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A Robust Optimization Model for Blood Supply Chain Network Design

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Location-allocation,
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ABSTRACT
The eternal need for humans' blood as a crucial commodity is the main stimulus for the healthcare systems to provide efficient blood supply chains (BSCs) by which the requirements are satisfied at the maximum level. To have an efficient supply of blood, an appropriate planning for blood supply chain is of a challenge which requires more attention. In this paper, we address a mixed integer linear programming model for blood supply chain network design (BSCND) with the need for making both strategic and tactical decisions throughout a multiple planning period. A robust programming approach is devised to deal with inherent randomness in parameters of the model. To illustrate the usefulness of the model as well as its solution approach, it is tested into a set of numerical examples, and the sensitivity analysis is conducted. Finally, two performance criteria, i.e., the mean and standard deviation of constraint violations, under a number of random realizations are employed to evaluate the performance of both of the proposed robust and deterministic models. For all test problems, the results imply the domination of robust approach over the deterministic one.

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1. Introduction

In spite of technological developments in medicine industries to find a substitution for blood, it is a life-saving commodity for which there is almost an everlasting need. Blood is donated fairly irregularly and demand for blood is as stochastic. Thus, an efficient conformity of blood supply and demand is not straightforward. Furthermore, any shortages and interruptions in blood supply lead to humans' death [1]. With respect to these difficulties, blood supply chain management is of a challenge for governments' healthcare systems. Moreover, it will be more complicated considering the perishability of blood products, besides the fact that blood outdates impose high wastage cost since blood donors are scarce precious resources.

In general, supply chain management (SCM) deals with planning, managing and controlling the operations of a supply chain [2]. The performance of a supply chain highly depends on supply chain network design (SCND), which

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totally corresponds to determining the optimal number, location, and capacity of facilities [3].
Healthcare systems are vast and complicated whose planning and designing are not straightforward [4]. Generally, a blood supply chain as a substantial segment of any healthcare systems is comprised of four stages (echelons) which are blood collection and production along with inventory control and distribution processes. The process of procurement of blood and blood products is handled in the collection stage which aims to support the quantity of blood and its products required to satisfy demands. The main sorts of decisions in blood collection management are the ones related to locating a facility and determining its capacity, collection methods, and donor management. Blood units received by blood centers are supposed to be tested and fractionated (broken down into components) in production echelon. Blood products are then stored at the blood centers banks considering their perishable nature, and finally, distribution will take place from one blood center to another, provided that there is a shortage in one location and an over-supply in another, and also from a blood center to hospitals when a demand is realized. [5]
The efficiency and effectiveness of blood supply chains can be remarkably improved through mathematical programming such as operational research methods. It is worth mentioning that to design an efficient blood supply chain network, having an optimal network of blood collection and distribution is of great significance [3].
Since blood demand as a critical parameter of blood supply chains is tainted with uncertainty, it is of great significance to take this specific issue into account while planning a blood supply chain by optimization models [6]. The uncertainty environment is divided into three main parts: fuzzy, stochastic, and robust environments [7]. To cope with data randomness, either stochastic or robust programming approaches can be applied. Notably, the stochastic programming approach is applicable, in case sufficient information about distribution functions of random data is accessible, or we face a repetitive action during the planning horizon. The robust programming approach is employed whenever we cannot get enough information about distribution functions of random variables [8, 9]. However, in some cases, we have to deal with epistemic uncertainty (an inherent impreciseness) when enough historical data are not available, or no repetition of a specific action is realized [10]. In these situations, the epistemic parameters will be estimated with respect to the field experts' subjective knowledge/professional opinions. In this paper, we devise a robust programming approach to deal with inherent randomness in the amount of blood demand.
The reminder of the paper is organized as follows: a review of the relevant literature is presented in Section 2. Section 3 is dedicated to define the problem and mathematical formulation of the model, and the solution technique is applied in Section 4. In Section 5, we examine the proposed model and its solution approach through several numerical experiments, and a number of sensitivity analyses are also carried out. At last, concluding remarks and future research trends comprise Section 6.

2. A review of the Relevant Literature

The importance of blood supply chain management has attracted researchers in recent years. In this section, we have a review of the existing literature of planning for blood supply chains. In line with the structured review provided by Osorio et al. [11], the quantitative models in blood supply chains can be categorized based on different attitudes. For instance, Prediction and classification of donor arrivals, planning for disasters and emergencies, donor motivation and behavior, different collection policies and capacity planning comprise the main body of problems studied.
One of the earliest studies in blood collection stage was addressed by Cumming et al. [12]. They developed a planning model to alleviate imbalances between blood supply and demand. Their model consists of transfusion and issuing sub-models, considering preferences as well as differences in the use of blood over a seven-day time period. In another work, Sahin et al. [13] conducted a bi-objective integer mathematical model for the Turkish Red Crescent Society blood bank location-allocation problem. In their developed model, the weighted traveled distance as well as the number of blood terminals were to be minimized while maximizing the covered population was the aim of the second objective function. Jacobs et al. [14] outlined the integer programming models to investigate a facility relocation problem for the American Red Cross in Norfolk, Virginia by which they provided insights into the current scheduling activities of blood collection and distribution along with handling the decisions such as donors' allocation to collection points, and so collection points to blood centers and quantities of blood to be collected. The main objective of their model was

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to minimize distance while satisfying capacity and demand constraints.

In other efforts, logistics regression and log-linear models along with chi-square tests (i.e., tests that measure how well a set of observed counts fits a matching set of expected counts) were devised by Glynn et al. [15] and Sonmezoglu et al. [16] to evaluate indicators, such as reaction rates and blood collection volume, over both normal and disaster periods. Their studies represent that higher adverse reaction rates for the first-time donors in comparison with those for regular donors lead to the risk increase. Furthermore, in their model, the volume of collections is remarkably increased as disasters have considerable impact on the donors' motivation for blood donation. Notably, it may not be always possible to collect a huge amount of blood in a very short-time period.

The configuration of collection points for different donor arrival rates was investigated by Brennan et al. [17] accounting for the allocation of staff and work rules. They applied a simulation approach and indicators such as the time taken in different stages in the collection process to measure the impact of changes. Custer et al. [18] employed Monte Carlo simulation and decision trees to investigate different aspects of blood collection including cost, strategies for blood collection, and deferral policies. Their findings indicated that improving the location of collection facilities and advertising strategies could assist operation managers and decision-makers to improve collection process.

Alfonso and Xie [19] investigated a mathematical model for blood collection planning. Their proposed model aimed to minimize products provided by external suppliers and optimize the quantity of blood to be collected in each period. Ghandforoush and Sen [20] presented a nonlinear integer programming model to determine the minimum cost of platelet production and blood mobile scheduling for a regional blood center. Their model was subsequently converted to a linear 0–1 problem applying a two-step conversion process to guarantee optimality since the initial formulation carried a non-convex objective function with no convergence to optimal solutions. Gunpinar [21] developed an optimization model for collection planning. The model investigated a vehicle routing problem for blood centers to minimize the distance travelled by mobile blood facilities over the blood collection process. He used three different methods including CPLEX solver, branch & bound, and column generation algorithms to determine optimal routing for each mobile blood facility. A mixed integer non-linear programming model was proposed by Sha and Huang [22] with the purpose of minimizing the total cost and unsatisfied demands. Then, a heuristic algorithm was developed based on lagrangean relaxation approach, and a case study in Beijing was implemented to illustrate the applicability of the proposed model.

A multi-objective mixed-integer programming (MOMIP) model for emergency services was addressed by Zhang and Jiang [23]. The allocation of demand zones to emergency facilities, the optimal number, and location of emergency facilities with the aim of minimizing total cost was determined by their proposed model. They applied the robust programming approach to handle data uncertainty. A mixed-integer linear programming model for blood supply chain in emergency situation was developed by Jokar and Hosseini-Motlagh [24] to reduce the total cost including blood shortage and wastage costs. Their model was supposed to determine the optimal number of blood facilities and their coverage area under several disaster scenarios. They considered the capacity of mobile blood facilities as a variable, and illustrated that the optimal number of permanent and mobile facilities is highly affected by changes in the capacity of mobile blood facilities. In another work, Cheraghi and Hosseini-Motlagh [25] addressed a fuzzy-stochastic model for blood supply chain in disaster condition. To handle data uncertainty, they applied a fuzzy programming approach and a combination of the expected value and chance-constrained programming approaches. The applicability of their considered problem was illustrated by applying a real case study. Zahiri et al. [26] presented a mixed-integer programming model for blood collection and distribution network design to minimize the total cost, as the sole objective function. They dealt with uncertain parameters of their model by utilizing a robust stochastic programming approach. The important features of the aforementioned papers are summarized and compared with the model developed in this work, as shown in Table 1.

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Tab. 1. The summary of the studied papers characteristics

Author	Planning horizon			approach				Solution method					Objectives					Time periods	
	Strategic	Tactical	Operational	Deterministic	Fuzzy	Robust	Robust -Possibilistic	Stochastic	Integer programming	Meta(heuristic)	Simulation	Statistical analysis	Minimizing cost	Minimizing distance	Minimizing shortage/ Maximizing responsiveness	Minimizing service time	Single-period	Multi-period
Cumming et al. [12]		•						•		•			•				•	
Sahin et al. [13]	•			•					•					•			•	
Jacobs et al. [14]	•							•	•					•			•	
Glynn et al. [15]			•	•								•						•
Sonmezoglu et al.[16]		•		•								•						
Brennan et al. [17]	•							•			•					•	•	
Custer et al. [18]	•							•			•		•					•
Alfonso and Xie [19]		•		•					•								•	
Ghandforoush and Sen [20]			•	•					•				•				•	
Gunpinar [21]	•	•						•	•				•	•	•			•
Sha and Huang [22]		•								•			•		•			•
Zhang and Jiang [23]	•					•			•				•		•		•	
Jokar and Hosseini-Motlagh [24]	•	•						•	•				•				•	
Cheraghi and Hosseini-Motlagh [25]	•				•				•				•					•
Zahiri et al. [26]	•	•						•	•				•					•
Our study	•	•				•			•				•					•

As far as we are concerned, there are only two studies [22] [26] with slightly similar models to ours which regard the location–allocation problem of mobile blood facilities in a multiple period of planning horizon. The majority of papers associated with blood management are mainly discussed in the inventory aspects. To fill this gap, this paper contributes to the area as follows by considering inherent randomness of input data, since no papers could be addressed in the literature taking into account the random uncertainty in the integrated collection and distribution problem for blood bank facilities.

- Integrated planning for blood collection and distribution network consisting of both temporary and fixed (main) blood facilities as collection sites and hospitals as demand points.
- Developing a mixed integer linear programming model to determine the optimal locations for blood collection facilities (i.e., both temporary and fixed facilities) during a multiple period of planning horizon.
- Employing a robust programming approach to deal with the inherent randomness in parameters with the aim of obtaining robust solution.

3. Problem Description

In this paper, a blood collection and distribution network is considered in which temporary blood facilities, fixed blood centers, and hospitals are the main components. The concerned network aims to minimize the total costs. The establishment cost of blood collection facilities, the cost of temporary facilities repositioning, blood delivery cost from temporary facilities to the main ones and from main facilities to demand zones comprise the network costs. The blood collection facilities are different in capacity and

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the nature of locations. The capacity of fixed blood collection sites is more than temporary sites, and the fixed centers must be established at the beginning of the planning horizon. In other words, the locations of fixed blood centers cannot be changed over the planning horizon while each temporary facility can move to a different location in each period at an extra cost. The volume of demand and geographic dispersion of the demand points in each period affect the associated cost. On the other hand, the opening cost for the fixed blood center is much more than that of a temporary blood facility. Moreover, blood donation can directly occur at either temporary collection sites or the fixed ones. Subsequently, the blood units collected by each temporary facility must be directed to one or more fixed blood banks at the end of each period. Fig. 1 depicts the concerned blood collection and distribution network schematically.

The following values are determined through solving the proposed model:

- The optimal locations of the fixed blood centers throughout the planning horizon.
- The optimal locations of the temporary blood facilities in each period.
- The optimal number of blood facilities needed during the planning horizon along with the optimal allocation of demand zones to the established blood sites
- The number of temporary blood collection sites repositioned in successive periods and the associated moving cost.
- The volume of blood donation in each period and blood transportation cost between facilities and demand points.

It is worth mentioning that we assume each planning period to be shorter than the blood lifetime for the sake of noting the perishability characteristics of blood units; however, this assumption makes the application of this model limited to city-wide levels. Besides, donors' regions along with the candidate locations for both temporary and fixed blood centers are assumed to be given. In addition, the center of each region represents donors' points.

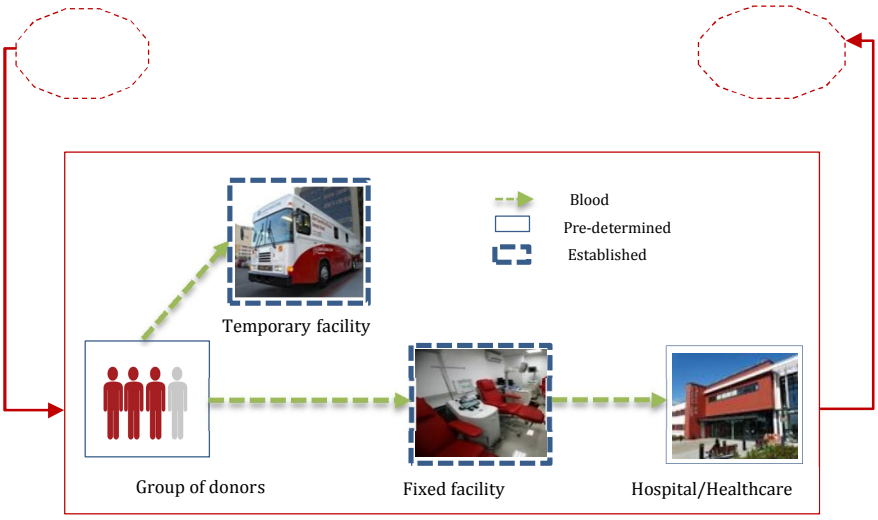

Fig. 1. An overview of the considered network

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3-1. Notations

The following notations are adopted to formulate the proposed model.

3-1-1. Indices

$d=1,2,...,I$	Index of d^{th} group of donors
$b=1,2,...,J$	Index of b^{th} candidate location for temporary blood facilities
$g=1,2,...,G$	Index of g^{th} candidate location for main (fixed) blood facilities
$h=1,2,...,H$	Index of h^{th} hospital / healthcare center
$t=1,2,...,T$	Index of t^{th} time period

3-1-2. Technical parameters

$demand_{h,t}$	Total blood demand of each hospital h in period t
$disdb_{db}$	Distance between d^{th} donors group and b^{th} candidate temporary blood facility
$disdg_{dg}$	Distance between d^{th} group of donors and g^{th} main blood center
$disbg_{bg}$	Distance between b^{th} candidate temporary blood facility and g^{th} main blood center
rdb	Coverage radius of temporary blood facilities by which group of donors d is served, provided that $disdb_{db} \le rdb$
rdg	Coverage radius of main blood centers by which group of donors d is served, provided that $disdg_{dg} \le rdg$
rbg	Coverage radius of main blood centers by which temporary blood facility b is served, provided that $\text{disbg}_{bg} \le \text{rbg}$
cap_b	The capacity of each candidate temporary blood facility
cap_g	The capacity of each main (fixed) blood facility
cap_h	The capacity of each hospital/healthcare center h
$donate_{dt}$	Total blood donation by d^{th} group of donors in period t
M	An arbitrary large number
β	Minimum demand satisfaction

3-1-3. Cost parameters

mc_{b_1,b_2}	Relocation cost of each temporary blood facility moving from location b_1 to location b_2 in two successive time periods
lc_g	Establishment cost of a main blood center in candidate location g
tc_{bg}	Transportation cost of blood units from b^{th} temporary blood facility to g^{th} main blood center
tc_{gh}	Transportation cost of blood units from main blood facility g to hospital h

3-1-4. Discrete decision variables

N	The number of temporary blood facilities needed in each period

3-1-5. Continuous decision variables

bv_{dbt}	The blood volume donated by d^{th} group of donors at b^{th} temporary blood facility in period t
bv'_{dgt}	The blood volume donated by d^{th} group of donors at g^{th} main blood facility in period t
bv''_{bgt}	The blood volume transferred from b^{th} temporary blood facility to g^{th} main blood facility in period t
bv'''_{ght}	The blood volume transported from main blood facility g to hospital h in period t

3-1-6. Binary decision variables

y_{dbt}	Is equal to 1 if d^{th} group of donors is assigned to a temporary blood facility which is located at b^{th} site in period t; 0, otherwise
y'_{dgt}	Is equal to 1 if d^{th} group of donors is assigned to a main blood facility which is located at g^{th} site in period t; 0, otherwise
y''_{bgt}	Is equal to 1 if a temporary blood facility located at b^{th} site is assigned to a main blood facility at g^{th} site in period t; 0, otherwise
$x_{b_1,b_2,t}$	Is equal to 1 if a temporary blood facility is located at ${b_1}^{th}$ site in period $t–1$, and moves to site b_2 in period t; 0, otherwise
p_g	Is equal to 1 if a main blood facility is located at g^{th} site; 0, otherwise

3-2. Mathematical formulation

The concerned problem can be formulated in the form of a MILP model as follows:

3-1-2. Objective function

$$Min\ Z = \sum_{b_1,b_2,t} x_{b_1,b_2,t} * mc_{b_1,b_2} + \sum_{g} p_g * lc_g + \sum_{b,g,t} bv''_{bgt} * tc_{bg} + \sum_{g,h,t} bv'''_{ght} * tc_{gh} \quad (1)$$

The above objective function aims to minimize the network total cost involving establishment cost of main

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blood centers, repositioning cost of temporary blood facilities as well as blood delivery cost from temporary facilities to main facilities and from main facilities to hospitals or healthcare centers over the multiple planning horizon.

3-2-2. Model constraints

$$\sum_{b_1} x_{b_1,b_2,t} \leq 1, \qquad \forall b_2, t \qquad (2)$$

Constraint (2) guarantees that only one temporary facility can move to candidate location b_2 from other locations in each period.

$$\sum_{b_1 \neq b_2} x_{b_1,b_2,t} = N, \qquad \forall t \qquad (3)$$

The number of temporary blood facilities opened in each period is determined by constraint (3). Notably, the same number of temporary sites is selected in each period so as to avoid costs caused by the facilities closure and opening at successive periods.

$$\sum_{b_2} x_{b_1,b_2,t} \leq \sum_{b} x_{b,b_1,t-1}, \qquad \forall b_1, t \geq 2 \qquad (4)$$

Each temporary facility can move to another location in the next period only if it has been established before. This constraint is held by relationship (4).

$$\sum_{b} y_{dbt} + \sum_{g} y'_{dgt} \leq 1, \qquad \forall d, t \qquad (5)$$

The blood from every group of donors can only be donated in at most one type of facilities either temporary or fixed ones represented by constraint (5).

$$y_{dbt} * disdb_{db} \leq rdb * \sum_{b_1} x_{b_1,b,t-1}, \qquad \forall d, b, t \qquad (6)$$

$$y'_{dgt} * disdg_{dg} \leq rdg * p_g, \qquad \forall d, g, t \qquad (7)$$

$$y''_{bgt} * disbg_{bg} \leq rbg * p_g, \qquad \forall b, g, t \qquad (8)$$

Relationships (6)–(8) represent the constraints on the coverage radius of facilities.

Constraint (6) determines that each group of donors can be assigned to a temporary facility, provided that it is within the facility coverage radius. Also, constraint (7) implies that a group of donors can be served by a main blood facility only if it is positioned within the facility service radius.

Similarly, constraint (8) indicates that a temporary blood facility can be supported by a main blood facility if it is covered by the main facility.

$$bv_{dbt} \leq M * y_{dbt}, \qquad \forall d, b, t \qquad (9)$$

$$bv'_{dgt} \leq M * y'_{dgt}, \qquad \forall d, g, t \qquad (10)$$

$$bv''_{bgt} \leq M * y''_{bgt}, \qquad \forall b, g, t \qquad (11)$$

Constraints (9)–(11) ensure that blood can be collected by both temporary and fixed facilities if they have already been opened. The blood would flow from donors to either temporary or main facilities and from temporary sites to fixed ones.

$$\sum_{d} bv'_{dgt} + \sum_{b} bv''_{bgt} \leq cap_g, \qquad \forall g, t \qquad (12)$$

The maximum capacity of g^{th} main facility is stated via constraint (12).

$$\sum_{b} bv_{dbt} + \sum_{g} bv'_{dgt} \leq donate_{dt}, \qquad \forall d, t \qquad (13)$$

Constraint (13) puts restrictions on the blood volume donated by each donor' group in each period.

$$\sum_{d} bv_{dbt} \leq capb, \qquad \forall b, t \qquad (14)$$

Constraint (14) limits the capacity of each temporary blood site.

$$y''_{bgt} \leq \sum_{b_1} x_{b_1,b,t}, \qquad \forall b, g, t \qquad (15)$$

The blood units can only be delivered from a temporary site to a main center, provided that it has been established before assured by constraint (15).

$$\sum_{g} bv'''_{ght} \geq \beta * demand_{h,t} \qquad \forall h, t \qquad (16)$$

In the concerned network, at least β percent of demand must be satisfied for each hospital/healthcare center in each period. This requirement is guaranteed by constraint (16).

$$\sum_{g} bv'''_{ght} \leq cap_h \qquad \forall h, t \qquad (17)$$

Constraint (17) defines the maximum capacity of hospital/ healthcare center h.

$$\sum_{d} bv_{dbt} = \sum_{g} bv''_{bgt}, \qquad \forall b, t \qquad (18)$$

All blood units collected by temporary blood facilities are supposed to be transferred to main blood banks at the end of each period, defined by constraint (18).

$$\sum_{d} bv'_{dgt} + \sum_{b} bv''_{bgt} = \sum_{h} bv'''_{ght} \qquad \forall g, t \qquad (19)$$

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Constraint (19) ensures that all blood units arrived at each main blood center are distributed to hospitals/ healthcare centers at the end of each period.

$$y_{dbt}, y'_{dgt}, y''_{bgt}, x_{b_1,b_2,t}, p_g \in \{0,1\}, \quad \forall d,b,g,t \quad (20)$$

$$bv_{dbt}, bv'_{dgt}, bv''_{bgt}, bv'''_{ght} \geq 0, \quad \forall d,b,g,h,t \quad (21)$$

Eventually, the type of decision variables is indicated via constraints (20) and (21).

4. Robust Programming Approach

To handle uncertainty in the optimization problems requiring both feasibility and optimality robustness simultaneously, the robust programming (RP) presents risk-averse methods. The feasibility robustness is defined as the feasibility of results obtained under almost all possible values of uncertain parameters. In the meantime, the obtained result will remain near-optimal under different realizations of the uncertain parameters by means of the optimality robustness [27]. Consequently, since uncertain parameters may possibly change over a long-term planning horizon, the critical role of robustness, especially in problems with strategic decision level, such as facility location, cannot be ignored.

A various number of robust approaches have been applied to optimization models so far. For instance, Soyster [28] addressed the first approach to cope with data uncertainty by mathematical models whose attempt often led to over-conservative models and poor solutions in term of optimality. Later, Ben-Tal and Nemirovski [29], [30] and [31] developed less conservative models by taking into account ellipsoidal uncertainties. Bertsimas and Sim (BS) [32, 33] proposed an approach according to the observation that in real situations, it is unrealistic to assume that all coefficients take their worst-case values simultaneously.

4-1. A light robust heuristic approach

In this paper, we devise an efficient uncertainty modelling approach called *Light robustness* which couples robust optimization with a simplified two-stage stochastic programming approach and is benefited from flexibility and ease of use. Furthermore, Light Robustness is sometimes able to produce solutions having comparable quality with those achieved via stochastic programming or robust models while it requires less effort in terms of model formulation and solution time [34]. The slack variables related to the constraints of the nominal problem are determined by this approach. The underlying assumption is that the degree of solution robustness corresponds to the slack left in the constraints employed to absorb variations of uncertain parameters. This method requires the solution of three LPs containing nominal problem and two other LP models discussed in the following.

Assume that x^* is an optimal solution to nominal problem (22)–(24).

$$\min \sum_{j \in N} c_j \, x_j \quad (22)$$

$$\sum_{j \in N} a_{ij} \, x_j \geq d_i \quad i \in M \quad (23)$$

$$x_j \geq 0 \quad j \in N \quad (24)$$

Now, let matrix D take a value, say $\tilde{d}_i \in [d_i, d_i + \hat{d}_i]$, and M and N represent the number of constraints and variables in the LP model, respectively. The maximum violation of the i^{th} uncertain constraint with respect to optimal solution x^* is defined via the following relationship:

$$L_i^* = \left(d_i + \hat{d}_i\right) - \sum_{j \in N} a_{ij} \, x_j{}^* \quad (25)$$

Also, we consider set $U = \{i \in M : L_i^* > 0\}$ comprised of the rows for which enough slack should be assigned such that $U \geq 1$, indicating that at least one row requires the slack variable since otherwise optimal solution x^* of the nominal problem would be feasible and optimal in any realizations of the uncertain parameter.

Firstly, the following LP model is solved:

$$max \; \sigma \quad (26)$$

$$\sum_{j \in N} a_{ij} \, x_j - s_i = d_i \quad i \in M \quad (27)$$

$$\sigma \leq \frac{s_i}{L_i^*} \quad i \in U \quad (28)$$

$$\sum_{j \in N} c_j \, x_j \leq (1+\delta) \, z^* \quad (29)$$

$$x_j \geq 0 \quad j \in N \quad (30)$$

$$s_i \geq 0 \quad i \in M \quad (31)$$

where the minimum slack that can be assigned to any uncertain rows would be maximized. The uncertainty for each row can be considered separately by normalizing slack variable s_i in the uncertain constraint i via dividing it by L_i^* ($i \in U$) as represented in "constraint (28)".

Notably, several equivalent optimal solutions can be obtained, owing to the max-min nature of the above LP model. Actually, there is no force to assign large slacks, which are of importance to improve robustness, to the

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remaining rows since only the minimum normalized slack is considered by the objective function. Thus, the slacks are supposed to be balanced among uncertain rows. To this end, the second LP is regarded as below.
Let (x^*,s^*,σ^*) be an optimal solution of models (26)–(31), so the average of the normalized slacks is defined as follows:

$$s_{avg} = \frac{\sum_{i\in U} s_i^*/L_i^*}{|U|} \quad (32)$$

Also, the minimum value of the normalized slacks is obtained as follows:

$$s_{min} = min\{s_i^*/L_i^* : i \in U\} \quad (33)$$

Then, the LP models (34)-(40) are solved.

$$min \sum_{i\in U} t_i \quad (34)$$

$$\sum_{j\in N} a_{ij}\, x_j - s_i = d_i \qquad i \in U \quad (35)$$

$$\sum_{j\in N} c_j\, x_j \le (1+\delta)\, z^* \quad (36)$$

$$\frac{s_i}{L_i^*} + t_i \ge s_{avg} \qquad i \in U \quad (37)$$

$$x_j \ge 0 \qquad j \in N \quad (38)$$

$$\frac{s_i}{L_i^*} \ge s_{min} \qquad i \in U \quad (39)$$

$$s_i \ge 0\,, t_i \ge 0 \qquad i \in U \quad (40)$$

Where objective function (34) penalizes the sum of variables t_i assigned to each uncertain constraint, which takes positive values, provided that the associated normalized slack is smaller than the average, with the aim of balancing the normalized slacks among all constraints.

4-2. The equivalent robust model

In this paper, the amount of blood demand, which plays a critical role in blood supply chain planning, is tainted with inherent random uncertainty, such that $\widetilde{demand}_{h,t} \in \left[demand_{h,t},\ demand_{h.t} + \widehat{de}_{h,t}\right]$, in which $demand_{h,t}$ represents the nominal value of the uncertain parameter and $\widehat{de}_{h,t}$ defines the maximum violation (worst case) of blood demand.
Regarding the steps of the aforementioned approach, our model would be formulated as below:
After the nominal models (1)-(21) are solved, the second LP problem would be modeled as follows with respect to $L_{h,t}^*$ such that:

$$L_{h,t}^* = \beta * [demand_{h,t} + \widehat{de}_{h,t}] - \sum_g bv'''_{ght} \qquad \forall h,t \quad (41)$$

Also, set U could be defined as:
$U = \{(h,t) \in M: L_{h,t}^* > 0\}$.
Thus, the second LP problem would be represented as:

$$max\ \sigma \quad (42)$$

$$\sum_g bv'''_{ght} = \beta * [demand_{h,t}] + s_{h,t} \qquad \forall h,t \in U \quad (43)$$

$$\sigma \le \frac{s_{h,t}}{L_{h,t}^*} \qquad \forall h,t \in U \quad (44)$$

$$\sum_{b_1,b_2,t} x_{b_1,b_2,t} * mc_{b_1,b_2} + \sum_g p_g * lc_k + \sum_{b,g,t} bv''_{bgt} * tc_{bg} + \sum_{g,h,t} bv'''_{ght} * tc_{gh} \le (1+\delta) * Z^* \quad (45)$$

In constraint (45), Z^* represents the objective function value of nominal modesl (1) – (21), and δ indicates deterioration degree in the objective function value resulted from the DM's conservative approach

$$s_{h,t} \ge 0 \qquad \forall h,t \in U \quad (46)$$

and relationships (1) – (21).
By defining s_{avg} as:

$$s_{avg} = \frac{\sum_{\forall (h,t)\in U} s_{h,t}^*/L_{h,t}^*}{|U|} \quad (47)$$

The third LP model could be formulated as follows:

$$min \sum_{h,t\in U} t_{h,t} \quad (48)$$

$$\frac{s_{h,t}}{L_{h,t}^*} + t_{h,t} \ge s_{avg} \qquad \forall h,t \in U \quad (49)$$

$$\frac{s_{h,t}}{L_{h,t}^*} \ge s_{min} \qquad \forall h,t \in U \quad (50)$$

In constraint (50), $s_{min} = \sigma^*$ represents the objective function value of the second LP problem.

$$t_{h,t} \ge 0 \qquad \forall h,t \in U \quad (51)$$

5. Computational Experiments

In order to cope with the uncertainty in parameters, robust programming approach is utilized due to its capability of obtaining robust solutions. In this section, we intend to evaluate the performance of the proposed

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robust model through implementing several numerical experiments. To this end, three different test problems, as shown in Table 2, are designed and the experiments are carried out for each one under different uncertainty levels.

First of all, both of the deterministic and robust models are solved under nominal values of the parameters which are randomly generated as specified in Table 3. Then, we conduct two types of sensitivity analyses: one on the demand satisfaction level (β) and uncertainty level (δ); another on the realization values to examine the efficiency of the robust strategy versus the deterministic approach. All experiments are conducted using GAMS software on a laptop computer with Intel Core i5, CPU 2.5GHz and 6GB of RAM. Eventually, to assess the robustness of the solutions obtained by the robust optimization model, they are compared to those generated by the deterministic mixed-integer linear programming model under a number of realizations for each test problem.

Tab. 2. The size of test problems

Problem No.	donors	Temporary Blood Facilities	Hospitals/Healthcare centers	Main Blood Facilities	Time periods
1	4	3	3	3	4
2	5	4	4	5	5
3	8	5	5	6	6

Tab. 3. Random generation of nominal parameters

parameters	Value	parameters	Value
$demand_{h,t}$	$\sim uniform$ (100,500)	$capb$	$\sim uniform$ (20,50)
$disdb_{db}$	$\sim uniform$ (100,150)	cap_g	$\sim uniform$ (70,100)
$disdg_{dg}$	$\sim uniform$ (200,250)	$donate_{dt}$	$\sim uniform$ (100,400)
$disbg_{bg}$	$\sim uniform$ (90,100)	β	$\sim uniform$ (0.6,0.9)
rdb	$\sim uniform$ (5,9)	mc_{b_1,b_2}	$\sim uniform$ (50,70)
rdg	$\sim uniform$ (10,17)	lc_g	$\sim uniform$ (1000,1500)
rbg	$\sim uniform$ (5,10)	tc_{bg}	$\sim uniform$ (0.05,0.06)
cap_h	$\sim uniform$ (200,300)		

It is noteworthy that we regard the amount of demand as the only uncertain parameter, while the rest are assumed to be deterministic. Therefore, we put the proposed robust and deterministic models into analysis via uniformly generating random realizations of the uncertain parameter in the respective uncertainty set. In this study, the value of $\widehat{de}_{h,t}$ is considered to be 20% of the demand nominal value.

5-1. Sensitivity analysis on demand satisfaction level (β) and uncertainty level (δ)

In this section, we analyze the impact of changing demand satisfaction level and uncertainty level on the objective function values of both deterministic and robust models. The impact of changing these parameters on the number of facilities required for blood collection is also considered. To this aim, the values of β and $\delta$are varied for each test problem, then the results are reported in Table 4.

As the results show, the number of blood collection facilities (|P|), and thus the supply chain cost will increase owing to an increase in the level of demand satisfaction. For instance, for the first test problem (see Table. 4), the number of established blood centers increases from 2 to 3 as the value of β changes from 0.6 to 0.7 which imposes about 25200$ cost on the system. For test problems 2 and 3, as presented in Table 4, the number of required blood facilities changes from 3 to 4 to satisfy the demand at the level of 80%. Additionally, higher uncertainty levels (i.e., conservation levels considered by the decision-maker) eventuate in increasing the objective function value of the robust approach.

Subsequently, we observe how different uncertainty levels affect the performance of robust approach in terms of both objective function values and constraint violation costs. To do so, we put the three test problems into practice by varying the uncertainty levels for each one, and then the results are shown in Table 5. Note that each unit of constraint violation imposes 20$ cost.

Now, we normalize the values of robust violation cost and objective function for each test problem via dividing each value by the sum of its respective column. Subsequently, for the three test problems, the normalized values are compared as represented in Figs. 2 - 7.

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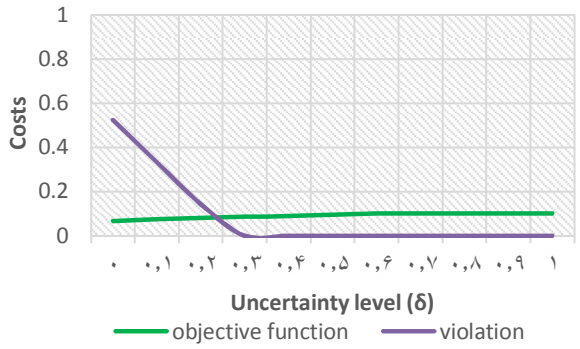

Fig. 2. Objective function value versus violation cost under different uncertainty levels for the first test problem

For the DM, the most pessimistic approach to determine the optimal conservation level (δ^*) may be to set δ as the level at which the constraint violation is equal to zero (i.e., 0.3, 0.3 and 0.4 for Figs. 2, 4, and 6, respectively). We must seriously regard the matter of customers' demand satisfaction, since in this case (i.e., blood supply chains), the shortage of blood can lead to humans' death.

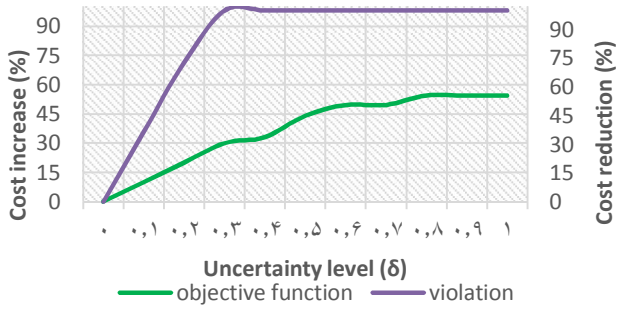

Fig. 3. Cost performance under different uncertainty levels for the first test problem.

However, the main disadvantage of this approach is that the supply chain costs are totally neglected and the main focus is on the violation cost.

Tab. 4. The summary of results under different demand satisfaction levels and uncertainty levels.

Problem no.	β	δ	|P|		Objective function values under nominal data ($)		CPU time (s)	
			Deterministic	Robust	Deterministic	Robust	Deterministic	Robust
1	0.6	0.2	2	2	20456	24547.2	0.228	1.521
		0.5	2	3		30684		1.507
		0.7	2	3		34775.2		1.469
		1	2	3		40912		1.446
	0.7	0.2	3	3	25255.5	30306.6	0.223	1.864
		0.5	3	3		37883.25		2.068
		0.7	3	3		42251.661		1.385
		1	3	3		45196.047		1.212
	0.8	0.2	3	3	29210	35052	0.247	1.704
		0.5	3	3		42086.542		1.489
		0.7	3	3		43704.542		1.316
		1	3	3		44523.810		1.905
	0.9	0.2	3	3	33218	39861.600	0.223	1.334
		0.5	3	3		44708.041		1.350
		0.7	3	3		44708.041		1.253
		1	3	3		44708.041		1.157
2	0.6	0.2	3	3	32104.199	38525.039	0.345	1.744
		0.5	3	4		48156.299		1.759
		0.7	3	4		54577.139		1.722
		1	3	4		64036.400		1.72
	0.7	0.2	3	4	37594.399	45113.279	0.255	2.041
		0.5	3	4		56391.599		1.292
		0.7	3	5		63581.235		1.380
		1	3	5		75188.799		1.049
	0.8	0.2	4	4	44534.599	50084.743	0.354	1.714
		0.5	4	4		62605.929		1.743
		0.7	4	4		70953.386		1.474
		1	4	4		75436.569		1.509
	0.9	0.2	4	4	50444.799	60533.759	0.239	1.523
		0.5	4	4		71134.061		1.511
		0.7	4	5		71134.061		1.273
		1	4	5		71134.061		1.385
3	0.6	0.2	3	3	30599.99	36719.999	0.459	3.915
		0.5	3	3		45899.999		3.915
		0.7	3	4		52019.999		3.335
		1	3	4		61199.999		2.98
	0.7	0.2	3	3	35921.49	43105.799	0.587	3.686
		0.5	3	4		53882.249		3.537
		0.7	3	4		61066.548		2.664
		1	3	4		71842.998		2.846

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0.8	0.2	4	4	42758.9	51310.7	0.571	3.57
	0.5	4	4		64138.4		3.521
	0.7	4	5		72690.2		3.083
	1	4	6		85517.9		2.446
0.9	0.2	4	4	47292.49	56750.999	0.559	2.984
	0.5	4	5		70938.749		2.364
	0.7	4	6		80397.249		2.632
	1	4	6		89240.375		2.446

Accordingly, the DM has to investigate other approaches to find the most appropriate value of δ. As can be observed in Figs. 2, 4, and 6, increased uncertainty level (δ) results in the increased supply chain costs on one hand and the reduced violation cost on the other hand. Additionally, for all test problems, as can be seen in Figs. 3, 5, and 7, by increasing the value of δ from zero to 0.23, the violation cost decreases dramatically to more than 70%; however, an increase of less than 30% in supply chain costs will be imposed on the network.Finally, we will have the maximum reduction (i.e. 100%) in violation cost at $\delta = 0.3$ for test problems 1 and 3 (see Figs. 5 and 9) and $\delta = 0.4$ for the second test problem (Fig. 7). In other words, at $\delta = 0.3$ and 0.4 for test problems 1, 3, and 2, respectively, no violation cost will be observed, while having an increase of 30% in network cost.

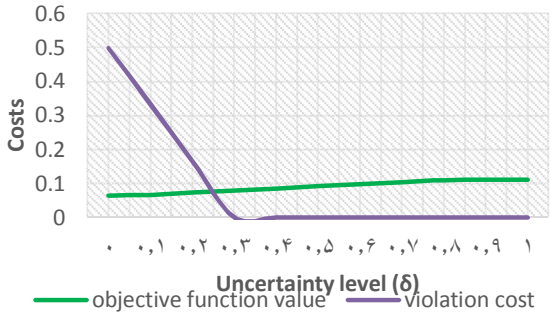

Fig. 4. Objective function value versus violation cost under different uncertainty levels for the second test problem.

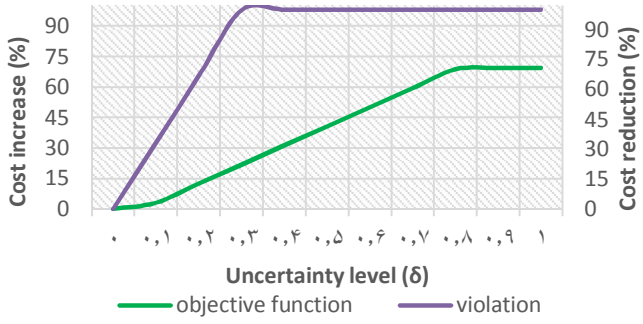

Fig. 5. Cost performance under different uncertainty levels for the second test problem.

It is worth mentioning that from these points on, increasing the uncertainty level only leads to further cost, called missed opportunity cost. This cost is due to indulgence in conservatism (i.e., taking a higher uncertainty level than required to minimize the constraint violations), which is determined by the decision maker. Note that missed opportunity cost can be calculated as the difference between the objective function values of robust and deterministic models when the violation cost is zero. Table 6 reports the values of violation cost and missed opportunity cost under different realizations for the uncertain parameter (i.e., demand amounts) and uncertainty levels.

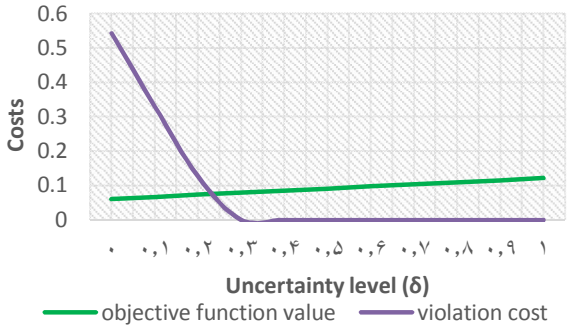

Fig. 6. Objective function value versus violation cost under different uncertainty levels for the third test problem.

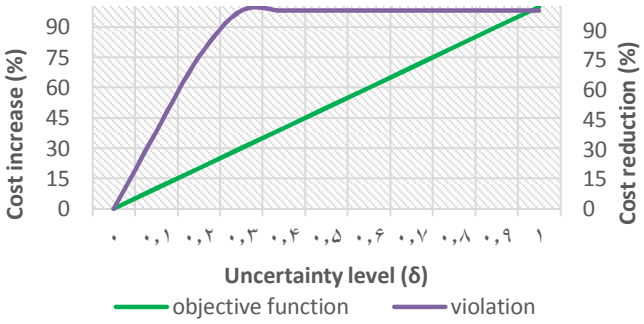

Fig. 7. Cost performance under different uncertainty levels for the third test problem.

Note that missed opportunity cost can be calculated as the difference between the objective function values of robust and deterministic models when the violation cost is zero. Table 6 reports the values of violation cost and missed opportunity cost under different realizations for the uncertain parameter (i.e., demand amounts) and uncertainty levels.

Figs. 8, 9, and 10 depict the average values of violation cost versus missed opportunity cost, respectively, for test problems 1, 2, and 3, respectively. A general observation shows that the increased uncertainty level resulting from the DM's conservative approach ends in decreased violation cost on one hand and increased missed opportunity cost on the other hand. In Fig.8, we

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will witness a decrease in violation cost, but simultaneously an increase in missed opportunity cost as the uncertainty level changes from 0 to 0.2. The average violation cost comes to 0$ when δ changes from 0.2 to 0.4, while the average value of missed opportunity cost increases to 6542$.

Figs.9 and 10 show quite similar patterns as the uncertainty level changes.

For the second test problem (Fig. 9), the average violation cost dramatically decreases when δ changes from 0 to 0.2 and reaches the lowest level (i.e., zero) at $\delta = 0.4$; however, at the same time, the average missed opportunity cost increases to 10647.3$ and continues sharply to 27647.3$ at $\delta = 1$. Finally, for test problem 3 (see Fig.10), the lowest violation cost will be obtained if the uncertainty level reaches 0.3 where the network carries a cost of more than 3456.31$ resulting from missed opportunities.

Fig. 8. Violation cost versus missed opportunity cost for the first test problem

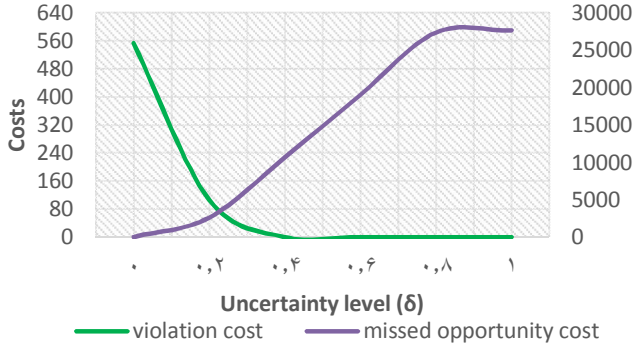

Fig. 9. Violation cost versus missed opportunity cost for the second test problem

Therefore, the trade-off between these two costs (i.e., violation cost and missed opportunity cost) could provide an insight for the DM to decide on an appropriate value of δ under different realizations.

In order to expose a better attitude to discussion which accounts for both the feasibility and optimality criteria by making a trade-off between constraint violation cost and missed opportunity cost, we consider a cost measure defined in relationship (52) which can assist the DM to determine an appropriate level of conservation by taking into account both the feasibility (by regarding constraint violation cost) and optimality (by considering missed opportunity cost) conditions, simultaneously.

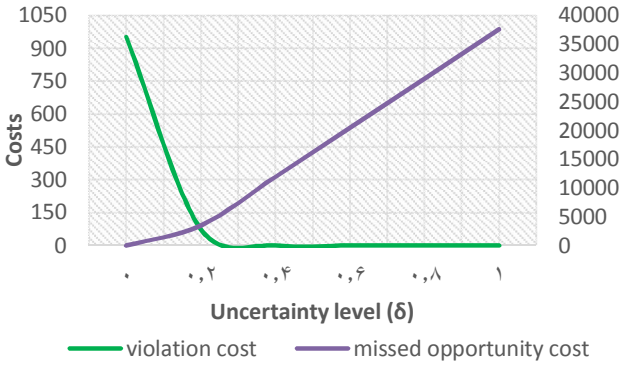

Fig. 10. Violation cost versus missed opportunity cost for the third test problem

$$C_T = w_1 \text{ (violation cost)} + w_2 \text{ (missed opportunity cost)} \quad (52)$$

Where w_1, $w_2 \in [0,1]$ are the weights determined by the DM to represent the importance degree of constraint violation cost and missed opportunity cost, respectively. Since in this case (i.e., blood supply chains), the constraint violation is much more important than missed opportunity cost, we consider weights of $w_1 = 0.8$ and $w_2 = 0.2$ for these two costs. We calculate C_T for each realization under different values of δ, and then find the minimum value of C_T for each column as shown in Table 7. Lastly, we choose the most repeated δ at which C_T has the minimum value. Fig.11 depicts the frequency of uncertainty levels at which the minimum value of C_T is realized.

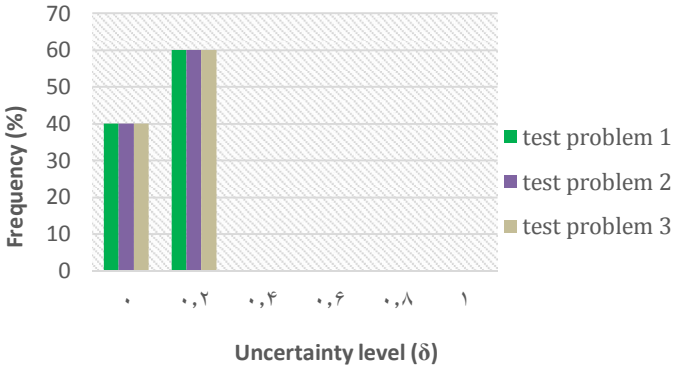

Fig. 11. The uncertainty levels' frequencies under different realizations

As can be observed in Fig. 11, for all test problems, the minimum value of cost measure (C_T) occurs at $\delta = 0.2$ in 60% of the realizations. Accordingly, we assume $\delta = 0.2$ as the basis for the next sensitivity analysis by which we compare the performance of the proposed

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robust model and the deterministic model under a number of realizations.

Tab. 5. The summary of results under different uncertainty levels. (Supply chain cost versus violation cost)

β=0.8								
Problem no.	δ	z_{robust}	$z_{deterministic}$	Supply chain cost increase (%)	Violation cost	Violation cost reduction (%)	CPU time (s)	
							Deterministic	Robust
1	0	29210	29210	0	1119.98	0	0.247	1.569
	0.1	32131		10	710.897	36.52		1.621
	0.2	35052		20	305.404	72.73		1.704
	0.3	37973		30	0	100		1.584
	0.4	38869.424		33.06	0	100		1.357
	0.5	42086.542		44.08	0	100		1.489
	0.6	43704.542		49.62	0	100		1.435
	0.7	43704.542		49.62	0	100		1.383
	0.8	44523.810		54.42	0	100		1.316
	0.9	44523.810		54.42	0	100		1.362
	1	44523.810		54.42	0	100		1.905
2	0	44534.599	44534.599	0	1221. 4	0	0.354	2.622
	0.1	45911.014		3.09	816.984	33.11		2.124
	0.2	50084.743		12.46	407.537	66.63		1.568
	0.3	54258.472		21.84	4.123	99.66		1.895
	0.4	58432.2		31.2	0	100		1.889
	0.5	62605.929		40.57	0	100		1.743
	0.6	66779.657		49.95	0	100		1.736
	0.7	70953.386		59.32	0	100		1.746
	0.8	75127.114		68.69	0	100		1.474
	0.9	75436.569		69.38	0	100		1.732
	1	75436.569		69.38	0	100		1.714
3	0	42758.9	42758.9	0	1599.9	0	0.571	3.715
	0.1	47034.89		10	975.64	39..1		3.57
	0.2	51310.7		20	374	76.62		3.426
	0.3	55586.69		30	0	100		5.029
	0.4	59862.59		40	0	100		3.156
	0.5	64138.4		50	0	100		3.521
	0.6	68414.3		60	0	100		2.9
	0.7	72690.2		70	0	100		3.138
	0.8	76966.1		80	0	100		2.637
	0.9	81242		90	0	100		2.477
	1	85517.9		100	0	100		2.446

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Tab. 6. The summary of results under different realizations and uncertainty levels. (Violation cost versus missed opportunity cost)

β=0.8										
Problem no.	δ	z_{robust}		Realization					Average ($)	CPU time (s)
				1	2	3	4	5		
1	0	29210	$z_{deterministic}$	29210	-	-	-	-		
			Violation cost	0	560	672	840	1119.98	638.396	1.53
			Missed opportunity cost	0	0	0	0	0	0	
	0.6	43704.54	$z_{deterministic}$	29210	32411.2	33056.6	33621.6	35643.6		
			Violation cost	0	0	0	0	0	0	1.39
			Missed opportunity cost	14494.5	11293.3	10647.9	10082.9	8060.94	10915.9	
	1	44523.81	$z_{deterministic}$	29210	32411.2	33056.6	33621.6	35643.6		
			Violation cost	0	0	0	0	0	0	1.48
			Missed opportunity cost	29210	32411.2	33056.6	33621.6	35643.6		
۲	0	47713.55	$z_{deterministic}$	-	-	-	-	-		
			Violation cost	140	560	672	840	1220. 4	553	2.54
			Missed opportunity cost	0	0	0	0	0	0	
	0.6	66779.65	$z_{deterministic}$	41737.28	47395.3	48188.9	49660.2	51942.8		
			Violation cost	0	0	0	0	0	0	1.36
			Missed opportunity cost	25042.37	19384.3	18590.7	17119.4	14836.85	18994.7	
	1	75432.2	$z_{deterministic}$	41737.28	47395.3	48188.9	49660.2	51942.8		
			Violation cost	0	0	0	0	0	0	1.54
			Missed opportunity cost	33694.92	28036.9	27243.3	25772	23489.4	27647.3	
۳	0	42758.9	$z_{deterministic}$	-	-	-	-	-		
			Violation cost	200	800	960	1200	1599.9	951.98	4.16
			Missed opportunity cost	0	0	0	0	0	0	
	0.6	68414.3	$z_{deterministic}$	43825.04	47142.9	48030	48963.3	51700.9		
			Violation cost	0	0	0	0	0	0	3.21
			Missed opportunity cost	24589.26	21271.4	20384.3	19451	16713.4	20481.8	
	1	85517.9	$z_{deterministic}$	43825.04	47142.9	48030	48963.3	51700.9		
			Violation cost	0	0	0	0	0	0	2.09
			Missed opportunity cost	41692.86	38375	37487.9	36554.6	33817	37585.4	

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5-2. Sensitivity analysis on different realization values

In this section, we evaluate the robustness of solutions obtained by the proposed robust model in comparison with the solutions obtained by the deterministic mixed-integer linear programming model. To this end, 10 random realizations for the uncertain demand are uniformly generated in the corresponding uncertainty set. Eventually, two criteria (i.e. the mean and standard deviation of constraint violations) are tailored under random realizations to assess both the proposed robust and deterministic models. Given $\delta = 0.2$, the test results are presented in Table 8. Figs. 12-14 show the performance of the robust strategy versus the deterministic approach.

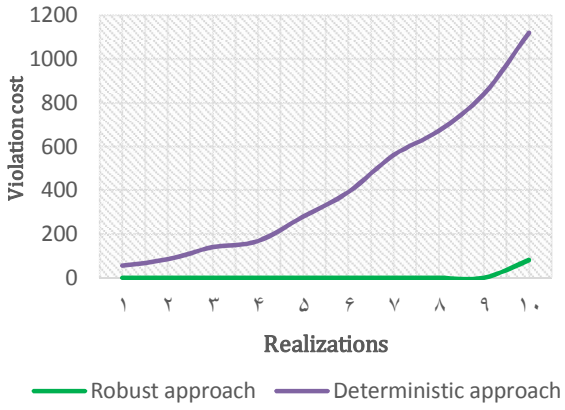

Fig. 12. Constraint violation cost under deterministic versus robust approaches for test problem 1

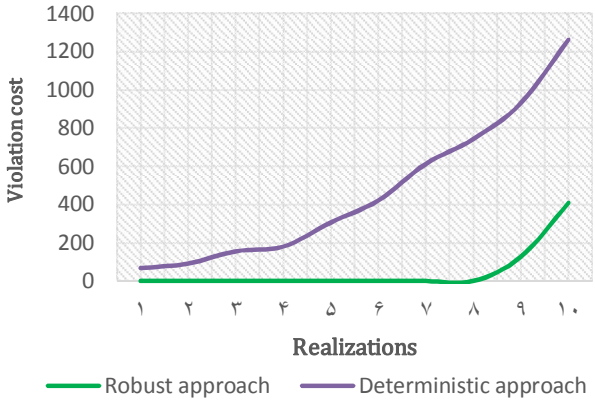

Fig. 13. Constraint violation cost under deterministic versus robust approaches for test problem 2

As can be seen, the robust model obtains high-quality solutions with lower standard deviations than the deterministic model. In other words, in all test problems, the robust approach highly outperforms the deterministic one with respect to the mean and standard deviation of constraint violations. As the results show, for test problem 1 (Fig. 12), no constraint violations will be observed in the robust model for realizations 1 to 9; however, the violation cost will reach 81.4$ under realization 10, while the violation cost of deterministic model increases from 56$ to 431.2$

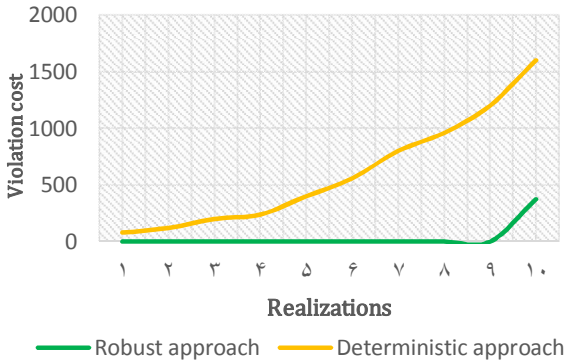

Fig. 14. Constraint violation cost under deterministic versus robust approaches for test problem 3

For the second test problem, as shown in Fig. 13, the robust model shows an average violation cost of 53.381$, which represents the superiority of the robust model over the deterministic one. Similarly, the domination of robust strategy over deterministic approach is obvious in test problem 3 (see Fig. 14), where we witness an average violation cost of 37.4$ under the robust model versus 615.99$ under the deterministic model.

6. Concluding Remarks and Future Research Recommendations

In this paper, a mixed integer linear programming model is addressed for designing a blood collection and distribution system under demand uncertainty. The objective function attempts to minimize the network total costs involving establishment cost of the main centers, relocation cost of temporary blood facilities along with blood delivery cost from temporary facilities to the main ones and from the main blood centers to hospitals or healthcare centers throughout a multiple planning horizon. To handle the inherent randomness of demand amounts, we have devised a robust programming approach with the aim of achieving robust and reliable solutions. The superiority of the proposed robust model in dealing with uncertainty as well as the robustness of corresponding solutions over the ones obtained by the deterministic model is proved by

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performing a number of computational experiments.

Tab. 7. Cost measure (C_T) under different realizations and uncertainty levels

Problem no.	δ	Realization				
		1	2	3	4	5
1	0	0	448	537.6	672	895.98
	0.2	1168.4	528.16	399.08	20.32	244.32
	0.4	1931.88	1291.644	1162.564	1049.564	645.164
	0.6	2898.9	2258.66	2129.58	2016.58	1612.188
	0.8	3062.762	2422.52	2293.44	2180.44	1776.042
	1	5842	6482.24	6611.32	6724.32	7128.72
	Min C_T	0	448	399.08	20.32	244.32
	Corresponding uncertainty level (δ)	0	0	0.2	0.2	0.2
2	0	112	448	537.6	672	896.32
	0.2	1669.492	537.888	379.168	101.024	325.0296
	0.4	3338.984	2207.38	2048.66	1754.4	1297.88
	0.6	5008.474	3876.86	3718.14	3423.88	2967.37
	0.8	6677.964	5546.36	5387.64	5093.38	4636.86
	1	6738.984	5607.38	5448.66	5154.4	4697.88
	Min C_T	112	448	379.168	101.024	325.0296
	Corresponding uncertainty level (δ)	0	0	0.2	0.2	0.2
3	0	160	640	768	960	1279.92
	0.2	1497.132	833.56	656.14	469.48	299.2
	0.4	3207.51	2543.92	2366.5	2179.84	1632.338
	0.6	4917.852	4254.28	4076.86	3890.2	3342.68
	0.8	6628.212	5964.64	5787.22	5600.56	5053.04
	1	8338.572	7675	7497.58	7310.92	6763.4
	Min C_T	160	639.66	462.24	275.58	299.2
	Corresponding uncertainty level (δ)	0	0	0.2	0.2	0.2

It is noteworthy to mention that we came up with several valuable insights via the results of the experiments.

Particularly, robust optimization significantly prevents the model against constraint violations. To be more specific, for the small-sized problem (Fig. 3), spending 3% more money will decrease the violation cost about 33%. As the uncertainty level (conservation level) gets higher, the network cost will increase, while the violation cost will decrease. Thus, having an estimation about the appropriate conservation level to make a balance between the two costs is of importance. In line with the two criteria, i.e., standard deviation and mean of constraint violation cost (see Table 8), applying robust optimization enables us to achieve a model with the least undesirable changes and costs in comparison with the deterministic model under a number of realizations.

A number of possible future research directions can be considered in this subject of investigation.

- Applying heuristic and metaheuristic approaches in order to reach efficient solutions within reasonable computing time when it comes to solving the concerned problem in larger size, one that cannot be solved by the exact solvers in polynomial time.
- The proposed model can be extended to a multi-objective model considering other objectives including minimizing delivery time, maximizing responsiveness of the network, etc.

Researchers could investigate other uncertainty approaches, such as fuzzy or stochastic approaches, to compare the respective results with the ones achieved by the current robust approach.

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Tab. 8. Constraint violation for robust model versus deterministic model under a number of realizations

Problem no.	δ	Realization	Objective function values		Constraint violation cost		CPU time (s)	
			Robust	Deterministic	Robust	Deterministic	Robust	Deterministic
١	0.2	1	35052	29511.84	0	56	١,٥	٠,٣٦
		٢	٣٥٠٥٢	29689.22	0	84	١,٤١	٠.34
		٣	٣٥٠٥٢	30008.7	0	140	١,٤٨	٠,٣٥
		٤	35052	30168.44	0	168	١,٦٢	٠.35
		٥	35052	30807.4	0	280	١,62	0.35
		٦	35052	31446.36	0	392	١,٥٩	0.33
		٧	35052	32411.2	0	560	١,46	0.35
		٨	35052	33056.6	0	672	١,62	0.34
		٩	35052	33549.6	0	840	١,٥٣	0.35
		١٠	35052	35614.8	81.4	1120	١,7	0.35
Average			35052	31626.42	8.14	431.2		
Standard deviation			0	1998.255	25.74	358.3806		
٢	0.2	١	50084.74	43281.4	0	68	١,٧٣	٠,٣٤
		٢	50084.74	43506.6	0	92	١,٣٢	0.34
		٣	50084.74	43952.35	0	156	١,٣٨	0.35
		٤	50084.74	44189.81	0	180	١,٥١	0.35
		٥	50084.74	45101.5	0	306	١,74	0.34
		٦	50084.74	46013.3	0	421	١,٧٥	٠,٣٤
		٧	50084.74	48964.9	0	613	١,٧١	0.34
		٨	50084.74	48292.66	0	742	1.75	0.36
		٩	50084.74	49660.27	126.28	930	١,96	٠,٣٤
		١٠	50084.74	51942.8	407.53	1260.1	2.97	٠,٣٤
Average			50084.74	46490.56	53.381	476.81		
Standard deviation			0	3022.873	130.61	400.87		
٣	0.2	١	51310.7	43201.2	0	80	3.48	0.69
		٢	51310.7	43531.4	0	120	3.38	0.71
		٣	51310.7	43982.62	0	200	3.02	0.8
		٤	51310.7	44389.81	0	240	3.14	0.7
		٥	51310.7	43982.62	0	400	3.16	0.72
		٦	51310.7	44013.3	0	560	3.12	0.72
		٧	51310.7	44996.9	0	800	3.36	0.71
		٨	51310.7	46313.8	0	960	3.26	0.84
		٩	51310.7	46960.17	0	1200	3.24	0.8
		١٠	51310.7	47142.9	374	1599.9	3.23	0.776
Average			51310.7	44851.472	37.4	615.99		
Standard deviation			0	1443.308	118.26	511.95		

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