A food bank network design examining food nutritional value and freshness: a multi objective robust fuzzy model

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Abstract

One main reason for food scarcity is its improper and uneven distribution amongst those who require aid. To overcome this issue, charities and food banks serve as the connection between beneficiaries and donors. They are mostly nonprofit organizations but they incur operational costs for storage and delivery of the donated food items. The donated food items are either canned and cold, or hot meals from over production of businesses; and therefore their freshness, inventory and shelf-life bring about additional operational challenges in distribution and logistics. The uncertainty of demand and supply is another challenge to overcome, which necessitates a robust plan. This article proposes a multi-objective mathematical programming model for a food bank network design to optimize the cost, food freshness and its nutritional value. A robust fuzzy counterpart of the model is developed together with three solution methods including ϵ-constraint, MOGWO and NSGA II. The MOGWO algorithm shows a better performance in our numerical experiment with large instances. Its application on a case study resulted in a supply network with lower cost, smaller fleet size and higher food quality, although less fresh distributed foods compared to the benchmark network. The trade-off between the cost and freshness of food is depicted here by examining shelf-life of products and vehicle capacity. The long lasting products incur less transportation cost due to compactness of packaging, and similarly, higher capacity vehicles lead to more cost efficient dispatch with longer routes which decrease the freshness of food. According to our numerical results, higher uncertainty rate in the network increases total cost, but also overall nutritional value of the distributed food over the network due to greater supply of food.

Keywords: Food-bank, Multi-objective, Freshness, Robust Fuzzy Model, MOGWO, NSGA II

1 Introduction

In 2016, the proportion of people in the EU at risk of poverty or social deprivation was estimated to be 23.4%, affecting 117.5 million people (Martins 2019). Approximately 20 to 30 percent of total food production in the EU is wasted each year across the food supply chain (FSC) from farm to family, valued at approximately 143 billion euros (Stenmarck et al. 2016). The European Union has taken a number of actions in recent years to decrease food waste across the FSC, including member states' commitments to cut food waste by 30%. Food scarcity is not the primary cause of food insecurity; as these numbers demonstrate, rather, the real challenge is to distribute the available food evenly among those who require aid. As a result, many charities such as food banks (FB) serve as middlemen between food resources and people (Sengul Orgut et al. 2016; Albala 2015). These organizations typically acquire the foods from businesses and donors and store them with necessary equipment, and then distribute them directly or indirectly to people in need through nonprofit and government agencies.

For socio-economic players such as FBs, the return on investment and other economic factors are not the most important considerations; instead, they are more concerned with social and environmental issues. As a result, FBs play a critical role in ensuring the long-term viability of the FSC. An FB is a charitable, non-profit organization that distributes food to those who are unable to obtain sufficient food (Glover et al. 2014). The St. Mary FB in Phoenix, Arizona, was the world's first FB, founded by John Van Hengel in 1967 (Neter et al. 2016). Since 1980s, FBs have expanded all over the world and currently there are active food banking groups in more than 30 countries as subsidiaries of the World Food Bank Network (FBN). Some FBs, operate on a "front-line" strategy, delivering food directly to beneficiaries. The remainder operate on a "warehouse" basis, supplying food to intermediaries such as food warehouses and other front-line organizations. In the United States, communities often have an FB that serves front-line agencies as a centralized warehouse.

Although most charities are free, some FBs levy a nominal "joint maintenance" fee to cover their storage and delivery costs. Foods can come from any part of the FSC, such as overproduction of producers or over-ordered of retailers and therefore, the majority of these items are nearing their "expiration" date. In such circumstances, FBs work with the food sector and regulatory agencies to ensure that they are distributed safely and legally (Riches 2018). Many FBs refuse to supply fresh products, preferring canned or packaged meals instead. Nevertheless, some have attempted to change this as part of a growing global understanding of nutritional needs. According to González-Torre and Coque (2016) the main activities of FBs are,

- Identification of additional food sources and food donor companies,

- Volunteer recruitment and food collection as the part of public awareness campaigns.

In most situations, FBs are not in charge of providing food directly to the citizens; instead, they distribute it to a variety of officially authorized charities who hand out the collected food to the recipients (Berner and OâĂŹBrien 2004). In other words, FBs are devoted to leading a good chain and bridging the gap between surplus food and an active demand. In fact, the goal of a FB is to create a value on food that would otherwise be wasted to landfill despite being safe and nutritious for human consumption. Thus, besides their common goal of assisting people in need, they are also ecologically beneficial by decreasing waste which has a significant environmental impact.

They generally rely on their suppliers such as food companies and other contributors, and essentially operate as wholesalers. According to Gentilini (2013), some of their main beneficiaries and stakeholders are:

- Families, children & youth organizations, addiction treatment organizations, religious lodging facilities, workers of unions, and so on.

- Food producers, distributors, shopping malls, wholesalers, warehouses, retailers, transportation companies, financial institutions, advertising and communications agencies, public institutions, and a variety of national and international organizations

In 2013, a national poll revealed that FB customers prefer wholesome foods, with fresh fruits and vegetables being the most popular products that customers have not received. The quality of fresh food has increased as a result of infrastructure for storage and distribution, as well as stakeholder demand for fresh and healthy food (Wetherill et al. 2019). Dealing mainly with perishable materials which might be lost in terms of quality and quantity, makes FB management difficult. FBs work in partnership with cold storage agencies to facilitate delivering fresh and dairy products to their clients. They have employed a variety practices to improve supply of fresh fruits and vegetables. For instance, by informing agencies and attempting to make direct contact with donors, they have shortened the distribution time which is more advantageous for maximizing products shelf-life (Gharehyakheh et al. 2019).

In the interest of FBs' role in the procurement and distribution of high-quality food to charities, this article studies a FSC network design model with the three objectives of minimizing total cost, maximizing the freshness, and nutritional value of the food baskets supplied to charities. The supply and demand balance of food supply in an FBN is another crucial concern because either the food amount given by donors, or the demand amount of charities varies over time. Therefore, a control method must be used in design to capture this uncertainty. We have used a fuzzy robust programming method to control the uncertain parameters in this paper and other contributing characteristics are listed below:

- Considering the nutritional value of the food basket in the FBN;

- Addressing the freshness of foods by employing an exponential deterioration function to quantify it over time;
- Considering the uncertainty in supply and demand in the FBN and fuzzy parametrization of unknown inputs;
- Using a hybrid model of location-allocation-routing-inventory problem (HLARIP) in the formulation;
- Defining a modified chromosome to encode the solution space to facilitate implementation of heuristic algorithms;
- Extensive numerical experiments to investigate the performance of proposed solution algorithms and also comparison between output of our model and a benchmark on real case study.

The rest of this article is structured as follows. Section 2 reviews the literature and identifies the potential research gaps. In Section 3, a three-echelon FBSCN model under uncertainty assumption is proposed where uncertain parameters are dealt with using the fuzzy robust programming method. Section 4 describes the methods used for solving our multi-objective model, including the augmented ϵ-constraint method, NSGA II and MOGWO algorithms. The numerical results of the presented model together with a sensitivity analysis are presented in Section 5 and finally, Section 6 concludes the paper with additional managerial insights and directions for future studies.

2 Literature review

The relevant literature is classified into four themes, discussed in the following subsections. A summary table is provided at the end of this section to assist readers with positioning this article among the existing studies.

Food bank

Neter et al. (2014) examined food security among recipients of Dutch FBs and identified possible demographic, lifestyle and nutrition-related factors. They studied 11 out of 135 Dutch FBs across the Netherlands. Their results showed a high prevalence of food insecurity among recipients of Dutch FBs. Orgut et al. (2016) developed a mathematical model for the North Carolina FBs aiming to maximize their effectiveness by minimizing the amount of undistributed food. Their model identifies optimal policies for allocating additional receiving capacity to cities in their serving area. Gonzalez-Torre et al. (2017) analyzed the impact of FBs on the SCs which they belong to. They first summarized the background of international studies on the subject and then presented the results of an empirical study in Spain where data were collected through a survey and analyzed using a cluster sampling method. Martins et al. (2019) presented a mixed integer linear model for redesigning a multi echelon FSCN to collect food aid and distribute it to charities, which covered all aspects of sustainability, economic, environmental and social factors through their three objective functions. Their study shows that the greatest correlation occurs between the economic objective and the other two ones.

Ataseven et al. (2020) used survey data from managers and secondary data collected from the Feeding America website to model and measure FBs performance; examining the relationship between supply integration, demand integration and internal integration in food banking. They employed regression and Monte Carlo simulation techniques to test their hypotheses on integration policies. According to their findings, external integration must take place before internal integration for non-profit FBs, and demand integration has a stronger effect on performance than supply integration. Chen et al. (2021) considered a vehicle routing problem with the aim of minimizing the traveled distance taking into account capacity and transmission time constraints. Their results showed that by correcting the route of vehicles, 94.4% of customers can benefit from the services of their FB. Mandal et al. (2021) studied a food SC problem considering its cost and environmental impact, while Mensah et al. (2021) explored the prospects and constraints of implementing food banking in the Ghanaian metropolitan area of Kumasi addressing food poverty and providing food aid during a pandemic (such as COVID-19). They used a multi-stage sampling method to select 385 respondents and applied descriptive statistics and Probit regression model to analyze the factors affecting the food banking. According to their results the most important limitations in implementation of food banking are financial. Among the most recent studies, Kaviyani-Charati et al. (2022) developed a mathematical model to design a non-profit FBSC in Iran. They considered the sustainability factors in their proposed multi-objective model and solved it by NSGA II algorithm and ϵ-constraint method. Their results suggest that applying a heterogeneous fleet is necessary to reduce food waste and transportation costs. Dubey and Tanksale (2022) investigated FBs in the India by identifying barriers that impede their growth and adoption. They developed a network of inter-relationship between those barriers, and argued that the lack of planning and coordination is the most significant obstacle. Finally, Blessley and Mudambi (2022) studied FBSC during the turbulence of

US-China trade war and the COVID-19 pandemic in 2018âĂŞ2020.

Food distribution routing

Davis et al. (2014) considered the collection and delivery of food to a humanitarian organization, where use of food delivery points (FDPs) is suggested to increase the access to food. They proposed a capacitated set covering model for identifying FDP locations, and a periodic vehicle routing problem to determine weekly schedules. Amorim and Almada-Lobo (2014) modeled a multi-objective model to minimize logistics costs and maximize product freshness. They used the ϵ-constraint method and a multi-purpose evolutionary algorithm to solve the problem. Morganti and Gonzalez-Feliu (2015) examined urban procurement for perishable products by studying the case of the food hub in Parma, Italy. They analyzed plans to deliver food to urban distributors such as corporate retail chains, independent retailers, hotels, restaurants and kit stores. In the context of humanitarian logistics Rey et al. (2018) proposed a model for allocation and distribution of the surplus food collected for hunger relief aiming to minimize the travel cost. They showed that the problem is NP-hard and proposed exact and heuristic solution algorithms. Dai et al. (2020) designed a cyclic inventory-routing problem with perishable products in a VMI supply chain. Their objective is to minimize the average total cost including not only the fixed and transportation cost of vehicles, inventory and shortage cost of retailers, but also startup and holding cost of the manufacturer. Akpinar (2021) modeled a vehicle routing problem with a time window for food industry aiming at minimizing the total traveled distance, and solved their model by genetic algorithm. Pratap et al. (2022) proposed a production-inventory-routing problem for perishable food under uncertainty and used a stochastic optimization approach to model it. In a different setting, Worasan et al. (2022) proposed a multi-product vehicle routing problem with cross-docking operations for food industry to ensure that products can be delivered on time and with minimum transportation and hiring costs. They considered both the supplier side and customer side and developed a heuristic algorithm to find the best neighborhood. Also, Yao et al. (2022) proposed a green vehicle-routing model for fresh agricultural products to minimize the total cost. They employed the ant-colony algorithm to solve their model. Their results show that the increase in carbon tax will restrict the carbon emission behaviors of the distribution companies, but it will also reduce their economic benefits to a certain extent at the same time.

Food supply chain

Yu and Nagurney (2013) proposed a network-based food SC model of competition and perishability taking into account the disposal costs of spoiled food products. Govindan et al. (2014) proposed a multi-objective optimization model by integrating sustainability decisions into a perishable FSCN aiming to minimize total costs and carbon emissions. They used MOPSO and AMOVNS algorithms to solve the problem. Similarly, Accorsi et al. (2016) proposed a linear programming model to balance logistics costs and carbon emissions in the agricultural-food ecosystem. According to their results, there is an interdependence between infrastructure, production, distribution and environmental resources. De Keizer et al. (2017) investigate a logistics network design for perishable products with a declining quality period where as time elapses or temperature increases, product quality decreases and more effort is required to deliver the product at the right time and with the right quality. Nagurney et al. (2018) presented a competitive food SC network model wherein in addition to the volume of freshly produced and distributed products, the initial quality of fresh products is also important. The quality of new products is determined by time, temperature and other characteristics related to processing, transportation, storage, etc. Wu et al. (2018) focused on the flow of the perishable food for a case of railway catering service. They proposed a Newsvendor-based model to address the demand uncertainty. Rohmer et al. (2019) presented a new model of the sustainable food SCNP by maintaining a proper diet that minimizes various economic and environmental goals. Using the ϵ-constraint method, they formed a Pareto frontier and argued that the target level of sustainability plays an important role in the food SC. Zhang et al. (2019a) modeled a multi period closed-loop SC problem for the food industry. They considered two goals including maximizing SC profits and minimizing greenhouse gas emissions. Addressing the global food insecurity and increasing global hunger, Mogale et al. (2020) proposed a multi period mathematical model to minimize the aggregate cost of installation, maintenance, carbon emission and risk penalty.

Huang et al. (2021) studied pricing and optimization policies of the perishable food SC under inflation, which has been increased due to SC disruptions from COVID-19 outbreaks. They used a discounted cash flow method to measure profit under inflation. Hamilton et al. (2021) studied the economic impact of the secondary food market by examining donations and pricing behavior for competing retailers. They used a structural model of retail oligopoly price discrimination and estimated the effect of food donation. Yadav et al. (2021) proposed a three-objective mathematical model for designing a fresh food distribution problem where sustainability is considered by formulating economic (total cost minimization), environmental (emission minimization) and social (delivery time minimization) objectives. They used the ϵ-constraint and LP-metric method to solve their model. Recently, Orjuela-Castro et al. (2022) presented big challenges of modeling in perishable food supply chain such as the inclusion of delivery times, losses and fresh food storage needs which depend of the transport time, the configuration and number of echelons. Finally, Abbas et al. (2022) studied supply chain network of China by using logistics regression and simulation techniques to estimate its robustness.

Uncertainty in the SCN

Kara and Dogan (2018) applied a learning-based modeling for inventory of perishable products at random demand and definite time to minimize total SC cost, while Aras and Bilge (2018) presented a multi echelon and multi product SCN model for the competitive snack market in Turkey. They solved different scenarios based on different demand growth rates. Similarly, under the uncertain demand scenario, Rafie-Majd et al. (2018) proposed an integrated strategic, tactical and operational optimization approach in SC management with a perishable product. Farrokh et al. (2018) presented a two echelon random scheduling model to reduce costs and reduce risk in a food and drug SCN. The first decisions included strategic decisions such as determining the number of suppliers according to their location and capacity. While the second decisions were related to transportation operations. Nasrollahi and Razmi (2019) provided a mathematical model for integrated SC design and maximum coverage of areas under uncertainty. Their main goal was to increase the maximum demand met by customers in addition to reducing the cost of the entire network. They used the centroid method to control their uncertain parameters. Gholami-Zanjani et al. (2021) designed a comprehensive two echelon scenario-based mathematical model for designing a food SCN under demand uncertainty. They developed a Monte Carlo method to produce plausible scenarios and used the Benders analysis technique to solve the problem. Manteghi et al. (2021) presented a sustainable food SC model to balance economic and environmental goals. Their main goal is to increase the profit and reduce the amount of carbon emissions. They have created several competitive models and identified optimal decisions based on the game theory approach. Kothamasu et al. (2021) developed a contingency planning model for FB disaster relief operations. They considered different scenarios for uncertain parameters minimizing network-related costs due to limited resources. Tirkolaee and Aydin (2022) designed a bi-level decision support system to optimize a sustainable multi-level multi-product supply chain and co-modal transportation network for perishable products distribution. They proposed perishability of products as a performance measure and applied a fuzzy weighted Goal Programming approach to solve it. Gholian-Jouybari et al. (2022) proposed a robust convex optimization approach to control the uncertainty of parameters in a sustainable agri-food SCN problem and solved it using the LP-metric method and Keshtel algorithm. Finally, Seydanlou et al. (2022) developed a sustainable closed-loop supply chain network for the olive industry in Iran aiming at minimizing the total cost and carbon emissions while maximizing job opportunities. They proposed four meta-heuristic algorithms to solve their model.

Table 1 provides a classification system for mathematical models in the field of FB is and Table 2 summarizes the differences between characteristics of the reviewed articles.

Table 1: Classification system for mathematical models in the context of FB

SC Setting	**Symbol**	**Parameters type**	**Symbol**
Single Product	SPr	Fuzzy	F
Multi Product	MPr	Stochastic	S
Single Period	Spe	Robust	R
Multi Period	Mpe	Robust-Fuzzy	RF
Single Echelon	SEc	Deterministic	D
Multi Echelon	MEc	**Solution Method**	**Symbol**
		Exact Solution	E
Model Objective	**Symbol**	Heuristics Algorithm	H
Min Cost	MCO	Simulation	S
Min Delivery Time	MDT	Meta-Heuristics Algorithm	M
Max Quality Level-Freshness	MQF	**Decisions**	**Symbol**
Min CO_2 Emission	MCE	Location	L
Min Distance	MDI	Allocation	A
Max Nutritional Value	MNV	Routing	R
Maximum Social Responsibilities	MSR	Inventoty	I

Table 2: Characteristics of various articles in the field of FB

Author	Structure	Objective(s)	Decisions	Parameters Type	Solution Method
Li et al. (2006)	Spe-Mec-Spr	MCO	A	D	E
Dabbene et al. (2008)	Mpe-Sec-Mpr	MCO	R-I-L	R	E
Bosona and Gebresenbet (2011)	Spe-Sec-Spr	MCE	A-I-L	D	E
Paleshi et al. (2011)	Mpe-Mec-Spr	MCO	A-I-L	D	E
Zhao and Dou (2011)	Spe-Mec-Spr	MCO	R-A-L	D	M
Rong et al. (2011)	Mpe-Mec-Mpr	MCO-MQF	R-I	D	E
Manzini and Accorsi (2013)	Spe-Mec-Spr	MCE	R-A-L	D	E
Cuevas-Ortuno and Gomez-Padilla (2013)	Mpe-Mec-Spr	MCO	R-A	D	E
Validi et al. (2014)	Spe-Sec-Spr	MCO-MCE	R	R	E
Govindan et al. (2014)	Mpe-Mec-Spr	MCO-MCE	R-A-L	D	M
Davis et al. (2014)	Spe-Mec-Spr	MDI	R-A-L	D	E
Amorim and Almada-Lobo (2014)	Spe-Mec-Spr	MCO	R-I	F	E
Agustina et al. (2014)	Spe-Mec-Spr	MDT	I-L	D	E
Accorsi et al. (2016)	Spe-Sec-Spr	MCO-MCE	A-L	D	E
Martins et al. (2016)	Mpe-Mec-Mpr	MCO-MCE	R-A-L	D	E
Orgut et al. (2016)	Mpe-Mec-Spr	MCO	A-L	R	H
Sengul Orgut et al. (2016)	Spe-Sec-Spr	MDT	R-A	D	E
Cuevas-Ortuño and Gómez Padilla (2017)	Spe-Mec-Spr	MCO	A-I	F	E
Reihaneh and Ghoniem (2017)	Spe-Mec-Spr	MCO-MQF	R-A	D	H
Musavi and Bozorgi-Amiri (2017)	Spe-Mec-Spr	MDT-MCO-MCE	R-A-L	D	M
Bocewicz et al. (2017)	Mpe-Sec-Mpr	MDT	R-I-L	D	S
Aras and Bilge (2018)	Mpe-Sec-Mpr	MCO	A-L	R	E
Bortolini et al. (2018)	Mpe-Mec-Mpr	MCO-MCE	R-A	D	E
Gharehyakheh and Sadeghiamirshahidi (2018)	Spe-Mec-Mpr	MCO	R-A-I	D	E
Rohmer et al. (2019)	Spe-Mec-Mpr	MCO-MCE	A-L	D	M
Mogale et al. (2018)	Mpe-Sec-Mpr	MDT-MCO	A-L	D	M
Schneider and Nurre (2019)	Spe-Sec-Spr	MDI	R	D	H
Martins et al. (2019)	Mpe-Mec-Mpr	MCE	A-L	D	E
Zhang et al. (2019a)	Mpe-Mec-Mpr	MCO	R-L	D	H
Zhang et al. (2019b)	Mpe-Mec-Spr	MCE	R-A	D	E
Li et al. (2020)	Spe-Mec-Spr	MCO	I	D	H
CastaÃśÃşn et al. (2020)	Spe-Mec-Spr	MCO	A	D	E
Marthak (2020)	Mpe-Sec-Mpr	MCO	R-A-L	D	E
Mogale et al. (2020)	Mpe-Mec-Spr	MCE	A-I-L	D	M
Pourmohammad-Zia et al. (2021)	Spe-Mec-Spr	MCO	A-I-L	D	H
Patidar et al. (2021)	Spe-Sec-Spr	MCO	A-I-L	F	E
Burgess and Sunmola (2021)	Spe-Sec-Spr	MDI	R-I	F	M

continuing in the next page...

Table 2: Cont'd

Author	Structure	Objective(s)	Decisions	Parameters Type	Solution Method
Manteghi et al. (2021)	Spe-Sec-Mpr	MCO	A-I-L	S	E
Solina and Mirabelli (2021)	Mpe-Sec-Spr	MCO	I	D	E
Mandal et al. (2021)	Mpe-Mec-Mpr	MCO-MCE	R	D	E
Long and Liao (2021)	Spe-Sec-Spr	MCO	A-I-L	S	H
Güner and Utku (2020)	Mpe-Mec-Spr	MCO	R-I	D	E
Kazancoglu et al. (2021)	Mpe-Mec-Spr	MCE	A-I-L	D	E
Taghikhah et al. (2021)	Mpe-Mec-Spr	MCE	I	D	E
Vostriakova et al. (2021)	Mpe-Mec-Spr	MDI	A-I-L	D	S
Jouzdani and Govindan (2021)	Mpe-Mec-Mpr	MCO-MCE	I-L	S	M
Gholami-Zanjani et al. (2021)	Mpe-Mec-Mpr	MCO	A-I-L	S	E
Kothamasu et al. (2021)	Spe-Mec-Spr	MCO	I-L	S	E
Chen et al. (2021)	Spe-Mec-Spr	MCO	A-I-L	D	E
Kaviyani-Charati et al. (2022)	Mpe-Mec-Mpr	MCO-MCE- MSR	L-A-I	S	M-E
Yadav et al. (2021)	Mpe-Mec-Mpr	MCO, MDT, MCE	L-A	D	E
Pratap et al. (2022)	Mpe-Mec-Mpr	MCE	A-R-I	S	M
Worasan et al. (2022)	Spe-Mec-Mpr	MCO	R-A	D	M
Tirkolaee and Aydin (2022)	Spe-Mec-Mpr	MCO, MDT	L-A	F	E
Yao et al. (2022)	Spe-Mec-Spr	MCO, MCE	A-R	D	M
Abbasian et al. (2022)	Mpe-Mec-Mpr	MCO- MCE	L-I-R	D	M- E
present Research	Mpe-Mec-Mpr	MCO-MQF-MNV	R-A-I-L	RF	M-E

Having reviewed the above-listed studies, it is observed that to the best of our knowledge, there is no comprehensive mathematical model in the context of food bank network modeling for perishable items, in which the freshness of products and the nutritional value of the food basket are considered. The comprehensive characterization of the existing studies with their decisions for the food distribution network did not exist either. Therefore, this article addresses the strategic and tactical decisions such as facility location, vehicle routing, allocation and inventory. In addition, applying a fuzzy robust programming method, as a new uncertainty control mechanism in this context, has led to more realistic results. From the solution approach perspective, a novel meta-heuristic algorithm is developed by providing a new encoding method to achieve near-optimal results.

3 Problem statement and modeling

A schematic three-echelon FBN is shown in Figure 1 wherein two types of food contributors donate to charities. The first one includes restaurants, hypermarkets, and other businesses which provide free foods to FBs, while the second one consists of financial donors. FBs create a variety of hot and cold food baskets and deliver them to charities using various vehicles. Hot foods should be provided to charity as soon as possible after being collected from donors, while the donated foods with longer shelf-life (cold) may be refrigerated in FBs for a longer period of time. As the distribution of food baskets by vehicles is a vehicle routing problem, selecting the right vehicle and FB is critical for the speedy distribution of the food baskets. Each food basket has a shelf-life that is inversely proportional to the amount of time passed (Piergiovanni and Limbo 2019). The relationship between time and product freshness is depicted in Figure 2. As shown, the freshness of the food basket declines when the transit time increases. Therefore, vehicles should deliver the appropriate food baskets to charities as quickly as possible. In addition, FBs must meet the minimal required nutritional value of each charity in the contents of their food baskets. As a result, the problem has three separate objective functions: minimizing total costs, maximizing product freshness, and maximizing food basket nutritional value. Choice of the right FB, determining the route of each vehicle for food baskets distribution, ruling the amount of cold food inventory in the FBs and dispatching schedule of food baskets are the decisions to make in a simultaneous optimization of these three objective functions.

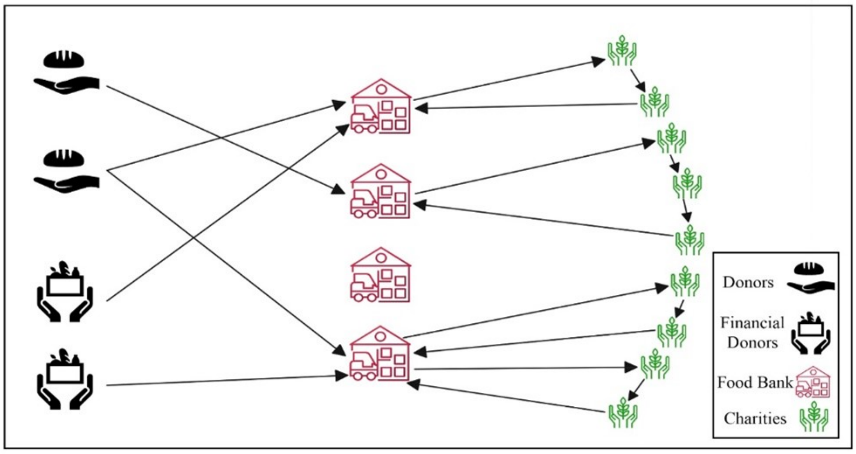


Figure 1: Food Bank Network in Three-Echelon Supply Chain

The following assumptions are made for modeling our food bank supply chain network problem (FBSCNP):

- Different types of foods with high and low durability are considered.

- Foods with high shelf-life (cold food) can be stored in FBs.

- The number and location of charities are known.

- The budget available to financial institutions to purchase food in each period is limited.

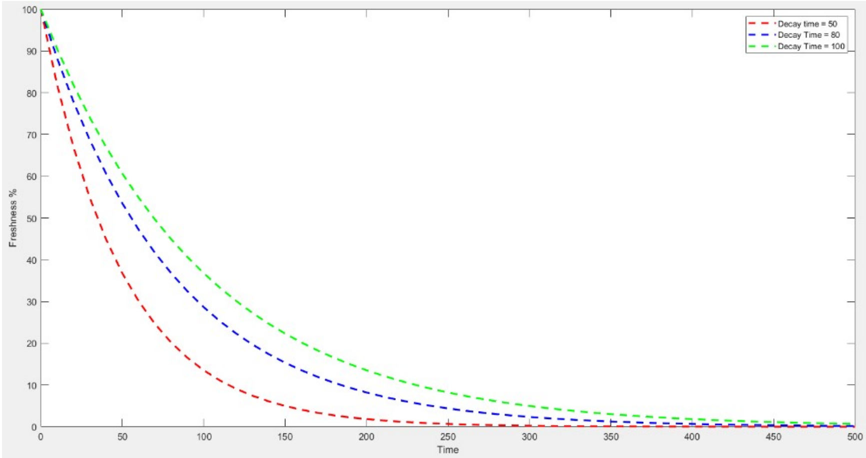


Figure 2: perishability rate of food over time

- The minimum nutritional value of the food basket is specified and should be met for each charity.

- The collection time of foods from donors is negligible.

A nonlinear mathematical programming model of FBSCNP with respect to the above-stated assumptions, decisions and objectives is presented below in the next subsection using the nomenclature in Table 3.

Table 3: Nomenclatures list for the model formulation

		Sets			
I'	*Set of food donors*	I''	*Set of financial donors*	I	*Set of Total donors* $I = I' \cup I''$
L	*Set of FBs*	C	*Set of Charities*	N	*Set of Total FBs and Charities locations*
V	*Set of vehicles*	T	*Set of time periods*	P'	*Set of foods with high shelf-life (Cold Foods)*
P''	*Set of foods with low shelf-life (Hot Foods)*	P	*Set of food baskets*		
		Parameters			
f_l	*Fixed cost of setting up a FB at location* $l \in L$	g_v	*Fixed cost of using vehicle* $v \in V$	$o_{l,p}$	*Operating cost of packaging and distribution food basket* $p \in P$ *in FB* $l \in L$
θ	*delay penalty for vehicles arriving late to FBs*	$\tilde{\xi}^1_{n,n'}$	*Transportation cost between node* $n \in N$ *and* $n' \in N$	$\tilde{\xi}^2_{i,l}$	*Transportation cost between food donor* $i \in I$ *and FB* $l \in L$
$h_{e,t}$	*storage cost of food* $e \in P'$ *in any FBs at period* $t \in T$	$\tilde{d}_{c,p,t}$	*Demand of charity* $c \in C$ *of food basket* $p \in P$ *at period* $t \in T$	ψ_l	*Maximum distribution capacity of FB* $l \in L$
$\tilde{\omega}_{i,e,t}$	*Maximum supply of food item* $e \in P \cup P''$ *by food donor* $i \in I'$ *at period* $t \in T$	γ_v	*Maximum capacity of vehicle* $v \in V$	$k_{n,n'}$	*Transportation time between node* $n \in N$ *and* $n' \in N$
ϕ_c	*Service time in charity* $c \in C$	$[\alpha_c, \beta_c]$	*Time window for delivery of the food basket to charity* $c \in C$	$\delta_{e,p}$	*Number of food* $e \in P' \cup P''$ *in a food basket* $p \in P$
κ_e	*The nutrition value of food item* $e \in P' \cup P''$	$\rho_{c,p,t}$	*Minimum required nutrition value of food basket* $p \in P$ *for charity* $c \in C$ *in period* $t \in T$	$\Omega_{i,e,t}$	*Cost on purchasing food* $e \in P' \cup P''$ *by financial donor* $i \in I''$ *in period* $t \in T$
$s_{i,t}$	*Budget of financial donor* $i \in I''$ *the purchase of food in period* $t \in T$	u_p	*shelf-life of food basket* $p \in P$	.	
		Decision variable			
$W_{l,p,v,t}$	*Number of food basket* $p \in P$ *distributed by vehicle* $v \in V$ *from FB* $l \in L$ *in period* $t \in T$	$G_{c,p,t}$	*satisfied demand ratio of food basket* $p \in P$ *by charity* $p \in P$ *in period* $t \in T$	$D_{l,c,v,t}$	*Arrival time of vehicle* $v \in V$ *to charity* $c \in C$ *which dispatched from FB* $l \in L$ *in period* $t \in T$
$M_{c,v,t}$	*Exceeding time from the arrival schedule for vehicle* $v \in V$ *at charity* $c \in C$ *in period* $t \in T$	$F_{l,c,v,p,t}$	*freshness of food basket* $p \in P$ *at charity* $c \in C$ *which distributed by vehicle* $v \in V$ *dispatched from FB* $l \in L$ *in period* $t \in T$	$Y_{i,l,e,v,t}$	*Number of food item* $e \in P' \cup P''$ *collected by donor* $i \in I' \cup I''$ *and shipped to FB* $l \in L$ *by vehicle* $v \in V$ *in period* $t \in T$
$Q_{l,e,t}$	*Inventory of food item* $e \in P'$ *at FB* $l \in L$ *in period* $t \in T$	$U_{c,v,t}$	*Auxiliary variable for sub tours elimination*	$X_{n,n',v,t}$	*equals if vehicle* $v \in V$ *passes between node* $n \in N$ *and* $n' \in N$ *in period* $t \in T$*; 0, otherwise.*
$R_{l,c,v,t}$	*equals 1 if vehicle* $v \in V$ *is used to dispatch food from FB* $l \in L$ *to charity* $c \in C$ *in period* $t \in T$*;0, otherwise.*	Z_l	*equals 1 if a FB is set at location* $l \in L$*; 0, otherwise.*	A_v, t	*equals 1 if vehicle* $v \in V$ *used to ship products between donors and FBs in period* $t \in T$ *(Allocation); 0 otherwise.*
$B_{v,t}$	*equals 1 if vehicle* $v \in V$ *is used to ship foods between FBs and charities in period* $t \in T$ *(Routing)*				

3.1 FBSCN model under uncertainty

location setup cost:

Vehicle usage cost:

packaging & storage costs:

delay cost in distribution

transportation cost:

$$\begin{aligned}\min\Big\{ & \textstyle\sum_{l} f_l Z_l \\ & + \textstyle\sum_{v,t} g_v (A_{v,t} + B_{v,t}) \\ & + \textstyle\sum_{l,p,v,t} o_{l,p} W_{l,p,v,t} + \sum_{l,e,t} h_{e,t} Q_{l,e,t} \\ & + \textstyle\sum_{c,v,t} \theta M_{c,v,t} \\ & + \textstyle\sum_{n,n',v,t} \tilde{\xi}^1_{n,n'} X_{n,n',v,t} + \sum_{i,l,e,v,t} \tilde{\xi}^2_{i,l} Y_{i,l,e,v,t} \\ & \Big\}. \end{aligned} \tag{1}$$

$$\max \sum_{l,c,p,v,t} F_{l,c,p,v,t} \tag{2}$$

$$\max \sum_{l,p,v,e,t} \delta_{e,p} \kappa_e W_{l,p,v,t} \tag{3}$$

s.t.

$$\sum_{v\in V}\sum_{n\in N} X_{n,c,v,t} = 1, \qquad \forall c \in C, t \in T \tag{4}$$

$$\sum_{n'\in N} X_{n',n,v,t} = \sum_{n'\in N} X_{n,n',v,t}, \qquad \forall n, n' \in N, v \in V, t \in T, \tag{5}$$

$$\sum_{l\in L}\sum_{c\in C} X_{l,c,v,t} \leq 1, \qquad \forall v \in V, t \in T, \tag{6}$$

$$\sum_{v\in V} R_{l,c,v,t} \leq 1, \qquad \forall l \in L, c \in C, , t \in T \tag{7}$$

$$\sum_{n\in N} (X_{l,n,v,t} + X_{n,c,v,t}) \leq 1 + R_{l,c,v,t}, \qquad \forall l \in L, c \in C, v \in V, t \in T \tag{8}$$

$$U_{c,v,t} - U_{c',v,t} + |C| X_{c,c',v,t} \leq |C| - 1, \qquad \forall c, c' \in C, v \in V, t \in T \tag{9}$$

$$W_{l,v,p,t} \geq \sum_{c\in C} G_{c,p,t} \tilde{d}_{c,p,t} R_{l,c,v,t}, \qquad \forall l \in L, p \in P, v \in V, t \in T \tag{10}$$

$$\sum_{v\in V}\sum_{p\in P} W_{l,p,v,t} \leq \psi_l Z_l, \qquad \forall l \in L, t \in T \tag{11}$$

$$\sum_{c\in C}\sum_{n\in N}\sum_{p\in P} G_{c,p,t} \tilde{d}_{c,p,t} X_{n,c,v,t} \leq \gamma_v B_{v,t}, \qquad \forall v \in V, t \in T \tag{12}$$

$$\sum_{e\in P' \cup P''} \delta_{e,p} \kappa_e G_{c,p,t} \tilde{d}_{c,p,t} \geq \rho_{c,p,t}, \qquad \forall c \in C, p \in P, t \in T \tag{13}$$

$$D_{l,c,v,t} \geq \kappa_{l,c} - \mathbf{M}(1 - X_{l,c,v,t}), \qquad \forall l \in L, c \in c, v \in V, t \in T \tag{14}$$

$$D_{l,c',v,t} \geq D_{l,c,v,t} + k_{c,c'} + \phi_{c'} - \mathbf{M}(2 - X_{c,c',v,t} - R_{l,c,v,t}), \qquad \forall l, c, c' \in C, v \in V, t \in T \tag{15}$$

$$F_{l,c,v,p,t} \geq 100 e^{-\frac{D_{l,c,v,t}}{u_p}} - \mathbf{M}(1 - R_{l,c,v,t}), \qquad \forall l \in L, c \in C, p, v \in V, t \in T \tag{16}$$

$$\alpha_c R_{l,c,v,t} - D_{l,c,v,t} \leq M_{c,v,t} \leq D_{l,c,v,t} - \beta_c R_{l,c,v,t}, \qquad \forall l \in L, c \in C, v \in V, t \in T \tag{17}$$

$$\sum_{i\in I}\sum_{v\in V} Y_{i,l,e,v,t} = \sum_{p\in P}\sum_{v\in V} \delta_{e,p} W_{l,p,v,t}, \qquad \forall l \in L, e \in P'', t \in T \tag{18}$$

$$Q_{l,e,t} = Q_{l,e,t-1} + \sum_{i\in I}\sum_{v\in V} Y_{i,l,e,v,t} - \sum_{p\in P}\sum_{v\in V} \delta_{e,p} W_{i,p,v,t}, \qquad \forall l \in L, e \in P'', t \in T \tag{19}$$

$$\sum_{l\in L}\sum_{v\in V} Y_{i,l,e,v,t} \le \tilde{\omega}_{i,e,t}, \qquad \forall i \in I', e \in P' \cup P'', t \in T \quad (20)$$

$$\sum_{i\in I}\sum_{e\in E}\sum_{l\in L} Y_{i,l,e,v,t} \le \mathbf{M}A_{v,t}, \qquad \forall v \in V, t \in T \quad (21)$$

$$\sum_{i,v,e} \Omega_{i,e,t} Y_{i,l,e,v,t} \le s_{i,t} + \sum_{t'<t}\Big(s_{i,t'} - \sum_{l,v,e} \Omega_{i,e,t'} Y_{i,l,e,v,t'}\Big) \qquad \forall i \in I'', t \in T \quad (22)$$

$$D_{l,c,v,t} \le \mathbf{M}R_{l,c,v,t}, \qquad \forall l \in L, c \in C, v \in V, t \in T \quad (23)$$

$$X_{l,l',v,t} = 0, \qquad \forall l, l' \in L, v \in V, t \in T \quad (24)$$

$$G_{c,p,t}, D_{l,c,v,t}, M_{c,v,t}, F_{l,c,v,p,t} Q_{l,e,t}, U_{c,v,t} \ge 0, \qquad \forall c \in C, l, e, p \in P, v \in V, t \in T \quad (25)$$

$$R_{l,c,v,t}, X_{n,n',v,t}, Z_l, A_{v,t}, B_{v,t} \in \{0,1\}, \qquad \forall l, c, n, n' \in N, v \in V, t \in T \quad (26)$$

$$W_{l,p,v,t}, Y_{i,l,e,v,t} \in \mathbb{Z}_+, \qquad \forall l \in L, i, e, p \in P, v \in V, t \in T. \quad (27)$$

Equation (1) shows the total cost of FB network including their setup, utilization of vehicles, the running costs of storage and packaging food baskets, the transportation costs of the food baskets and potential delay penalties, and also the food procurement cost associated with financial donors. In each time period, Equation (2) aims to maximize the total freshness of the food basket supplied to charities. Equation (3) aims to maximize overall nutritional value of all charities. Equation (4) assures that only one vehicle is authorized to deliver food baskets to each charity at any time period. According to Equation (5), each vehicle must depart the charity after visiting it. Equations (6) and (7) guarantee that only one vehicle may provide food baskets to charity during each time period. Equation (8) assures that any vehicle must leave and return to the same FB after visiting charities at any time period. Sub tour elimination restrictions are represented by equation (9). The total number of food baskets donated to charities by each vehicle is shown in Equation (10). Equation (11) assures that the total number of food baskets supplied by each FB does not exceed its distribution capacity. Equation (12) assures that the number of food baskets transported is less than the maximum capacity of vehicles. Equation (13) guarantees that the minimum nutritional content of food packets for each charity is met at each period. Equations (14) and (15) determine the arrival time of vehicles to each charity. Equation (16) calculates the freshness of food baskets based on the arrival time of vehicles. The time window limitation is shown in Equation (17). The number of hot food items needed for each food basket is imposed in Equation (18), while the number of cold food items that can be refrigerated in FBs is shown in Equation (19). The quantity of food donated at each time period is controlled by Equation (20). The utilization of vehicles for food collection is detected by Equation (21). The quantity of food delivered by financial donors at each time period is handled by Equation (22). The logical relationship between variables are shown in equations (23) and (24), while the type and domain of variables are shown in constraints (25) – (27).

The proposed FBSCN model subsumes an allocation sub-problem and a routing one, which are both known as NP-hard problems. Hence, FBSCN is also NP-hard as it can be reduced to one of them.

3.2 Robust Fuzzy Optimization Model

Due to the dynamic nature of several important parameters (such as transportation costs, supply and demand) that are beyond planning, as well as the lack of necessary historical data at the design stage, these parameters are based mostly on comments and experiences of experts. Other approaches such as stochastic programming might be applicable if we could benefit from such historical data to estimate the probability distribution of parameters. Thus, the parameters above are expressed as uncertain data in trapezoidal fuzzy numbers. The probabilistic programming approach is often used to deal with uncertain constraints that include non-deterministic data on the left or right side of the equation. A minimum degree of certainty is used in this approach to manage the confidence level for satisfaction of these uncertain constraints. To this end, the pessimistic standard fuzzy approach whose abstract form is shown in (28a)–(28d).

$$\min Z = fY + \tilde{c}X \tag{28a}$$

s.t.

$$aX \geq \tilde{d} \tag{28b}$$

$$bX \leq \tilde{s}Y \tag{28c}$$

$$Y \in \{0, 1\}, \quad X \geq 0. \tag{28d}$$

The vectors f, $\tilde{c}$, $\tilde{d}$ and $\tilde{s}$ indicate the fixed cost, variable cost (transport), demand and supply, respectively. Furthermore, a and b are coefficient matrices, while X and Y are continuous and binary variables, respectively. The objective function is dealt with its expected value, while the uncertain constraints with their pessimistic fuzzy form of chance constraint programming as shown in (29a)–(29d):

$$\min \mathbb{E}[Z] = fY + \mathbb{E}[\tilde{c}]X \tag{29a}$$

s.t.

$$NEC\{aX \geq \tilde{d}\} \geq \alpha \tag{29b}$$

$$NEC\{bX \leq \tilde{s}Y\} \geq \beta \tag{29c}$$

$$Y \in \{0,1\}, \quad X \geq 0 \tag{29d}$$

where α and β control the minimum degree of certainty of uncertain constraints with a (pessimistic) decision-making approach. Considering trapezoidal fuzzy parameters, the general form of equation (29a)–(29d) will become (see Zahiri et al. 2018; Ghahremani-Nahr et al. 2019):

$$\min fY + \left(\frac{c^1 + c^2 + c^3 + c^4}{4}\right) X \tag{30a}$$

s.t.

$$aX \geq (1-\alpha)d^3 + \alpha d^4 \tag{30b}$$

$$bX \leq (1-\beta)s^2 + \beta S^1 \tag{30c}$$

$$Y \in \{0,1\}, \quad X \geq 0. \tag{30d}$$

The minimum confidence level required to meet the uncertain constraints is specified according to the preference of decision-makers. The objective function in the suggested model is insensitive to the deviation from its expected value, implying that robust solutions are not assured in the base model. That is, a considerable risk may be imposed on such a decision-making, particularly in strategic ones, while solution consolidation is crucial. Thus, it is worthwhile employing the robust fuzzy optimization technique to the problem to benefit from the advantages of both robust and fuzzy programming. The robust fuzzy optimization framework employed in this article is given in (RFOF):

$$\text{(RFOF)} \quad \min \mathbb{E}[Z] + \zeta(Z_{(max)-Z_{min}}) + \eta_1[d^4 - (1-\alpha)d^3 - \alpha d^4] + \eta_2[\beta s^1 + (1-\beta)s^2 - s^1]Y \tag{31a}$$

s.t.

$(30b)$, $(30c)$, $(30d)$

where $Z_{(max)} = fY + c^4X$, $Z_{(min)} = fY + c^1X$ and $\mathbb{E}[Z] = \left(\frac{c^1+c^2+c^3+c^4}{4}\right)X$. To calculate these for FBSCN model, first let

$$\Gamma := \sum_{l} f_l Z_l + \sum_{v,t} g_v(A_{v,t} + B_{v,t}) + \sum_{l,p,v,t} o_{l,p} W_{l,p,v,t} + \sum_{c,v,t} \theta M_{c,v,t} + \sum_{l,e,t} h_{e,t} Q_{l,e,t}.$$

Then,

$$\mathbb{E}[Z] = \Gamma + \sum_{n,n',v,t} \left[\frac{\xi^1_{n,n'} + \xi^2_{n,n'} + \xi^3_{n,n'} + \xi^4_{n,n'}}{4} \right] X_{n,n',v,t} + \sum_{i,l,e,v,t} \left[\frac{\xi^1_{i,l} + \xi^2_{i,l} + \xi^3_{i,l} + \xi^4_{i,l}}{4} \right] Y_{i,l,e,v,t}, \tag{32}$$

$$Z_{(max)} = \Gamma + \sum_{n,n',v,t} \xi^4_{n,n'} X_{n,n',v,t} + \sum_{i,l,e,v,t} \xi^4_{i,l} Y_{i,l,e,v,t}, \tag{33}$$

$$Z_{(min)} = \Gamma + \sum_{n,n',v,t} \xi^1_{n,n'} X_{n,n',v,t} + \sum_{i,l,e,v,t} \xi^1_{i,l} Y_{i,l,e,v,t}. \tag{34}$$

Thus, the robust fuzzy counterpart of FBSCN is obtained as follows.

$$\begin{aligned} \min \quad & \mathbb{E}[Z] + \zeta \left(Z_{(max)} - Z_{(min)} \right) \\ & + \eta_1 \sum_{c,p,t} \left[d^4_{c,p,t} - (1-\alpha) d^3_{c,p,t} - \alpha d^4_{c}, p, t \right] \\ & + \eta_2 \sum_{i,e,t} \left[\beta \omega^1_{i,e,t} + (1-\beta) \omega^2_{i,e,t} - \omega^1_{i,e,t} \right] \end{aligned} \tag{35}$$

Objectives (2) and (3)

s.t.

$$W_{l,p,v,t} \geq \sum_{c} G_{c,p,t} \left[(1-\alpha) d^3_{c,p,t} + \alpha d^4_{c,p,t} \right] R_{l,c,v,t}, \qquad \forall l \in L, p \in P, v \in V, t \in T \tag{36}$$

$$\sum_{c,n,p} G_{c,p,t} \left[(1-\alpha) d^3_{c,p,t} + \alpha d^4_{c,p,t} \right] X_{n,c,v,t} \leq \gamma_v B_{v,t}, \qquad \forall c \in C, p \in P, t \in T \tag{37}$$

$$\sum_{e} \delta_{e,p} \kappa_e G_{c,p,t} \left[(1-\alpha) d^3_{c,p,t} + \alpha d^4_{c,p,t} \right] \geq \rho_{c,p,t}, \qquad \forall c \in C, p \in P, t \in T \tag{38}$$

$$\sum_{l,v} Y_{i,l,e,v,t} \leq \left[\beta \omega^1_{i,e,t} + (1-\beta) \omega^2_{i,e,t} \right], \qquad \forall i \in I', e \in P' \cup P'', t \in T, \tag{39}$$

$$(4) - (9), (11), (14) - (19), (21) - (27).$$

The first expression in Equation (35) refers to the expected value of the first objective function based on the mean values of the unknown parameters. The second term imposes the penalty cost of deviation from the expected value of the first objective function (robustness of optimality). The third and fourth terms reflect the penalty costs of supply and demand deviations (uncertain parameter). Coefficients ζ, η_1 and η_2 denote the weight of such penalties, respectively, while α and β show the minimal degree of confidence for the fuzzy numbers which should be between 0.1 and 0.9.

4 Solution approaches

Various methods are used to solve the multi-objective problems. This section describes three of them used in this article including the augmented ϵ-constraint, the NSGA II and MOGWO algorithms. The first one is used for solving and evaluation of the model in small size, while the other two are employed for solving larger samples. They are both population-based algorithms which have high efficiency in searching the solution space. The other motive behind their choice here, is the fact that they are old and new meta-heuristics, respectively (Deb et al. 2002; Mirjalili et al. 2016). The most important part of meta-heuristic algorithms might be the representation of initial solution (initial chromosome) and decoding it.

4.1 The Augmented ϵ-constraint Method

This method is an extension of ϵ-constraint method in solving multi-objective problems (Mavrotas 2009). Despite its advantages, there are some challenges as well: *(i)* calculating the range of objective functions in the efficient solution set, *(ii)* ensuring the efficiency of the obtained solution, *(iii)* increasing solving time of the problems if there are more than two objective functions. To overcome these drawbacks of the ϵ-constraint method, the augmented version uses the lexicographic method to calculate the objective values and converts the constraints related to the sub-objective functions to equation by auxiliary variables. The objective functions are ranked by the decision-maker based on their importance. That is, the objective function with the higher priority is optimized as a single objective model. Let $f_1(x)$ be the objective function with the highest priority and its optimal value equals to f_1^*. Then, to optimize the second objective function, by adding the constraint $f_1(x) = f_1^*$, the optimal solution of the first objective function is maintained and the second objective value, f_2^*, is obtained and used to optimize the objective function with the next priority. This approach can be applied to our three-objective FBSCN problem as follows:

$$\min Z_1 + \delta \left(\frac{s_2}{r_2} + \frac{s_3}{r_3} \right) \tag{40}$$

s.t.

$$Z_2 - s_2 = \epsilon_2 \tag{41}$$

$$Z_3 - s_3 = \epsilon_3 \tag{42}$$

$(4) - (9), (11), (14) - (19), (21) - (27), (36) - (39).$

In the above model $r_i, i = 2, 3$ are the domains of the objective functions, $\epsilon_i, i = 2, 3$ are the solution obtained in each iteration and δ is a small positive number. As FBSCN model is nonlinear, Baron solver is used to implement the augmented ϵ-constraint method to solve problems in small size. This solver is not able to solve large sample sizes. Therefore, NSGA II (Deb et al. 2002) and MOGWO (Rezaei et al. 2018) algorithms are used to solve larger sample. The flowcharts of the proposed algorithms are as shown in Figures 3 and 4.

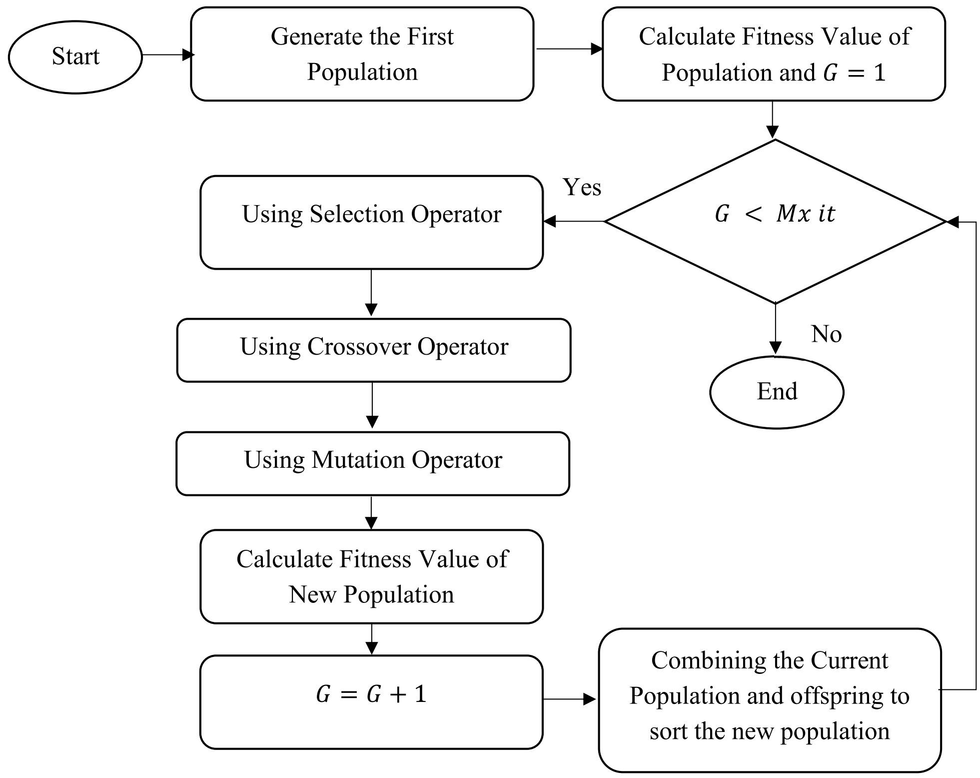


Figure 3: The Flowchart of NSGA II Algorithm

4.2 Initial Solution (Chromosome) and Decoding

FBSCN model is made up of a variety of decision variables. Decisions related to the amount of food supply basket (demand satisfaction) are made in the first part; decisions related to vehicle routing are made in the second part, and decisions related to the optimal allocation of food / finance from donors to the FB are made in the third part. Figure 5 depicts the initial solution instance with five charities, three FBs, four food/financial donors, three types of vehicles, and only one period and product. The coded solution is shown in a $3 \times (|I| + |J| + |C|)$ matrix in the bottom of this figure and the data used for decoding the chromosome is listed in Table 4.

To decode the initial solution, we do the following steps in each section:

Decoding the real demand of charities

It is determined according to the percentage of unmet demand of each charity (second row)

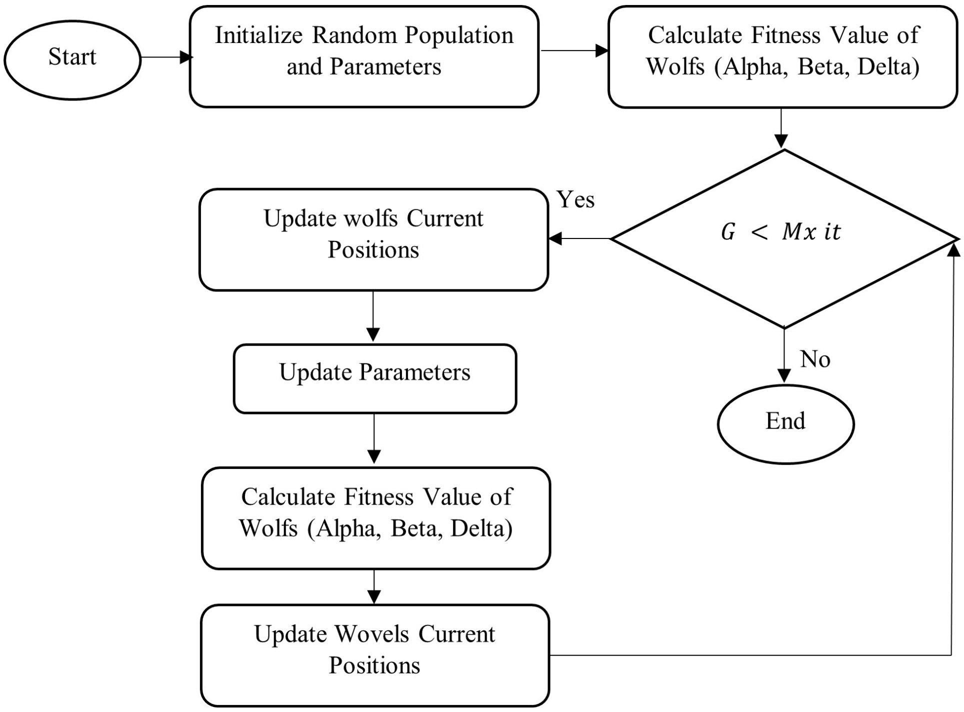


Figure 4: The Flowchart of MOGWO Algorithm

Table 4: The random data used in chromosome decoding

ξ	i_1	i_2	i_3	i_4	ψ
j_1	15	7	12	10	60
j_2	9	13	10	14	60
j_3	10	12	18	20	50
ω	30	20	40	20	

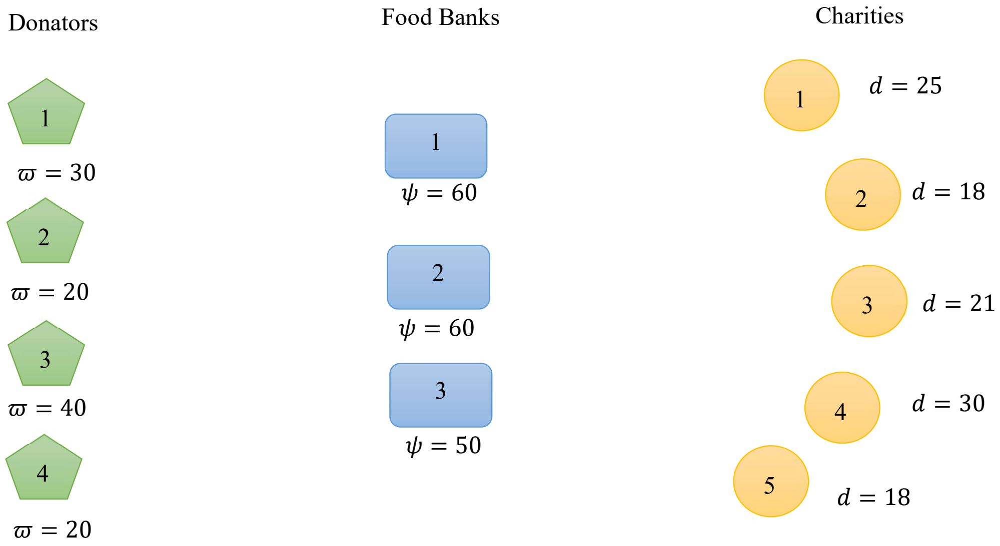
below:

Charities	c_1	c_2	c_3	c_4	c_5
$Demand$	25	18	21	30	18
UD	0.231	0.180	0.166	0.688	0.513
$d = Demand(1 - UD)$	19.225	14.76	17.514	21.36	15.966

Decoding the Vehicle Routing part

The sequence of visits to charities is determined based on the initial solution in the first step and the amount of met demand is calculated. Thus, the charity with the lowest priority is considered as the first node to be visited by the vehicle. If the amount of food transported by each vehicle exceeds the allocated capacity of the vehicle, the demand of high-priority charities will be met by another vehicle. For example based on Figure 5, $\{C_1 - C_3 - C_5\}$ can be allocated to Vehicle 1 and $\{C_2 - C_4\}$ can be allocated to Vehicle 2.

$Vehicle\ 1 \rightarrow C_1 - C_3 - C_5$	$Based\ on\ Priority \rightarrow$	$Vehicle\ 1 \rightarrow C_1 \rightarrow C_5 \rightarrow C_3$	$\sum d = 52.705$
$Vehicle\ 2 \rightarrow C_2 - C_4$	$Based\ on\ Priority \rightarrow$	$Vehicle\ 2 \rightarrow C_4 \rightarrow C_2$	$\sum d = 36.120$



Node	$\lvert I \rvert + \lvert J \rvert$							$\lvert C \rvert$				
	i_1	i_2	i_3	i_4	j_1	j_2	j_3	c_1	c_2	c_3	c_4	c_5
$Rand()$	6	1	3	4	2	5	7	1	3	5	2	4
UD	-	-	-	-	-	-	-	0.231	0.180	0.166	0.288	0.113
VN	3	2	1	3	-	-	-	1	2	1	2	1

Figure 5: Initial Solution instance of FBSCN

Decoding FB selection

To select the FBs and their location, first the highest priority is selected. If the center alone cannot meet the total demand of charities other FBs will be selected with the next highest priority. In the instance of Figure 5, FBs 2 and 3 are selected to meet the demand of charities and therefore there is no need to locate and select FB 1. Hence, its priority is reduced to 0.

$Food\ Bank$	j_1	j_2	j_3
$Priority-old$	2	5	7
ψ	60	60	50
$Priority-new$	0	5	7

As a result, vehicle routing from FBs can be described as follows:

$Routing$	$Vehicle$
$j_3 \rightarrow C_4 \rightarrow C_2 \rightarrow j_3$	2
$j_2 \rightarrow C_1 \rightarrow C_5 \rightarrow C_3 \rightarrow j_2$	1

Decoding the Flow between Donors and FBs

Node	$\lvert I \rvert + \lvert J \rvert$						
	i_1	i_2	i_3	i_4	j_1	j_2	j_3
$Rand()$	6	1	3	4	0	5	7
VN	3	2	1	3	-	-	-

In this part, based on the amount of food distribution of FBs and the capacity of donors, the optimal flow allocation is performed on the modified chromosome of the previous part. It is performed based on the following steps.

Step 1: The highest priority is selected from the modified chromosomes as the starting part of the allocation (eg. FB 3 with priority 7)

Step 2: The donor / FB is selected based on the lowest transportation cost with the FB / donor obtained from Step 1 (eg. Donor 1 with transportation cost of 10)

Step 3: The vehicle needed to transport food is selected between the two nodes (eg. Vehicle 3).

Step 4: Optimal flow allocation between selected nodes is achieved based on the minimum amount (eg. Donor supply, FB requirement and vehicle capacity) ($\min\{36.120, 30, 50\} = 30$).

Step 5: Donor supply and FB needs are updated ψ_3 = 36.120-30 = 6.120 and $\omega_1 = 30 - 30 = 0$

Step 6: If the donor supply or the need for the FB is zero, the priority associated with that center will be reduced to 0.

Step 7: Steps 1 to 6 will continue until the total donor priority is reduced to 0.

Step 8: If all FB priorities are not met, financial donors will be used to supply food to meet the remaining needs of FBs.

The routing-location and allocation of the problem instance of Figure 5 is shown in Figure 6 after this decoding process.

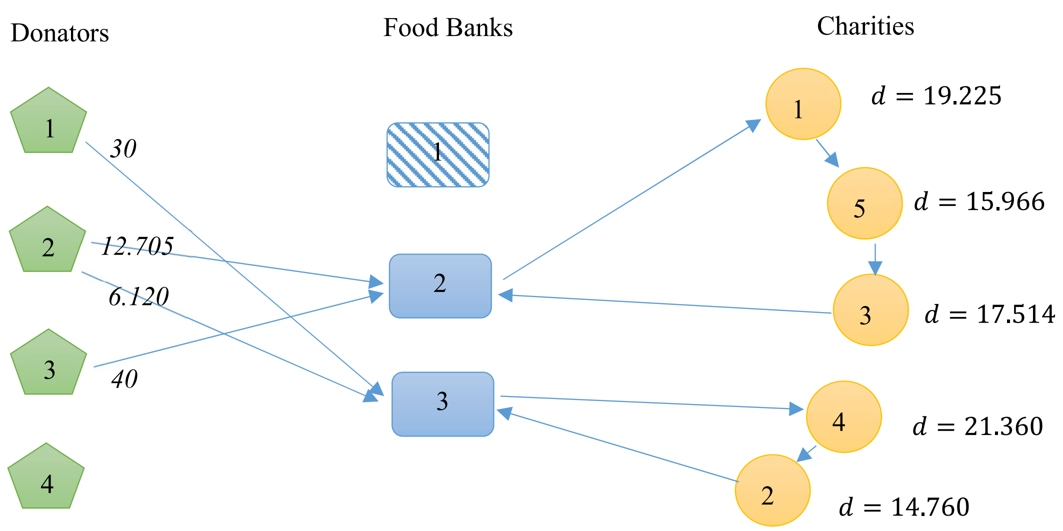


Figure 6: Routing-locating and allocation based on initial solution decoding

4.3 Comparison indicators of solution methods

Each of the aforementioned methods leads to creation of different efficient solutions. Thus, different measures should be used to compare them and here, 5 of them are introduced.

- **Number of Pareto Frontier (NPF):** Shows the number of undefeated solutions in the Pareto frontier obtained for each method, and the higher the value of NPF, the more efficient the method.

- **Maximum spread Index (MSI):** This measure shows how many of the solution of a Pareto frontier are distributed in the solution space, which is calculated from the following equation wherein f_k^{max} and f_k^{min} denote the maximum and minimum objective values for the k^{th} objective.

$$MSI = \sqrt{\sum_{k=1}^{K} \left(\max_{k=1} f_k^{max} - f^{min} \right)^2} \tag{43}$$

  The higher the value of this index, the more appropriate the diversity of Pareto frontier solutions are (Javid 2021).

- **Space Metric (SM):** Indicates the uniformity of the solutions, which is calculated from the following equation. A solution algorithm whose SM value is less is more desirable.

$$SM = \frac{\sum_{i=1}^{K-1} |\bar{d} - d_i|}{(K-1)\bar{d}} \tag{44}$$

$$\text{where } d_i = \min_{j=1,\ldots,n, j\neq i} \left\{ \sum_{k=1}^{K} |f_k^i - f_k^j| \right\}, \quad \forall i = 1, \ldots, n \tag{45}$$

- **Mean of ideal deviations (MID):** This index is used to measure the degree of proximity to the optimal level of the real Pareto, which is calculated from the following equation. The algorithm that has the lowest value of this measure has a higher efficiency. In this relation n is the number of solution in the Pareto optimal front.

$$MID = \frac{\sum_{k=1}^{K} \sqrt{(f_k^1 - f_k^{min})^2 + \ldots + (f_k^n - f_k^{min})^2}}{K} \tag{46}$$

  where f_k^i and f_k^{min} are the objective value of the i^{th} efficient solution and minimum value for the k^{th} objective function.

- **Computation time (CPU-Time):** An algorithm with less computational time is obviously more desirable.

5 Numerical analyses

5.1 Parameter settings for the solution algorithms

In order to increase the efficiency of the algorithms in optimizing the objective functions, it is necessary to tune the initial parameters of both meta-heuristic algorithms. Therefore, 9 experiments are designed by Taguchi method and the proposed algorithms are tested based on the levels presented in Table 5. The mean of S/N ratios diagram for selecting the optimal level of meta-heuristic algorithm parameters is shown in Figure 7 where the highest points is the desired level to set the parameters. Therefore, for the NSGA II algorithm the value of $Npop$ is 200, the value of $Maxit$ is 200, and values of P_c and P_m are 0.08 and 0.9, and in the MOGWO algorithm, the value of $Nwolf$ is 300, the value of $Maxit$ is 200 and values of A and C are 1 and 2, respectively.

Table 5: The initial value of the parameters at different levels

Algorithm	Parameter	Level 1	Level 2	Level 3
NSGA II	$Maxit$	100	150	200
	$Npop$	150	200	300
	P_c	0.03	0.05	0.08
	P_m	0.7	0.8	0.9
MOGWO	$Maxit$	100	150	200
	$Nwolf$	150	200	300
	P_c	1	2	3
	P_m	1	2	3

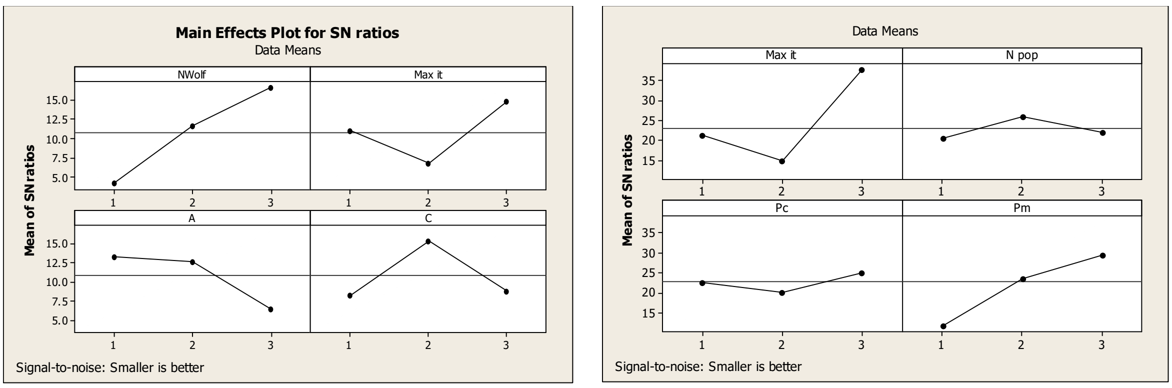


Figure 7: The mean of SN ratios plot obtained for Taguchi experimental design

5.2 Small problem instance

We first start with small sample size of the problem to examine the decisions. Hence, the size and parameters of the small instance are set according Table 6 and 7.

The additional parameters corresponding to the robustness of the model are set as $\alpha =$

Table 6: Sample problem size in small size

Set	Size	Set	Size	Set	Size
I'	1	C	6	P	2
I''	2	N	9	P'	1
I	3	V	8	P''	2
L	3	T	3		

Table 7: The parameters interval based on the uniform distribution function

Parameter	Range	Parameter	Range
f_l	$\sim U(10000, 12000)$	ϕ_c	$\sim U(2, 5)$
g_v	$\sim U(300, 400)$	$[\alpha_c, \beta_c]$	$\sim U([10, 12], [40, 50])$
$o_{l,p}$	$\sim U(2, 3)$	κ_e	$\sim U(5, 8)$
$k_{n,n'}$	$\sim U(15, 20)$	$\rho_(c, p, t)$	$\sim U(100, 110)$
$h_{e,t}$	$\sim U(2, 3)$	$\Omega_(i, e, t)$	$\sim U(1, 5)$
$\psi_{l,p}$	$\sim U(200, 220)$	u_p	$\sim U(60, 900)$
γ_v	$\sim U(60, 80)$	s_it	5000
θ	6		
Uncertain parameter	Fuzzy number $\sim U(\lambda^1, \lambda^2, \lambda^3, \lambda^4)$		
$\tilde{\xi}_{n,n'}$	$\sim U([20, 25], [25, 30], [30, 40], [40, 45])$		
$\tilde{\xi}_{i,l}$	$\sim U([5, 10], [10, 15], [15, 20], [20, 25])$		
$\tilde{d}_{c,p,t}$	$\sim U([5, 10], [10, 15], [15, 20], [20, 25])$		
$\tilde{\omega}_{i,e,t}$	$\sim U([120, 140], [140, 160], [160, 180], [180, 200])$		

$\beta = 0.5$, $\eta_1 = \eta_2 = 2$ and $\zeta = 10$. The augmented ϵ-constraint method was implemented by Baron solver for this small size instance and 34 efficient solution were obtained in the average execution time of 1687.4 seconds. The corresponding Pareto frontier is shown in Figure 8.

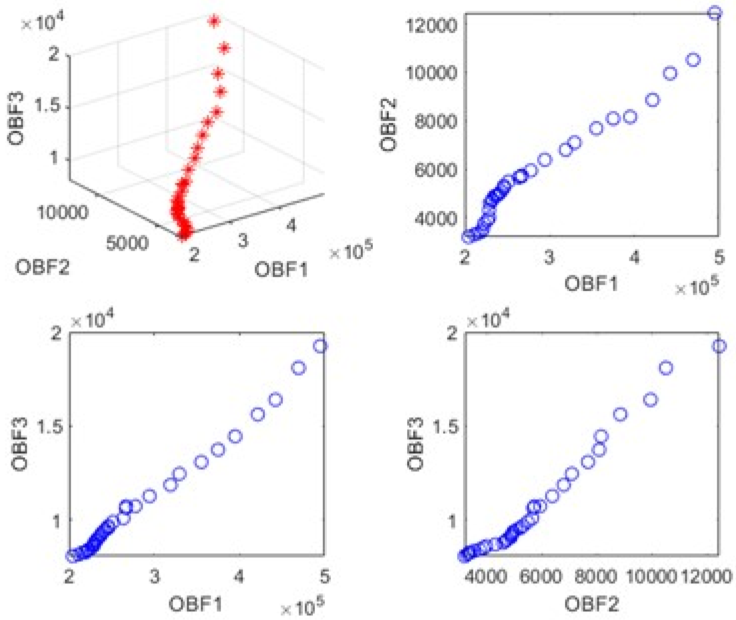


Figure 8: Pareto frontier obtained by solving a small instance

As shown in this figure, the nutritional value of the food baskets of charities has positive correlation with the total cost because more food baskets should be distributed and it needs to increase the food supply from food and financial donors, which in turn increases the cost of supply, packaging, maintenance and transportation in FB Supply chain. In addition, to increase the freshness of the distributed food more vehicles and closer facilities to charities should be used, which leads to an increase in costs. Therefore, objective 3 and 1 also have a positive correlation.

To demonstrate the details of the output, the pictorial representation of the first efficient solution is shown in Figure 9 wherein, two centers (2 and 3) out of three FBs are selected to cover the food baskets of charities. Also, two donation centers (1 and 2) are selected for food supply as well as financing the FBs. The freshness of the dispatched foods over time is also shown in Figure 10. As seen, the freshness decays exponential in time but with much higher rate for hot meals. Finally, Table 8 shows the percentage of demand met for each charity.

Table 8: Percentage of satisfied demand of charities from hot and cold food baskets

Charities	*Packet*	*Period 1*	*Period 2*	*Period 3*
1	*Warm*	*0.478*	*0.478*	*0.454*
	Cold	*0.971*	*0.971*	*0.923*
2	*Warm*	*0.478*	*0.413*	*0.413*
	Cold	*0.923*	*0.839*	*0.879*
3	*Warm*	*0.432*	*0.478*	*0.413*
	Cold	*0.971*	*0.879*	*0.923*
4	*Warm*	*0.454*	*0.454*	*0.454*
	Cold	*0.879*	*0.971*	*0.839*
5	*Warm*	*0.432*	*0.432*	*0.432*
	Cold	*0.923*	*0.971*	*0.923*
6	*Warm*	*0.432*	*0.432*	*0.432*
	Cold	*0.971*	*0.923*	*0.971*

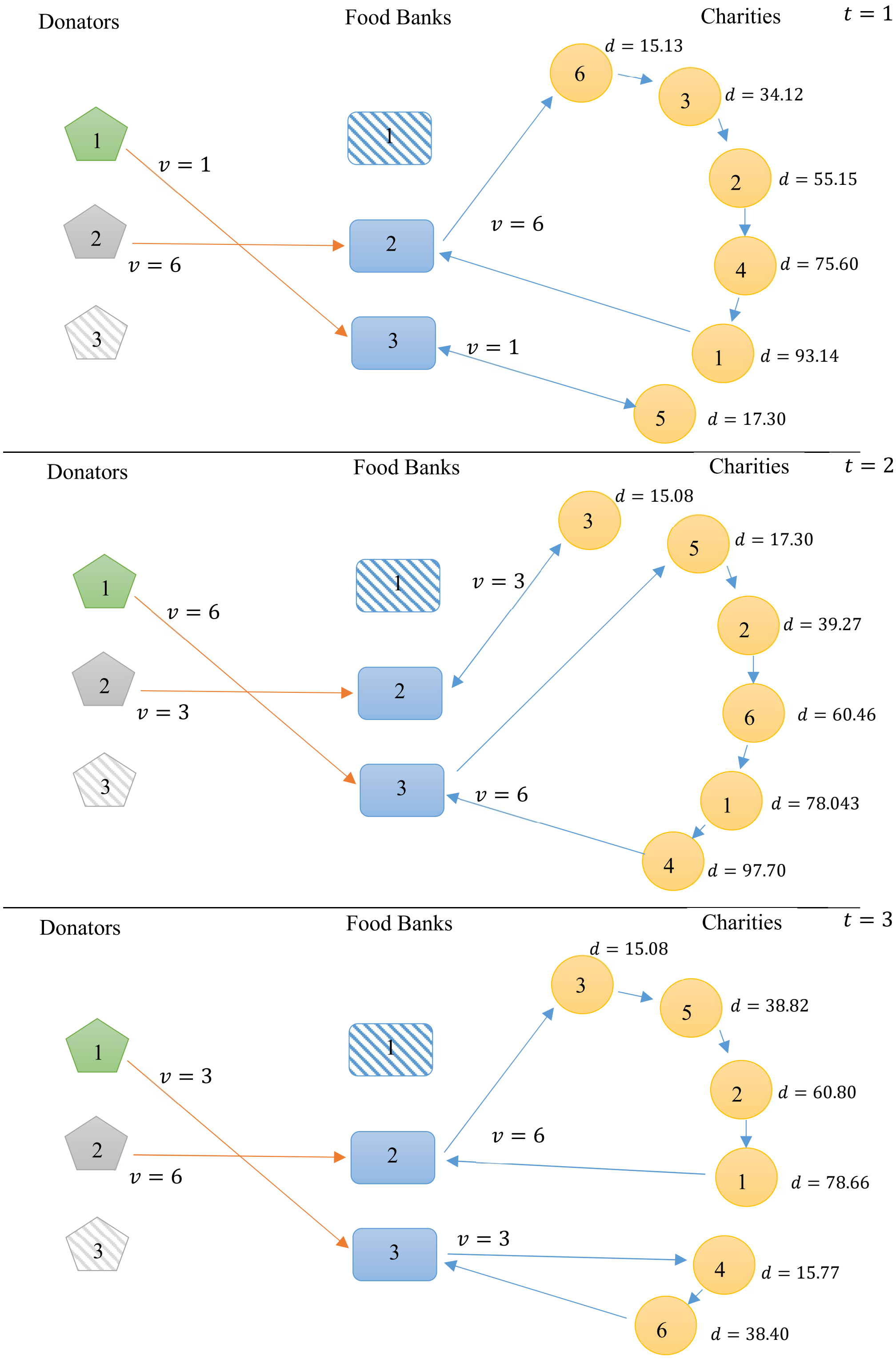


Figure 9: Optimal location-routing and flow allocation in the efficient solution of the small sample problem

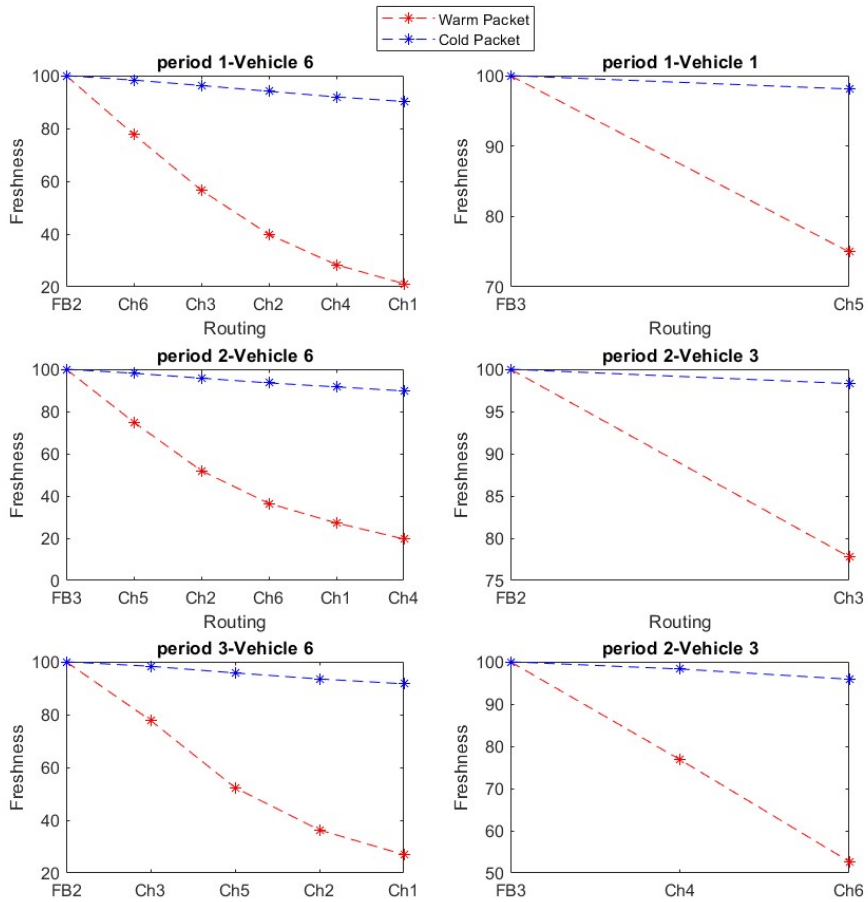


Figure 10: Fresh amount of hot and cold food packages at the time of delivery to charities

5.2.1 Sensitivity analysis on uncertainty level

In the previous subsection, the uncertainty rates were considered as $\alpha = \beta = 0.5$. The higher the uncertainty rate goes, the higher demand level in charities for various foods, and in contrast the less food supply by donors will be imposed to the supply chain system. Figure 11 depicts the trend of optimal objective values under different uncertainty rates. As shown, with the increase in the rate of uncertainty, the total nutritional value of food baskets has increased due to the increase in demand for variety of products. Furthermore, with the increase in demand, due to the limited capacity of vehicles, more vehicles have been used to distribute food baskets. This has led to an increase in the freshness and quality of the food basket through the timely delivery of food to charities. Unsurprisingly, this has caused to higher transportation and total cost of the FB supply chain.

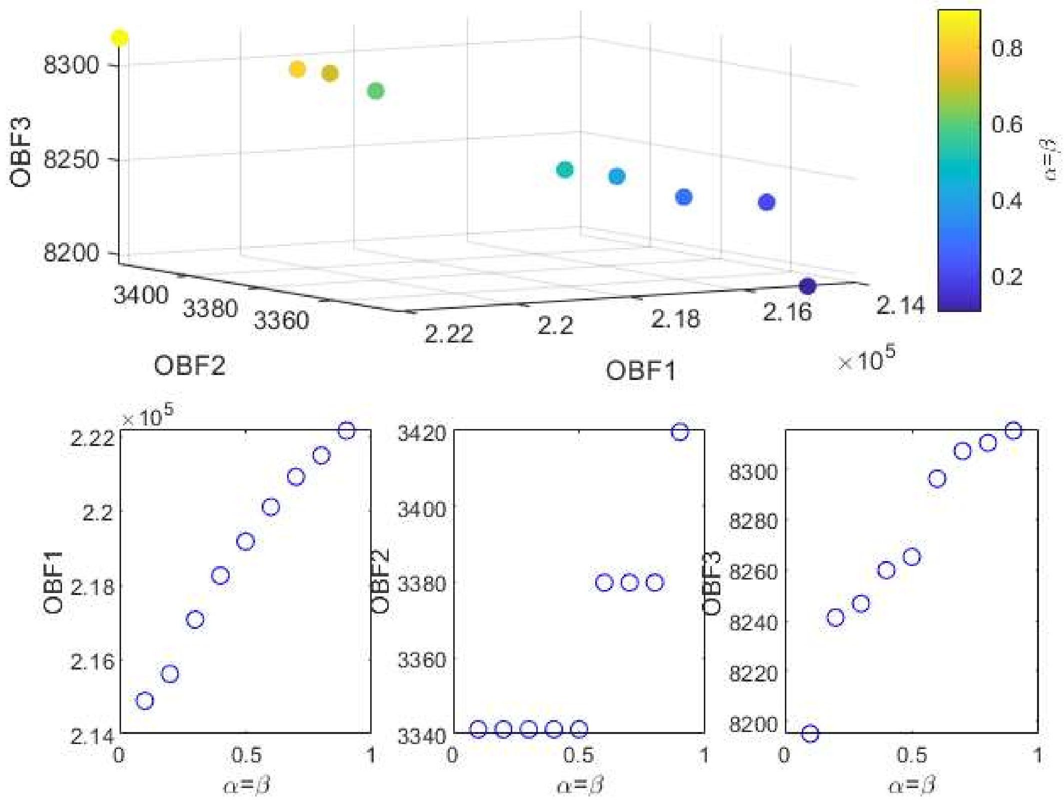


Figure 11: The process of changing the value of the objective functions under different rates of uncertainty

5.2.2 Sensitivity analysis on the impact of vehicle capacity

The next factor analyzed is the vehicle capacity. Accordingly, the effect of reducing the capacity of the vehicle by 15% and 30% on the freshness of the delivered food basket delivered is investigated in three different scenarios. Figure 12 shows the average trend of foods freshness

Figure 12: The trend of changes in food freshness under reduced vehicle capacity

changes in charities for both warm and cold food baskets. The general increasing trend in this figure is because of more frequent and shorter travel time of the vehicles when they have less capacity.

5.2.3 Sensitivity analysis on the impact of shelf-life

Another influential factor in network decisions is the distribution time of food baskets related to the shelf-life parameter. Figure 13 shows the shift in objective values by increasing and decreasing the shelf-life of both hot and cold foods in the FB network. For the sake of simplicity, it is represented by percentage with respect to the base shelf-life of the items in food baskets. Thus, 10, 15 and 20% longer or shorter shelf-life are tested with positive and negative values on the figure, respectively. It is not surprising to see the transportation costs in the network increases for more perishable products in order to deal with their delivery in a tighter time window. Thus, a declining trend is observed in the first part (Objective 1) of Figure 13. Also, as the shelf-life of product shortens, the freshness of products (Objective 2) drops off during the distribution of food baskets to charities. It is due to the fact that the nonlinear function in the right hand side of (16) is increasing in u_p. However, the overall nutritional value (Objective 3) shows an insensitive behavior to the shelf-life and remains unchanged.

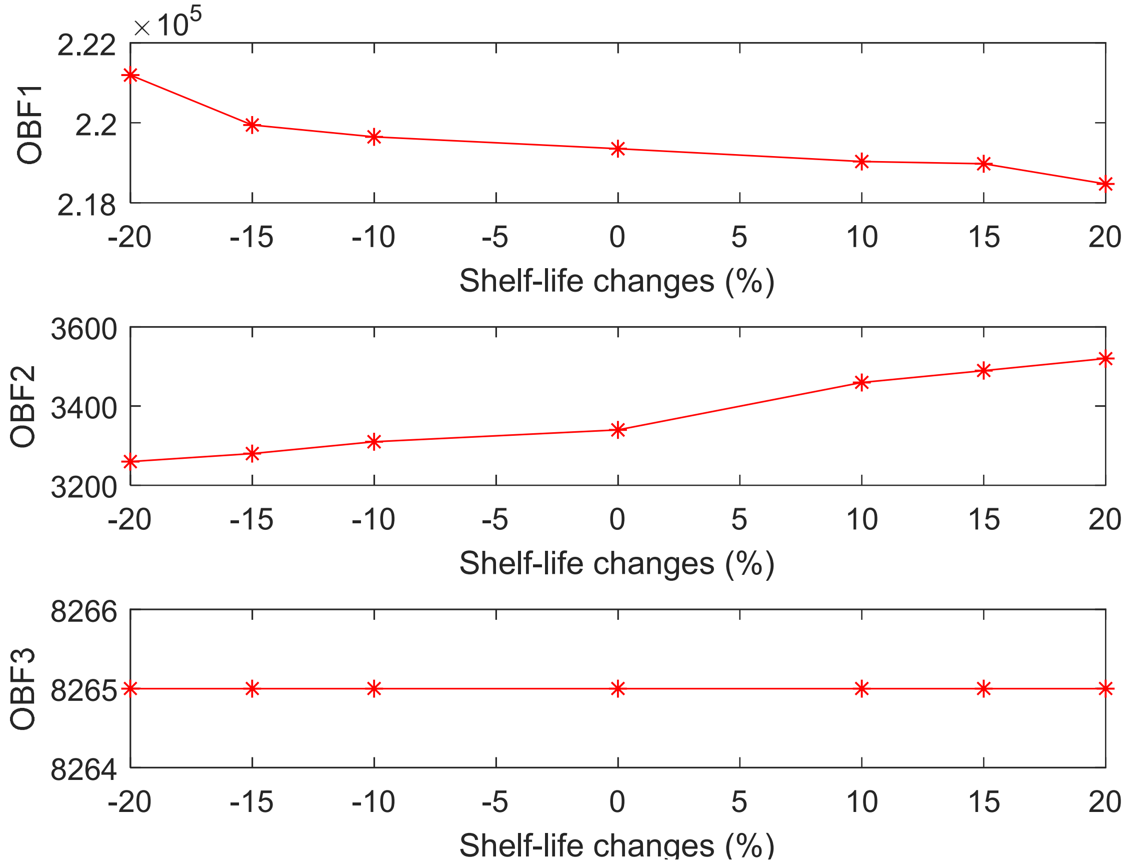


Figure 13: The sensitivity of objective functions to the shelf-life of food items

5.2.4 Inspecting performance of the meta-heuristics

The NSGA II and MOGWO meta-heuristic algorithms are also used to solve small instances for evaluation purpose. The objective values as well as other the performance indicators are used to compare them. The Pareto frontier obtained obtained by these algorithms are illustrated in Figure 8 where in their trend is close to the exact solution (ϵ-constraint) from BARON solver. NSGA II has obtained 61 efficient solutions in 117.3 seconds and the MOGWO has obtained 54 efficient solutions in 124.16 seconds, which are much faster than that of the ϵ-constraint implemented by BARON solver. Based on a comparison of the mean objective value of the efficient solutions, the relative deviation of the cost objective function obtained by the NSGA II and MOGWO meta-heuristic algorithms from that of the modified ϵ-constraint method are 2.81% and 2.29%, respectively. Other indicators for comparing efficient solutions are summarized in Table 9. The numbers associated with the winner algorithm with respect to each index is bold in this table.

Table 9: Comparison of efficient solution indicators for the algorithms in small instance

Index	ϵ-constraint	MOGWO	NSGA II
NPF	34	54	**61**
MSI	290680.3	**316020.6**	302652.3
SM	77435.2	162180.9	**155081.9**
MID	**0.944**	0.705	0.694
CPU-time (s)	1687.5	124.2	**117.3**

5.3 Large problem instances

To examine the problem in larger sizes 12 instances are designed according to dimensions listed in Table 10 and parameters given in Table 7. As the solver is unable to deal with larger sizes of the problem they are solved only by NSGA II and MOGWO and the corresponding results are summarized in Tables 11 and 12. The NPF, MSI, SM, MID and CPU-Time indices in these tables depicts the average results over 3 replication of each instance for both algorithms, separately.

Table 10: Size of sample problems in larger sizes

Sample #	I	L	C	V	T	P	P'	P''
1	5	6	10	10	3	3	4	4
2	6	8	15	15	3	3	4	4
3	8	12	18	20	3	3	6	6
4	10	18	25	25	6	4	6	6
5	12	20	32	30	6	4	8	8
6	15	25	40	35	6	4	8	8
7	20	30	50	40	9	5	10	10
8	25	35	62	45	9	5	10	10
9	30	40	70	50	9	5	12	12
10	35	50	80	55	12	6	12	12
11	40	60	90	60	12	6	15	15
12	50	70	100	65	12	6	15	15

Table 11: Mean comparison indices of efficient answers in NSGA II meta-heuristic algorithm

Sample #	NPF	MSI	SM	MID	CPU time
1	63	25787.94	30191.61	0.63	165.1
2	69	39884.08	28961.60	0.88	241.4
3	75	35945.16	46713.31	0.59	325.9
4	67	30651.97	53775.69	0.64	442.7
5	58	31256.82	33778.50	0.55	618.8
6	55	39801.00	51220.79	0.79	774.6
7	51	28298.03	47013.28	0.84	993.5
8	56	45948.33	20268.61	0.77	1334.5
9	80	41482.35	44086.82	0.71	1468.2
10	65	49358.23	35470.85	0.82	1584.3
11	62	49496.07	56639.65	0.82	1699.5
12	61	47348.58	20046.04	0.84	1812.2

The pictorial comparison of NSGA II and MOGWO algorithms over all large instances are

Table 12: Mean comparison indices of efficient answers in MOGWO meta-heuristic algorithm

Sample #	NPF	MSI	SM	MID	CPU time
1	75	48271.61	43104.79	0.85	121.3
2	78	51361.14	29674.15	0.62	167.8
3	74	45190.48	43542.18	0.56	217.2
4	66	55499.53	34140.71	0.80	272.9
5	71	52958.97	21072.88	0.73	334.5
6	80	59216.23	25276.23	0.73	409.8
7	66	48283.35	41652.74	0.83	479.8
8	72	43128.64	34204.58	0.89	520.1
9	73	37640.73	24581.64	0.68	663.0
10	50	50273.97	30233.74	0.83	763.7
11	65	54470.06	38221.68	0.71	905.2
12	70	45586.32	25752.36	0.92	1338.2

illustrated in Figure 14. We can observe the superiority of NSGA II in CPU-time. However, with respect to other indices the winner algorithm may change from over different instances.

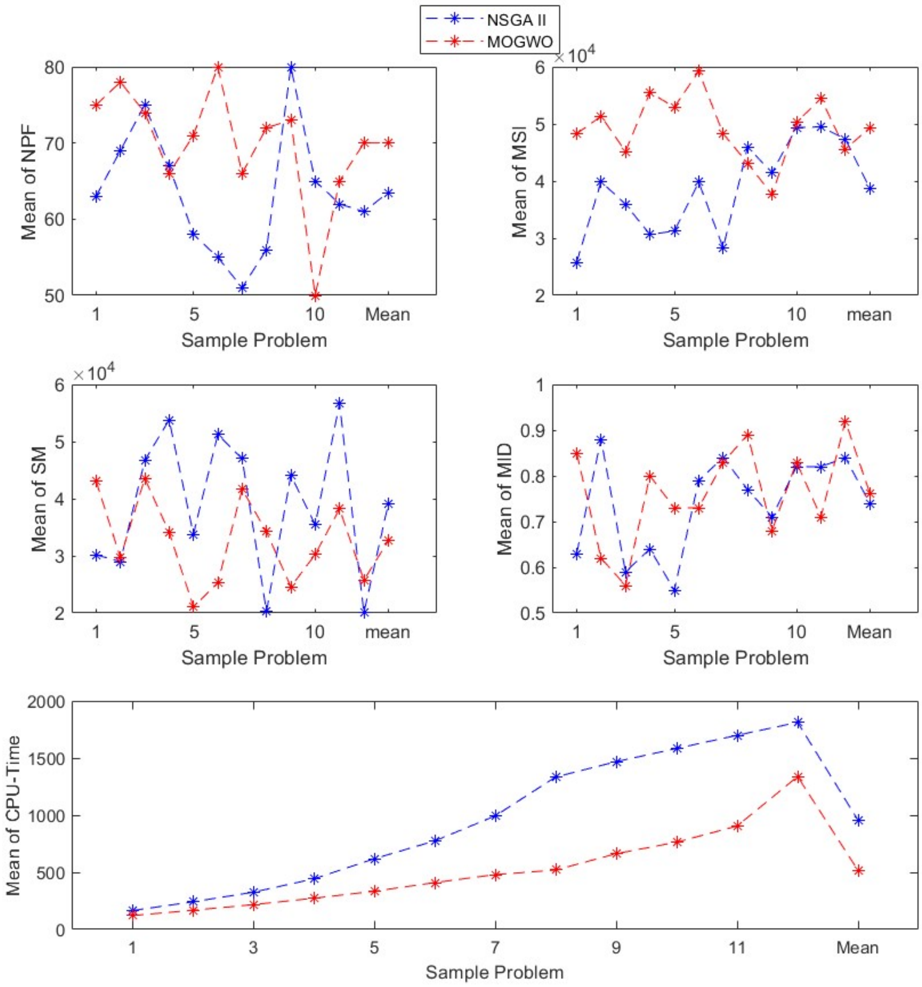


Figure 14: Comparison between efficient solution of meta-heuristic algorithm for large problem instances

5.4 Case study

After examining the effectiveness of two meta-heuristic algorithms (MOGWO and NSGA II) in solving numerical examples in larger sizes, in this subsection a case study from the capital city in Iran is analyzed. As the analyses in previous subsections show the efficiency of MOGWO algorithm is more than NSGA II algorithm, this case study is solved by the former one. The case study, which is adopted from Kaviyani-Charati et al. (2022), has been conducted in Iran over 22 municipal regions of Tehran province with an area of about 730 square kilometers. According to the demographic structure and population growth of the studied region during the last 50 years, its population has increased from 3 million people to more than 9 million (amar.org.ir). This has led to more challenges in metropolitan management and also food deficiencies of residents. Figure 15 shows the map of 22 municipal regions in Tehran province.

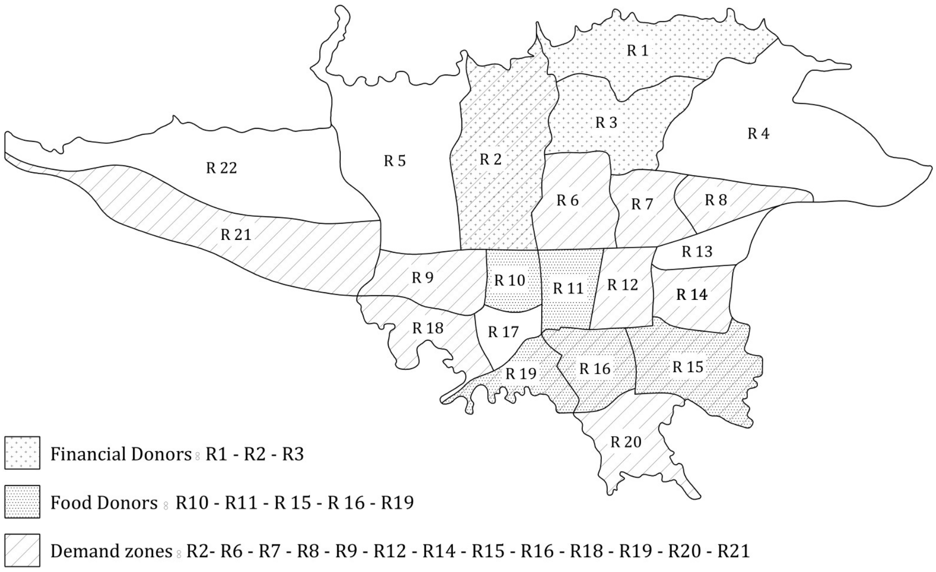


Figure 15: Urban regions of Tehran in Iran

Due to the Covid-19 pandemic in recent years, the economic recession has deteriorated in Iran. According to recent studies conducted by Food and Agriculture Organization of the United Nations (FAO), Ministry of Health (HM), field research (FR), non-governmental organizations (NGO) and Imam Khomeini Relief Foundation (IKRF), about 5 million people in Iran are facing hunger and food insecurity. According to recent statistics, it can be said that this figure for Tehran is around 6% of the population (Kaviyani-Charati et al. 2022). This happens while about 35% of produced foods is wasted due to its fast perishability nature (Fami et al. 2019), which explains the importance of an efficient food bank network model.

In this case study there are 3 different types of food packages including warm (cooked meat with 243 calories and a perishable time of 2 hours), refrigerated (vegetables and fruits with

229 calories and a perishable time of 5-7 days), and dry (bread, rice and canned food with 456 calories and perishability time of 5 hours) during one week of the year. According to studies, the average amount of calories needed by the body for an adult man is about 2800 calories while for a woman is about 2200 calories. The donors of these items include great restaurants in the city, universities, grocery stores and residential houses. Table 13 summarizes the number of food donors in the city and urban areas. In addition to donating food by donors, some fresh food can be purchased from stores and supermarkets at an affordable price using donations (money) and funds. Donations are first collected from both public and private sectors, and then given to local food banks. The demand zones as well as financial and food donor regions are illustrated in Figure 15 while all regions of Tehran are considered as potential food banks locations.

Table 13: The number of food donors in the different regions of Tehran province

Region	Groceries	Restaurants	Universities
10	6	4	3
11	9	6	4
15	9	6	2
16	7	5	1
19	8	6	2

Following Kaviyani-Charati et al. (2022), the parameters have been set based on the opinions of experts including ten experts from the National Relief Foundation (NRF), Iran Food and Drug Administration (IFDA) and four academics. Thus, the fuzzy trapezoid parameters are drawn from the following uniform distributions:

- demand amount of charities: $\sim U(960, 1400) * [0.9, 0.95, 1.05, 1.1]$,
- food supply amount by donors: $\sim U(600, 820) * [0.9, 0.95, 1.05, 1.1]$,
- transportation cost($) per kilometer: $\sim U(10, 15) * [0.9, 0.95, 1.05, 1.1]$.

Food storage costs are estimated at $2 and operational costs at $1 . The service time at each demand point is equal to 10 minutes and the transit time is considered proportional to the average vehicle speed (60 km/h). The transportation costs and transit time between different regions of Tehran are based on the distance matrix given in Table 15 in Appendix. Also, the transportation capacity of each vehicle is equal to 3000 packages while its fixed usage cost is 1000 dollars. Finally, the fixed setup cost of food banks equals 100,000 dollars based on the average cost of buildings.

Solving the model by MOGWO algorithm resulted in 3 food bank locations. As shown on Figure 16 regions 11, 15 and 19 are selected for food bank locations while their covered demand points are specified by the same color. The allocation of food or financial donors to the food banks, and the suggested routes for transportation of food to the demand points are given in Figure 17.

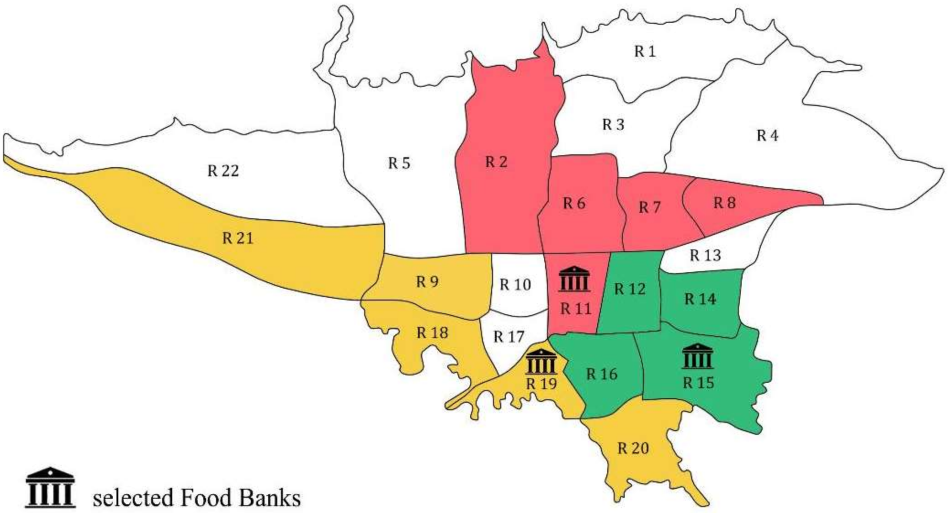


Figure 16: The optimal location of food banks and the areas covered by each food bank in the Tehran case study

According to the obtained results, the average cost of the food bank network in Tehran equals 479,173.8 dollars. Also, the average freshness of distributed foods over regions equals 92.47 (out of 100). Moreover, the total nutritional value of the distributed foods equals 32382.42 kilo-calories. Comparing this network with that of Kaviyani-Charati et al. (2022) proposed by their allocation-location model, it can be stated that our network is 4.58% more cost-efficient due to less allocation of vehicles in food distribution; the average value of distributed food is 3.51% more in our network; but the freshness of distributed food is 4.21% less in our configuration. In particular, the aforementioned benchmark model requires 24 vehicles, while with an efficient vehicle routing in our model, this number has reduced to 14. That is why the freshness of is slightly compromised, which is due to the nature of this trade-off. Thus, from the managerial point of view as long as the freshness of food is kept above the satisfactory level a huge amount of logistics operations and investment on facilities can be avoided. Moreover, the proportion of cold and warm foods can shed light on choice of vehicle fleet. As observed in Section 5.2.2 the higher capacity vehicles may lead to about 15% less fresh warm food while the sensitivity of freshness for cold foods is shown to less than 3%. Thus, a more cost efficient fleet can be chosen provided that the proportion of cold foods are higher. The region-wise freshness of the distributed food obtained by our model is compared with the benchmark network in Table 14.

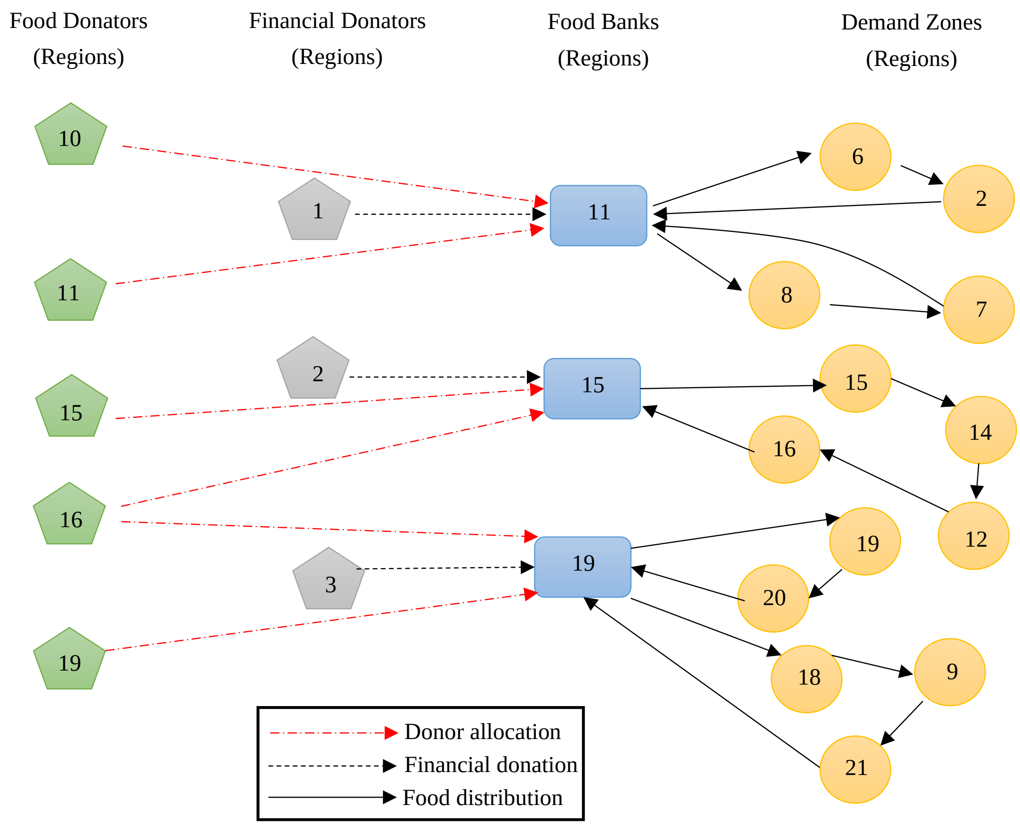


Figure 17: Allocation and Vehicle routing in a case study

Table 14: Pairwise comparison of food freshness for each demand point: our network vs. benchmark

Region	Benchmark	Our model
2	95.10	90.126
6	97.35	97.35
7	95.87	95.87
8	94.14	90.29
9	95.39	91.017
12	97.95	86.99
14	96.82	93.23
15	100.00	100.00
16	97.01	81.93
18	97.05	97.05
19	100.00	100.00
20	95.72	92.20
21	92.61	86.06
Mean	96.54	92.47

Note: Kaviyani-Charati et al. (2022) have not considered food freshness in their study. The numbers above is based on application of their network as a benchmark rather than their direct results.

6 Conclusion

This paper has introduced a model for solving an FBSCN problem under uncertainty. The proposed model simultaneously adopted all strategic and tactical decisions, including the location of FBs, routing the distribution of food baskets to charities, and the amount of food supply from food or financial donors. The main objectives of the paper were to minimize the total cost of supply network, maximize the freshness of the food baskets supplied to the charities, and maximize overall nutritional value of food baskets offered. Uncertainty of supply and demand necessitates a parameter controlling method without which the demand of charities is not properly met. Thus, a fuzzy robust optimization method was used to control the parameters of supply and demand as well as transportation costs. The robustness reassures that with slight increase in network costs the minimum requirement of charities and freshness of the distributed food are retained.

Due to the complexity of the problem, direct application of off-the-shelf optimizer is inefficient, which is in favor of heuristic solution approaches. Therefore NSGA II and MOGWO algorithms were designed based on a modified chromosome definition. The numerical study over small instances proved their close performance to the ϵ-constraint method as the exact solution while they were computationally much faster. Further, our numerical results for large instance showed that in general NSGA II generated efficient solutions closer to the ideal point (MID), while MOGWO algorithm has performed better with respect to other indicators NPF, MSI, SM and CPU-Time.

From the managerial perspective, as discussed on our case study with the focus on the cost factor, the distribution fleet size can be significantly reduced with minor compromise to the freshness, or by a shift in type of the food. Also, our numerical results showed that with the increase in uncertainty rate, the costs associated with network design increases as well. Also, the Pareto frontier showed that the higher targets for nutritional value of the food basket will increase the FB supply chain costs as it necessitates an increase in supply, food storage and transportation. Moreover, to increase the freshness of food more vehicles should be used. In a similar analogy, which might sound counter-intuitive, it was observed that by reducing vehicles capacity the number of food baskets distributed to charities increased because more vehicles are employed.

This study had some limitations that can be addressed in future studies as follows: *(i)* Potentially a creative exact solution can be designed to tackle medium size problem instances. As discussed, this problem is NP-hard and a polynomial-time exact solution method to obtain the optimal solution of large instances is unlikely to exist. However, a decomposition-based algorithm which decouples the routing and allocation sub-problems to deal with might be interesting to examine. Such a math-heuristic algorithm can be designed based on combination of heuristics and off-the-shelf optimizers , (see Kian et al. 2022); *(ii)* the uncertainty nature of the problem can be viewed in a different setting and approach such as scenario-based stochastic programming. The addressed problem here is a network design rather than its redesign under some unobserved data where no a priori probability distribution exists for parameters to construct their corresponding scenarios. However, investigating a similar setting benefiting from a set of experienced collected data can facilitate the application of a scenario-based stochastic programming approach; *(iii)* additional heuristics can be designed and compared. The two meta-heuristic algorithms proposed in this study contrasted a traditional one (NSGA II) with a contemporary one (MOGWO). However, the comparison of existing several other meta-heuristic algorithms such as such as MOALO, MOPSO and MOSCA is always an interesting research question that can be considered as a direction future studies.

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Appendix

Table 15: Distance matrix of Tehran regions in kilometers

Regions	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	15.4	6.9	14.5	19.7	14.1	15.1	14.6	27.4	24.3	20.2	21.2	19.8	23.7	24.1	26.4	24.7	32.2	28.2	31.2	33.7	28.5
2	-	12.7	19.6	4.5	10.6	14.3	18.1	12.7	9.3	13	18.2	22.1	26	27.3	21.5	13.4	17.4	16.6	27.1	18.3	17.3
3	-	-	13.6	13.9	7.5	7.9	13.5	22.6	19.5	16.3	13.4	19.3	23.2	23.5	18.7	18.6	24.1	22	30.6	27.5	23.5
4	-	-	-	22.1	17.1	12.5	6.7	28.5	27.1	23.7	18.8	6.9	10.8	17.1	23.2	28	34.7	27.9	23.6	35.9	34.2
5	-	-	-	-	13.5	17.3	21.1	14.8	13	16.5	22.9	25.1	27.9	30.1	24.4	20.3	19.6	20.2	30	16.8	13.7
6	-	-	-	-	-	5.6	10.4	15	9	6.9	10.2	12.1	14.2	15.3	12.8	12.6	19.7	16.1	22.3	20	25.6
7	-	-	-	-	-	-	6.1	22.1	20.6	10.9	8.5	7.8	12.7	13	13.7	20.9	31.5	24.7	20.1	27.2	27.4
8	-	-	-	-	-	-	-	25.5	14.8	15.7	15.4	2.8	7.7	14.1	20.4	24.9	32.9	26.1	21.5	30.6	33
9	-	-	-	-	-	-	-	-	9	13.1	20.5	33.6	31	28.3	21.8	9.9	7.1	12.2	21.9	5.7	25.6
10	-	-	-	-	-	-	-	-	-	4.2	9.9	15.1	16.7	17.1	11.3	4.2	10.6	10.7	16.9	14.6	24.5
11	-	-	-	-	-	-	-	-	-	-	5.3	21	13.3	13.6	7.8	5.2	9.2	9.4	15.6	17.7	29
12	-	-	-	-	-	-	-	-	-	-	-	15.5	9.1	9.9	7.5	7.9	16.6	11.4	8.5	21.2	40.1
13	-	-	-	-	-	-	-	-	-	-	-	-	4.8	12.8	18.9	23.7	30.4	23.6	19.3	46.2	32.5
14	-	-	-	-	-	-	-	-	-	-	-	-	-	8.3	12.7	17.2	25.9	19.2	14.9	41.8	49.4
15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	7.8	12.3	21.4	14.6	10.3	37.3	44.9
16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9.6	16.7	10	4.9	32.6	40.2
17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	6.2	5.4	15.3	16.6	26.5
18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	7.7	18.2	12.5	28.3
19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	11.3	20.1	33.2
20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33.1	40.8
21	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	19