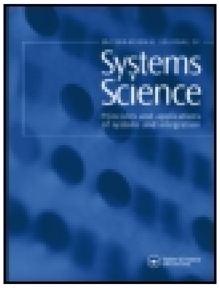

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An interactive possibilistic programming approach for a multi-objective closed-loop supply chain network under uncertainty

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In this article, we first propose a closed-loop supply chain network design that integrates network design decisions in both forward and reverse supply chain networks into a unified structure as well as incorporates the tactical decisions with strategic ones (e.g., facility location and supplier selection) at each period. To do so, various conflicting objectives and constraints are simultaneously taken into account in the presence of some uncertain parameters, such as cost coefficients and customer demands. Then, we propose a novel interactive possibilistic approach based on the well-known STEP method to solve the multi-objective mixed-integer linear programming model. To validate the presented model and solution method, a numerical test is accomplished through the application of the proposed possibilistic-STEM algorithm. The computational results demonstrate suitability of the presented model and solution method.

Keywords: closed-loop supply chain network design; possibilistic programming; STEP method; multiple-criteria decision making; supplier selection

1. Introduction

In recent years, the intensity of competition in the market, lead companies to focus on the supply chain and integrated logistics. The design of a closed-loop supply chain network (CSCN), including both forward and reverse flows, has attracted particular attention among managers and researchers because of its beneficial business factors. A well-organised supply chain network (SCN) has a maintainable competitive profit for companies and assist them to deal with the growing environmental disarray (Dullaert, Braysy, Goetschalckx, and Raa 2007). Configuration of SCNs, including design for structural, informational and organisational systems, is one of the most important strategic decisions. Usually, the SCN design in both forward and reverse flows addresses the number of facilities, their location and capacities and the quantity of flow between them (Fleischmann, Bloemhof-Ruwaard, Beullens, and Dekker 2004). In many cases (e.g., Azaron, Borwn, Tarim, and Modarres 2008; Thanh, Bostel, and Peton 2008; Torabi and Hassini 2008), logistics networks are only designed for forward logistics activities without considering the reverse flow of return products (Jayaraman, Guide, and Srivastava 1999). Nevertheless, environmental and economic aspects of reverse logistics are motivated by many real-life applications and some researchers (e.g., Anbuudayasankara, Ganeshb, Lenny Kohc, and Mohandas 2010) have taken this into account in their problem.

The configuration of both forward and reverse SCN, however, has an intense effect on the performance of each other. As demonstrated in the literature of SCN areas, many companies and considerable number of papers have focused on developing integrated logistics and achieved significant success in this subject (Fleischmann et al. 2004; Üster, Easwaran, Akçali, and Çetinkaya 2007). Meanwhile, separated design of the forward and reverse logistics leads to sub-optimal designs concerning to costs, service level and responsiveness. Hence, an integrated design of both forward and reverse logistics is regarded (Fleischmann, Beullens, Bloemhof-Ruwaard, and Wassenhove 2001; Pishvaee, Jolay, and Razmi 2009).

In addition, supplier selection is a crucial issue concerned in the process of managing global supply chains (Vinodh, Ramiya, and Gautham 2011). It can result in better and more efficient services/products and totally can influence the SCN. If a process is done correctly, a higher quality and longer lasting relationship are more attainable. In other words, selection of a wrong supplier can be enough to upset the company's

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financial and operational position. However, selecting the right suppliers significantly reduces a purchasing cost, improves competitiveness in a market and enhances end user satisfaction. Many papers have considered supplier selection as an important multiple criteria decision making (MCDM) problem in supply chain management. The analytical hierarchy process (AHP) method introduced by Saaty (1980) has many applications in the supplier selection process and many researchers have utilised this method in order to rank suppliers. A number of researches (e.g., Pyong Sik, Kiichiro, and Yutaka 1987) utilised the AHP method for solving their MCDM problem. The AHP method deals only with comparison ratios, which are crisp whereas most of parameters in nature are uncertain.

However, in most of the real life problems there are linguistic and/or imprecise variables and constraints. Supply uncertainty in supply chain management, is an important subject that has been receiving the extensive consideration of both practitioners and researchers (Zhou, Zhao, and Zhao 2010). The fuzzy set theory (FST) introduced by Zadeh (1965) is a generalisation of conventional set theory to represent vagueness or imprecision in everyday life in a strict mathematical framework. Various authors have applied FST to enhance AHP to be able to cope with uncertain parameters (e.g., Van Laarhoven and Pedrycz (1983) approach, Buckley (1985) fuzzy AHP and Chang (1992) extent analysis method). The interested reader is referred to comprehensive reviews (e.g., De Boer, Labro, and Morlacchi 2001; Aissaoui, Haouari, and Hassini 2007) for more information on the topic. Among all fuzzy AHP methods, Van Laarhoven and Pedrycz's approach which was proposed in 1983 both utilises and obtains triangular fuzzy numbers for weights of alternatives. This method offers an algorithm that is the direct extension of Saaty's AHP method. Align with considering the aforementioned view point and also on the basis of CSCN design (CSCND) problem and solution approach which are described with details in the next sections, we apply Laarhoven and Pedrycz's FAHP method in our paper.

SCN has a dynamic and multifaceted nature, which enforces a high degree of uncertainty in supply chain planning decisions (Klibi, Martel, and Guitouni 2010). Dubois, Fargier, and Fortemps (2003) classified the uncertainty into two groups: (1) flexibility in constraints and goals and/or (2) uncertainty in data. Flexibility is associated with flexible target value of goals and constraints which is modelled by fuzzy sets. Mathematical programming models are used to deal with this kind of uncertainty flexible (e.g., Torabi and Hassini 2008). Baykasoglu and Gocken (2008) reviewed methods to deal with the fuzzy mathematical problem and classified these approaches into four major categories, according to the fuzzy components. They pointed out that in a fuzzy mathematical programming model, the aspiration level of the objective(s), the limit values of the constraints, the coefficients of the objectives and the coefficients of the constraints can be uncertain. Therefore, the fuzzy mathematical programming models are defined in 15 types.

Subsequently, uncertainty in data can be presented as: (1) randomness in the model parameters and (2) uncertainty of epistemic. In general, stochastic programming and possibilistic approaches are, respectively, used to deal with these kinds of uncertainty. Listes and Dekker (2005) presented a stochastic mixed-integer programming model for different situations and scenarios. Salema, Barbosa-Povoa, and Novais (2007) developed a stochastic model for multi-product closed-loop network under demand uncertainty by using stochastic mixed-integer programming. A stochastic mixed integer nonlinear programming model to solve multi-product multi-buyer single vendor supply chain problem was offered by Taleizadeh, Niaki, and Makui (2012). Hsu and Wang (2001) proposed a possibilistic linear programming model for determining appropriate strategies concerning the inventory level, demands and number of machines. Recently, Pishvaee and Torabi (2010) proposed a bi-objective possibilistic programming approach for CSCND under uncertainty including the design of both forward and reverse SCN at the same time.

Alves and Climaco (2007) reviewed interactive methods for multi-objective integer and mixed-integer programming. Wang and Liang (2005) provided an interactive possibilistic linear programming approach for solving the problem of multi-product aggregate production planning with imprecise demands. Liang (2006) proposed an interactive multi-objective linear programming model for solving an integrated production and transportation planning problem. Selim and Ozkarahan (2008) developed an interactive fuzzy goal programming for the supply chain distribution network design. Sakawa, Katagiri, and Matsui (2011) considered an interactive fuzzy random two-level linear programming through fractile criterion optimisation; they introduced α-level sets of fuzzy random variables to formulate fuzzy random two-level linear programming problems. Torabi and Hassini (2008) provided an interactive possibilistic programming approach for solving an integrated procurement, production and distribution plans in a multi-objective SCN.

To the best of our knowledge, the fuzzy optimisation approach in the area of CSCND is one of the primary studies. Some research works (e.g., Selim and Ozkarahan 2008) apply fuzzy optimisation methods for forward SCN design; however, a few ones use this approach in the subject of CSCND.

Based on aforementioned considerations, at the outset, we introduce a new CSCND which considers design of both forward and reverse SCNs simultaneously under demand and cost uncertainties. Afterwards, due to solve the problem, we develop a multi-objective possibilistic model by proposing a novel interactive possibilistic approach.

The main contributions of this article can be summarised as follows:

- Offering a well-organised new closed-loop supply network design that (1) synthesises multi-objective decision making and chain network multi-attribute decision making (MADM) at the same time and interactively to obtain decision maker's (DM) preferences by the different compromise solutions proposed, (2) integrates the network design decisions in both forward and reverse SCNs as well as incorporate the tactical decisions (e.g., material flows and vehicle type) with strategic ones (e.g., facility location) at each period, to avert sub-optimality resulting from separated design, (3) considers production of one product through an assembly of various components supplied by various suppliers and different usage rate and (5) importance value of customer zones.
- Proposing a novel interactive fuzzy solution approach, namely possibilistic-STEM, by hybridising a number of efficient methods from the literature to solve the introduced multi-objective possibilistic mixed-integer programming (MOPMILP) model. The best of our knowledge, the offered multi-objective optimisation algorithm is one of the initial studies that (1) considers trade-off between optimality of the objective functions and the certainty degree of achieving the objective value, (2) finds efficient solutions according to priority of the DMs.

The remainder of this article is structured as follows. The problem definition is given in Section 2. Model formulation, including assumptions, decisions and notation, is presented in Section 3. Section 4 presents a new interactive possibilistic approach in order to solve a MOPMILP model for the proposed CSCND problem. The computational results are reported in Section 5. Finally, concluding remarks and possible future research are expressed in Section 6.

2. Problem definition

The closed-loop supply chain considered in this article is a multi-stage network, containing assembly, distribution, customer zone, collection, recovery and disposal centres, which integrates the network design decisions in both forward and reverse flows. As illustrated in Figure 1, the raw materials and components are shipped to the plant in forward flows. Then, final products assembled by plant are packaged and shipped to distribution centres. In real world situations, customer zones may have different importance values, and those with higher importance, should be satisfied sooner. Thus, demands at the customer zones are met through various distribution centres and

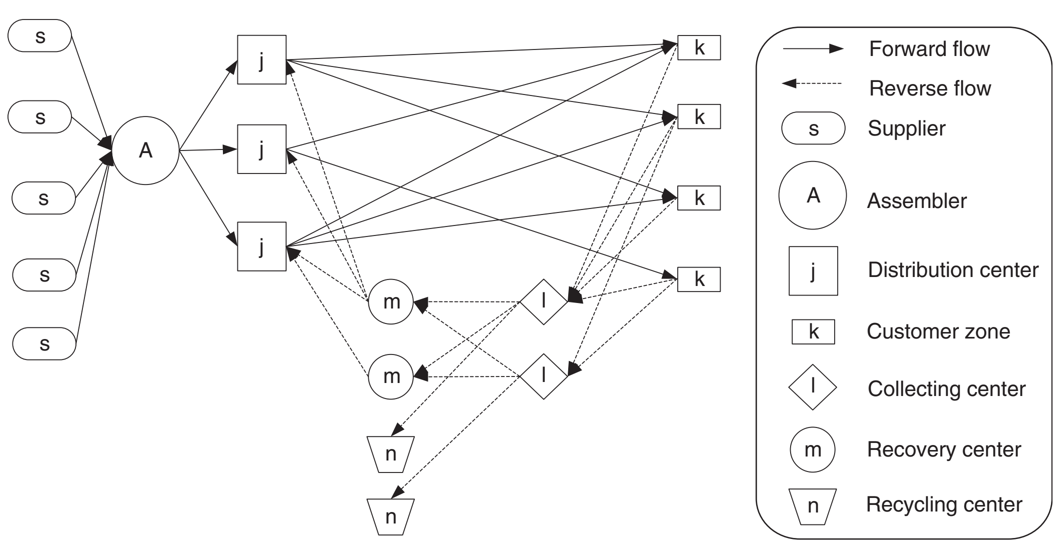

Figure 1. Structure of a closed-loop supply chain in the studied network.

vehicles by considering their preferences. In the reverse side, the returned products in the first place are collected in collection centres. After quality testing and disassembly activities, the recoverable products are shipped to recovery facilities and scraped products are shipped to recycling centres. The recovered products are inserted in the forward SCN and redistributed to the customer zones. As Figure 1 shows, SCN in this article has a general structure. Since proposed network supports recovery and recycling activities, it can be applied in different industries (Pishvaee and Torabi 2010).

Usually, parameters in real world have an imprecise, unavailable or incomplete nature. As indicated by some researchers (e.g., Inuiguchi and Ramik 2000), two major different kinds of uncertainties, ambiguity and vagueness exist in the real life. Particularly, in a long-term horizon, most of the parameters in a SCN have an imprecise, unavailable or incomplete nature. Thus, in order to model the problem under uncertainty, appropriate possibility distributions have been applied (Zadeh 1965; Lai and Hwang 1992). Besides, decision horizon in the proposed model includes multi periods. As a result, flow quantities between each facility belonging to different echelons are determined according to demand, capacity, cost and other periodic-based parameters at each period. This approach enables us to integrate the tactical decision such as selection of vehicle type or material flow decisions with the strategic level decision like location of facilities (Shen 2007).

Our proposed CSCND model belongs to the possibilistic programming category because we are coping with some ill-known parameters. In possibilistic programming, fuzzy coefficients (ill-known parameters) can be regarded as possibility distributions on coefficient values (Inuiguchi and Ramik 2000). These possibility distributions stand for the possibility degree of occurrence for each data, which are usually determined impartially (Pishvaee and Torabi 2010).

Following are the other main characteristics and assumptions used in the problem definition:

- Each product is assembled by different components and usage rates supplied by various suppliers.
- All demands of customers must be satisfied at the same period and all the returned products from customers must be collected.
- Each customer zone has a different predefine weight value.
- Products are shipped through a pull mechanism in the forward side of network, and stockout is not allowed at each echelon.
- Returned products are shipped through a push mechanism in the reverse side of network.
- Locations of plant, customer zones, recovery and recycling centres are fixed.
- A predefined value is determined as unit volume of assembled product and an average scrap fraction.
- Products flow only between two consecutive centres.
- Demands, costs and rank of suppliers are uncertain.

Considering assumptions mentioned before, the following decisions are discussed in the given problem:

- Supplier selection and quantity of supplied components from each of them.
- Determining the number and location of distribution and collecting centres.
- Determining the type of vehicle needed to deliver products to the customers on time.
- Flow quantities between different facilities at each period.

3. Model formulation

In this section, a possibilistic CSCND model is proposed. Different notations used for the model are given below. Parameters with a tilde sign on them considered uncertain.

3.1. *Indices*

s	suppliers ($s = 1, \ldots, S$)
r	resources and components ($r = 1, \ldots, R$)
j	candidate location for distribution centeres ($j = 1, \ldots, J$)
k	fixed location of customer zones ($k = 1, \ldots, K$)
l	candidate location for collection centeres ($l = 1, \ldots, L$)
m	fixed location for recovery centeres ($m = 1, \ldots, M$)
n	fixed location for recycling centeres ($n = 1, \ldots, N$)
vv	vehicle types ($vv = 1, \ldots, VV$)
t	time periods ($t = 1, \ldots, T$)

3.2. *Parameters*

$\tilde{d}_{kt}$	demand of customer zone k at period t
$\widetilde{ct}_s$	fixed cost of treaty ratification to supplier s

$\tilde{f}_j$	fixed cost of opening distribution centere j
$\tilde{g}_l$	fixed cost of opening collection centere l
$\tilde{b}_m$	fixed cost of opening recovery centere m
$\widetilde{aa}_n$	fixed cost of opening recycling centere j
$\widetilde{cx}_s$	transportation cost per product unit from supplier s to assembler
$\widetilde{co}_j$	transportation cost per product unit from assembler to distribution centere j
$\widetilde{cu}_{jk}^{vv}$	transportation cost per product unit from distribution centere j, to customer zone k by vehicle type vv
$\widetilde{cq}_{kl}$	transportation cost per unit of returned products from customer zone k to collection centere l
$\widetilde{cr}_{lm}$	transportation cost per unit of returned products from collection centere l to recovery centere m
$\widetilde{cs}_{\ln}$	transportation cost per unit of scraped products from collection centere l to recycling centere n
$\widetilde{ch}_{mj}$	transportation cost per unit of recovered products from recovery centere m to distribution centere j
$\widetilde{sp}_{sr}$	processing cost per unit of product r at supplier s
$\widetilde{ap}$	processing cost per unit of a product at assembler
$\widetilde{dp}_j$	processing cost per unit of a product at distribution centere j
$\widetilde{cp}_l$	processing cost per unit of a product at collection centere l
$\widetilde{rp}_m$	recovery cost per unit of a product at recovery centere m
pp_s	maximum capacity of supplier s allocated for product p at each period
pa	maximum capacity of assembler A allocated for product p at each period
pv_j	maximum capacity of distribution centere j at each period
pvv_{vv}	maximum capacity of vehicle type vv at each period
py_l	maximum capacity of collection centere l at each period
pz_m	maximum capacity of recovery centere m at each period
pw_n	maximum capacity of recycling centere n at each period
ts_{sr}	processing time per unit of resource r at supplier s
ta	processing time per unit of product at assembler
ρ	unit volume of the assembled product
rr_{kt}	rate of return percentage from customer zone k at period t
sf	average scrap fraction at period t
sp^{vv}	delivery speed from distribution by vehicle type vv
wv_k	weight value of customer zone k
ru_r	rate of usage resource r at unit product
dis_{jk}	distance between distribution centere j and customer zone k

3.3. *Variables*

x_{srt}	quantity of resources r shipped from supplier s to assembler at period t
o_{jt}	quantity of products shipped from assembler to distribution centere j at period t
u_{jkt}^{vv}	quantity of products shipped from distribution centere j to customer zone k by vehicle type vv at period t
q_{klt}	quantity of returned products shipped from customer zone k to collection centere l at period t
r_{lmt}	quantity of recoverable products shipped from collection centere l to recovery centere m at period t
$ss_{\ln t}$	quantity of scrapped products shipped from collection centere l to recycling centere n at period t
h_{mjt}	quantity of recovered products shipped from recovery centere m to distribution centere j at period t
$\widetilde{rs}_s$	rank of supplier s

$$\sigma_s = \begin{cases} 1 & \text{If supplier } s \text{ is selected} \\ 0 & \text{Otherwise} \end{cases}$$

$$v_j = \begin{cases} 1 & \text{If a distribution center is opened at location } j \\ 0 & \text{Otherwise} \end{cases}$$

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

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

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

Regarding these notations, the CSCND is formulated by:

$$\begin{aligned}\min f_1 = &\sum_t \sum_s \sum_r (\widetilde{cx}_s + \widetilde{sp}_{sr}) x_{srt} \\ &+ \sum_t \sum_j (\widetilde{co}_{Aj} + \widetilde{ap}) o_{Ajt} \\ &+ \sum_t \sum_j \sum_k \sum_{vv} (\widetilde{cu}^{vv}_{jk} + \widetilde{dp}_j) u^{vv}_{jkt} \\ &+ \sum_t \sum_k \sum_l \widetilde{cq}_{kl} q_{klt} \\ &+ \sum_t \sum_l \sum_n (\widetilde{cs}_{\ln} + \widetilde{cp}_l) ss_{\ln t} \\ &+ \sum_t \sum_l \sum_m (\widetilde{cr}_{lm} + \widetilde{cp}_l) r_{lmt} \\ &+ \sum_t \sum_m \sum_j (\widetilde{ch}_{mj} + \widetilde{rp}) h_{mjt} + \sum_s \widetilde{ct}_s \sigma_s \\ &+ \sum_j \tilde{f}_j v_j + \sum_l \tilde{g}_l y_l + \sum_m \tilde{b}_m z_m + \sum_n \tilde{a}_n w_n \end{aligned} \tag{1}$$

$$\max f_2 = \sum_s \widetilde{\widetilde{rs}}_s \sigma_s \tag{2}$$

$$\min f_3 = \sum_t \sum_j \sum_k \sum_{vv} wv_k \frac{u^{vv}_{jkt}\left(\frac{dis_{jk}}{sp^{vv}}\right)}{\tilde{d}_{kt}} \tag{3}$$

s.t.

$$\sum_r x_{srt} ts_{sr} \le pp_s; \quad \forall s, t \tag{4}$$

$$\frac{\sum_s x_{srt}}{ru_r} \ge o_{Ajt}; \quad \forall r, t \tag{5}$$

$$ta(o_{Ajt}) \le pa; \quad \forall t \tag{6}$$

$$\rho\left(o_{Ajt} + \sum_m h_{mjt}\right) \le v_j pv_j; \quad \forall j, t \tag{7}$$

$$\sum_k q_{klt} \le y_l py_l; \quad \forall l, t \tag{8}$$

$$\sum_l r_{lmt} \le z_m pz_m; \quad \forall m, t \tag{9}$$

$$\sum_l ss_{\ln t} \le w_n pw_n; \quad \forall n, t \tag{10}$$

$$\sum_j \sum_{vv} u^{vv}_{jkt} \ge \tilde{d}_{kt} + \sum_l q_{kl,t-1}; \quad \forall k, t \tag{11}$$

$$\sum_l q_{klt} \ge rr_{kt} \tilde{d}_{k,t-1}; \quad \forall k, t \tag{12}$$

$$o_{Ajt} + \sum_m h_{mjt} = \sum_k \sum_{vv} u^{vv}_{jkt}; \quad \forall j, t \tag{13}$$

$$sf_t \sum_k q_{klt} = \sum_n ss_{tnl}; \quad \forall l, t \tag{14}$$

$$(1 - sf_t) \sum_k q_{klt} = \sum_m p_{lmt}; \quad \forall l, t \tag{15}$$

$$\sum_m \sum_j h_{mjt} = \sum_l \sum_m r_{lm,t-1}; \quad \forall t \tag{16}$$

$$\sum_r x_{srt} \le \sigma_s M; \quad \forall s, t \tag{17}$$

$$v_j, y_l, z_m, w_n \in \{0, 1\}; \quad \forall j, l, m, n \tag{18}$$

$$\begin{aligned} &x_{srt}, o_{Ajt}, u^{vv}_{jkt}, q_{klt}, ss_{lnt}, p_{lmt}, h_{mjt} \ge 0; \\ &\forall s, r, A, k, j, vv, l, m, n, t \end{aligned} \tag{19}$$

It involves three objective functions: (1) minimisation of the total costs, (2) maximisation of suppliers' ranks and (3) minimisation of total delivery time of products (by considering importance value and demand of each customer zone) being in conflict with each other. The first and second objective functions are related to the efficiency of the SCN, and the third one is related to network responsiveness. A number of studies have also taken into account similar objectives (e.g., Selim and Ozkarahan 2008; Torabi and Hassini 2008; Pishvaee and Torabi 2010).

The objective function (1) minimises the total costs including variable transportation and processing costs and fixed opening costs. The objective function (2) maximises the total rank of suppliers, and the objective function (3) minimises the total delivery time of products. Constraints (4)–(10) are capacity constraints related to suppliers and facilities. Constraint (4) expresses that each supplier may allocate only a part of its capacity to produce the component r for an assembler. Constraint (5) prohibits excessive product flow concerning available raw materials. Constraint (6) declares that like the suppliers, assembler has a certain capacity allocated to a product. Constraints (7)–(10) are related to capacity restrictions. They enforce the flow of the assembled and recovered products, returned products, recoverable and recyclable products only on facilities that are opened. For instance, Equation (7) shows that the total quantity of products shipped from assembler and also recovered products shipped from recovery centre cannot be greater than maximum capacity of distribution centre j at each period. Constraint (11) assures that the demands of all customer zones are satisfied. Constraint (12) ensures that the returned products of all customer zones are collected. Equations (13)–(16) are balanced constraints at distribution, collection, recovery and recycling centres. Constraint (17) enforces that raw materials and components are only produced by selected suppliers. In this constraint M is a big number. Finally, Constraint (18) and (19) assures the binary and non-negativity constraints on decision variables.

4. Proposed solution method

Considering above-mentioned model, the proposed CSCND is a multi-objective possibilistic mixed-integer linear programming problem. To cope with the possibilistic models involving the imprecise coefficients in both objective function and constraints, several methods have been developed in the literature (e.g., Lai and Hwang 1992; Inuiguchi and Ramik 2000; Wang and Liang 2005; Jimenez, Arenas, Bilbao, and Rodriguez 2007; Shen 2007; Torabi and Hassini 2008). Pokharel (2008) used STEP method (STEM) proposed by Benayoun, Demontgolfier, Tergny, and Laritchev (1971) in his multi-objectives deterministic SCN design model. This method is an interactive exploration procedure, where the best compromise is reached after a certain number of iterations (Benayoun et al. 1971). STEM can be applied to locate non-dominated solutions through progressive articulation of preference by DMs for both linear and non-linear applications (Pokharel 2008).

Nevertheless, some major objections to this method could be mentioned. In STEM approach, if some of the objective functions are satisfactory and others not, the DM accepts a certain amount of relaxation of a satisfactory objective to allow an improvement of the unsatisfactory ones in the next iteration. However, if the DM does not want to relax the satisfactory objectives, this method virtually is useless. In addition, there is no guarantee with this approach (relaxation) optimal unsatisfactory solution, obtain the DM's satisfactory level. Another deficiency of STEM occurs when faced with uncertainty parameters, because STEP is a multi-objective optimisation method under deterministic. As a result, it cannot be directly used to solve MOPMILP. Hence, to solve the problem, a two-phased approach is proposed here. In the first place, the original model is converted into an equivalent auxiliary crisp model by applying an appropriate possibilistic approach through hybridising the methods of Benayoun et al. (1971), Torabi and Hassini (2008) and Inuiguchi and Ramik (2000). After that, in the second phase, we propose a novel interactive fuzzy programming approach for obtaining a preferred compromise solution.

4.1. *Equivalent auxiliary crisp model*

We apply an efficient possibilistic approach to transform the MOPMILP model into an auxiliary crisp multiple objective mixed-integer linear programming one. Here, we propose a novel possibilistic approach by hybridising the methods of Benayoun et al. (1971), Torabi and Hassini (2008) and Inuiguchi and Ramik (2000).

4.1.1. *Treating the objective functions*

Zadeh (2008) classified fuzzy logic into four facets: the logical facet (FLl), the fuzzy-set-theoretic facet (FLs), the epistemic facet (Fle) and the relational facet (FLr). He points out that the epistemic facet of FL, FLe, is concerned with knowledge representation, semantics of natural languages and information analysis. Two major important branches of FLe are possibility theory and computational theory of perceptions (Zadeh 1978; Zadeh 1981; Dubois and Prade 1998).

In the case of ambiguous parameters in both objective functions and right-hand side of the constraints, different fuzzy numbers ranking methods have been proposed by various researchers (see Wang and Kerre (1996) and Bortolan and Degani (1985) for a review). Among these methods, transforming the fuzzy numbers into crisp ones is a prevalent approach. As stated by Campos and Verdegay (1998), there are two main approaches to ranking fuzzy numbers, according to either to (a) the use of a ranking function (index) or (b) by using the methods assuming that the DMs priori choose a degree of conformity for which the inequality may be considered as true for them. Indexes simply map each fuzzy number into the real line; they are easy to use and most of the times straightforward.

Regarding the second approach, from the point of view of possibilistic optimisation, Dubois and Prade (1980) proposed four comparison indices. These are namely called (1) grade of possibility of dominance, (2) grade of necessity of dominance (3) grade of possibility of strict dominance and (4) grade of necessity of strict dominance. Given two fuzzy numbers A and B, the measures of $\tilde{a} * \tilde{b}$ in optimistic and pessimistic sense are as Equations (20) and (21).

$$Pos(\tilde{a} * \tilde{b}) = \sup\left\{\min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re, x * y\right\} \tag{20}$$

$$Nes(\tilde{a} * \tilde{b}) = \inf\{\max(1 - \mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re, x * y\} \tag{21}$$

where the abbreviation Pos and Nes represent possibility and necessity respectively and * can be each of the relations: $\leq$, $\geq$, $=$, $<$, $>$.)

We suppose that the DM has optimistic approach to the problem. When $\tilde{a}$ and $\tilde{b}$ are triangular fuzzy numbers:

$$Pos(\tilde{a} > \tilde{b}) > \eta \; iff \; \frac{a_3 - b_1}{b_2 - b_1 + a_3 - a_2} > \eta, \quad (a_2 < b_2, a_3 > b_1) \tag{22}$$

To proof Equation (22), consider $Pos(\tilde{a} > \tilde{b}) > \eta$. From Figure 2, it can be concluded that

$$Pos(\tilde{a} > \tilde{b}) = \begin{cases} 1 & ; a_2 \geq b_2 \\ \zeta = \frac{a_3 - b_1}{b_2 - b_1 + a_3 - b_2} & ; a_2 < b_2, a_3 > b_1 \\ 0 & ; a_3 \leq b_1 \end{cases}$$

Hence,

$$Pos(\tilde{a} > \tilde{b}) > \eta \; iff \; \zeta = \frac{a_3 - b_1}{b_2 - b_1 + a_3 - b_2} > \eta, (a_2 < b_2, a_3 > b_1).$$

For more information, see Bhuina and Maiti (2007). Inuiguchi and Ramik (2000) classified a number of methods of dealing with objective functions in the possibilistic programming into fractile and modality approaches. With this interpretation, p-fractile is the value u that meets:

$$\Pr(X \leq u) = p, \tag{23}$$

where X is a random variable.

In this definition, p-fractile does not generally exist for all $p \in (0, 1)$. That is why we define p-fractile as the smallest value u_p of u that satisfies the following equation.

$$\Pr(X \leq u) \geq p, \tag{24}$$

By considering the theory of evidence proposed by Dempster (1967), $Pos(X \leq u)$ and $Nes(X \leq u)$ can be regarded as upper and lower bounds of $\Pr(X \leq u)$. Then the p-possibility fractile as the smallest value of u that satisfies

$$Pos(X \leq u) \geq p; \tag{25}$$

the drawback of the modality approach is that it results in a non-linear mathematical problem transformed into a linear one by substituting some auxiliary variables. Since this is a time consuming process, we adhere to fractile approach which is straightforward.

Considering the equivalent formulation of an objective function in the fractile approach, obviously we can perform a trade-off between optimality of the objective function and the certainty degree of achieving the objective value; in the sense that lessening the degree of certainty will result in a better objective value in both minimisation and maximisation problems. We apply this trait in our proposed multiple objective optimisation approach. Therefore, unlike almost all the other relevant methods which relax some optimality from other objective functions for the sake of improving a specific unsatisfactory objective function; we try to boost its value by a controlled reduction in the certainty degree of achieving that particular value. By application of this tactic, we may acquire a satisfactory solution by simply sacrificing a trifle amount of the pre-defined certainty of the achieved value without a need for searching another Pareto optimal solution, yielding a significant computational saving.

According to what mentioned above, treating to objective functions is summarised as follows. Consider the objective functions such as Equation (26), where $\tilde{c}$ is a triangular fuzzy number.

$$\max: \{\tilde{c}_1 x + \tilde{c}_2 x + \cdots + \tilde{c}_k x\} \tag{26}$$

At first by using p-possibility fractile approach transformation, as Equation (25), problem can be treated by:

$$\begin{aligned} &\max: \{f_1, f_2, \ldots, f_k\} \\ &\text{s.t., } pos\{\tilde{c}_i x \geq f_i\} \geq \alpha_i, \quad i = 1, 2, \ldots, k \end{aligned} \tag{27}$$

Then, the equivalent auxiliary crisp model, by using explained lemma in Equation (22), can be formulated by

$$\begin{aligned} &\max: \{f_1, f_2, \ldots, f_k\} \\ &\text{s.t., } c_i^{(3)} x - \alpha_i (c_i^{(3)} x - c_i^{(2)} x), \quad i = 1, 2, \ldots, k \end{aligned} \tag{28}$$

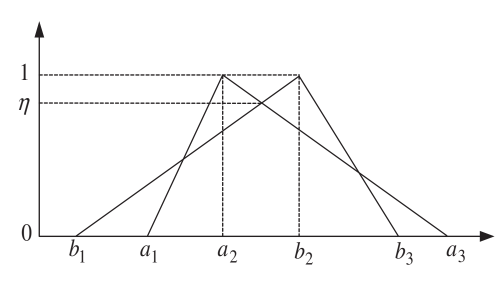

Figure 2. $Pos(\tilde{a} > \tilde{b})$.

4.1.2. *Treating the soft constraints*

We use the Torabi and Hassini (2008) method to resolve the imprecise demands in the right-hand sides of constraints (11) and (12), the weighted average method is applied for the defuzzification process and converting the $\tilde{d}_{kt}$ parameter into a crisp number. Thus, if the minimum acceptable degree of feasibility, λ, is given, then the equivalent auxiliary crisp constraints could be represented as follows:

$$\sum_j \sum_{vv} u_{jkt}^{vv} \geq (w_1 d_{kt,\lambda}^p + w_2 d_{kt,\lambda}^m + w_3 d_{kt,\lambda}^o) + \sum_l q_{kl,t-1} \quad \forall k, t \tag{29}$$

$$\sum_l q_{klt} \geq rr_{kt}(w_1 d_{k,t-1,\lambda}^p + w_2 d_{k,t-1,\lambda}^m + w_3 d_{k,t-1,\lambda}^o) \quad \forall k, t \tag{30}$$

Where $w_1 + w_2 + w_3 = 1$, and w_1, w_2 and w_3 denotes the weight of the most pessimistic, the most possible and the most optimistic value of the fuzzy demand, respectively. The suitable values for these weights as well as λ usually are concluded subjectively by the knowledge of the DM. Considering the concept of most likely values proposed by Lai and Hwang (1992) and numerous relevant papers (e.g., Hsu and Wang 2001; Listes and Dekker 2005), we set these parameters as $w_1 = w_3 = 1/6$, $w_2 = 4/6$ and $\lambda = 0.5$.

To the best of our knowledge, a multi-objective optimisation approach proposed in this article which considers adjustment of certainty degree between possibility solution and objective function value as well as DM's preferences is of preliminary works for CSCND in the presence of uncertainty. The proposed algorithm and the relevant formulations will be thoroughly described in the forthcoming section.

4.2. *Possibilistic-STEM algorithms*

According to the above explanations, the optimisation algorithm is proposed here. Consider the following problem

$$\begin{aligned} \max:\ & \{\tilde{c}_1 x + \tilde{c}_2 x + \cdots + \tilde{c}_k x\} \\ \text{s.t.}\ \ & Ax \leq \tilde{b} \\ & x \geq 0 \end{aligned} \tag{31}$$

Step 0: Transformation into the auxiliary crisp model

At first by using the fractile approach transformation, the problem can be treated by:

$$\begin{aligned} \max:\ & \{f_1, f_2, \ldots, f_k\} \\ \text{s.t.,}\ \ & pos\{\tilde{c}_i x \geq f_i\} \geq \alpha_i, \quad i = 1, 2, \ldots, k \\ & Ax \leq \tilde{b} \\ & x \geq 0 \end{aligned} \tag{32}$$

Then, the equivalent auxiliary crisp model by using the explained lemma in Equation (22) and treating the soft constraint proposed by Torabi and Hassini (Equations (29) and (30)) can be formulated by

$$\begin{aligned} \max:\ & \{f_1, f_2, \ldots, f_k\} \\ \text{s.t.,}\ \ & c_i^{(3)} x - \alpha_i (c_i^{(3)} x - c_i^{(2)} x), \quad i = 1, 2, \ldots, k \\ & Ax \leq b \\ & x \geq 0 \end{aligned} \tag{33}$$

Now, the DM defines a certainty degree for each objective function, subjected to $\alpha_i \in [\alpha_i^l, \alpha_i^u]$ and the upper bound of α will result the highest preferable response. For example if the DM feels that a certainty degree 0.9 is high enough for the first objective,α_i would be equal to 0.9.

Step 1: Construction of the pay-off table

Considering the following problem, we calculate the optimum for each objective in turn and construct the pay-off table:

$$\begin{aligned} \max:\ & z_j(\alpha) = f_j(x, \alpha) = c_j^{(3)} x - \alpha_j (c_i^{(3)} x - c_j^{(2)} x), \\ & j = 1, 2, \ldots, k \\ \text{s.t.,}\ \ & Ax \leq b \\ & x \geq 0 \end{aligned} \tag{34}$$

Step 2: Calculations

For each iteration m, the problem is to seek a non-dominated solution that is nearest (γ), in the minimax sense, to the ideal solution. Hence, the problem is reformulated as given in Equation (35).

$$\begin{aligned} \min:\ & \gamma \\ \text{s.t.,}\ \ & \gamma \geq (f_j^* - f_j(x, \alpha)).\pi_j, \quad j = 1, 2, \ldots, k \\ & x \in D^m \\ & \gamma \geq 0 \end{aligned} \tag{35}$$

At first iteration D^1 is D (D^m is the feasible region at iteration m).

Weight on each objective (π_j) giving the relative importance of the distances to the optima is calculated using the maximum values for that objective.

$$\omega_j = \frac{f_j^* - f_j^{\min}}{f_j^*} \left(\frac{1}{\sqrt{\sum_{i=1}^k (c_{ji})^2}} \right) \forall j;$$
$$c_{ji} = c_{ji}^{(3)} - \alpha_j (c_{ji}^{(3)} - c_{ji}^{(2)}), \tag{36}$$

$$\pi_j = \frac{\omega_j}{\sum_{j=1}^k \omega_j}. \tag{37}$$

Where c_{ji} and α_j are coefficient of jth objective function with n variable in problem and certainty degree, respectively.

Step 3: Decision making

The solution to Equation (35) gives the first non-dominated solution to the DMs to start with. If the DMs are happy with this solution (all $f_j(x,\alpha)$ are satisfactory compared to f_j^*), they will adopt this as the best and stop future iterations. Otherwise, the DMs classify the solution into satisfactory and unsatisfactory.

Step 4: Manipulation of certainty degree for unsatisfactory components of the solution

In Step 2, a feasible solution (X) has been achieved for the multiple objective problem. By substituting X in $(j \in U,\ \forall f_j(x,\alpha))$, the objectives will be only the function of certainty degree. Therefore by gradual reduction of α in its permissible interval, because of linearity of objective functions, we can clearly investigate gained improvement in the respective objective function. All of the objective functions belonging to the unsatisfactory group are tested by gradual reduction of their relative certainty degrees to check whether they reach an acceptable level or not. If a function reaches an acceptable level, its respective rows and columns in the pay-off table are updated; otherwise, even if by considering the lowest acceptable certainty degree, namely α^l, an admissible objective value is not acquired, its certainty degree will be rolled back to its primary value and afterwards the classical method of the STEP will be applied to optimise the function. If all of the objective functions belonging to U reach an admissible value by manipulation of their certainty levels, go to Step 5; else, add only those functions that turned satisfactory to s and go to Step 6.

Step 5: Seeking for a non-dominated solution

All of the non-admissible objective functions in the previous step have attained an acceptable value by manipulation of their certainty degrees. However, due to alteration in cost parameters, the fixed X solution applied in certainty degree manipulation phase may not be the optimal solution anymore. To ensure an optimal solution, the following model is solved, and the related results are presented to the DM as the final optimal solution. The coefficients π_j are set to zero for functions belonging to S, and for the rest of them it is recomputed regarding the pay-off table.

$$\begin{aligned} \min:\ & \gamma \\ \text{s.t.,}\quad & \gamma \geq (f_j^* - f_j(x^m,\alpha)).\pi_j, \quad j \in U \\ & f_j^* \leq f_j(x^m,\alpha), \quad j = 1,2,\ldots,k \\ & x \in D^m \\ & \gamma \geq 0 \end{aligned} \tag{38}$$

Step 6: DMs sacrifice some amount (Δf_j) for satisfactory objectives

For the next iteration, the feasible region is modified as

$$D^{m+1} = \begin{cases} D^m \\ f_j(x) \geq f_j(x^m) - \Delta f_j,\ j \in S \\ f_j(x) \geq f_j(x^m), \quad j \in U \end{cases} \tag{39}$$

Weight π_j for objectives $j (j \in S)$ is set to zero and for the remaining objectives ($j \in U$) should be calculated as Equation (37). Then, calculation of iteration $m+1$ begins.

Step 7: Repeat all steps

All above-mentioned steps are repeated so that the DMs are happy with the solution. Figure 3 depicts the flow chart of proposed possibilistic-STEM algorithm.

5. Computational results

To demonstrate the validity and practicality of the proposed model and the solution method, a numerical experiment is presented, and the related results are indicated in this section. Table 1 shows the size of this problem. The suppliers are ranked and selected based on the Van Laarhoven and Pedrycz's FAHP approach, because this method is used to derive fuzzy weights and fits to our proposed algorithm (Appendix A). The hierarchy structure of supplier selection consist of four criteria, namely financial (F), quality (Q), service (S) and extent of fitness (EF) and seven suppliers is shown in Figure A.1.

To generate the triangular fuzzy number, based on Lai and Hwang (1992) the three points for each ill-known parameter are estimated. Initially, the most likely (c^m) value by using the uniform distribution shown in Table 2 is generated randomly. It is assumed that this value is equal to the corresponding crisp one. Thenceforth, two random numbers (r_1,r_2) are generated between 0.2 and 0.8 using uniform distributions, and optimistic (c^o) and pessimistic (c^p) values are considered as follows.

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

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

All of the mathematical models are coded in GAMS 22.0 and the CPLEX 9.0 solver optimisation software on a Pentium dual-core 2.2 GHz computer with 3 GB RAM. Data for capacity allocation in the proposed network are given in Table 3.

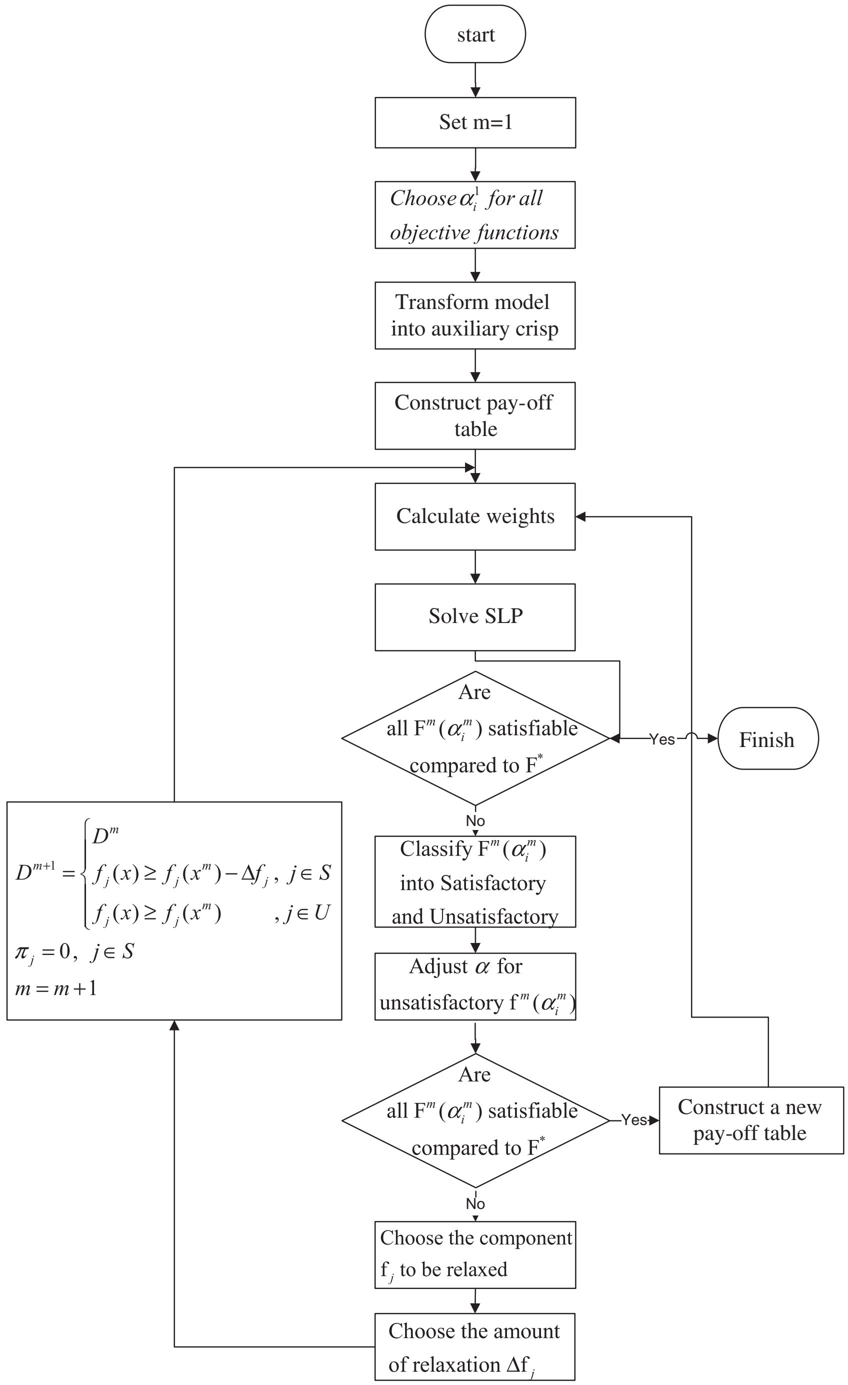

Figure 3. Flow chart of the proposed possibilistic-STEM algorithm.

Table 1. Size of numerical experiments.

No. test	No. of suppliers	No. of plants	No. of potential distribution centres	No. of customer zones	No. of potential collection centres	No. of potential recovery centres	No. of potential recycling centres	No. of vehicle type	No. of time periods
1	7	1	6	4	2	1	1	2	3

Table 2. Source of a random generation of the most likely values.

Parameters	Corresponding random distribution
d_{kt}	~ Uniform (1000, 3500)
cx_s, co_j, cs_{ln}, cp_{lm}, ch_{mj}	~ Uniform (1, 2.5)
cq_{kl}	~ Uniform (2, 3)
cu_{jk}, ap, rp	~ Uniform (1, 2)
sp	~ Uniform (1, 3)
dp, cp	~ Uniform (0.5, 1.5)
f_j	~ Uniform (300, 600)
g_l, b_m, a_n	~ Uniform (150, 250)
ct_s	~ Uniform (1000, 2000)

Table 3. Capacity data for the example network in each period.

Suppliers ($s=1$–7)	Assembler	Distribution centre ($l=1$–6)	Vehicle type ($vv=1$–2)	Collection centre ($l=1$–2)	Recovery centre (m)	Recycling centre (n)
(800, 1000, 700, 1100, 1000, 1000, 1250)	2200	(1000, 700, 300, 800, 800, 1200)	(8000, 5000)	(700, 300)	900	300

The proposed CSCND model by using our possibilistic-STEM optimisation algorithm is explained here.

Step 0: The CSCND model is transferred into an auxiliary crisp one by using Equation (34) and the certainty degree is set to 0.9 for all α_i.

Step 1: In this step all three objectives are separately optimised and the solutions are arranged in the pay-off table as shown in Table 4.

Steps 2: Weights π_j on objectives are calculated as (8.75E-08, 6.09E-04 and 9.99E-01). Subsequently, the first iteration solution using Equations (35)–(37) gives the following value at CPU time of 3 s.

$$F^1_{(0.9,0.9,0.9)} = (-547606.0, 0.695, -17.46)$$

Step 3: Although the DMs are happy with the composite number of costs and supplier ranks, they are not happy with the solution and tend to choose a lower value of delivery time.

Steps 4: In this step, the DMs adjust the certainty degree for the delivery time objective, so that be satisfied with the number. The component number (17.05) and certainty degree ($\alpha = 0.7$), given in Table 5 and Figure 4, are satisfactory for the DMs, hence we go to Step 5.

Table 4. Pay-off table.

Variable	Cost	Supplier rank	Delivery time
Cost	(509,894)	(889,703)	(916,213)
Supplier rank	0.70	1.01	1.01
Delivery time	(42.2)	(40.5)	(14.17)

Table 5. Adjustment of certainty degree for the delivery time objective.

α_3	0.90	0.85	0.80	0.75	0.70
f_3	−17.46	−17.36	−17.27	−17.18	−17.05

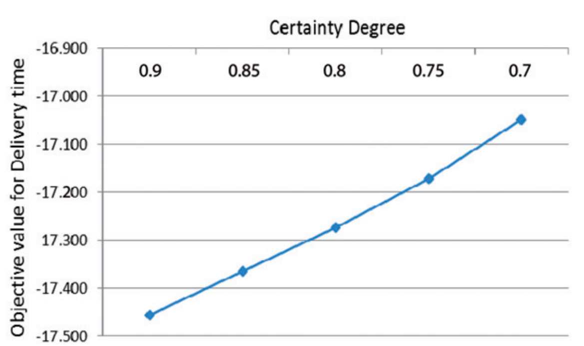

Figure 4. Adjustment of a certainty degree for 3rd objective (delivery time).

Step 5: Using Equation (38) gives $F^{1}_{(0.9,0.9,0.7)} = (-547606.0, 0.795, -17.05)$ which assures the obtained solution as a non-dominated one.

6. Conclusion and future research

This aticle has presented an interactive MOPMILP model to formulate a CSCN problem in a multi-echelon, multi-period under uncertainty. The proposed CSCN integrates the network design decisions in both forward and reverse SCNs and also incorporates the tactical decisions with strategic ones simultaneously to prevent sub-optimality caused by the separated design. To adapt the model to real-world conditions, fundamental and logical issues, such as selection of optimal suppliers and importance value of customer zones, which strongly affect to the overall supply chain performance, are considered in this article. Then, to solve the MOPMILP model, a novel interactive fuzzy solution approach, namely possibilistic-STEM, is presented by combining the methods of Benayoun et al. (1971), Torabi and Hassini (2008) and Inuiguchi and Ramik (2000). The best of our knowledge, the proposed multi-objective optimisation algorithm is one of the primary studies in this area that (1) considers trade-off between optimality of the objective function and the certainty degree of achieving the objective value, (2) finds efficient solutions based on the preferences of the DM. Finally, there are some directions to improve this article in future research. To match the model to actual conditions, other parameters such as rate of return and scrap fraction can be defined in a fuzzy nature. In addition, considering some other tactical decisions (e.g., inventory) and strategic one (e.g., selection of transportation system) is also a valuable research direction. At the end, although time complexity is not addressed in this study, this might be of an importance issue in large-sized and NP-hard problems, and so other efficient exact or heuristic solution methods can be developed.

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Appendix A. Supplier selection process

The FAHP approach proposed by De Boer et al. (2001) is MADM method which both utilises and obtains triangular fuzzy numbers for weights of alternatives. Due to prioritize the suggested suppliers, first the hierarchy structure is organized and then related steps are performed. The criteria, as is shown in Figure A.1, are financial (F), quality (Q), service (S) and extent of fitness (EF). Furthermore, two DMs are graded for the four criteria.

Step 1: The two DMs obtain $n+1$ fuzzy reciprocal matrix ($n=$number of criteria). Their opinions about the relative importance of a pair of criteria ($\tilde{a}_{ij}p_{ij}$) are shown in Tables A.1–A.5.

Step 2: Let $z_i=(l_i, m_i, u_i)$. Solve the following linear equations:

$$l_i\left(\sum_{j=1,j\neq i}^{n} p_{ij}\right)-\sum_{j=1,j\neq i}^{n} p_{ij}u_j=\sum_{j=1,j\neq i}^{n}\sum_{k=1}^{p_{ij}}(\ln l_{ijk}),\quad \forall i \tag{A.1}$$

$$m_i\left(\sum_{j=1,j\neq i}^{n} p_{ij}\right)-\sum_{j=1,j\neq i}^{n} p_{ij}m_j=\sum_{j=1,j\neq i}^{n}\sum_{k=1}^{p_{ij}}(\ln m_{ijk}),\quad \forall i \tag{A.2}$$

$$u_i\left(\sum_{j=1,j\neq i}^{n} p_{ij}\right)-\sum_{j=1,j\neq i}^{n} p_{ij}l_j=\sum_{j=1,j\neq i}^{n}\sum_{k=1}^{p_{ij}}(\ln u_{ijk}),\quad \forall i \tag{A.3}$$

As $\ln(l_{ijk})$ and $\ln(u_{ijk})$ are lower and upper values of $\ln(a_{ijk})=-\ln(a_{jik})$, the following must hold true [see Equation (A.1)]:

$$\ln(l_{ijk})+\ln(l_{jik})=\ln(u_{ijk})+\ln(u_{jik})=0,\quad \forall i,j,k \tag{A.4}$$

Thus, Equations (A.1) and (A.3) are linear dependent. The same holds for Equation (A.2). In general, a solution for Equations (A.1), (A.2) and (A.3) is given as below, where t_1 and t_2 can be chosen randomly.

$$z_i=(l_i+t_1, m_i+t_2, u_i+t_1),\quad \forall i \tag{A.5}$$

Step 3: The right sides of the equations above are operated using logarithmic operations. Then, fuzzy weight is obtained in Equation (A.6). This equation can also be used to determine the performance score r_{ij}.

$$w_i=(\lambda_1\exp(l_i), \lambda_2\exp(m_i), \lambda_3\exp(u_i)),\quad \forall i \tag{A.6}$$

where

$$\lambda_1=\left[\sum_{i=1}^{n}\exp(u_i)\right]^{-1}=0.093,$$

$$\lambda_2=\left[\sum_{i=1}^{n}\exp(m_i)\right]^{-1}=0.103,$$

$$\lambda_3=\left[\sum_{i=1}^{n}\exp(l_i)\right]^{-1}=0.109$$

Therefore, the fuzzy weights are $w=[(0.355, 0.401, 0.458), (0.282, 0.353, 0.383), (0.125, 0.143, 0.191), (0.094, 0.104, 0.137)]$.

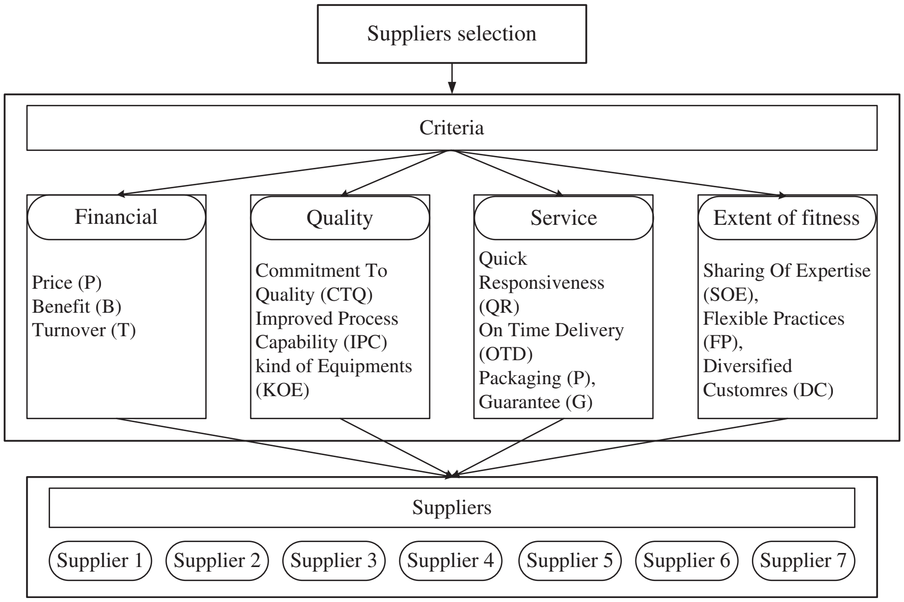

Figure A.1. Hierarchy of the supplier selection model.

Table A.1. Pair-wise comparison of applicants for the financial criteria.

	A1	A2	A3	A4	A5	A6	A7
A1	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2) (3/2, 2, 5/2)	(1, 1, 1) (1, 1, 1)	(1, 1, 1) (1, 1, 1)	(5/2, 3, 7/2) (5/2, 3, 7/2)	(5/2, 3, 7/2)
A2	(2/3, 1, 3/2)	(1, 1, 1)	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2)
A3	(2/5, 1/2, 2/3) (2/5, 1/2, 2/3)	(2/3, 1, 3/2)	(1, 1, 1)	(2/3, 1, 3/2)	(2/3, 1, 3/2)	(1, 1, 1)	(2/3, 1, 3/2)
A4	(1, 1, 1) (1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A5	(1, 1, 1) (1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A6	(2/7, 1/3, 2/5) (2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 1)
A7	(2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)	(2/3, 1, 3/2)	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(1, 1, 1)	(1, 1, 1)

Table A.2. Pair-wise comparison of applicants for the quality criteria.

	A1	A2	A3	A4	A5	A6	A7
A1	(1, 1, 1)	(2/3, 1, 3/2)	(2/3, 1, 3/2) (1, 1, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2) (1, 1, 1)	(3/2, 2, 5/2) (3/2, 2, 5/2)	(5/2, 3, 7/2)
A2	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A3	(2/3, 1, 3/2) (1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A4	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)
A5	(2/5, 1/2, 2/3) (1, 1, 1)	(2/5, 1/2, 2/3)	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(5/2, 3, 7/2)
A6	(2/5, 1/2, 2/3) (2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)
A7	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)	(2/7, 1/3, 2/5)	(2/3, 1, 3/2)	(1, 1, 1)

Table A.3. Pair-wise comparison of applicants for the service criteria.

	A1	A2	A3	A4	A5	A6	A7
A1	(1, 1, 1)	(1, 1, 1)	(1, 1, 1) (1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)
A2	(1, 1, 1)	(1, 1, 1)	(1, 1, 1) (1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
A3	(1, 1, 1) (1, 1, 1)	(1, 1, 1) (1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/7, 1/3, 2/5)
A4	(3/2, 2, 5/2)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/7, 1/3, 2/5)
A5	(3/2, 2, 5/2)	(1, 1, 1)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/7, 1/3, 2/5)
A6	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
A7	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(5/2, 2, 7/2)	(5/2, 2, 7/2)	(5/2, 2, 7/2)	(1, 1, 1)	(1, 1, 1)

Table A.4. Pair-wise comparison of applicants for an extent of the fitness criteria.

	A1	A2	A3	A4	A5	A6	A7
A1	(1, 1, 1)	(2/3, 1, 3/2)	(2/3, 1, 3/2) (1, 1, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2) (1, 1, 1)	(3/2, 2, 5/2) (3/2, 2, 5/2)	(5/2, 3, 7/2)
A2	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A3	(2/3, 1, 3/2) (1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)
A4	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)
A5	(2/5, 1/2, 2/3) (1, 1, 1)	(2/5, 1/2, 2/3)	(2/3, 1, 3/2)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(5/2, 3, 7/2)
A6	(2/5, 1/2, 2/3) (2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(2/3, 1, 3/2)
A7	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)	(2/7, 1/3, 2/5)	(2/3, 1, 3/2)	(1, 1, 1)

Table A.5. Pair-wise comparison of applicants for an extent of the attributes criteria.

	F.	Q.	S.	E.F.
F.	(1, 1, 1)	(3/2, 2, 5/2) (1, 1, 1)	(5/2, 3, 7/2)	(5/2, 3, 7/2) (5/2, 3, 7/2)
Q.	(2/5, 1/2, 2/3) (1, 1, 1)	(1, 1, 1)	(5/2, 3, 7/2) (3/2, 2, 5/2)	(5/2, 3, 7/2)
S.	(2/7, 1/3, 2/5)	(2/7, 1/3, 2/5) (2/5, 1/2, 2/3)	(1, 1, 1)	(3/2, 2, 5/2)
E.F.	(2/7, 1/3, 2/5) (2/7, 1/3, 2/5)	(2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)	(1, 1, 1)

Step 4: Steps 1–3 are repeated several times until all reciprocal matrices are solved. With the fuzzy weights and performance scores, the fuzzy score for alternative A_i is calculated as

$$u_i = \sum_{j=1}^{n} w_j r_{ij} \tag{A.7}$$

Consequently, fuzzy score of suppliers calculated based on Van Laarhoven and Pedrycz's FAHP method is as follows:

$\mathrm{rs}_1 = (0.138, 0.171, 0.211)$	$\mathrm{rs}_5 = (0.115, 0.155, 0.169)$
$\mathrm{rs}_2 = (0.124, 0.167, 0.196)$	$\mathrm{rs}_6 = (0.078, 0.115, 0.125)$
$\mathrm{rs}_3 = (0.102, 0.144, 0.163)$	$\mathrm{rs}_7 = (0.065, 0.099, 0.117)$
$\mathrm{rs}_4 = (0.111, 0.146, 0.159)$	