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Environmental supply chain network design using multi-objective fuzzy mathematical programming

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Abstract

The concern about environmental impact of business activities has spurred an interest in designing environmentally conscious supply chains. This paper proposes a multi-objective fuzzy mathematical programming model for designing an environmental supply chain under inherent uncertainty of input data in such problem. The proposed model is able to consider the minimization of multiple environmental impacts beside the traditional cost minimization objective to make a fair balance between them. A life cycle assessment-based (LCA-based) method is applied to assess and quantify the environmental impact of different options for supply chain network configuration. Also, to solve the proposed multi-objective fuzzy optimization model, an interactive fuzzy solution approach is developed. A real industrial case is used to demonstrate the significance and applicability of the developed fuzzy optimization model as well as the usefulness of the proposed solution approach.

Keywords: Environmental supply chain, Supply chain network design, Life cycle assessment, Fuzzy mathematical programming, Multi-objective optimization.

1. Introduction

A well-structured supply chain is an important strategic competency that enables firms to be competitive in today’s marketplace. Along this important issue, the concern about environmental impact of business activities results in governmental legislations and environmentally conscious consumers. As such, consumers and governments put pressures on firms to reduce the environmental impact of their products and processes [1, 2]. Triggered by these driving forces, environmental supply chain management has attracted significant attentions by researchers and practitioners in the recent years. Environmental or green supply chain management can be defined as integrating environmental aspects into supply chain management covering both forward and reverse supply chains from product design to end-of-life management of used products. The ultimate goal is to consider environment in every decision making process across supply chain, especially the strategic level decisions [3, 4].

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Supply chain network design, as the most important strategic decision in supply chain management, plays an important role in overall environmental and economic performance of the supply chain. In general, supply chain network design includes determining the locations, numbers and capacities of network facilities and the aggregate material flow between them [5]. Recently Ilgin and Gupta [1] present a comprehensive review on environmentally conscious manufacturing and product recovery; below we have surveyed some relevant papers on environmental supply chain network design.

Since the end-of-life (EOL) products have significant impact on environment, a considerable part of literature is dedicated to EOL product management. This has created a need to develop models for reverse supply chain (logistics) network design. Reverse supply chain network design problem addresses the number of collection, recovery, recycling and disposal centers needed, their location and capacities and material flows between them [6]. As seminal works in this area, Barros et al. [7], Jayaraman et al. [8] and Krikke et al. [9] proposed mathematical models for reverse supply chain network design. Several years later more complex models such as multi-objective (e.g. [10, 11]) and multi-product (e.g. [12, 13]) models are developed in this context. Also, to overcome the complexity of such models a number of metaheuristic (e.g. [12, 14]) and heuristic (e.g. [15]) algorithms are proposed.

To gain the benefits results from integrated design of forward and reverse supply chain networks (see [16]) and to support the whole life cycle of product, a number of papers have addressed the design of closed-loop supply chain networks in recent years. To this aim, both case-based (e.g. [17]) and general (e.g. [16, 18]) models are considered by researchers.

The dynamic and imprecise nature of quantity and quality of EOL products imposes a high degree of uncertainty in reverse and closed-loop supply chain network design decisions. Most of the relevant literature addressing the issue of uncertainty, applied stochastic programming approaches to cope with this problem (see [19, 20, 21]). However, the need of sufficient historical data that is rarely available in real-life cases and the high computational complexity are major drawbacks that make the use of stochastic programming models somehow impossible in real cases. Thus, a few number of works in recent years used more flexible approaches such as fuzzy (e.g. [22, 23]) and robust (e.g. [24]) programming approaches.

Additionally, a thin part of literature is dedicated to environmental supply chain network design aimed to incorporate the environmental impact into supply chain network design decisions. Hugo and Pistikopoulos [25] proposed a bi-objective mathematical programming model to address an environmental forward chemical supply chain network problem. The proposed model minimizes the environmental impact using LCA principles besides maximizing the total profit. Quariguasi Frota Neto et al. [26] developed a bi-objective linear programming model for environmental forward logistics network design in European pulp and paper industry. However, the proposed model is only able to optimize the
quantity of flow between facilities and ignores the other network design decisions such as determining the location, capacity and number of facilities. Also, a work is presented by Quariguasi Frota Neto et al. [27] for EOL electrical and electronic equipment recycling network aimed to minimize cumulative energy demand and wastes in addition to traditional economic objective. All of the above mentioned papers in the context of environmental supply chain network design neglected the integrated design of forward and reverse networks besides incorporating the environmental impact of network configuration into decision making model. Also, all of these papers are unable to model the uncertainty of parameters as an important factor in supply chain network design problem.

To overcome the literature gap, this paper proposes a practical, but tractable, multi-objective fuzzy mathematical programming model for environmental supply chain network design problem that is able to (1) consider both economic and environmental objectives in the design of the supply chain network, (2) integrate the design of reverse and forward supply chain networks to avoid the sub-optimalities results from separated design of forward and reverse supply chains and to move towards a “cradle-to-grave” perspective, (3) integrate a prominent LCA-based quantitative environmental impact assessment method (i.e., Eco-indicator 99) into supply chain network design problem to model the environmental impact of different supply chain network configurations, (4) handle the epistemic uncertainty in parameters in real cases results from unavailability or incompleteness and imprecise nature of input data. Also, this paper proposes an efficient solution approach that is able to generate both balanced and unbalanced solutions through making a reasonable tradeoff between environmental and economic objectives. Altogether, the above mentioned properties differentiate this paper from the existing ones in the related literature.

The rest of this paper is organized as follows. The concerned problem, motivated from a real industrial case, is defined in Section 2. The proposed multi-objective fuzzy mathematical programming model is elaborated in Section 3 and the proposed interactive solution method is given in Section 4. The proposed model is implemented for the case study and the computational results as well as some managerial implications are reported in Section 5. Finally, the concluding remarks and some directions for future research are given in Section 6.

2. Problem definition

The concerned integrated supply chain network in this paper is motivated by a real industrial case. The case is an Iranian single-use medical needle and syringe manufacturer that supplies about 70 percent of domestic demand and recently receives significant orders from two neighbor countries. Now, the manufacturer has one production plant with about 600 million production capacity per one year. Notably, single-use medical needle and syringe has significant environmental impact, especially in the EOL phase. World Health Organization (WHO) reported that approximately 16 billion injections are administered
annually throughout the world and 8-16 million hepatitis B, 2.3 - 4.7 million hepatitis C and 80000 - 160000 human immunodeficiency virus (HIV) infections are estimated to occur yearly from reused unsterilized needles and syringes [28]. Therefore, the EOL medical needle and syringe is classified as potentially infectious wastes and the concern about needle sticks, i.e., accidental piercing by a needle, that can results to harmful diseases as serious as Hepatitis and HIV, makes the EOL management of this product very critical [29, 30]. In order to boost the reduction of burden of disease attributable to infectious wastes, especially sharps (e.g., needles and syringes) WHO has provided a policy paper indicating the organization’s strategy in the immediate, the mid- and long-term (see [31]). In this policy paper WHO engaged to support countries in developing and implementing national plan, policies and legislation for health-care waste management.

To avoid the aforementioned risks, safety boxes are first utilized to collect and keep the potentially infectious needles and syringes after the injection process [32]. Thereafter, to cope with the used medical needles and syringes, three EOL options are available: (1) incineration methods, such as cement incinerator and rotary kiln incinerator, (2) non-incineration methods, such as steam autoclave with sanitary landfill and microwave disinfection, and (3) recycling.

Incineration is one of mostly used options to cope with EOL medical needle and syringe. Besides the low cost, convenient use and the capability of energy recovery, incineration has significant negative environmental impact such as air pollution and ranked among the top sources of emissions [28, 29, 33]. Another, EOL option for medical needle and syringe is non-incineration methods (e.g. steam autoclave and microwave disinfection) that can also results in energy recovery with different efficiencies. Generally, in medical waste management, recycling materials is known as a forbidden activity according to regulations and high hazardous potential of medical waste [34]. However, recently the possibility of recycling medical needle and syringe has been investigated in India under supervision of World Health Organization (see [28]). The result shows that this EOL option can be also used for medical needle and syringe by considering solutions for disinfecting the used products [28]. Particularly, in this study we have focused on two EOL options according to the context of the studied case: (1) incineration and (2) recycling. For detail information about environmental impacts of these EOL options we refer the readers to WHO [28] and Zhao et al. [34].

The structure of the concerned single-product, multi-echelon supply chain network including both forward and reverse networks is illustrated in Figure 1. Through forward network the new products manufactured by plants (production centers) are distributed among customer zones. In the reverse network, the EOL products are shipped to incineration and/or recycling centers through collection/disassembly centers. All demands of customers must be satisfied and all of the returned products from customers must be collected. Also, a predefined percent of demand from each customer is
assumed as returned products from corresponding customer. As it is mentioned before, this network is motivated by a single-use medical needle and syringe supply chain, however, it can also support other types of medical devices, particularly the category of “sharps” (see [34]), and other recyclable products such as paper (e.g. [35]) with some little modifications.

![Diagram](image_url)

**Fig.1.** The depiction of the concerned integrated supply chain network.

Unavailability or incompleteness of data in real world network design problems is an important challenge that imposes a high degree of uncertainty in such problem. The unavailability of historical data and the imprecise nature of parameters make the use of probability distribution impossible in these cases (see [24]). Even though the historical data existed, the behavior of parameters does not necessarily complying with their historical pattern in future according to dynamic nature and strategic horizon of network design problem. To cope with this challenge in the concerned problem, the uncertain parameters are presented by fuzzy numbers described by their possibility distribution. The possibility distributions are estimated based on current insufficient data and the decision makers’ knowledge (see [36, 37, 38]).

The main issues to be addressed in this integrated supply chain under uncertain condition, includes determining the numbers and locations of production and collection centers, as well as the EOL options and the material flow quantities between different facilities with respect to two conflicting objective functions: (1) minimization of total cost and (2) minimization of total environmental impact. Therefore, optimizing the strategic configuration of the supply chain network involves a reasonable trade-off
between these two objectives. To quantify and model the second objective, we have used a LCA-based environmental impact assessment method called Eco-indicator 99 [39]. LCA is a popular tool for environmental impact assessment and is widely used by researchers and practitioners in the last two decades. Particularly, LCA is a methodology that enables quantification of environmental loads and their potential impacts over the whole life cycle of a product, process or activity [40]. However, the LCA process is costly, time consuming and complicated that usually needs expertise of environmental management to be performed. Additionally, the results of LCA are not straightforward and needs to be weighted and interpreted [39, 41]. Eco-indicator 99 is a LCA-based damage-oriented method that resolved the aforementioned problems. Eco-indicator 99 is able to aggregate LCA results into easily understandable and user friendly units, called Eco-indicators. Eco-indicators are numbers that express the total environmental burden of a process or product. By the aid of standard eco-indicators, designers can compare the design alternatives according to total environmental impact. This method includes three damage categories: (1) human health, (2) ecosystem quality and (3) resources [39, 42].

3. Model formulation

The indices, parameters and variables used to formulate the concerned environmental supply chain network design (ESCND) problem are described below.

**Indices:**

- $i$: index of candidate locations for production centers $i = 1, \ldots, I$
- $j$: index of fixed locations of customer zones $j = 1, \ldots, J$
- $k$: index of candidate locations for collection centers $k = 1, \ldots, K$
- $l$: index of existing steel recycling centers $l = 1, \ldots, L$
- $m$: index of existing plastic recycling centers $m = 1, \ldots, M$
- $n$: index of existing incineration centers $n = 1, \ldots, N$

**Parameters:**

- $\tilde{d}_j$: demand of customer zone $j$
- $\tilde{p}_j$: rate of return percentage from customer zone $j$
- $\tilde{f}_i$: fixed cost of opening production center $i$
- $\tilde{g}_k$: fixed cost of opening collection center $k$
- $\tilde{c}_{ij}$: transportation cost per product unit from plant $i$ to customer zone $j$
- $\tilde{a}_{ik}$: transportation cost per used product unit from customer zone $j$ to collection center $k$
- $\tilde{b}_{kl}$: transportation cost per steel part of used product unit from collection center $k$ to steel recycling center $l$
\( \tilde{h}_{km} \) transportation cost per plastic parts of used product unit from collection center \( k \) to plastic recycling center \( m \)
\( \tilde{c}_{kn} \) transportation cost per used product unit from collection center \( k \) to incineration center \( n \)
\( \tilde{p}_i \) manufacturing cost per unit of product at production center \( i \)
\( \tilde{\phi}_k \) processing cost per unit of used product at collection center \( k \)
\( \tilde{\beta}_l \) processing cost per steel part of used product unit at steel recycling center \( l \)
\( \tilde{\tau}_m \) processing cost per plastic part of used product unit at plastic recycling center \( m \)
\( \tilde{\theta}_n \) processing cost per used product unit at incineration center \( n \)
\( \tilde{\theta}_i \) maximum capacity of production center \( i \)
\( \tilde{\Theta}_k \) maximum capacity of collection center \( k \)
\( \tilde{\delta}_l \) maximum capacity of steel recycling center \( l \)
\( \tilde{\zeta}_m \) maximum capacity of plastic recycling center \( m \)
\( \tilde{\zeta}_n \) maximum capacity of incineration center \( n \)
\( e_{i\text{pro}} \) environmental impact per production of one unit product
\( e_{i\text{ij}} \) environmental impact of shipping one unit of product from plant \( i \) to customer zone \( j \)
\( e_{i\text{jk}} \) environmental impact of shipping one unit of used product from customer zone \( j \) to collection center \( k \)
\( e_{i\text{kn}} \) environmental impact of shipping one unit of collected used product from collection center \( k \) to incineration center \( n \)
\( e_{i\text{kl}} \) environmental impact of shipping steel part of used product unit from collection center \( k \) to steel recycling center \( l \)
\( e_{i\text{km}} \) environmental impact of shipping plastic part of used product unit from collection center \( k \) to plastic recycling center \( m \)
\( e_{i\text{col}} \) environmental impact per handling one unit collected used product at collection centers
\( e_{i\text{inc}} \) environmental impact of incinerating one unit of used product
\( e_{i\text{src}} \) environmental impact of recycling the steel part of one unit of used product
\( e_{i\text{prc}} \) environmental impact of recycling the plastic part of one unit of used product

**Variables:**
\( u_{ij} \) quantity of products shipped from plant \( i \) to customer zone \( j \)
\( q_{jk} \) quantity of used products shipped customer zone \( j \) to collection center \( k \)
\( w_{kl} \) quantity of steel part of used products shipped from collection center \( k \) to steel recycling center \( l \)
\( w_{km} \) quantity of plastic part of used products shipped from collection center \( k \) to plastic recycling center \( m \)
\( z_{kn} \) quantity of used products shipped from collection center \( k \) to incineration center \( n \)
\( x_i \) \[ \begin{cases} 1 & \text{if a production center is opened at location } i, \\ 0 & \text{otherwise} \end{cases} \]
\( y_k \) \[ \begin{cases} 1 & \text{if a collection center is opened at location } k, \\ 0 & \text{otherwise} \end{cases} \]
It should be noted that symbols with a tilde on indicate coefficients tainted with uncertainty. These parameters are estimated by appropriate possibility distributions. In terms of the above notation, the concerned problem can be formulated as follows.

3.1. Objective functions

As mentioned in Section 1, two important and conflicting objective functions are considered in the formulation of ESCND problem: (1) minimization of total cost and (2) minimization of total environmental impact.

3.1.1. First objective: minimizing the total cost. The total cost of supply chain network design includes the fixed opening costs of facilities and variable processing and transportation costs of flows between network facilities (i.e., Total cost = Fixed opening costs + Transportation and processing costs). Thus, the first objective function can be formulated as follows.

\[
\text{Min } W_t = \sum_i \tilde{f}_i x_i + \sum_k \tilde{g}_k y_k + \sum_i \sum_j (\tilde{a}_i + \tilde{c}_i) u_{ij} + \sum_i \sum_j (\tilde{\varphi}_i + \tilde{a}_{jk}) q_{jk} + \sum_k \sum_l (\tilde{\beta}_l + \tilde{b}_{lk}) v_{kl}
\]

\[
+ \sum_k \sum_m (\tilde{\tau}_m + \tilde{h}_{km}) w_{km} + \sum_k \sum_n (\tilde{\sigma}_m + \tilde{h}_{kn}) z_{kn}
\]

(1)

Notably, the transportation costs between facilities are calculated by multiplying the transportation cost of one unit of shipping object per unit of distance (i.e., one kilometer) by the corresponding shipping distance.

3.1.2. Second objective: minimizing the total environmental impact. As it was mentioned is Section 2, the Eco-indicator 99 method is used to estimate the total environmental impact of different supply chain network configurations. To use this method, first, the system boundary, functional unit and the purpose of using Eco-indicator should be defined. Here, the boundary of the studied system can be determined as the boundary around the integrated supply chain network illustrated in Figure 1 and the functional unit of such supply chain network can defined as the effective fulfillment of customer demand by producing and distributing the products at forward network and the safe management of EOL products through the reverse network. Also, the purpose of using the Eco-indicator is to estimate the environmental impact of different supply chain network configurations.

At the second step, the life cycle should be defined. In the concerned ESCND problem the life cycle stages include: (1) production (pro), (2) transportation form production centers to customers zones (tpc),
(3) transportation form customers zones to collection centers \((tcc)\), (4) handling the used products at collection centers \((col)\), e.g., inspection and sorting, (5) transportation from collection centers to incineration centers \((tci)\), (6) incineration of used products \((inc)\), (7) transportation from collection centers to steel recycling centers \((tcs)\), (8) steel recycling \((src)\), (9) transportation from collection centers to plastic recycling centers \((tcp)\) and (10) plastic recycling \((prc)\). It should be noted that usage phase at customer zones is omitted from life cycle stages because it has no impact on the model decision variables and therefore on the overall configuration of the concerned supply chain network.

At the third step, the material and processes through the life cycle stages should be quantified and then, at the fourth step, the final score is calculated by (1) finding the relevant Eco-indicator (see Addendum of [42]), (2) multiplying the amounts by the indicator values and (3) adding up the subsidiary results. For example for incineration of steel, the amount of steel (kg) should be multiplied to the corresponding Eco-indicator, i.e., -32 (millipoints per kg) and then for calculating the final environmental impact of incineration phase \((e_i^{inc})\), the results for steel and plastic (i.e., PP and PVC) parts should be added together. According to the model decision variables the environmental impact values \((e_i^s)\) are calculated per one unit of product.

Eco- Indicator 99 method provides three different perspectives, i.e., (1) Hierarchist, (2) Individualist and (3) Egalitarian, based on the Cultural Theory, In this study the Average Hierarchist version of the method is used to calculate Eco-indicator scores. In the Average Hierarchist version human health, ecosystem quality and resource depletion contribute 40%, 40% and 20% in the Eco-indicator 99 score respectively (see [42]). Based on the aforementioned descriptions the second objective function can be formulated as follows.

\[
\text{Min } W_2 = \sum_{i} \sum_{j} (e_i^{pro} + e_i^{prc})u_{ij} + \sum_{j} \sum_{k} (e_i^{col} + e_i^{tci})q_{jk} + \sum_{k} \sum_{a} (e_i^{inc} + e_i^{tcp})z_{kn}
\]

\[
+ \sum_{k} \sum_{l} (e_i^{tcs} + e_i^{src})v_{kl} + \sum_{l} \sum_{m} (e_i^{prc} + e_i^{prc})w_{lm}
\]

\[
(2)
\]

3.2. **Constraints**

3.2.1. **Demand and return satisfaction constraints.** Constraints (3) and (4) ensure that the demands of all customers are satisfied and all the used products are collected from customer zones.

\[
\sum_{i} u_{ij} \geq \tilde{d}_j, \quad \forall j,
\]

\[
(3)
\]
\[ \sum_{k} q_{jk} \geq \tilde{d}_{j} \tilde{\omega}_{j}, \quad \forall j, \quad (4) \]

3.2.2. Flow balance constraints. Constraints (5) and (6) ensure the flow balance at collection centers. Since two EOL options are considered in the proposed model, the collected used products should be sent to incineration centers or being disassembled into plastic and steel parts and then being sent to corresponding recycling centers. Therefore, the number of plastic and steel parts sent to recycling centers should be equal (see constraint 6), because they are disassembled from one used product.

\[ \sum_{j} q_{jk} = \sum_{m} w_{km} + \sum_{n} z_{kn}, \quad \forall k, \quad (5) \]

\[ \sum_{m} w_{km} = \sum_{l} v_{kl}, \quad \forall k, \quad (6) \]

3.2.3. Capacity constraints. All relevant capacity constraints are summarized as follows.

\[ \sum_{j} u_{ij} \leq x_{i} \tilde{r}_{i}, \quad \forall i, \quad (7) \]

\[ \sum_{j} q_{jk} \leq y_{k} \tilde{\eta}_{k}, \quad \forall k, \quad (8) \]

\[ \sum_{k} v_{kl} \leq \tilde{\delta}_{l}, \quad \forall l, \quad (9) \]

\[ \sum_{k} w_{km} \leq \tilde{\xi}_{m}, \quad \forall m, \quad (10) \]

\[ \sum_{k} z_{kn} \leq \tilde{\zeta}_{n}, \quad \forall n, \quad (11) \]

Constraints (7) to (11) are capacity constraints on production, collection, steel recycling, plastic recycling and incineration centers respectively. Also, constraints (7) and (8) prohibit the units of new and used products from being transferred from/to production and collection centers which are not opened respectively.

3.2.3. Decision variables constraints. The following constraints are related to the binary and non-negativity restrictions on the corresponding decision variables.
\[ x_i, y_k \in \{0, 1\}, \quad \forall i, k \] (12)

\[ u_{ij}, q_{jk}, v_{ki}, w_{km}, z_{kn} \geq 0, \quad \forall i, j, k, l, m, n. \] (13)

4. The proposed solution method

Uncertainty can be classified as (1) flexibility in constraints and goals, and (2) uncertainty in data [43]. Flexibility is related to flexible target value of goals and constraints and flexible mathematical programming models are used to cope with flexible target values [44, 45]. The uncertainty in data can be classified into two groups: (1) randomness, that comes from the random nature of parameters and usually stochastic programming approaches were used to model this kind of uncertainty; (2) Epistemic uncertainty that deals with ill-known parameters and usually possibilistic programming approaches are used to handle the epistemic uncertainty [22, 45].

According to aforementioned descriptions and since we are confronting imprecise parameters in the ESCND problem, possibilistic programming approach is used to handle the uncertain parameters in the proposed model. In this approach each ill-known parameter has its possibility distribution. The possibility distribution represents the possibility degree of occurrence of possible values for each uncertain parameter and is mostly determined based on available data as well as experts’ knowledge. Therefore, it can be concluded that proposed model is a multi-objective possibilistic mixed integer programming (MOPMIP). To solve this MOPMIP model a two-phased approach is proposed. In the first phase, the method of Jimenez et al. [46] is applied to convert the proposed MOPMIP model into an equivalent auxiliary crisp model. In the second phase, we have proposed a modified version of \( \varepsilon \)-constraint method to find the final preferred compromise solution.

4.1. The equivalent auxiliary crisp model

A number of methods have been proposed in the literature to deal with possibilistic programming models (e.g. [38, 46, 47]). Among these methods the Jimenez et al. [46] method is selected in this paper to cope with proposed MOPMIP model. The Jimenez et al. [46] method is formed based on the strong mathematical concepts, i.e., expected interval and expected value of fuzzy numbers, and also relies on Jimenez [48] general ranking method which can support different kinds of membership functions such as triangular, trapezoidal and nonlinear ones in both symmetric and asymmetric forms. Also, this method is computationally efficient to solve fuzzy linear problems as it can preserve its linearity and do not increase the number of objective functions and inequality constraints. The detail of this method is given in Appendix.
According to Jimenez et al. [46] method described in the Appendix, the equivalent auxiliary crisp model of the ESCND model can be formulated as follows.

\[
\min W_1 = \sum_i \left( \frac{f^{pes}_i + 2f^{mos}_i + f^{opt}_i}{4} \right) x_i + \sum_k \left( \frac{g^{pes}_k + 2g^{mos}_k + g^{opt}_k}{4} \right) y_k \\
+ \sum_i \sum_j \left( \frac{\rho^{pes}_i + 2\rho^{mos}_i + \rho^{opt}_i + c^{pes}_{ij} + 2c^{mos}_{ij} + c^{opt}_{ij}}{4} \right) u_{ij} \\
+ \sum_j \sum_k \left( \frac{\varphi^{pes}_k + 2\varphi^{mos}_k + \varphi^{opt}_k + a^{pes}_{jk} + 2a^{mos}_{jk} + a^{opt}_{jk}}{4} \right) q_{jk} \\
+ \sum_k \sum l \left( \frac{\beta^{pes}_l + 2\beta^{mos}_l + \beta^{opt}_l + b^{pes}_{kl} + 2b^{mos}_{kl} + b^{opt}_{kl}}{4} \right) v_{kl} \\
+ \sum m \sum n \left( \frac{\tau^{pes}_m + 2\tau^{mos}_m + \tau^{opt}_m + h^{pes}_{km} + 2h^{mos}_{km} + h^{opt}_{km}}{4} \right) w_{km} \\
+ \sum k \sum n \left( \frac{\theta^{pes}_n + 2\theta^{mos}_n + \theta^{opt}_n + o^{pes}_{kn} + 2o^{mos}_{kn} + o^{opt}_{kn}}{4} \right) z_{kn}
\]

\[
\min W_2 = \sum i \sum j \left( e^{pes}_{ij} + e^{mos}_{ij} \right) u_{ij} + \sum j \sum k \left( e^{rel}_{jk} + e^{opt}_{jk} \right) q_{jk} + \sum k \sum n \left( e^{inc}_{kn} + e^{rel}_{kn} \right) z_{kn} \\
+ \sum k \sum l \left( e^{rel}_{kl} + e^{opt}_{kl} \right) v_{kl} + \sum l \sum m \left( e^{inc}_{lm} + e^{rel}_{lm} \right) w_{km}
\]

Subject to

\[
\sum_j u_{ij} \geq \alpha \left( \frac{d^{mos}_{ij} + d^{opt}_{ij}}{2} \right) + (1 - \alpha) \left( \frac{d^{pes}_{ij} + d^{mos}_{ij}}{2} \right), \quad \forall j,
\]

\[
\sum_k q_{jk} \geq \left[ \alpha \left( \frac{d^{mos}_{jk} + d^{opt}_{jk}}{2} \right) + (1 - \alpha) \left( \frac{d^{pes}_{jk} + d^{mos}_{jk}}{2} \right) \right] \left[ \alpha \left( \frac{\omega^{mos}_{jk} + \omega^{opt}_{jk}}{2} \right) + (1 - \alpha) \left( \frac{\omega^{pes}_{jk} + \omega^{mos}_{jk}}{2} \right) \right], \quad \forall j,
\]

\[
\sum_j q_{jk} = \sum m w_{km} + \sum n z_{kn}, \quad \forall k,
\]

\[
\sum m w_{km} = \sum l v_{kl}, \quad \forall k,
\]

\[
\sum_j u_{ij} \leq \alpha \left( \frac{\pi^{pes}_{ij} + \pi^{mos}_{ij}}{2} \right) + (1 - \alpha) \left( \frac{\pi^{opt}_{ij} + \pi^{mos}_{ij}}{2} \right), \quad \forall i,
\]
\[
\sum_{j} q_{jk} \leq y_k \left[ \alpha \left( \eta_k^{\text{pes}} + \eta_k^{\text{mos}} \right) + (1 - \alpha) \left( \eta_k^{\text{mos}} + \eta_k^{\text{opt}} \right) \right], \quad \forall k,
\]

\[
\sum_{k} v_{kl} \leq \left[ \alpha \left( \delta_l^{\text{pes}} + \delta_l^{\text{mos}} \right) + (1 - \alpha) \left( \delta_l^{\text{mos}} + \delta_l^{\text{opt}} \right) \right], \quad \forall l,
\]

\[
\sum_{k} w_{km} \leq \left[ \alpha \left( \xi_m^{\text{pes}} + \xi_m^{\text{mos}} \right) + (1 - \alpha) \left( \xi_m^{\text{mos}} + \xi_m^{\text{opt}} \right) \right], \quad \forall m,
\]

\[
\sum_{k} z_{kn} \leq \left[ \alpha \left( \epsilon_n^{\text{pes}} + \epsilon_n^{\text{mos}} \right) + (1 - \alpha) \left( \epsilon_n^{\text{mos}} + \epsilon_n^{\text{opt}} \right) \right], \quad \forall n,
\]

\[x_j, y_k \in \{0,1\}, \quad \forall i, k \]

\[u_{ij}, q_{jk}, v_{kl}, w_{km}, z_{kn} \geq 0, \quad \forall i, j, k, l, m, n.\]

4.2. Interactive fuzzy solution approach

To solve the multi-objective programming (MOP) models several approaches have been developed in the literature. Fuzzy programming methods are among the highly used approaches in this area because of their capability in measuring and adjusting the satisfaction level of each objective function explicitly. Fuzzy programming approaches for MOP models range from simple and preliminary approaches such as Zimmermann [49], Sakawa et al. [50] and Lai and Hwang [51] to more advanced methods such as Selim and Ozkarahan [52], Torabi and Hassini [53] and Li et al [54].

Here, we have proposed a fuzzy solution method based on \(\varepsilon\)-constraint method. The \(\varepsilon\)-constraint method is known as a posteriori or generation method (see Hwang and Masud [55]) that is able to provide an appropriate picture of whole Pareto-optimal set for decision maker and then the decision maker can select the most preferred solution. Therefore, all of the solutions are discovered and the decision maker can determine the final decision more confidently according to comprehensive available information. This is the main advantage of generation methods compared with priori methods. For detail information on \(\varepsilon\)-constraint method we refer the readers to Ehrigott [56].

There are two important points about \(\varepsilon\)-constraint method that should be considered when this method is used: (1) the range of every objective function should be determined over the efficient set and (2) the value of epsilon(s), i.e., the right hand side of \(\varepsilon\)-constraints, should be systemically varied in the range of each objective function to generate different Pareto optimal solutions. Usually payoff table is used to
determine the optimal and nadir values of each objective function. However, the range obtained by this method may include weakly efficient solutions (see [57]). To escape from this pitfall and to provide an appropriate tool for decision maker to vary and adjust the value of epsilons according to satisfaction level of each objective function, we have proposed an interactive fuzzy solution approach based on ε-constraint method. The steps of the proposed method can be summarized as follows.

Step 1: Convert the MOPMIP model into an equivalent auxiliary crisp model by applying the Jimenez et al. [46] method. To this aim first the imprecise objective functions are converted to crisp ones using the expected value of imprecise parameters, and secondly the minimum acceptable feasibility degree of decision vector (i.e., α) is determined and then the fuzzy constraints are converted into the crisp ones (see section 4.1).

Step 2: Determine the range of each objective function over the efficient set by calculating the α-optimal and α-nadir solutions for each objective function. To calculate the α-optimal solutions, i.e., \((W_1^{α-optimal},x_1^{α-optimal})\) and \((W_2^{α-optimal},x_2^{α-optimal})\), the equivalent crisp model should be solved for each objective function separately, and then the α-nadir solution for each objective function can be estimated as follows.

\[
W_2^{α-nadir} = \min\{W_2 \mid W_1 \leq W_1^{α-optimal} \land x \in F(x)\}
\]

\[
W_1^{α-nadir} = \min\{W_1 \mid W_2 \leq W_2^{α-optimal} \land x \in F(x)\}
\]

Where, \(F(x)\) indicates the feasible region involving the constraints of equivalent crisp model.

Step 3: Determine a linear membership function for each objective function as follows:

\[
\mu_1(x) = \begin{cases} 
1, & \text{if } W_1 < W_1^{α-optimal} \\
\frac{W_1^{α-nadir} - W_1}{W_1^{α-nadir} - W_1^{α-optimal}}, & \text{if } W_1^{α-optimal} \leq W_1 \leq W_1^{α-nadir} \\
0, & \text{if } W_1 > W_1^{α-nadir}
\end{cases}
\]

\[
\mu_2(x) = \begin{cases} 
1, & \text{if } W_2 < W_2^{α-optimal} \\
\frac{W_2^{α-nadir} - W_2}{W_2^{α-nadir} - W_2^{α-optimal}}, & \text{if } W_2^{α-optimal} \leq W_2 \leq W_2^{α-nadir} \\
0, & \text{if } W_2 > W_2^{α-nadir}
\end{cases}
\]

Which \(\mu_h(x)\) represents the satisfaction degree of \(h\)th objective function.

Step 4: Convert the equivalent multi-objective crisp model into a single-objective model based on ε-constraint method as follows.

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\[
\begin{align*}
\max & \quad \mu_2(x) \\
\text{s.t.} & \quad \mu_1(x) \geq \varepsilon, \\
& \quad x \in F(x), \\
& \quad \varepsilon \in [0, 1].
\end{align*}
\]

In the above formulation, satisfaction degree of second objective function is kept in the objective function and the satisfaction degree of first one is used as a side constraint. It should be noted that there is no limitation on choosing the satisfaction degree of any objectives for being used as a side constraint or objective function.

**Step 5:** Vary the value of epsilon systemically to generate different Pareto-optimal solutions over the whole efficient set. In traditional \( \varepsilon \)-constraint method the value of epsilon is selected in the range of corresponding objective function. To this aim usually the range of objective function is segmented into equal parts and the grid points are used as the value of epsilon. However, since in the proposed solution method the satisfaction degree of objective function is used, the decision maker can simply segment the range between 0 and 1, and use the grid points as the value of epsilon (for example for 10 equal segments we have 11 grid points: \( 0, 0.1, 0.2, \ldots, 1 \) ) to obtain a range of balanced (i.e., no significant difference between satisfaction degrees of objectives) and unbalanced (i.e., considerable difference between satisfaction degrees of objectives) efficient solutions.

**Step 6:** If the decision maker is satisfied with one of the generated solutions, stop and select the preferred solution as the final decision. otherwise select the most preferred segment (for example the segment between 0.6 and 0.7) and go to step 5 to vary the value of \( \varepsilon \) in the new range (the selected segment) and to generate new Pareto-optimal solutions. Also, in some cases, decision maker may interest to change the value of \( \alpha \); If the value of \( \alpha \) is changed the algorithm should be restart from step 1.

5. **Implementation and evaluation**

In this section, the validity of the developed ESCND model as well as the usefulness of the proposed solution method is investigated via the data withdrawn from the considered case study. The manufacturer firm has 13 domestic customer zones and 2 foreign customers from two neighbor countries. The firm is only responsible to collect the used products from domestic customers, therefore, the return rate from foreign customers is considered equal to zero. To estimate the possibility distribution of imprecise parameters, first the objective data is gathered and then at the consensus session the experts and firm’s managers determined the three prominent values (i.e., the most likely, the most pessimistic and the most
optimistic values) of triangular fuzzy parameters (see [38]) according to available data and their 
knowledge. The fuzzy data for demand and rate of return of each customer is represented in Table 1. It 
should be noted that the demand reported in Table 1 is the aggregate demand over three year horizon.

Table 1
The demand ($\tilde{d}_j$) and rate of return ($\tilde{\omega}_j$) data

<table>
<thead>
<tr>
<th>Customer zone</th>
<th>Demand (millions)</th>
<th>Rate of return</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Mashhad</td>
<td>(234, 254.5, 292)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(2) Yazd</td>
<td>(295, 330.6, 390)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(3) Shiraz</td>
<td>(112, 124, 138)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(4) Uromieh</td>
<td>(101, 108.8, 133)</td>
<td>(0.55, 0.65, 0.75)</td>
</tr>
<tr>
<td>(5) Ardebil</td>
<td>(98, 110, 127)</td>
<td>(0.55, 0.65, 0.75)</td>
</tr>
<tr>
<td>(6) Rasht</td>
<td>(210.5, 263.4, 275)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(7) Kermanshah</td>
<td>(52, 63.5, 75)</td>
<td>(0.55, 0.65, 0.75)</td>
</tr>
<tr>
<td>(8) Karaj</td>
<td>(84, 93, 110)</td>
<td>(0.7, 0.8, 0.9)</td>
</tr>
<tr>
<td>(9) Zanjan</td>
<td>(100, 118.5, 131)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(10) Hamedan</td>
<td>(37, 42.6, 52)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(11) Ghazvin</td>
<td>(198, 211, 228)</td>
<td>(0.65, 0.75, 0.85)</td>
</tr>
<tr>
<td>(12) Esfahan</td>
<td>(255, 285, 305)</td>
<td>(0.7, 0.8, 0.9)</td>
</tr>
<tr>
<td>(13) Tehran</td>
<td>(215, 240, 270)</td>
<td>(0.7, 0.8, 0.9)</td>
</tr>
<tr>
<td>(14) Foreign I</td>
<td>(320, 344, 360)</td>
<td>(0, 0, 0)</td>
</tr>
<tr>
<td>(15) Foreign II</td>
<td>(200, 215, 230)</td>
<td>(0, 0, 0)</td>
</tr>
</tbody>
</table>

Table 2
The fixed cost ($\tilde{f}_i$) and capacity ($\tilde{r}_i$) data for production centers

<table>
<thead>
<tr>
<th>Location</th>
<th>Fixed cost (million Rials)</th>
<th>Capacity (millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Varamin</td>
<td>(133000, 145000, 153000)</td>
<td>(1900, 2000, 2100)</td>
</tr>
<tr>
<td>(2) Saveh</td>
<td>(135000, 147000, 154000)</td>
<td>(1900, 2000, 2100)</td>
</tr>
<tr>
<td>(3) Semnan</td>
<td>(136000, 148000, 155000)</td>
<td>(2000, 2100, 2200)</td>
</tr>
<tr>
<td>(4) Ghom</td>
<td>(130000, 140000, 150000)</td>
<td>(1650, 1800, 1950)</td>
</tr>
<tr>
<td>(5) Arak</td>
<td>(135000, 147000, 154000)</td>
<td>(1900, 2000, 2100)</td>
</tr>
<tr>
<td>(6) Zanjan</td>
<td>(135000, 147000, 154000)</td>
<td>(1900, 2000, 2100)</td>
</tr>
<tr>
<td>(7) Ghazvin</td>
<td>(136000, 148000, 155000)</td>
<td>(1900, 2000, 2100)</td>
</tr>
<tr>
<td>(8) Ashtian (current plant)</td>
<td>(0, 0, 0)</td>
<td>(1650, 1800, 1950)</td>
</tr>
</tbody>
</table>

The firm’s managers consider 7 candidate locations to open new production centers. Also, since the 
firm has already one opened plant with about 600 million production capacity per one year, one other 
location is added to potential locations. However, this production center has no fixed cost and the 
corresponding binary variable is always equal to 1 (i.e., $x_k=1$). At the reverse network, 11 candidate 
locations are considered for collection centers and four steel and plastic recycling centers and three 
incineration centers are available for handling EOL products. The fixed costs of opening production and 
collection centers as well as the corresponding capacities are represented in Table 2 and Table 3. It should
be noted that all of the monetary data are presented in the Iranian currency, Rial, and the capacities reported in Table 2 and Table 3 are aggregate capacities over three year horizon.

Table 3
The fixed cost \((\vec{g}_k)\) and capacity \((\vec{h}_k)\) data for collection centers

<table>
<thead>
<tr>
<th>Location</th>
<th>Fixed cost (million Rials)</th>
<th>Capacity (millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Varamin</td>
<td>(17000, 17400, 17800)</td>
<td>(2400, 2450, 2500)</td>
</tr>
<tr>
<td>(2) Saveh</td>
<td>(17500, 17900, 18300)</td>
<td>(2400, 2450, 2500)</td>
</tr>
<tr>
<td>(3) Semnan</td>
<td>(17000, 17400, 17800)</td>
<td>(2500, 2550, 2600)</td>
</tr>
<tr>
<td>(4) Shahrood</td>
<td>(16800, 17200, 17400)</td>
<td>(2500, 2550, 2600)</td>
</tr>
<tr>
<td>(5) Arak</td>
<td>(17800, 18300, 18800)</td>
<td>(2200, 2250, 2300)</td>
</tr>
<tr>
<td>(6) Zanjan</td>
<td>(17600, 18100, 18600)</td>
<td>(2300, 2350, 2400)</td>
</tr>
<tr>
<td>(7) Abhar</td>
<td>(17400, 17800, 18200)</td>
<td>(2200, 2250, 2300)</td>
</tr>
<tr>
<td>(8) Uromieh</td>
<td>(17600, 18000, 18600)</td>
<td>(2000, 2050, 2100)</td>
</tr>
<tr>
<td>(9) najafabad</td>
<td>(17200, 17500, 17800)</td>
<td>(2200, 2250, 2300)</td>
</tr>
<tr>
<td>(10) Abyek</td>
<td>(17500, 17900, 18300)</td>
<td>(2100, 2150, 2200)</td>
</tr>
<tr>
<td>(11) Salafchegan</td>
<td>(17300, 17700, 18100)</td>
<td>(2250, 2300, 2350)</td>
</tr>
</tbody>
</table>

Other imprecise parameters are also estimated by determining the three prominent values as described above. According to space limitation the detail value of other parameters are not presented in the paper. However, interested readers can find the detail data at [58]. The method of calculating the environmental impact parameters and the transportation costs are also described in subsections 3.1.1 and 3.1.2.

To analyze the performance of the proposed model and the interactive solution method the model is coded and solved by LINGO 8.0 optimization software and all tests are carried out on a Pentium dual-core 1.40 GHz computer with 3 GB RAM. Different minimum acceptable feasibility degrees (i.e., \(\alpha\)-levels: 0.6, 0.7, 0.8, 0.9 and 1) are used in performance testing and for each \(\alpha\)-level six Pareto-optimal solutions are generated by the aid of the modified \(\varepsilon\)-constraint method described in subsection 4.2. To implement the modified \(\varepsilon\)-constraint method, the satisfaction degree of cost objective is used as a side constraint and the satisfaction degree of environmental objective is kept in the model objective function. The results are reported in Table 4.

As it can be seen from Table 4, the value of both objective functions increases when the minimum acceptable feasibility degree (\(\alpha\)-level) is increased. In other words, as the decision maker decided to response to uncertainty with a higher confidence level, the environmental loads and costs are also augmented. The result could be simply explained by the need for spending more resources (raw material, products, transportations, etc.) to satisfy the demand and return of customers in higher \(\alpha\)-levels. As it was mentioned in Section 4.2, the value of minimum acceptable feasibility degree (\(\alpha\)) can be varied based on decision maker preferences at the end of each iteration of solution method (see Step 6).

Also, the results confirm that the two objective functions (i.e., minimization of total cost and minimization of total environmental impact) are in conflict with each other as a decrease of total
environmental impact leads to an increase in total costs and vice versa. The first objective function \(W_1\) has a tendency towards supply chain network centralization to minimize the total costs. Therefore, less number of production and collection centers is opened at higher satisfaction degrees of first objective function compared to lower ones. For example when \(\mu_i(x) = 1\), only two production centers and one collection center are opened, whereas, six production and ten collection centers are opened when \(\mu_i(x)\) is equal to 0.2. On the other hand, results reported in Table 4 show that the second objective function has a tendency towards decentralized network to minimize the total environmental impact. The environmental impact shortened in decentralized network, because more facilities are opened in this case compared to centralized structure and therefore more and probably shorter paths are available to transport products from origins to destinations. As the results in Table 4 show, more facilities or facilities with higher capacities are opened when decision maker gives more importance to second objective function.

The last column of Table 4 shows the “price” paid for environmental protection. This price is calculated by subtracting the minimum cost obtained by optimizing the model for the first objective function (or the minimum cost obtained when \(\mu_i(x) = 1\)) from the value of first objective function at each Pareto-optimal solution. In other words, the price of environmental protection shows the additional cost paid to protect the environment compared to the most cost-optimum solution. This indicator has twofold importance: (1) it can be used as a quantitative and transparent indicator by firms and managers to show their efforts to their stakeholders (e.g. customers, government and local community) in protecting the environment; (2) it can be considered as an appropriate baseline by government to regulate the incentive policies (e.g. financial aids) for firms. It is obvious that this price increases when more importance is given to the second objective function.

As it was mentioned at subsection 4.2., at the last step of the proposed solution approach, the decision maker can adjust the range of epsilon throughout the whole process. As such the decision maker may start with a coarse range in the early iterations to quickly cover the whole range of Pareto-optimal solutions. However, at the late iterations the decision maker may be interested in selecting the final preferred solution through a fine tuning. Therefore, at the late iterations, interesting areas (segments) can be investigated more precisely using a denser grid. In the studied case, at the second iteration the decision maker select the range between 0.7 and 0.95 as the interested area and the 0.9 as the preferred minimum acceptable feasibility degree. At the second iteration new Pareto-optimal solutions are generated using a denser grid between 0.7 and 0.95 that the results are reported in Table 5. Also, Figure 2 represents the iterations graphically.
Table 4
The summary of results according to different $\alpha$-levels

<table>
<thead>
<tr>
<th>$\alpha$-level</th>
<th>Satisfaction degree $\mu_1(W_j)$</th>
<th>Satisfaction degree $\mu_2(W_j)$</th>
<th>Objective function values $W_1$ (Rials)</th>
<th>Objective function values $W_2$ (Points)</th>
<th>CPU time (seconds)</th>
<th>No. of opened facilities</th>
<th>Price of environmental protection</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>1</td>
<td>0</td>
<td>9.0588E+11</td>
<td>3.5345E+07</td>
<td>8</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.766</td>
<td>1.1754E+12</td>
<td>1.6836E+07</td>
<td>3</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>0.942</td>
<td>1.4067E+12</td>
<td>1.2603E+07</td>
<td>3</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.985</td>
<td>1.6786E+12</td>
<td>1.1548E+07</td>
<td>3</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.998</td>
<td>1.9627E+12</td>
<td>1.1255E+07</td>
<td>2</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2.2537E+12</td>
<td>1.1208E+07</td>
<td>6</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>0.7</td>
<td>1</td>
<td>0.001</td>
<td>9.2241E+11</td>
<td>3.6099E+07</td>
<td>5</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.766</td>
<td>1.1914E+12</td>
<td>1.7568E+07</td>
<td>2</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>0.94</td>
<td>1.4207E+12</td>
<td>1.3363E+07</td>
<td>3</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.985</td>
<td>1.6922E+12</td>
<td>1.2285E+07</td>
<td>4</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.998</td>
<td>1.9761E+12</td>
<td>1.1985E+07</td>
<td>3</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2.2671E+12</td>
<td>1.1937E+07</td>
<td>5</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>0.001</td>
<td>9.3070E+11</td>
<td>3.6498E+07</td>
<td>11</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.767</td>
<td>1.1993E+12</td>
<td>1.7934E+07</td>
<td>3</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>0.94</td>
<td>1.4276E+12</td>
<td>1.3743E+07</td>
<td>4</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.985</td>
<td>1.6990E+12</td>
<td>1.2653E+07</td>
<td>3</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.997</td>
<td>1.9829E+12</td>
<td>1.2351E+07</td>
<td>5</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2.2739E+12</td>
<td>1.2302E+07</td>
<td>3</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>0.9</td>
<td>1</td>
<td>0.001</td>
<td>9.3901E+11</td>
<td>3.6854E+07</td>
<td>5</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.767</td>
<td>1.2073E+12</td>
<td>1.8300E+07</td>
<td>3</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>0.939</td>
<td>1.4346E+12</td>
<td>1.4123E+07</td>
<td>2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.985</td>
<td>1.7058E+12</td>
<td>1.3022E+07</td>
<td>2</td>
<td>4</td>
<td>10</td>
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<td></td>
<td>0.2</td>
<td>0.997</td>
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<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2.2806E+12</td>
<td>1.2666E+07</td>
<td>4</td>
<td>8</td>
<td>10</td>
</tr>
</tbody>
</table>

Finally, based on firm’s preferences the decision maker selects the solution with $\mu_1(x) = 0.85$ and $\mu_2(x) = 0.694$ as the final preferred solution. As it can be seen from Table 5, in this solution two production centers and five collection centers should be opened.
Table 5
The summary of results for the second iteration

<table>
<thead>
<tr>
<th>α-level</th>
<th>Satisfaction degrees</th>
<th>Objective function values</th>
<th>CPU time (seconds)</th>
<th>No. of opened facilities</th>
<th>Price of environmental protection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu(\tilde{W}_1)$</td>
<td>$\mu(\tilde{W}_2)$</td>
<td>$W_1$ (Rials)</td>
<td>$W_2$ (Points)</td>
<td>Production centers</td>
</tr>
<tr>
<td>0.9</td>
<td>0.95</td>
<td>0.362</td>
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Fig 2. The graphical representation of the proposed interactive solution approach

6. Conclusions

Environmental issues have become a critical topic in recent years. The design of the environmental supply chain is a very important and complex decision that forms in a dynamic and uncertain environment. To cope with this issue, this paper proposes a multi-objective fuzzy mathematical programming model. Despite the past research works, this model integrates the design of both forward and reverse supply chains besides considering the environmental impacts in the whole supply chain. Also, a LCA-based method, i.e., Eco-indicator 99, is applied to assess and quantify the environmental impact of different options for supply chain network configuration. To solve the proposed optimization model, an interactive fuzzy solution approach is developed based on the $\varepsilon$-constraint method and the possibilistic programming approach proposed by Jimenez et al. [46]. The proposed hybrid solution approach is able to generate both balanced and unbalanced solutions and making a reasonable tradeoff between environmental and economic objectives. The effectiveness of the developed fuzzy optimization model as well as the usefulness of the proposed solution approach is investigated through a real industrial case.
As the relevant literature shows (see section 1), the work considering environmental aspects in supply chain planning is still scarce. Therefore, many possible future research directions can be defined in this area. For example addressing other supply chain planning problems such as tactical and operational planning problems are attractive research avenues with significant practical relevance. Additionally, social aspect is not addressed in this paper, however this issue is important regarding the supply chain sustainability, therefore incorporating the social aspect into supply chain planning optimization models can be considered as another attractive future research direction.
Appendix: The Jimenez et al. [46] method

The Jimenez et al. [46] method is based on the definition of the “expected interval” and the “expected value” of a fuzzy number. Assume that $\tilde{c}$ is a triangular fuzzy number. The following equation can be defined as the membership function of $\tilde{c}$

$$\mu_{\tilde{c}}(x) = \begin{cases} 
    f_{\tilde{c}}(x) = \frac{x-c^{pes}}{c^{max} - c^{pes}}, & \text{if } c^{pes} \leq x \leq c^{max} \\
    1, & \text{if } x = c^{max} \\
    g_{\tilde{c}}(x) = \frac{c^{opt} - x}{c^{opt} - c^{max}}, & \text{if } c^{max} \leq x \leq c^{opt} \\
    0, & \text{if } x \leq c^{pes} \text{ or } x \geq c^{opt} 
\end{cases}$$

Which $c^{max}$, $c^{pes}$ and $c^{opt}$ are the three prominent points (the most likely, the most pessimistic and the most optimistic values), respectively. Equations (14) and (15) define the expected interval (EI) and the expected value (EV) of triangular fuzzy number $\tilde{c}$.

$$EI(\tilde{c}) = [E_1^c, E_2^c] = \left[ \int_0^1 f_{\tilde{c}}^{-1}(x) \, dx, \int_0^1 g_{\tilde{c}}^{-1}(x) \, dx \right] = \left[ \frac{1}{2}(c^{pes} + c^{max}), \frac{1}{2}(c^{max} + c^{opt}) \right]$$

$$EV(\tilde{c}) = \frac{E_1^c + E_2^c}{2} = \frac{c^{pes} + 2c^{max} + c^{opt}}{4}$$

According to the ranking method of Jimenez [48], for any pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the degree in which $\tilde{a}$ is bigger than $\tilde{b}$ can be defined as follows.

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 
    0, & \text{if } E_2^a - E_1^b < 0 \\
    \frac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)}, & \text{if } \ 0 \in [E_1^a - E_2^b, E_2^a - E_1^b] \\
    1, & \text{if } E_1^a - E_2^b > 0
\end{cases}$$

When $\mu_M(\tilde{a}, \tilde{b}) \geq \alpha$ it will be said that $\tilde{a}$ is bigger than, or equal to, $\tilde{b}$ at least in degree of $\alpha$ and it will be represented as $\tilde{a} \geq_{\alpha} \tilde{b}$. Now, consider the following fuzzy mathematical programming model in which all parameters are defined as triangular or trapezoidal fuzzy numbers.
\[
\begin{align*}
\text{min} \quad & z = \tilde{c}'x \\
\text{s.t.} \quad & \tilde{a}_i x \geq \tilde{b}_i, \quad i = 1,...,l \\
& x \geq 0
\end{align*}
\]
(17)

Based on Jimenez et al. [46], a decision vector \( x \in \mathbb{R}^n \) is feasible in degree of \( \alpha \) if
\[
\min_{i=1,...,m} \{ \mu_M(\tilde{a}_i x, \tilde{b}_i) \} = \alpha.
\]
According to (16), equation \( \tilde{a}_i x \geq \tilde{b}_i \) is equivalent to the following equation.
\[
\frac{E_2^{a_i} - E_1^{b_i}}{E_2^{a_i} - E_1^{a_i} + E_2^{b_i} - E_1^{b_i}} \geq \alpha \quad i = 1,...,l,
\]
(18)

Equation (18) can be rewritten as follows.
\[
[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i} \quad i = 1,...,l
\]
(19)

Also, Jimenez et al. [46] showed that a feasible solution like \( \tilde{x}^0 \) is an \( \alpha \)-acceptable optimal solution of the model (17) if and only if for all feasible decision vectors say \( x \) such that \( \tilde{a}_i x \geq_{\alpha} \tilde{b}_i \), \( i = 1,...,l \), and \( x \geq 0 \), the following equation holds.
\[
\tilde{c}'x \geq_{1/2} \tilde{c}'\tilde{x}^0
\]
(20)

Therefore, with the objective of minimizing, \( \tilde{x}^0 \) is a better choice at least in degree 1/2 as opposed to the other feasible vectors. The above equation can be rewritten as follows.
\[
\frac{E_2^{c_i}x + E_1^{c_i}x}{2} \geq \frac{E_2^{c_i}\tilde{x}^0 + E_1^{c_i}\tilde{x}^0}{2}
\]
(21)

Finally, by the aid of the definition of expected interval and expected value of a fuzzy number, the equivalent crisp \( \alpha \)-parametric model of the model (17) can be written as follows.
\[
\begin{align*}
\text{min} & \quad EV(\tilde{c})x \\
\text{s.t.} \quad & [(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, \quad i = 1,...,l \\
& x \geq 0
\end{align*}
\]
(22)
References


