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A Stochastic Optimization Approach to a Location-Allocation Problem of Organ Transplant Centers

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Abstract

Decision-making concerning the location of critical resource on the geographical network is important in many industries. In the healthcare system, these decisions include location of emergency and preventive care. The decisions of location play a crucial role due to determining the travel time between supply and demand points and response time in emergencies. Organs are considered as highly perishable products, whose variety of each product has a specific perish time. Despite the importance of this field, only a small proportion of healthcare sector is dedicated to this field. Matching and finding the best recipient for a donated organ is one of the major problems in this field, which is also crucial for the overall organ transplantation process. Balancing the demand and supply in a transplant organ supply chain in order to decrease the waiting list needs certain scheduling and management. The main contribution of this paper consists of considering recipient regions as another component of the supply chain; inaddition, importance of transportation time and waiting lists has led us to consider a bi-objective model. In addition, uncertainty of input data has led us to consider a stochastic approach.

Keywords: Organ transplant supply chain, Location-allocation, Healthcare, Stochastic optimization approach.

1. Introduction

The supply chain network design is one of the most important strategic decisions. Among the different kinds of facility problems, healthcare location has an important role in minimizing the cost or maximizing the people benefit. Many previous studies have been devoted to facility location problems (Drira et al., 2007; Farahani et al., 2010).Syam and Côté (2012) addressed a location–allocation model fora treatment department related to traumatic brain injuries. A common resource constraint is also assumed, and minimization of the total cost is considered as objective function. The derived data from the Department of Veterans Affairs (DVA) have been used for testing applicability of the model. They also examined the effects of five critical factors (i.e., degree of service centralization, service level mandates by acuity, and lost admission cost) by equity, facility overload penalty cost by equity, and target utilization level by acuity and treatment unit. Benneyan et al. (2012) also proposed a multi-period integer programming model that would establish trade-offs between cost, coverage, service location and capacity for a location-allocation problem.
Sheriff et al. (2012) addressed a capacitated maximal covering healthcare location problem and applied it to one of the districts of Malaysia, utilizing a new genetic algorithm. A multi-period location-allocation problem of an emergency blood supply system for a case study in Beijingwas presented by Sha and Huang (2012).They proposed a heuristic algorithm based on a Lagrangian relaxation method. Most studies related to organ donations and organ transplants have focused on policies to allocate organs to recipients (Bruni et al., 2006; Rais and Viana, 2011). For a recent overview of organ allocation and the acceptance of kidneys and livers, we refer to (Alagoz et al., 2009). Nevertheless, when looking at the broader healthcare literature, we observe that facility location is not a new issue at all (Rais and Viana, 2011).Belien et al. (2011)proposed a mixed-integer linear programming (MILP) to optimize location of organ transplant centers as one of the most vital subsets of a supply chain network. Minimizing the transportation time between hospitals as supply point and transplant centers as demand point is considered as objective function. The model is applied to the Belgium organ transplant path. Zahiri et al. (2014a) presented a dynamic location-allocation problem of organ transplant centers under uncertainty. The uncertain nature of the input data was handled via a robust possibilistic programming approach. In another paper, Zahiri et al. (2014b) presented a bi-objective MINLP model for designing an organ transplant network under uncertainty.

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A priority queuing system was applied to the model, and large-scale problems were solved using two meta-heuristic algorithms. Ebbini et al. (2015) presented a fuzzy lung allocation system (FLAS) in order to determine which potential recipients would receive a lung for transplantation when it became available in the USA.
According to Uehlinger et al. (2010), each organ is constrained by a specific cold ischemia time defined as the maximum period an organ can be kept outside the body. In this area, Bruniet al. (2006) presented a mixed-integer linear programming (MILP) model to obtain an efficient system and equalize the waiting lists in Italy. To optimize their transplant system, they assumed that special centers play critical rules in managing and procuring the organs. Kong et al. (2010) used a branch-and-price approach aiming at the maximization of the efficiency of the liver allocation systems in the USA. The study benefits from the clinical data for computational experiments. Furthermore, Belien et al. (2010)considered optimal locations of shipping agents solved with limited numbers of potential locations. A numerical example was obtained from real data in Belgium.Shishebori et al. (2015) presented an efficient mixed-integer linear programming model for a robust and reliable medical service center location network design problem, which simultaneously takes uncertain parameters, system disruptions, and investment budget constraint taken into account. The proposed model was formulated based on an efficient robust optimization approach to protect the network against uncertainty.Mousazadeh et al. (2015) presented a bi-objective mixed-integer linear programming model developed for a pharmaceutical supply chain network design problem. Since the critical parameters are tainted with a great degree of epistemic uncertainty, a robust possibilistic programming approach is used to handle uncertain parameters. Zahraee et al. (2015) applied the dynamic simulation and Taguchi method to design a robust blood supply chain system to improve the blood supply chain efficiency. The National Blood Center (NBC) in Iran is selected as the case of study.
The main contribution of this paper consists of considering recipient regions as another component of the supply chain, and importance of transportation time and waiting lists has led us to consider a bi-objective model. Another aspect of the proposed model is to determine location–allocation of each mentioned center under uncertainty via a scenario-based stochastic approach.
An organ transplant network consists of a donor (i.e., a person who donates an organ), a recipient (i.e., a patient who receives the organ), hospitals, transplant centers, and shipping agents. The network of the transplant system consists of donors (D), recipient zones (RZ), hospitals (H), transplant centers (TC), and shipping agents (Sh.A).Brain death patients and donors are kept in hospital; blood sampling, registration, and organ transplant surgery are accomplished in the transplant centers, and also shipping agents are ready to transport the organ between the transplant center and the hospital.

2. Problem Definition

This paper presents a bi-objective stochastic mathematical model for a location-allocation problem of organ transplant centers. First, a deterministic bi-objective mixed-integer nonlinear programming model is developed that minimizes the total transportation time and the maximum shortage of organ simultaneously. Additionally, this proposed model uses a scenario-based stochastic approach, and then is solved by the ε-constraint method. The efficiency of this model is demonstrated by some numerical experiments and two test problems in small and large sizes. Finally, the conclusion and future studies are provided.
According to Fig. 1, when a donor is volunteered for donating an organ (1), a shipping agent team will be sent to the hospital (2) and delivers donor's information and blood samples to the transplant center (3), then the shipping agent team will return to the hospital (4). The surgical operation of removing an organ from the donor's body is applied in the hospital, then the removed organ will be sent to the transplant center for transplantation (5, 5'). Subsequently, qualified recipient is notified and should be at the current time (6).

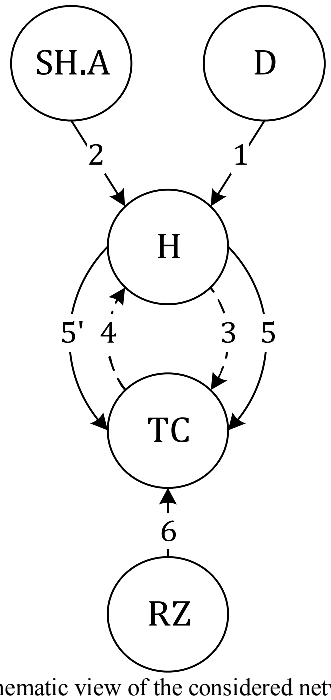

Fig. 1.Schematic view of the considered network.

As an international organ supply chain, both domestic and foreign surgical operations have been taken in to consideration with a little difference. In case of a foreign recipient or donator, the organ recipient can be foreigner, so an organ should be delivered to the airport to arrive at the TC for operation (5'). One of the important issues that can be considered in this paper is perishability of the organs. Maximum time that an organ can be kept outside the body is referred to cold ischemia time. Cold ischemia time has a direct negative influence on the chances of a successful transplant; if the transport time between a hospital and a transplant center exceeds this time for a particular organ, we assume that the organ cannot be transported to the transplant center. Hence, in this paper, we develop a location-allocation of organ transplant centers under different possible scenarios of input data. The minimization of the transportation time and minimization of the maximum shortage of an organ are considered as bi-objective functions.

In this section, a bi-objective mathematical model for a location-allocation problem of an organ supply chain under uncertainty is taken into consideration. The aim of this model is to minimize the transportation time and maximum shortage of the organ. We utilize the ε-constraint method for solving this problem. The notations of the model represented below.

Sets:

H	Set of hospitals $h \in H$
	Set of organs $o \in O$
´	Set of shipping agent$v \in V$
	Set of airports$a \in A$
I	Set of transplant centers $i \in I$
K	Set of recipient zone$k \in K$

Parameters:

C_i	Fixed cost of locating TC at potential location
C_h	Fixed cost of locating hospital at potential location
C_v	Fixed cost of locating shipping agent at potential location
$C_{\ h}$	h with shipping agent
$t_{\ h}$	
$t_{\ i}$	
t_{ai}	
t_{ki}	
t_o	Cold ischemia time of organ
S_{ol}^{D}	Arrival flow of organ
S_{ol}^{A}	Arrival flow of organ
D_{ko}	k for organ
B	Available budget

Decision variables:

$x'_{\ io}$	Flow of organ o from hospital h to TC
$x_{\ io}$	Flow of information and blood requirement of organ from hospital h to TC
$x_{\ ao}$	Flow of organ o from hospital h to airport
x_{aio}	Flow of organ o from airport a to TC
x_{kio}	Flow of organ o from recipient zone to TC
B_k	Organ shortage in recipient zone
z_h	1, if hospital h is open, and0; otherwise
z'_i	1, if transplant center i is open, and 0; otherwise
$y_{\ o}$	1, if hospital h is open for at least one organ o, and 0; otherwise
y'_{io}	1, if transplant center i is open for at least one organ o, and 0; otherwise
$x_{\ h}$	1, if hospital h is covered by shipping agent v, and 0; otherwise
w_v	1 `shipping agent v is selected, and 0; otherwise

Model formulation:

$$\text{Min} Z_1 = \underset{k}{\text{Max}}\, B_k \tag{1}$$

$$\text{Min } Z_2 = \sum_{o}\sum_{i}\sum_{h}((t_{\ i} + t_{\ h}\ x_{\ io} + (t_{\ i} x'_{\ io})) + \sum_{o}\sum_{i}\sum_{k}^{K} t_{ki}x_{kio} + \sum_{o}\sum_{i}\sum_{a} t_{ai}x_{aio} \tag{2}$$

$$\sum_{h} c_h z_h + \sum_{i} c_i z'_i + \sum_{v} c_v w_v + \sum_{h}^{H}\sum_{v}^{V} c_{\ h} x_{\ h} \le B' \tag{3}$$

$$y_{\ o} \le z_h, \qquad h \in H, o \in O, \tag{4}$$

$$y'_{io} \le z'_i, \qquad i \in I, o \in O, \tag{5}$$

$$\sum_{h}^{H} y_{ho} \geq 1, \qquad \forall o \in O, \tag{6}$$

$$\sum_{i}^{I} y'_{io} \geq 1, \qquad \forall o \in O, \tag{7}$$

$$x'_{hio} = 0, \qquad t_{hio} > t_o, \tag{8}$$

$$\sum_{i}^{I} x_{hio} = (s^D_{oh} + s^A_{oh}) y_{ho}, \qquad \forall h \in H, o \in O, \tag{9}$$

$$x_{hio} \leq (s^D_{oh} + s^A_{oh}) y'_{io}, \qquad \forall h \in H, i \in I, o \in O, \tag{10}$$

$$\sum_{i}^{I} x'_{hio} \leq s^D_{oh} y_{ho}, \qquad \forall h \in H, o \in O, \tag{11}$$

$$x'_{hio} \leq s^D_{oh} y'_{io}, \qquad \forall h \in H, i \in I, o \in O, \tag{12}$$

$$\sum_{a}^{A} x_{hao} \leq s^A_{oh} y_{ho}, \qquad \forall h \in H, a \in A, \tag{13}$$

$$\sum_{i}^{I} x_{aio} - \sum_{h}^{H} x_{hao} = 0, \qquad \forall a \in A, o \in O, \tag{14}$$

$$\sum_{k}^{K} x_{kio} = \sum_{h}^{H} x'_{hio} + \sum_{a}^{A} x_{aio}, \qquad \forall i \in I, o \in O, \tag{15}$$

$$\sum_{a}^{A} x_{aio} \leq \sum_{h}^{H} s^A_{oh}\, y'_{io}, \qquad \forall i \in I, o \in O, \tag{16}$$

$$\sum_{v}^{V} x_{vh} \leq 1, \qquad \forall h \in H, \tag{17}$$

$$\sum_{i}^{I} x_{kio} + B_{ko} \geq D_{ko}, \qquad \forall k \in K, o \in O, \tag{18}$$

$$y_{ho} \leq \sum_{v}^{V} x_{vh}, \qquad \forall h \in H, o \in O, \tag{17}$$

$$\sum_{v}^{V} w_v \geq 1, \tag{18}$$

$$x_{vh} \leq w_v, \qquad \forall v \in V, h \in H, \tag{19}$$

$$w_v \leq \sum_{h}^{H} x_{vh}, \qquad \forall v \in V, \tag{20}$$

$$z_h, z'_i, y_{ho}, y'_{io}, w_v, x_{vh} \in \{0,1\}, \forall i, h, o, v, \tag{21}$$

$$x'_{hio}, x_{hao}, x_{aio}, x_{kio}, x_{hio}, B_{ok} \geq 0, int, \qquad \forall i, h, o, a, k. \tag{22}$$

The first (1) and second (2) objective functions minimize the maximum organ shortage and organ transportation time, respectively. Constraint (3) defines the budget constraint. Constraint (4) indicates that a hospital can only be able to donate a particular organ if the hospital itself is open. Constraint (5) has the same definition for each transplant centers. Constraints (6) and (7) indicate that at least one hospital and one transplant center should be open, respectively. Constraint (8) ensures that organ transportation time between hospital and TC should not exceed the cold ischemia time of each organ. Constraints (9) and (10) ensure that flows of information and blood samples are only able to be transported from hospital to TC if hospital and TC are open. Constraints (11) and (12) have the same definition for flow of organ from hospital to TC. Constraint (13) ensures that flow of organ from hospital to airport is only possible if a hospital for particular organ is open. Constraint (14) ensures that the total flows of an organ from a hospital to an airport are equal to the flow from an airport to a TC. Constraint (15) ensures that flows of an organ from a recipient zone to a TC are equal to flows from a hospital and an airport to a TC. Constraint (16) indicates that the flow of an organ is feasible only if a TC is open. Constraint (17) ensures that each hospital should be covered by at most one shipping agent. Constraint (18) indicates that the total demand is satisfied. Constraint (19) ensures that each opened hospital should be covered by at least one shipping agent.

Constraint (20) ensures that at least one shipping agent should be located. Constraint (21) indicates that a hospital is covered by shipping agent only if the shipping agent is selected. Finally, Constraint (22) minimizes the number of unused shipping agents and flows.

3. Stochastic Optimization Model

Since a demand for an organ is not certain, we consider the presented model under uncertainty parameters under different scenarios. To develop the stochastic optimization model, the demands, the supply, the fixed opening facility, the transportation time between facility, the cost of having a contract between facility, and the budget are considered as uncertain parameters with uniform distribution. Let Ω be the set of all possible scenarios and θ a particular scenario. According to the above description, the presented model and notations aremodified as follows:

Sets:

Ω	Set of potential scenarios$\theta \in \Omega$

Parameters:

π_θ	Probability of scenario θ
$C_{i\theta}$	Fixed cost of locating TC at potential location *i* for scenario θ
$C_{\ \theta}$	Fixed cost of locating hospital at potential location h for scenario θ
$C_{v\theta}$	Fixed cost of locating shipping agent at potential location *v* for scenario θ
$C_{\ \ \theta}$	Cost of having a contract of hospital i with shipping agent *v* for scenario θ
$t_{\ \theta}$	Transportation time between TC and hospital for scenario θ
$t_{\ i\theta}$	Transportation time between hospital and TC for scenario θ
$t_{ai\theta}$	Transportation time between airport and TC for scenario θ
$t_{ki\theta}$	Transportation time between recipient zone and TC for scenario θ
s_{ol}^{D}	Arrival flow of organ *o* coming from domestic donors for scenario θ
s_{ol}^{A}	Arrival flow of organ *o* coming from abroad for scenario θ
$B_\theta^{'}$	Available budget for scenario θ
$D_{ko\theta}$	Demand of recipient zone k for organ o for scenario θ

Decision variables:

$x_{\ \ \theta}$	1, if hospital h is covered by shipping agent v for scenario θ; and 0 otherwise
$B_{k\theta}$	Organ shortage in recipient zone k for scenario θ
$x^{'}_{\ io\theta}$	Flow of organ *o* from hospital *h* to TC for scenario θ
$x_{\ io\theta}$	Flow of information and blood requirement of organ *o* from hospital *h* to TC for scenario θ
$x_{hao\theta}$	Flow of organ *o* from hospital *h* to airport a for scenario θ
$x_{aio\theta}$	Flow of organ *o* from airport a to TC for scenario θ
$x_{kio\theta}$	Flow of organ *o* from recipient zone *k* to TC for scenario θ

Formulation:

$$\text{Min}Z_1 = \underset{k}{\text{Max}} \sum_{\theta} \pi_\theta B_{k\theta} \tag{23}$$

$$\text{Min } Z_2 = \sum_{\theta} \pi_\theta \left(\sum_{o} \sum_{i} \sum_{h} ((t_{\ \theta} + t_{\ \theta}\, x_{\ \ \theta} + t_{\ \theta} x^{'}_{\ \ \theta}) + \sum_{o} \sum_{i} \sum_{k}^{K} t_{ki\theta} x_{kio\theta} + \sum_{o} \sum_{i} \sum_{a} t_{\ \theta} x_{\ \ \theta} \right) \tag{24}$$

$$\sum_{h} c_h z_h + \sum_{i} c_i z_i^{'} + \sum_{v} c_v w_v + \sum_{h}^{H} \sum_{v}^{V} c_{\ \theta} x_{\ \theta} \le B_\theta^{'}, \quad \forall\theta, \tag{25}$$

$$y_{\ o} \le z_h, \qquad \forall h \in H, o \in O, \quad (26$$

$$y_{io}^{'} \le z_i^{'}, \qquad i \in I, o \in O, \tag{27}$$

$$\sum_{h} y_{\ o} \ge \ , \qquad o \in O, \tag{28}$$

$$\sum_{i} y_{io}^{'} \ge \ , \qquad \forall o \in O, \tag{29}$$

$$x^{'}_{\ \theta} = \ , \qquad t_{\ \theta} > t_o, \tag{30}$$

$$\sum_{i}^{I} x_{hio\theta} = (s_{oh\theta}^{D} + s_{oh\theta}^{A}) y_{ho}, \qquad \forall h \in H, o \in O, \theta, \tag{31}$$

$$x_{hio\theta} \leq (s_{oh\theta}^{D} + s_{oh\theta}^{A}) y_{io}^{'}, \qquad \forall h \in H, i \in I, o \in O, \theta, \tag{32}$$

$$\sum_{i}^{I} x_{hio\theta}^{'} \leq s_{oh\theta}^{D} y_{ho}, \qquad \forall h \in H, o \in O, \theta, \tag{33}$$

$$x_{hio\theta}^{'} \leq s_{oh\theta}^{D} y_{io}^{'}, \qquad \forall h \in H, i \in I, o \in O, \theta, \tag{34}$$

$$\sum_{a}^{A} x_{hao\theta} \leq s_{oh\theta}^{A} y_{ho}, \qquad \forall h \in H, a \in A, \theta, \tag{35}$$

$$\sum_{i}^{I} x_{aio\theta} - \sum_{h}^{H} x_{hao\theta} = 0, \qquad \forall a \in A, o \in O, \theta, \tag{36}$$

$$\sum_{k}^{K} x_{kio\theta} = \sum_{h}^{H} x_{hio\theta}^{'} + \sum_{a}^{A} x_{aio\theta}, \qquad \forall i \in I, o \in O, \theta, \tag{37}$$

$$\sum_{a}^{A} x_{aio\theta} \leq \sum_{h}^{H} s_{oh\theta}^{A} \, y_{io}^{'}, \qquad \forall i \in I, o \in O, \theta, \tag{38}$$

$$\sum_{v}^{V} x_{vh\theta} \leq 1, \qquad \forall h \in H, \theta, \tag{39}$$

$$\sum_{i}^{I} x_{kio\theta} + B_{k\theta} \geq D_{ko\theta}, \qquad \forall k \in K, o \in O, \theta, \tag{40}$$

$$y_{ho} \leq \sum_{v}^{V} x_{vh\theta}, \qquad \forall h \in H, o \in O, \theta, \tag{41}$$

$$\sum_{v}^{V} w_{v} \geq 1, \tag{42}$$

$$x_{vh\theta} \leq w_{v}, \qquad \forall v \in V, h \in H, \theta, \tag{43}$$

$$w_{v} \leq \sum_{h}^{H} x_{vh\theta}, \qquad \forall v \in V, \theta, \tag{44}$$

$$z_{h}, z_{i}^{'}, y_{ho}, y_{io}^{'}, w_{v}, x_{vh\theta} \in \{0,1\}, \forall i, h, o, v, \theta, \tag{45}$$

$$x_{hio\theta}^{'}, x_{hao\theta}, x_{aio\theta}, x_{kio\theta}, x_{hio\theta}, B_{k\theta} \geq 0, int, \qquad \forall i, h, o, a, k, \theta, \tag{46}$$

In this model, probabilities are associated with scenarios, and a solution is sought which is immunized against all possible scenarios. The probabilities assigned to scenarios represent the importance of each scenario in an uncertain environment. A scenario is a description of a future situation and the course of events that enables one to progress from the original situation to the future situation. The hypotheses used to build a suitable scenario must simultaneously be relevant, consistent, plausible, important, and transparent to meet all of desirable criteria (Pishvaei et al., 2009).

4. Numerical Example

In this section, theε-constraint method is described briefly. Assume the following MOMP problem:

$\mathrm{Min}(f_1(x), f_2(x), \ldots, f_p(x))$
s.t.

$X \epsilon S.$

where$x$ is the vector of decision variables,$f_1(x), f_2(x), \ldots, f_p(x)$are p objective functions, and S is the feasible region. In the ε-constraint method, we optimize one of the objective functions using the other objective functions as constraints, incorporating them in the constraint part of the model as shown below.

$\mathrm{Min} f_1(x)$
s.t.
$f_2(x) \geq e_2,$
$f_3(x) \geq e_3,$
$f_p(x) \geq e_p,$
$X \epsilon S.$

In order to properly apply the ε-constraint method, the ranges of at least p−1 objective functions are needed, which will be founded by calculating the utopia and nadir points of each objective function. By parametrical variation in the RHS of the constrained objective functions (e_i),the efficient solutions tothe problem are obtained in the objective functions range.This method is applied to the small and large-sized problems and the obtained Pareto solution, as shown in Table 1.

Table 1
E-constraint method

Problem Size	OF_2	ε	OF_1
4∗7∗7∗1∗2∗2	592332.4	30	556
	458042		586
	361373.5		616
	308515.8		646
	202773.1		676
	125690.2		706
	85401.2		736
	73539.2		766
	67497.7		796
	64005.7		826

5. Computational Results

In order to assess the performance of the proposed stochastic model, two test problems are selected; in each size, three scenarios are considered.The scenarios for the two test problems are described in Table 2. The first scenario in each problem that has a higher probability has been used as nominal data for deterministic model; the number of variables and constraints for the two models shows the higher degree of complexity of the stochastic model. For applicability evaluation of the proposed models, a numerical example is implemented and reported in this section. Table 3 shows the obtained Pareto solution tithe two test problems. As shown in Table 3, the objective function has a conflict that increasing one of the objective function causes reduction in the other one. It should be noted that all the results are obtained by GAMS 22.9 software using Core i7 and 8.0GB of RAM.

Table 2
Value of the parameters used in the model

K∗ A∗ V∗	Ω	π_θ	D_{ok}	s_{oh}^{D}	s_{oh}^{A}	c_h	c_i	c_v	c_{vh}	t_{ki}	t_{ai}	t_{hi}	B'
4∗7∗7∗1∗2∗2	1	.5	uniform~ [700,850]	uniform~ [180,300]	uniform~ [90,150]	uniform~ [300,700]	uniform~ [800,1000]	uniform~ [100,200]	uniform~ [1,2]	uniform~ [10,60]	uniform~ [40,110]	uniform~ [40,90]	uniform~ [4000,7000]
	2	.3	uniform~ [750,900]	uniform~ [230,350]	uniform~ [100,200]	uniform~ [450,650]	uniform~ [700,900]	uniform~ [70,200]	uniform~ [1,3]	uniform~ [20,70]	uniform~ [60,150]	uniform~ [50,120]	uniform~ [6000,12000]
	3	.2	uniform~ [630,890]	uniform~ [150,280]	uniform~ [70,130]	uniform~ [500,650]	uniform~ [950,1200]	uniform~ [90,170]	uniform~ [2,4]	uniform~ [30,90]	uniform~ [70,160]	uniform~ [30,95]	uniform~ [7000,10000]
8∗22∗30∗1∗4∗2	1	.5	uniform~ [350,450]	uniform~ [100,200]	uniform~ [70,120]	uniform~ [300,700]	uniform~ [800,1000]	uniform~ [100,200]	uniform~ [1,2]	uniform~ [10,60]	uniform~ [40,110]	uniform~ [40,90]	uniform~ [12000,18000]
	2	.3	uniform~ [450,600]	uniform~ [150,350]	uniform~ [100,200]	uniform~ [450,650]	uniform~ [700,900]	uniform~ [70,200]	uniform~ [1,3]	uniform~ [20,70]	uniform~ [60,150]	uniform~ [50,120]	uniform~ [13000,17000]
	3	.2	uniform~ [330,390]	uniform~ [90,150]	uniform~ [70,100]	uniform~ [500,650]	uniform~ [950,1200]	uniform~ [90,170]	uniform~ [2,4]	uniform~ [30,90]	uniform~ [70,160]	uniform~ [30,95]	uniform~ [15000,21000]

Table 3
Computational result under nominal data

Problem Size	Stochastic Model		Deterministic Model	
	OFV_2	OFV_1	OFV_2	OFV_1
4∗7∗7∗1∗2∗2	123842.8	735	592332.4	556
	122590.7	736	458042	586
	114326.7	745	361373.5	616
	108752	751	308515.8	646
	90534	781	202773.1	676
	79794	811	125690.2	706
	77904	828	85401.2	736
	--	--	73539.2	766
	--	--	67497.7	796
	--	--	64005.7	826
	--	--	62892.5	842
8∗22∗30∗1∗4∗2	150399.9	785	2227959.2	608
	124096	798	1370975	643
	86131	808	904458	683
	75718	818	475748	723
	70268	828	205603	763
	67893	838	76897	803
	67396	842	51620	843
	--	--	51230	846

Opening and closing a facility is both an expensive and time-consuming process; thus, changing facility location is impossible in the short run. On the other hand, determining the quantity of flow between network facilities as a tactical decision is more flexible to change in the short run. Therefore, to assess the performance of the deterministic and stochastic models under each scenario, firstly, the small-scalemodelwassolved by GAMS22.9. Then, the solutions were assessed under each scenario by allowing the model to update their decision variables on quantity of flows between facilities (continuous variables) under each scenario. It should be mentioned that the location and the number of facilities (binary variables) cannot be changed, as shown in Table 4.

Table 4
Computational result under realization

Problem size	Scenarios	Scenario probability	Feasibility state		No. of constraints		No. of variables	
I∗H∗K∗A∗V∗O			Deterministic	Stochastic	Deterministic	Stochastic	Deterministic	Stochastic
4∗7∗7∗1∗2∗2	1	0.5	feasible	49076.8	372	1044	248	670
	2	0.3	infeasible	39906.9				
	3	0.2	feasible	17099.3				

The optimal value of binary variables shows that the stochastic model determines the number and location of facilities in a way that they can satisfy all the scenarios. It is obvious from Table 4that the deterministic model results in infeasiblesolutions for scenarios 2. Therefore, it can be concluded that deterministic model is unable to handle data uncertainty.

6. Conclusion

In this paper, we have developed mixed-integer nonlinear programming model that minimizes the total transportation time and maximum organ shortage. With regard to handling the uncertain nature of some input parameters, a scenario-based stochastic approach has been utilized. Computational results show that the stochastic model could handle data uncertainty; therefore, it can be concluded that the proposed MINLP model can be used as a powerful tool in practical cases. Considering the model under the dynamic nature of facilities and facility disruptions, utilizing other efficient methods to cope with the uncertainty can be taken into account as the future research in this field.

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