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A fuzzy optimization approach to strategic organ transplantation network design problem: A real case study

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A B S T R A C T

Designing an efficient supply chain for organ transplant networks which is intimately related to humans' life plays a primary role in improving the network's performance. This research is focused on proposing a new multi-period location-allocation modeling approach to make appropriate strategic decisions for designing organ transplant networks under supply and budget uncertainties. To serve this purpose, a bi-objective possibilistic programming model is formulated the aim of which is to maximize network responsiveness and minimize the total cost. A fuzzy goal programming approach is adopted to solve multiple objective function models and control their deviations from the corresponding aspiration levels. As an important contribution of this study, the chance of success of transplantation processes is taken into consideration by proposing appropriate utility functions according to transportation criteria. Moreover, for the purpose of coping with the inherent uncertainty of the input parameters, a possibilistic programming model based on *Me* measure converted to three optimistic, realistic and pessimistic models is developed. Three new formulations have also been developed to tackle equality chance constraints. Finally, the optimal solutions of the developed models are analyzed through conducting a real case study in Iran. According to the results, for the considered organ transplant network, the possibilistic programming model based on the realistic measure is better than the optimistic and pessimistic measure in most confidence levels.

1. Introduction

Organ transplantation, as one of the crucial subsets of the healthcare system, has become the most preferable treatment for the end stage organ (Platt, 1998; Mota et al., 2020). In the organ transplantation process, a healthy organ harvested from the donor body is transplanted to a suitable recipient who is a candidate for receiving the organ (Beliën et al., 2013). Organ donors may be alive, brain-dead, or dead via circulatory death. Despite the long history of solid organ transplantation, it is not possible to transplant every organ. In spite of the ever-increasing clinical advances in organ transplantation, the medical profession is able to transplant a few solid organs such as kidney, liver, pancreas, heart, lung and small intestine (O'Leary et al., 2016). Furthermore, certain combined organ transplants are done as well. They involve such organ combinations as kidney-pancreas, kidney-heart, heart-lung, heart-kidney-liver, and heart-kidney-pancreas (Wolfe et al., 2010; Ahmad et al., 2015; Lui et al., 2020). It is very important to protect the harvested organs until they start their function within the recipient's body. One of the most important factors during the protection process is cold ischemia time (CIT) defined as a time from harvesting an organ from a donor's body until starting the organ transplant in a recipient. (Najafizadeh et al., 2007). In fact, the most important limitation of organ transplant operations is the CIT of organs, which has been examined in some studies (see Najafizadeh et al., 2007; Bruni et al., 2006). A donated organ must be transplanted according to the corresponding CIT precepts; otherwise, the organ becomes functionless and of no use to save a life. Therefore, a transplantation process has to be managed efficiently to ensure that it is implemented at exactly the right time. There are a lot of clinical and non-clinical parameters involved in an organ transplantation network among which this study focuses on the non-clinical parameters

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such as financial issues, location, and the number of facilities. A shortage in any of these non-clinical parameters can result in a large gap between potential donated organs and the potential benefit which patients can receive. In such a case, organ transplantation is not as effective as desired (Pretto et al., 2015). There is also a supply problem to face in organ transplantation; supply often does not meet demand (Stahl et al., 2005). The gap between demand and supply keeps recipients on long waiting lists, which leads to the death of many of them annually. In this system, there is no control on the amount of supply. Therefore, the network should focus on using up all of the organ supplies. In such case, it is crucial to design an organ transplant supply chain network so as to achieve maximum responsiveness. A supply chain network design typically determines the optimal number and location of the facilities as well as the flows among them (Pishvaee & Razmi, 2012). Since inappropriate location of facilities may result in more deaths, precise selection of locations is vital for transplantation networks (Daskin & Dean, 2005). Moreover, unlike an archetypal supply chain, perishability should be considered as an essential factor in organ transplant supply chain (Zahiri et al., 2014a).

1.1 Literature review

In general, facility design in healthcare systems is used to serve different clinical and non-clinical objectives (Halawa et al., 2020). The location of facilities is vital in healthcare systems. Inappropriate selection of facility location will result in the increase of mortality and morbidity (Daskin & Dean, 2005). There are a large number of studies in this area some of which published recently are mentioned here. Zarrinpoor et al. (2017) designed a health service network under the risk of disruptions through proposing a hierarchical location-allocation model and they applied a new Benders decomposition type algorithm to solve it. Ahmadi-Javid and Ramesh (2020) designed the integrated primary healthcare facilities with workforce cross-training through proposing a stochastic location model. Memari et al. (2020) developed a bi-objective model for designing temporary emergency stations. The model maximized the coverage after a disaster. Unlike the other healthcare systems, there are a few studies that have focused on facility location-allocation of organ transplant networks. In this area, Stahl et al. (2005) formulated a multi-objective integer programming model to optimally reorganize liver transplant regions in the United States. The purpose of the model was simultaneously maximizing geographic parity and the number of transplants in every region. According to their analysis, optimizing the configuration of regions has positive effects on the liver transplantation network in the United States. Bruni et al. (2006) formulated a mathematical location-allocation programming model to determine the optimum organization of transplant networks in which the organ allocation is done with the aim of increasing regional equality. They considered time and spatial distribution of the facilities as two deciding factors in such networks and applied the model for a real case in Italy. Kong et al. (2010) formulate a set-partitioning model to geographically redesign the liver allocation system in the United States. The aim of the model was having a system with maximum efficiency in every region and they solved it by applying the branch and price approach. Some computational studies were presented to evaluate their model and solution approach. Beliën et al. (2013) designed an organ transplant network in Belgium through formulating a MILP model to spatially organize the transplantation centres and minimize the total time of transplantation process in the network. Zahiri et al. (2014a) formulated a MILP model for designing an organ transplantation network determining the optimal location-allocation of the facilities. They considered uncertainty of supply, demand and cost in the proposed model and applied a robust possibilistic programming approach to tackle uncertainty in the network. The aim of the developed model was minimizing the total cost and they evaluated the model by applying a case study in Iran. Zahiri et al. (2014b) developed a bi-objective location-allocation model minimizing both time and cost in the organ transplant network. They applied the optimistic-pessimistic possibilistic programming model based on *Me* measure to handle the uncertain parameters in the network. To solve the large-sized application of the model, two meta-heuristic approaches were introduced. Savaşer et al. (2019) developed a mathematical model to optimize the clustering structure of Turkey's organ transplant network aiming to maximize the number of intra-regional donor-recipient matches. Different transportation modes were considered in the model and the performance of the model was assessed through a simulation model. Despite all the advanced studies and expanded investigations to design efficient and realistic organ transplant networks, the existing literature does not sufficiently address certain essential factors in such networks. For example, it is somehow ignored that most donors are brain-dead in organ transplantation networks (Deffains & Ythier, 2010), and identification of these donors is the basis and the start point of organ transplantation processes (Najafizadeh et al., 2007). Also, despite the advancement of knowledge and technology, diagnosing a brain-death is one the difficult and challenging issues for nurses in the hospitals and they are uncertain about the concept and diagnosis of the brain-death (Yazdimoghaddam et al., 2020). Therefore, establishing identification centers is an important step to take in organ transplant networks.

1.2 Contributions

To address the aforementioned concerns, this study focuses on designing efficient and timely organ transplantation supply chain networks. To do so, a novel bi-objective possibilistic programming (BOPP) model is proposed. The model helps to make appropriate long-term decisions about an organ transplantation network design which is able to 1) locate Identification Centers (IC) (i.e., the centers where donors are identified) and Organ Procurement Units (OPU) (i.e., the units where organs are harvested), 2) allocate facilities and specify organ flows between the network nodes, and 3) tackle the uncertainty of supply and budget. In addition, a number of utility functions (UFs) are proposed to assure the successful transplantation of organs according to the transportation criteria.In this study, the issue is proposed to be handled as follows:

- Considering the trade-off between maximum responsiveness and minimum total cost as an objective function. To do so, the weighted max-min fuzzy goal programming approach is applied, where responsiveness includes the identified donors, the process of donation, and the donated organs.
- Developing a possibilistic programming method based on *Me* measure to tackle uncertainty. *Me* is an optimistic-pessimistic measure. In previous studies which applied this measure, the models were solved using optimistic and pessimistic approaches (see references Zahiri et al., 2014b; Xu & Zhou, 2013; Zhalechian et al., 2016). In this study, however, for the first time, a realistic approach based on credibility measure is developed. Moreover, three different formulations are proposed to convert the equality fuzzy chance constraints to deterministic constraints.
- Proposing appropriate UFs to assure the success of organ transplantation according to traveling and ischemia times. In fact, a transplant process is affected by important factors during different stages (i.e., identification of donors, transferring donors and transferring donated organs), in which the process may fail.

2. Model description

In this research, the proposed model consists of hospitals (those which have appropriate services to care about donors), donors, Transplant Centers (TCs), OPUs and ICs. A location-allocation model has been provided to support decision making by locating and allocating ICs and OPUs. In each IC, there are specialists who are authorized to identify potential donors (i.e. suspected brain-dead patients). In case of identifying a donor, they inform the nearest OPU. In each OPU, donor identification and organ removal are both carried out. A schematic diagram of the studied network and the interactions among the components is provided in Fig.1. As the figure suggests, in the first step, an identification team is dispatched from the nearest IC to the hospital in order to recognize the donor (1). Then, the donor is transferred to the closest OPU to remove his/her donated organs (2). Finally, the harvested organ is sent to the recipients TC (3).

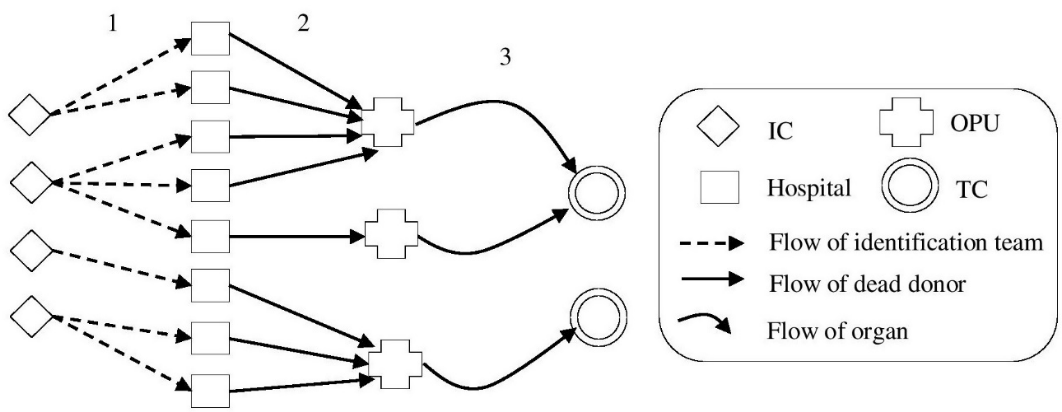

Fig. 1. The schematic view of the developed organ transplant network

The predominant assumptions of the developed network are listed as follows:

a) OPU can carry out all the tasks of the IC independently.
b) Maximum permissible distances between facilities are fixed and known according to the expected norms in the healthcare sector and experts' opinions.
c) The demand for organs in TCs is significantly greater than the supply of organs. Therefore, there are suitable recipients for each donated organ at TCs. This assumption complies with real-life transplantation situations.
d) All the donors are brain-dead persons.

2.1. Nomenclature

The sets, variables, and parameters (the uncertain parameters are shown with a tilde on) used in the mathematical formulation are defined as follows.

Sets:

H	Set of hospital locations, $h \in H$
K	Set of potential IC locations,$k \in K$
M	Set of potential OPU locations, $m \in M$

N	Set of TCs, $n \in N$
O	Set of types of organs, $o \in O$
T	Set of time periods, $t, t' \in T$

Parameters:

C_{mt}	Fixed cost of equipping OPU in location *m* at time period *t*
C^{I}_{kt}	Fixed cost of equipping IC in location *k* at time period *t*
CI_{tkh}	Traveling cost from IC *k* to hospital *h* at time period *t*
CD_{tmh}	Traveling cost from hospital *h* to OPU *m* at time period *t*
CO_{tmn}	Cost of organ transportation from OPU *m* to TC *n* at time period *t*
TI_{kh}	Traveling time from IC *k* to hospital *h*
TD_{mh}	Traveling time from hospital *h* to OPU *m*
TO_{mn}	Traveling time from OPU *m* to TC
$\widetilde{sd_{ht}}$	Number of donors in hospital *h* at time period *t*
p_o	The probability of existing organ *o* in a donor body
$\widetilde{B_t}$	Available budget for transplant organizations at time period *t*
V	A great number
ϑ	Maximum allowable traveling time from ICs to hospitals
$L\vartheta$	Maximum traveling time from ICs to hospitals in order to have full success in identifying donors
φ	Maximum allowable traveling time from hospitals to OPUs
$L\varphi$	Maximum traveling time from hospitals to OPUs in order to have full success in transporting donors.
τ	Maximum allowable traveling time from OPUs to TCs
γ, ω, ρ	Corresponding importance weight of objective function terms

Decision Variables:

U_{mt}	1 if an OPU is opened at location *m* at time period *t*, and 0 otherwise
Z_{kt}	1 if an IC is opened at location *k* at time period *t*, and 0 otherwise
Y_{hkt}	1 if IC *k* is assigned to hospital *h* at time period *t*, and 0 otherwise
q_{hmt}	1 if hospital *h* is assigned to OPU *m* at time period *t*, and 0 otherwise
w_{mnt}	1 if OPU *m* is assigned to TC *n* at time period *t*, and 0 otherwise
x^{I}_{kht}	Flow of identification team from IC *k* to hospital *h* at time period *t*
x^{D}_{hmt}	Flow of donors from hospital *h* to OPU *m* at time period *t*
x^{T}_{omnt}	Flow of organ *o* from OPU *m* to TC *n* at time period *t*
nb_{hmt}	Number of donors that arrives to OPU *m* from hospital *h* at time period *t*
Tnb_{mt}	Total number of donors that arrives to OPU *m* at time period *t*
s_{omnt}	Number of organ *o* that arrives to TC *n* from OPU *m* at time period *t*
rb_t	Real budget at time period *t*
Cc_t	Total cost at time period *t*

2.2. Determination of utility functions according to transportation criteria

As a rule, traveling time is a primary factor in all the three stages of transplantation networks. First, there is no doubt, as the traveling time between IC and the hospital increases, the number of recognized donors decreases. Therefore, they are missed without being utilized to save any life. Secondly, experimental results and medical investigations demonstrate that the quality of donated organs decreases over time, and this may affect the transplant outcome (Quiroga et al., 2006). Accordingly, it is crucial to transfer the donor from the hospital to OPU as fast as possible so as to harvest the intended organ. Finally, the quality of donated organs decreases over time, and they become useless (Totsuka et al., 2002). Thus, reducing the CIT is of utmost importance in the organ transplant process (Quiroga et al., 2006). In this research, three UFs are defined as shown in Fig. 2 for different stages of a transplant process in order to enhance the chance of success for the process.

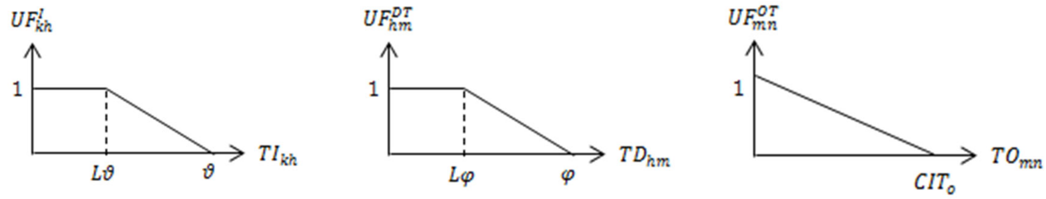

Fig. 2a. UF of donor identification.

Fig. 2b. UF of donor transportation.

Fig. 2c. UF of organ transportation.

Fig. 2. Utility functions of different stages of the transplant process

In the figures above, $\mathrm{UF}^{\mathrm{I}}_{\mathrm{kh}}$, $\mathrm{UF}^{\mathrm{DT}}_{\mathrm{hm}}$ and $\mathrm{UF}^{\mathrm{OT}}_{\mathrm{mn}}$ are the UFs of donor identification, donor transfer, and organ transfer, respectively. Donor identification and donor transfer are completely done (with no donor missed) if the traveling time from IC to the hospital and from the hospital to OPU is lower than specific times $\mathrm{L}\vartheta$ and $\mathrm{L}\varphi$, respectively. These specific time durations are determined with respect to different factors such as demographic and geographic factors and the number of donors in the region. Generally, it is to be noted that the quality and functionality of harvested organs decrease continuously. To sum up, any plan to establish UFs in a certain place should take the above concerns into consideration.

2.3. Formulation

$$Maximize\ OF1 = \gamma \sum_{t\in T}\sum_{k\in K}\sum_{h\in H} x^{I}_{kht} + \omega \sum_{t\in T}\sum_{h\in H}\sum_{m\in M} nb_{hmt} + \rho \sum_{t\in T}\sum_{o\in O}\sum_{m\in M}\sum_{n\in N} s_{omnt} \tag{1}$$

$$Minimize\ OF2 = \sum_{t\in T} Cc_t \tag{2}$$

s.t.

$$Cc_t = \sum_{m\in M} C_{mt}\,U_{mt} + \sum_{k\in K} C^{I}_{kt}\,Z_{kt} + \sum_{k\in K}\sum_{h\in H} CI_{tkh}\,x^{I}_{kht} + \sum_{h\in H}\sum_{m\in M} CD_{tmh}\,x^{D}_{hmt} + \sum_{m\in M}\sum_{n\in N}\sum_{o\in O} CO_{tmn}\,x^{T}_{omnt},\ \ \forall t\in T \tag{3}$$

$$Cc_t \le rb_t, \quad \forall t\in T \tag{4}$$

$$rb_t = (rb_{t-1} - Cc_{t-1}) + \widetilde{B_t}\,, \quad \forall t\in T \tag{5}$$

$$\sum_{m\in M}\sum_{t\in T} U_{mt} \ge 1 \tag{6}$$

$$\sum_{t\in T} U_{mt} \le 1,\ \ \forall m\in M \tag{7}$$

$$\sum_{k\in K}\sum_{t\in T} Z_{kt} \ge 1 \tag{8}$$

$$\sum_{t\in T} Z_{kt} \le 1,\ \ \forall k\in K \tag{9}$$

$$U_{mt} \le Z_{Kt},\ \ \forall m\in M, k\in K, t\in T, |m = k \tag{10}$$

$$\sum_{t\in T}\sum_{k\in K} Y_{hkt} = 1,\ \ \forall h\in H \tag{11}$$

$$Y_{hkt} = 0,\ \ \forall h\in H, k\in K, t\in T, |TI_{Kh} > \vartheta \tag{12}$$

$$Y_{hkt} \leq \sum_{t'=1}^{t} Z_{kt'}, \quad \forall h \in H, k \in K, t \in T \tag{13}$$

$$\sum_{t \in T} \sum_{m \in M} q_{hmt} = 1, \quad \forall h \in H \tag{14}$$

$$q_{hmt} = 0, \quad \forall h \in H, m \in M, t \in T, |TD_{mh} > \varphi \tag{15}$$

$$q_{hmt} \leq \sum_{t'=1}^{t} U_{mt'}, \quad \forall h \in H, m \in M, t \in T \tag{16}$$

$$\sum_{t \in T} \sum_{n \in N} w_{mnt} \leq 1, \quad \forall m \in M \tag{17}$$

$$w_{mnt} = 0, \quad \forall m \in M, n \in N, t \in T, |TO_{mn} > \tau \tag{18}$$

$$w_{mnt} \leq \sum_{t'=1}^{t} U_{mt'}, \quad \forall m \in M, n \in N, t \in T \tag{19}$$

$$x_{kht}^{I} = \sum_{t=1}^{t} Y_{hkt} \widetilde{sd_{ht}}, \quad \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta \tag{20}$$

$$x_{kht}^{I} = \sum_{t'=1}^{t} Y_{hkt'} ((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta)) \widetilde{sd_{ht}}, \quad \forall h \in H, k \in K, t \in T | TI_{Kh} \geq L\vartheta \tag{21}$$

$$\sum_{m \in M} x_{hmt}^{D} = \sum_{k \in K} x_{kht}^{I}, \quad \forall h \in H, t \in T \tag{22}$$

$$x_{hmt}^{D} \leq \sum_{t'=1}^{t} q_{hmt'} V, \quad \forall h \in H, m \in M, t \in T \tag{23}$$

$$nb_{hmt} = x_{hmt}^{D}, \quad \forall h \in H, k \in K, t \in T | \, TD_{hm} < L\varphi \tag{24}$$

$$nb_{hmt} = ((TD_{hm} - \varphi)/(L\varphi - \varphi)) x_{hmt}^{D}, \quad \forall h \in H, m \in M, t \in T | \, TD_{hm} \geq L\varphi \tag{25}$$

$$Tnb_{mt} = \sum_{h \in H} nb_{hmt}, \quad \forall m \in M, t \in T \tag{26}$$

$$\sum_{n \in N} x_{omnt}^{T} = Tnb_{mt} p_o, \quad \forall m \in M, o \in O, t \in T \tag{27}$$

$$x_{omnt}^{T} \leq \sum_{t'=1}^{t} w_{mnt'} V, \quad \forall m \in M, n \in N, o \in O, t \in T \tag{28}$$

$$s_{omnt} = ((\, TO_{mn} - CIT_o)/(0 - CIT_o)) x_{omnt}^{T}, \quad \forall m \in M, o \in O, t \in T \tag{29}$$

$$U_{mt}, Z_{kt}, Y_{hkt}, q_{hmt}, w_{mnt}, \in \{0, 1\}, \quad \forall h \in H,, k \in K, m \in M, n \in N, t \in T \tag{30}$$

$$rb_t, Cc_t, x_{kht}^{I}, x_{hmt}^{D}, x_{omnt}^{T}, nb_{mt}, Tnb_{mt}, s_{omnt} \geq 0, \quad \forall o \in O, h \in H, k \in K, m \in M, n \in N, t \in T \tag{31}$$

Objective function (1) maximizes the network responsiveness at all the stages of the organ transplantation network. Each term is multiplied by its corresponding importance weight. Objective function (2) minimizes the total cost. Constraint set (3) calculates the total cost in each time period, including the fixed costs of equipping facilities and the costs of transportation between facilities. Constraint set (4) guarantees that the total cost will not exceed the real budget at any time period. Constraint set (5) calculates the required real budget in each time period, including the budget of each time period and the surplus budget of previous time periods. Constraint sets (6) and (7) guarantee that at least one OPU shall be established during the planning horizon and that it can be opened at most once in each location. Constraint sets (8) and (9) assure that at least one IC shall be established during the planning horizon and that it can be opened at most once in each location. Constraint set (10) ensures that the OPU can do the duty of the IC. Constraint set (11) guarantees that every hospital is allocated to exactly one IC. Constraint set (12) ensures that the hospital cannot be assigned to an IC whenever the traveling time between them exceeds the maximum permissible traveling time. Constraint set (13) assures that each hospital is assigned to an IC whenever that IC has been opened beforehand. Constraint set (14) guarantees that every hospital can be assigned to exactly one OPU during planning. Constraint set (15) ensures that the hospital cannot be assigned to an OPU whenever the traveling time between them exceeds the maximum permissible traveling time. Constraint set (16) assures that each hospital is assigned to an OPU whenever the OPU has been opened once already. Constraint set (17) ensures that each opened OPU can be assigned to only one TC. Constraint set (18) ensures that an OPU cannot be assigned to a TC whenever traveling between them exceeds the permissible time. It should be mentioned that the permissible traveling time must be shorter than the shortest cold ischemia time. Constraint set (19) ensures that each OPU is assigned to a TC whenever the OPU has been opened beforehand. Constraint sets (20) and (21) ensure the donors in each hospital are recognized according to the UF of donor identification. Constraint set (22) guarantees that all the identified donors are transported to an OPU for their organs to be harvested. Constraint set (23) assures that the flow from a hospital to an OPU can exist whenever the hospital has been assigned to the OPU beforehand. Constraint sets (24) and (25) calculate the number of donors who go from a hospital to an OPU with regard to the UF of donor transportation. Constraint set (26) calculates the total number of donors who arrive at an OPU at every time period. Constraint set (27) ensures that all the donated organs in each OPU will be transported to a TC for transplantation. It is to be noted that the total number of each organ in each OPU during each time period has been calculated with respect to the probability of the existing organs in a donor's body. Constraint set (28) ensures that the organ flow between an OPU and a TC can exist whenever the OPU has been assigned to the TC. Constraint set (29) calculates the number of organs transported from an OPU to a TC (i.e. transplanted organs) with regard to the UF of organ transportation. Constraint set (30) presents the binary nature of decision variables. Finally, Constraint set (31) presents the non-negativity restriction.

3. Proposed possibilistic programming model

Supply chain network design and establishment are strategic decisions having long-term effects on the network (Meepetchdee & Shah, 2007). Organ transplant industries have a dynamic nature and therefore, some crucial parameters, such as patient demands and organ supplies, may be changed based on uncertain circumstances. Furthermore, the establishment of such networks may take a long time and the available budget at each time period cannot be determined at the outset of the planning horizon. On the other hand, spatially reorganizing the facilities needs significant time and cost. Thus, it is not possible to make changes in the location of facilities due to fluctuations of above mentioned parameters in a short time (Pishvaee et al., 2011). Since the organ transplant network deals with human lives in consequence directly, the designed network should be modelled and solved with respect to uncertain parameters. Possibilistic programming (PP) as one of the main categories of fuzzy programming is an efficient method for problems including the uncertain parameters for which sufficient historical data is not available. PP converses with ambiguous coefficients in objective functions and constraints (Torabi & Hassini, 2008). Accordingly, in the proposed model in this study PP is applied and the chance constrained programming method is utilized among the available PP approaches to tackle probability constraint sets in. Furthermore, Xu and Zhou (2013) produced an optimistic-pessimistic measure named *Me* measure to satisfy decision makers with different points of view, in uncertain decision making processes. However, Possibility and Necessity measures used as the traditional measures are entirely optimistic or pessimistic (2014). In fact, according to this approach, the model is transformed into optimistic and pessimistic PP models; namely, the upper approximation model (UAM) and the lower approximation model (LAM) are based on possibility and necessity measures, respectively (see Zahiri et al., 2014b;, Xu & Zhou, 2013; Zhalechian et al., 2016). In this study, the mediocre approximation model (MAM) based on credibility measure has been also used in addition to aforementioned models. The MAM is a realistic PP model. It should be mentioned that the amount of budget and supply are considered to be uncertain in the form of trapezoidal fuzzy numbers ($\widetilde{B_t} = (B(1)_t, B(2)_t, B(3)_t, B(4)_t)$ and $\widetilde{sd_{ht}} = (sd(1)_{ht}, sd(2)_{ht}, sd(3)_{ht}, sd(4)_{ht})$). Also, there is not any uncertain parameter in the objective function of the proposed model. With respect to the aforementioned descriptions, the proposed possibilistic chance constrained programming (PCCP) model is presented as follows:

$$Me\left\{rb_t = (rb_{t-1} - Cc_{t-1}) + \widetilde{B_t}\,, \quad \forall t \in T\right\} \geq \alpha_1 \tag{32}$$

$$Me\left\{x^I_{kht} = \sum_{t=1}^{t} Y_{hkt}\, \widetilde{sd_{ht}}, \quad \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta\right\} \geq \alpha_2 \tag{33}$$

$$Me\left\{x^I_{kht} = \sum_{t=1}^{t} Y_{hkt}\, ((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta))\widetilde{sd_{ht}}, \quad \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta\right\} \geq \alpha_2 \tag{34}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

In the above formulation, α_1 and α_2 are considered as minimum confidence levels for satisfying the chance constraints. In this study, three new definitions have been introduced as follows in order to tackle equality constraints. Accordingly, Equations (38), (48) and (58) have been developed.

Considering proposed assumptions, the above model can be transformed into UAM, MAM and LAM as follows:

- UAM:

$$Pos\{rb_t = (rb_{t-1} - Cc_{t-1}) + \widetilde{B_t}\,,\quad \forall t \in T\} \geq \alpha_1 \tag{35}$$

$$Pos\left\{x_{kht}^I = \sum_{t=1}^{t} Y_{hkt}\,\widetilde{sd_{ht}},\;\; \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta\right\} \geq \alpha_2 \tag{36}$$

$$Pos\left\{x_{kht}^I = \sum_{t=1}^{t} Y_{hkt}\,((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta))\widetilde{sd_{ht}},\;\; \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta\right\} \geq \alpha_2 \tag{37}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

Definition 1. In the possibility measure, the real number r and the trapezoidal fuzzy number $\tilde{\zeta} = (\zeta_{(1)}, \zeta_{(2)}, \zeta_{(3)}, \zeta_{(4)})$ are roughly equal if and only if $\zeta_{(1)} \leq \mathrm{r} \leq \zeta_{(4)}$.

Then, the possibility measure of the equality chance constraints can be written as follows:

$$Pos\{\tilde{\zeta} = r\} \geq \alpha \Leftrightarrow \begin{cases} (r - \zeta_{(1)})/(\zeta_{(4)} - \zeta_{(1)}) \geq \alpha/2 \;\;\Leftrightarrow\;\; r \geq (\alpha/2)\,\zeta_{(4)} + (1 - \alpha/2)\zeta_{(1)} \\ \\ (\zeta_{(4)} - r)/(\zeta_{(4)} - \zeta_{(1)}) \geq \alpha/2 \;\;\Leftrightarrow\;\; r \leq (1 - \alpha/2)\zeta_{(4)} + (\alpha/2)\zeta_{(1)} \end{cases} \tag{38}$$

Therefore, with respect to the formulation (38), the proposed optimistic model is written as follow:

$$rb_t \geq (rb_{t-1} - Cc_{t-1}) + (\alpha_1/2)\,B(4)_t + (1 - \alpha_1/2)B(1)_t,\quad \forall t \in T \tag{39}$$

$$rb_t \leq (rb_{t-1} - Cc_{t-1}) + (1 - \alpha_1/2)B(4)_t + (\alpha_1/2)B(1)_t,\quad \forall t \in T \tag{40}$$

$$x_{kht}^I \geq \sum_{t=1}^{t} Y_{hkt}\,((\alpha_2/2)sd(4)_{ht} + (1 - \alpha_2/2)sd(1)_{ht},),\;\; \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta \tag{41}$$

$$x_{kht}^I \leq \sum_{t=1}^{t} Y_{hkt}\,((1 - \alpha_2/2)sd(4)_{ht} + (\alpha_2/2)sd(1)_{ht}),\;\; \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta \tag{42}$$

$$x_{kht}^I \geq \sum_{t=1}^{t} Y_{hkt}\,((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta))\,((\alpha_2/2)sd(4)_{ht} + (1 - \alpha_2/2)sd(1)_{ht}),\;\; \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta \tag{43}$$

$$x_{kht}^I \leq \sum_{t=1}^{t} Y_{hkt}\,((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta))\big((1 - \alpha_2/2)sd(4)_{ht} + (\alpha_2/2)\,sd(1)_{ht}\big),\;\; \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta \tag{44}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

MAM:

$$Cr\{rb_t = (rb_{t-1} - Cc_{t-1}) + \widetilde{B_t}\,,\quad \forall t \in T\} \geq \alpha_1 \tag{45}$$

$$Cr\left\{x_{kht}^I = \sum_{t=1}^{t} Y_{hkt}\,\widetilde{sd_{ht}},\;\; \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta\right\} \geq \alpha_2 \tag{46}$$

$$Cr\left\{x_{kht}^I = \sum_{t=1}^{t} Y_{hkt}\,((TI_{Kh} - \vartheta)/(L\vartheta - \vartheta))\,\widetilde{sd_{ht}},\;\; \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta\right\} \geq \alpha_2 \tag{47}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

Definition 2. In the credibility measure, the real number r and the trapezoidal fuzzy number $\tilde{\zeta}$ are roughly equal if and only if $0.5(\zeta_{(1)} + \zeta_{(2)}) \leq \mathrm{r} \leq 0.5(\zeta_{(3)} + \zeta_{(4)})$.

Then, the credibility measure of the equality chance constraints can be written as follows:

$$Cr\{\tilde{\zeta}=r\}\geq\alpha\Leftrightarrow\begin{cases}\dfrac{r-0.5(\zeta_{(1)}+\zeta_{(2)})}{0.5(\zeta_{(3)}+\zeta_{(4)})-0.5(\zeta_{(1)}+\zeta_{(2)})}\geq\alpha/2\ \Leftrightarrow\\ r\geq(\alpha/4)(\zeta_{(4)}+\zeta_{(3)}-\zeta_{(2)}-\zeta_{(1)})+0.5(\zeta_{(1)}+\zeta_{(2)})\\ \\ \dfrac{0.5(\zeta_{(3)}+\zeta_{(4)})-r}{0.5(\zeta_{(3)}+\zeta_{(4)})-0.5(\zeta_{(1)}+\zeta_{(2)})}\geq\alpha/2\ \Leftrightarrow\\ r\leq\ 0.5(\zeta_{(3)}+\zeta_{(4)})-(\alpha/4)(\zeta_{(4)}+\zeta_{(3)}-\zeta_{(2)}-\zeta_{(1)})\end{cases}\tag{48}$$

Therefore, with respect to the formulation (48), the proposed realistic model is written as follow:

$$rb_t\geq(rb_{t-1}-Cc_{t-1})+(\alpha_1/4)\,(B(3)_t+B(4)_t)+0.5(B(1)_t+B(2)_t)(1-(\alpha_1/2)),\quad\forall t\in T\tag{49}$$

$$rb_t\leq(rb_{t-1}-Cc_{t-1})+(\alpha_1/4)\,(B(1)_t+B(2)_t)+0.5(B(3)_t+B(4)_t)(1-(\alpha_1/2)),\quad\forall t\in T\tag{50}$$

$$x_{kht}^I\geq\sum_{t=1}^{t}Y_{hkt}((\alpha_2/4)\,(sd(3)_{ht}+sd(4)_{ht})+0.5(sd(1)_{ht}+sd(2)_{ht})(1-(\alpha_2/2))),\ \ \forall h\in H,k\in K,t\in T|TI_{Kh}<L\vartheta\tag{51}$$

$$x_{kht}^I\leq\sum_{t=1}^{t}Y_{hkt}\,((\alpha_2/4)\,(sd(1)_{ht}+sd(2)_{ht})+0.5(sd(3)_{ht}+sd(4)_{ht})(1-(\alpha_2/2))),\ \ \forall h\in H,k\in K,t\in T|TI_{Kh}<L\vartheta\tag{52}$$

$$x_{kht}^I\geq\sum_{t=1}^{t}Y_{hkt}\,((TI_{Kh}-\vartheta)/(L\vartheta-\vartheta))((\alpha_2/4)\,(sd(3)_{ht}+sd(4)_{ht})+0.5(sd(1)_{ht}+sd(2)_{ht})(1-(\alpha_2/2))),\ \ \forall h\in H,k\in K,t\in T|L\vartheta\leq TI_{Kh}\leq\vartheta\tag{53}$$

$$x_{kht}^I\leq\sum_{t=1}^{t}Y_{hkt}\,((TI_{Kh}-\vartheta)/(L\vartheta-\vartheta))((\alpha_2/4)\,(sd(1)_{ht}+sd(2)_{ht})+0.5(sd(3)_{ht}+sd(4)_{ht})(1-(\alpha_2/2))),\qquad\forall h\in H,k\in K,t\in T|L\vartheta\leq TI_{Kh}\leq\vartheta\tag{54}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

LAM:

$$Nec\{rb_t=(rb_{t-1}-Cc_{t-1})+\widetilde{B_t}\,,\quad\forall t\in T\}\geq\alpha_1\tag{55}$$

$$Nec\left\{x_{kht}^I=\sum_{t=1}^{t}Y_{hkt}\,\widetilde{sd_{ht}},\ \ \forall h\in H,k\in K,t\in T|TI_{Kh}<L\vartheta\right\}\geq\alpha_2\tag{56}$$

$$Nec\left\{x_{kht}^I=\sum_{t=1}^{t}Y_{hkt}\,((TI_{Kh}-\vartheta)/(L\vartheta-\vartheta))\,\widetilde{sd_{ht}},\ \ \forall h\in H,k\in K,t\in T|L\vartheta\leq TI_{Kh}\leq\vartheta\right\}\geq\alpha_2\tag{57}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

Definition 3. In the necessity measure, the real number *r* and the trapezoidal fuzzy number $\tilde{\zeta}$ are roughly equal if and only if $\zeta_{(2)}\leq r\leq\zeta_{(3)}$.

Then, the necessity measure of equality chance constraints can be written as follows:

$$Nec\{\tilde{\zeta}=r\}\geq\alpha\Leftrightarrow\begin{cases}((r-\zeta_{(2)})/(\zeta_{(3)}-\zeta_{(2)}))\geq(\alpha/2)\ \ \Leftrightarrow\ \ r\geq(\alpha/2)\,\zeta_{(3)}+(1-(\alpha/2))\zeta_{(2)}\\ \\ ((\zeta_{(3)}-r)/(\zeta_{(3)}-\zeta_{(2)}))\geq(\alpha/2)\ \ \Leftrightarrow\ \ r\leq(1-(\alpha/2))\zeta_{(3)}+(\alpha/2)\,\zeta_{(2)}\end{cases}\tag{58}$$

Therefore, with respect to the formulation (58), the proposed pessimistic model is written as follow:

$$rb_t\geq(rb_{t-1}-Cc_{t-1})+(\alpha_1/2)\,B(3)_t+(1-\ (\alpha_1/2))B(2)_t,\quad\forall t\in T\tag{59}$$

$$rb_t\leq(rb_{t-1}-Cc_{t-1})+(1-\ (\alpha_1/2))B(3)_t+(\alpha_1/2)\,B(2)_t,\quad\forall t\in T\tag{60}$$

$$x_{kht}^{I} \geq \sum_{t=1}^{t} Y_{hkt}\left((\alpha_2/2)\, sd(3)_{ht} + (1-(\alpha_2/2))sd(2)_{ht},\right),\ \ \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta \tag{61}$$

$$x_{kht}^{I} \leq \sum_{t=1}^{t} Y_{hkt}\left((1-(\alpha_2/2))sd(3)_{ht} + (\alpha_2/2)\, sd(2)_{ht}\right),\ \ \forall h \in H, k \in K, t \in T | TI_{Kh} < L\vartheta \tag{62}$$

$$x_{kht}^{I} \geq \sum_{t=1}^{t} Y_{hkt}\left((TI_{Kh}-\vartheta)/(L\vartheta-\vartheta)\right)\left((\alpha_2/2)\, sd(3)_{ht} + (1-(\alpha_2/2))sd(2)_{ht},\right),\ \ \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta \tag{63}$$

$$x_{kht}^{I} \leq \sum_{t=1}^{t} Y_{hkt}\left((TI_{Kh}-\vartheta)/(L\vartheta-\vartheta)\right)\left((1-(\alpha_2/2))sd(3)_{ht} + (\alpha_2/2)\, sd(2)_{ht}\right),\ \ \forall h \in H, k \in K, t \in T | L\vartheta \leq TI_{Kh} \leq \vartheta \tag{64}$$

Eqs. (1)-(4), (6)-(19), (22)-(31).

4. Weighted max–min fuzzy GP model

Almost all of the decision making problems in the real world are multi-objectives and the solutions are usually a trade-off between them (Mavrotas, 2007; Mavrotas, 2009; Singh & Kumar, 2012). Researchers have proposed different methods to solve the bi-objective optimization problems (i.e. Buch & Trivedi, 2021). Hwang and Masu (2012) presented three classification for these methods named priori, interactive and posteriori methods. In a priori methods, objective functions are weighted with respect to the preferences of decision makers. The most commonly known priori approach in multi-objective programming is goal programming (GP) (Aouni & Kettani, 2001). Two main categories of the GP are lexicographic and weighted GP both of which focus on solution techniques minimizing the deviations of every goal (Chang and Wang, 1997). The objective targets usually are not specific in the real world. The fuzzy set theory, as one of the powerful tools for handling the uncertainty, can be utilized in such cases. In fuzzy GP the ideal values are considered as targets. Chen and Tsai (2001) considered different lexicographic priorities in their fuzzy goal programming (FGP) model. Choudhary and Shankar (2014) applied preemptive GP, non-preemptive GP, and weighted max–min fuzzy GP to solve a bi-objective optimization problem. Several other researchers have solved multi-objective optimization problems using FGP approaches (see Ghodratnama et al., 2015; Tu & Chang, 2016). This study aims to provide an efficient tool to support decision makers to attain levels of fuzzy targets. Therefore, the weighted max–min FGP model developed by Amid et al. (2011) are applied in this study. Hence, Eq. (1) and Eq. (2) are transformed to Eq. (65) to Eq. (69) in LAM, MAM, and UAM.

$$Maximize\ \lambda \tag{65}$$

s.t

$$W_1\lambda \leq (OF1 - OF1^{nadir})/(OF1^{ideal} - OF1^{nadir}) \tag{66}$$

$$W_2\lambda \leq (OF2^{nadir} - OF2)/(OF2^{nadir} - OF2^{ideal}) \tag{67}$$

$$OF1 = \sum_{t\in T}\sum_{k\in K}\sum_{h\in H} x_{kht}^{I} + \sum_{t\in T}\sum_{h\in H}\sum_{m\in M} nb_{hmt} + \sum_{t\in T}\sum_{o\in O}\sum_{m\in M}\sum_{n\in N} s_{omnt} \tag{68}$$

$$OF2 = \sum_{t\in T} Cc_t \tag{69}$$

where $OF1^{ideal}$ and $OF2^{ideal}$ are the best values of OF1 and OF2 in the problem solved as a single objective model whereas $\mathrm{OF1}^{\mathrm{Nadir}}$ and $\mathrm{OF2}^{\mathrm{Nadir}}$ are the worst values of OF1 and OF2, respectively. To do so, the model is solved by maximizing OF1, and then, the result is considered as $OF1^{ideal}$ and $\mathrm{OF2}^{\mathrm{Nadir}}$. Additionally, the model is solved by minimizing OF2 and the result is considered as $OF2^{ideal}$ and $\mathrm{OF1}^{\mathrm{Nadir}}$. In addition, $W_1$and $W_2$are the weights of OF1 and OF2, respectively. Where $W_1 + W_2 = 1$.

5. Case study

Location-allocation decisions can be considered as the most important issue in the management of organ transplantation networks in developing countries. Designing these networks with maximum responsiveness but minimum cost is a crucial task in such countries. In this research, to assess the performance and usefulness of the developed models, they are put to tests in Fars province, Iran. There are 31 provinces in Iran, among which Fars is one of the largest. The province also has one of the most equipped liver and kidney TCs. The TC is located in Shiraz, the provincial capital, where all liver and kidney transplantations are done.

5.1. Data

Fars province has 22 hospitals which accommodate donors. Among them, candidate locations for ICs and OPUs are determined on the basis of expert opinions and illustrated on a geographic map, as in Fig.3. It should be mentioned that the location of hospital 1 and the TC are the same. However, they are shown separately in Fig.3 to distinguish their duty as OPU and TC. Because of the space limitation, the parameters are available in the Appendix section. The proposed model is applied for kidney ($\mathbf{o} = \mathbf{1}$) and liver ($\mathbf{o} = \mathbf{2}$) in five time periods. Each period marks one year of the planning horizon. Also, the time figures are in minutes, costs are in ten million Rials, and distances are in kilometers. Moreover, all the experiments are conducted on a core i5 PC with a 4-GB RAM and the GAMS 24.1.2 software.

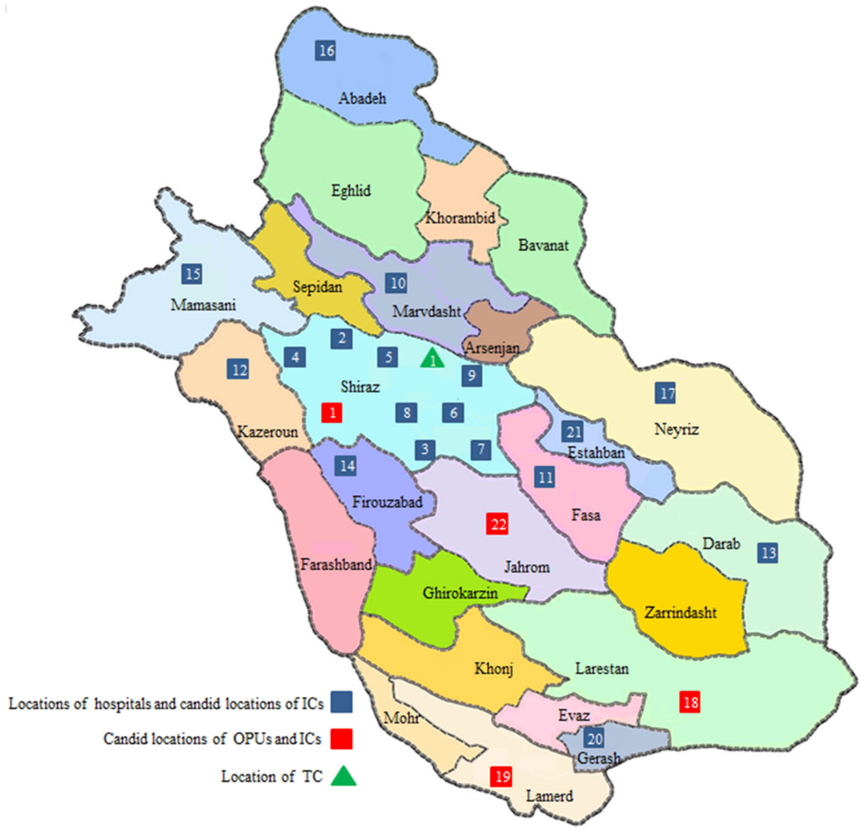

Fig. 3. Locations of facilities

5.2. Sensitively analysis and result

In this section, the payoff diagrams of LAM, MAM and UAM with different confidence levels are shown in Fig. 4. Pareto forepart solutions are obtained in two stages. In the first stage, the original models are solved for every objective function separately. Then, the two farthest points of the Pareto bounds are obtained (i.e., ideal and nadir values for each objective function). In the second stage, the higher-priority objective function (i.e., OF1) is selected to be transformed into a lateral constraint. Then, a random number in the range of the Pareto bounds of OFV1 is chosen as its right-hand side parameter. Finally, the obtained model is solved to achieve the corresponding optimal value for the lower-priority objective function (i.e., OF2). Furthermore, Pareto optimal solutions are obtained for each model (i.e., LAM, MAM and UAM) at different confidence levels (i.e., α = 0.7, 0.8 and 0.9). The results are presented in Figs. 4a-c. As it can be seen in the figures, when the confidence levels are increased in a model, the Pareto optimal solutions deteriorate for the objective functions. In addition, the Pareto bound has fewer intervals in more conservative models. The Pareto solutions of all the above models are compared at the same confidence level (α), and the results are presented in Figs. 4d-f. As the figures suggest, at each confidence level, the Pareto optimal solutions deteriorate in more conservative models. In addition, the solutions of different models (i.e., LAM, MAM and UAM) tend to be closer to one another as the confidence levels increase. They become equal at the maximum confidence level (i.e. $\alpha = 1$). It should be noted that this occurs in accordance with the type of the uncertainty parameters involved (i.e., symmetric trapezoidal fuzzy numbers). In fact, according to definitions 1 to 3 in LAM, MAM and UAM with symmetric trapezoidal fuzzy numbers, the most conservative values for uncertainty parameters turn out to be the same in terms of possibility, credibility and necessity. As a result, the solutions for the LAM, MAM and UAM models are the same. Due to the weighted max–min FGP method, the two farthest points of the Pareto bound are considered as the optimal and the worst solutions for every objective. The linear membership function (LMF) is used to fuzzify the objective functions, and, thus, the optimal and the worst values of the objective functions are found to be $\mu = 1$ and $\mu = 0$ respectively. In these values, μ is the satisfaction level of the objective functions. The LMFs are shown in Figs. 5 and 6. The optimal solutions are considered as objective targets, but what results from the models (with the values $w_1 = 0.7$ and $w_2 = 0.3$) is taken as objective achievements. In addition, on account of the LMFs, the satisfaction levels of the objective functions and, then, the performance of each model (i.e., weighted average) are calculated as shown in Table 2.

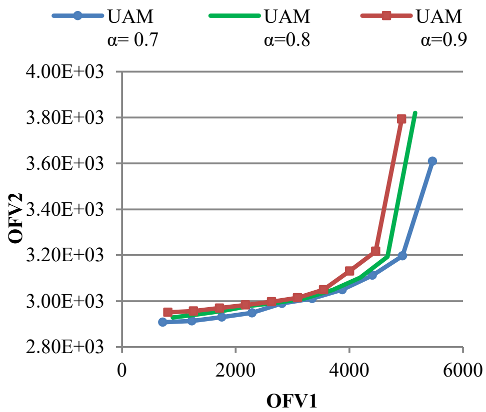

Fig. 4a. Pareto optimal solutions of UAM

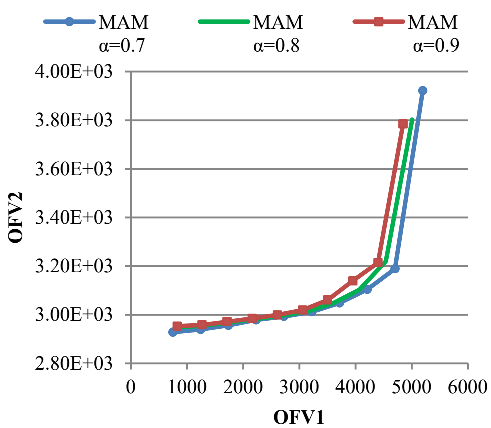

Fig. 4b. Pareto optimal solutions of MAM

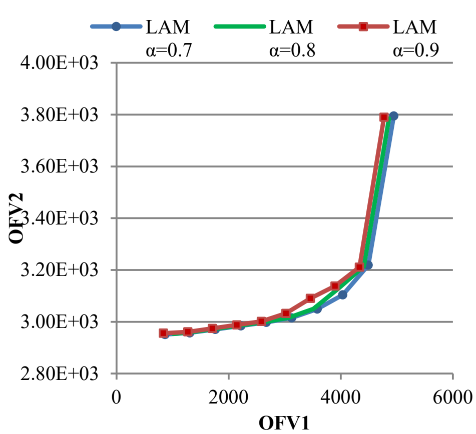

Fig. 4c. Pareto optimal solutions of LAM

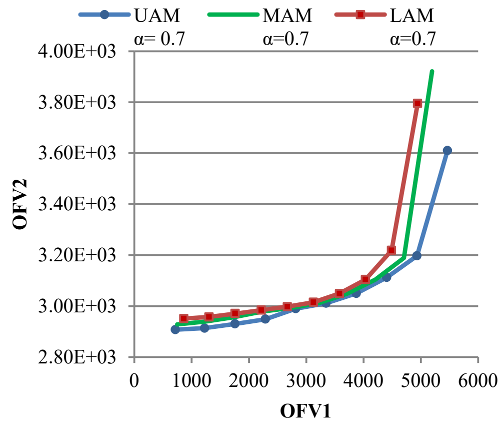

Fig. 4d. Pareto optimal solutions of LAM, MAM and UAM under $\boldsymbol{\alpha} = \mathbf{0.7}$

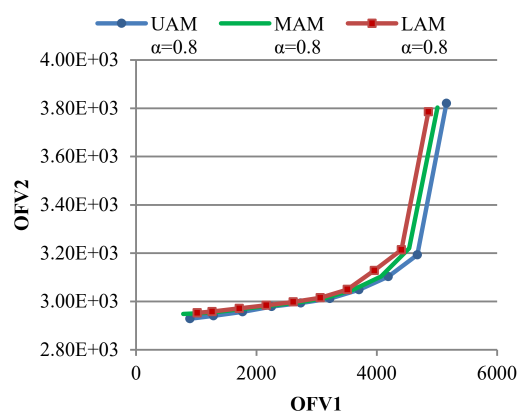

Fig. 4e. Pareto optimal solutions of LAM, MAM and UAM under $\boldsymbol{\alpha} = \mathbf{0.8}$

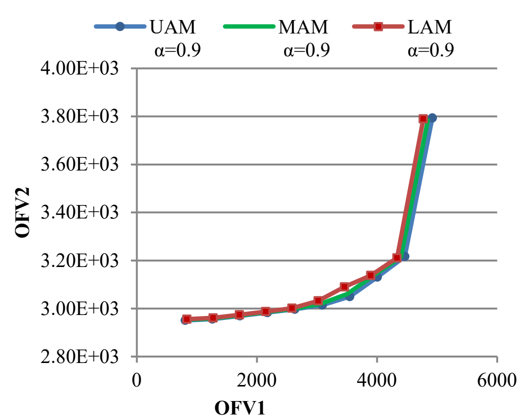

Fig. 4f. Pareto optimal solutions of LAM, MAM and UAM under $\boldsymbol{\alpha} = \mathbf{0.9}$

Fig. 4. Pareto optimal solutions

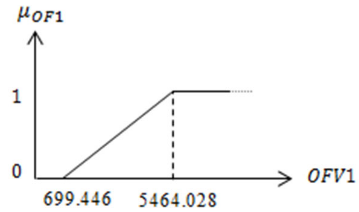

Fig. 5a. LMF for OF1 of UAM under $\alpha = 0.7$

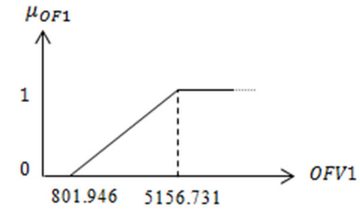

Fig. 5b. LMF for OF1 of UAM under $\alpha = 0.8$

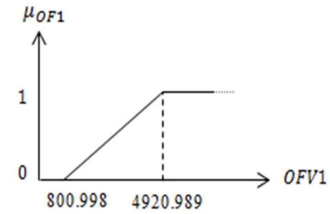

Fig. 5c. LMF for OF1 of UAM under $\alpha = 0.9$

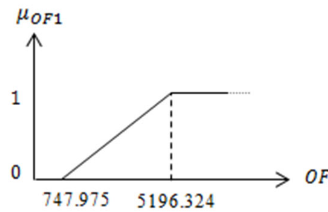

Fig. 5d. LMF for OF1 of MAM under $\alpha = 0.7$

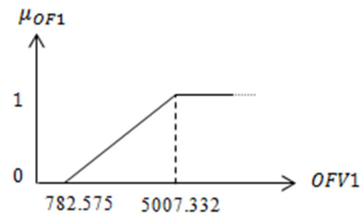

Fig. 5e. LMF for OF1 of MAM under $\alpha = 0.8$

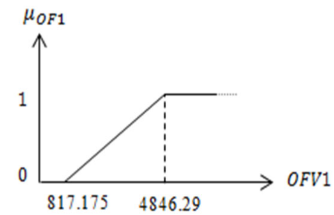

Fig. 5f. LMF for OF1 of MAM under $\alpha = 0.9$

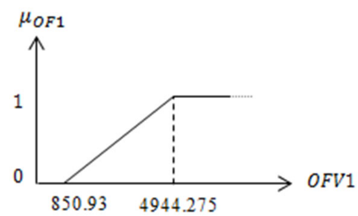

Fig. 5g. LMF for OF1 of LAM under $\alpha = 0.7$

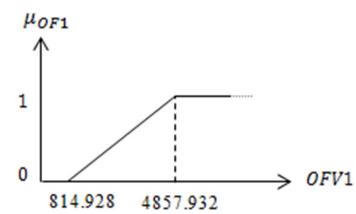

Fig. 5h. LMF for OF1 of LAM under $\alpha = 0.8$

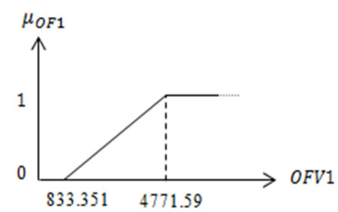

Fig. 5i. LMF for OF1 of LAM under $\alpha = 0.9$

Fig. 5. The linear Membership functions for OF1

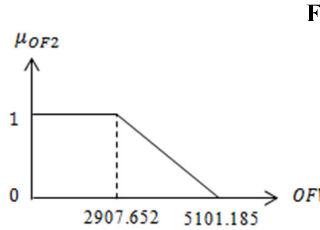

Fig. 6a. LMF for OF2 of UAM under $\alpha = 0.7$

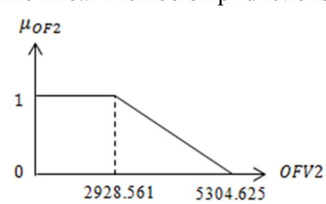

Fig. 6b. LMF for OF2 of UAM under $\alpha = 0.8$

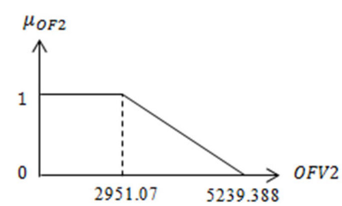

Fig. 6c. LMF for OF2 of UAM under $\alpha = 0.9$

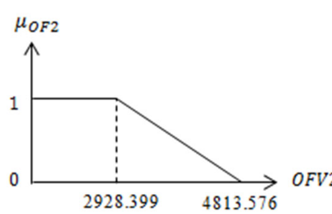

Fig. 6d. LMF for OF2 of MAM under $\alpha = 0.7$

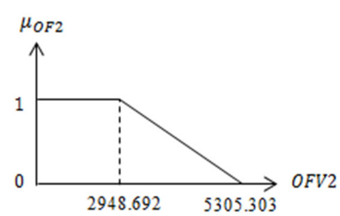

Fig. 6e. LMF for OF2 of MAM under $\alpha = 0.8$

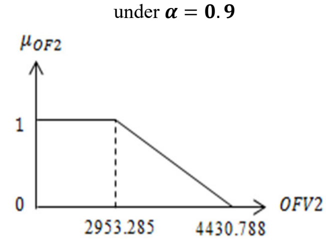

Fig. 6f. LMF for OF2 of MAM under $\alpha = 0.9$

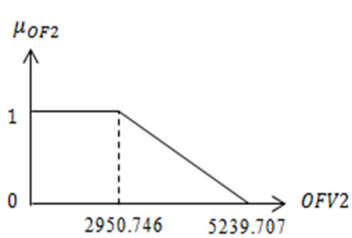

Fig. 6g. LMF for OF2 of LAM under $\alpha = 0.7$

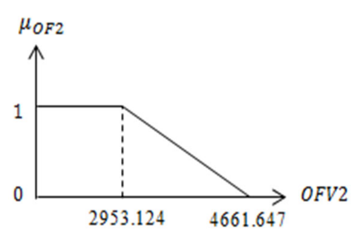

Fig. 6h. LMF for OF2 of LAM under $\alpha = 0.8$

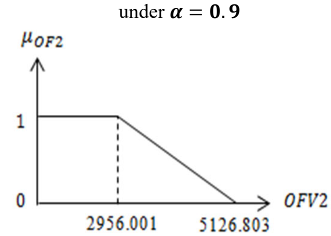

Fig. 6i. LMF for OF2 of LAM under $\alpha = 0.9$

Fig. 6. The linear Membership functions for OF2

Table 2
The weighted max–min FGP solution of the problem

		Objective target		Objective achieve		Level of satisfaction of OFs		Performance
		OFV1	OFV2	OFV1	OFV2	μ_{OF1}	μ_{OF2}	
UAM	0.7	5464.028	652.2907	816.793	4218.71	0.025	0.402	0.138
	0.8	5156.731	561.2928	829.112	4216.601	0.006	0.458	0.142
	0.9	4920.989	070.2951	4689.959	3772.226	0.944	0.641	0.853
MAM	0.7	5196.324	399.2928	777.209	4210.257	0.007	0.320	0.101
	0.8	5007.332	692.2948	800.878	4210.738	0.004	0.464	0.142
	0.9	4846.290	285.2953	2892.989	3831.996	0.515	0.405	0.482
LAM	0.7	4944.275	746.2950	3998.59	5211.134	0.769	0.012	0.542
	0.8	4857.932	124.2953	4006.298	4154.143	0.789	0.297	0.642
	0.9	4771.590	001.2956	1913.783	4228.871	0.274	0.414	0.316

According to the results in Table 2, if the confidence level rises, the performance of UAM and MAM is improved. However, the performance of LAM is enhanced and then declines. In comparison with UAM and MAM, LAM has a better performance at a lower confidence level, while UAM performs better at a higher confidence level. A simulation method has been devised to validate the proposed models. In this method, a certain realization model is formulated to compare and analyze the proposed models in terms of performance. Indeed, for the model to realize, four steps have been taken. The compact form of the realization model with the objective function of one (i.e. $\mu = 1$) is presented below:

$$Maximize\ (OFV1^* - OFV1_{min})/(OFV1_{max} - OFV1_{min}) + \gamma_1((P_{1max} - P_1)/(P_{1max} - P_{1min})) + \gamma_2((P_{2max} - P_2)/(P_{2max} - P_{2min})) + \gamma_3((P_{3max} - P_3)/(P_{3max} - P_{3min})) + \gamma_4((P_{4max} - P_4)/(P_{4max} - P_{4min})) \quad (70)$$

$s.t.$

$$AX^* + CY^* \leq E \quad (71)$$

$$MX^* + UY^* = F \quad (72)$$

$$LX^* = B_{real} + P_1 - P_2 \quad (73)$$

$$GX^* = HY^* sd_{real} + P_3 - P_4\ , \quad (74)$$

$$Y^* \in \{0, 1\}, X^* \geq 0, P_i \geq 0 \quad (75)$$

where,

P_is: the decision variables determining the deviation of constraints (which include the uncertain variables) under different realizations.
$P_{1max} = P_{2max} = B(4)_t - B(1)_t$ and $P_{1min} = P_{2min} = 0$.
$P_{3max} = P_{4max} = sd(4)_{ht} - sd(1)_{ht}$ and $P_{1min} = P_{2min} = 0$.
γ_is: the penalty values of violations (see Pishvaee et al., 2012).

In order to realize, four following steps have been utilized.

1. LAM, MAM and UAM are solved under OF1 and different confidence levels (i.e., α = 0.7, 0.8 and 0.9). The results are considered as nominal data (X*, Y*).
2. As many as 100 random realizations are generated uniformly for uncertain parameters ($B_{real}\ and\ sd_{real}$).
3. The realization model is solved using the results of steps 1 and 2 with different penalty values (γ_i). The penalty values vary from the lowest to the highest.
4. Coefficients of variation (CV) are calculated for the results of step 3.

For realization under OF2 and the weighted max–min FGP method, the above four steps are applied again, but OF1 is sequentially replaced by OF2 and the weighted max–min FGP method in step 1, respectively. Moreover, equations (76) and (77) are applied sequentially instead of equation (70), respectively.

$$Maximize\ (OFV2_{max} - OFV2^*)/(OFV2_{max} - OFV2_{min}) + \gamma_1((P_{1max} - P_1)/(P_{1max} - P_{1min})) + \gamma_2((P_{2max} - P_2)/(P_{2max} - P_{2min})) + \gamma_3((P_{3max} - P_3)/(P_{3max} - P_{3min})) + \gamma_4((P_{4max} - P_4)/(P_{4max} - P_{4min})) \quad (76)$$

$$Maximize\ GPOFV^* + \gamma_1((P_{1max} - P_1)/(P_{1max} - P_{1min})) + \gamma_2((P_{2max} - P_2)/(P_{2max} - P_{2min})) + \gamma_3((P_{3max} - P_3)/(P_{3max} - P_{3min})) + \gamma_4((P_{4max} - P_4)/(P_{4max} - P_{4min})) \quad (77)$$

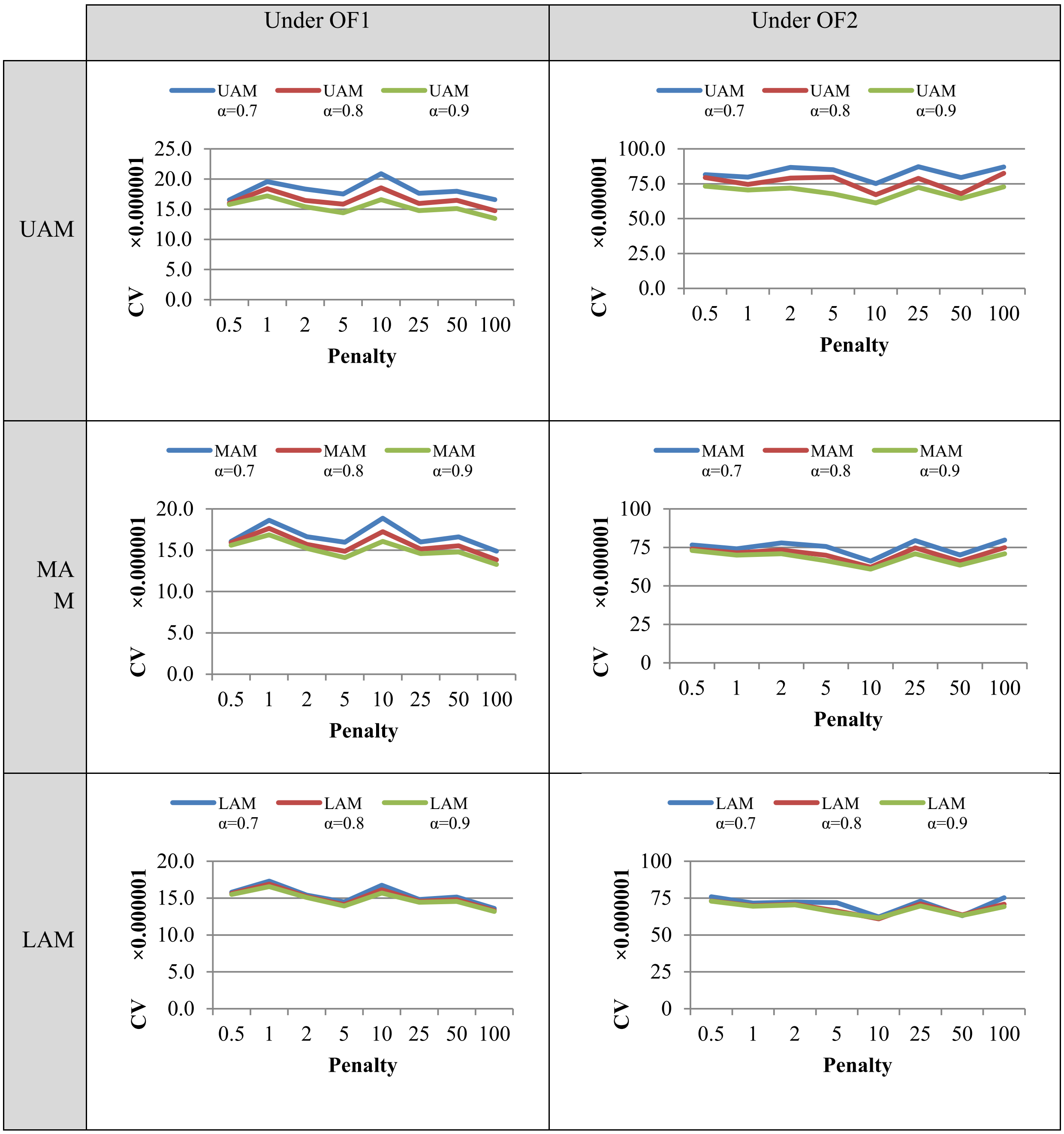

Fig.7 Performance of each single-objective model with different confidence levels (α) under realization.

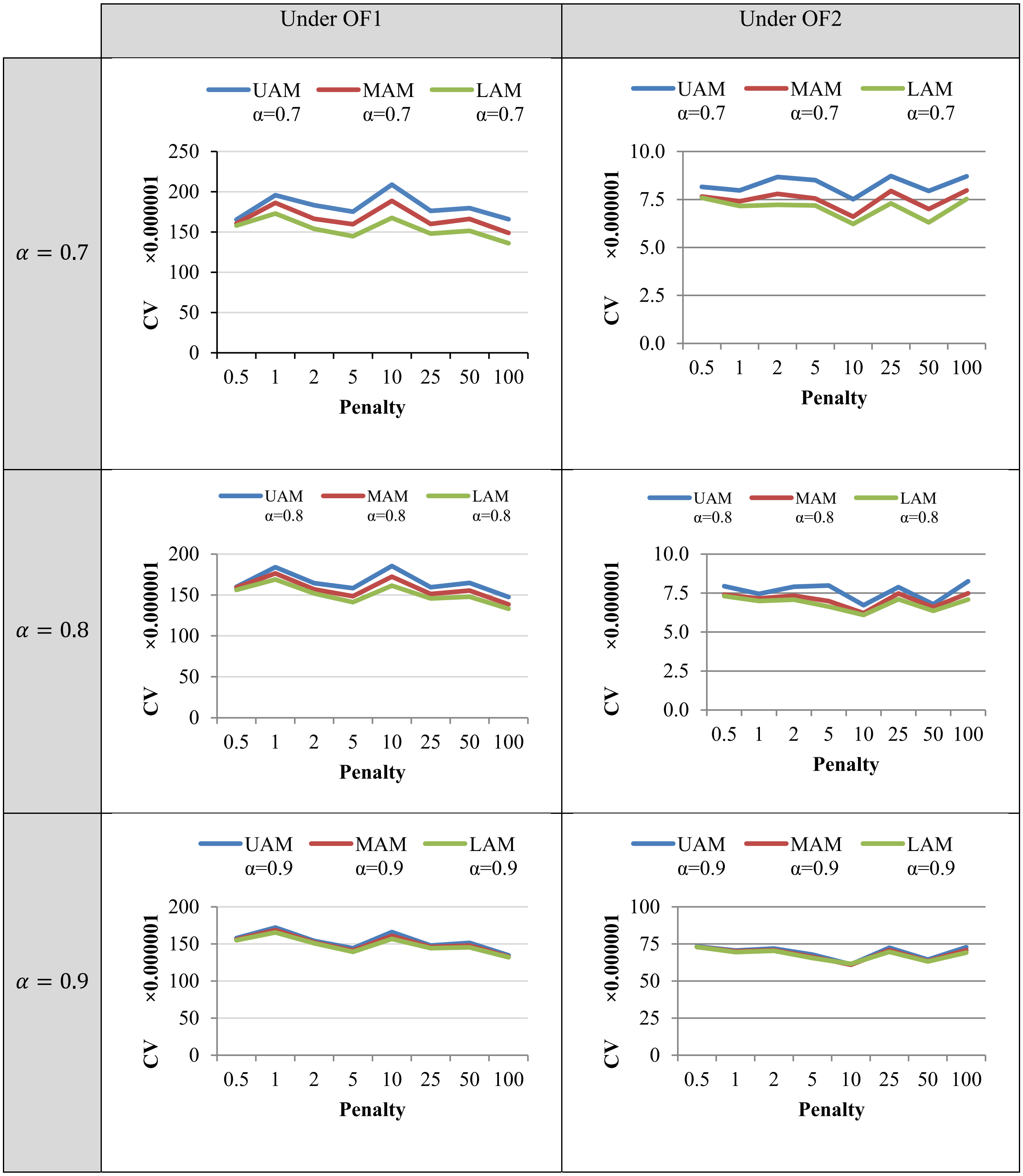

Fig. 8 Performance of single-objective models with different conservative levels (UAM, MAM and LAM)and the same confidence level ($\boldsymbol{\alpha}$) under realization.

In order to compare and analyze the performance of the developed models, the realization results have been illustrated in Figs. 7-9. According to Figs. 7 and 8, the performance of each proposed single-objective model (i.e. LAM, MAM and UAM) is improved when the confidence level increases. Furthermore, the more conservative a model, the better it performs under the same confidence level α. As Fig. 9 indicates, in the weighted max–min FGP method, the performance of UAM and MAM is improved and then declined when the confidence level increases. However, the performance of the most conservative model (i.e. LAM) is enhanced as the confidence level increases. In addition, to compare the models with different conservative levels, it is revealed that the realistic PP model performs better under a lower confidence level α while the most conservative model has a better performance under a higher level of α. As a result, MAM is believed to perform better than UAM and LAM under $\alpha = 0.7$ and $\alpha = 0.8$. On the other hand, for $\alpha = 0.9$, LAM demonstrates a better performance. As it is noted, MAM performs better than UAM at all confidence levels. It should be mentioned that, according to Figs. 7, 8 and 9, all these derivations are valid for different penalty values (γ).

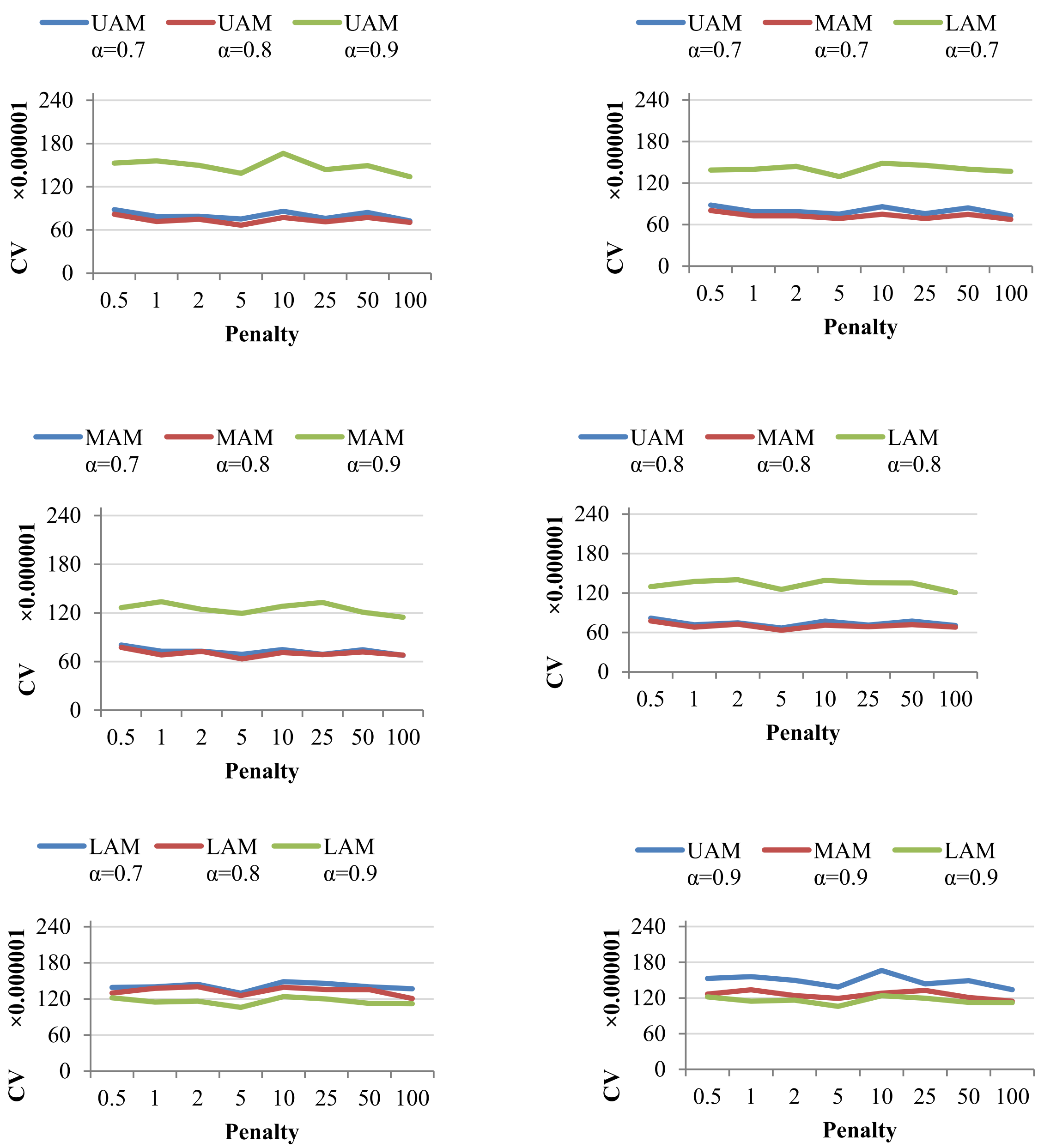

Fig. 9. Performance of the proposed models after applying the weighted max–min FGP method under realizations

Since the realistic PP model under $\alpha = 0.8$ has the best performance, its optimal solution is shown graphically in Fig.10. Accordingly, two OPUs and ten ICs are opened to cover Fars province. Indeed, one of the OPUs is used to cover the north of Fars province and the other one is employed to cover the south of this region. Since only one OPU and one IC are located in Shiraz, the current transplantation network is not capable of serving many brain-dead donors. Additionally, in the current extremely centralized network, accessibility of the healthcare facilities is poor for both donors and patients that may impose high risks and costs. However, as Fig.10 shows, the proposed transplantation network becomes more decentralized and it can cover the demand and potential donors more efficiently.

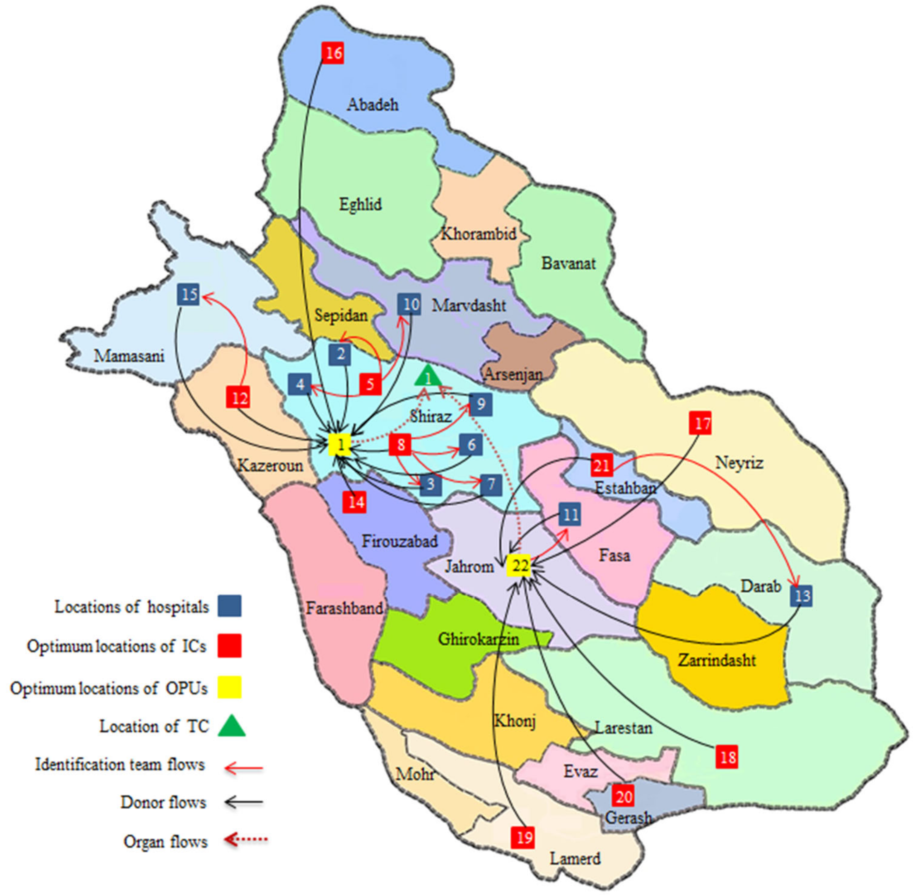

Fig. 10 MAM optimum facilities and their interactions under $\alpha = 0.8$.

6. Conclusions

In this study, a new BOPP model was proposed under uncertainty of supply and budget. The weighted max-min fuzzy GP approach was applied to solve a bi-objective model. Also, possibilistic programming was done based on *Me* measure to handle uncertainty. Unlike previous studies considering just the optimistic and pessimistic approach for *Me* measure, we considered also a realistic measure. Actually, in this approach, the model was converted into three models with different conservative levels. The models included UAM, LAM and MAM which were optimistic, pessimistic and realistic PP models respectively. Finally, a real case study was conducted, and the results of proposed models were compared in both single- and bi-objective models. As it was observed, the performance of the proposed single-objective models would improve when the confidence level increased. Moreover, the more conservative a model was, the better it performed at the same confidence level. However, in the multi-objective models, the results showed, in most confidence levels the realistic model has better performance in comparison to the optimistic and pessimistic models. Also, equality fuzzy chance constraints usually are challenging constraints to convert to the crisp one. Thus, the previous researchers avoided to use such constraints in their models. However, in this study three formulations proposed to tackle such constraints in all optimistic, realistic and pessimistic measures. Moreover, considering the utility functions with respect to the transportation criteria to calculate the chance of success in different stages of the transplantation process made the results more valid and trustable in the real organ transplant network. For future research in this field, it is suggested that better models be proposed by zooming closer on such significant issues as location of TCs, uncertainty of CIT, costs, travel times and the other input data, and robustness of models to prioritize patients for organ allocation.

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Appendix

Table A1

Fixed cost of equipping facilities

		Time period(t)				
		$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
OPU (m)	$m = 1$	65	74.8	84.5	93.8	102
	$m = 18$	100	115	130	144	157
	$m = 19$	97.5	112	127	140.6	153
	$m = 22$	96.5	111	125.5	139	151.2
IC (k)	$k = 1$	6.5	7.5	8.45	9.37	10.2
	$k = 2$	10	11.5	13	14.4	15.7
	$k = 3$	9.6	11.05	12.47	13.85	15.1
	$k = 4$	9.6	11.05	12.47	13.85	15.1
	$k = 5$	9.4	10.8	12.2	13.55	14.8
	$k = 6$	9.9	11.4	12.85	14.3	15.6
	$k = 7$	9.5	10.9	12.3	13.7	15
	$k = 8$	9.9	11.4	12.85	14.3	15.6
	$k = 9$	9.8	11.3	12.7	14.1	15.4
	$k = 10$	9.8	11.3	12.7	14.1	15.4
	$k = 11$	9.6	11.05	12.47	13.85	15.1
	$k = 12$	9.7	11.15	12.6	14	15.25
	$k = 13$	9.5	10.9	12.3	13.7	15
	$k = 14$	10	11.5	13	14.4	15.7
	$k = 15$	9.5	10.9	12.3	13.7	15
	$k = 16$	9.7	11.15	12.6	14	15.25
	$k = 17$	9.8	11.3	12.7	14.1	15.4
	$k = 18$	9.5	10.9	12.3	13.7	15
	$k = 19$	9.6	11.05	12.47	13.85	15.1
	$k = 20$	9.5	10.9	12.3	13.7	15
	$k = 21$	9.6	11.05	12.47	13.85	15.1
	$k = 22$	9.4	10.8	12.2	13.55	14.8

Table A2

Traveling cost from hospitals to OPUs

Time period (t)	Hospital (h)	Traveling cost from hospital h to OPU m at time period t (CD_{tmh})			
		$m = 1$	$m = 18$	$m = 19$	$m = 22$
$t = 1$	$h = 1$	0	0.0739	0.0852	0.0461
	$h = 2$	0.008	0.0739	0.0852	0.0461
	$h = 3$	0.008	0.0739	0.0852	0.0461
	$h = 4$	0.008	0.0739	0.0852	0.0461
	$h = 5$	0.008	0.0739	0.0852	0.0461
	$h = 6$	0.008	0.0739	0.0852	0.0461
	$h = 7$	0.008	0.0739	0.0852	0.0461
	$h = 8$	0.008	0.0739	0.0852	0.0461
	$h = 9$	0.008	0.0739	0.0852	0.0461
	$h = 10$	0.0211	0.0799	0.0920	0.0525

Time period (t)	Hospital (h)	Traveling cost from hospital h to OPU m at time period t (CD_{tmh})			
		$m = 1$	$m = 18$	$m = 19$	$m = 22$
	$h = 11$	0.0389	0.0509	0.0770	0.0232
	$h = 12$	0.0368	0.0921	0.0923	0.0646
	$h = 13$	0.0578	0.0421	0.0783	0.0333
	$h = 14$	0.0316	0.0565	0.0610	0.0340
	$h = 15$	0.0406	0.0954	0.1071	0.0671
	$h = 16$	0.0614	0.1206	0.1326	0.0916
	$h = 17$	0.0514	0.0606	0.0968	0.0432
	$h = 18$	0.0739	0	0.0430	0.0381
	$h = 19$	0.0852	0.0430	0	0.0608
	$h = 20$	0.0780	0.0106	0.0349	0.0421
	$h = 21$	0.0431	0.0626	0.0884	0.0344
	$h = 22$	0.0461	0.0381	0.0608	0
$t = 2$	$h = 1$	0	0.08597	0.0992	0.05363
	$h = 2$	0.0092	0.08097	0.0942	0.04863
	$h = 3$	0.0092	0.08097	0.0942	0.04863
	$h = 4$	0.0092	0.08097	0.0942	0.04863
	$h = 5$	0.0092	0.08097	0.0942	0.04863
	$h = 6$	0.0092	0.08097	0.0942	0.04863
	$h = 7$	0.0092	0.08097	0.0942	0.04863
	$h = 8$	0.0092	0.08097	0.0942	0.04863
	$h = 9$	0.0092	0.08097	0.0942	0.04863
	$h = 10$	0.02444	0.09315	0.10722	0.06123
	$h = 11$	0.04523	0.05934	0.08979	0.027
	$h = 12$	0.04271	0.10743	0.10764	0.0753
	$h = 13$	0.06728	0.04905	0.09126	0.03876
	$h = 14$	0.03662	0.06585	0.0711	0.0396
	$h = 15$	0.04712	0.11121	0.12486	0.07824
	$h = 16$	0.07148	0.14061	0.15468	0.1068
	$h = 17$	0.05972	0.07068	0.11289	0.05031
	$h = 18$	0.08597	0	0.0501	0.04443
	$h = 19$	0.0992	0.0501	0	0.07089
	$h = 20$	0.0908	0.0123	0.04065	0.04905
	$h = 21$	0.05006	0.07299	0.10302	0.04002
	$h = 22$	0.05363	0.04443	0.07089	0
$t = 3$	$h = 1$	0	0.096345	0.11115	0.060155
	$h = 2$	0.0104	0.090645	0.10545	0.054455
	$h = 3$	0.0104	0.090645	0.10545	0.054455
	$h = 4$	0.0104	0.090645	0.10545	0.054455
	$h = 5$	0.0104	0.090645	0.10545	0.054455
	$h = 6$	0.0104	0.090645	0.10545	0.054455
	$h = 7$	0.0104	0.090645	0.10545	0.054455
	$h = 8$	0.0104	0.090645	0.10545	0.054455
	$h = 9$	0.0104	0.090645	0.10545	0.054455
	$h = 10$	0.02749	0.104275	0.12002	0.068555
	$h = 11$	0.050755	0.06644	0.100515	0.03025
	$h = 12$	0.047935	0.120255	0.12049	0.0843
	$h = 13$	0.07543	0.054925	0.10216	0.04341
	$h = 14$	0.04112	0.073725	0.0796	0.04435
	$h = 15$	0.05287	0.124485	0.13976	0.08759
	$h = 16$	0.08013	0.157385	0.17313	0.11955
	$h = 17$	0.06697	0.07913	0.126365	0.056335
	$h = 18$	0.096345	0	0.0561	0.049755
	$h = 19$	0.11115	0.0561	0	0.079365
	$h = 20$	0.10175	0.0138	0.045525	0.054925
	$h = 21$	0.05616	0.081715	0.11532	0.04482
	$h = 22$	0.060155	0.049755	0.079365	0
$t = 4$	$h = 1$	0	0.10672	0.1231	0.06668
	$h = 2$	0.0116	0.10032	0.1167	0.06028
	$h = 3$	0.0116	0.10032	0.1167	0.06028
	$h = 4$	0.0116	0.10032	0.1167	0.06028
	$h = 5$	0.0116	0.10032	0.1167	0.06028
	$h = 6$	0.0116	0.10032	0.1167	0.06028
	$h = 7$	0.0116	0.10032	0.1167	0.06028
	$h = 8$	0.0116	0.10032	0.1167	0.06028
	$h = 9$	0.0116	0.10032	0.1167	0.06028
	$h = 10$	0.03054	0.1154	0.13282	0.07588
	$h = 11$	0.05628	0.07354	0.11124	0.0335
	$h = 12$	0.05316	0.13308	0.13334	0.0933
	$h = 13$	0.08358	0.0608	0.11306	0.04806
	$h = 14$	0.04562	0.0816	0.0881	0.0491
	$h = 15$	0.05862	0.13776	0.15466	0.09694
	$h = 16$	0.08878	0.17416	0.19158	0.1323
	$h = 17$	0.07422	0.08758	0.13984	0.06236
	$h = 18$	0.10672	0	0.0621	0.05508
	$h = 19$	0.1231	0.0621	0	0.08784
	$h = 20$	0.1127	0.0153	0.0504	0.0608
	$h = 21$	0.06226	0.09044	0.12762	0.04962
	$h = 22$	0.06668	0.05508	0.08784	0
$t = 5$	$h = 1$	0	0.116795	0.13475	0.072905
	$h = 2$	0.0126	0.109895	0.12785	0.066005
	$h = 3$	0.0126	0.109895	0.12785	0.066005
	$h = 4$	0.0126	0.109895	0.12785	0.066005

Time period (t)	Hospital (h)	Traveling cost from hospital h to OPU m at time period t (CD_{tmh})			
		$m = 1$	$m = 18$	$m = 19$	$m = 22$
	$h = 5$	0.0126	0.109895	0.12785	0.066005
	$h = 6$	0.0126	0.109895	0.12785	0.066005
	$h = 7$	0.0126	0.109895	0.12785	0.066005
	$h = 8$	0.0126	0.109895	0.12785	0.066005
	$h = 9$	0.0126	0.109895	0.12785	0.066005
	$h = 10$	0.03329	0.126425	0.14552	0.083105
	$h = 11$	0.061505	0.08054	0.121865	0.03665
	$h = 12$	0.058085	0.145805	0.14609	0.1022
	$h = 13$	0.09143	0.066575	0.12386	0.05261
	$h = 14$	0.04982	0.089375	0.0965	0.05375
	$h = 15$	0.06407	0.150935	0.16946	0.10619
	$h = 16$	0.09713	0.190835	0.20993	0.14495
	$h = 17$	0.08117	0.09593	0.153215	0.068285
	$h = 18$	0.116795	0	0.068	0.060305
	$h = 19$	0.13475	0.068	0	0.096215
	$h = 20$	0.12335	0.0167	0.055175	0.066575
	$h = 21$	0.06806	0.099065	0.13982	0.05432
	$h = 22$	0.072905	0.060305	0.096215	0

Table A3
Cost of organ transportation.

OPU (m)	Cost of organ transportation (CO_{tmn}) , n=1				
	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$m = 1$	0	0	0	0	0
$m = 18$	0.0739	0.08597	0.096345	0.10672	0.116795
$m = 19$	0.0852	0.0992	0.11115	0.1231	0.13475
$m = 22$	0.0461	0.05363	0.060155	0.06668	0.072905

Table A4
Available budget

Time period (t)	$(B(1)_t, B(2)_t, B(3)_t, B(4)_t)$
$t = 1$	(70,80,100,110)
$t = 2$	(72,82,102,112)
$t = 3$	(84,94,114,124)
$t = 4$	(95,105,125,135)
$t = 5$	(106,116,136,146)

Table A5
Number of donors in hospitals.

Hospital (h)	$(sd(1)_{ht}, sd(2)_{ht}, sd(3)_{ht}, sd(4)_{ht})$				
	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$h = 1$	(12,17,23,28)	(10,15,21,26)	(8,13,19,24)	(7,12,18,23)	(5,10,16,21)
$h = 2$	(6,11,17,22)	(5,10,16,21)	(4,9,15,20)	(4,9,15,20)	(3,8,14,19)
$h = 3$	(11,16,22,27)	(9,14,20,25)	(7,12,18,23)	(7,12,18,23)	(6,11,17,22)
$h = 4$	(7,12,18,23)	(5,10,16,21)	(5,10,16,21)	(4,9,15,20)	(3,8,14,19)
$h = 5$	(10,15,21,26)	(9,14,20,25)	(7,12,18,23)	(5,10,16,21)	(5,10,16,21)
$h = 6$	(8,13,19,24)	(7,12,18,23)	(4,9,15,20)	(4,9,15,20)	(3,8,14,19)
$h = 7$	(11,16,22,27)	(9,14,20,25)	(7,12,18,23)	(7,12,18,23)	(6,11,17,22)
$h = 8$	(7,12,18,23)	(7,12,18,23)	(5,10,16,21)	(4,9,15,20)	(3,8,14,19)
$h = 9$	(9,14,20,25)	(8,13,19,24)	(7,12,18,23)	(7,12,18,23)	(5,10,16,21)
$h = 10$	(27,32,38,43)	(25,30,36,41)	(23,28,34,39)	(20,25,31,36)	(17,22,28,33)
$h = 11$	(9,14,20,25)	(8,13,19,24)	(7,12,18,23)	(7,12,18,23)	(5,10,16,21)
$h = 12$	(21,26,32,37)	(19,24,30,35)	(17,22,28,33)	(15,20,26,31)	(14,19,25,30)
$h = 13$	(14,19,25,30)	(13,18,24,29)	(13,18,24,29)	(10,15,21,26)	(7,12,18,23)
$h = 14$	(9,14,20,25)	(8,13,19,24)	(7,12,18,23)	(5,10,16,21)	(5,10,16,21)
$h = 15$	(3,7,11,15)	(3,7,11,15)	(2,6,10,14)	(2,6,10,14)	(1,5,9,13)
$h = 16$	(23,31,39,47)	(21,29,37,45)	(19,27,35,43)	(17,25,33,41)	(15,23,31,39)
$h = 17$	(3,7,11,15)	(3,7,11,15)	(2,6,10,14)	(2,6,10,14)	(1,5,9,13)
$h = 18$	(12,17,23,28)	(10,15,21,26)	(8,13,19,24)	(8,13,19,24)	(6,11,17,22)
$h = 19$	(8,13,19,24)	(7,12,18,23)	(6,11,17,22)	(5,10,16,21)	(4,9,15,20)
$h = 20$	(3,6,8,11)	(3,6,8,11)	(2,5,7,10)	(2,5,7,10)	(1,4,6,9)
$h = 21$	(2,5,7,10)	(2,4,7,10)	(1,4,6,9)	(1,4,6,9)	(1,4,6,9)
$h = 22$	(12,20,28,36)	(10,18,26,34)	(8,16,24,32)	(6,14,22,30)	(5,13,21,29)