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A STOCHASTIC MULTI-OBJECTIVE MODEL FOR LOCATING ELECTRONIC CHARITY BOXES USING CHANCE CONSTRAINED BOUNDED OBJECTIVE FUNCTION

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Abstract. This paper introduces a new and practical generalization of the stochastic location problem, with an aim to find the optimal location of electronic charity boxes. In this problem, there exist a set of potential locations and a limited number of e-charity boxes. It is the first time in the literature that "stochastic donation motivation", as a new concept, is introduced into a mathematical model and maximized in one of our objectives in a stochastic bi-objective formulation. To extract the donation motivation at any potential location, a number of criteria are defined including district impact factor, location type impact factor, and pedestrian traffic factor. Next, the motivation score for each potential location is determined using the Evaluation based on the Distance from the Average Solution method (EDAS). In this novel study, the existence of two stochastic parameters, namely the amount of benefit and the pedestrian traffic factor, turns the model into a stochastic multi-objective problem, while the constraints of the problem are defined so as to avoid the cumulation of e-charity boxes in one type of location and one district. Besides, the proposed stochastic location model was based on Chance Constrained Bounded Objective Function. Finally, the proposed model was applied in a real and large-scale example and the results illustrated the effectiveness of the proposed model.

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1. Introduction

Poverty is a major concern of governments in improving the welfare of society [1]. Protecting underprivileged families and individuals is a social responsibility of society's members, as well as the major concern of non-governmental charity organizations. Accordingly, two flows of *donation aggregation* and *donation allocation* are introduced in the process of collecting public donations [2]. Scientific and practical steps on these two issues can be effective to reduce the poverty and protect underprivileged families and individuals. In donation aggregation, one of the main goals is to make optimal use of donation facilities to obtain the optimal amount of gathered

Keywords. Stochastic multi-objective location problem, charity boxes, stochastic donation motivation, chance constrained bounded objective function, Evaluation based on Distance from Average Solution (EDAS).

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Figure 1. Different types of electronic charity boxes.

donations. Examined below is the flow of donation aggregation in a way that optimizes the location of charity boxes in a new stochastic mathematical model using the novel concept of "stochastic donation motivation".

To collect the donations, charity organizations put charity boxes in different locations in a city. Nowadays, the inefficiency of conventional boxes, the financial costs of their maintenance, insecurity, etc. have justified the replacement of these conventional boxes with electronic charity boxes. Electronic charity boxes have been designed to easily and quickly collect non-cash donations through payment cards. In these boxes, data transfer to the information center is either through a SIM card or telecommunication wires. According to Figure 1, these boxes can either be designed as simple and low-cost or with more facilities and construction costs. They can be installed in different location types like hospitals, universities, and libraries.

Nevertheless, deciding on the location of these electronic boxes is not a simple decision since individuals' demands and desires to refer to them are different. For instance, the public desires to use these boxes near a hospital or a restaurant are not the same. Therefore, the optimal location of these boxes may lead to the increase or decrease of the gathered money. Consequently, the present study aimed to define a new concept in the location problem, *i.e.*, stochastic donation motivation. The motivation for donation gets the people to pay donation instantly or works as a reminder for later donations. To clarify this concept, the present study presented some criteria for different districts and different location types in the location problem. To the best of our knowledge, the calculation of the stochastic state of donation motivation was defined for the first time in the current study by proposing a new mathematical model for the location problem. In our proposed model, two important objectives – the stochastic gathered money (stochastic benefit) and the stochastic donation motivation – are considered at their maximized level. Moreover, defining the criteria and subcriteria for absorbing the donations, useful for calculating the donation motivation as the study's second objective, was conducted for the first time in the literature. On the other hand, two random parameters were applied in the model, namely the amount of obtained benefit and the pedestrian traffic factor that make the formulation serve as a stochastic multi-objective model (SMOM). Besides, in defining the constraints, the following three issues were considered: the limited number of facilities, cultivating the use of e-charity boxes instead of conventional boxes by wide distribution across all districts and location types, and preventing the cumulation of e-charity boxes in one type of location and one district. The proposed model is based on a chance-constrained bounded objective function.

2. Literature review

Since the present study's problem was defined for the first time in the literature, very few direct relevant research articles were found to review. Nevertheless, considering the problem and the proposed model, this section is presented in three parts; (1) location of public services, (2) stochastic location problem, and (3) stochastic multi-objective location problem.

Considering the location of public services, Rahman and Smith [3], in the development planning of health services in developing nations, have reviewed the application of location–allocation models and demonstrated that, despite resource limitations, the use of these models can enhance service accessibility and efficiency. For the location design of a service-providing agency, Narasimhan *et al.* [4] have presented a decision support system that employs mixed-integer programming (MIP) and data envelopment analysis (DEA) models incorporating a number of factors including demand requirements, capacity limitations for transaction processing, budget restrictions, and branch office efficiencies. Azad and Boushehri [5] addressed billboard advertising modeling using the Network Count Location Problem. They proposed a mathematical model for optimal billboard placement in transportation networks, aiming to maximize visibility and impact based on the advertising cost per billboard, the total cost, and the number of visitors. Lotfi *et al.* [6] developed a multi-objective multi-product model for billboard location, incorporating attraction factors. Their approach considers economic and strategic aspects – such as billboard attractiveness, installation and design costs, visitor numbers, sales revenue, and the number of billboards, products, and potential locations – to optimize both profitability and viewer engagement. For locating the bicycle-sharing stations to reduce short car trips, based on the Maximal Covering Location Problem and P-median models, Park and Sohn [7] have proposed a new framework according to Taxi Trajectory Data. Gupta *et al.* [8], considering electronic governance plan, used the Fuzzy C-Means clustering algorithm in locating a cluster center for Common Service allocation to determine optimal locations for service centers in rural areas, enhancing service accessibility. Tali *et al.* [9] have proposed a gradual optimization method of fire station location, using a geographic information system location–allocation model, for determining where and how many facilities are needed to improve emergency response times and service coverage in urban areas. Banerjee *et al.* [10] have developed a location–allocation model to maximize the market share of bike stations and calculated bike station suitability score with regard to the existing bike stations, and proximity to attractions and transit. In charity non-governmental organizations, Omrani *et al.* [11] have proposed an electronic charity boxes location model for charity NGOs using deterministic objectives and running TOPSIS, SAW, and LP-Metric methods. Salami *et al.* [12] proposed a two-stage optimization approach for healthcare facility location–allocation, which not only determines the facility sites but also addresses patient assignment under capacity constraints and fairness considerations. Their solution method, based on a hybrid of Genetic Algorithm and Successive Quadratic Programming, demonstrates high efficiency in solving large-scale problems.

Regarding the stochastic location problem, Shiode and Drezner [13] considered a competitive facility location problem and presented an efficient solution procedure to find a Stackelberg equilibrium solution by hypothesizing that the weights of demand points at the entry time of the follower are stochastic. Drezner *et al.* [14], offered a stochastic gradual cover model in which the distances are random. They have claimed that this model illustrates customer behavior more accurately. Their gradual cover formulation allows the coverage intensity to decrease progressively as the stochastic distance increases, which provides a more realistic representation of service accessibility. Dell'Amico and Novellani [15] have presented a two-echelon facility location problem with a set of features such as stochastic demands and multiple depots, materials, and periods for establishing the consolidation centers in the construction supply chain in urban areas and they highlighted the importance of urban logistics efficiency and sustainability issues when randomness in demand and resource allocation is present. De Armas *et al.* [16] proposed a three-stage simheuristic algorithm for solving the stochastic uncapacitated facility location problem (SUFLP). They first presented a very fast savings-based heuristic; next, into a metaheuristic framework, the heuristic is integrated; and finally, the algorithm is developed by integrating it with simulation techniques. Marković *et al.* [17], with the aim to intercept the stochastic traffic flows, have introduced the problem of facility locating over a finite time horizon by offering a mixed-integer and multi-stage stochastic program, emphasizing the role of dynamic traffic patterns. Alizadeh *et al.* [18] have formulated a Casualty Collection Points location problem as a two-stage robust stochastic optimization model in an uncertain environment using the feasibility restoration technique and proposing a robust sample average approximation method. Mousavi *et al.* [19] have conducted research to investigate the location problem of trauma centers and helicopter stations by considering the waiting time at the trauma center, the transfer time, the total cost, and the stochastic characteristics of the system (*e.g.*, the stochastic demand, the stochastic transfer time of the patients, and stochastic service time of the patients). Liu *et al.* [20] developed a robust stochastic facility location model with a detailed sensitivity analysis, in which they studied how demand distributions affect facility placement and decision robustness. Marín *et al.* [21] proposed a multi-period stochastic covering location problem that incorporates temporal dynamics and uncertainty across planning horizons, providing an extended modeling framework and solution approach for covering-type facility problems.

Taking into account the stochastic multi-objective location problem, Doerner *et al.* [22] have presented a model for multi-objective optimization of facility location decisions considering tsunami hazards. Their model utilizes three objective functions, namely the maximum and minisum coverage criterion, the costs, and the risk of possible tsunami events. Hassanpour *et al.* [23] presented a new mathematical model for a stochastic location-routing problem including its objective functions, the probability of delivery to customers, the facilities establishment cost, and transportation cost. They decomposed the main problem into two subproblems – the facility location problem which is presented by a stochastic set covering problem approach, and the multi-depot multi-objective vehicle routing problem. Gang *et al.* [24] have proposed a model for a stone industry park location problem, considering the production costs and the stochastic nature of the transportation. To deal with the uncertainties in this programming model, in the objective functions, the expected value is used, and in the constraints, a chance constraint method is employed. Tian *et al.* [25] focused on the vehicle inspection station problem and presented a new multi-objective stochastic optimization model to address the problem by developing two multi-objective stochastic programs considering regional constraints, varying velocity, transportation time, and stochastic demand. Zhalechian *et al.* [26], for a P-hub location problem, have presented a novel stochastic multi-objective model focusing on transportation and traffic noise pollution costs, and transportation time. This model employs a possibilistic programming approach to handle uncertainty in costs and environmental factors. El Itani *et al.* [27] have proposed a bi-objective stochastic program for ambulances covering location problems by applying the Maximum Expected Covering Location Problem model intending to consider the cost of ambulance coverage. The approach optimizes coverage within cost constraints using the expected coverage metric. Maharjana and Hanaoka [28] have developed a multi-objective location and allocation model for the relief distribution and supply that considers the time-varying and imprecise nature of parameters and coverage. Their mathematical model minimizes the operational and transportation costs and under time-varying coverage distance, maximizes the demand coverage. Parragh *et al.* [29] have modeled a multi-objective stochastic facility location problem in disaster public facility location, considering both a deterministic objective (cost) and a stochastic one (population coverage). Ebrahimi [30] proposed a robust multi-objective mixed-integer programming model for optimizing the supply chain of the steel industry under a sustainability-oriented framework, considering stochastic elements. The model focuses on balancing economic, environmental, and social objectives. Peng *et al.* [31] proposed a multi-objective multimodal transportation routing model considering stochastic transportation time based on data-driven approaches, aiming to balance multiple objectives in multimodal logistics systems.

As can be observed and to the best of our knowledge, the abstract concept of stochastic donation motivation has not been explicitly addressed in the existing literature. Therefore, considering the significance of this gap in helping poor people and increasing the benefits for them, the researchers of this study defined a new stochastic multi-objective location problem based on stochastic donation motivation and stochastic benefit.

3. Problem statement and modeling

In the present study, a limited number of e-charity boxes were installed for collecting public donations in different districts of Mashhad, Iran. Due to high security and installation issues, and the limited number of e-charity boxes, they were located only in special places such as schools and hospitals.

Let's consider m as the number of districts, n the number of location types, and o_{ij} the number of location type i in district j. As mentioned above, the researchers focused on the concept of stochastic donation motivation in the proposed model. It should be noted that the data available from the "stochastic benefit" (stochastic gathered money) could not be the only basis for determining the objective of this problem because the observation shows that there are many cases where despite the donating desire, the donation rate was low and *vice versa*. In other words, although in some districts people are much more motivated to donate and more donations are expected, the number of boxes was low or there were no boxes at all, which resulted in a small amount of collected money.

Besides, considering the large number of urban areas, the number of conventional boxes was few, and some of the previously installed ones were out of order. Thus, focusing on the motivation of donation in different locations is another important research objective added to the current study. Just paying attention to the motivation for donation (the second objective), without paying attention to the stochastic benefit, was not of interest to the decision-makers, too. Hence, the model had two objectives: maximizing the stochastic donation motivation and the total amount of the obtained stochastic benefit. The "stochastic donation motivation" was defined based on a number of criteria that were extracted after a comprehensive review of the scientific texts [32–34], as well as interviews with experts in the public donation field and the available data. The collected criteria affecting the donation (concerning the available data) were divided into three general factors, *i.e.*, district type, location type, and pedestrian traffic (Tab. 2).

The district impact factor, according to the district vulnerability for donation, helped to differentiate among diverse areas and it was identified with eight sub-criteria as illustrated in Table 2. The location type impact factor, with six criteria in its subset, helped to select the best location type, and determined, for instance, the differences between the number of donations in schools and hospitals. The pedestrian traffic factor, with six criteria in its subset, showed the difference between the two same locations (*e.g.*, two hospitals) in the same district. For example, if one hospital is larger and more crowded, it can receive more donations than the smaller one. The details for these definitions were provided in Section 4.1. These three factors together determine the concept of donation motivation in each potential location. Considering that some criteria of pedestrian traffic factors (in Tab. 2) can have different values, the pedestrian traffic factor was considered stochastic, and thus the concept of "stochastic donation motivation" is determined. Therefore, the "stochastic donation motivation" is the significant basis of the second function of this problem.

The model variable was as follows:

$$x_{ijk} = \begin{cases} 1 & \text{if the facility is installed in location } k \text{ of location type } j \text{ in district } i \\ 0 & \text{otherwise.} \end{cases}$$

Table 1 defines the parameters of the E-charity location problem in this problem.

We proposed the following stochastic multi-objective model for the problem in which $\widetilde{osb}_{ijk}$ and $\widetilde{\mathrm{PTF}}_{ijk}$ were random parameters.

$$\text{Max } Z_1 = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk}\, x_{ijk} \tag{1}$$

$$\text{Max } Z_2 = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \left(\mathrm{LIFM}_j \times \mathrm{DIFM}_i \times \widetilde{\mathrm{PTF}}_{ijk}\right)\; x_{ijk} \tag{2}$$

subject to:

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MNB} \tag{3}$$

$$\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \ge \mathrm{MIFD}_i \qquad \forall i \in I \tag{4}$$

$$\sum_{i\in I}\sum_{k\in K_{ij}} x_{ijk} \ge \mathrm{MIFL}_j \qquad \forall j \in J \tag{5}$$

$$\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MXFD}_i \qquad \forall i \in I \tag{6}$$

$$\sum_{i\in I}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MXFL}_j \qquad \forall j \in J \tag{7}$$

$$x_{ijk} \in \{0,1\} \qquad \forall k \in K_{ij},\quad \forall j \in J,\quad \forall i \in I. \tag{8}$$

TABLE 1. E-charity location problem parameters.

Parameter	Symbol	Definition/related index
Set of districts	I	$i \in I = \{1, 2, \ldots, m\}$
Number of districts	m	
Set of location types	J	$j \in J = \{1, 2, \ldots, n\}$
Number of location types	n	
Set of locations of type j in the district i	K_{ij}	$k \in K_{ij} = \{1, 2, \ldots, o_{ij}\}$
Number of type j locations in district i	o_{ij}	
The obtained stochastic benefit from installing the facilities in location k of location type j in district i	$\widetilde{osb}_{ijk}$	
The uncertain pedestrian traffic factor in location k of type j in district i	$\widetilde{\mathrm{PTF}}_{ijk}$	
The district impact factor for donation motivation in district i	DIFM_i	
The impact factor for donation motivation in location type j	LIFM_j	
Maximum number of installable facilities	MNB	
Maximum number of installable facilities in district i	MXFD_i	
Maximum number of installable facilities in location type j	MXFL_j	
Minimum number of installable facilities in district i	MIFD_i	
Minimum number of installable facilities in location type j	MIFL_j	
The minimum expected amount of total obtained benefit in the first objective	γ	

The objective functions (1) and (2) were maximizing the total amount of the obtained stochastic benefit of the e-charity boxes and the stochastic donation motivation. In equation (2), the stochastic donation motivation at each potential location was determined by three independent parameters: DIFM_i, LIFM_j and $\widetilde{\mathrm{PTF}}_{ijk}$. Since each factor contributes a relative weight to the outcome, the most natural way to combine them is through multiplication rather than addition, as we have done in equation (2) [35]. Constraint (3) was a threshold in the total number of available charity boxes. Aiming to familiarize people with e-charity boxes, we applied thresholds in the model to allocate at least MIFD_i e-charity boxes in districts and MIFL_j boxes in location types (constraints (4) and (5)). To prevent the cumulation of e-charity boxes in types of locations and districts, a maximum number of e-charity boxes in each location or district for installation were considered in constraints (6) and (7). Finally, in constraint (8), the variables were defined.

4. Solution method

Our solution method consisted of two sections: Firstly, the method of defining the model parameters, especially the method of obtaining $\widetilde{\mathrm{PTF}}_{ijk}, \mathrm{DIFM}_i$, and LIFM_j, being applied in stochastic donation motivation with the EDAS method, was described. Next, the method of changing the proposed multi-objective stochastic model to a deterministic single-objective one was presented.

4.1. EDAS method for determining the stochastic donation motivation

As discussed previously, the criteria affecting donation motivation were divided into three general factors, namely district type, location type, and pedestrian traffic. Therefore, the values of $\widetilde{\mathrm{PTF}}_{ijk}, \mathrm{DIFM}_i$, and LIFM_j, ought to be determined scientifically. For these criteria, some subcriteria were defined (Tab. 2).

We applied the Evaluation based on the Distance from Average Solution approach (EDAS) as one of the multi-attribute decision-making methods (MADMs) with the aim to determine the parameters weights in the donation motivation factor. Keshavarz Ghorabaee *et al.* introduced the Evaluation based on the Distance from

TABLE 2. The impact factors on stochastic donation motivation and their criteria.

Factors	Criteria
District Impact Factor (DIFM)	– Mean of donations in pathways in terms of the number of boxes – Mean of donations in the households in terms of the number of boxes – Mean of total donations in terms of population – The proportion of the number of households in the population of the districts – The proportion of the number of above twenty-year-old individuals in the population of the district – The proportion of the number of employed people in the population of the district – The percentage of homeowners – The percentage of houses larger than one hundred square meters
Location type Impact Factor (LIFM)	– Religiosity status – Recreation status – The probability of hazard in the location – The probability of the presence of women – Donation availability for the donators – Pedestrian traffic rate
Pedestrian traffic Factor (PTF)	– Approximity to pilgrimage and tourist locations – The possibility of the presence of passengers or pilgrims – Access to the location in three periods of annual, monthly, and daily – District population – The amount of pedestrian traffic in the type of location – Famous or large location

Average Solution approach (EDAS) method which is an innovative and new method for solving the problems of MCDM. The procedure of the EDAS method with p criteria and q alternatives is introduced below [36].

Step 1. First, according to equation (9), the average value per each criterion is calculated:

$$\mathrm{AV}_j = \frac{\sum_{i=1}^{p} r_{ij}}{p}; \qquad j = 1, \ldots, q, \quad i = 1, \ldots, p \tag{9}$$

where r_{ij} is the performance score of the alternative i on the criterion j and $r_{ij} \geq 0$.

Step 2. Based on whether the criterion is beneficial or non-beneficial, the positive distance from the average (PDA_{ij}) and negative distance from the average (NDA_{ij}) are computed (Eq. 10) as shown below:

$$\mathrm{PDA}_{ij} = \begin{cases} \frac{\max(0,(r_{ij}-\mathrm{AV}_j))}{\mathrm{AV}_j} & \text{if criterion } j \text{ is beneficial} \\ \frac{\max(0,(\mathrm{AV}_j-r_{ij}))}{\mathrm{AV}_j} & \text{if criterion } j \text{ is non beneficial} \end{cases}$$
$$\mathrm{NDA}_{ij} = \begin{cases} \frac{\max(0,(\mathrm{AV}_j-r_{ij}))}{\mathrm{AV}_j} & \text{if criterion } j \text{ is beneficial} \\ \frac{\max(0,(r_{ij}-\mathrm{AV}_j))}{\mathrm{AV}_j} & \text{if criterion } j \text{ is non beneficial.} \end{cases} \tag{10}$$

Step 3. In this step for all alternatives, according to equation (11), the weighted sum of PDA_{ij} and NDA_{ij} are determined, where w_j is the non-zero weight of the criterion j:

$$\mathrm{WPDA}_{ij} = \sum_{j=1}^{q} \mathrm{PDA}_{ij} w_j;$$
$$\mathrm{WNDA}_{ij} = \sum_{j=1}^{q} \mathrm{NDA}_{ij} w_j. \tag{11}$$

Step 4. In this step, according to equation (12), the weighted sum scores of PDA_{ij} and NDA_{ij} are normalized for each alternative:

$$\mathrm{NWPDA}_{ij} = \frac{\mathrm{WPDA}_{ij}}{\max(\mathrm{WPDA}_{ij})};$$
$$\mathrm{NWNDA}_{ij} = 1 - \frac{\mathrm{WNDA}_{ij}}{\max(\mathrm{WNDA}_{ij})}. \tag{12}$$

Step 5. According to equation (13), the appraisal values AS_i are calculated for each alternative:

$$\mathrm{AS}_i = \frac{1}{2}\left(\mathrm{NWPDA}_{ij} + \mathrm{NWNDA}_{ij}\right). \tag{13}$$

Lastly, the alternatives are ranked in decreasing sequence of appraisal values. The maximum value of AS_i is chosen as the prime alternative [36].

In this problem, based on the collected data for each criterion and the determination of criteria weights using the Shannon Entropy method and the EDAS method, first, the ranking or score of each district (the DIFM_i values for each district i) and each location type (the LIFM_j for each location type j) were obtained. Due to the stochastic form of some criteria (such as the amount of pedestrian traffic in the type of location) in the parameter $\widetilde{\mathrm{PTF}}_{ijk}$, this parameter was stochastic and could have different scores. Therefore, to be able to use this parameter in the mathematical model, it was necessary to calculate the expected value and the standard deviation of each potential location in a long process.

4.2. Moving from a multi-objective model toward a single-objective one

The proposed model was considered a multi-objective formulation of the problem. Besides, since the two parameters of benefit and pedestrian traffic were random, the model was a stochastic model. Therefore, the problem can be solved more easily because the model changes from a stochastic multi-objective model to a deterministic single-objective one.

To this aim, the model, firstly, was changed to a single-objective stochastic formulation from a multi-objective stochastic model using the Chance Constrained Bounded Objective Function Programming (CCBOFP) method. This method is a combination of Chance Constrained Programming (CCP) and Bounded Objective Function (BOF) methods. In the Bounded Objective Function, it is possible to determine a lower or upper bound for the objective transferred to the constraint. It also optimizes the single most important objective function $z_s(x)$, (an objective that is more important from the decision-makers' points of view). Other objective functions are also applied to form the additional constraints such as $l_i \leq z_i(x) \leq u_i, i = 1, 2, 3, \ldots, k, i \neq s$, where l_i and u_i are the lower and upper bounds for $z_i(x)$, respectively [37]. Besides, Chance-Constrained Programming (CCP) is an important approach for optimization problem solving under different uncertainties. CCP ensures that the probability of meeting a specific constraint is higher than a certain level [38]. In this method, it is assumed that $\sum_j a_{ij}X_j \leq b_i$, $j = 1, 2, 3, \ldots, u$ and $i = 1, 2, 3, \ldots, v$, is a constraint in the mathematical programming model and a_{ij} are the corresponding coefficients, b_i the right-hand side value, and X_j decision variables. If the probability of violating the ith constraint is allowed to the maximum extent of α, then equation (14) is a chance constraint of $\sum_j a_{ij}X_j \leq b_i$ [39, 40].

$$p\left(\sum_j a_{ij}X_j \leq b_i\right) \geq 1 - \alpha_i \qquad 0 \leq \alpha_i \leq 1. \tag{14}$$

Then, based on the CCBOFP method [41], except for one objective, the other objectives should be transferred to the constraints. Accordingly, in the general model, assuming the first objective as the problem objective function and using the chance constraint method for other objectives in addition to the system constraints, the final CCBOFP model was presented as follows, where ε_i is upper (to minimize) or lower (to maximize) bounds for the objective function $\sum_{j=1}^{n} \tilde{a}_{ij} x_j$ and other model-specific constraints remain in effect.

$$\text{Max } z = \sum_{j=1}^{n} \tilde{a}_{1j} x_j \tag{15}$$

subject to:

$$Prob\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \text{ or } \geq \varepsilon_i\right) \geq 1 - \alpha \qquad \forall_i = 2, \ldots, m. \tag{16}$$

In this model, there are two objectives: equations (1) and (2). Since it is important for the decision-maker to determine the desired level of the total amount of benefit obtained, the first objective equation (1) was transferred to the constraints equation (18), and the second objective equation (2) was considered as the objective function of the problem equation (17), where γ is the minimum expected amount of the total obtained benefit. Equations (19) to (24) were the same constraints defined in equations (3) to (8).

$$\text{Max } z = \sum_{i\in I} \sum_{j\in J} \sum_{k\in K_{ij}} \left(\text{LIFM}_j \times \text{DIFM}_i \times \widetilde{\text{PTF}}_{ijk}\right) x_{ijk} \tag{17}$$

subject to:

$$Prob\left(\sum_{i\in I} \sum_{j\in J} \sum_{k\in K_{ij}} \widetilde{osb}_{ijk} x_{ijk} \geq \gamma\right) \geq 1 - \alpha \tag{18}$$

$$\sum_{i\in I} \sum_{j\in J} \sum_{k\in K_{ij}} x_{ijk} \leq \text{MNB} \tag{19}$$

$$\sum_{j\in J} \sum_{k\in K_{ij}} x_{ijk} \geq \text{MIFD}_i \qquad \forall i \in I \tag{20}$$

$$\sum_{i\in I} \sum_{k\in K_{ij}} x_{ijk} \geq \text{MIFL}_j \qquad \forall j \in J \tag{21}$$

$$\sum_{j\in J} \sum_{k\in K_{ij}} x_{ijk} \leq \text{MXFD}_i \qquad \forall i \in I \tag{22}$$

$$\sum_{i\in I} \sum_{k\in K_{ij}} x_{ijk} \leq \text{MXFL}_j \qquad \forall j \in J \tag{23}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall k \in K_{ij}, \quad \forall j \in J, \quad \forall i \in I. \tag{24}$$

4.3. Converting the stochastic model to a deterministic one

In this section, to convert the stochastic program to a deterministic model, equations (17) and (18) must be changed. For optimizing the objective functions with stochastic variables, Sakawa *et al.* [42] have considered some decision rules, one of which is the application of the maximum expected value model. Hence, equation (17) was converted to equation (25).

$$\max Z = \sum_{i\in I} \sum_{j\in J} \sum_{k\in K_{ij}} \left(\text{LIFM}_j \times \text{DIFM}_i \times E\left(\widetilde{\text{PTF}}_{ijk}\right)\right) x_{ijk}. \tag{25}$$

In equation (18), let us assume the $\widetilde{osb}_{ijk}$ has a normal distribution with an average $E(\widetilde{osb}_{ijk})$ and variance $Var(\widetilde{osb}_{ijk})$, and $\tilde{h} = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk}x_{ijk}$, then we get the following formula:

$$Prob\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk}x_{ijk} \geq \gamma\right) \geq 1-\alpha \quad \Rightarrow \quad Prob\left(\frac{\tilde{h}-E(\tilde{h})}{\sqrt{Var(\tilde{h})}} \geq \frac{\gamma-E(\tilde{h})}{\sqrt{Var(\tilde{h})}}\right) \geq 1-\alpha. \tag{26}$$

Since $Prob\,(x > y) = 1 - Prob\,(x \leq y) = 1 - F\,(y)$ then equation (27) can be obtained from equation (26). According to equations (27) and (28), equation (18) was converted to the deterministic inequality relationship in equation (29), where F is the standard normal probability distribution function, and Z_α is the inverse function of F.

$$Prob\left(\frac{\tilde{h}-E(\tilde{h})}{\sqrt{Var(\tilde{h})}} \geq \frac{\gamma-E(\tilde{h})}{\sqrt{Var(\tilde{h})}}\right) = 1 - F\left(\frac{\left(\gamma-E(\tilde{h})\right)}{\left(\sqrt{Var(\tilde{h})}\right)}\right) \overset{\text{Eq.(26)}}{\Rightarrow} F\left(\frac{\left(\gamma-E(\tilde{h})\right)}{\left(\sqrt{Var(\tilde{h})}\right)}\right) \leq \alpha \tag{27}$$

$$\begin{aligned} F\,(Z_\alpha) = \alpha \Rightarrow F\left(\frac{\left(\gamma-E(\tilde{h})\right)}{\left(\sqrt{Var(\tilde{h})}\right)}\right) \leq \; F\,(Z_\alpha) \Rightarrow \frac{\left(\gamma-E(\tilde{h})\right)}{\left(\sqrt{Var(\tilde{h})}\right)} \leq Z_\alpha \\ \Rightarrow \left(\gamma - E(\tilde{h})\right) \leq Z_\alpha\left(\sqrt{Var(\tilde{h})}\right) \end{aligned} \tag{28}$$

$$\begin{aligned} \left(\gamma - E(\tilde{h})\right)^2 \leq {Z_\alpha}^2 Var(\tilde{h}) \Rightarrow \left(\gamma - E\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk} \;\; x_{ijk}\right)\right)^2 \\ \leq {Z_\alpha}^2 Var\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk} \;\; x_{ijk}\right). \end{aligned} \tag{29}$$

Following equations (30) and (31) and considering the lack of correlation between $\widetilde{osb}_{ijk}$ or the independencies between $\widetilde{osb}_{ijk}$, *i.e.*: $Cov(\widetilde{osb}_{ijk}, \widetilde{osb}_{ijk}) = 0$, equation (29) was converted to equation (32), which is the deterministic version of equation (18).

$$E\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk}\; x_{ijk}\right) = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} E(\widetilde{osb}_{ijk})\; x_{ijk} \tag{30}$$

$$\begin{aligned} Var\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \widetilde{osb}_{ijk}\; x_{ijk}\right) &= \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} Var(\widetilde{osb}_{ijk}) \cdot x_{ijk}^2 \\ &+ \sum_{\substack{i\in I \\ ijk\neq ijk}}\sum_{j\in J}\sum_{k\in K_{ij}} Cov(\widetilde{osb}_{ijk}, \widetilde{osb}_{ijk}) x_{ijk}x_{ijk} \end{aligned} \tag{31}$$

$$\left(\gamma - \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} E(\widetilde{osb}_{ijk})\; x_{ijk}\right)^2 - \mathrm{Z_\alpha}^2 \sum_{i\in I}\sum_{j\in J}\sum_{k\in Kij} Var(\widetilde{osb}_{ijk}) x_{ijk}^2 \leq 0. \tag{32}$$

Now, based on the primary model, *i.e.*, equations (1) to (8), the one-objective model, *i.e.*, equations (17) to (24), and the steps of changing from a stochastic model to a deterministic one, the final mathematical model based on CCBOFP method was determined as follows:

$$\max Z = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} \left(\mathrm{LIFM}_j \times \mathrm{DIFM}_i \times E\left(\widetilde{\mathrm{PTF}}_{ijk}\right)\right) x_{ijk} \tag{33}$$

subject to:

$$\left(\gamma - \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} E(\widetilde{osb}_{ijk})x_{ijk}\right)^2 - {Z_\alpha}^2 \sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} Var(\widetilde{osb}_{ijk})x_{ijk}^2 \le 0 \tag{34}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MNB} \tag{35}$$

$$\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \ge \mathrm{MIFD}_i \qquad \forall i \in I \tag{36}$$

$$\sum_{i\in I}\sum_{k\in K_{ij}} x_{ijk} \ge \mathrm{MIFL}_j \qquad \forall j \in J \tag{37}$$

$$\sum_{j\in J}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MXFD}_i \qquad \forall i \in I \tag{38}$$

$$\sum_{i\in I}\sum_{k\in K_{ij}} x_{ijk} \le \mathrm{MXFL}_j \qquad \forall j \in J \tag{39}$$

$$x_{ijk} \in \{0,1\} \qquad \forall k \in K_{ij},\quad \forall j \in J,\quad \forall i \in I. \tag{40}$$

In this model, equation (33) shows maximizing the stochastic donation motivation using the values of DIF_i and LIF_j and the maximum expected value of $\widetilde{\mathrm{PTF}}_{ijk}$. Equation (34) shows that the obtained benefit should be greater than γ with the probability of $(1-\alpha)$. This equation was the deterministic equation of equation (18). Finally, equations (35) to (40) were the same constraints defined in equations (3) to (8). The mathematical model for this problem was coded based on Integer quadratically constrained problems (IQCP) and the CCBOFP method, using CPLEX[1] and Optimization Programming Language (OPL), and the dynamic search algorithm was used in solving this model.

5. Computational results

This section first introduces the characteristics of the studied problem and then discusses the results obtained from solving the stochastic model. Finally, the sensitivity analysis of some parameters is provided.

5.1. Introducing the real problem

As a real example, we considered the Mashhad branch of the Imam Khomeini Relief Foundation (IKRF) as a large and old Iranian charitable organization, using the same dataset as in [11]. The population of Mashhad is about 3 million people, and there are 21 location types and 1020 potential locations in 43 districts as illustrated in Figure 2. Location types are hospitals, clinics, public health centers, universities, higher education institutions, schools of seminaries, high schools, mosques and Hussainiya, bus terminals, subway stations, gas stations, CNG stations, governmental offices, shopping centers, supermarkets, movie theaters, museums, libraries, pilgrims residential places, hotels, motels, and inns.

[1]IBM ILOG CPLEX 12.6.

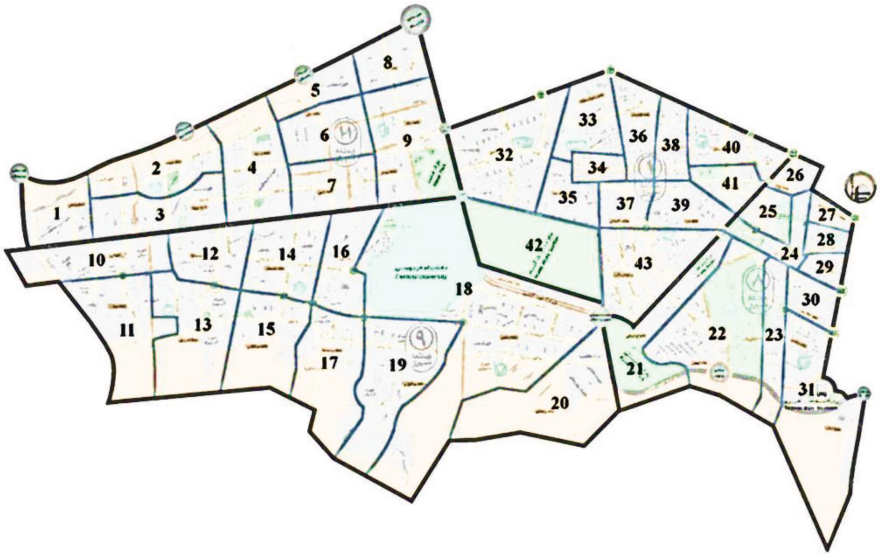

FIGURE 2. The 43 under studied districts.

TABLE 3. The amounts of the impact factor in district i (DIFM_i) in terms of 10 thousandths.

District	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
impact factor	42	30	45	52	41	56	87	48	63	179	75	70	44	157	57
District	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
impact factor	97	34	57	34	40	479	123	198	729	779	688	1130	790	874	249
District	31	32	33	34	35	36	37	38	39	40	41	42	43		
impact factor	126	134	47	148	116	166	117	863	82	266	180	295	117		

Extraction of the districts, location types, and the total number of potential locations were based on the existing information on SDI[2] and MSMICTO[3]. The extraction of locations and the amount of donations in conventional boxes were based on the existing information at the IKRF. The data related to DIFM_i, LIFM_j and $\widetilde{\mathrm{PTF}}_{ijk}$ criteria that were used in the EDAS method were obtained from Information and Communication Technology Organization of Mashhad Municipality. Despite the fact that gathering all these data was very time-consuming, it was worth the effort once used in solving the model in its real application.

5.2. The results

The results are presented and discussed in two sections. First, the calculation of the parameters was described and, then, the model solution results were provided. In the first part, we calculated the values of the district impact factor (DIFM), location type impact factor (LIFM), and the pedestrian traffic factor (PTF) according to the criteria in Table 2.

Based on the eight criteria in Table 2, their weights, and the EDAS method, the district impact factor was obtained (Tab. 3). The first row of Table 3 shows the index of each district, and the second row presents the obtained values of the district impact factor.

[2]Spatial Data Infrastructure.

[3]Map System of Mashhad's municipality Information and Communications Technology Office.

TABLE 4. The amount of location type Impact Factor (LIFM_i) in terms of 10 thousandths.

j	Location type	Impact factor	j	Location type	Impact factor
1	Inn	63	12	Governmental Office	265
2	Motel	45	13	Subway Station	649
3	Hotel	70	14	Bus Terminal	902
4	Pilgrim Residential	271	15	Mosque and Hussainiya	864
5	Library	64	16	High School	168
6	Museum	26	17	University and Institute	424
7	Movie Theater	32	18	Seminaries	706
8	CNG Station	487	19	Health Center	687
9	Gas Station	500	20	Clinic	1224
10	Supermarket	253	21	Hospital	1954
11	Shopping Center	346			

TABLE 5. The expected value (Mean) of ($\widetilde{\mathrm{PTF}}_{ijk}$) for each potential location.

Number	Potential location (ijk)	$E\left(\widetilde{\mathrm{PTF}}_{ijk}\right)$	Number	Potential location (ijk)	$E\left(\widetilde{\mathrm{PTF}}_{ijk}\right)$
1	01,06,01	0.2043	6	02,05,01	0.3160
2	01,07,01	0.2046	7	02,06,01	0.2741
3	01,09,01	0.3347	8	02,07,01	0.2744
4	01,10,01	0.2220	...	...	...
5	02,03,01	0.2776	1020	43,19,03	0.3428

Next, based on the six criteria in Table 2, their weights, and the EDAS method, the location type impact factor was obtained (Tab. 4).

Also, based on the six criteria in Table 2, and using the expected value due to the conversion of equations (17)–(25), the pedestrian traffic factor expected value (Mean) for each potential location (1020 potential locations) was obtained (Tab. 5). Due to a large amount of data and to save space, Table 5 illustrates just a portion of the obtained results.

The amount of the obtained benefit of the previous years in conventional charity boxes was used for determining the $\widetilde{osb}_{ijk}$ value at each potential location. This choice is justified because, as highlighted in the existing literature, donor behavior in traditional and digital contexts is influenced by similar determinants such as trust, transparency, social norms, and perceived responsibility [43, 44]. Moreover, case studies on digital fundraising technologies [45] indicate that electronic channels generally complement rather than fundamentally change donation behavior, making the transferability of data from conventional to electronic boxes plausible under controlled conditions. Also, according to Section 4.3, in order to convert a stochastic model into a deterministic one, it must be ensured that the distribution function $\widetilde{osb}_{ijk}$ was normal at each potential location. We utilized EasyFit Version 5.5 software and Kolmogorov–Smirnov test to determine the distribution function of each potential location. The amount of the obtained monthly benefit of the previous years in conventional charity boxes, in 1020 potential locations, was used for this purpose. Based on the results of this test, $\widetilde{osb}_{ijk}$ in all potential locations had a normal distribution with the average $E(\widetilde{osb}_{ijk})$ and variance $Var(\widetilde{osb}_{ijk})$.

Concerning the other parameters, the maximum number of e-charity boxes (MNB) was considered equal to 100, and the threshold value of constraint (α) was five percent. Moreover, each e-charity box was expected to obtain at least a benefit equal to the average obtained benefit from the conventional boxes in the previous years. Accordingly, the γ value was equal to the MNB multiplied by the expressed average.

FIGURE 3. The final locations based on the location type.

The mathematical model for this problem was coded based on the CCBOFP method. The final locations of the model (100 locations) were extracted, as provided in Figure 3. In this figure, the final locations were determined based on the location type.

For further analysis and evaluation of the effectiveness of the proposed model, the dispersion of the answers in different districts and types of locations was presented in Figures 4 and 5.

Figure 4 shows the amount of allocation to each district based on the CCBOFP method. As can be seen in this figure, 16 districts had the highest number of allocations, and the rest had only one allocation in the model, which is not shown in Figure 4. Based on this model, districts 27, 18, and 43 had the highest number of allocations, and approximately 30% of the allocations belonged to these districts.

The final locations extracted from the mathematical model delineated the effectiveness of the proposed model because the amount of the allocation to each district (Fig. 4) corresponded with the situation of the districts in district impact factor (Tab. 3), the total donations (the amount of obtained benefit from the conventional charity boxes in the previous years) in each district, and the sum of the total pedestrian traffic factor of potential locations in each district. For example, district 27, which had the best DIFM according to Table 3 and was the second district in terms of the amount of public donations, had the highest allocation in Figure 4.

Also, Figure 5 shows the amount of allocations to each location type based on the CCBOFP method. As can be observed in this figure, 7 location types had the highest number of allocations while the rest had only one allocation in the model. Based on this model, Clinics, Subway Stations, Hospitals, and Mosques and Hussainiyas had the highest number of allocations, and approximately 80% of the allocations belonged to these location types.

As for the location type, similar to the districts, the final locations extracted from the mathematical model delineated the effectiveness of the proposed model because the amounts of allocation to the location type (Fig. 5) corresponded with the status of the location type in location type impact factor (Tab. 4), the total donations in each location type, and the sum of the total pedestrian traffic of the potential locations in each location type. For example, Clinics and Hospitals had very good conditions in each of these three indicators.

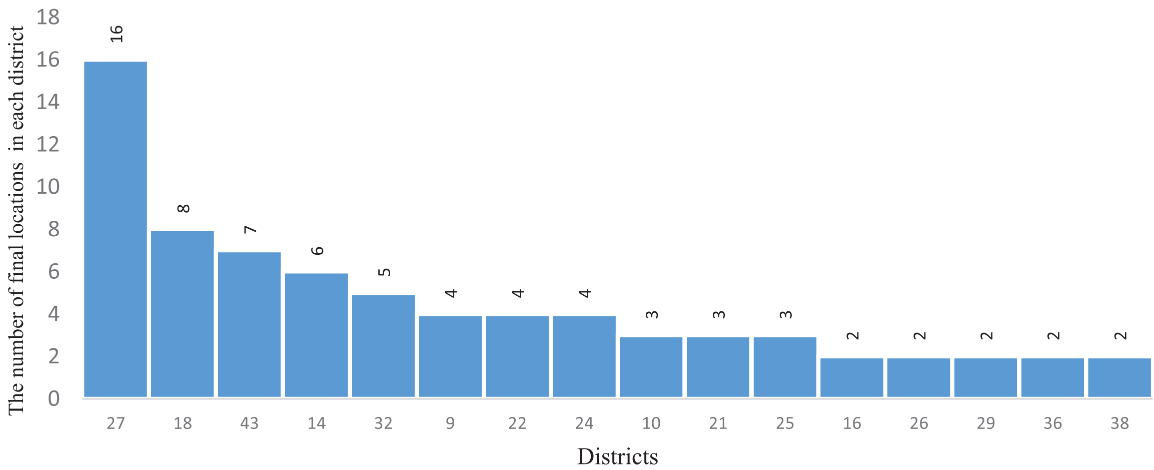

FIGURE 4. The amount of allocation to each district based on the CCBOFP method.

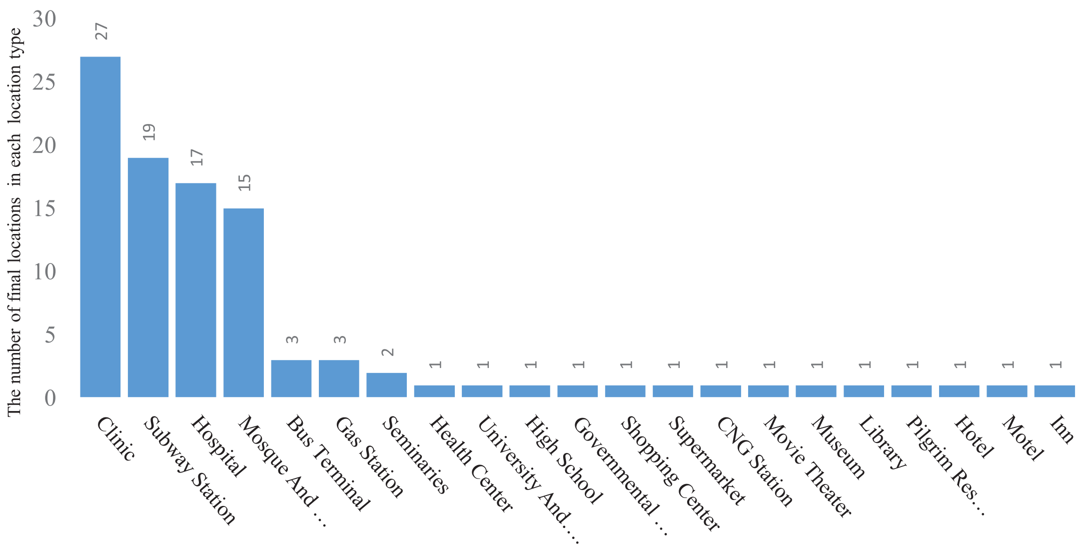

FIGURE 5. The amount of allocation to each location type based on the CCBOFP method.

5.3. Sensitivity analysis

In the proposed formulation, the values of α and γ, as the parameters of the chance constraint model, can be changed. To calculate γ, it is possible to change the expected benefit from 1 time average (γ_1) to 1.5 times ($\gamma_{1.5}$) and 2 times (γ_2) the average obtained the benefit of total conventional boxes in the previous years.

Figure 6 shows the changes in the γ values in three states (γ_1), ($\gamma_{1.5}$), and (γ_2), while $\alpha = 5\%$. In Figure 6, graph a and graph b show the frequency of allocation to each district, and the frequency of allocation to each location type, respectively, while graph c shows the changes in the objective values (Eq. (28)) based on γ changes.

As can be observed in graph c (Fig. 6), the objective value improved along with the increase in the γ value. It should be noted that, as shown in Figure 6, increasing the γ value from 1.5 to 2 times the average has a

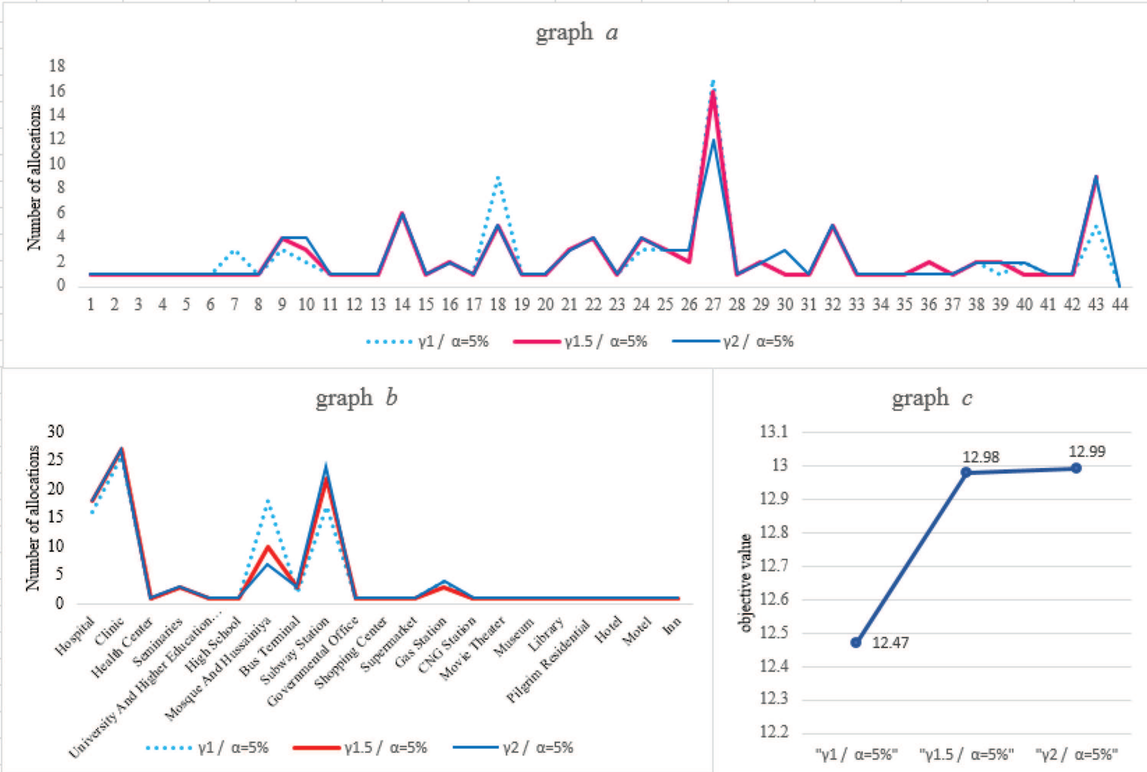

FIGURE 6. Frequency of allocation to districts and location types in different values of γ.

negligible impact on the objective value. Moreover, raising it further from 2 to 3 times the average produces no additional change, and for values greater than 3 times the average, the mathematical model fails to yield a solution. Increasing the γ, according to the graph a, decreased the allocation in some districts such as Districts 18 and 27 while increasing it in other districts such as Districts 9 and 43. Moreover, according to graph b, the allocation decreased in some location types such as Mosques and Hussainiyas while increasing in other location types such as Subway stations.

Figure 7 shows the changes in α value in three positions, namely ($\alpha = 10\%$), ($\alpha = 5\%$), and ($\alpha = 1\%$), while the amount of γ is equal to the average. Graph a in Figure 7 shows the frequency of allocation to each district; Graph b in Figure 7 shows the frequency of allocation to each location type, and graph c in Figure 7 shows the changes in the objective value (Eq. (28)) based on α changes.

Regarding the α changes in all the three positions explained above, the locations were extracted almost identically; nevertheless, these small changes in the allocation to some districts and to some location types made it clear that the lower the α is, the more the objective value improves. These changes were observed in the allocation to some districts, including Districts 7, 9, 22, and 40, and to some location types including mosques and hussainiyas, bus terminals, and gas stations.

Based on Figures 6 and 7, along with the decrease in α and the increase in γ, the objective value in this model improves. Although this improvement in sensitivity analysis is confirmed, still, the decision makers decided that the values of α and γ should be the same as in Section 5.2.

FIGURE 7. Frequency of allocation to districts and location types in different values of α.

6. CONCLUSIONS AND SUGGESTIONS

Using e-charity boxes as new public donation tools can help the revenue resource development of charities. Mathematical programming can be used for finding the optimal location of e-charity boxes to make them more efficient.

In this paper, we proposed the new concept of "stochastic donation motivation" and entered it into the objective function. In fact, we proposed a novel stochastic multi-objective model in which the first objective maximized the "stochastic donation motivation" while the second one maximized the gathered "stochastic benefit". In defining the constraints of the problem, three topics were considered, namely the limited number of facilities, acculturating the people to use e-charity boxes instead of conventional boxes through wide distribution of e-charity boxes across all districts and location types, and preventing the cumulation of e-charity boxes in one type of location and one district.

Next, we changed the stochastic multi-objective model, using the chance-constrained bounded objective function method to a single-objective deterministic formulation. We also introduced, with twenty sub-criteria, the district impact factor, the location type impact factor, and the pedestrian traffic factor. The district impact factor, with eight criteria in its subset, helped to differentiate among the identified districts; the location type impact factor, with six criteria in its subset, helped to select the best location type; and finally, the pedestrian traffic factor, with six criteria in its subset, had the capability to show the difference between even two same locations in a same district. Ranking all potential locations based on the above criteria was one of the most important challenges of the present paper, which was carried out based on the EDAS method. The final locations extracted from the mathematical model delineated the effectiveness of the proposed model because the amount of allocation to each district and each location type corresponded with the situation of the districts in the district impact factor, the status of the location type in location type impact factor, the total donations in each district, and the sum of the total pedestrian traffic factor of the potential locations in each district. Through a sensitivity analysis in the proposed formulation, the values of α and γ changed, and their impact on the amount of allocation to districts, the location types, and the objective value were examined.

One of the limitations of this research was that DIFM and LIFM parameters are deterministic. In addition to this issue, due to the limitation of the number of facilities, the amount of allocation to each potential point was considered equal to 1. Besides, another limitation of the research was the lack of access to urban pathways data. It should also be recognized as a limitation that empirically validated data are required for certain variables, such as the stochastic nature of donation motivation. Due to the novelty of this concept, "stochastic donation motivation" was estimated based on a set of criteria derived from a comprehensive review of the literature, interviews with experts in charitable giving and the available data. Based on these limitations, for further research, it is suggested to model the problem *via* fuzzy stochastic programming by considering the benefit as a random parameter and the DIFM, the LIFM, and the PTF as fuzzy parameters. Also, the model can be written as an integer quadratic programming with the assumption that the variables can get values larger than 1. Likewise, the problem can be considered by the assumption of allocating the e-charity boxes in both locations and pathways or just in pathways.

Data availability statement

The data that support the findings of this study are available at https://docs.google.com/spreadsheets/d/1l4YS-HHpoppxjE5z1d7g1Uv9HeUfCnh-/edit?usp=sharing&ouid=113168231517851972746&rtpof=true&sd=true.

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