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A food upcycling model by food bank collection-distribution networks

Javid Ghahremani-Nahr [a], Ramez Kian [b,*], Abdolsalam Ghaderi [c,*]

[a] Academic Center for Education, Culture and Research (ACECR), Tabriz, Iran
[b] Nottingham Business School, Nottingham Trent University, Nottingham, UK
[c] Department of Industrial Engineering, University of Kurdistan, Sanandaj, Iran

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ABSTRACT

Nowadays, the collection and distribution of food products with high nutritional value and freshness for people in poverty has become a global problem due to financial, drought, or other crises. Food banks (FBs) are important entities that mitigate food waste by reusing surplus food at critical points in the food supply chain. This article investigates an FB network design problem for the collection and distribution of food items. An FB network comprises donors mapped from the food supply chain, FB itself, and beneficiaries mapped from charities. The problem addresses synchronous strategic, tactical, and operational decisions, including the location of FBs, the assignment of donors to main streams, the control of inventory, and the routing of vehicles in collection and distribution levels to optimize the amount of food reused. As the demand and supply of food items from charities and donors are uncertain, a robust fuzzy stochastic model is developed to model the problem with three objectives including cost, nutritional value, and freshness of food. An extensive numerical study compares these algorithms with respect to several criteria. The proposed novel MOGGWA heuristic showed superior performance and was ranked first by applying the TOPSIS multi-criteria decision-making method. The value of stochastic programming and the impact of the model on a real-size case study problem are shown, as well.

1. Introduction

In 2016, approximately 23.4% of the European Union's population (about 117.5 million people) faced poverty or social exclusion risks [1]. At the same time, an estimated 20%–30% of all food produced annually in the EU (valued at €143 billion) was wasted across the supply chain, from farms to households. Over the past few years, the European Union has taken various measures to reduce food waste throughout the food supply chain. One of these measures is the commitment of member states in order to reduce food waste by 30%. Despite food waste reduction initiatives, the challenge lies not in food scarcity but in the equitable distribution of existing resources. Food banks have emerged as critical intermediaries, connecting surplus food sources with communities in need [2,3]. FBs, established in the 1980s, operate globally under varying models. While some directly serve individuals, others act as warehouses, distributing food to secondary organizations such as pantries. Historically, canned and packaged foods have dominated FB supplies, but increasing nutrition awareness has shifted focus toward fresh, perishable items. However, incorporating fresh products into FB operations poses unique logistical and operational challenges due to perishability, nutritional value degradation, and limited storage capacity [4]. In other words, FBs are responsible for leading a commodity chain and building a bridge between surplus food and human needs. The operation of FBs depends on their suppliers (food companies and other donors) and in effect, they act as wholesalers. Management of FBs is also complicated due to the distribution of perishable products, which in many cases may decrease in quality and quantity. In addition to the common goal of providing food to people in poverty, FBs are also compatible with the environment [5]. They can have a positive impact on the environment and society by reducing food waste and distributing surplus food to the beneficiaries. In fact, the purpose of FB is to preserve the value of food. That is, meeting the demand of charities by maintaining and maximizing the freshness and value of food in line with the health of consumers. In case of not paying attention to this issue, food is considered as waste and thrown away. Unlike other profit-making organizations, FBs aims at equitable, effective, and efficient distribution of donated foods [6]. A national survey of FB clients conducted in 2013 found that many FB clients preferred nutritious foods and fresh fruits, whilst vegetables are among the ingredients that customers did not receive in food packages. The limited facilities for storage and distribution of fresh food on one hand, and the desire of the beneficiaries for fresh and nutritious food on the other hand, have led to the improvement of quality and emergence

* Corresponding authors.
E-mail addresses: j.ghahremani@acecr.ac.ir (J. Ghahremani-Nahr), ramez.kian@ntu.ac.uk (R. Kian), ab.ghaderi@uok.ac.ir (A. Ghaderi).

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of research initiatives [7]. In order to solve this issue, managers are trying to increase human resources and create physical capacity in FBs. They have considered refrigerated warehouses in FBs to store fresh products and other perishable items such as dairy products. To improve and accelerate access to perishable foods, including fresh fruits and vegetables, FBs use several strategies, including notifying agencies or attempting to contact food donors directly. This strategy offers an additional advantage to maximizing the shelf life of perishable food products by shortening the distribution time. This makes it possible to store food with a long shelf life for a limited period of time so that it can be distributed at the right time. This is quite important as it facilitates meeting the demand of charities.

At the operational level, food freshness has an inverse relationship with vehicle travel time in logistics. That is, the longer the transportation time of the food is, the less fresh it will be at the time of delivery. Therefore, vehicles should deliver food to charities or collect it from donors as soon as possible. Also, each food product has a certain nutritional value; therefore, FBs while ensuring fulfillment of the minimum required nutritional value of charities, also strive to maximize their total nutritional value.

The critical challenges FBs face include minimizing food waste, ensuring nutritional adequacy, and maintaining food freshness while addressing the complex logistics of supply chain operations. Notably, these challenges are compounded by uncertainties in supply and demand, such as varying food donation volumes and the fluctuating needs of recipient charities. Addressing these challenges requires advanced decision-making across all strategic, tactical and operational levels, including facility location, inventory management, vehicle routing, and distribution scheduling.

Based on the different decisions in the FB network, there are three main performance indices addressed in this paper. Minimization of total costs, maximization of minimum food freshness, and maximization of foods' nutritional value. In order to simultaneously achieve these three goals, choosing the appropriate FB location, determining vehicle routing for food basket distribution, determining the inventory of cold food in FBs, and also the dispatching time of food baskets by vehicles should be specified.

As a result, different strategic, tactical and operational decisions must be made simultaneously in the FB network, which increases the complexity of decision-making. In addition, the supply of food in FB networks is a major issue in the network design. Usually, the amount of food supplied by donors or the amount of demand for food by charities are different in each time period indicating uncertain parameters. As it is not possible to determine the exact value of these parameters in advance to make the most appropriate executive decision, an appropriate uncertainty control method should be applied to deal with the uncertainty. Therefore, this article proposes a robust fuzzy stochastic approach for the defined FB network design problem.

To tackle the multi-objective model in this study, in addition to the augmented epsilon constraint (AEC) method, three meta-heuristic algorithms, namely, NSGA II, MOGWO and MOGGWA also developed since the exact solution method is computationally expensive for real size instances. The multiplicity of objectives in the mathematical model leads to the creation of multiple efficient solutions, which are compared based on various indexes such as the Number of Pareto Front (NPF), Maximum Spread index (MS), Space Metric (SM), Mean of Ideal Deviations (MID), and Solution Time (CPT). The efficacy of the problem parameters on the objectives and choosing the appropriate solution method is also examined for the FB network problem. This study investigates the following research questions:

1. How can FBs optimize their network design to achieve equitable and efficient food distribution?
2. How can food freshness and nutritional value be preserved while minimizing supply chain costs?
3. How can uncertainties in supply and demand be effectively managed in FB network operations?

Despite significant advances in the field, important gaps remain unaddressed. First, few studies incorporate food freshness as a primary objective in the network design. This paper proposes a novel integration of food freshness alongside cost minimization and nutritional value maximization, ensuring equitable and effective distribution. Second, uncertainties in food supply and demand have often been simplified or ignored in prior models. This study addresses these challenges by developing a robust fuzzy stochastic model that accommodates supply and demand variations. Finally, advanced multi-objective solution methods, including the augmented epsilon constraint method and metaheuristic algorithms are employed to solve the proposed model efficiently. The detailed research gaps and contributions are discussed in Section 2.3. In addition, a case study conducted in Tehran validates the practicality of the proposed model and solution methods. The rest of this article is compiled into six sections. Section 2 reviews the research literature under related themes. Section 3 proposes a robust fuzzy stochastic mathematical model for our FB network problem to tackle uncertain parameters and probable scenarios. In Section 4, solution methods, construction of the initial solution, and comparison indexes are discussed, while in Section 5, the numerical results are presented, and a real case study is provided together with some managerial insights. Finally, Section 6 concludes the article and provides future research directions.

2. Literature review

Food insecurity continues to pose worldwide health-threatening concerns, while according to the FAO, approximately 30% of food produced for human consumption is lost or wasted annually due to inappropriate management of food supply chains, including improper storage and transportation practices [8]. In addition, food donation and distribution face uncertainty as the amount of food and demand can differ over time. Other parameters such as distribution time can be uncertain affecting food safety and demand satisfaction. Moreover, food production consumes natural resources such as water and energy, so reducing food waste can save these natural resources for future generations [9]. Dubey and Tanksale [10] identify challenges in the growth of FBs and cluster them into seven categories among which are uncertainty, characteristics of the donated food, financial, and planning & coordination. Thus, the design of the food supply chain network can play a vital role in preventing a significant amount of food wastage, thereby reducing greenhouse gas emissions and increasing food security. Using FBs and volunteer work, surplus or expiring food can be collected and managed to meet food demand before it becomes waste. FBs operate with limited resources that depend mainly on donations and volunteer work. Therefore, they must design and manage their supply chain network efficiently and effectively to ensure the highest possible amount of food aid [11]. The current configuration of most FB networks is not the result of a strategic planning process but has emerged through operational decisions and donation opportunities identified over the past 20 years [1]. The supply chain network of FBs includes different entities from suppliers to end users such as warehouses, food donors, and people in need, which makes it difficult to manage. In particular, coordination between different sectors are challenging when food or financial aid must be collected from donors in different locations and then repackaged and distributed to those in need [2,7].

In the rest of this section, studies related to the above-mentioned challenges in the context of FBs are briefly summarized in two main themes. For a more comprehensive literature review the readers may refer to Rivera et al. [12], Esmaeilidouki et al. [13].

2.1. Food bank network

Orgut et al. [14] develop a mathematical model for a North Carolina FB to maximize its effectiveness by minimizing the amount of undistributed food. Their model identifies optimal policies for allocating additional receiving capacity to cities in the service area. Reihaneh and Ghoniem [15] propose a heuristic for pallet distribution in intermediary deliveries of FBs. Wetherill et al. [7] conduct a study to describe the best strategies for promoting nutrition-focused food banking in the United States. They used qualitative interviews to obtain information about food banking practices and processes. Chen et al. [16] study a vehicle routing problem to minimize the traveled distance considering constraints such as capacity and transit time. The results of their model showed that by modifying the vehicles' route, 94.4% of customers can benefit from food bank services. In a different study, Mandal et al. [17] presented a decision support model for collectors to reduce food waste by allocating donated food items from retailers to FBs and maximizing the profitability of collectors while minimizing environmental impacts. Kaviyani-Charati et al. [8] present a mathematical model considering sustainability factors in the multi-objective model. They conduct a real case study in the city of Tehran, taking into account many uncertain parameters and time constraints. Firouz et al. [18] propose a model to invoke equity and efficiency in a food bank donation allocation problem using a penalty factor in the objective function. Ghahremani-Nahr et al. [19] present an FB network to minimize the total costs, maximize the value of the food basket, and maximize the freshness of the food. They proposed a robust fuzzy method to control their uncertain parameters and proposed a meta-heuristic algorithm and ϵ-constraint method to solve it. Martins and Pato [20] also investigate a three-tier FB network design with a focus on the allocation and capacity of the facilities. Their optimization problem considers three objectives including cost, waste and carbon footprint, and number of served charities.

2.2. Uncertainty in the food supply chain

According to the systematic review of Luo et al. [21], *uncertainty* forms 5% of the keywords contained in studies of food loss and waste within supply chain operations. They report that stochastic and robust optimization approaches are the most used methods in capturing uncertainty in the objective od constraints. Here, for the sake of brevity, we review some most recent and related studies considering uncertainty in the context of FB and food supply chain. For a more comprehensive review the reader may refer to Chen et al. [22].

Hassanpour et al. [23] develop a mathematical model to integrate food supply and distribution decisions under uncertain conditions (vehicle travel time) to minimize purchase and transportation costs and maximize customer satisfaction. Gholami-Zanjani et al. [24] present a comprehensive two-stage scenario-based mathematical model to design a food supply chain network under demand uncertainty. They develop acceptable scenarios using the Monte Carlo method and applied Bender's decomposition technique to solve the problem. Krishnan et al. [25] develop a multi-objective robust model for an agri-food supply chain network considering the uncertainty in the supply to optimize the sustainability factors. Similarly, Fathollahzadeh et al. [26] propose a bi-objective stochastic model to address the uncertainty. Both studies use ϵ-constraint and heuristic methods in their solution approaches.

Li and Song [27] present a model to investigate the effects of uncertainties on the food supply chain and found that the combination of effects intensifies or reduces food supply chain risks. Gholian-Jouybari et al. [28] investigate the design of meta-heuristic algorithms for a sustainable supply chain of agricultural products by considering marketing practices under conditions of uncertainty. For this purpose, they develop a stochastic multi-objective planning model, whose effectiveness is confirmed by a case study on saffron trade using the LP-metric method, and developed a meta-heuristic method to solve it. Partovi et al. [29] present a two-level programming formulation for the location-inventory-routing problem in a two-stage supply chain that minimizes the total operating costs at both levels subject to capacity constraints. Considering the uncertainty of the problem, they use scenario-based programming, and designed a multi-criteria goal programming model for the problem. Table 1, summarizes the characteristics of various articles related discussed above.

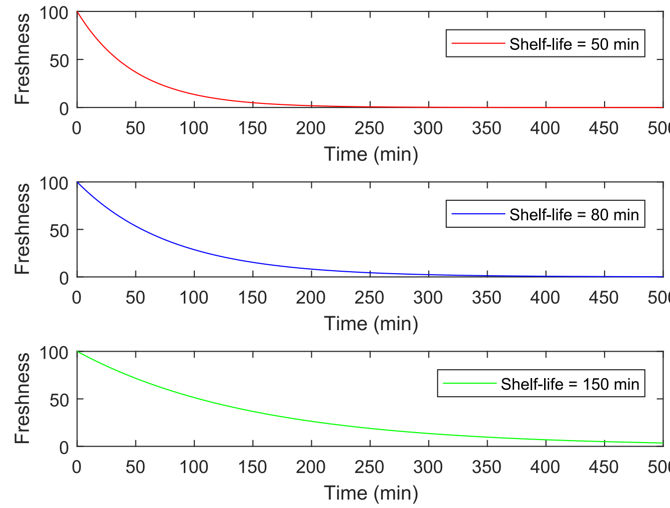

Fig. 1. Freshness of food to their shelf-life over time: $\Gamma(t) = 100e^{-\theta t}$.

2.3. Research gap and contributions

Based on the literature review and the analysis in Table 1, the following research gaps have been identified and addressed in this study:

1. **Objective function:** Most studies in the field of food supply chains and food banks focus on minimizing total costs, maximizing profit, improving customer satisfaction, or reducing greenhouse gas emissions. Although some address minimizing unmet demand, none explicitly considers the goal of maximizing food freshness for end-users. This gap highlights the need to incorporate food freshness as a critical objective in the design of food bank networks.
2. **Constraint:** While existing research incorporates various strategic and tactical decisions, such as facility location, production capacity, and transfer flow allocation, few integrate constraints related to product shelf life and freshness. Incorporating these constraints can make models more realistic and enhance decision-making. Additionally, considering constraints tied to financial donors' daily budgets and integrating these into the network design presents another research opportunity.
3. **Assumptions:** Existing studies primarily focus on individual segments of the food supply chain, often neglecting the interconnectedness of upstream and downstream operations. This paper addresses this gap by simultaneously optimizing routing decisions for both upstream (donor-to-FB) and downstream (FB-to-charity) flows, thereby ensuring food freshness is preserved across the entire supply chain.
In addition, most reviewed studies focus primarily on the flow of items between facilities without considering the freshness or nutritional value of food baskets. Incorporating assumptions about preserving food freshness and maximizing nutritional value adds significant richness to the problem formulation. Furthermore, supply and demand uncertainties are often overlooked in deterministic models. This study addresses these uncertainties by modeling supply and demand parameters as stochastic variables.
4. **Solution methods:** Based on Table 1, over 70% of the reviewed studies employ exact methods for deterministic problems. However uncertain models often rely on meta-heuristic algorithms like MOPSO and NSGA II. This study contributes by implementing advanced hybrid methods, including robust fuzzy stochastic

Table 1
Characteristics of selected articles in the context of food supply network and FBs.

Paper	Assumptions			Objectives							Decisions				Uncertainty				Solution method			
	Single/Multi Period	Single/Multi Echelon	Single/Multi Product	Cost	Delivery time	Quality-Freshness	Carbon Footprint	Travelled Distance	Nutritional Value	Social responsability	Location	Allocation	Routing	Inventory	Fuzzy	Stochastic	Robust	Deterministic	Heuristic	Meta heuristic	Exact	Simulation
[30]	S	S	S	✓			✓				✓	✓						✓			✓	
[31]	S	M	S	✓	✓		✓				✓	✓	✓					✓		✓		
[32]	M	S	M		✓						✓		✓	✓				✓				✓
[33]	M	S	M	✓							✓	✓			✓						✓	
[34]	M	S	M	✓	✓						✓	✓						✓		✓		
[35]	S	S	S					✓					✓					✓	✓			
[36]	S	M	S	✓									✓					✓	✓			
[37]	M	M	S	✓			✓				✓	✓		✓				✓		✓		
[38]	M	M	S	✓			✓					✓						✓				✓
[39]	M	M	S				✓							✓				✓				✓
[40]	M	M	M	✓			✓			✓	✓			✓		✓				✓		
[41]	S	M	M	✓			✓			✓	✓	✓		✓				✓			✓	
[25]	M	M	S	✓			✓			✓	✓	✓		✓			✓				✓	
[27]	M	M	S	✓								✓		✓		✓					✓	
[42]	M	M	S	✓			✓				✓		✓	✓				✓		✓		
[43]	S	M	S	✓						✓	✓		✓					✓		✓		
[44]	S	M	S	✓			✓						✓					✓	✓			
[29]	M	M	M	✓							✓		✓	✓		✓					✓	
[28]	S	M	M	✓							✓	✓					✓			✓	✓	
[19]	M	M	M	✓		✓			✓		✓	✓	✓	✓	✓	✓				✓	✓	
[45]	S	M	S	✓						✓		✓	✓				✓				✓	
[20]	M	M	M	✓		✓			✓		✓		✓					✓	✓			
[26]	M	M	M	✓			✓				✓	✓		✓		✓				✓		
Current article	M	M	M	✓		✓			✓		✓	✓	✓	✓	✓	✓	✓			✓	✓	

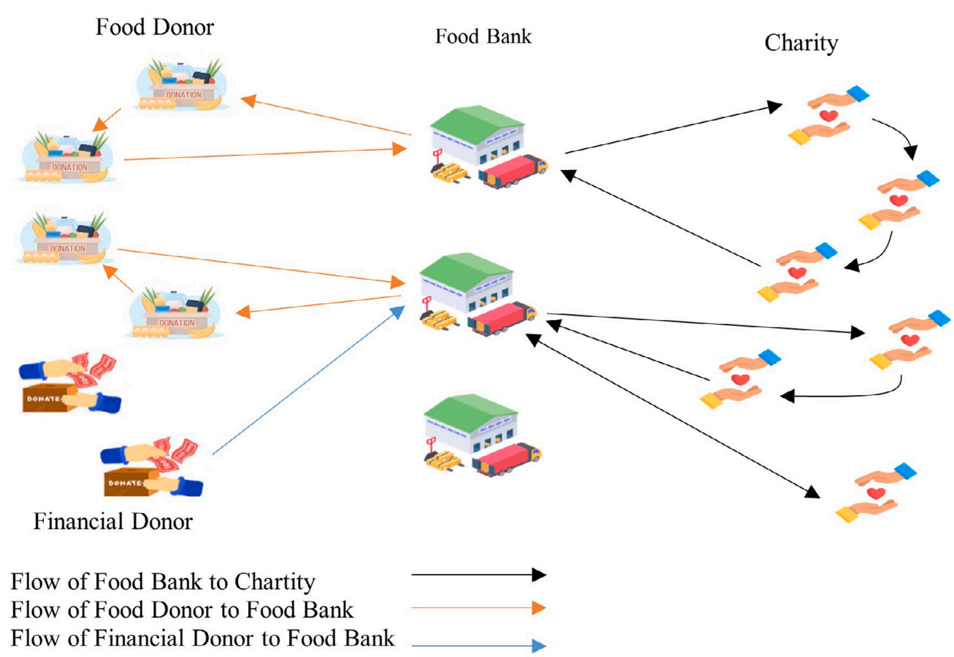

Fig. 2. A three-echelon food bank network.

modeling combined with meta-heuristic algorithms, to solve complex uncertain problems effectively.

5. **Uncertainty control method:** Various uncertainty control techniques, such as fuzzy programming, robust optimization, and probabilistic methods, have been utilized in prior research. However, hybrid methods that combine these approaches remain underexplored. This study proposes a robust fuzzy stochastic method to address uncertainty in supply and demand, offering a more adaptable and comprehensive solution.

In summary, this research contributes to the field of food bank network design by addressing these gaps and proposing novel objectives, constraints, and solution methodologies.

3. Food bank network problem

The FB network considered here includes a set of donors either food or financial, FBs, and charities. The donors are composed of either restaurants, hypermarkets, and similar businesses that provide FBs with food for free; or benefactors who buy and donate food to the FBs. Food items donated by donors encompass two types: warm (with a short shelf-life), and cold/canned (with a long shelf-life), which can form diverse food baskets. Charities announce their daily demand for food items or food baskets to the FBs whereas FBs dispatch them after procurement. Among the challenges of this process is the durability of food items. Although cold foods can be held in a FB due to their long shelf-life, according to [46] the freshness of hot meals exponentially deteriorates over time as shown in Fig. 1.

As food baskets are comprised of cold and hot foods with different nutritional values, the other factor in the FB network to be considered is fulfilling the maximum nutritional value of the donated food. Additionally, the supply and demand are non-deterministic which complicates the planning and network design, whereas financial donors buy and provide food to the FBs upon their request.

FBs are responsible for the distribution of food to charities and also for collecting them from donors. Thus, they deal with a routing problem both for the collection and distribution of foods in the network as illustrated in Fig. 2.

The aim of our model is to make strategic, tactical and operational decisions such as the location of the FBs, routing of the food collection and distribution, allocation of food to financial donors, and determining the inventory level of cold food in FBs. In the proposed model the transportation cost, food supply amount (from the donors), and food demand (from the charities) are considered non-deterministic in different scenarios. The objectives of these decisions are to minimize the total cost of the network, maximize the minimum freshness of the distributed food, and maximize the total nutritional value of the distributed food. Thus, the assumptions of the model are summarized as follows:

- Multiple types of food with long and short shelf-life are considered;
- Only foods with long shelf-life can be stored in FBs.
- The number and location of charities are known.
- The total budget of financial donors is limited and time-dependent.
- The freshness of food items is measured from the dispatching moment in FBs.
- The supply, demand, and transportation costs are uncertain, and are evaluated in different scenarios.
- The capacity of the vehicles and FBs are known.
- Both the collection and distribution of the food are based on supply and demand, which leads to different vehicle routing problems.
- Each food donor donates food to only one FB, but each FB can collect donations from multiple donors. Financial donors can donate to multiple FBs.
- Each charity receives food only from one FB, but each FB can deliver food to multiple charities.

Based on the assumptions above, the notations used for the mathematical model are listed below. **Sets:**

$\mathcal{I}$	Set of food donors $i \in 1,\dots,I$
$\mathcal{J}$	Set of financial donors $j \in 1,\dots,J$
$\mathcal{L}$	Set of candidate locations for FBs $l \in 1,\dots,L$
$\mathcal{C}$	Set of charities $c \in 1,\dots,C$
$\mathcal{V}$	Set of vehicles as a fleet $v \in 1,\dots,V$
$\mathcal{T}$	Set of time period $t \in 1,\dots,T$
$\mathcal{P}$	Set of food items $p \in 1,\dots,P$
$\mathcal{P}'$	Set of hot food items with short shelf-life $p \in 1,\dots,P'$
$\mathcal{P}''$	Set of cold food items with long shelf-life $p \in 1,\dots,P''$
$\mathcal{S}$	Set of scenarios $s \in 1,\dots,S$

Parameters:

f_l	Fixed setup cost of establishing a FB in location $l \in \mathcal{L}$
ψ_{lp}	Maximum distribution capacity of FB $l \in \mathcal{L}$ for food item $p \in \mathcal{P}$
$\tilde{d}_{cpts}$	Demand of charity $c \in \mathcal{C}$ for food item $p \in \mathcal{P}$ in period $t \in \mathcal{T}$ under scenario $s \in \mathcal{S}$
$\tilde{\sigma}_{ipts}$	Supply amount of donor $i \in \mathcal{I}$ for item $p \in \mathcal{P}$ in period $t \in \mathcal{T}$ under scenario $s \in \mathcal{S}$
o_{lp}	Operational cost of packaging and procuring food item $p \in \mathcal{P}$ in FB $l \in \mathcal{L}$
$h_{p''}$	Holding cost of food item $p'' \in \mathcal{P}''$
ϕ_l^L	Loading time of food items in FB $l \in \mathcal{L}$
ϕ_c^U	Unloading time of food baskets in delivery to charity $c \in \mathcal{C}$
$\delta_{nn'}$	Distance between locations $n, n' \in \mathcal{L} \cup \mathcal{I} \cup \mathcal{C} \cup \mathcal{J}$
g_v	Fixed cost of employing a vehicle $v \in \mathcal{V}$
ρ	Per kilometer transportation cost
λ	Average speed of vehicles
γ_v	Capacity of vehicle $v \in \mathcal{V}$
ω_{jpt}	Procuring cost of food item $p \in \mathcal{P}$ by financial donor $j \in \mathcal{J}$ in period $t \in \mathcal{T}$
b_{jt}	Budget for donation by financial donor $j \in \mathcal{J}$ in period $t \in \mathcal{T}$
ℓ_p	Shelf-life of food item $p \in \mathcal{P}$
κ_p	Nutritional value of the food item $p \in \mathcal{P}$
ζ_p	Volume of the unit pack of food item $p \in \mathcal{P}$
p_s	probability of scenario $s \in \mathcal{S}$
$\mathbf{M}$	a big number

Decision Variables:

W_{lpts}	Amount of food item p distributed by FB l in period t under scenario s
D_{lpts}	Amount of food item p collected by FB l in period t under scenario s
F_{jlpts}	Amount of food item p provided by financial donor j to FB l in period t under scenario s
G_{cpts}	Proportion of met demand for food item p in charity c at period t under scenario s
Γ_{lcvpts}	Freshness of food item p supplied by FB l and delivered by vehicle v at the moment of visiting charity c at period t under scenario s
$Q_{lp''ts}$	Inventory of food item p'' in FB l at period t under scenario s
U_{cvts}	Auxiliary variable for sub-tour elimination
E_{ivts}	Auxiliary variable for sub-tour elimination
$X_{nn'vts}$	Binary variable which equals 1 if vehicle v travels from location n to n' (both $\in \mathcal{L} \cup \mathcal{C}$) at period t under scenario s; 0, otherwise
$Y_{mm'vts}$	Binary variable which equals 1 if vehicle v travels from location m to m' (both $\in \mathcal{L} \cup \mathcal{I}$) at period t under scenario s; 0, otherwise
R_{lcvts}	Binary variable which equals 1 if charity c is assigned to FB l and visited by vehicle v in at period t under scenario s; 0, otherwise
S_{livts}	Binary variable which equals 1 if donor i is assigned to FB l and visited by vehicle v in at period t under scenario s; 0, otherwise
C_{jlvts}	Binary variable which equals 1 if vehicle v is employed to collect food from financial donor j at period t under scenario s; 0, otherwise
Z_l	Binary variable which equals 1 if a FB is set in location l; 0, otherwise
A_{vts}	Binary variable which equals 1 if vehicle v is employed to collect food from donors at period t under scenario s; 0, otherwise
B_{vts}	Binary variable which equals 1 if vehicle v is employed to distribute food to charities at period t under scenario s; 0, otherwise

As deciding on the location is a strategic and long-term decision, while routing-assignment-inventory decisions are day-to-day operational, summing these two may not be precise due to their scale. Thus, to facilitate their aggregation the rate of investment conversion factor shown in Eq. (1) is used to obtain the equivalent annual cost of the investment cost (FB location cost).

$$A = P\left[\frac{r(1+r)^{\mathbb{n}}}{(1+r)^{\mathbb{n}}-1}\right] \tag{1}$$

It is assumed that the nominal interest rate r is fixed over each year and considered as 20%. In the equation above, $\mathbb{n}$ is the planning horizon which is usually 20 years in such networks. To aggregate the equivalent annual cost of location with the operational costs, it should be projected on a daily scale. Thus, after plugging the investment return factor to P in (1), its annual equivalent, A, can be mapped to daily basis, A' by,

$$A' = \frac{A}{365} \quad \text{or,}$$

$$A' = P\tau, \quad \text{where } \tau = \left[\frac{r(1+r)^{\mathbb{n}}}{(1+r)^{\mathbb{n}}-1}\right]\frac{1}{365}. \tag{2}$$

The stochastic fuzzy mixed integer mathematical programming model developed for the problem is given in the following.

Objective Functions:

$$\begin{aligned}
&\text{Vehicle usage cost:} && \min Obj_1 = \Big\{ \textstyle\sum_t \sum_v \sum_s p_s g_v (A_{vts} + B_{vts}) \\
&\text{Collection transportation cost:} && + \textstyle\sum_n \sum_{n'} \sum_v \sum_t \sum_s p_s \rho \delta_{nn'} X_{nn'vts} \\
&\text{Collection financial donor cost:} && + \textstyle\sum_j \sum_l \sum_v \sum_t \sum_s p_s \rho \delta_{jl} C_{jlvts} \\
&\text{Distribution transportation cost:} && + \textstyle\sum_m \sum_{m'} \sum_v \sum_t \sum_s p_s \rho \delta_{mm'} Y_{mm'vts} \\
&\text{Packaging cost:} && + \textstyle\sum_l \sum_p \sum_t \sum_s p_s o_{lp} W_{lpts} \\
&\text{Storage costs:} && + \textstyle\sum_l \sum_{p''} \sum_t \sum_s p_s h_{p''} Q_{lp''ts} \\
&\text{location setup cost:} && + \textstyle\sum_l f_l \tau Z_l \\
& && \Big\}.
\end{aligned} \tag{3}$$

$$\max Obj_2 = \min_{v,p,t,c} \sum_l \sum_s p_s \Gamma_{lcvpts} \tag{4}$$

$$\max Obj_3 = \sum_l \sum_p \sum_t \sum_s p_s \kappa_p W_{lpts} \tag{5}$$

The objective function (3) minimizes the total cost of the network including vehicle costs, transportation, packaging and storing, and establishment of FBs. The second objective function in (4) maximizes the minimum freshness of the distributed food among all charities, and (5) maximizes the total nutritional value of all distributed foods as the third objective function.

Vehicle Routing constraints between FBs and Charities:

$$\sum_{v\in\mathcal{V}} \sum_{n\in\mathcal{C}\cup\mathcal{L}} X_{ncvts} = 1, \qquad \forall c\in\mathcal{C}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{6}$$

$$\sum_{\substack{n\in\mathcal{C}\cup\mathcal{L}\\ n\neq c}} X_{ncvts} = \sum_{\substack{n\in\mathcal{C}\cup\mathcal{L}\\ n\neq c}} X_{cnvts}, \qquad \forall v\in\mathcal{V}, c\in\mathcal{C}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{7}$$

$$\sum_{l\in\mathcal{L}} \sum_{c\in\mathcal{C}} X_{lcvts} \le 1, \qquad \forall v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{8}$$

$$\sum_{n\in\mathcal{C}\cup\mathcal{L}} \left(X_{lnvts} + X_{ncvts}\right) \le 1 + R_{lcvts}, \qquad \forall l\in\mathcal{L}, c\in\mathcal{C}, v\in\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{9}$$

$$U_{cvts} - U_{c'vts} + |C| X_{cc'vts} \le |C| - 1, \qquad \forall c, c'\in\mathcal{C}, v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{10}$$

Constraint (6) ensures that each charity is served by a vehicle, and (7) indicates that each vehicle should leave the charity after delivering the food. Constraint (8) indicates that there is at most one route for each vehicle and (9) forces the vehicle to return to the FB after visiting the charities. Constraint (10) avoids the creation of sub-tours in solutions based on Miller-Tucker-Zemlin formulation wherein the dummy variables $U_{....}$ keeps track of the order in which charities are visited [47].

Vehicle Routing constraints between donors and FBs:

$$\sum_{v\in\mathcal{V}} \sum_{m\in\mathcal{I}\cup\mathcal{L}} Y_{mivts} = 1, \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{11}$$

$$\sum_{\substack{m\in\mathcal{I}\cup\mathcal{L}\\ m\neq i}} Y_{mivts} = \sum_{\substack{m\in\mathcal{I}\cup\mathcal{L}\\ m\neq i}} Y_{imvts}, \qquad \forall v\in\mathcal{V}, i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{12}$$

$$\sum_{l\in\mathcal{L}} \sum_{i\in\mathcal{I}} Y_{livts} \le 1, \qquad \forall v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{13}$$

$$\sum_{m\in\mathcal{I}\cup\mathcal{L}} \left(Y_{lmvts} + Y_{mivts}\right) \le 1 + S_{livts}, \qquad \forall l\in\mathcal{L}, i\in\mathcal{I}, v\in\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{14}$$

$$E_{ivts} - E_{i'vts} + |I| Y_{ii'vts} \le |I| - 1, \qquad \forall i, i'\in\mathcal{I}, v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{15}$$

Constraint (11) ensures that each donor is visited by a vehicle, and (12) indicates that each vehicle should leave the donor after collecting the food. Constraint (13) indicates that there is at most one route for each vehicle and (14) forces the vehicle to return to the FB after visiting the donors. Constraint (15) avoids the creation of sub-tours in solutions for the upstream of the network. Similar to (10), MTZ formulation is used wherein the auxiliary variables $E_{....}$ control the sequence of visits between donors.

Flow balance equation between tiers:

$$W_{lpts} = \sum_{c\in C} \sum_{v\in\mathcal{V}} \tilde{d}_{cpts} G_{cpts} R_{lcvts}, \qquad \forall l\in\mathcal{L}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{16}$$

$$D_{lpts} = \sum_{i\in\mathcal{I}} \sum_{v\in\mathcal{V}} \tilde{\sigma}_{ipts} S_{livts}, \qquad \forall l\in\mathcal{L}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{17}$$

$$D_{lp'ts} + \sum_{j\in\mathcal{J}} F_{jlp'ts} = W_{lp'ts}, \qquad \forall l\in\mathcal{L}, p'\in\mathcal{P}', t\in\mathcal{T}, s\in\mathcal{S}, \tag{18}$$

$$D_{lp''ts} + \sum_{j\in\mathcal{J}} F_{jlp''ts} + Q_{lp'',t-1,s} - Q_{lp''ts} = W_{lp''ts}, \qquad \forall l\in\mathcal{L}, p''\in\mathcal{P}'', t\in\mathcal{T}, s\in\mathcal{S}, \tag{19}$$

Constraint (16) calculates the total distributed food, while (17) sums the total collected food. Eqs. (18) and (19) determines the amount of food with high and low shelf-life, respectively.

Vehicle capacity:

$$\sum_{c\in C} \sum_{l\in\mathcal{L}} \sum_{p\in\mathcal{P}} \zeta_p \tilde{d}_{cpts} G_{cpts} R_{lcvts} \le \gamma_v B_{vts}, \qquad v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{20}$$

$$\sum_{i\in\mathcal{I}} \sum_{l\in\mathcal{L}} \sum_{p\in\mathcal{P}} \zeta_p \tilde{\sigma}_{ipts} S_{livts} \le \gamma_v A_{vts}, \qquad v\in\mathcal{V}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{21}$$

$$\sum_{p\in\mathcal{P}} \zeta_p F_{jlpts} \le \sum_{v\in\mathcal{V}} \gamma_v C_{jlvts}, \qquad j\in\mathcal{J}, l\in\mathcal{L}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{22}$$

Constraints (20), (21) and (22) impose the vehicle capacity in distributing food among charities, collecting food from donors, and financial donors, respectively.

Food bank capacity:

$$W_{lpts} \le \psi_{lp} Z_l, \qquad l\in\mathcal{L}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{23}$$

$$D_{lpts} \le \psi_{lp} Z_l, \qquad l\in\mathcal{L}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{24}$$

Constraints (23) and (24) impose the capacity limitations of FBs in the distribution and collection of food items, respectively.

Budget balance of financial donors:

$$\sum_{l\in\mathcal{L}}\sum_{p\in\mathcal{P}}\omega_{jpt}F_{jlpts} \le b_{jt} + \sum_{t'<t}\left(b_{jt'} - \sum_{l\in\mathcal{L}}\sum_{p\in\mathcal{P}}\omega_{jpt'}F_{jlpt's}\right), \quad j\in\mathcal{J}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{25}$$

Constraint (25) ensures that the total purchased food by financial donors does not exceed their budget. The LHS of the constraint corresponds to the total spending on food items at each period, while the RHS sums the available budgets of that period with the total surplus of budgets from previous periods.

Food freshness:

$$\Gamma_{lcvpts} \le 100\exp\left(-\frac{\frac{\delta_{lc}}{\lambda} + \phi_l^L + \phi_c^U}{\ell_p}\right) + \mathbf{M}(2 - X_{lcvts} - R_{lcvts}), \quad l\in\mathcal{L}, c\in\mathcal{C}, v\in\mathcal{V}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{26}$$

$$\Gamma_{lc'vpts} \le \Gamma_{lcvpts}\exp\left(-\frac{\frac{\delta_{cc'}}{\lambda} + \phi_{c'}^U}{\ell_p}\right) + \mathbf{M}(2 - X_{cc'vts} - R_{lc'vts}), \quad l\in\mathcal{L}, c, c'\in\mathcal{C}, v\in\mathcal{V}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{27}$$

As shown in Fig. 1, the freshness of food items follows an exponential function of time, which is calibrated by 100 as the coefficient and inverse of the shelf-life in the exponent (i.e., $100e^{-t/\ell_p}$). Thus, Constraint (26) determines the freshness of foods in the first visited charity in the route of the assigned vehicle, whereas (27) helps to calculate the freshness in all subsequently visited charities. Note that these constraints are linear as the arguments of the exponential function are all parameters. To clarify the logic behind this formulation, consider the nonlinear counterpart of the freshness equation in two nodes. Let t_i and t_j be the delivery time of the food in locations i and j and Γ^i and Γ^j be their corresponding freshness. Thus,

$$\Gamma^i = 100\exp(-t_i/\ell_p), \tag{28}$$

$$\Gamma^j = 100\exp(-t_j/\ell_p). \tag{29}$$

If node j is visited immediately after i, then $t_j = t_i + \frac{\delta_{ij}}{\lambda} + \phi_j^U$. Plugging this into (29) with simple algebra will provide the relation between freshness values at node j and node i as,

$$\Gamma^j = \Gamma^i * \exp(\frac{\delta_{ij}}{\lambda} + \phi_j^U). \tag{30}$$

This key relation helps to avoid nonlinear constraints once the first visit is considered as in (26) and then (27) rests on the relation unfolded in (30).

Variables type and domain:

$$R_{lcvt}, S_{licvts}, X_{nn'vts}, Y_{mm'vts}, Z_l, A_{vts}, C_{jlvts} \in \{0,1\}, \quad l\in\mathcal{L}, c\in\mathcal{C}, v\in\mathcal{V}, i\in\mathcal{I}, n,n'\in\mathcal{C}\cup\mathcal{L}, m,m'\in\mathcal{I}\cup\mathcal{L}, j\in\mathcal{J}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{31}$$

$$W_{lpts}, D_{lpts}, F_{jlp'ts}, Q_{lp''ts} \in \mathbb{Z}^+, \quad l\in\mathcal{L}, p'\in\mathcal{P}', p''\in\mathcal{P}'', p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}, \tag{32}$$

$$\Gamma_{lcvpts}, U_{cvts}, E_{ivts}, G_{cpts} \in \mathbb{R}^+, \quad l\in\mathcal{L}, c\in\mathcal{C}, i\in\mathcal{I}, v\in\mathcal{V}, p\in\mathcal{P}, t\in\mathcal{T}, s\in\mathcal{S}. \tag{33}$$

3.1. Linearization of the model

The mathematical model above is nonlinear due to the constraints (4), (16), and (20). The first one is straightforward to linearize as given below for the generic form:

$$\left\{\begin{array}{l} \max Z = \min X \\ \text{s.t.} \\ aX \le b, \\ X \ge 0, \end{array}\right. \iff \left\{\begin{array}{l} \max Z = w \\ \text{s.t.} \\ aX \le b, \\ w \le X, \quad X \ge 0. \end{array}\right. \tag{34}$$

The other two have a multiplication of a binary variable by a continuous one, which in a generic form can be linearized as follows.

$$\left\{\begin{array}{l} \max Z = \min XY \\ \text{s.t.} \\ Y \in \{0,1\}, \\ X \ge 0, \end{array}\right. \iff \left\{\begin{array}{l} \max Z = w \\ \text{s.t.} \\ w \le X, \\ w \le \mathbf{M}Y, \\ w \ge X - \mathbf{M}(1-Y), \\ Y \in \{0,1\}, \\ w, X \ge 0. \end{array}\right. \tag{35}$$

3.2. Robust Fuzzy stochastic model for uncertainty

The supply and demand parameters are uncertain and considered as trapezoidal fuzzy numbers in different scenarios. To deal with these uncertainties a robust fuzzy stochastic programming model is used based on the following generic model [48]. The robust fuzzy stochastic model is a powerful tool for addressing uncertainty in supply network design. By combining the strengths of fuzzy, stochastic, and robust methodologies, it provides a flexible and resilient framework capable of handling diverse sources of uncertainty. This integration ensures that the model not only captures parameter imprecision and scenario variability but also safeguards against extreme risks, making it an indispensable approach for modern supply chain challenges. The generic formulation is shown as,

$$\left\{\begin{array}{l} \text{Base model} \\ \max Z = fY + p_s cX_s \\ \text{s.t.} \\ aX_s \ge \tilde{d}_s, \\ eX_s \le \tilde{s}_s Y, \\ Y \in \{0,1\}, X_s \ge 0, \end{array}\right. \Rightarrow \left\{\begin{array}{l} \text{Pessimistic fuzzy basic model} \\ \max Z = fY + p_s cX_s \\ \text{s.t.} \\ NEC\{aX_s \ge \tilde{d}_s\} \ge \alpha_s, \\ NEC\{eX_s \le \tilde{s}_s Y\} \ge \beta_s, \\ Y \in \{0,1\}, X_s \ge 0, \end{array}\right. \Rightarrow \left\{\begin{array}{l} \text{Pessimistic fuzzy model script} \\ \max Z = fY + p_s cX_s \\ \text{s.t.} \\ aX_s \ge (1-\alpha_s)d_s^3 + \alpha_s d_s^4, \\ eX_s \le ((1-\beta_s)s_s^2 + \beta_s s_s^1)Y, \\ Y \in \{0,1\}, X_s \ge 0, \end{array}\right. \tag{36}$$

where vectors f, c, $\tilde{d}_s$, and $\tilde{s}_s$ are corresponding to the fixed setup costs, variable costs, demand, and supply, respectively. Denoted by a and e are the coefficient matrices, while X_s and Y are associated with the continuous and binary variables under scenario s. The uncertainty rate of the model is determined by α_s and β_s as in chance-constrained models a minimum confidence level should be defined for them to hold.

In the presented models, the objective function is not sensitive to its deviation from its desired level. Therefore, attaining robust solutions is not guaranteed via the base model in (36). In such situations, a high level of risk is imposed on the decision-makers, particularly in strategic decisions. Thus, to overcome this high-risk situation, the robust counterpart of this fuzzy stochastic model can be employed which differentiates it from other programming approaches for uncertainty.

That is,

$$\min Z = fY + p_s c X_s + \eta_1 \sum_s p_s \left[d_s^4 - \frac{(\alpha_s - \theta) d_s^4 + (1-\alpha_s) d_s^3}{1-\theta} \right] + \eta_2 \sum_s p_s \left[\frac{(\beta_s Y - \theta) s_s^1 + (Y - \beta_s Y) s_s^2}{1-\theta} - s_s^1 Y \right] \tag{37}$$

s.t.

$$aX_s \geq (1-\alpha_s) d_s^3 + \alpha_s d_s^4, \tag{38}$$

$$eX_s \leq \left((1-\beta_s) s_s^2 + \beta_s s_s^1 \right) Y, \tag{39}$$

$$Y \in \{0,1\}, \quad X_s \geq 0. \tag{40}$$

In the objective (37), the first two terms refer to the expected value of the first objective under the stochastic assumption. The third and fourth expressions correspond to the penalty for deviations from the demand and supply. Thus, η_1 is the penalty factor for unmet demand, while η_2 is the penalty factor for supply surplus. The robust-possiblistic adjustment factor is denoted by θ. Applying the above-stated generic models to our FB network model will result in the following.

$$\begin{aligned} \min Obj_1 = & \sum_t \sum_v \sum_s p_s g_v (A_{vts} + B_{vts}) + \sum_n \sum_{n'} \sum_v \sum_t \sum_s p_s \rho \delta_{nn'} X_{nn'vts} \\ & + \sum_j \sum_l \sum_v \sum_t \sum_s p_s \rho \delta_{jl} C_{jlvts} + \sum_m \sum_{m'} \sum_v \sum_t \sum_s p_s \rho \delta_{mm'} Y_{mm'vts} \\ & + \sum_l \sum_p \sum_t \sum_s p_s o_{lp} W_{lpts} + \sum_l \sum_{p''} \sum_t \sum_s p_s h_{p''} Q_{lp''ts} + \sum_l f_l \tau Z_l \\ & + \eta_1 \sum_c \sum_p \sum_t \sum_s p_s \left[d_{cpts}^4 - \frac{(\alpha_s - \theta) d_{cpts}^4 + (1-\alpha_s) d_{cpts}^3}{1-\theta} \right] \\ & + \eta_2 \sum_i \sum_p \sum_t \sum_s p_s \left[\frac{(\beta_s - \theta) \sigma_{ipts}^1 + (1-\beta_s) \sigma_{ipts}^2}{1-\theta} - \sigma_{ipts}^1 \right] \end{aligned} \tag{41}$$

$$\max Obj_2 = \mathcal{X} \tag{42}$$

$$\max Obj_3 = \sum_l \sum_p \sum_t \sum_s p_s \kappa_p W_{lpts} \qquad \text{[the same as (5)]}$$

s.t.

$$\mathcal{X} \leq \sum_l \sum_s p_s \Gamma_{lcvpts}, \qquad c \in \mathcal{C}, v \in \mathcal{V}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{43}$$

$$GR_{lcvpts} \leq G_{cpts}, \qquad l \in \mathcal{L}, c \in \mathcal{C}, v \in \mathcal{V}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{44}$$

$$GR_{lcvpts} \leq R_{lcvts}, \qquad l \in \mathcal{L}, c \in \mathcal{C}, v \in \mathcal{V}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{45}$$

$$GR_{lcvpts} \geq G_{cpts} - (1 - R_{lcvts}), \qquad l \in \mathcal{L}, c \in \mathcal{C}, v \in \mathcal{V}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{46}$$

$$W_{lpts} = \sum_c \sum_v \left[(1-\alpha_s) d_{cpts}^3 + \alpha_s d_{cpts}^4 \right] GR_{lsvpts}, \qquad c \in \mathcal{C}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{47}$$

$$D_{lpts} = \sum_i \sum_v \left[(1-\beta_s) \sigma_{ipts}^2 + \beta_s \sigma_{ipts}^1 \right] S_{livts} \qquad l \in \mathcal{L}, p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{48}$$

$$\sum_i \sum_l \sum_p \zeta_p \left[(1-\beta_s) \sigma_{ipts}^2 + \beta_s \sigma_{ipts}^1 \right] S_{livts} \leq \gamma_v A_{vts}, \qquad v \in \mathcal{V}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{49}$$

$$\sum_c \sum_l \sum_p \zeta_p \left[(1-\alpha_s) d_{cpts}^3 + \alpha_s d_{cpts}^4 \right] GR_{lcpvts} \leq \gamma_v B_{vts}, \qquad v \in \mathcal{V}, t \in \mathcal{T}, s \in \mathcal{S}, \tag{50}$$

(11)–(15), (18), (19), (22)–(33).

Constraint (43) is the application of (34) to linearize the max–min function, while (44)–(46) translates (35) to the model's variables. Constraints (47)–(50) are the robust possiblistic counterparts of (16)–(17) and (20)–(21).

4. Solution methods and evaluation metrics

This section presents several algorithms to solve the problem at hand. Among them are augmented ϵ-constraint, NSGA II, MOGWO, and a novel hybrid one. Due to a combination of location, assignment, and routing decisions the problem is as difficult as each of them. The literature review shows that NSGA II and MOGWO algorithms are widely used in location-routing [49,50], machine scheduling [51], flight scheduling [52] and other problems. Each of these algorithms has strengths in searching the feasible solution region. Zhao et al. [53] state that it is the most popular multi-objective evolutionary algorithm. According to Rahimi et al. [54] advantages of NSGA II are:

- It has a lower computational cost due to non-dominated sorting.
- It is less sensitive to parameters and therefore, it is more used in real-life problems.
- It holds a good balance between elitism and diversity, and this avoids premature convergence.

Similarly, Makhadmeh et al. [55] have stated the following advantages for MOGWO:

- It reduces the computational cost by its dynamic behavior in searching the solution space.
- It searches optimal solutions fast thanks to its dynamic design.
- It has a high capability is storing non-dominant solutions.

Here, in addition to NSGA II and MOGWO algorithms, a novel hybrid algorithm is developed. We call this algorithm *MOGGWA (Multi-Objective Genetic Gray Wolf Algorithm)*. In the rest of this section first, the construction of an initial solution and its encoding is explained, and then the pseudo-code of all solution methods is presented.

4.1. Initial solution

As illustrated in Fig. 3, an initial solution for the problem comprises a $2 \times (|S|.|T|.|P|.(|I|+|J|+|V|+|C|+|L|))$ matrix corresponding to the decision variable. The first row represents labels of charities, FBs, food donors, financial donors, and vehicles while the second row includes random numbers from $[0,1]$ indicating their associated priorities to be selected. This figure shows an example with 4 charities, 3 FBs, 5 donors (3 food and 2 financial), and a fleet size of 4 with 1 period and 1 food item under a single scenario. The illustrated pattern repeats as many times as the time horizon and number of food items for each scenario. Algorithm 1 depicts how such an encoded solution can be decoded.

4.2. Augmented ϵ-constraint

This method uses a lexicographic approach to obtain each objective value and converts all the constraints related to the other objectives to equality constraints using auxiliary variables. In the lexicographic method, the objective functions are sorted based on their importance stated by the decision-maker. First, the objective function with the highest priority, $f_1(x)$, is optimized to obtain its objective value f^*. Then, by adding a constraint $f_1(x) = f^*$, the objective value of the first objective is preserved, and the second objective function is optimized. These steps are summarized for our problem in Algorithm 2.

Algorithm 1 Decoding a heuristic encoded solution

```
Input: Sets, parameters.
Output: Assignments, routes, and objective values.
for s = 1 to S do
    for t = 1 to T do
        for p = 1 to P do

            //Decoding First Stage (Food Banks-Charities):
            Step 1- Select the highest value among FBs as a located FB
            Step 2- Select the highest value among vehicles as a selected vehicle
            Step 3- Select the highest value among charities as thefirst visited charity
            Step 4- Form a tour with the following conditions:
            if capacity of selected FB less than total selected charities demand then
                if capacity of selected vehicle less than total selected charities demand then
                    Visit next highest value among charities
                    Decrease the highest value among charities to zero.
                    Decrease the highest value among vehicles to zero.
                    Decrease the highest value among FBs to zero.
                else
                    repeat steps 2 to 4
                end if
            else
                repeat steps 1 to 4
            end if

            //Decoding second Stage (Food Donors-Food Banks):
            Step 1- Select the highest value among FBs as a located FB
            Step 2- Select the highest value among vehicles as a selected vehicle
            Step 3- Select the highest value among food donors as the first visited donor
            Step 4- Form a tour with the following conditions:
            if capacity of selected FB less than total selected donors then
                if capacity of selected vehicle less than total selected donors supply then
                    Visit the next highest value among food donors
                    Decrease the highest value among food donors to zero.
                    Decrease the highest value among vehicles to zero.
                    Decrease the highest value among FBs to zero.
                else
                    repeat steps 2 to 4
                end if
            else
                repeat steps 1 to 4
            end if

            //Decoding third Stage (Financial Donors-Inventory)
            if Total demand less than total supply then
                Select the highest value among FBs as a located FB
                Calculate the difference between total supply and demand at the selected FB
                Assign the value of Step 2 as a food inventory
            else
                Select the highest value among financial donors as a located donor
                Calculate the amount of donated food according to the budget of each period
            end if

            //Decoding forth Stage (Constraints)
            Check the all constraints
            if a constraint is not satisfied then
                Add a violation to objective F_1
            end if
        end for
    end for
end for

    //Decoding fifth Stage (Objectives)
Calculate the objective functions
```

4.3. NSGA II

This evolutionary algorithm was first developed by Deb et al. [56] to rectify the weaknesses of other algorithms which are weak in elitism and use shared parameters to keep the diverse Pareto sets. NSGA II uses crossover and mutation operators to generate a new generation as shown in Figs. 4 and 5. Its pseudo-code is given in Algorithm 3.

Algorithm 2 Pseudo-code of augmented ϵ-constraint

Input: formulae of F_1, F_2, F_3, g.
Output: A set of solutions

1. Select F_1 with the highest priority and determining its optimal value
2. Form a lexicographic payoff table (best and worst objective values).
3. Define s_2,s_3 as auxiliary variables.
4. calculate r_2,r_3 as the range of variations F_2 and F_3
5. Define δ as an adequately small number
6. **for** $i = 1$ to $g-1$ **do**
7. $\quad \epsilon_2 = \frac{r_2}{g}, \quad \epsilon_3 = \frac{r_2}{g}$
8. $\quad$ solve $F_1+\delta(\frac{s_2}{r_2}+\frac{s_3}{r_3})$ s.t. $F_2-s_2=\epsilon_2$, $F_3-s_3=\epsilon_3$ and constraints (6)–(33).
9. **end for**

4.4. MOGWO

MOGWO is a heuristic algorithm inspired by nature imitating the hierarchical leading behavior of gray wolves [57]. In this algorithm, solutions are classified into group Alpha, Beta, and Delta according to the group hunting method of gray wolves. Alpha is the leader wolf, Beta is probably the best alternative for Alpha playing the deputy role, and Delta wolves follow them both. With this proxy, the best solutions are the leading Alphas. It is depicted in Algorithm 4.

Algorithm 3 Pseudo-code of NSGA II

```
Input: Parameters, Npop, p_c, p_m, MaxIt
Output: solution
Generate initial population based on Algorithm 1
Evaluate objective values for each initial solution
Rank based on Pareto dominance
for i = 1 to MaxIt do
    for j = 1 to Npop do
        Select two individuals as selected children
        Perform 2-point crossover operation [shown in Fig. 4]
    end for
    for j = 1 to Npop do
        Select an individual as the selected child
        Perform 1-point mutation operation [shown in Fig. 5]
    end for
    Repair new population based on combining offspring and parents
    Reassign Rank based on Pareto dominance
    Calculate the crowded distance
    Select the best individual-based Rank and crowded distance
end for
```

4.5. MOGGWA

In this new novel hybrid algorithm proposed here, to benefit from the strength of both NSGA II and MOGWO in addition to determining the position of the solutions corresponding to gray wolves the two 2-point crossover and 1-point mutation operators are also employed. The pseudo-code is given in Algorithm 5.

Charities				Food Banks			Food Donors			Financial Donors		Vehicles			
1	2	3	4	1	2	3	1	2	3	1	2	1	2	3	4
0.34	0.68	0.16	0.25	0.44	0.91	0.27	0.27	0.18	0.32	0.47	0.33	0.2	0.74	0.29	0.34

Fig. 3. Encoding the initial solution.

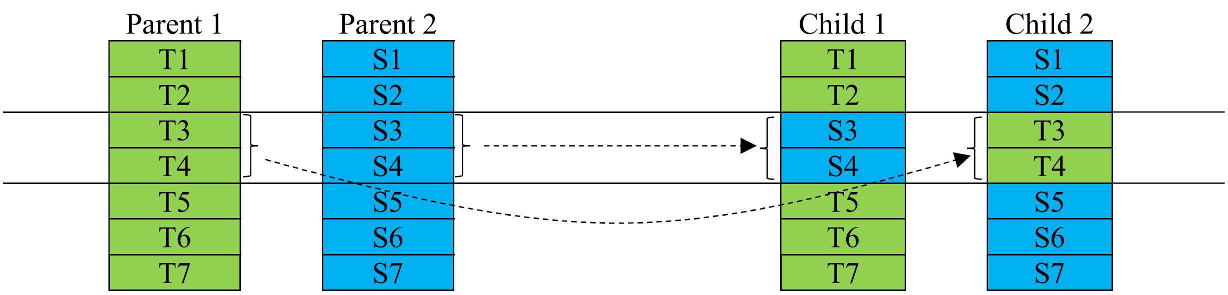

Fig. 4. Illustration of the 2-point crossover operator.

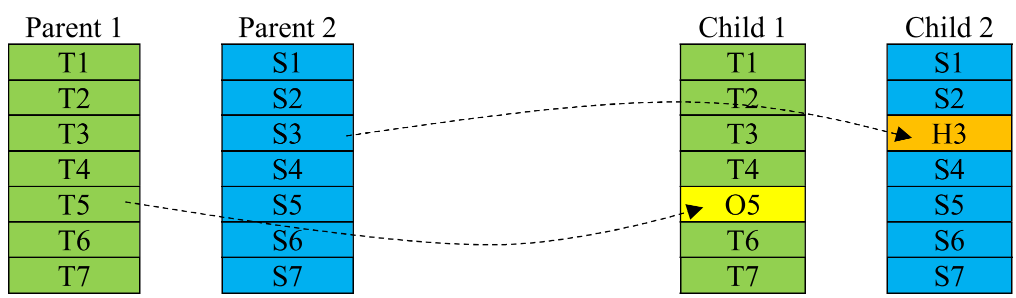

Fig. 5. Illustration of the 1-point mutation operator.

Algorithm 4 Pseudo-code of MOGWO

Input: Parameters, $Npop, A, C, MaxIt$
Output: solution

Generate initial population based on Algorithm 1
Evaluate objective values for each initial solution
Define $X_\alpha, X_\beta, X_\delta$ as the best, second best and third best solutions
Assign Rank based on Pareto dominance sort
for $i = 1$ to *MaxIt* **do**
  for $j = 1$ to $Npop$ **do**
    Update the position of the current solution:
    $\vec{D} = |\vec{C}.\vec{X}_p(i) - \vec{X}(i)|; |\vec{X}(i+1) = \vec{X}(i) - \vec{A}.\vec{D}|$
    $\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a}$; $\vec{C} = 2\vec{r}_2$
    $\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}|$, $\vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|$, $\vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}|$
    $\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha$, $\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta$, $\vec{X}_3 = \vec{X}_\beta - \vec{A}_3.\vec{D}_\delta$
    $\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3}$
  end for
  Update A, C
  Calculate the objective values for each new solution
  Do fast Non-dominated sorting
  Update $X_\alpha, X_\beta, X_\delta$
end for

4.6. Evaluation criteria of solutions

The efficient solutions obtained by different algorithms for a multi-objective problem are likely to differ. Therefore, they can be compared from multiple aspects. Table 2 summarizes some of the well-known metrics to evaluate those solutions that we have used in the next section.

5. Numerical study and evaluation

For validation and preliminary assessment of the model, first, a small instance of the problem is used. Then, real-life problem sizes are used to evaluate the performance of our algorithms.

5.1. Small instances

The small instance of the problem is constructed with (4 donors, 3 financial donors, 5 charities, 3 FB, 6 vehicles, 2 hot meals, 1 cold meal, and 2 periods under 2 scenarios) and all the parameters are set according to Table 3. By evaluating the solutions of small problem instances with the AEC method, 9 efficient ones are identified as listed in Table 4. As shown in this table, as the second objective value (minimum freshness of the distributed food) increases (worsens), the first objective function (total cost of the network) also increases (improves) which indicates their conflicting nature. Inspection of the solutions shows that this increase in cost is due to the rising fleet size for the distribution of food to charities. It is also observed that the total network cost increases as the third objective (nutritional value of the food) increases, implying another trade-off between the first and third objectives as they are desired to be minimized and maximized, respectively. This is due to the rising value of the distributed foods. This happens when financial donors procure more food items and therefore, the shortage of food in charities decreases. The second and third objective functions change in the same direction without necessarily showing a conflicting pattern.

To depict the decisions suggested by the model the efficient Solution #9 is decoded in Tables 5 and 6 while the freshness of its distributed foods is depicted in Fig. 6.

Table 2
Comparison metrics for efficient solutions.

Metric	Formula	Interpretation
Number of Pareto Front [58]	NPF	A higher value is better
Maximum Spread Index [59]	$MS = \sqrt{\sum_{k=1}^{K} \left(f_k^{max} - f_k^{min}\right)^2}$	A higher value is better
Space Metric [60]	$SM = \frac{\sum_{i=1}^{K-1} \lvert\bar{d}-d_i\rvert}{(K-1)\bar{d}}$ where $d_i = \min_{\substack{j=1,\ldots,n \\ j\neq i}} \left\{ \sum_{k=1}^{K} \lvert f_k^i - f_k^j \rvert \right\}, \forall i$	A lower value is better
Mean ideal Deviations [61]	$MID = \frac{\sum_{k=1}^{K} \sqrt{\sum_{i=1}^{n} (f_k^i - f_k^*)^2}}{K}$	A lower value is better
CPU time	CPT	A lower value is better

Table 3
Parameters for the small instance.

Parameter	Value	Parameter	Value	Parameter	Value
f_1	$\sim U(100000, 200000)$	ϕ_l^L, ϕ_c^U	$\sim U(0.01, 0.03)$	g_v	$\sim U(500, 1000)$
δ_{kl}	$\sim U(10, 30)$	κ_p	$\sim U(5, 8)$	$h_{p''}$	$\sim U(0.2, 0.5)$
ω_{jpt}	$\sim U(1, 5)$	γ_v	$\sim U(80, 120)$	ψ_{lp}	$\sim U(100, 150)$
ℓ_p	$\sim U(1, 10)$	o_{lp}	$\sim U(2, 3)$	ρ	$\sim U(2, 5)$
α_s, β_s	0.5	ζ_p	$\sim U(1, 2)$	η_1, η_2	2
b_{jt}	5000	λ	$\sim U(40, 60)$	p_s	0.5
r	0.2	θ	0.1		
$\tilde{d}_{cpts}$	$\sim U([10, 15], [15, 20], [20, 25], [25, 30]). \frac{1.2s}{\lvert S\rvert}$		$\tilde{\sigma}_{cpts}$	$\sim ([15, 18], [18, 20], [20, 22], [22, 25]). \frac{1.2s}{\lvert S\rvert}$	

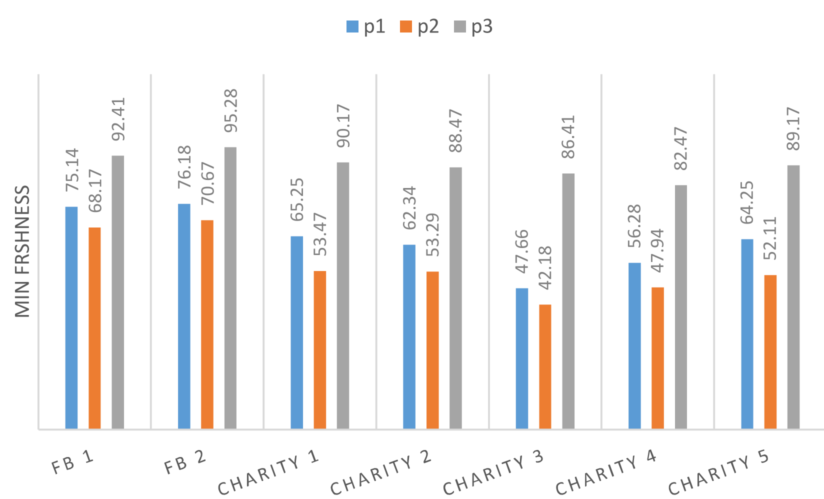

Fig. 6. Freshness of distributed food corresponding to efficient Solution #9.

Table 4
The efficient solutions obtained from the numerical example with AEC.

Soln.#	F_1	F_2	F_3
1	172 094.28	36.12	2527.48
2	179 801.75	37.58	2551.46
3	183 028.25	37.58	2566.15
4	188 647.89	39.23	2618.56
5	190 119.89	39.23	2622.21
6	191 783.15	40.84	2643.85
7	193 004.37	41.21	2659.22
8	207 432.77	43.33	2696.81
9	211 814.89	45.94	2724.54

In this numerical example, the uncertainty parameter was set as $\alpha_s = \beta_s = 0.5$. However, it can be changed within the interval from 0 (optimistic) to 1 (pessimistic). The next subsection provides such a sensitivity analysis.

5.1.1. Sensitivity to uncertainty level

Table 7 shows the changes in objective functions for different uncertainty levels. As shown, with the increase of supply and demand uncertainty the total demand in the network rises which is met by financial donors. Thus, more vehicles for collection and distribution are needed which justifies the upturn of transportation cost and freshness of distributed foods. The increase in nutritional value of distributed foods in this case might be surprising but it occurs due to the more purposeful donations from the financial donors.

5.1.2. Sensitivity to robustness parameter

The other influencing factors in the network management are penalty coefficients corresponding to the robustness: η_1 for unmet demand, and η_2 for excess supply. Fig. 7 illustrates the changes in objective functions against three levels of robustness parameters. It can be observed that with an increase in penalty coefficients, the total network cost increases as the model tries to avoid shortage. This in turn leads to a change in freshness due to a change of routes for collection and distribution, and a minor increase in demand results

Table 5
Decisions based on allocation- routing in the efficient Solution #9.

Vehicle routing for the food collection		Vehicle routing for the food distribution	
Period 1	Period 2	Period 1	Period 2
Scenario 1		Scenario 1	
$l_1 \to i_1 \to i_3 \to l_1$ by v_3	$l_1 \to i_1 \to i_3 \to l_1$ by v_2	$l_1 \to c_2 \to c_4 \to l_1$ by v_3	$l_1 \to c_2 \to c_4 \to l_1$ by v_3
$l_3 \to i_4 \to i_2 \to l_3$ by v_4	$l_3 \to i_4 \to i_2 \to l_3$ by v_4	$l_1 \to c_5 \to l_1$ by v_2	$l_1 \to c_5 \to l_1$ by v_2
$j_1 \to l_1$ by v_2	$j_1 \to l_1$ by v_3	$l_3 \to c_1 \to c_3 \to l_3$ by v_1	$l_3 \to c_1 \to c_3 \to l_3$ by v_4
Scenario 2		Scenario 2	
$l_1 \to i_1 \to i_4 \to l_1$ by v_1	$l_1 \to i_1 \to i_4 \to l_1$ by v_1	$l_1 \to c_2 \to l_1$ by v_2	$l_1 \to c_2 \to l_1$ by v_2
$l_3 \to i_3 \to i_2 \to l_3$ by v_4	$l_3 \to i_3 \to i_2 \to l_3$ by v_4	$l_1 \to c_5 \to c_4 \to l_1$ by v_3	$l_1 \to c_5 \to c_4 \to l_1$ by v_3
$j_3 \to l_1$ by v_2	$j_3 \to l_3$ by v_2	$l_3 \to c_1 \to c_3 \to l_3$ by v_1	$l_3 \to c_1 \to c_3 \to l_3$ by v_4

Table 6
Amount of food distribution and collection by each FB in the efficient Solution # 9.

Food bank	Period	Total distributed	Total collected	Total distributed	Total collected
		Scenario 1		Scenario 1	
		$(p_1 - p_2 - p_3)$	$(p_1 - p_2 - p_3)$	$(p_1 - p_2 - p_3)$	$(p_1 - p_2 - p_3)$
l_1	1	35–50–28	37–42–30	30–30–15	38–40–25
	2	19–20–30	21–26–25	42–37–19	17–18–45
l_3	1	30–38–36	35–35–39	29–38–40	35–38–37
	2	29–51–43	46–51–43	53–59–48	55–59–48

Table 7
Comparison of the objective values under different uncertainty rates.

$\alpha_s = \beta_s$	F_1	F_2	F_3
0.1	198 563.47	43.24	2659.34
0.2	200 498.66	43.24	2686.57
0.3	205 487.39	43.24	2700.67
0.4	209 478.21	45.94	2712.25
0.5	211 814.89	45.94	2724.54
0.6	216 437.43	45.94	2733.28
0.7	220 745.92	45.95	2751.64
0.8	225 487.69	48.34	2779.16
0.9	231 478.24	48.34	2817.64

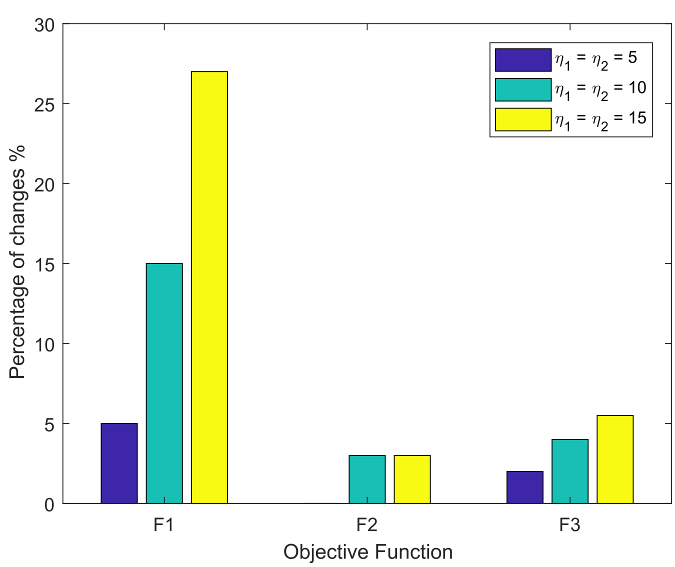

Fig. 7. Effect of penalty coefficients on the objective values.

in total nutritional value. In summary with the increase of penalty coefficient from 2 (default value) to 15, the first, second, and third objective functions have increased by 26.72%, 2.63%, and 5.16%, respectively.

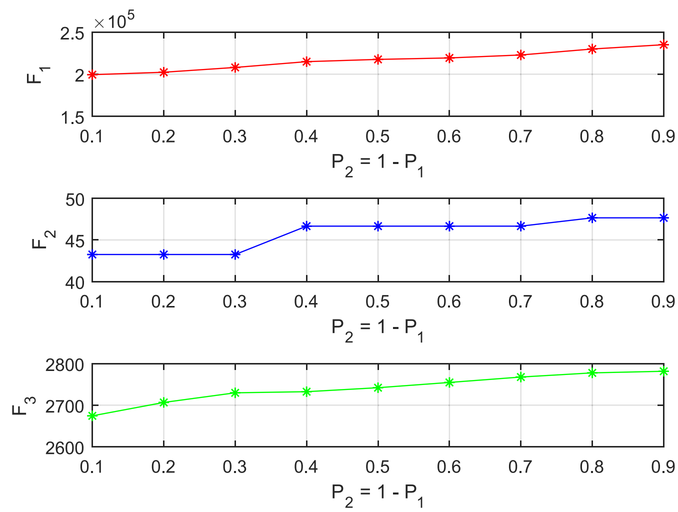

Fig. 8. Changes in the value of the objective functions in different scenarios.

5.1.3. Sensitivity to supply–demand probabilities

As demand and supply are the main driving factors in decisions, it is worthwhile conducting a sensitivity analysis regarding the decline or rise of supply or demand in different scenarios. According to the last row of Table 3, the scenario with a smaller index has lower demand and supply while their probabilities were equal (both 0.50) in the numerical example above. The sensitivity of objective values to the probability of Scenario 1, p_1, (or equivalently Scenario 2, $p_2 = 1 - p_1$) is presented in Fig. 8. As shown, when the probability of Scenario 2 is higher i.e., when it is more likely to have higher supply and demand, based on our parameter, the total cost increases. Freshness and nutritional values improve, which could be due to a lower capacity of the vehicles with respect to demand. This necessitates more frequent trips with additional vehicles (less transit time), and more planned food choices from financial donors.

Algorithm 5 Pseudo-code of MOGGWA

Input: Parameters, $Npop, p_c, p_m, A, C, MaxIt$
Output: solution

```
Generate initial population based on Algorithm 1
Evaluate objective values for each initial solution
Define X_α, X_β, X_δ as the best, second best, and third best solutions
Assign Rank based on Pareto dominance sort
for i = 1 to MaxIt do
    for j = 1 to Npop do
        Update the position of the current solution:
        D = |C.X_p(i) − X(i)|;|X(i + 1) = X(i) − A.D|
        A = 2a.r_1 − a; C = 2r_2
        D_α = |C_1.X_α − X|, D_β = |C_2.X_β − X|, D_δ = |C_3.X_δ − X|
        X_1 = X_α − A_1.D_α, X_2 = X_β − A_2.D_β, X_3 = X_β − A_3.D_δ
        X(t + 1) = (X_1 + X_2 + X_3)/3
        Select two individuals based on selected wolves and perform a 2-point crossover
        Select an individual as a selected child and perform 1-pint mutation operator
    end for
    Update A, C
    Repair new population based on combining offspring and parents
    Reassign Rank based on Pareto dominance sort
    Calculate the crowded distance
    Select the X_α based on rank and crowded distance
    Update X_α, X_β, X_δ
end for
```

Where the listing's vectors are: $\vec{D} = |\vec{C}.\vec{X}_p(i) - \vec{X}(i)|;|\vec{X}(i+1) = \vec{X}(i) - \vec{A}.\vec{D}|$; $\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a}$; $\vec{C} = 2\vec{r}_2$; $\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}|$, $\vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|$, $\vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}|$; $\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha$, $\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta$, $\vec{X}_3 = \vec{X}_\beta - \vec{A}_3.\vec{D}_\delta$; $\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3}$

Table 8
EVPI for supply and demand uncertainties.

Parameter	Index	F_1	F_2	F_3
Supply	SP	190 826.6	42.12	2633.18
	WS	192 367.3	43.18	2652.81
	EVPI	1540.64	1.06	19.63
Demand	SP	190 248.7	42.84	2637.26
	WS	192 284.6	44.12	2663.86
	EVPI	2035.93	1.28	26.6

5.1.4. The value of stochastic programming

The two measures mainly used for assessing the benefit of stochastic modeling are *Expected value of perfect information* (EVPI) and *Value of the Stochastic Solution* (VSS). EVPI is calculated as a difference between stochastic and *wait-and-see* (WS) solutions, and it shows how valuable it is to know the future. Considering probability distributions of supply and demand in the network, EVPI is obtained by calculating the difference between expected value solutions and stochastic solutions ($EVPI = WS - SP$). That is, the stochastic problem is solved for each scenario separately. Then using the probability of each scenario, their weighted average is computed, which represents WS.

Table 8 summarizes SP, WS, and EVPI for all three objectives separately. As depicted, the uncertainty in demand has a greater impact on the food network. Numerically speaking, the demand information is about 30% more valuable to know in advance than the supply information.

The difference between the solution obtained from the deterministic equivalent of the problem (EV) and the stochastic solution determines the VSS measures. Considering supply and demand as the first and second-stage uncertainties, the expected value of using the EV solution (EEV) can be calculated. The higher level of this measure indicates that stochastic modeling is a capable approach against uncertainty.

Table 9 summarizes this measure for all objective functions tested with small problem instances. The VSS measures are all positive which justifies the modeling approach.

Table 9
Value of Stochastic Solution.

Index	F_1	F_2	F_3
SP	190 858.58	40.12	2623.36
EEV	188 568.14	39.48	2517.66
VSS	2290.44	0.64	105.70

Table 10
Dimensions of the large problem instances.

Sample#	$\|\mathcal{I}\|$	$\|\mathcal{J}\|$	$\|\mathcal{L}\|$	$\|\mathcal{C}\|$	$\|\mathcal{V}\|$	$\|\mathcal{T}\|$	$\|\mathcal{S}\|$	$\|\mathcal{P}\|$
1	4	3	3	5	6	2	2	3
2	6	4	5	8	6	2	2	3
3	8	4	67	10	8	2	2	4
4	10	6	87	12	8	3	3	4
5	12	6	10	15	12	3	3	4
6	15	8	10	18	12	3	3	4
7	18	8	12	22	12	4	3	4
8	22	10	12	25	15	4	4	5
9	28	12	15	28	15	4	4	5
10	35	15	15	32	15	4	4	5
11	42	15	18	36	18	6	4	5
12	48	18	21	42	18	6	6	6
13	52	18	24	48	18	6	6	6
14	55	20	28	52	20	8	6	6
15	60	22	30	60	20	8	6	6

Table 11
ANOVA results for algorithm comparisons.

Criterion	F-Value	P-Value
NPF	0.13	0.881
MS	0.96	0.390
SM	3.14	0.054
MID	0.14	0.087
CPT	0.49	0.614

5.2. Large instances

The NP-hard nature of the problem encourages the deployment of heuristic algorithms NSGA II, MOGWO, and MOGGWA for larger problem sizes. Here, 15 instances with the dimensions given in Table 10 are used to examine the scalability of our heuristics. All other parameters are kept as Table 3.

Fig. 9 compares our algorithms with different problem sizes according to the metrics defined in Table 2. As shown, apart from CPU time, the values of other metrics fluctuate over instance sizes with no definite deterioration or improvement pattern. But they remain in a reasonable range with no sudden change or outlier value, which testifies the reliability of algorithms for higher scales of the problem. Not surprisingly, the heuristics are much faster than AEC, while NSGA II is the fastest. NSGA II is the winner for SM and CPU time; MOGWO is the winner for MID; Since MOGGWA uses the operators of both other algorithms, it is the winner for three criteria with the highest NPF, MS, and MID among all algorithms. To decide on the significance of difference between algorithms an ANOVA analysis with a confidence level of 95% is used. Any P-value less than 0.05 will indicate a meaningful difference between algorithms for the criterion of interest. Table 11 illustrates the ANOVA analysis wherein no statistically significant difference was detected. As no significant difference in the mean of comparison criteria is observed, the TOPSIS method is used here to rank the algorithms with respect to these 5 metrics as shown in Table 12.

With equal weights for criteria, the scores obtained for NSGA II, MOGWO, and MOGGWA are respectively 0.305, 0.453, and 0.812 which shows rank MOGWWA as the superior one.

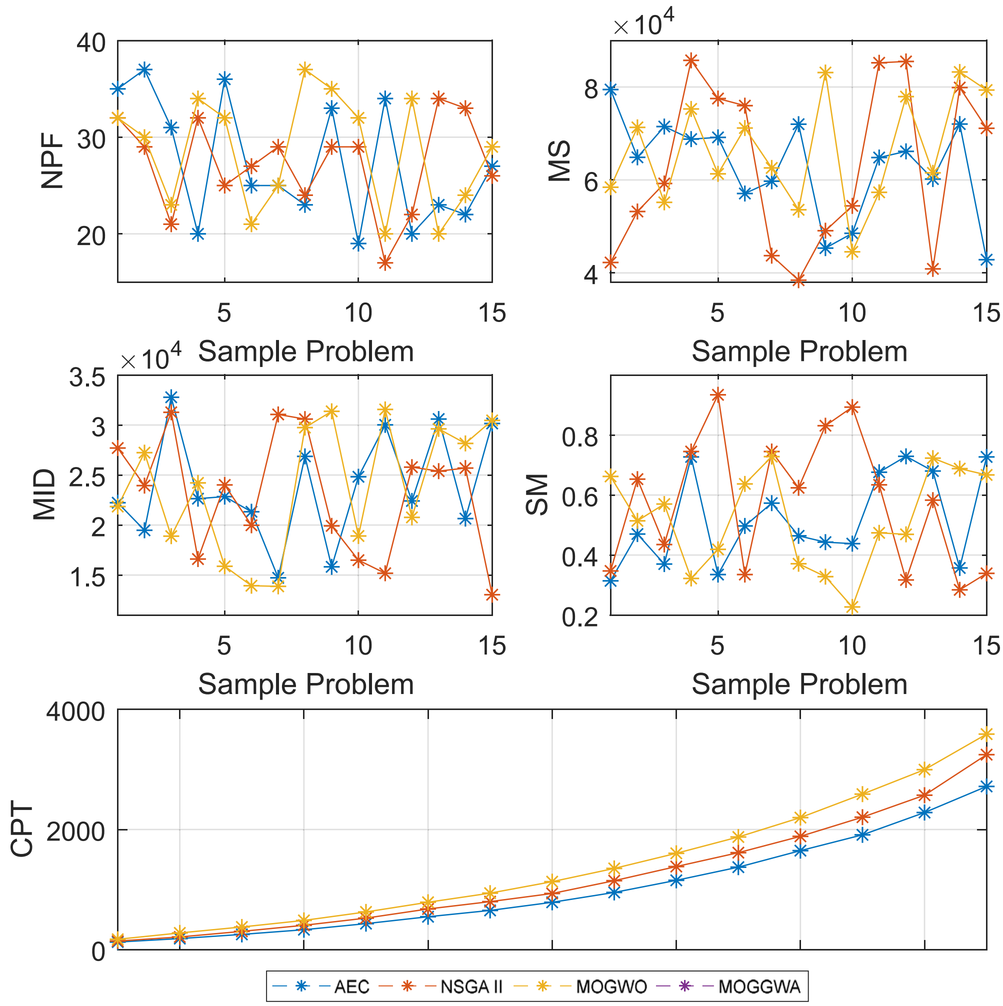

Fig. 9. Comparison of solution methods using different criteria.

Table 12
TOPSIS decision matrix.

Index	NSGA II	MOGWO	MOGGWA
NPF	27.33	27.20	28.53
MS	62 831.07	62 808.87	66 392.60
SM	0.52	0.58	0.52
MID	23 823.27	23 109.60	23 763.00
CPT	1022.84	1202.88	1399.93

5.3. Case study analysis

In this section, we examine a real-scale problem, which is adopted from Kaviyani-Charati et al. [8]. The case explores the capital city of Iran, Tehran, with 22 regions and an area of nearly 730 square meters (see Fig. 10). Three food items are considered including cooked meat with 243 kcal and a shelf-life of 2 h, fruits and vegetables with 229 kcal and 5 h of shelf-life, and canned foods with an average of 456 kcal and 5–7 days of shelf-life. Donors of these items comprise big restaurants, catering of universities, groceries, and residential houses. Based on the demographic information regions 2, 6, 7, 8, 12, 14, 15, 16, 18, 19, 20, and 21 were identified as demand points (charities) while all regions were considered as potential locations for FBs. Food demands in charities were determined based on the opinions of experts including 10 people from national aid organizations and the Food and Drug Administration, and 4 academics as $\sim U(960, 1400).[0.90, 0.95, 1.05, 1.10]$. The food supply by donors was also estimated as $\sim U(600, 820).[0.90, 0.95, 1.05, 1.10]$. Two scenarios each with 50% chance were considered wherein the uncertain parameter was set at 0.9 for the first, and 1.1 for the second scenario. The service time at each node was estimated as 10 min while the transit times were calculated based on an average speed of 45 km/h. Each vehicle had a capacity equivalent to 3,000 items. Standardizing all cost units to cents (¢), the per kilometer transportation cost was $\sim U(10, 15)$ while the fixed cost was 1000. The holding cost and operational costs per item were set as 2 and 1, respectively. Finally, the location and facility investment costs are estimated at 100000. All the parameters by which our numerical results obtained, are available at https://doi.org/10.17632/mr9kbjkjk8.1.

All the corresponding numerical analyses have been done via MOGWWA as it was shown that it has superior performance to others in the previous section. It found 11 efficient solutions one of which is illustrated in Fig. 10. In this solution 7 vehicles are used for collection and 6 for distribution while 93.2% of demand is met in charities.

5.4. Managerial insights

5.4.1. Navigating trade-offs in food bank operations

The conflicting objectives of cost, freshness, and nutritional value require food bank managers to make strategic trade-offs. For instance, while minimizing costs is critical for sustainability, investing in refrigerated vehicles or faster delivery routes may be justified for perishable items to preserve freshness. Conversely, non-perishable items

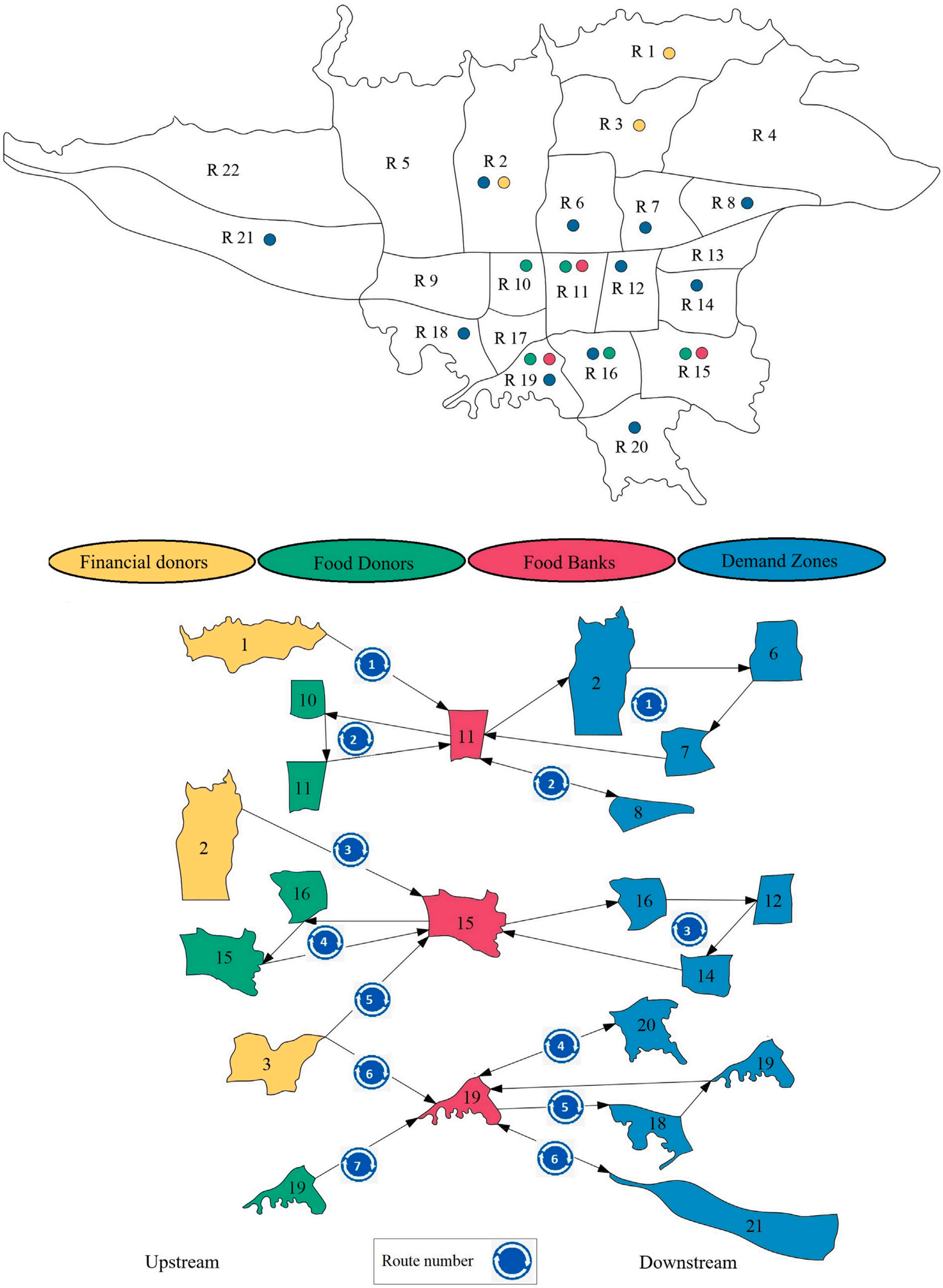

Fig. 10. The geographical distribution of the food bank network.

(e.g., canned goods) allow for cost-efficient bulk transportation. Similarly, partnering with financial donors to procure high-nutrient foods can elevate nutritional value but may strain budgets. To navigate these trade-offs, managers should: Assess Priorities: Align decisions with organizational goals (e.g., hunger relief vs. nutrition-focused missions). Optimize Routing: Use the model's Pareto solutions to identify routes that balance freshness and cost. Leverage Stakeholders: Collaborate with donors to secure funding for high-impact investments (e.g., cold storage). Such strategies ensure efficient resource use while meeting diverse objectives under constraints.

5.4.2. Remarks

The findings of this study provide actionable recommendations for food bank managers striving to optimize their operations while addressing uncertainties in supply and demand. From the managerial perspective, numerical analyses demonstrated that changes in uncertainty rates significantly affect key objectives, such as total cost, freshness, and nutritional value of distributed food. By understanding these dynamics, food bank managers can gain deeper insights into how uncertainty impacts their operations and adapt strategies accordingly to execute the most efficient solutions based on ongoing nationwide conditions.

One key takeaway is the importance of sensitivity analysis on parameters like vehicle capacity. For example, our analysis reveals that increasing vehicle capacity not only reduces total costs but also enhances overall operational efficiency. When optimized routing is implemented for food collection rather than simple assignments, the network cost decreases while accommodating a larger fleet size. This underscores the significance of strategic investments in fleet expansion and routing technologies to achieve cost-effective and efficient food distribution.

Additionally, trade-offs between objectives such as cost minimization, freshness, and nutritional value provide essential insights for decision-making. Managers can expect increased costs when prioritizing higher nutritional value or freshness due to the need for more purposeful donations and increased fleet usage. Sensitivity analyses further reveal that higher supply and demand probabilities often lead to improved freshness and nutritional value, attributed to more frequent and targeted food distribution trips.

Finally, leveraging stochastic programming methods equips managers with the ability to navigate uncertainty effectively. These tools help quantify the value of predictive decision-making, enabling managers to implement resilient operational strategies that align with organizational priorities. By combining these insights with scenario-based planning, food bank managers can ensure more sustainable, efficient, and beneficiary-focused operations.

6. Conclusion

The importance of food distribution for people in need was the motive behind this study which addressed a food network design model. The network encompasses three tiers corresponding to donors, FBs, and charities which are critical spots and proxies to supply, packaging, and demand points in a classic supply chain setting, respectively. Our approach not only prevents the waste of leftover food in restaurants and similar establishments but also supports the social mission and promotes sustainable development within the food industry. Additionally, the network optimization minimizing the traveled distance will indirectly reduce the carbon footprint. The freshness of food items from the collection to the delivery moments was taken into account from the operational perspective together with the nutritional value of the food supplied for the beneficiaries. Thus, combining with the cost a multi-objective MINLP was proposed for the problem considering the uncertain nature of supply and demand. The uncertainty is translated both by scenarios to address the possible trends of parameters, and by fuzzy Parameterization to undertake their value and range. To overcome worst-case outcomes under uncertainty a robust approach was also employed in our modeling process resulting in a robust fuzzy stochastic model.

For solution approaches, in addition to the augmented ϵ-constraint (AEC) two existing meta-heuristics MOGWO and NSGA II were tailored to encode solutions for the model. Then, a novel algorithm was developed by combining them. The hybrid MOGGWA proved a superior performance based on our numerical tests, while the AEC method showed a limited capability as it can only handle small instances of the problem. The expected rise in total cost by an increase in nutritional value or freshness of the food was observed in the results of all algorithms.

This study has some limitations that can be addressed in future studies. First, a fleet of normal vehicles is used while employing refrigerated ones may significantly change the freshness function during the transit and, in turn, will bring about new trade-offs with regard to their investment and running cost. Second, the supply and demand parameters may have seasonal changes, or the required nutritional value as well as the food freshness might be subject to seasonal changes that can make the problem time-dependent which would be interesting to inspect. Finally, the transit times for collection and distribution may vary depending on the road congestion or vehicle breakdowns during the day and that might be of interest for researchers to develop scenario-based transit times for the collection and delivery operations. While our model assumes fixed budgets and single-FB donations, real-world networks may require stochastic funding cycles and decentralized donor flows. Future research will explore these dynamics via chance-constrained programming and multi-tier assignment heuristics, building on the routing foundation established here. In addition, the proposed design model can be extended to a redesign problem by including decisions on the location of the newly emerging charities or the closure of the existing ones.

CRediT authorship contribution statement

Javid Ghahremani-Nahr: Writing – original draft, Visualization, Software, Methodology, Data curation. **Ramez Kian:** Writing – review & editing, Visualization, Supervision, Resources, Conceptualization. **Abdolsalam Ghaderi:** Writing – review & editing, Validation, Supervision, Investigation, Formal analysis, Conceptualization.

Data availability

We have shared the link to the case study data. (https://doi.org/10.17632/mr9kbjkjk8.1.)

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Javid Ghahremani-Nahr graduated with a B.Sc., an M.Sc. and a Ph.D. in industrial engineering respectively from Payam Noor University, Kharazmi University and Kurdistan University in Iran. He is currently serving as Head-of-Department for Development Management at the Academic Center for Education, Culture and Research (ACECR), Tabriz, Iran. His current research projects focus on meta-heuristic and hybrid algorithms in supply chain models. He has published articles in journals such as *Expert Systems with Applications*, and *Soft Computing*.

Ramez Kian graduated with a B.Sc. and an M.Sc. from Sharif University of Technology in Iran, and a Ph.D. from Bilkent University in Turkey all in Industrial Engineering. He is currently a senior lecturer in logistics operations management at Nottingham Business School, Nottingham Trent University. He has also been a researcher and faculty member at the University of Southampton (UK), Istanbul Bilgi University (Turkey), and Tabriz University (Iran). His current research projects focus on humanitarian logistics, supply network design and sustainability. He has published articles in journals such as *European Journal of Operational Research, OMEGA, International Journal of Production Economics,*and *Annals of Operations Research*.

Abdolsalaam Ghaderi is an associate professor in the Department of Industrial Engineering at the University of Kurdistan, Iran. He graduated with a B.Sc. from the same university. He has received his M.Sc. and Ph.D. degrees from Iran University of Technology in Iran in Industrial Engineering. He has served in different academic positions such as head of educational affairs office, vice-president for education and graduate studies, and head of department in his current institution. He has been a visiting scholar at the School of Mathematical & Physical Sciences, University of Newcastle, Australia. His research interests sit in the exact, meta-heuristic and hybrid solution algorithms for optimization models and he has published articles in journals such as *Transportation Research Part E, Industrial and Systems Engineering, and Computers & Operations Research*.