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A possibilistic programming approach for closed-loop supply chain network design under uncertainty

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Abstract

The design of closed-loop supply chain networks has attracted more attention in recent years according to business and environmental factors. The significance of accounting for uncertainty and risk in such networks spurs an interest to develop appropriate decision making tools to cope with uncertain and imprecise parameters in closed-loop supply chain network design problems. This paper proposes a bi-objective possibilistic mixed integer programming model to deal with such issues. The proposed model integrates the network design decisions in both forward and reverse supply chain networks, and also incorporates the strategic network design decisions along with tactical material flow ones to avoid the sub-optimalities led from separated design in both parts. To solve the proposed possibilistic optimization model, an interactive fuzzy solution approach is developed by combining a number of efficient solution approaches from the recent literature. Numerical experiments are conducted to demonstrate the significance and applicability of the developed possibilistic model as well as the usefulness of the proposed solution approach.

Keywords: Fuzzy mathematical programming; Closed-loop supply chain network design; Possibilistic programming; Fuzzy multi-objective optimization

1. Introduction

In today's world, fast economic changes and the increasing pressure of market competition, lead firms to focus on supply chain and integrated logistics. A well-structured supply chain network is a sustainable competitive advantage for firms and helps them to cope with the increasing environmental turbulences [1]. Along the same lines, the concern about environmental protection and also the economic benefits of using returned products has spurred an interest in designing and implementing reverse logistics networks and closed-loop supply chains [2,3]. In recent decades, many companies focused on recovery and recycling activities and they have achieved significant successes in this area [4,5].

In general, supply chain network design in both forward and reverse networks includes determining the numbers, locations and capacities of facilities, buffer inventories in each facility and the quantity of flow between them [4]. As the body of literature about reverse supply chain network design shows, mixed integer programming (MIP) models are the common models used in this area. These MIP models range from simple single-product uncapacitated models (e.g., [6]) to complex multi-product capacitated (e.g., [7]) or multi-objective (e.g., [8]) models. Since most of these

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MIP models belong to the class of NP-hard problems, many heuristic algorithms (e.g., [9]) and metaheuristics such as genetic algorithm (e.g., [10]), simulated annealing (e.g., [11]), tabu search (e.g., [12]) and scatter search (e.g., [8]) are developed and used to solve these models. Also, there is a few works using continuous models in the context of reverse supply chain network design (e.g., [13]).

Since the configuration of both forward and reverse supply chain networks has a strong influence on the performance of each other, a number of researches (e.g., [12,14,15]) have recently focused on developing integrated models for simultaneous forward/reverse supply chain network design to avoid the sub-optimalities resulting from the separated design.

The dynamic and complex nature of supply chain imposes a high degree of uncertainty in supply chain planning decisions and significantly influences the overall performance of the supply chain network [16]. Ho [17] classified the uncertainty affecting the real world production systems into two groups: (1) environmental uncertainty and (2) system uncertainty. In the context of supply chain, environmental uncertainty is related to uncertainties in demand and supply derived from the performance of suppliers and behavior of customers. System uncertainty includes the uncertainties within the production, distribution, collection and recovery processes, such as, uncertainty in delivery time, production cost and actual capacity of different processes. The strategic horizon of supply chain network design decisions intensifies the impact of uncertainty in this problem. Moreover, Fleischmann et al. [4] mention that since it is more difficult to control and estimate the quantity and quality of returned products, the issue of uncertainty is more important in the context of reverse supply chains. Thus, the significance of accounting for uncertainty has prompted the researchers to address uncertain parameters in supply chain network design (see [16]). To cope with this issue, Listes and Dekker [18] propose a stochastic mixed integer programming (SMIP) model in a sand recycling industry to maximize the total profit. They develop their model for different situations regarding several scenarios. Salema et al. [19] develop a stochastic model for multi-product closed-loop network under demand uncertainty using stochastic mixed integer programming. El-Sayed et al. [15] present a SMIP model for integrated–forward/reverse logistics network design under demand and return uncertainty. The objective is maximization of the total profit.

However, there are two major drawbacks in using stochastic approach: (1) in many real cases there is not enough historical data for uncertain parameters, thus, we can rarely obtain the actual and exact random distributions of the uncertain parameters. Moreover, the chance constraints elevate significantly the computational complexity of the original problem and (2) in most of previous works on reverse supply chain network design under uncertainty, the uncertainty is modeled through scenario based stochastic programming. In these cases, a large number of scenarios used in representing the uncertainty can lead to computationally challenging problems.

As an alternative, fuzzy set theory [20] provides a framework to handle different kind of uncertainty, including fuzzy coefficients for lack of knowledge or epistemic uncertainty as well as flexibility in constraints and goals (fuzziness), at the same time [21].

To the best of our knowledge, there is no research work applying the fuzzy optimization approach in the context of closed-loop supply chain network design. However, a few research works use fuzzy optimization approach for forward supply chain network design (e.g., [22,23]). Wang and Shu [23] develop a possibilistic model for the supply chain network design of a new product. A genetic algorithm is applied to find near optimal solutions. Also, there are other works using fuzzy approach in the area of supply chain planning at tactical and operational levels (e.g., [24,25]).

The main objective of this paper is to develop a multi-objective possibilistic optimization model for a closed-loop supply chain network design including the design of both forward and reverse supply chain networks at the same time under uncertain demands, returns, delivery times, costs and capacities. The concerned objectives include total cost minimization and minimization of the total tardiness of delivered products.

The main contributions of this paper that differentiate this paper from the existing ones in the related literature; can be summarized as follows:

- Introducing an efficient new network design model that integrates the design of the reverse and forward supply chains and also integrates the strategic network design decisions with tactical planning decisions, i.e., the quantity of flows between facilities at each period to avoid the sub-optimalities resulting from the separated design of the forward and reverse chains and the separated decision making processes between strategic and tactical levels. To the best of our knowledge there is no research paper considering both of these integrations in a single model. For example, references [12,14] consider the integration of the forward and reverse chains but ignoring the integration of the tactical and

strategic level decisions. On the other hand, some research papers (e.g., [26]) consider the integration of decision making processes in strategic and tactical levels but ignoring the integration of forward and reverse supply chains design.

- Despite the case-based models (e.g., [18]) or models with only considering the recycling (or recovery) process (e.g., [5,6,11,12,18,19]), the proposed model addresses a general network structure supporting both recovery and recycling processes, and therefore can be applied to the different kind of industries such as vehicle (e.g., [5]) and electronic industries (e.g., [12]). Besides, our model also considers the recycled material customer, as a second group of customers. Notably, all of the previous works only consider the product customers.
- Offering a possibilistic programming model which handles different sources of uncertainty influencing closed-loop integrated forward/reverse supply chains by jointly considering unavailability or incompleteness and imprecise nature of data.
- Proposing an efficient interactive fuzzy solution approach by combining a number of efficient solution approaches from the recent literature to solve the proposed multi-objective possibilistic mixed integer linear programming model which is able to generate both balanced and unbalanced efficient solutions based on decision maker preferences.

Briefly, this paper proposes a comprehensive and practical, but tractable, multi-objective possibilistic model for closed-loop integrated forward/reverse supply chain network design that is able to: (1) integrate the design of reverse and forward flows in supply chains, as well as strategic facility location decisions with tactical material flow ones at each period, (2) support both recovery and recycling processes as a general structure, (3) consider the second kind of customers, i.e., the customers of recycled material, as a layer of reverse supply chain, (4) allow to trade-off between two important objectives in this area, i.e., the total costs and the total network responsiveness to offer different compromise efficient solutions to the decision makers and finally (5) handle different environmental and system uncertainties influencing the design of closed-loop integrated forward/reverse supply chain by considering unavailability or incompleteness and imprecise nature of model parameters using the possibilistic programming approach. The need for a such model overcoming the aforementioned drawbacks of using stochastic optimization models and at the same time, integrating the design of forward and reverse chains as well as strategic and tactical decisions, have recently been emphasized by researchers and practitioners (see [14,16,26]).

The remainder of this paper is organized as follows. The concerned problem is defined in Section 2. The proposed multi-objective possibilistic mixed integer linear programming model is elaborated in Section 3 and the proposed hybrid interactive solution method is given in Section 4. Computational experiments are reported in Section 5 and finally the concluding remarks as well as some directions for future research are given in Section 6.

2. Problem definition

The concerned closed-loop supply chain network in this paper is a multi-echelon network including both forward and reverse flows in an integrated system. As is it shown in Fig. 1, through forward flows the new products manufactured by plants are shipped to distribution centers and then to customers. In the reverse side, the used products are first collected in collection centers and after quality testing and disassembly activities, the recoverable products are shipped to recovery facilities and unrecoverable (scraped) products are shipped to recycling centers. The recovered products are inserted in forward supply chain and redistributed to customers. On the other hand, scrapped products are transformed into the raw material at recycling facilities and are shipped to material customers. As it can be seen in Fig. 1, the considered network in this paper has a general structure which is able to support both recovery and recycling processes and therefore can be applied to different kind of industries such as vehicle (e.g., [5]) and electronic industries (e.g., [12]).

Because of unavailability or incompleteness of data in real world situations, especially in long-term horizon, most of the parameters embedded in such closed-loop supply chain network design problem have an imprecise nature. So, in order to model the lack of knowledge about these ill-known parameters we use appropriate possibility distributions (see [20,28,29]) We also consider a decision horizon including multiple periods in the proposed model and therefore the flow quantities between facilities belonging to different echelons are determined according to demand, return and other periodic-based parameters at each period. This approach enables us to integrate the tactical material flow decisions with strategic level location decisions (see [26]).

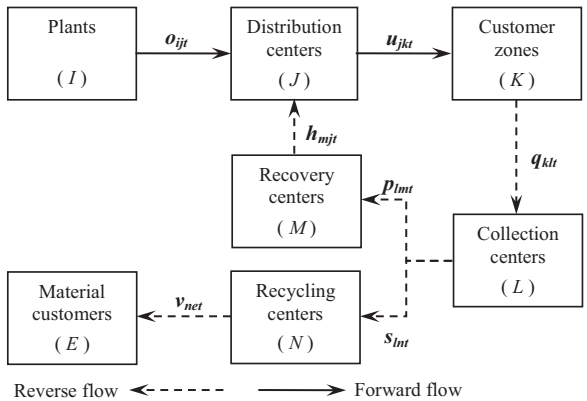

Fig. 1. The structure of concerned closed-loop supply chain network.

The other main assumptions used in the problem formulation are as follow:

- All demands of customers must be satisfied and all of the returned products from customers must be collected.
- Products are shipped through a pull mechanism in the forward side of network.
- Except the shipment between recycling centers and material customers, returned products are shipped through a push mechanism in the reverse side of network. Note that recycled products are shipped from recycling centers to material customers through a pull mechanism.
- Locations of customers, material customers and plants are fixed and predefined.
- A predefined percent of demand from each customer in the previous period is assumed as returned products from corresponding customer in the current period.
- A predefined value is determined as an average scrap fraction.
- Without loss of generality, a single product is moved through the network.

The main issues to be addressed in this closed-loop network under uncertain demands, returns, delivery times, costs and capacities consist of determining the numbers of distribution, collection, recovery and recycling centers, as well as their locations along with the flow quantities between different facilities at each period. In order to design this closed-loop supply chain network, two objective functions are considered: (1) minimization of total costs and (2) minimization of total delivery tardiness. The first objective is related to supply chain network efficiency and the second one is related to network responsiveness. Indeed, the second objective enables the supply chain to satisfy the customers' expected delivery times and therefore being the order winner in its product-markets (see [16]). Notably, these two objective functions are in conflict with each other. This means that an increase in one objective leads to a decrease in another one; therefore optimizing the network involves a trade-off between these two objectives.

3. Model formulation

The following notation is used in the formulation of the closed-loop supply chain network design (CSCND) model. To avoid any notation ambiguity, it should be noted that symbols with a tilde on indicate coefficients tainted with possibilistic uncertainty.

Indices:

$\boldsymbol{i}$	index of fixed locations of plants $i = 1, \ldots, I$
$\boldsymbol{j}$	index of candidate locations for distribution centers $j = 1, \ldots, J$
$\boldsymbol{k}$	index of fixed locations of customer zones $k = 1, \ldots, K$
$\boldsymbol{l}$	index of candidate locations for collection centers $l = 1, \ldots, L$
$\boldsymbol{m}$	index of candidate locations for recovery centers $m = 1, \ldots, M$
$\boldsymbol{n}$	index of candidate locations for recycling centers $n = 1, \ldots, N$
$\boldsymbol{e}$	index of fixed locations of material customers $e = 1, \ldots, E$
$\boldsymbol{t}$	index of time periods $t = 1, \ldots, T$

Parameters:

$\tilde{d}_{kt}$ demand of customer zone k at period t
$\tilde{\omega}_{kt}$ rate of return percentage from customer zone k at period t
$\tilde{r}_{kt}$ amount of return from customer zone k at period t, i.e., $\tilde{r}_{kt} = \tilde{\omega}_{kt} \cdot \tilde{d}_{k,t-1}, \tilde{d}_{k0} = 0$
$\tilde{c}_{et}$ demand of material customer e at period t
$\tilde{\eta}_t$ average scrap fraction at period t
$\tilde{f}_j$ fixed cost of opening distribution center j
$\tilde{g}_l$ fixed cost of opening collection center l
$\tilde{a}_n$ fixed cost of opening recycling center n
$\tilde{b}_m$ fixed cost of opening recovery center m
$c\tilde{o}_{ij}$ transportation cost per product unit from plant i to distribution center j
$c\tilde{u}_{jk}$ transportation cost per product unit from distribution center j to customer zone k
$c\tilde{q}_{kl}$ transportation cost per unit of returned products from customer zone k to collection center l
$c\tilde{p}_{lm}$ transportation cost per unit of recoverable products from collection center l to recovery center m
$c\tilde{s}_{\mathrm{ln}}$ transportation cost per unit of scrapped products from collection center l to recycling center n
$c\tilde{h}_{mj}$ transportation cost per unit of recovered products from recovery center m to distribution center j
$c\tilde{v}_{ne}$ transportation cost per unit of recycled products (material) from recycling center n to material customer e
$\tilde{\rho}_i$ manufacturing cost per unit of product at plant i
$\tilde{\varphi}_j$ processing cost per unit of product at distribution center j
$\tilde{\beta}_l$ processing cost per unit of product at collection center l
$\tilde{\tau}_m$ remanufacturing cost per unit of product at recovery center m
$\tilde{\theta}_n$ recycling cost per unit of product at recycling center n
$p\tilde{p}_i$ maximum capacity of plant i at each period
$p\tilde{x}_j$ maximum capacity of distribution center j at each period
$p\tilde{y}_l$ maximum capacity of collection center l at each period
$p\tilde{z}_m$ maximum capacity of recovery center m at each period
$p\tilde{w}_n$ maximum capacity of recycling center n at each period
$t\tilde{d}_{jk}$ delivery time from distribution center j to customer zone k
$t\tilde{e}_{kt}$ expected delivery time of customer k in period t
$\boldsymbol{D_t}$ $= \{j | t\tilde{d}_{jk} \geq t\tilde{e}_{kt}\}$ in period t

Variables:

$\boldsymbol{o_{ijt}}$ quantity of products shipped from plant i to distribution center j at period t
$\boldsymbol{u_{jkt}}$ quantity of products shipped from distribution center j to customer zone k at period t
$\boldsymbol{q_{klt}}$ quantity of returned products shipped from customer zone k to collection center l at period t
$\boldsymbol{p_{lmt}}$ quantity of recoverable products shipped from collection center l to recovery center m at period t
$\boldsymbol{s_{lnt}}$ quantity of scrapped products shipped from collection center l to recycling center n at period t
$\boldsymbol{h_{mjt}}$ quantity of recovered products shipped from recovery center m to distribution center j at period t
$\boldsymbol{v_{net}}$ quantity of recycled products (materials) shipped from recycling center n to material customer e at period t

$$\boldsymbol{x_j} = \begin{cases} 1 & \text{if a distribution center is opened at location } j \\ 0 & \text{otherwise} \end{cases}$$

$$\boldsymbol{y_l} = \begin{cases} 1 & \text{if a collection center is opened at location } l \\ 0 & \text{otherwise} \end{cases}$$

$$\boldsymbol{z_m} = \begin{cases} 1 & \text{if a recovery center is opened at location } m \\ 0 & \text{otherwise} \end{cases}$$

$$\boldsymbol{w_n} = \begin{cases} 1 & \text{if a recycling center is opened at location } n \\ 0 & \text{otherwise} \end{cases}$$

In terms of the above notation, the CSCND problem can be formulated as follows:

$$\text{Min W}_1 = \sum_j \tilde{f}_j x_j + \sum_l \tilde{g}_l y_l + \sum_m \tilde{b}_m z_m + \sum_n \tilde{a}_n w_n + \sum_t \sum_i \sum_j (c\tilde{o}_{ij} + \tilde{\rho}_i) o_{ijt}$$

$$+\sum_t\sum_j\sum_k(c\tilde{u}_{jk}+\tilde{\varphi}_j)u_{jkt}+\sum_t\sum_k\sum_l c\tilde{q}_{kl}q_{klt}+\sum_t\sum_l\sum_m(c\tilde{p}_{lm}+\tilde{\beta}_l)p_{lmt}$$

$$+\sum_t\sum_l\sum_n(c\tilde{s}_{\ln}+\tilde{\beta}_l)s_{\ln t}+\sum_t\sum_m\sum_j(c\tilde{h}_{mj}+\tilde{\tau}_m)h_{mjt}+\sum_t\sum_n\sum_e(c\tilde{v}_{ne}+\tilde{\theta}_n)v_{net} \tag{1}$$

$$\text{Min W}_2=\sum_t\sum_k\sum_{j\in D_t}(t\tilde{d}_{jk}-t\tilde{e}_{kt})u_{jkt} \tag{2}$$

$$\sum_j u_{jkt}\geq\tilde{d}_{kt}\quad\forall k,t \tag{3}$$

$$\sum_n v_{net}\geq\tilde{c}_{et}\quad\forall e,t \tag{4}$$

$$\sum_l q_{klt}\geq\tilde{r}_{kt}=\tilde{\omega}_{kt}\cdot\tilde{d}_{kt-1}\quad\forall k,t \tag{5}$$

$$\sum_i o_{ijt}+\sum_m h_{mjt}=\sum_k u_{jkt}\quad\forall j,t \tag{6}$$

$$\tilde{\eta}_t\sum_k q_{klt}=\sum_n s_{\ln t}\quad\forall l,t \tag{7}$$

$$(1-\tilde{\eta}_t)\sum_k q_{klt}=\sum_m p_{lmt}\quad\forall l,t \tag{8}$$

$$\sum_j h_{mjt}=\sum_l p_{lmt}\quad\forall m,t \tag{9}$$

$$\sum_e v_{net}\leq\sum_l s_{\ln t}\quad\forall n,t \tag{10}$$

$$\sum_j o_{ijt}\leq p\tilde{p}_i\quad\forall i,t \tag{11}$$

$$\sum_i o_{ijt}+\sum_m h_{mjt}\leq x_j p\tilde{x}_j\quad\forall j,t \tag{12}$$

$$\sum_k q_{klt}\leq y_l p\tilde{y}_l\quad\forall l,t \tag{13}$$

$$\sum_l p_{lmt}\leq z_m p\tilde{z}_m\quad\forall m,t \tag{14}$$

$$\sum_l s_{\ln t}\leq w_n p\tilde{w}_n\quad\forall n,t \tag{15}$$

$$x_j,y_l,z_m,w_n\in\{0,1\}\quad\forall j,l,m,n \tag{16}$$

$$o_{ijt},u_{jkt},h_{mjt},q_{klt},p_{lmt},s_{\ln t},v_{net}\geq 0\quad\forall i,j,k,l,m,n,e,t \tag{17}$$

Objective function (1) minimizes the total costs including fixed opening costs and variable transportation and processing costs. Objective function (2) minimizes the total delivery tardiness. Constraints (3) and (4) ensure that the demands of all customers and material customers are satisfied Constraint (5) ensures that the returned products of all customers are collected. Constraints (6)–(10) assure the flow balance at distribution, collection, recovery and recycling

centers. Eqs. (11)–(15) are capacity constraints on facilities and also prohibit the units of products, returned products, recoverable and recyclable products from being transferred to facilities which are not opened. Finally, Constraints (16) and (17) enforce the binary and non-negativity restrictions on decision variables.

It is noteworthy that uncertainty can be presented as: (1) flexibility in constraints and goals and/or (2) uncertainty in data (see [21]). Flexibility (fuzziness) is related to flexible target value of goals and constraints which is modeled by fuzzy sets [27]. To cope with this kind of uncertainty flexible mathematical programming models are used (for example see [28,29]). The uncertainty in data can be classified into two groups: (1) randomness in the model parameters that comes from the random nature of events and copes with uncertainty regarding membership or non-membership of an element in a set [30]. Usually stochastic programming approaches were used to model the randomness of model parameters (see for example [15,18]) and (2) epistemic uncertainty that deals with lack of knowledge about model parameters and possibilistic programming approaches are used to cope with this kind of uncertainty (see for example [30]).

Since we are dealing with ill-known parameters in our CSCND model (epistemic uncertainty), the proposed model belongs to the class of possibilistic programming models. In possibilistic programming each ill-known parameter has its possibility distribution. These possibility distributions represent the possibility degree of occurrence of each data and are mostly determined objectively based on available data as well as experts' knowledge Notably, we avoid giving more explanation to justify the imprecision of parameters of the proposed model and refer the interested readers to Mula et al. [30], Peidro et al. [31] and Torabi and Hassini [25] for more details. It also should be mentioned that in all expressions involving ill-known parameters like constraints (7), what we mean is that the actual value of the possibilistic quantity (for instance the left-hand side of Eq. (7)) should be equal to the crisp value (on the right-hand side).

4. The proposed solution method

The proposed CSCND model is actually a multi-objective possibilistic mixed integer linear programming one (MOPMILP). To solve this model a two-phased approach is proposed. In the first phase, the original model is converted into an equivalent auxiliary crisp model by applying an efficient possibilistic method through hybridizing the novel methods of Jimenez et al. [34] and Parra et al. [37]. Then, in the second phase, we apply two recently proposed fuzzy methods, i.e., Torabi and Hassini [25] (TH) and Selim and Ozkarahan [22] (SO) fuzzy multi-objective methods to find the final preferred compromise solution.

4.1. The equivalent auxiliary crisp model

Several methods have been developed in the literature to deal with the possibilistic models involving the imprecise coefficients in both objective functions and constraints (e.g., [29,34–37]). Here, we propose an efficient possibilistic method by hybridizing the methods of Jimenez et al. [34] and Parra et al. [37], to convert the proposed possibilistic mixed integer programming model into an equivalent auxiliary crisp model. Notably, the main part of proposed possibilistic method is based on Jimenez et al. method [34] because of its several advantages as follows:

- The method is computationally efficient to solve fuzzy linear problems because it both preserves its linearity and do not increase the number of objective functions and inequality constraints. Therefore, the method can be conveniently used and implemented for large MILP models such as proposed CSCND model.
- The method relies on the Jimenez [33] general ranking method which can be applied to different kinds of membership functions such as triangular, trapezoidal and nonlinear ones in both symmetric and asymmetric forms.
- The method is based on the strong mathematical concepts such as expected interval and expected value of fuzzy numbers.

Noteworthy, the Jimenez et al. [34] method has recently been used as the defuzzification method in some relevant works in the supply chain planning area as well (e.g., [32]).

The Jimenez et al. [34] method is based on the definition of the "expected value" and the "expected interval" of a fuzzy number which was firstly developed by Yager [38] and Dubois and Prade [39] respectively, and followed by Heilpern [40] and Jimenez [33]. Assume that $\tilde{c}$ is a triangular fuzzy number, the following equation can be defined as the membership

function of $\tilde{c}$:

$$\mu_{\tilde{c}}(x) = \begin{cases} f_c(x) = \dfrac{x - c^p}{c^m - c^p} & \text{if } c^p \le x \le c^m \\ 1 & \text{if } x = c^m \\ g_c(x) = \dfrac{c^o - x}{c^o - c^m} & \text{if } c^m \le x \le c^o \\ 0 & \text{if } x \le c^p \text{ or } x \ge c^o \end{cases}$$

According to Jimenez [33], the expected interval (EI) and expected value (EV) of triangular fuzzy number $\tilde{c}$ can be defined as follow:

$$EI(\tilde{c}) = [E_1^c, E_2^c] = \left[\int_0^1 f_c^{-1}(x)\,\mathrm{d}x, \int_0^1 g_c^{-1}(x)\,\mathrm{d}x\right] = \left[\frac{1}{2}(c^p + c^m), \frac{1}{2}(c^m + c^o)\right] \tag{18}$$

$$EV(\tilde{c}) = \frac{E_1^c + E_2^c}{2} = \frac{c^p + 2c^m + c^o}{4} \tag{19}$$

It is noted that the same equations can be used for a trapezoidal fuzzy number. Moreover, according to the ranking method of Jimenez [33] for any pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the degree in which $\tilde{a}$ is bigger than $\tilde{b}$ is defined as follows:

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 & \text{if } E_2^a - E_1^b < 0 \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & \text{if } 0 \in [E_1^a - E_2^b, E_2^a - E_1^b] \\ 1 & \text{if } E_1^a - E_2^b > 0 \end{cases} \tag{20}$$

When $\mu_M(\tilde{a}, \tilde{b}) \ge \alpha$ it will be said that $\tilde{a}$ is bigger than, or equal to, $\tilde{b}$ at least in degree α and it will be represented as $\tilde{a} \ge_\alpha \tilde{b}$. It should be noted that the Jimenez [33] ranking method is somehow similar to those of Gonzalez [41] and Fortemps and Roubens [42]. Also, for more details on fuzzy numbers including ranking indices similar to Jimenez [33], the interested reader may consult with Dubois et al. [43].

Also, according to the definition of fuzzy equations in Parra et al. [37], for any pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, it will be said that $\tilde{a}$ is indifferent (equal) to $\tilde{b}$ in degree of α if the following relationships hold simultaneously:

$$\tilde{a} \ge_{\alpha/2} \tilde{b}, \quad \tilde{a} \le_{\alpha/2} \tilde{b} \tag{21}$$

The above equations can be rewritten as follows:

$$\frac{\alpha}{2} \le \mu_M(\tilde{a}, \tilde{b}) \le 1 - \frac{\alpha}{2} \tag{22}$$

Now, we consider the following fuzzy mathematical programming model in which all parameters are defined as triangular or trapezoidal fuzzy numbers

$$\begin{aligned} \min \quad & z = \tilde{c}^t x \\ \text{s.t.} \quad & \\ & \tilde{a}_i x \ge \tilde{b}_i, \quad i = 1, \ldots, l \\ & \tilde{a}_i x = \tilde{b}_i, \quad i = l+1, \ldots, m \\ & x \ge 0 \end{aligned} \tag{23}$$

As mentioned by Jimenez et al. [34], a decision vector $x \in \Re^n$ is feasible in degree α if $\min_{i=1,\ldots,m}\{\mu_M(\tilde{a}_i x, \tilde{b}_i)\} = \alpha$. According to (20) and (21), the equations $\tilde{a}_i x \ge \tilde{b}_i$ and $\tilde{a}_i x = \tilde{b}_i$ are equivalent to the following ones, respectively:

$$\frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} - E_1^{a_i x} + E_2^{b_i} - E_1^{b_i}} \ge \alpha, \quad i = 1, \ldots, l \tag{24-1}$$

$$\frac{\alpha}{2} \le \frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} - E_1^{a_i x} + E_2^{b_i} - E_1^{b_i}} \le 1 - \frac{\alpha}{2}, \quad i = l+1, \dots, m \tag{24-2}$$

These equations can be rewritten as follows:

$$\begin{aligned}
&[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \ge \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, \quad i = 1, \dots, l \\
&\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i} + \frac{\alpha}{2}E_1^{a_i}\right]x \ge \frac{\alpha}{2}E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i}, \quad i = l+1, \dots, m \\
&\left[\frac{\alpha}{2}E_2^{a_i} + \left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \le \left(1-\frac{\alpha}{2}\right)E_2^{b_i} + \frac{\alpha}{2}E_1^{b_i}, \quad i = l+1, \dots, m
\end{aligned} \tag{25}$$

Similarly, by using Jimenez [33] ranking method, it can be proved (see [34]) that a feasible solution like x^0 is an α-acceptable optimal solution of the model (23) if and only if for all feasible decision vectors say x such that $\tilde{a}_i x \ge_\alpha \tilde{b}_i,\ i = 1, \dots, l$, and $\tilde{a}_i x \approx_\alpha \tilde{b}_i,\ i = l+1, \dots, m, x \ge 0$, the following equation holds:

$$\tilde{c}^t x \ge_{1/2} \tilde{c}^t x^0 \tag{26}$$

Therefore, x^0 is a better choice (with the objective of minimizing) at least in degree $\frac{1}{2}$ as opposed to the other feasible vectors. The above equation can be rewritten as follows:

$$\frac{E_2^{c^t x} + E_1^{c^t x}}{2} \ge \frac{E_2^{c^t x^0} + E_1^{c^t x^0}}{2} \tag{27}$$

Consequently, using the definition of expected interval and expected value of a fuzzy number, the equivalent crisp α-parametric model of the model (23) can be written as follows:

$$\min \quad EV(\tilde{c})x \tag{28}$$

s.t.

$$\begin{aligned}
&[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \ge \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, \quad i = 1, \dots, l \\
&\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i} + \frac{\alpha}{2}E_1^{a_i}\right]x \ge \frac{\alpha}{2}E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i}, \quad i = l+1, \dots, m \\
&\left[\frac{\alpha}{2}E_2^{a_i} + \left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \le \left(1-\frac{\alpha}{2}\right)E_2^{b_i} + \frac{\alpha}{2}E_1^{b_i}, \quad i = l+1, \dots, m \\
&x \ge 0
\end{aligned} \tag{29}$$

According to above descriptions, the equivalent auxiliary crisp model of the CSCND model can be formulated as follows:

$$\begin{aligned}
\text{Min W}_1 = &\sum_j \left(\frac{f_j^p + 2f_j^m + f_j^o}{4}\right) x_j + \sum_l \left(\frac{g_l^p + 2g_l^m + g_l^o}{4}\right) y_l + \sum_m \left(\frac{b_m^p + 2b_m^m + b_m^o}{4}\right) z_m \\
&+ \sum_n \left(\frac{a_n^p + 2a_n^m + a_n^o}{4}\right) w_n + \sum_t \sum_i \sum_j \left(\frac{co_{ij}^p + 2co_{ij}^m + co_{ij}^o + \rho_i^p + 2\rho_i^m + \rho_i^o}{4}\right) o_{ijt} \\
&+ \sum_t \sum_j \sum_k \left(\frac{cu_{jk}^p + 2cu_{jk}^m + cu_{jk}^o + \varphi_j^p + 2\varphi_j^m + \varphi_j^o}{4}\right) u_{jkt} \\
&+ \sum_t \sum_k \sum_l \left(\frac{cq_{kl}^p + 2cq_{kl}^m + cq_{kl}^o}{4}\right) q_{klt} \\
&+ \sum_t \sum_l \sum_m \left(\frac{cp_{lm}^p + 2cp_{lm}^m + cp_{lm}^o + \beta_l^p + 2\beta_l^m + \beta_l^o}{4}\right) p_{lmt}
\end{aligned}$$

$$+\sum_t\sum_l\sum_n\left(\frac{cs^p_{\ln}+2cs^m_{\ln}+cs^o_{\ln}+\beta^p_l+2\beta^m_l+\beta^o_l}{4}\right)s_{\ln t}$$

$$+\sum_t\sum_m\sum_j\left(\frac{ch^p_{mj}+2ch^m_{mj}+ch^o_{mj}+\tau^p_m+2\tau^m_m+\tau^o_m}{4}\right)h_{mjt}$$

$$+\sum_t\sum_n\sum_e\left(\frac{cv^p_{ne}+2cv^m_{ne}+cv^o_{ne}+\theta^p_n+2\theta^m_n+\theta^o_n}{4}\right)v_{net}$$

$$\text{Min W}_2=\sum_t\sum_k\sum_{j\in D_t}\left(\frac{td^p_{jk}+2td^m_{jk}+td^o_{jk}-te^p_{kt}-2te^m_{kt}-te^o_{kt}}{4}\right)u_{jkt}$$

$$\sum_j u_{jkt}\geq\alpha\left(\frac{d^m_{kt}+d^o_{kt}}{2}\right)+(1-\alpha)\left(\frac{d^p_{kt}+d^m_{kt}}{2}\right),\quad\forall k,t$$

$$\sum_n v_{net}\geq\alpha\left(\frac{c^m_{et}+c^o_{et}}{2}\right)+(1-\alpha)\left(\frac{c^p_{et}+c^m_{et}}{2}\right),\quad\forall e,t$$

$$\sum_l q_{klt}\geq\alpha\left(\frac{r^m_{kt}+r^o_{kt}}{2}\right)+(1-\alpha)\left(\frac{r^p_{kt}+r^m_{kt}}{2}\right),\quad\forall k,t$$

$$\sum_i o_{ijt}+\sum_m h_{mjt}=\sum_k u_{jkt},\quad\forall j,t$$

$$\left[\left(\frac{\alpha}{2}\right)\frac{\eta^o_t+\eta^m_t}{2}+\left(1-\frac{\alpha}{2}\right)\frac{\eta^p_t+\eta^m_t}{2}\right]\sum_k q_{klt}\leq\sum_n s_{\ln t},\quad\forall l,t$$

$$\left[\left(1-\frac{\alpha}{2}\right)\frac{\eta^o_t+\eta^m_t}{2}+\left(\frac{\alpha}{2}\right)\frac{\eta^p_t+\eta^m_t}{2}\right]\sum_k q_{klt}\geq\sum_n s_{\ln t},\quad\forall l,t$$

$$\left[1-\left(\frac{\alpha}{2}\right)\frac{\eta^p_t+\eta^m_t}{2}-\left(1-\frac{\alpha}{2}\right)\frac{\eta^o_t+\eta^m_t}{2}\right]\sum_k q_{klt}\leq\sum_m p_{lmt},\quad\forall l,t$$

$$\left[1-\left(1-\frac{\alpha}{2}\right)\frac{\eta^p_t+\eta^m_t}{2}-\left(\frac{\alpha}{2}\right)\frac{\eta^o_t+\eta^m_t}{2}\right]\sum_k q_{klt}\geq\sum_m p_{lmt},\quad\forall l,t$$

$$\sum_j h_{mjt}=\sum_l p_{lmt},\quad\forall m,t$$

$$\sum_e v_{net}\leq\sum_l s_{\ln t},\quad\forall n,t$$

$$\sum_j o_{ijt}\leq\alpha\left(\frac{pp^p_i+pp^m_i}{2}\right)+(1-\alpha)\left(\frac{pp^o_i+pp^m_i}{2}\right),\quad\forall i,t$$

$$\sum_i o_{ijt}+\sum_m h_{mjt}\leq x_j\left[\alpha\left(\frac{px^p_j+px^m_j}{2}\right)+(1-\alpha)\left(\frac{px^o_j+px^m_j}{2}\right)\right],\quad\forall j,t$$

$$\sum_k q_{klt} \le y_l \left[\alpha \left(\frac{py_l^p + py_l^m}{2} \right) + (1-\alpha) \left(\frac{py_l^o + py_l^m}{2} \right) \right], \quad \forall l, t$$

$$\sum_l p_{lmt} \le z_m \left[\alpha \left(\frac{pz_m^p + pz_m^m}{2} \right) + (1-\alpha) \left(\frac{pz_m^o + pz_m^m}{2} \right) \right], \quad \forall m, t$$

$$\sum_l s_{\ln t} \le w_n \left[\alpha \left(\frac{pw_n^p + pw_n^m}{2} \right) + (1-\alpha) \left(\frac{pw_n^o + pw_n^m}{2} \right) \right], \quad \forall n, t$$

$$x_j, y_l, z_m, w_n \in \{0, 1\}, \quad \forall j, l, m, n$$

$$o_{ijt}, u_{jkt}, h_{mjt}, q_{klt}, p_{lmt}, s_{\ln t}, v_{net} \ge 0, \quad \forall i, j, k, l, m, n, e, t$$

4.2. The proposed fuzzy solution approach

Generally, to solve the multi-objective linear programming (MOLP) models several approaches have been proposed in the literature. Among them, fuzzy programming approaches are highly applied especially in the recent years because of their capability in measuring the satisfaction level of each objective function directly.

The first fuzzy solution approach for MOLP problems was developed by Zimmermann [44] called min–max approach. However, this method sometimes results in non-efficient solutions [29]. To obviate the weakness of min–max approach, Sakawa et al. [45] proposed an interactive fuzzy approach for solving MOLP problems based on min–max approach. Also, Lai and Hwang [29] developed an augmented min–max approach. Recently, Torabi and Hassini [25] proposed a new single-phase approach for solving MOLP problems, called TH method. They also proved analytically that their method yields efficient solutions. Also, Selim and Ozkarahan [22] proposed a new fuzzy solution approach for solving MOLP problems by modifying the Werner's [46] aggregation function. However, in this paper to solve the proposed CSCND model, we propose an interactive fuzzy solution approach by combining the Jimenez et al. [34], Parra et al. [37] and TH/SO methods.

The steps of the proposed hybrid method can be summarized as follows.

Step 1: Determine the appropriate triangular or trapezoidal possibility distributions for imprecise parameters and formulate the MOPMILP model for CSCND problem.

Step 2: Convert the imprecise objective functions into the crisp ones by using the expected value of corresponding imprecise parameters.

Step 3: Determine the minimum acceptable feasibility degree of decision vector, α, and convert the fuzzy constraints into the crisp ones, and formulate the equivalent auxiliary crisp MOMILP model.

Step 4: Determine the α-positive ideal solution (α-PIS) and α-negative ideal solution (α-NIS) for each objective function and α-feasibility level. To obtain the α-positive ideal solutions, i.e., $(W_1^{\alpha\text{-}PIS}, x_1^{\alpha\text{-}PIS})$ and $(W_2^{\alpha\text{-}PIS}, x_2^{\alpha\text{-}PIS})$, the equivalent crisp MOMILP model should be solved for each objective function separately, and then the α-negative ideal solution for each objective function can be estimated as follows:

$$W_1^{\alpha\text{-}NIS} = W_1(x_2^{\alpha\text{-}PIS}), \quad W_2^{\alpha-NIS} = W_2(x_1^{\alpha\text{-}PIS})$$

Step 5: Determine a linear membership function for each objective function as follows:

$$\mu_1(x) = \begin{cases} 1 & \text{if } W_1 < W_1^{\alpha\text{-}PIS} \\ \dfrac{W_1^{\alpha\text{-}NIS} - W_1}{W_1^{\alpha\text{-}NIS} - W_1^{\alpha-PIS}} & \text{if } W_1^{\alpha\text{-}PIS} \le W_1 \le W_1^{\alpha\text{-}NIS} \\ 0 & \text{if } W_1 > W_1^{\alpha\text{-}NIS} \end{cases}$$

$$\mu_2(x) = \begin{cases} 1 & \text{if } W_2 < W_2^{\alpha\text{-}PIS} \\ \dfrac{W_2^{\alpha\text{-}NIS} - W_2}{W_2^{\alpha\text{-}NIS} - W_2^{\alpha-PIS}} & \text{if } W_2^{\alpha\text{-}PIS} \le W_2 \le W_2^{\alpha\text{-}NIS} \\ 0 & \text{if } W_2 > W_2^{\alpha\text{-}NIS} \end{cases}$$

where $\mu_h(x)$ denotes the satisfaction degree of hth objective function.

Step 6: Convert the equivalent crisp MOMILP model into a single-objective MILP model using the Torabi and Hassini [25] or Selim and Ozkarahan [22] aggregation functions. It should be noted that both of these methods ensure obtaining the efficient solutions. The TH aggregation function is as follows:

$$\begin{aligned} \max \quad & \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_h \theta_h \mu_h(x) \\ \text{s.t.} \quad & \lambda_0 \le \mu_h(x), \quad h = 1, 2 \\ & x \in F(x), \quad \lambda_0 \text{ and } \lambda \in [0, 1] \end{aligned}$$

where $F(x)$ denotes the feasible region involving the constraints of equivalent crisp model. Also, θ_h and γ denote the importance of the hth objective function and the coefficient of compensation, respectively. Notably, the optimal value of variable $\lambda_0 = \min_h\{\mu_h(x)\}$ indicates the minimum satisfaction degree of objective functions and the TH aggregation function actually looks for a compromise value between the min operator and the weighted sum operator based on the value of γ. In other words, the decision makers can obtain both balanced and unbalanced compromised solution via manipulating the value of parameters θ_h and γ, based on their preferences (see [23] for details).

Also, Selim and Ozkarahan [22] formulate their aggregation function as follows:

$$\begin{aligned} \max \quad & \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_h \theta_h \lambda_h \\ \text{s.t.} \quad & \lambda_0 + \lambda_h \le \mu_h(x), \quad h = 1, 2 \\ & x \in F(x), \quad \lambda_0 \text{ and } \lambda \in [0, 1] \end{aligned}$$

In this model, λ_h denotes the difference between the satisfaction level of each objective with minimum satisfaction level of objectives ($\lambda_h = \mu_h(x) - \lambda_0$).

Step 7: Specify the value of the coefficient of compensation (γ) and relative importance of the fuzzy goals (θ_h), and solve the respective single-objective MILP model. If the decision maker is satisfied with the current solution, stop, otherwise provide another compromise solution by changing the value of γ and α (and if necessary the value of θ_h) and go to step 3.

5. Computational experiments

To illustrate the validity of the proposed model and the usefulness of the proposed solution method, several numerical experiments are implemented and the related results are reported in this section. To this end, two test problems are designed that their sizes are shown in Table 1. The corresponding results obtained by both TH and SO methods are compared with each other on these test problems.

To generate the triangular fuzzy parameters, based on Lai and Hwang [24], the three prominent points (i.e., the most likely, the most pessimistic and the most optimistic values) are estimated for each imprecise parameter. To do so, the most likely (c^m) value of each parameter is first generated randomly (using the uniform distributions specified in Table 2) and it is assumed that the corresponding crisp value is equal to the most likely value for all parameters when the proposed crisp model is used. Thereafter, without loss of generality two random numbers (r_1, r_2) are generated

Table 1
The size of test problems.

Problem no.	No. of plants	No. of potential distribution centers	No. of customer	No. of potential collection centers	No. of potential recovery centers	No. of potential recycling centers	No. of material customers	No. of time periods
1	2	4	5	3	3	2	5	2
2	4	8	10	6	4	4	8	2

Table 2
The sources of random generation of the most likely values.

Parameter	Corresponding random distribution
d_{kt}	∼ uniform (80, 150)
ω_{kt}	∼ uniform (0.75, 0.85)
c_{et}	∼ uniform (20, 30)
η_t	∼ uniform (0.15, 0.20)
b_m	∼ uniform (300000, 400000)
g_l, f_j	∼ uniform (180000, 260000)
a_n	∼ uniform (150000, 220000)
$co_{ij}, cu_{jk}, cq_{kl}, cv_{ne}, cp_{lm}, cs_{\ln}, ch_{mj}$	∼ uniform (4, 10)
ρ_i	∼ uniform (3, 5)
φ_j, β_l	∼ uniform (1.5, 3)
τ_m, θ_n	∼ uniform (2, 4)
pp_i	∼ uniform (500, 750)
px_j	∼ uniform (180, 300)
py_l	∼ uniform (220, 350)
pz_m	∼ uniform (250, 350)
pw_n	∼ uniform (150, 250)
te_{kt}	∼ uniform (4, 6)
td_{jk}	∼ uniform (5, 8)

between 0.2 and 0.8 using uniform distribution, and the most pessimistic (c^p) and optimistic (c^o) values of a fuzzy number ($\tilde{c}$) are calculated as follows.

$$c^o = (1 + r_1)c^m$$

$$c^p = (1 - r_2)c^m$$

Also the decision maker provides the relative importance of objectives linguistically. However, in the numerical experiments we set the objective weight vector as: $\theta = (0.8, 0.2)$. It should be noted that if the number of objectives are more than two, the well-known MCDM techniques such as analytic hierarchy process (AHP) can be used to set the objective weights more precisely.

To compare the possibilistic and crisp models, all of the mathematical models are coded in LINGO 8.0 optimization software and all tests are carried out on a Pentium dual-core 1.60 GHZ computer with 1 GB RAM.

To compare the two proposed fuzzy methods, first, the value of γ is set as 0.4 and the two methods are compared in different α levels. The reason of selecting 0.4 for γ is that the first objective is more important than the second one as indicated by vector θ and therefore unbalanced solutions with higher degree of satisfaction for the first objective is more attractive in CSND problem.

As it can be seen from Table 3 the TH method obtains more balanced solutions than SO method. Particularly, in high α-levels (i.e., 0.9–1) the solutions found by SO method are unbalanced, that is to say that the minimum satisfaction level is small and the method pays more attention to more important objectives than to the minimum satisfaction level. In the low α-levels (i.e., 0.6–0.7) the performance of the two methods are similar and both of them find the same solutions. The computational times indicate that in most of the cases the TH method could find the solution a little quicker than SO method.

Also the two methods are tested according to different values of γ and the results are reported in Table 4. The experiments of this part are implemented on the first problem at 0.9 α-level. As the results show, TH method could provide more diverse solutions than the SO method according to different values of γ. Therefore, it is concluded that the TH method is more sensitive to γ value than the SO method. On the other hand SO method obtains unique solutions for γ values between 0.1–0.5 and 0.6–0.9 in our tests.

Totally, it can be concluded that the TH and SO methods are both appropriate and qualified methods for solving the auxiliary MOLP problem, since they can obtain efficient solutions. But, the TH method is more appropriate when decision makers have a tendency toward obtaining balanced efficient solutions and they pay more attention to minimum satisfaction level of objectives. On the other hand, since the SO method usually yields unbalanced efficient

Table 3
The summary of test results according to different α-levels.

Problem no.	α-level	TH method					SO method				
		W_1	W_2	$\mu(W_1)$	$\mu(W_2)$	CPU time (s)	W_1	W_2	$\mu(W_1)$	$\mu(W_2)$	CPU time (s)
1	0.6	178604.9	327.45	0.98	0.90	3	178604.9	327.45	0.98	0.90	3
	0.7	178907.6	331.85	0.98	0.90	2	178907.6	331.85	0.98	0.90	2
	0.8	179214.8	336.262	0.98	0.89	3	179214.8	336.262	0.98	0.89	3
	0.9	209053.7	335.092	0.75	0.91	4	177512.3	480.013	0.99	0.41	4
	1	212658.0	321.187	0.97	0.97	2	210028.4	338.88	0.99	0.90	3
2	0.6	244345.1	309.022	0.98	0.87	137	245149.0	309.022	0.98	0.87	188
	0.7	264322.0	314.626	0.98	0.88	602	265235.4	314.626	0.98	0.88	583
	0.8	270371.8	305.797	0.97	0.89	254	263446.9	401.787	0.99	0.82	263
	0.9	293254.4	221.90	0.91	0.92	93	269789.4	312.892	0.98	0.83	167
	1	292864.2	225.875	0.91	0.92	474	271603.4	448.337	0.98	0.74	493

Table 4
Results of sensitivity analysis on γ value.

α-value	γ-value	TH method				SO method			
		W_1	W_2	$\mu(W_1)$	$\mu(W_2)$	W_1	W_2	$\mu(W_1)$	$\mu(W_2)$
0.9	0.1, 0.2	177512.3	480.013	0.99	0.41	177512.3	480.013	0.99	0.41
	0.3	212351.2	316.965	0.73	0.98	177512.3	480.013	0.99	0.41
	0.4, 0.5	209053.7	335.092	0.75	0.91	177512.3	480.013	0.99	0.41
	0.6–0.9	209731.4	335.092	0.75	0.91	209731.4	335.0925	0.75	0.91

solutions, it is appropriate in the case that decision makers pay more attention to more important objectives not to the minimum satisfaction level although the TH method can also yields such a solution as well by choosing a small value for γ.

6. Conclusions

To cope with the issue of uncertainty in closed-loop supply chain network design, a multi-objective possibilistic mixed integer programming model is proposed in this paper. The considered closed-loop network includes both forward and reverse supply chain network design decisions as well as corresponding tactical material flow decisions at the same time to avoid the sub-optimalities resulting from the separated design. Since most of the parameters in such a problem have imprecise nature, a possibilistic programming approach is used to model this problem To solve the proposed MOPMILP model, an interactive fuzzy solution approach is proposed by combining the Jimenez [33], Jimenez et al. [34], Parra et al. [37], Torabi and Hassini [25] and Selim and Ozkarahan [22] methods. The proposed hybrid method is able to find both balanced and unbalanced efficient solutions based on decision maker preferences.

To the best of our knowledge this research is one of the primary works using possibilistic programming approach for closed-loop supply chain network design under uncertainty and the literature considering this approach in supply chain network design is still scarce. Therefore, according to the significance of uncertainty and risk in supply chain network design (see [16]), many possible future research avenues can be defined in this context. For example addressing multi-product closed-loop supply chain network design under different kind of uncertainties and risks is an attractive research avenue with significant practical relevance. Moreover, time complexity is not addressed in this paper, however, this issue might be important in large-sized problems, therefore developing efficient exact or heuristic solution methods can be appealing in this area.

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