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Credibility-based fuzzy mathematical programming model for green logistics design under uncertainty

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1. Introduction

Logistics network design decisions, as the most important strategic level decisions in logistics management, address the locations, numbers and capacities of required facilities in a logistics network as well as aggregate material flow between them (Pishvae, Farahani, & Dullaert, 2010). Most of the network design mathematical models have been constructed based on the facility location theory. As the body of literature shows, the primary works regarding to logistics network design problem start with simple facility location models (e.g. Jayaraman & Pirkul, 2001; Melkote & Daskin, 2001). Afterwards, more complex models are developed to consider the real life properties of logistics systems, such as multiple products (e.g. Miranda & Garrido, 2004), multiple objectives (e.g. Altiparmak, Gen, Lin, & Paksoy, 2006; Pishvae et al., 2010), multiple capacities for network facilities (e.g. Amiri, 2006), as well as direct and indirect shipment mechanisms (e.g. Lin, Gen, & Wang, 2009; Pishvae & Rabbani, 2011).

Logistics activities are significant sources of environmental pollution and greenhouse emissions, which have harmful impacts on human health and ecosystem quality. Therefore, customers and governments mandate the firms to reduce the environmental impacts (e.g. carbon emissions) of their activities. In this respect, many firms such as the IKEA and Xerox have applied a number of initiatives to implement green practices in their logistics network (Tsai & Hung, 2009). Green logistics management can be defined as integrating the environmental aspects into logistics management to take into account the environment in every decision making process across logistics networks (Srivastara, 2007). Green logistics network design problem has attracted significant academic attention in the recent years. Hugo and Pistikopoulos (2005) develop a bi-objective mathematical programming model to address a green chemical logistics network design problem. The proposed model uses Eco-indicator 99 (Goedkoop & Spriensma, 2000) to minimize the total environmental impact while maximizing the total profit. To optimize the flow quantities between network facilities, Quariguasi Frota Neto, Bloemhoff-Ruwaard, van Nunen, and van Heck (2008) propose a bi-objective linear programming model for green logistics network design in the European pulp and paper industry. Additionally, Quariguasi Frota Neto, Walther, Bloemhoff, van Nunen, and Spengler (2009) propose a multi-objective mathematical programming model for electrical and electronic equipment recycling network in which the minimization of cumulative energy demand and total produced wastes are used as environmental objectives.

The concern about dealing with the uncertain nature of logistics network design parameters (e.g. transportation cost and demand), especially when environmental and social measures are taken into...
account (see Erol, Sencer, & Sari, 2011), has received considerable efforts of researchers and practitioners for developing appropriate decision making tools. The uncertainty of parameters can significantly affect the overall performance of logistics network in both environmental and economical aspects; therefore, neglecting it during the design phase may impose high risks to firms afterwards.

As the related literature shows, most of the previous works addressing the issue of uncertainty in logistics network design, apply stochastic programming approaches (e.g. El-Sayed, Afi, & El-Kharbotly, 2010; Pishvae, Jolai, & Razmi, 2009; Schütz, Tomaszgard, & Ahmed, 2009). However, the lack of sufficient historical data for the uncertain parameters as well as the high computational complexity of stochastic programming models make the use of this approach somehow impossible and at the same time unreasonable especially in the real life cases (Pishvae, Rabbani, & Torabi, 2011). To overcome this deficiency, the fuzzy mathematical programming approaches are recently employed in the context of logistics network design (e.g. Pishvae & Torabi, 2010; Qin & Ji, 2010). Fuzzy mathematical programming is a flexible tool for handling epistemic uncertainty that comes from lack of knowledge of decision maker about the actual value of parameters. To the best of our knowledge, the work by Guillén-Gosálbez and Grossmann (2010) is the only research work that considers both the environmental impact of logistics network and the issue of uncertainty beside each other in a mathematical model. However, this research also uses stochastic programming approach to model uncertain parameters that suffers from the abovementioned drawbacks.

To overcome this deficiency in the literature, this paper proposes a novel bi-objective credibility-based fuzzy mathematical programming model for green logistics network design problem that is able to (1) consider both economical and environmental aspects when designing a logistics network, (2) integrate the transportation mode and production technology selection issues as tactical decisions with strategic network design decisions, (3) cope with epistemic uncertainty in the model parameters resulting from unavailability and imprecise nature of input data in real cases and (4) incorporate the CO₂ equivalent index to model the environmental impact of logistics network. Furthermore, a customized version of recently developed fuzzy solution method based upon the credibility measure is applied to solve the proposed model. Altogether, the abovementioned properties differentiate this paper from those existed in the related literature.

The rest of this paper is organized as follows. The concerned problem is described in Section 2. The proposed bi-objective credibility-based fuzzy optimization model is developed in Section 3 and its interactive solution method is given in Section 4. The proposed model is implemented for a 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 description

The logistics network discussed in this paper is of multi-echelon, single product logistics network type that includes three layers: (1) production centers, (2) distribution centers and (3) customer zones. A new product, manufactured by different production centers, is shipped to the given customer zones via multiple distribution centers to meet the given demand of each customer zone. The location of customer zones are fixed and predefined and the demand of customers must be fully satisfied without any shortages. We also suppose there are multiple capacity levels for establishing production and distribution centers in each candidate location. Notably, accounting for different capacity levels is crucial in real-life applications (see Amiri, 2006) since has strong influence on the logistics network costs and its environmental impact. The underlying structure of considered logistics network is illustrated in Fig. 1.

The decisions to be addressed under abovementioned conditions include determining locations, capacities, and the number of required production and distribution centers, suitable production technology at each production center, as well as aggregated material flow between network nodes and their corresponding transportation modes. As mentioned earlier, our model incorporates the decisions about transportation modes and production technologies in the strategic logistics network design problem. Our motivation for such incorporation goes back to significant impact of transportation modes and production technologies on total environmental impact as well as total cost of logistics network. Also, the integration of such tactical decisions with the strategic network design ones ensure to escape from the sub-optimality resulting from separated decision making for the tactical and strategic level decisions (see Pishvae et al., 2010; Shen, 2007).

Furthermore, when creating such a green logistics network it is important to provide an economic and environmental trade-off for the decision maker. For this reason, it is more desirable to formulate both of environmental and economic aspects as decision objectives rather than constraints. Therefore, the ultimate goal could be expressed as determining the problem’s decisions while making a reasonable tradeoff between these two conflicting objectives and satisfying the system constraints.

2.1. Environmental impact

Usually, environmental management experts use the life cycle assessment (LCA) method to assess environmental impact of activities and processes. However, the LCA is a complicated, time consuming and costly process which needs to be weighted and interpreted (Chiu, Hsu, & Yang, 2008). Therefore, when a credible estimation of the total environmental impact can satisfy the decision maker’s expectation, it is not reasonable to employ a complex method such as the LCA. Here, to quantify and assess the environmental burden of logistics activities, we have used the CO₂ equivalent index based on the Eco-indicator 99 database (Goedkoop & Spriensma, 2000) in our model formulation. The CO₂ equivalent index is a popular and credible index that can easily quantify environmental impact and has already been used by various researchers to assess the environmental impact of logistics activities (see Demir, Bektas, & Laporte, 2011; Harris, Naim, Palmer, Potter, & Mumford, 2011; Paksoy, Bektas, & Özceylan, 2011; Sundarakani, de Souza, Goh, Wagner, & Manikandan, 2010).

![Fig. 1. Underlying structure of considered logistics network.](image-url)
To apply the CO2 equivalent index to measure total environmental impact, first, we have followed the Eco-indicator manual guidelines [Ministry of Housing, Spatial Planning and the Environment, 2000]. Following this instruction, the boundary of concerned system and the purpose of environmental impact assessment should be first defined. Here, the studied system is a three stage logistics network depicted in Fig. 1 and the purpose is to estimate the environmental impact of concerned logistics network. Secondly, the corresponding life cycle should be defined. In the concerned logistics network, the life cycle stages include production, transportation from production centers to distribution centers, and transportation from distribution centers to customer zones. At the third step, the materials and processes being used at each stage of life cycle should be determined and then, at the fourth step, the environmental burden of each material and process should be calculated based on the Eco-indicator database and the equivalent CO2 value. All the above mentioned steps can be implemented simply by using the ECO-it 1.4 software and its database (http://www.pre.nl/eco-it). This software uses the method developed by the International Panel on Climate Change, called IPCC 2007, to calculate the CO2 equivalent value for each process and material. The IPCC method uses the climate change factors within a timeframe of 20, 100 and 500 years. In this research, the 100 years timeframe of the IPCC 2007 method is applied. It should be noted that the IPCC characterization factors only include the characterization factors for the direct global warming potential of air emissions. For more information about the IPCC 2007 method, the interested readers may consult with Climate Change (2007).

3. Model formulation

The indices, parameters and variables used to formulate the concerned green logistics network design (GLND) problem are described below.

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

\[
\begin{align*}
\text{Min } & W_1 = \sum_i \sum_m \sum_l f_{iml} x_{iml} + \sum_j \sum_l \sum_n g_{ln} y_{ln} \\
& + \sum_i \sum_j \sum_l \sum_p \sum_k \rho_{i} \nu_{ij} u_{ij} + \sum_j \sum_k \sum_p \sum_n \theta_{jk} q_{jk} \\
& = \sum_i \sum_m \sum_l f_{iml} x_{iml} + \sum_j \sum_p \sum_n \theta_{jk} q_{jk} \\
\text{Min } & W_2 = \sum_i \sum_j \sum_l \sum_p \sum_n \xi_{i} y_{ij} + \sum_j \sum_k \sum_p \sum_n \xi_{jk} q_{jk} \\
& = \sum_i \sum_m \sum_l f_{iml} x_{iml} + \sum_j \sum_k \sum_p \sum_n \xi_{jk} q_{jk} \\
\text{s.t. } & \sum_j \sum_p q_{jk} \geq d_k, \ \forall k, \\
& \sum_i \sum_j \sum_p u_{ij} = \sum_k \sum_p q_{jk}, \ \forall j, \\
& \sum_j \sum_p u_{ij} \leq \sum_{l=1}^{M} x_{iml} \nu_{ij}, \ \forall i, l, \\
& \sum_k \sum_p q_{jk} \leq \sum_{n=1}^{N} x_{jk} \eta_{jk}, \ \forall j, \\
& \sum_i \sum_m x_{iml} \leq 1, \ \forall i,
\end{align*}
\]

Indices:

\[
i \quad \text{index of potential locations for production centers } i = 1, \ldots, I \\
j \quad \text{index of potential locations for distribution centers } j = 1, \ldots, J \\
k \quad \text{index of fixed (given) locations of customer zones } k = 1, \ldots, K \\
m \quad \text{index of capacity levels available for production centers } m = 1, \ldots, M \\
n \quad \text{index of capacity levels available for distribution centers } n = 1, \ldots, N \\
l \quad \text{index of different technologies available for production centers } l = 1, \ldots, L \\
p \quad \text{index of available transportation modes } p = 1, \ldots, P
\]

Parameters:

\[
d_k \quad \text{demand of customer zone } k \\
f_{iml} \quad \text{fixed cost of opening production center } i \text{ with capacity level } m \text{ and technology } l \\
g_{ln} \quad \text{fixed cost of opening distribution center } j \text{ with capacity level } n \\
c_{ij} \quad \text{transit cost per product unit from production center } i \text{ to distribution center } j \text{ with transportation mode } p \\
p_{ij} \quad \text{transit cost per product unit from distribution center } j \text{ to customer zone } k \text{ with transportation mode } p \\
p_{i} \quad \text{manufacturing cost per unit of product at production center } i \text{ with technology } l \\
\nu_{ij} \quad \text{capacity with level } m \text{ for production center } i \\
\rho_{jk} \quad \text{capacity with level } n \text{ for distribution center } j \\
\eta_{ij} \quad \text{CO2 equivalent emission per unit product produced by technology } l \\
\nu_{ij} \quad \text{CO2 equivalent emission per unit product shipped from production center } i \text{ to distribution center } j \text{ by transportation mode } p \\
\theta_{jk} \quad \text{CO2 equivalent emission per unit product shipped from distribution center } j \text{ to customer zone } k \text{ by transportation mode } p
\]

Variables:

\[
u_{ij} \quad \text{quantity of products manufactured at production center } i \text{ with technology } l \text{ and shipped to distribution center } j \text{ by transportation mode } p \\
q_{jk} \quad \text{quantity of products shipped from distribution center } j \text{ to customer zone } k \text{ by transportation mode } p \\
\xi_{iml} = \begin{cases} \\
1 & \text{if a production center with capacity level } m \text{ and technology } l \text{ is opened at location } i, \\
0 & \text{otherwise}
\end{cases} \\
\eta_{ij} = \begin{cases} \\
1 & \text{if a distribution center with capacity level } n \text{ is opened at location } j, \\
0 & \text{otherwise}
\end{cases}
\]
Objective function (1) minimizes the total cost including the fixed opening costs and the variable production and transportation costs. Objective function (2) minimizes the total CO2 equivalent emission. Constraint set (3) assures that the demands of all customer zones are fully satisfied. Constraint set (4) indicates the flow balance at distribution centers. Eqs. (5) and (6) denote non-negativity restrictions on the corresponding decision variables. Also, constraint set (8) indicates that at most one capacity level can be assigned to each candidate location. Finally, constraints (9) and (10) enforce the binary and non-negativity restrictions on the corresponding decision variables.

3.1. Proposed credibility-based fuzzy chance constrained programming model

All parameters of the above-mentioned model are assumed to be deterministic. However, as it was mentioned in Section 1, in most of real life situations, the input parameters of a logistics network design problem are tainted by high degree of epistemic uncertainty. To cope with this challenging issue, a new hybrid credibility-based chance constrained programming model is proposed in this research. Generally, the credibility-based chance constrained programming (Liu, 2004; Liu & Li, 2002) is a computationally efficient fuzzy mathematical programming approach that relies on strong mathematical concepts (i.e., the expected value of a fuzzy number and the credibility measure) and can support different kinds of fuzzy numbers such as triangular and trapezoidal forms as well as enabling the decision maker to satisfy some chance constraints in at least some given confidence levels. Additionally, despite the possibility measure that has no self-duality property, the credibility measure is a self-dual measure (Li & Liu, 2006). That is, if the credibility value of a fuzzy event attains 1, decision maker believes the fuzzy event will surely happen; however, when the corresponding possibility value achieves 1, the fuzzy event may fail to happen. In other words, a fuzzy event may fail even though its possibility achieves 1, and hold even though its necessity is 0. However, the fuzzy event must hold if its credibility is 1, and fail if its credibility is 0.

Let \( z \) be a fuzzy variable with membership function \( \mu(x) \), and let \( r \) be a real number. Based on Liu and Liu (2002) the credibility measure is defined as follows:

\[
\text{Cr}(\bar{z} \leq r) = \frac{1}{2} \left( \sup_{x \in \bar{z}} \mu(x) + 1 - \sup_{x \in \bar{z}} \mu(x) \right).
\]

Noteworthy, since \( \text{Pos}(\bar{z} \leq r) = \sup_{x \in \bar{z}} \mu(x) \) and \( \text{Nec}(\bar{z} \leq r) = 1 - \sup_{x \in \bar{z}} \mu(x) \), the credibility measure can also be defined as follows:

\[
\text{Cr}(\bar{z} \leq r) = \frac{1}{2} (\text{Pos}(\bar{z} \leq r) + \text{Nec}(\bar{z} \leq r)).
\]

Accordingly, the credibility measure could be defined as an average of the possibility (Pos) and necessity (Nec) measures.

Also, the expected value of \( z \) can be determined based on the credibility measure as follows (Liu & Liu, 2002):

\[
E[z] = \int_{0}^{\infty} \text{Cr}(\bar{z} \geq r) \, dr - \int_{-\infty}^{0} \text{Cr}(\bar{z} \leq r) \, dr.
\]

Now, assume that \( z \) is a trapezoidal fuzzy number denoted by four prominent points as \( z = (\xi_1, \xi_2, \xi_3, \xi_4) \). According to the Eq. (13), the expected value of \( z \) is \( (\xi_1 + \xi_2 + \xi_3 + \xi_4)/4 \) and the corresponding credibility measures are as follows:

\[
\text{Cr}(\bar{z} \leq r) = \begin{cases} 0, & r \in (-\infty, \xi_1), \\ \frac{1}{2}, & r \in (\xi_1, \xi_2], \\ \frac{2(\xi_2 - \xi_1)}{4(\xi_2 - \xi_3)}, & r \in (\xi_2, \xi_3], \\ 1, & r \in (\xi_3, +\infty). \end{cases}
\]

\[
\text{Cr}(\bar{z} \geq r) = \begin{cases} 1, & r \in (-\infty, \xi_1), \\ \frac{1}{2}, & r \in (\xi_1, \xi_2], \\ \frac{2(\xi_2 - \xi_1)}{4(\xi_2 - \xi_3)}, & r \in (\xi_2, \xi_3], \\ 0, & r \in (\xi_3, +\infty). \end{cases}
\]

Based on (14.1) and (14.2), it can be proven (see Zhu & Zhang, 2009) that if \( \bar{z} \) is a trapezoidal fuzzy number and \( a > 0.5 \) then:

\[
\text{Cr}(\bar{z} \leq r) \geq \alpha \iff r \geq (2 - 2x)\xi_3 + (2x - 1)\xi_4.
\]

\[
\text{Cr}(\bar{z} \geq r) \geq \alpha \iff r \leq (2x - 1)\xi_1 + (2 - 2x)\xi_2.
\]

Eqs. (15.1) and (15.2) can be applied directly and more conveniently when compared to \( a \)-critical values proposed by Liu (2004), to convert fuzzy chance constraints into their equivalent crisp ones.

To cope with uncertainty in the GLND model the uncertain parameters are assumed to be independent trapezoidal fuzzy numbers. Uncertain parameters include the demands of customers, facilities’ capacities and fixed opening costs, unit transportation and production costs and CO2 equivalent emissions factors. More explanation about the imprecision of most of these parameters can be found in Peidro, Mula, Poler, and Verdugay (2009) and Pishvae et al. (2011).

Generally, there are three distinct credibility-based fuzzy mathematical programming models, i.e., the expected value (Liu & Liu, 2002); the chance constrained programming (Liu & Iwamura, 1998) and the dependent-chance constrained programming (Liu, 1999), which have been used in parallel in most of published works applying this approach in various contexts without mentioning to their differences, weaknesses, strengths and the most suitable conditions for being used. The expected value model is the simplest one that can be applied more conveniently without increasing the computational complexity of the original model but at the same time it has no control on the confidence level of chance constraints’ satisfactions. On the other hand, the chance constrained programming is able to control the satisfaction degree of chance constraints but at the same time increases the computational complexity of the original model by adding a constraint for each objective function and also needs additional information about the ideal value of objective functions to determine the right hand side of the added constraints. The dependent-chance programming model is somehow similar to chance constrained programming model but it is more suitable for conservative decision maker since it gives more importance to confidence levels. Nevertheless, to form a credibility-based fuzzy mathematical programming framework for the concerned problem, we have combined the expected value and the chance constrained programming models as the expected value is used to model the objective functions and the chance constrained programming approach is applied to model.
the chance constraints including imprecise parameters. Despite the pure credibility-based chance constrained programming (e.g. Huang, 2007; Yang & Liu, 2007), this hybrid approach does not increase the number of constraints and does not need additional information for objective function such as confidence level or the ideal solution, and also is benefited from advantages of the chance constrained programming approach while dealing with the model constraints. According to above mentioned descriptions and justifications, the proposed credibility based fuzzy mathematical programming can be formulated as follows:

\[
\begin{align*}
\text{Min } E[W_1] &= \sum_i \sum_j \sum_m E[f_i^{m}] x_i^{m} + \sum_i \sum_j \sum_m E[g_i^{m}] y_j^{m} + \sum_j \sum_k \sum_l E[e_{jk}^{l}] q_k^{l}, \\
&\quad \times \sum_j \left(E[p_j] + E[q_j^{m}]\right) u_j^{m} + \sum_j \sum_k E[e_{jk}^{l}] q_k^{l} \\
\text{Min } E[W_2] &= \sum_i \sum_j \sum_m \sum_l E[f_i^{m}] x_i^{m} + \sum_i \sum_j \sum_m E[g_i^{m}] y_j^{m} + \sum_j \sum_k \sum_l E[e_{jk}^{l}] q_k^{l}, \\
&\quad \times \sum_j \left(E[p_j] + E[q_j^{m}]\right) u_j^{m} + \sum_j \sum_k E[e_{jk}^{l}] q_k^{l} \\
\text{s.t. } &\quad \text{Cr}\left\{ \sum_j u_j^{m} \geq d_k \right\} \geq \beta_k, \quad \forall k, \\
&\quad \sum_i \sum_j u_j^{m} = \sum_k q_k^{l}, \quad \forall j, \\
&\quad \text{Cr}\left\{ \sum_j u_j^{m} \leq \sum_m x_i^{m} y_j^{m} \right\} \geq \lambda_i, \quad \forall i, l, \\
&\quad \text{Cr}\left\{ \sum_k q_k^{l} \leq \sum_j y_j^{m} \theta_j \right\} \geq \theta, \quad \forall j, \\
&\quad \sum_m x_i^{m} \leq 1, \quad \forall i, \\
&\quad \sum_j y_j^{m} \leq 1, \quad \forall j, \\
&\quad x_i^{m}, y_j^{m} \in \{0,1\}, \quad \forall i, j, l, m, n. \\
&\quad u_j^{m}, q_k^{l} \geq 0, \quad \forall i, j, k, p.
\end{align*}
\]

According to Eqs. (15.1) and (15.2) and by considering the expected value of trapezoidal fuzzy numbers, the above-mentioned credibility-based chance constraint programming model can be converted to the crisp equivalent MILP model.

\[
\begin{align*}
\text{Min } E[W_1] &= \sum_i \sum_j \sum_m \left( f_{ijm}^{m} + f_{ijm}^{m} + f_{ijm}^{m} + f_{ijm}^{m} \right) x_i^{m} \quad + \sum_i \sum_j \sum_m \left( g_{ijm}^{m} + g_{ijm}^{m} + g_{ijm}^{m} + g_{ijm}^{m} \right) y_j^{m} \quad + \sum_j \sum_k \sum_l E[e_{jk}^{l}] q_k^{l}, \\
&\quad \times \sum_j \left(E[p_j] + E[q_j^{m}]\right) u_j^{m} + \sum_j \sum_k E[e_{jk}^{l}] q_k^{l} \\
\text{Min } E[W_2] &= \sum_i \sum_j \sum_m \sum_l \left( f_{ijm}^{m} + f_{ijm}^{m} + f_{ijm}^{m} + f_{ijm}^{m} \right) x_i^{m} \quad + \sum_i \sum_j \sum_m \left( g_{ijm}^{m} + g_{ijm}^{m} + g_{ijm}^{m} + g_{ijm}^{m} \right) y_j^{m} \quad + \sum_j \sum_k \sum_l E[e_{jk}^{l}] q_k^{l}, \\
&\quad \times \sum_j \left(E[p_j] + E[q_j^{m}]\right) u_j^{m} + \sum_j \sum_k E[e_{jk}^{l}] q_k^{l} \\
\text{s.t. } &\quad \sum_j u_j^{m} \geq (2 - 2\beta_k) d_{ij} + (2 - 2\beta_k - 1) d_{ij}, \quad \forall k, \\
&\quad \sum_j d_{ij} - \sum_j u_j^{m} \leq \sum_m x_i^{m} \left(2\beta_k - 1\right) + \left(2 - 2\beta_k\right) d_{ij}, \quad \forall j, l, \\
&\quad \sum_k q_k^{l} \leq \sum_j y_j^{m} \left(2\beta_k - 1\right) + \left(2 - 2\beta_k\right) d_{ij}, \quad \forall j, l, \\
&\quad u_j^{m}, q_k^{l} \geq 0, \quad \forall i, j, k, p.
\end{align*}
\]

4. The solution method

The resulted crisp equivalent model is a multi-objective parametric mixed integer linear programming (MOPMILP) model. To solve the MOPMILP model, an interactive method is applied in this research. To cope with multiple objective problems, various methods have been proposed that can be classified into the three main categories including priori, interactive and posteriori methods (Hwang & Masud, 1979). Among these methods, fuzzy interactive methods are one of the most attractive approaches in this area because of their ability to measure and adjusting the satisfaction level of each objective function based on the decision maker preferences in an interactive and progressive way. Noteworthy, the proposed interactive method applied in this paper uses the TH aggregation function (Torabi & Hassini, 2008) to convert the original bi-objective model to an equivalent single objective one. Despite the classical methods (e.g. Guu & Wu, 1999; Lai & Hwang, 1993; Sakawa, Yano, & Yumine, 1987) that may result in weakly efficient solutions, the TH method guarantees to find just efficient solutions. The steps of the proposed fuzzy interactive method can be summarized as follows.

- **Step 1:** Use the expected value of imprecise parameters to convert the fuzzy objective functions into their crisp ones.
- **Step 2:** Determine the minimum acceptable confidence level for each chance constraint, i.e., \(\beta_k, \gamma_i, \eta_j\) and use Eqs. (15.1) and (15.2) to convert the chance constraints into their equivalent crisp ones.
- **Step 3:** Specify the \(\alpha\)-positive ideal solution (\(\alpha\)-PIS) and \(\alpha\)-negative ideal solution (\(\alpha\)-NIS) for each objective function (Pishvavee & Torabi, 2010). To obtain the \(\alpha\)-positive ideal solutions and the corresponding objective functions values, i.e., \(W_{1}^{\alpha\text{-PIS}}, W_{2}^{\alpha\text{-PIS}}\), and \(W_{1}^{\alpha\text{-NIS}}, W_{2}^{\alpha\text{-NIS}}\), the equivalent crisp model should be solved for each objective function separately, and thereafter the \(\alpha\)-negative ideal solutions can be estimated as follows.

\[
\begin{align*}
W_{1}^{\alpha\text{-NIS}} &= W_{1}(x_{2}^{\alpha\text{-PIS}}), \quad W_{2}^{\alpha\text{-NIS}} = W_{2}(x_{2}^{\alpha\text{-PIS}})
\end{align*}
\]
- **Step 4:** Determine a linear membership function for each objective function as follows:
Table 1
The demand of customer zones.

<table>
<thead>
<tr>
<th>Customer zone (k)</th>
<th>Demand (Millions) (d_{k1}, d_{k2}, d_{k3}, d_{k4})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Mashhad</td>
<td>(234, 254, 264, 292)</td>
</tr>
<tr>
<td>(2) Yazd</td>
<td>(295, 330, 350, 390)</td>
</tr>
<tr>
<td>(3) Shiraz</td>
<td>(138, 146, 152, 175)</td>
</tr>
<tr>
<td>(4) Uromieh</td>
<td>(101, 109, 115, 133)</td>
</tr>
<tr>
<td>(5) Ardebeh</td>
<td>(98, 110, 117, 127)</td>
</tr>
<tr>
<td>(6) Rasht</td>
<td>(210.5, 248, 254, 275)</td>
</tr>
<tr>
<td>(7) Kermanshah</td>
<td>(78, 89, 97, 109)</td>
</tr>
<tr>
<td>(8) Karaj</td>
<td>(84, 98, 110, 124)</td>
</tr>
<tr>
<td>(9) Zanjan</td>
<td>(100, 114, 118, 131)</td>
</tr>
<tr>
<td>(10) Hamedan</td>
<td>(58, 68, 72, 89)</td>
</tr>
<tr>
<td>(11) Chazvin</td>
<td>(198, 208, 218, 228)</td>
</tr>
<tr>
<td>(12) Tehran</td>
<td>(215, 240, 250, 270)</td>
</tr>
<tr>
<td>(13) Foreign I</td>
<td>(320, 344, 354, 360)</td>
</tr>
<tr>
<td>(14) Foreign II</td>
<td>(200, 212, 218, 230)</td>
</tr>
</tbody>
</table>

Table 2
The fixed cost and capacity data of production centers.

<table>
<thead>
<tr>
<th>Potential production centers (i)</th>
<th>Production technology</th>
<th>Fixed cost (Million Rials) (f_{ml}^{i1}, f_{ml}^{i2}, f_{ml}^{i3}, f_{ml}^{i4})</th>
<th>Capacity (Millions) (c_{m1}^{i1}, c_{m2}^{i2}, c_{m3}^{i3}, c_{m4}^{i4})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Ashat (current plant)</td>
<td>type 1</td>
<td>(0, 0, 0, 0)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 1</td>
<td>(259, 310, 380, 420)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(950, 1010, 1300, 1500)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(3800, 4200, 5600, 6100)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
<tr>
<td>(2) Saveh</td>
<td>type 1</td>
<td>(135,000, 143,000, 184,000, 152,000)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(142,000, 149,000, 154,000, 158,000)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(171,000, 179,000, 182,000, 186,000)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(171,000, 178,000, 184,000, 192,000)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
<tr>
<td>(3) Semnan</td>
<td>type 1</td>
<td>(132,000, 139,000, 144,000, 150,000)</td>
<td>(1650, 1750, 1850, 1980)</td>
</tr>
<tr>
<td></td>
<td>type 1</td>
<td>(140,000, 147,000, 151,000, 155,000)</td>
<td>(1700, 1790, 1880, 2100)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(170,000, 177,000, 180,000, 185,000)</td>
<td>(1650, 1750, 1850, 1980)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(170,000, 179,000, 187,000, 191,000)</td>
<td>(1700, 1790, 1880, 2100)</td>
</tr>
<tr>
<td>(4) Varamin</td>
<td>type 1</td>
<td>(133,000, 140,000, 146,000, 152,000)</td>
<td>(1650, 1750, 1850, 1980)</td>
</tr>
<tr>
<td></td>
<td>type 1</td>
<td>(140,000, 148,000, 152,000, 157,000)</td>
<td>(1700, 1790, 1880, 2100)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(170,500, 178,000, 181,000, 186,000)</td>
<td>(1650, 1750, 1850, 1980)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(178,000, 181,000, 190,000, 197,000)</td>
<td>(1700, 1790, 1880, 2100)</td>
</tr>
<tr>
<td>(5) Ghom</td>
<td>type 1</td>
<td>(137,000, 142,000, 150,000, 157,000)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 1</td>
<td>(139,000, 145,000, 153,000, 161,000)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(171,000, 180,000, 188,000, 192,000)</td>
<td>(1550, 1650, 1750, 1850)</td>
</tr>
<tr>
<td></td>
<td>type 2</td>
<td>(180,000, 184,000, 197,000, 200,000)</td>
<td>(1850, 1950, 2050, 2150)</td>
</tr>
</tbody>
</table>

Table 3
The fixed cost and capacity data for distribution centers.

<table>
<thead>
<tr>
<th>Potential distribution centers (j)</th>
<th>Fixed cost (Million Rials) (c_{ml}^{j1}, c_{ml}^{j2}, c_{ml}^{j3}, c_{ml}^{j4})</th>
<th>Capacity (Million Rials) (c_{ml}^{j1}, c_{ml}^{j2}, c_{ml}^{j3}, c_{ml}^{j4})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Varamin</td>
<td>(16,500, 16,900, 17,100, 17,400)</td>
<td>(2000, 2060, 2080, 2120)</td>
</tr>
<tr>
<td>(2) Saveh</td>
<td>(16,500, 16,900, 17,100, 17,400)</td>
<td>(2400, 2440, 2460, 2500)</td>
</tr>
<tr>
<td>(3) Shahrood</td>
<td>(16,100, 16,200, 16,300, 16,500)</td>
<td>(2100, 2140, 2160, 2200)</td>
</tr>
<tr>
<td>(4) Arak</td>
<td>(17,200, 17,400, 17,600, 17,900)</td>
<td>(2500, 2540, 2560, 2600)</td>
</tr>
<tr>
<td>(5) Abhar</td>
<td>(16,900, 17,000, 17,100, 17,300)</td>
<td>(2000, 2040, 2060, 2100)</td>
</tr>
<tr>
<td>(6) Uromieh</td>
<td>(17,400, 17,700, 17,900, 18,200)</td>
<td>(2200, 2240, 2260, 2300)</td>
</tr>
<tr>
<td>(7) Salafcheghan</td>
<td>(16,900, 17,100, 17,200, 17,300)</td>
<td>(1950, 2000, 2050, 2100)</td>
</tr>
<tr>
<td></td>
<td>(17,300, 17,600, 17,900, 18,100)</td>
<td>(2250, 2290, 2310, 2350)</td>
</tr>
</tbody>
</table>
min operator and the weighted sum operator based on the value of \( \gamma \) (see Torabi and Hassini (2008) for more details).

- Step 6: Determine the importance of the fuzzy goals \((v_n)\) and the value of compensation coefficient \(\gamma\) based upon the decision maker preferences and solve the resulting single-objective crisp model. If the decision maker is satisfied with the obtained efficient solution, then stop and select the current solution as the final decision; otherwise go to the step 2 for seeking a new efficient solution by altering the required parameters such as \(b_k, i_k, t_k\) and \(c\) according to the revised and updated preferences of the decision maker.

5. Case study implementation and evaluation

To demonstrate the usefulness of the proposed credibility-based fuzzy mathematical model and its interactive solution method for the concerned GLND problem, an industrial case study is provided here. The studied case is an Iranian medical device manufacturer that already covers eight customer zones. The firm is going to cover six new markets including two foreign markets from neighbor countries. Therefore, the firm’s logistics network should be redesigned being able to satisfy the new markets demands. To estimate the required parameters, a group of field ex-

<table>
<thead>
<tr>
<th>Minimum feasibility degree ((b_k = i_k = t_k))</th>
<th>Importance of first objective function ((v_1 = 1 - v_2))</th>
<th>Satisfaction degrees</th>
<th>Objective function degrees (\mu(W_1), \mu(W_2))</th>
<th>Objective function values</th>
<th>CPU time (seconds)</th>
<th>Location and type of center (*^a)</th>
<th>Production center ((a, b))</th>
<th>Distribution centers ((a))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.989</td>
<td>0.526</td>
<td>5.384E+11</td>
<td>1.240E+07</td>
<td>11</td>
<td>Ahstian (1, 2)</td>
<td>Varamin (1)</td>
</tr>
<tr>
<td>0.9</td>
<td>0.979</td>
<td>0.628</td>
<td>5.448E+11</td>
<td>1.195E+07</td>
<td>8</td>
<td>Ahstian (1, 1)</td>
<td>Varamin (1)</td>
<td></td>
</tr>
<tr>
<td>0.8–0.2</td>
<td>0.932</td>
<td>0.997</td>
<td>5.750E+11</td>
<td>1.032E+07</td>
<td>12</td>
<td>Ahstian (1, 2)</td>
<td>Varamin (1)</td>
<td></td>
</tr>
<tr>
<td>0.1</td>
<td>0.92</td>
<td>0.998</td>
<td>5.828E+11</td>
<td>1.031E+07</td>
<td>8</td>
<td>Ahstian (1, 1)</td>
<td>Uromieh (1)</td>
<td></td>
</tr>
<tr>
<td>0.05</td>
<td>0.908</td>
<td>0.998</td>
<td>5.904E+11</td>
<td>1.031E+07</td>
<td>8</td>
<td>Ahstian (1, 2)</td>
<td>Varamin (1)</td>
<td></td>
</tr>
</tbody>
</table>

- 0.95 | 0.95 | 0.989 | 0.534 | 5.357E+11 | 1.226E+07 | 12 | Ahstian (1, 2) | Varamin (1) |
| 0.9 | 0.979 | 0.637 | 5.421E+11 | 1.181E+07 | 12 | Ahstian (1, 1) | Varamin (1) |
| 0.8–0.1 | 0.932 | 0.997 | 5.750E+11 | 1.032E+07 | 10 | Ahstian (1, 2) | Varamin (1) |
| 0.05 | 0.92 | 0.998 | 5.828E+11 | 1.031E+07 | 12 | Ahstian (1, 2) | Varamin (1) |

- 0.9 | 0.95 | 0.988 | 0.542 | 5.331E+11 | 1.212E+07 | 10 | Ahstian (1, 2) | Varamin (1) |
| 0.9 | 0.979 | 0.645 | 5.393E+11 | 1.167E+07 | 8 | Ahstian (2, 2) | Savhe (2) |
| 0.8–0.1 | 0.932 | 0.997 | 5.688E+11 | 1.015E+07 | 8 | Ahstian (1, 2) | Varamin (1) |
| 0.05 | 0.912 | 0.997 | 5.818E+11 | 1.014E+07 | 7 | Ahstian (1, 2) | Varamin (1) |

- 0.85 | 0.95 | 0.988 | 0.55 | 5.304E+11 | 1.198E+07 | 8 | Ahstian (1, 2) | Varamin (1) |
| 0.9 | 0.978 | 0.654 | 5.363E+11 | 1.153E+07 | 7 | Ahstian (2, 2) | Varamin (1) |
| 0.8–0.2 | 0.933 | 0.997 | 5.658E+11 | 1.006E+07 | 8 | Ahstian (1, 2) | Varamin (1) |
| 0.1 | 0.923 | 0.998 | 5.717E+11 | 1.006E+07 | 13 | Ahstian (2, 2) | Varamin (2) |
| 0.05 | 0.907 | 0.998 | 5.820E+11 | 1.006E+07 | 7 | Ahstian (1, 2) | Varamin (1) |

- 0.8 | 0.95 | 0.987 | 0.558 | 5.278E+11 | 1.185E+07 | 7 | Ahstian (1, 1) | Varamin (1) |
| 0.9 | 0.978 | 0.664 | 5.334E+11 | 1.140E+07 | 8 | Ahstian (2, 2) | Varamin (1) |
| 0.8–0.1 | 0.933 | 0.997 | 5.627E+11 | 9.976E+06 | 8 | Ahstian (1, 2) | Varamin (1) |
| 0.05 | 0.918 | 0.998 | 5.720E+11 | 9.970E+06 | 8 | Ahstian (1, 2) | Varamin (2) |

* Capacity level.
* Type of production technology.
erts and firm’s managers has been formed to specify the four prominent values used to determine the corresponding trapezoidal fuzzy numbers according to the available data and their knowledge. As such, the estimation of customer zone demands is given in Table 1.

Currently, the firm has one active production center and four other locations are also considered for opening new production center(s) or relocate the current one if it is needed. Two production technologies and capacity levels are available for each production center and their respective fixed opening costs are reported in Table 2. It should be noted that the fixed cost of the active production center is considered equal to zero and all monetary data are presented in the Iranian currency, i.e., Rial.

To locate the distribution center(s), seven candidate locations are considered. The corresponding fixed costs are reported in Table 3 according to the two available capacity levels. Also, two types of transportation vehicles, including 6 ton and 9 ton trucks, can be used to deliver the products to customers via distribution centers. Due to space limitation, we avoid providing the value of other parameters such as transportation costs here, but they can be provided upon request.

To show the performance of the developed credibility-based fuzzy mathematical model and the applied interactive solution method, they are coded and solved by LINGO 8.0 optimization software and all tests are implemented on a Pentium dual-core 1.40 GHz computer with 3 GB RAM. Numerical tests are carried out under different feasibility degrees and importance weights \( (b_k) \) of objective functions (see the first and second columns of Table 4). It should be noted that the compensation coefficient \( (\gamma) \) is set to 0.4 in all numerical tests.

As it can be seen from Table 4, the cost and \( \text{CO}_2 \) equivalent minimization objective functions are in conflict with each other as an increase of total \( \text{CO}_2 \) equivalent leads to an increase in total costs and vice versa. Additionally, as the results show this conflict is widen when the importance weight of the cost minimization objective function is equal or greater than 0.9 (i.e., \( v_1 \geq 0.9 \)). On the other hand, more balanced solutions are achieved when \( v_1 \) varies between 0.8 and 0.05.

Also, it is obvious that the value of both objective functions increases when the minimum feasibility degree is increased, because, more resources (e.g. raw material, products and交通运输s) should be utilized to satisfy the demands and reduce the infeasibility risk under higher confidence levels.

The behavior of objective functions shows that the second objective function (\( \text{CO}_2 \) equivalent minimization) has a tendency towards establishing production centers with technology type 2 as it is a more environmentally suitable production technology, assigning higher capacity level to such production centers and configuring more decentralized logistics network to minimize the total \( \text{CO}_2 \) equivalent emissions. On the other hand, the cost minimization objective has a tendency towards network centralization to minimize the total costs. Also, this objective prefers to establish production centers with technology type 1 as it is a less expensive one.

As the relevant literature shows, many practitioners and researchers address two important questions about green production–distribution networks which are as follows: (1) is greening logistics networks costly? and if yes (2) how much is the cost? As it is mentioned before in this section, the cost and \( \text{CO}_2 \) equivalent minimization objective functions are in conflict with each other; therefore it can be concluded that making the studied logistics network greener, requires additional cost. To calculate the additional cost (price) of greenness, we have subtracted the minimum cost obtained by optimizing the model for the first objective function (\( \text{C}^* \)) from the value of first objective function at each compromised solution (\( W_1 \)). By the aid of this index, the additional cost paid for greening the logistics network can be estimated for each compromised solution. For example, the greenness cost when the minimum feasibility degree is equal to 1 is represented in Fig. 2 for each compromise solution. As it can be seen from Fig. 2, the absolute value of price of greenness is significant especially when more importance is given to the second objective function. But despite the absolute value, if the additional cost is being divided by the minimum cost obtained by optimizing the model for the first objective function, i.e. \( (W_1 - \text{C})/\text{C}^* \), it can be seen that the relative greenness cost vary between 0% and 11%. For example, when the minimum feasibility degree is equal to 1 if the decision maker decides to satisfy the second objective function with degree of 0.998, only 0.11% additional cost should be paid when compared to the optimum cost solution (\( \text{C}^* \)).

The importance of this greenness cost index is twofold. It can be used as a quantitative and transparent indicator by firms and managers to show their efforts to their stakeholders in greening their business activities and also it can be considered as an appropriate baseline by governmental policy makers to regulate the incentive policies (e.g. financial aids) to firms.

6. Concluding remarks

To cope with green logistics network design problem under uncertain conditions, a new hybrid credibility-based fuzzy mathematical programming model is presented in this paper. The proposed model takes into account both environmental and economical aspects when designing the concerned multi stage logistics network. The \( \text{CO}_2 \) equivalent index is employed to measure the environmental impact of concerned logistics network. Production technology and transportation mode selection decisions are also integrated with the strategic network design decisions in the proposed model. To deal with imprecise parameters, the proposed model applies a hybrid credibility-based approach that combines the expected value and chance constrained programming approaches. As such, the proposed model uses the expected value to cope with imprecise objective functions and the chance constrained programming approach is applied to control the confidence level of satisfaction of imprecise constraints. An interactive fuzzy solution method is applied to solve the respective bi-objective crisp equivalent MILP model. An industrial case is also provided to show the practicality of the proposed model as well as the interactive solution approach.

The future research could be aimed at addressing both the dynamic and uncertain nature of parameters. To cope with this issue a combination of optimization and simulation tools should be
used. Also, to move the concerned network towards sustainability, it is necessary to include the social aspect beside the environmental and economical dimensions. Therefore, incorporating social considerations into logistics network design problem is another possible future research work.

References


