{bjts}^{(2)} + d_{bjts}^{(3)}}{2}\right) + \left(1-\frac{\alpha}{2}\right)\left(\frac{d_{bjts}^{(1)} + d_{bjts}^{(2)}}{2}\right)\right) Y_{ij} - I_{baits}\right) \qquad \forall a \geq 3, b, i, t, s \tag{42}$$

$$\pi_{bits} - N_{bits} \leq \sum_j \left(\left(\left(1-\frac{\alpha}{2}\right)\left(\frac{d_{bjts}^{(2)} + d_{bjts}^{(3)}}{2}\right) + \left(\frac{\alpha}{2}\right)\left(\frac{d_{bjts}^{(1)} + d_{bjts}^{(2)}}{2}\right)\right) Y_{ij} - I_{baits}\right) \qquad \forall a \geq 3, b, i, t, s \tag{43}$$

$$\sum_h \sum_b \sum_a Q_{baits} \leq \left(\alpha\left(\frac{Cap_{is}^{(2)} + Cap_{is}^{(3)}}{2}\right) + (1-\alpha)\left(\frac{Cap_{is}^{(1)} + Cap_{is}^{(2)}}{2}\right)\right) Z_i \qquad \forall i, t, s \tag{44}$$

4-3-Multi-objective optimization method

The developed methods for multi-objective programming can be divided into five main classes: scalar methods, interactive methods, fuzzy methods, meta-heuristics methods, and decision aided methods (Collette and Siarry, 2013; Mohamadi and Yaghoubi, 2017).

In this paper, we apply Ɛ –constraint to solve our proposed bi-objective model, this method is selected due to (Haimes et al., 1971; Mavrotas, 2009):

1. Ɛ –constraint is a simple and fast computational method due to not imposing extra variables to the model.
2. The number of generated efficient solutions can be controlled in this method by properly adjusting the number of grid points in each objective.
3. In this method, changing the scale of objective functions to a common scale is not required, and each objective function has its own scale.
4. Unsupported Pareto optimal solutions and non-extreme efficient solutions can be produced by the Ɛ –constraint to provide a clear framework to analyze the results.

This method was first introduced by Haimes et al. (1971) which is one of the widely used methods for solving multi-objective programming.

According to this method, one objective function is optimized while other objective functions are bounded as constraints. Consider equation (45) as a multi-objective problem with K objectives:

$$Min_{X\in\chi}\left\{F(x)=\left(F_1(x),F_2(x),...,F_k(x)\right)\right\} \tag{45}$$

Where χ is the feasible solutions space, X and $F(x)$ respectively represent the vector of decision variables and the vector of K objective functions. Equation (46) obtains Pareto solutions from the optimal solution of the problem through converting all objective function except primary objective function into constraints with enforcing upper bounds:

$$\begin{aligned}&MinF_k(x)\\&Subject\quad to\\&F_i(x)\le\varepsilon_i \qquad \forall i\ne k \qquad x\in X\end{aligned} \tag{46}$$

Applying the Ɛ –constraint as the solution method, we optimized z_1 over the mathematical model while z_2 is transferred into constraint with ε_2. Thus, the bi-objective proposed model is changed to a single objective one as follows:

$$
\begin{aligned}
&Max Z_1(x) \\
&Subject \quad to \\
&Z_2(x) \le \varepsilon_2 \\
&other \quad constraints
\end{aligned} \tag{47}
$$

Now, we define the value of ε_2 by ignoring first objective function in solving the model, next, this value is replaced by the values near to the optimal solution which have been obtained, finally, we analyze the quantity of the first objective by considering each value of ε_2 according to equation (47) and acquire corresponded Pareto frontiers.

5- Results

5-1-Case study

Between the years 1990 to 2010, earthquakes have left more than 1.87 million killed people with an average of 2,052 fatalities per event in the world (Doocy et al., 2013). Iran is among the most earthquake-prone countries and has faced many devastating earthquakes during the past decades (Sabzehchian et al., 2006). The Iran-Iraq earthquake on 12 November 2017 devastated the Iraqi Kurdish city of Halabja, and the Sunni Kurdish dominated places of Ezgeleh, Salas-e Babajani County, Kermanshah Province in Iran. According to the report provided by the United States Geological Survey, the earthquake measured 7.3 on the moment magnitude scale, it was considered as the deadliest earthquake of 2017, such that it caused at least 630 deaths and more than 7000 injured people. This paper selects the Kermanshah province as the case problem which was involved with the earthquake by its 8 cities (Sarpol Zahab, Ghasr-e Shirin, Javanrud, Gilan-e Gharb, Salas-e Babajani, Eslamabad-e Gharb, Dlaho, Kermanshah) and 526 villages.
Sarpol Zahab, Ghasr-e Shirin, and Salas-e Babajani were the cities with a higher number of victims and injured (2017 Iran–Iraq earthquake online on wikipedia). Figure 2 demonstrates the understudy province and its cities which are the potential AAs and BDCs, table 3 shows the number of different cities and their related number of injured.

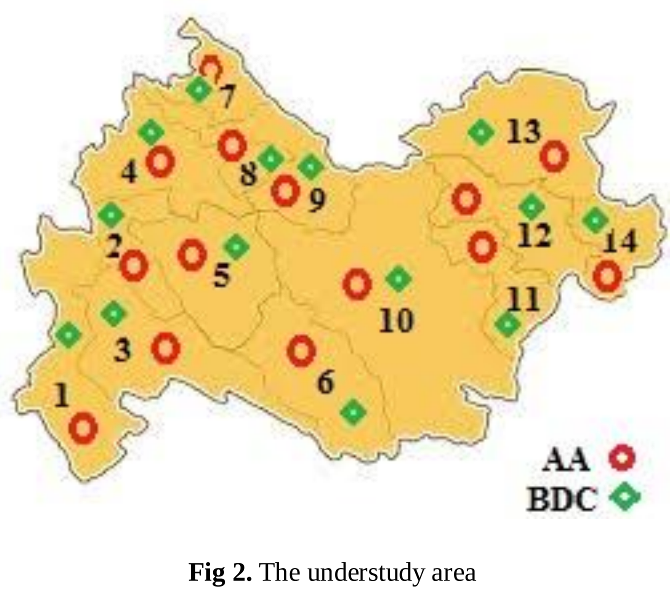

Fig 2. The understudy area

Table 3. The number of different cities and the related injured

Number	City	Injured
1	Ghasr-e Shirin	109
2	Sarpol Zahab	372
3	Gilan-e Gharb	170
4	Salas-e Babajani	5
5	Dlaho	6
6	Eslamabad-e Gharb	54
7	**Pave**	**1**
8	Javanrud	-
9	**Ravansar**	**12**
10	Kermanshah	-
11	**Harsin**	-
12	**sahne**	-
13	**Songhar**	-
14	**Kangavar**	-

Three scenarios of s_1, s_2 and s_3 are defined and their probabilities are set to be 0.3, 0,4 and 0.3. Note that these scenarios and their associated probabilities are considered by the subject matter experts. s_1, s_2 and s_3 are respectively associated with optimistic, realistic, and pessimistic modes. We assume the blood demand of each injured people on each of AAs under s_1, in the interval of 200 and 400, under s_2 in the interval of 400 and 600, and under s_3 in the interval of 600 and 800.

5-2-Computational results

In this section, we present the results, all tests are done by *GAMS/Cplex* on a Pentium Core ™ i5 computer with 2GB RAM under win10. As mentioned, Ɛ-constraint is employed to solve the model, according to the explanations (see Section 4-3), we solve the model without notice to the first objective function (z_1) and obtain ε_2 equal to the achieved value of the objective function and then z_2 is transferred to a constraint. Tables 4, 5 and 6 investigate the behavior of the model which is observed by changing the value of ε_2 where α is set to be 0.5, 0.7 and 0.9, respectively. As can be seen, the value of the first objective function (z_1) decreases when ε_2 increases because the higher cost of the supply chain for establishing blood distribution centers and blood procurement, the less amount of unsatisfied demand in AAs, therefore, DMs can gain insight to select the best path considering the tradeoff between the first and second objective functions, figure 3 provides this tradeoff.

Table 4. Calculated results for different values of ε_2 where $\alpha = 0.5$

State	ε_2	OBJ1	The current location of AAs	Optimal location of blood distribution centers
1	39200	276	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9
2	43200	202	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9,10
3	47200	183	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9,10
4	51200	97	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12
5	55200	52	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12
6	59200	32	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,14
7	63200	32	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
8	67200	32	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
9	71200	32	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
10	75200	32	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14

Table 5. Calculated results for different values of ε_2 where $\alpha = 0.7$

State	ε_2	OBJ1	The current location of AAs	Optimal location of blood distribution centers
1	43650	202	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9
2	47650	174	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9,10
3	51650	143	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10
4	55650	73	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12
5	59650	46	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12,13
6	63650	23	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
7	67650	23	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
8	71650	23	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
9	75650	23	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
10	79650	23	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14

Table 6. Calculated results for different values of ε_2 where $\alpha = 0.9$

State	ε_2	OBJ1	The current location of AAs	Optimal location of blood distribution centers
1	48921	197	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9,10
2	52921	165	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10
3	56921	123	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10
4	60921	67	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12
5	64921	38	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,12,13
6	68921	21	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
7	72921	21	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
8	76921	21	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
9	80921	21	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14
10	74921	21	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14

The change in the first objective function against different values of ε_2 is shown graphically in figure 3 where α is examined among option 0.5, 0.7 and 0.9. Firstly, figure 3 demonstrates the opposite interaction of the objective functions, when the value of ε_2 increases the unsatisfied demand is decreased due to the fact that spending more costs for establishing more number of distribution centers to procurement the suitable amount of blood units by considering penalties for shortages, wastages leads to the lower amount of unsatisfied demand in AAs.

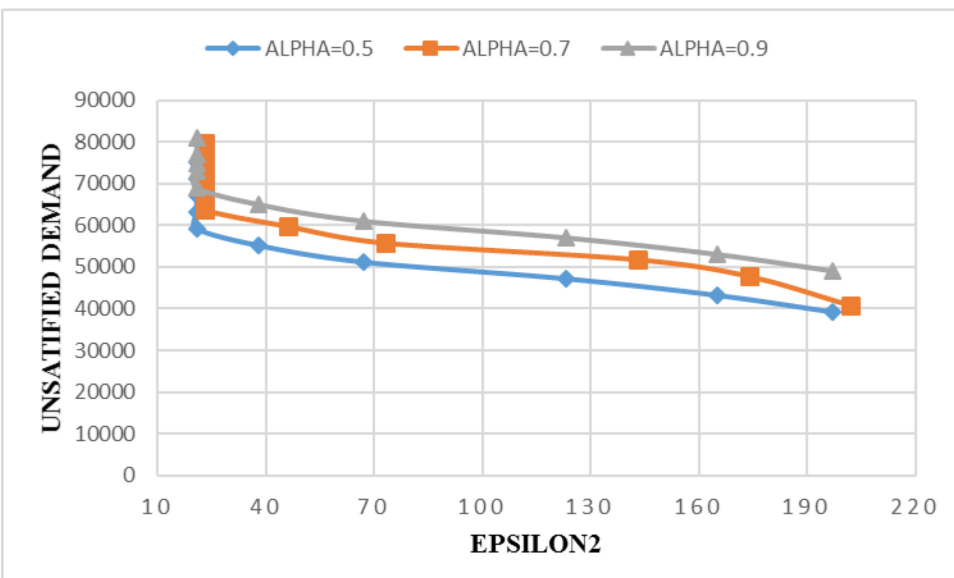

Fig 3. Tradeoff between cost and ε_2 through different values of α

Secondly, in all Pareto frontiers for different values of α, the first objective function remains constant from a point of ε_2, thus it is rational for DMs to select these values of ε_2 or higher. Finally, figure 3 demonstrates that the Pareto frontiers move towards the upper left when the value of α increases. It means that the DM could here select the best value for α based on their preference. A risk-averse DM tends to select the lower values of α and risk-seeking decision maker may prefer higher values for α. Therefore, the more DM wants to deal with uncertainty, the higher values of minimum confidence level, because more awareness about unexpected conditions should be provided when DMs want to deal with uncertainty with a higher degree of confidence.

5-3-The benefit of the model

In this section, we analyzed the usefulness of the proposed model in two ways (1) defining different modes of the problem and comparing the results, (2) investigating the performance of the problem before and after implementing the proposed model (non-optimal conditions against optimal conditions).
To demonstrate the role of simultaneously considering the fuzzy and the Stochastic programming methods, as incorporated in our proposed model, the following three modes are defined for sensitivity analysis:

1. WS mode: The model is separately solved under each scenario and then Wait-and-See problem (WS) is obtained through the arithmetic mean of these two optimal objective functions.
2. SP mode: The stochastic scenario-based model is solved and SP is obtained.
3. FSP mode: The stochastic scenario-based model is solved by considering fuzzy parameters and FSP is obtained.

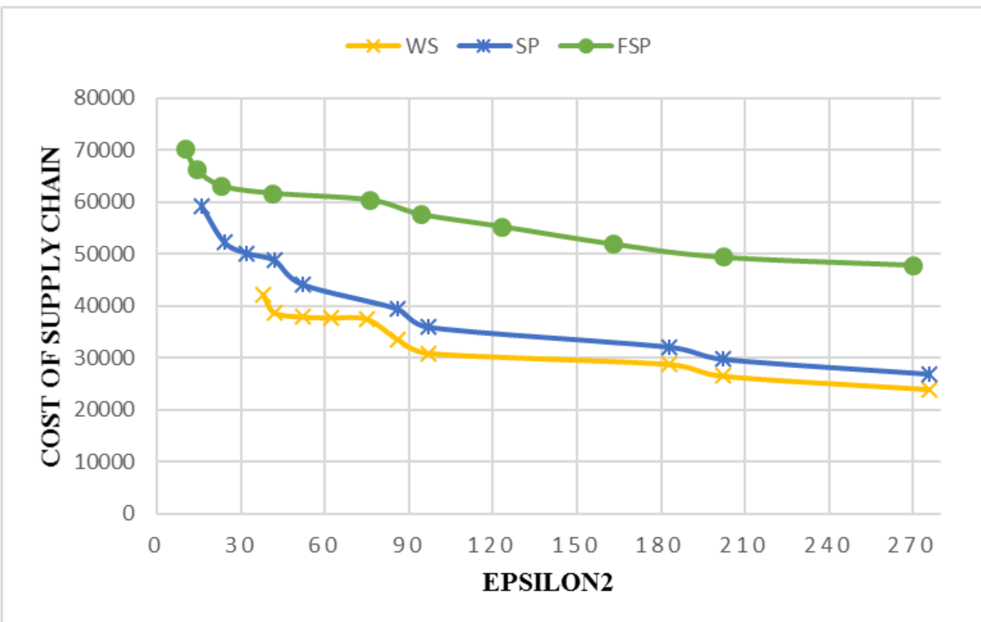

Fig 4. Tradeoff between Cost of supply chain and ε_2 for different modes of the problem

Comparison of different modes of the problem is pictured in figure 4. As can be seen, the Pareto frontiers of SP mode are above the Pareto frontier of WS, because SP mode has more awareness about conditions. In addition, the objective function of FSP mode is better than that of SP in all cases due to simultaneously considering stochastic programming and fuzzy programming.

To emphasize the importance of considering uncertainty, components of cost objective function for SP, WS, and FSP are compared with each other. Figure 6 shows different components of cost or OBJ2. As it can be inferred from figure 5 the optimal value of objective functions noticeably improves when uncertainty is considered.

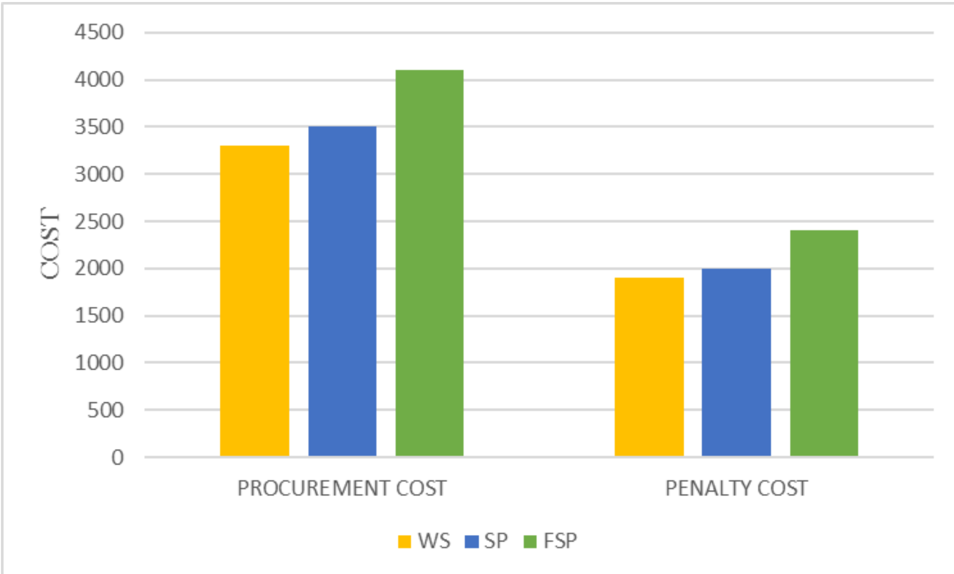

Fig 5. Different components of cost transfusion for different modes of the problem

To investigate the expected improvements by the proposed model the conditions of the case study are compared with the optimal conditions after implementing the proposed model.

The steps of this comparison can be explained as follows:

1. Obtaining optimal solution by considering blood distribution centers.
2. Obtaining the non-optimal conditions by removing blood distribution centers.
3. Comparing optimal solution of the model with defined non-optimal conditions.

Table 7. Computational results for comparing non-optimal conditions with optimal conditions

	Cost of supply chain	**Unsatisfied demand on AAs**
Non-optimal Condition	43200	101
Optimal condition	55900	63
Improvement rate	-29%	38%

An efficient insight can be gained from table 7 where the blood distribution centers are removed.

by removing distribution centers although the less cost for establishing them, the higher cost for shortages and wastages due to not having a resilient way to manage the supply chain and consequently the lower level of satisfied demand in AAs. Therefore, table 7 confirms the outperformance of the model based on establishing blood distribution centers.

6-Conclusion

In this paper, we developed a fuzzy scenario-based mixed integer bi-objective model for the concept of blood distribution management in disastrous conditions, where the level of satisfied blood demand can be enhanced by establishing blood distribution centers. Two objectives including minimizing total cost and unsatisfied demand were considered in the model. Demand, capacity, and cost were exposed to uncertainty in the proposed model; fuzzy programming and stochastic programming were simultaneously applied to cope with uncertainty. Mathematical approximations were used to linearize the nonlinear terms and ε-constraint was adapted to solve the bi-objective model, afterward, we analyzed our model by using different values of ε_2, this analysis could give insight to DMs in selecting the best approach.

The effects of the proposed model were assessed and the results illustrated that it caused an increase in the safety level of AAs. Also, to investigate the benefit of fuzzy stochastic scenario-based approach, WS, SP and FSP modes were defined, FSP mode proved to be more reliable than the other modes.

Future research can complete our proposed model in four ways: (1) Aggregating the proposed model with inventory management problem which involves more consideration. (2) Incorporating vehicle routing problem in the model for delivery of blood. (3) Employing the other applicable and novel approaches to capture the inherent uncertainty of the model parameters and also considering other sources of uncertainty to assess the robustness of the model. (4) Adopting other approaches such as data mining and neural network, and etc to develop practical models.

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