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An Inexact-Fuzzy-Stochastic Optimization Model for a Closed Loop Supply Chain Network Design Problem

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Abstract

The development of optimization and mathematical models for closed loop supply chain (CLSC) design has attracted considerable interest over the past decades. However, the uncertainties that are inherent in the network design and the complex interactions among various uncertain parameters are challenging the capabilities of the developed tools. The aim of this paper, therefore, is to propose a new mathematical model for designing a CLSC network that integrates the network design decisions in both forward and reverse supply chain networks. Moreover, another objective of this research is to introduce an inexact-fuzzy-stochastic solution methodology to deal with various uncertainties in the proposed model. Computational experiments are provided to demonstrate the applicability of the proposed model in the CLSC network design.

Keywords: Supply chain management; Facility location; Two-stage optimization; Multiple uncertainties.

1. Introduction

The significance of remanufacturing, product recovery and recycling of end-of-life products has progressively increased due to the rapid diminishment of raw material resources, greater consciousness of the environmental impacts of disposal, reducing space in landfills and growing levels of pollution (Kerr and Ryan, 2001, Hong and Ke, 2011). As these issues start to impact the manufacturers' behavior and customers' decisions, manufacturers are increasingly demanded to consider the impacts of their products on the environment. In order to deal with these concerns, manufacturers have to extend the traditional supply chain and consider the environmental influences of all products and procedures until they are returned at the end-of-life, which is referred to as the closed loop supply chain (CLSC) (Kooi et al., 1996; Beomon, 1999). CLSCs are supply chains in which, in addition to the conventional forward flow of materials from suppliers to consumers, there are flows of products back to manufacturers. Instances involve products returns from retailers to the manufacturers, consumed products that are exchanged in for a discount on the purchase price of a new product and end-of-life products that are returned for recovery, disposal or recycling (Schultmann et al. 2006, Wang and Hsu, 2010). The well-organized implementation of CLSC enables the companies to generate a more economical source of supplying parts, assemblies and products. Another recognized advantage of CLSC is protecting the environment from a variety of hazardous elements through waste management (Chang *et al.* 2011, Pires *et al.* 2011 and Vahdani *et al.* 2012a).

One of the biggest challenges in designing CLSC networks is the simultaneous consideration of forward and backward flows of products. Products are returned to the manufacturers by consumers for many reasons. Also, these returns are mostly delayed, in reality, due to the lack of a predefined process for putting returns back into the forward chain. Moreover, another challenge is the shortened life cycle of returned products. Therefore, most of activities and occurrences in the CLSCs are subject to uncertainties (Vahdani *et al.* 2012b). As pointed out before, the uncertainties involved in the reverse flow due to their natures are higher than those involved in the forward flow of supply chain (Fleischmann *et al., 2004*). These uncertainties are further intensified through not only interactions among the parameters that show uncertainties but also combinations of these uncertainties. Hence, effective CLSC management under the uncertainties should be based on a variety of decision support studies. Thus, advanced optimization methodologies are desired (Vahdani *et al.* 2012a).

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A major part of the literature on supply chain network design deals with forward supply chains in which products are transmitted from suppliers to manufacturers, from manufacturers to distributors, from distributors to retailers and ultimately to customers. However, in the last ten years, a considerable amount of empirical research has been done in the area of reverse logistics and CLSCs. A comprehensive survey of the field is provided by Vahdani *et al*. (2012b). We now provide a brief review of the literature that is relevant to the focus of the present paper. Listes (2007) developed a generic two-stage stochastic programming model for the design of CLSC networks and utilized a decomposition based approach to solve the problem. Du and Evans (2008) presented a bi-objective optimization problem that minimizes overall costs and total tardiness of a reverse logistic network for repair services. Outputs of the model are facility capacity arrangements, the flow of defect, and repaired products between the customers and the service facilities. Pati *et al*. (2008) proposed a mixed-integer goal programming model to determine the facility location, channel and flow of different varieties of recyclable wastepaper CLSC network. They investigated the maximization of product quality improvement and environmental benefits as well as the minimization of reverse logistics costs.

Pishvaee and Torabi (2010) investigated a bi-objective possibilistic optimization model in order to minimize the total cost of CLSC and the total tardiness of delivered products in a CLSC network design. Franca *et al*. (2010) also developed a bi-objective model under uncertainty in order to maximize the profit and minimize the total number of defective raw material parts. Vahdani *et al*. (2012a) proposed a bi-objective interval fuzzy possibilistic chance-constraint mixed integer linear programming model for designing a reliable network of facilities in the CLSC under uncertainty. Similarly, Vahdani *et al*. (2012c) presented a fuzzy multi-objective robust optimization model to configure a reliable CLSC network. Ramezani *et al*. (2013) developed a multi-objective mathematical programming model under uncertainty for CLSC network design, in which maximization of the profit and responsiveness as well as minimization of defective parts from suppliers are the three objective functions.

With regard to the matters enumerated, the aim of this study is to introduce a mathematical programming model for designing a logistics network of facilities under uncertainty. To make the model more applicable, the developed model incorporates both environmental and system uncertainties (Ho, 1989). Furthermore, we develop a solution approach for a better inclusion of dynamic aspects and multiple uncertainties in order to incorporate inexact programming, fuzzy programming and stochastic programming into the mathematical optimization model.

The main innovations in this paper (to differentiate our efforts from those already published on the subject) are as follows:

- Designing a new logistics model for facility location in the steel scrap recycling network to integrate strategic and tactical decisions in the supply chain.
- Addressing a conventional network structure which supports the cooperation collection, recycling, transfer and disposal processes; therefore, it can be applied to various industrial fields.
- Considering multi-suppliers with different requirements to approximate the current industrial practice. This issue gives rise to having various routes for waste collection.
- Consideration of the constraints of capacity of bidirectional facilities and disposal centers in the model.
- Proposing a mathematical programming model under uncertainty which handles different sources of uncertainties by jointly considering the unavailability or incompleteness and imprecise nature of data.
- Proposing a hybrid solution approach by combining a number of efficient solution methods from the recent literature, namely inexact programming, fuzzy programming and stochastic programming to solve the proposed mathematical programming model.

The rest of the paper is organized as follows. Problem definition and formulation are described in Section 2 in detail. The proposed hybrid solution methodology is given in Section 3. Computational experiments are provided in Section 4. Finally, the paper is concluded in Section 5.

2. Problem Description and the Proposed Model

In this study, a CLSC network is investigated that is concerned with the iron and steel industry. The structure of the CLSC network is depicted in Figure 1. In this problem setting, we generalize capacitated remanufacturing network design problem settings by deciding on the locations of the forward and reverse channel facilities, i.e., we determine the optimal locations of the manufacturing/ remanufacturing facilities, distribution centers, collection centers and disposal centers. This setting is applicable to a company that wishes to establish a new CLSC network for managing multiple types of products. Under this setting, we coordinate the forward and reverse flows using capacitated bidirectional facilities and product-specific hybrid metal manufacturing facilities, which lead to a common infrastructure for managing the forward and reverse flows.

We note that the capacities at the bidirectional facilities represent aggregate capacities that can be shared by all products. Thus, for the purpose of incorporating the non-uniformity in the capacity usage, as before, we utilize product-specific coefficients as modifiers to one capacity use unit. Moreover, we do not consider any capacity limitation on the candidate hybrid metal manufacturing facilities. It is worthwhile to note that the inclusion of capacities in bidirectional facilities induces a stronger relation among the forward and reverse flows associated with different types of products. In the CLSC setting, we are interested in determining the best locations of the hybrid metal manufacturing facilities, bidirectional facilities and the disposal centers with respect to the known customer zone locations and the best flow of products in the CLSC network such that the total cost of location, processing and transportation is minimized.

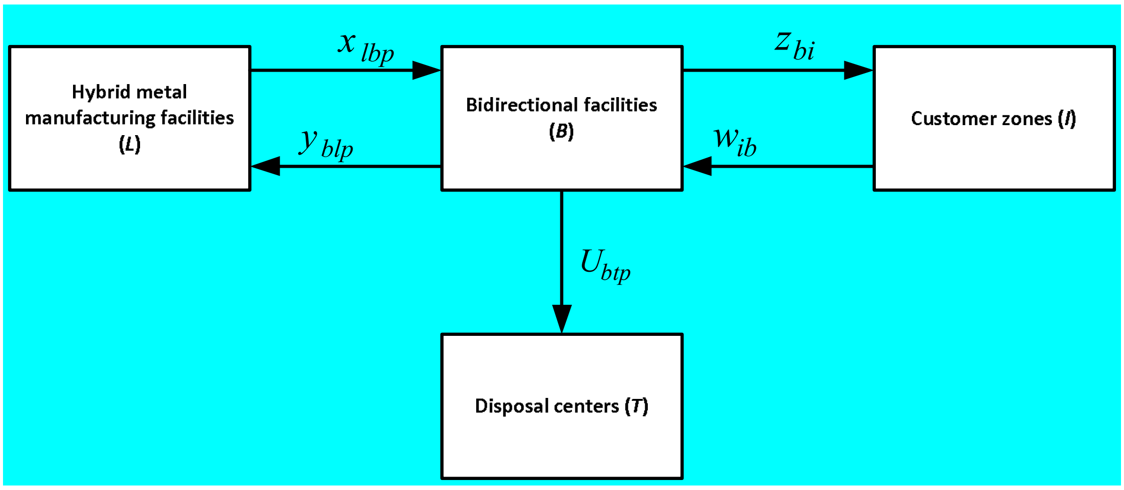

Fig. 1. The underlying structure of the CLSC network

2.1. Assumptions

- The locations of the customer zones are predetermined.
- The locations of the hybrid metal manufacturing facilities, bidirectional facilities and disposal centers are undefined.
- Capacities of the bidirectional facilities and disposal centers are limited.
- On account of the fact that accessibility to reliable and sufficient historical data are scantily possible and also because of the some parameters with uncertain natures, appropriate approaches are utilized to model the lack of knowledge regarding certain ill-known parameters.
- Multiple types of steel scraps are moved through the network.
- In the proposed model, shortages are not permissible and the supply capacity of the selected supplier is unlimited.

2.2. Sets and indices

P: The number of products ($p = 1,2,\dots,P$)
L: The number of candidate hybrid metal manufacturing facilities ($l = 1,2,\dots,L$)
I: The number of customer zones ($i = 1,2,\dots,I$)
T: The number of potential disposal centers ($t = 1,2,\dots,T$)
B: The number of candidate bidirectional facilities ($b = 1,2,\dots,B$)
Ω: Set of potential scenarios ($\theta \in \Omega$)

2.3. Parameters

${F_b}^{\pm}$: The fixed cost of opening a bidirectional facility at location b
${F'_{tp}}^{\pm}$: The fixed cost of opening a disposal center for product p at location t
${F''_{lp}}^{\pm}$: The fixed cost of opening a hybrid metal manufacturing facility for product p at location l
${C_{aq\theta}}^{\pm}$: The unit transportation cost from a location a to a location q for $a, q \in L, I, T, B$ in scenario θ
${\gamma_p}^{\pm}$: Storage capacity coefficient at the bidirectional facility for distribution processing for product p
${\gamma'_p}^{\pm}$: Storage capacity coefficient at the bidirectional facility for collection processing for product p
${\eta_{bp\theta}}^{\pm}$: The unit distribution processing cost of product p at bidirectional facility b in scenario θ
${\eta'_{tp\theta}}^{\pm}$: The unit obliterate cost of product p at disposal center t in scenario θ
${\rho_{bp\theta}}^{\pm}$: The unit collection processing cost of product p at bidirectional facility b in scenario θ
${\varepsilon_{lp\theta}}^{\pm}$: The unit manufacturing cost of product p shipped out at hybrid metal manufacturing facility l in scenario θ
${DE_{ip\theta}}^{\pm}$: Demand of customer zone i for product p in scenario θ
${\delta_{ip\theta}}^{\pm}$: Return fraction at customer zone i for product p in scenario θ
${\beta_{lp\theta}}^{\pm}$: The unit remanufacturing cost of product p shipped out hybrid metal manufacturing facility l in scenario θ

$\alpha_{lp\theta}{}^{\pm}$: Recovery fraction for product p at hybrid metal manufacturing facility l in scenarioθ

$CAP_{b\theta}{}^{\pm}$: Storage capacity at bidirectional facility b in scenarioθ

$CAP'_{tp\theta}{}^{\pm}$: Storage capacity for disposal product p at disposal center t in scenarioθ

$\xi_{pi\theta}{}^{\pm}$: The recycling rate of product p return of customer zone i in scenarioθ

π_{θ}: Probability of scenario θ

2.4. Decision variables

$$V_b{}^{\pm} = \begin{cases} 1; \text{if bidirectional facility } b \text{ is open} \\ 0; \text{otherwise} \end{cases}$$

$$s_{lp}{}^{\pm} = \begin{cases} 1; \text{if hybrid metal manufacturing facility } l \text{ is used for product } p \\ 0; \text{otherwise} \end{cases}$$

$$f_{tp}{}^{\pm} = \begin{cases} 1; \text{if disposal center } t \text{ is used for product } p \\ 0; \text{otherwise} \end{cases}$$

$$z_{bi}{}^{\pm} = \begin{cases} 1;\text{if customer zone i is assigned to bidirectional facility b for the reverse flow of product} \\ 0;\text{otherwise} \end{cases}$$

$$w_{ib}{}^{\pm} = \begin{cases} 1; \text{if customer zone } i \text{ is assigned to bidirectional facility } b \text{ for the forward flow of product} \\ 0; \text{otherwise} \end{cases}$$

$y_{blp\theta}{}^{\pm}$: The total quantity of product p transported from bidirectional facility b to hybrid metal manufacturing facility l in scenarioθ

$x_{lbp\theta}{}^{\pm}$: The total quantity of new and remanufactured product p transported from hybrid metal manufacturing facility l to bidirectional facility b in scenarioθ

$U_{btp\theta}{}^{\pm}$: The total quantity of waste product p transported from bidirectional facility b to disposal center t in scenarioθ

2.5. Model

$$\min z^{\pm} \cong \sum_{b=1}^{B} F_b{}^{\pm} V_b{}^{\pm} + \sum_{p=1}^{P}\sum_{t=1}^{T} F'_{tp}{}^{\pm} f_{tp}{}^{\pm} + \sum_{p=1}^{P}\sum_{l=1}^{L} F''_{lp}{}^{\pm} s_{lp}{}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{i=1}^{I} \pi_\theta (\rho_{bp\theta}{}^{\pm} + C_{ib\theta}{}^{\pm})\delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} w_{ib}{}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{l=1}^{L} \pi_\theta (\alpha_{lp\theta}{}^{\pm}\beta_{lp\theta}{}^{\pm} + C_{bl\theta}{}^{\pm}) y_{blp\theta}{}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{b=1}^{B} \pi_\theta \varepsilon_{lp\theta}{}^{\pm}(x_{lbp\theta}{}^{\pm} - \alpha_{lp\theta}{}^{\pm} y_{blp\theta}{}^{\pm}) + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{b=1}^{B} \pi_\theta C_{lb\theta}{}^{\pm} x_{lbp\theta}{}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{i=1}^{I} \pi_\theta (\eta_{bp\theta}{}^{\pm} + C_{bi\theta}{}^{\pm}) DE_{ip\theta}{}^{\pm} z_{bi}{}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{t=1}^{T} \pi_\theta (\eta'_{tp\theta}{}^{\pm} + C_{bt\theta}{}^{\pm}) U_{btp\theta}{}^{\pm} \quad (1)$$

S. t.:

$$\sum_{b=1}^{B} w_{ib}{}^{\pm} = 1 \quad \forall i \in (1,2,\dots,I) \quad (2)$$

$$\sum_{b=1}^{B} z_{bi}{}^{\pm} = 1 \quad \forall i \in (1,2,\dots,I) \quad (3)$$

$$\sum_{t=1}^{T} f_{tp}{}^{\pm} = 1 \quad \forall p \in (1,2,\dots,P) \quad (4)$$

$$\sum_{l=1}^{L} s_{lp}{}^{\pm} = 1 \quad \forall p \in (1,2,\dots,P) \quad (5)$$

$$\sum_{l=1}^{L} y_{blp\theta}{}^{\pm} = \sum_{i=1}^{I} \xi_{pi\theta}{}^{\pm} \delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} w_{ib}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \quad (6)$$

$$\sum_{t=1}^{T} U_{btp\theta}{}^{\pm} = \sum_{i=1}^{I} (1 - \xi_{pi\theta}{}^{\pm}) \delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} w_{ib}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \quad (7)$$

$$\sum_{b=1}^{B} y_{blp\theta}{}^{\pm} = \sum_{i=1}^{I} \xi_{pi\theta}{}^{\pm} \delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} s_{lp}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \theta \in \Omega \quad (8)$$

$$\sum_{b=1}^{B} U_{btp\theta}{}^{\pm} = \sum_{i=1}^{I} (1 - \xi_{pi\theta}{}^{\pm}) \delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} f_{tp}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \theta \in \Omega \quad (9)$$

$$\sum_{b=1}^{B} x_{lbp\theta}{}^{\pm} = \sum_{i=1}^{I} DE_{ip\theta}{}^{\pm} s_{lp}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \theta \in \Omega \quad (10)$$

$$\sum_{l=1}^{L} x_{lbp\theta}{}^{\pm} = \sum_{i=1}^{I} DE_{ip\theta}{}^{\pm} z_{bi}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \quad (11)$$

$$\sum_{p=1}^{P}\sum_{i=1}^{I} \gamma_p{}^{\pm} DE_{ip\theta}{}^{\pm} z_{bi}{}^{\pm} + \sum_{p=1}^{P}\sum_{i=1}^{I} \gamma'_p{}^{\pm} \delta_{ip\theta}{}^{\pm} DE_{ip\theta}{}^{\pm} w_{ib}{}^{\pm} \lesssim CAP_{b\theta}{}^{\pm} V_b{}^{\pm} \quad \forall b \in (1,2,\dots,B), \theta \in \Omega \quad (12)$$

$$\sum_{b=1}^{B} U_{btp\theta}{}^{\pm} \lesssim CAP'_{tp\theta}{}^{\pm} f_{tp}{}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \theta \in \Omega \quad (13)$$

$$V_b{}^{\pm}, s_{lp}{}^{\pm}, f_{tp}{}^{\pm}, w_{ib}{}^{\pm}, z_{bi}{}^{\pm} \in \{0,1\} \quad \forall b \in (1,2,\dots,B), \forall l \in (1,2,\dots,L), \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \forall i \in (1,2,\dots,I) \quad (14)$$

$$y_{blp\theta}{}^{\pm}, x_{lbp\theta}{}^{\pm}, U_{btp\theta}{}^{\pm} \geq 0 \quad \forall b \in (1,2,\dots,B), \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \forall t \in (1,2,\dots,T), \theta \in \Omega \quad (15)$$

The first three terms in the objective function represent the fixed costs associated with locating the product-specific bidirectional facilities, disposal centers and hybrid metal manufacturing facilities, respectively.

The fourth term shows the transportation costs from the customer zones and collection processing costs at the bidirectional facilities. The fifth term denotes the transportation costs from the bidirectional facilities to the hybrid metal manufacturing facilities, in addition to the remanufacturing costs at the hybrid metal manufacturing facilities. The sixth term represents the total cost of manufacturing the new products. The seventh term shows the transportation costs from the hybrid metal manufacturing facilities to the bidirectional facilities. The eighth term denotes the transportation costs from the bidirectional facilities to the customer zones, in addition to the distribution processing costs at the bidirectional facilities. Finally, the ninth term represents the transportation costs from the bidirectional facilities to the disposal centers, in addition to the obliterate costs at the bidirectional facilities. Constraint set (2) ensures that a customer zone i is assigned to exactly one bidirectional facility for the reverse flow of products. Constraint set (3) ensures that a customer zone i is assigned to exactly one bidirectional facility for the forward flow of products. Constraint set (4) guarantees that, for each product p, a single dedicated disposal center location t is established. Constraint set (5) guarantees that, for each product p, a single dedicated hybrid metal manufacturing facility location l is established. Constraint sets (6)–(11) represent the flow conservation for each product type at the hybrid metal manufacturing facilities, bidirectional facilities, customer zones and disposal centers. Constraint set (12) ensures that the total forward and reverse shipment at any bidirectional facilities does not exceed its aggregate processing capacity. Constraint set (13) enforces the capacity restrictions at the disposal centers. Constraint sets (14) and (15) are the restrictions on the decision variables.

3. Methodology

3.1. Inexact-fuzzy linear programming

Consider an inexact-fuzzy linear programming model as follows (Huang *et al.* 1993):

$$\min Z \cong C^{\pm}X^{\pm} \tag{16}$$

$S.t.$:

$$A^{\pm}X^{\pm} \lesssim B^{\pm} \tag{17}$$

$$X^{\pm} \geq 0 \tag{18}$$

Where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $B^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$, $\{R^{\pm}\}$ denotes a set of interval numbers, $X^{\pm}$ represents a set of decision variables; the $(-)$ and $(+)$ superscripts denote the lower and upper bounds of parameters or decision variables; and symbols $\cong$ and $\lesssim$ represent fuzzy equality and inequality, respectively. In fact, a decision in a fuzzy environment can be defined as the intersection of membership functions equivalent to fuzzy objective and constraints (Chang *et al.* 1997; Li *et al.* 2009; Li *et al.* 2010). Set a fuzzy goal (G) and a fuzzy constraint (E) in a space of decision alternatives, a fuzzy decision set (D) can then be formed in the intersection of G and E. Hence, we have $D = G \cap E$, and correspondingly:

$$\mu_D = min\{\mu_G, \mu_E\} \tag{19}$$

where μ_D, μ_G and μ_E denote membership functions of the fuzzy decision, fuzzy goal and fuzzy constraint, respectively (Zimmermann, 1985). Let $\mu_{E_i}(X^{\pm})$; $(i = 1,2,\dots,m)$ be the membership functions of constraints and $\mu_{G_j}(X^{\pm}); (j = 1,2,\dots,n)$ be those of goals. A decision can then be defined by the following membership function (Huang *et al.* 2001; Li *et al.* 2009; Li *et al.* 2010):

$$\mu_D(X^{\pm}) = \mu_{E_i}(X^{\pm}) * \mu_{G_j}(X^{\pm}) \tag{20}$$

$$\mu_D(X^{\pm}) = \min_i\{\mu_i(X^{\pm})\} \tag{21}$$

where $(*)$ denotes a possibly context-dependent aggregator, and $\mu_i(X^{\pm})$ can be interpreted as the degree to which $X^{\pm}$ satisfies fuzzy inequality in the objective and constraints. A desired decision is thus the one with the highest $\mu_D(X^{\pm})$ value (Li *et al.* 2010):

$$\max \mu_D(X^{\pm}) = \max\min \mu_i(X^{\pm}),\ \ X^{\pm} \geq 0 \tag{22}$$

where $\mu_i(X^{\pm})$ should be zero if the objective and constraints are violated; and 1 if they are totally satisfied. Consequently, the inexact fuzzy linear problem can be converted into a common linear programming model by introducing a new variable of $\lambda = \mu_D(X^{\pm})$ which corresponds to the membership function of the fuzzy decision (Zimmermann, 1985; Chang *et al.* 1997; Huang *et al.* 2001; Li *et al.* 2009; Li *et al.* 2010). Thus, model (16-18) can be converted into:

$$\max \lambda^{\pm} \tag{23}$$

$S.t.$:

$$C^{\pm}X^{\pm} \leq Z^{+} - \lambda^{\pm}(Z^{+} - Z^{-}) \tag{24}$$

$$A^{\pm}X^{\pm} \leq B^{+} - \lambda^{\pm}(B^{+} - B^{-}) \tag{25}$$

$$X^{\pm} \geq 0 \tag{26}$$

$$0 \leq \lambda^{\pm} \leq 1 \tag{27}$$

where Z^{-} and Z^{+} are the lower and upper bounds of the objective's aspiration level, respectively, and $\lambda^{\pm}$ is the control variable equivalent to the degree of satisfaction for the fuzzy decision. Huang *et al.* (1995) developed an interactive two-step algorithm to solve the above problem. The sub-model for λ^{+} equivalent to Z^{-} can be formulated in the first step when the system objective is to be minimized; the other sub-model for λ^{-} can then be formulated based on the solution of the first sub-model.

3.2. Multistage-stochastic programming

In several problems, uncertainties may be expressed as random variables. Thu,s the relevant decisions must be made at each time stage under varying probability levels. Such a problem can be formulated as a scenario-based multistage stochastic programming model as follows (Li *et al.* 2009; Li *et al.* 2010):

$$\min Z = \sum_{s=1}^{S} C_s X_s + \sum_{s=1}^{S} \sum_{t=1}^{T_s} P_{st} L_{st} Y_{st} \quad (28)$$

$S.t.$:

$$A_{hs} X_s \leq B_{hs}, \quad h = 1,2,\dots,m_1; s = 1,2,\dots,S \quad (29)$$

$$A_{ks} X_s + \acute{A}_{kst} Y_{st} \leq D_{kst}, \quad k = 1,2,\dots,m_2; s = 1,2,\dots,S; t = 1,2,\dots,T_s \quad (30)$$

$$X_s \geq 0, \ s = 1,2,\dots,S \quad (31)$$

$$Y_{st} \geq 0, s = 1,2,\dots,S; t = 1,2,\dots,T_s \quad (32)$$

where P_{st} is the probability of occurrence in scenario$t$ in period s, with $P_{st} \leq 1$ and $\sum_{t=1}^{T_s} P_{st} = 1$; and T_s is the number of scenarios in period s, with the total number of scenarios being $T = \sum_{s=1}^{S} T_s$.

3.3. Interval-fuzzy multistage linear programming

One of the approaches that can deal with multiple uncertainties presented in terms of fuzzy sets, inexact values, and random variables is an interval-fuzzy multistage linear programming mode which is as follows (Li *et al.* 2008c; Li *et al.* 2009; Li *et al.* 2010):

$$\max \lambda^{\pm} \quad (33)$$

$S.t.$:

$$\sum_{s=1}^{S} C_s^{\pm} X_s^{\pm} + \sum_{s=1}^{S} \sum_{t=1}^{T_s} P_{st} L_{st}^{\pm} Y_{st}^{\pm} \leq Z^+ - \lambda^{\pm}(Z^+ - Z^-) \quad (34)$$

$$A_{hs}^{\pm} X_s^{\pm} \leq B_{hs}^{+} - \lambda^{\pm}(B_{hs}^{+} - B_{hs}^{-}), \quad h = 1,2,\dots,m_1; s = 1,2,\dots,S \quad (35)$$

$$A_{ks}^{\pm} X_s^{\pm} + \acute{A}_{kst}^{\pm} Y_{st}^{\pm} \leq D_{kst}^{+} - \lambda^{\pm} \nabla D_{kst}^{\pm}, \quad k = 1,2,\dots,m_2; s = 1,2,\dots,S; t = 1,2,\dots,T_s \quad (36)$$

$$X_s^{\pm} \geq 0, \ s = 1,2,\dots,S \quad (37)$$

$$Y_{st}^{\pm} \geq 0, s = 1,2,\dots,S; t = 1,2,\dots,T_s \quad (38)$$

$$0 \leq \lambda^{\pm} \leq 1 \quad (39)$$

In model (7), a $\lambda^{\pm}$ level close to 1 would correspond to a high possibility of satisfying the objective under advantageous conditions; conversely, a $\lambda^{\pm}$ value near 0 would be related to a solution that has a low possibility of satisfying the objective under demanding conditions. A two-stage method is proposed for solving the interval-fuzzy-stochastic programming model. The sub-model for λ^{+}corresponding to Z^- can be formulated in the first step when the system objective is to be minimized; the other sub-model (Z^-) can then be formulated based on the solution of the first sub-model. Thus, the first sub-model is formulated as follows (Qin *et al.* 2007; Li *et al.* 2008c; Li *et al.* 2010):

$$\max \lambda^{+} \quad (40)$$

S.t.:

$$\sum_{s=1}^{S}\left(\sum_{j=1}^{j_1} c_{js}^{-} x_{js}^{-} + \sum_{j=j_1+1}^{n_1} c_{js}^{-} x_{js}^{+}\right) + \sum_{s=1}^{S} \sum_{t=1}^{T_s} P_{st}\left(\sum_{j=1}^{j_2} l_{st}^{-} y_{st}^{-} + \sum_{j=j_2+1}^{n_2} l_{st}^{-} y_{st}^{+}\right) \leq Z^+ - \lambda^{+}(Z^+ - Z^-) \quad (41)$$

$$\sum_{j=1}^{j_1} |a_{hsj}|^{+} Sign(a_{hsj}^{+})\, x_{js}^{-} + \sum_{j=j_1+1}^{n_1} |a_{hsj}|^{-} Sign(a_{hsj}^{-})\, x_{js}^{+} \leq B_{hs}^{+} - \lambda^{+}(B_{hs}^{+} - B_{hs}^{-}), \quad h = 1,2,\dots,m_1; s = 1,2,\dots,S \quad (42)$$

$$\sum_{j=1}^{j_1} |a_{ksj}|^{+} Sign(a_{ksj}^{+})\, x_{js}^{-} + \sum_{j=j_1+1}^{n_1} |a_{ksj}|^{-} Sign(a_{ksj}^{-})\, x_{js}^{+} + \sum_{j=1}^{j_2} |\acute{a}_{kstj}|^{+} Sign(\acute{a}_{kstj}^{+})\, y_{stj}^{-} + \sum_{j=j_2+1}^{n_2} |\acute{a}_{kstj}|^{-} Sign(\acute{a}_{kstj}^{-})\, y_{stj}^{+} \leq D_{kst}^{+} - \lambda^{+}(D_{kst}^{+} - D_{kst}^{-}), \quad k = 1,2,\dots,m_2; s = 1,2,\dots,S; t = 1,2,\dots,T_s \quad (43)$$

$$x_{js}^{-} \geq 0, \ j = 1,2,\dots,j_1, s = 1,2,\dots,S \quad (44)$$

$$x_{js}^{+} \geq 0, \ j = j_1+1, j_1+2,\dots,n_1, s = 1,2,\dots,S \quad (45)$$

$$y_{stj}^{-}, j = 1,2,\dots,j_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s \quad (46)$$

$$y_{stj}^{-}, j = j_2+1, j_2+2,\dots,n_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s \quad (47)$$

$$0 \leq \lambda^{+} \leq 1 \quad (48)$$

where $x_{js}^{\pm}(j = 1,2,\dots,j_1)$ are the first-stage decision variables with positive coefficients in the objective function, and $x_{js}^{\pm}(j = j_1+1, j_1+2,\dots,n_1)$ with negative coefficients; $y_{stj}^{\pm}(j = 1,2,\dots,j_2, t = 1,2,\dots,T_s)$ are the second-stage decision variables with positive coefficients in the objective function, and $y_{stj}^{\pm}(j = j_2+1, j_2+2,\dots,n_2, t = 1,2,\dots,T_s)$ with negative coefficients. Solutions to $x_{jsopt}^{-}(j = 1,2,\dots,j_1), x_{jsopt}^{+}(j = j_1+1, j_1+2,\dots,n_1)$, $y_{stjopt}^{-}(j = 1,2,\dots,j_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s), y_{stjopt}^{+}(j = j_2+1, j_2+2,\dots,n_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s)$ and λ_{opt}^{+} can be obtained from the above sub-model. Based on the above solutions, the second sub-model for λ^{-} (corresponding to Z^+) can be formulated as follows (Qin *et al.* 2007; Li *et al.* 2008c, 2010):

$$\max \lambda^{-} \quad (49)$$

S.t.:

$$\sum_{s=1}^{S}\left(\sum_{j=1}^{j_1} c_{js}^{+} x_{js}^{+} + \sum_{j=j_1+1}^{n_1} c_{js}^{+} x_{js}^{-}\right) + \sum_{s=1}^{S} \sum_{t=1}^{T_s} P_{st}\left(\sum_{j=1}^{j_2} l_{st}^{+} y_{st}^{+} + \sum_{j=j_2+1}^{n_2} l_{st}^{+} y_{st}^{-}\right) \leq Z^+ - \lambda^{-}(Z^+ - Z^-) \quad (50)$$

$$\sum_{j=1}^{j_1} \left|a_{hsj}\right|^{-} Sign\left(a_{hsj}^{-}\right) x_{js}^{+} + \sum_{j=j_1+1}^{n_1} \left|a_{hsj}\right|^{+} Sign\left(a_{hsj}^{+}\right) x_{js}^{-} \le B_{hs}^{+} - \lambda^{-}\left(B_{hs}^{+} - B_{hs}^{-}\right), \quad h = 1,2,\dots,m_1; s = 1,2,\dots,S \qquad (51)$$

$$\sum_{j=1}^{j_1} \left|a_{ksj}\right|^{-} Sign\left(a_{ksj}^{-}\right) x_{js}^{+} + \sum_{j=j_1+1}^{n_1} \left|a_{ksj}\right|^{+} Sign\left(a_{ksj}^{+}\right) x_{js}^{-} + \sum_{j=1}^{j_2} \left|á_{kstj}\right|^{-} Sign\left(á_{kstj}^{-}\right) y_{stj}^{+} + \sum_{j=j_2+1}^{n_2} \left|á_{kstj}\right|^{+} Sign\left(á_{kstj}^{+}\right) y_{stj}^{-} \le D_{kst}^{+} - \lambda^{-}\left(D_{kst}^{+} - D_{kst}^{-}\right), \quad k = 1,2,\dots,m_2; s = 1,2,\dots,S; t = 1,2,\dots,T_s \qquad (52)$$

$$x_{js}^{+} \ge x_{jsopt}^{-}, j = 1,2,\dots,j_1, s = 1,2,\dots,S \qquad (53)$$

$$0 \le x_{js}^{-} \le x_{jsopt}^{+}, j = j_1+1, j_1+2,\dots,n_1, s = 1,2,\dots,S \qquad (54)$$

$$y_{stj}^{+} \ge y_{stjopt}^{-}, j = 1,2,\dots,j_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s \qquad (55)$$

$$0 \le y_{stj}^{-} \le y_{stjopt}^{+}, j = j_2+1, j_2+2,\dots,n_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s \qquad (56)$$

$$0 \le \lambda^{-} \le 1 \qquad (57)$$

Solutions to $x_{jsopt}^{+}(j = 1,2,\dots,j_1), x_{jsopt}^{-}(j = j_1 + 1, j_1 + 2,\dots,n_1)$, $y_{stjopt}^{+}(j = 1,2,\dots,j_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s), y_{stjopt}^{-}(j = j_2 + 1, j_2 + 2,\dots,n_2, s = 1,2,\dots,S, t = 1,2,\dots,T_s)$ and λ_{opt}^{-} can be obtained from the above sub-model. Therefore, combining the solutions of sub-models (40-48) and (49-57), the solution for the inexact fuzzy-stochastic programming model can be obtained as follows:

$$x_{jsopt}^{\pm} = \left[x_{jsopt}^{-}, x_{jsopt}^{+}\right], \forall j, s \qquad (58)$$

$$y_{stjopt}^{\pm} = \left[y_{stjopt}^{-}, y_{stjopt}^{+}\right], \forall j, s, t \qquad (59)$$

$$\lambda_{opt}^{\pm} = \left[\lambda_{opt}^{-}, \lambda_{opt}^{+}\right] \qquad (60)$$

$$Z_{opt}^{\pm} = \left[Z_{opt}^{-}, Z_{opt}^{+}\right] \qquad (61)$$

Based on the above-mentioned description, an interval-fuzzy-stochastic logistics model can be formulated as follows:

$$\max \lambda^{\pm} \qquad (62)$$

S.t.:

$$\sum_{b=1}^{B} F_b^{\pm} V_b^{\pm} + \sum_{p=1}^{P}\sum_{t=1}^{T} F_{tp}'^{\pm} f_{tp}^{\pm} + \sum_{p=1}^{P}\sum_{l=1}^{L} F_{lp}''^{\pm} s_{lp}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{i=1}^{I} \pi_\theta\left(\rho_{bp\theta}^{\pm} + C_{ib\theta}^{\pm}\right)\delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} w_{ib}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{l=1}^{L} \pi_\theta\left(\alpha_{lp\theta}^{\pm}\beta_{lp\theta}^{\pm} + C_{bl\theta}^{\pm}\right) y_{blp\theta}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{b=1}^{B} \pi_\theta \varepsilon_{lp\theta}^{\pm}\left(x_{lbp\theta}^{\pm} - \alpha_{lp\theta}^{\pm} y_{blp\theta}^{\pm}\right) + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{b=1}^{B} \pi_\theta C_{lb\theta}^{\pm} x_{lbp\theta}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{i=1}^{I} \pi_\theta\left(\eta_{bp\theta}^{\pm} + C_{bi\theta}^{\pm}\right) DE_{ip\theta}^{\pm} z_{bi}^{\pm} + \sum_{\theta\in\Omega}\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{t=1}^{T} \pi_\theta\left(\eta_{tp\theta}'^{\pm} + C_{bt\theta}^{\pm}\right) U_{btp\theta}^{\pm} \le Z^{+} - \lambda^{\pm}\left(Z^{+} - Z^{-}\right) \qquad (63)$$

$$\sum_{b=1}^{B} w_{ib}^{\pm} = 1 \quad \forall i \in (1,2,\dots,I) \qquad (64)$$

$$\sum_{b=1}^{B} z_{bi}^{\pm} = 1 \quad \forall i \in (1,2,\dots,I) \qquad (65)$$

$$\sum_{t=1}^{T} f_{tp}^{\pm} = 1 \quad \forall p \in (1,2,\dots,P) \qquad (66)$$

$$\sum_{l=1}^{L} s_{lp}^{\pm} = 1 \quad \forall p \in (1,2,\dots,P) \qquad (67)$$

$$\sum_{l=1}^{L} y_{blp\theta}^{\pm} = \sum_{i=1}^{I} \xi_{pi\theta}^{\pm}\, \delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} w_{ib}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \qquad (68)$$

$$\sum_{t=1}^{T} U_{btp\theta}^{\pm} = \sum_{i=1}^{I}\left(1 - \xi_{pi\theta}^{\pm}\right) \delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} w_{ib}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \qquad (69)$$

$$\sum_{b=1}^{B} y_{blp\theta}^{\pm} = \sum_{i=1}^{I} \xi_{pi\theta}^{\pm}\, \delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} s_{lp}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \theta \in \Omega \qquad (70)$$

$$\sum_{b=1}^{B} U_{btp\theta}^{\pm} = \sum_{i=1}^{I}\left(1 - \xi_{pi\theta}^{\pm}\right) \delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} f_{tp}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \theta \in \Omega \qquad (71)$$

$$\sum_{b=1}^{B} x_{lbp\theta}^{\pm} = \sum_{i=1}^{I} DE_{ip\theta}^{\pm} s_{lp}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \theta \in \Omega \qquad (72)$$

$$\sum_{l=1}^{L} x_{lbp\theta}^{\pm} = \sum_{i=1}^{I} DE_{ip\theta}^{\pm} z_{bi}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall b \in (1,2,\dots,B), \theta \in \Omega \qquad (73)$$

$$\sum_{p=1}^{P}\sum_{i=1}^{I} \gamma_p^{\pm} DE_{ip\theta}^{\pm} z_{bi}^{\pm} + \sum_{p=1}^{P}\sum_{i=1}^{I} \gamma_p'^{\pm} \delta_{ip\theta}^{\pm} DE_{ip\theta}^{\pm} w_{ib}^{\pm} \le \left[CAP_{b\theta}^{+} - \lambda^{\pm}\left(CAP_{b\theta}^{+} - CAP_{b\theta}^{-}\right)\right] V_b^{\pm} \quad \forall b \in (1,2,\dots,B), \theta \in \Omega \qquad (74)$$

$$\sum_{b=1}^{B} U_{btp\theta}^{\pm} \le \left[CAP_{tp\theta}'^{+} - \lambda^{\pm}\left(CAP_{tp\theta}'^{+} - CAP_{tp\theta}'^{-}\right)\right] f_{tp}^{\pm} \quad \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \theta \in \Omega \qquad (75)$$

$$V_b^{\pm}, s_{lp}^{\pm}, f_{tp}^{\pm}, w_{ib}^{\pm}, z_{bi}^{\pm} \in \{0,1\} \quad \forall b \in (1,2,\dots,B), \forall l \in (1,2,\dots,L), \forall p \in (1,2,\dots,P), \forall t \in (1,2,\dots,T), \forall i \in (1,2,\dots,I) \qquad (76)$$

$$y_{blp\theta}^{\pm}, x_{lbp\theta}^{\pm}, U_{btp\theta}^{\pm} \ge 0 \quad \forall b \in (1,2,\dots,B), \forall p \in (1,2,\dots,P), \forall l \in (1,2,\dots,L), \forall t \in (1,2,\dots,T), \theta \in \Omega \qquad (77)$$

The Z^{+} and Z^{-} are the lower and upper bounds of the objective function values obtained from a corresponding interval-stochastic integer programming model (Li *et al.* 2008a,b; Li and Chen, 2011; Wang et al., 2012). Hence, the inexact-fuzzy-stochastic programming model can be converted into two deterministic sub-models. Interval solutions can then be obtained by solving the two sub-models sequentially. The detailed solution process can be summarized as follows:

Step 1: Identify all uncertain variables and acquire the related distribution functions.

Step 2: Formulate a specific inexact-fuzzy-stochastic programming model.

Step 3: Transform the developed model in step 2 into two sub-models, where Z^{-} is desired since the objective is to minimize $Z^{\pm}$; formulate the first sub-model which corresponds to Z^{-}.

Step 4: Solve the Z^- sub-model and obtain the solutions for $\lambda^+_{opt}, Z^-_{opt}, V_b{}^-, s_{lp}{}^-, f_{tp}{}^-, w_{ib}{}^-, z_{bi}{}^-, y_{blp\theta}{}^-, x_{lbp\theta}{}^-, U_{btp\theta}{}^-$

Step 5: Formulate the second sub-model which corresponds to Z^+.

The objective is to minimize $Z^{\pm}$; formulate the first sub-model which corresponds to Z^-.

Step 6: Solve the Z^+ sub-model and obtain the solutions for $\lambda^-_{opt}, Z^+_{opt}, V_b{}^+, s_{lp}{}^+, f_{tp}{}^+, w_{ib}{}^+, z_{bi}{}^+, y_{blp\theta}{}^+, x_{lbp\theta}{}^+, U_{btp\theta}{}^+$.***Step 7:*** Combine the two sub-models' solutions to obtain the solution of model.

4. Computational Experiments

To illustrate the validity of the proposed model and the usefulness of the solution methodology, several numerical experiments are implemented and the related results are reported in this section. To this end, three test problems are designed and their sizes are shown in Table 1. Moreover, in each size of these problems three scenarios are considered. Depending on the characteristics and the quality of available data, it is assumed that the parameters of these models could be described by either discrete intervals or probability distributions. The detailed uncertain parameters are listed in Table 2. All the mathematical models are coded in the optimization software (i.e. GAMS).

Table 1
Sizes of the test problems

Problem No.	No. of products (P)	No. Hybrid metal manufacturing facilities (L)	No. Potential disposal centers (T)
1	3	3	2
2	5	5	3
3	5	7	8
Problem No.	**No. of customer zones (I)**	**No. Candidate bidirectional facilities(B)**	
1	7	3	
2	10	5	
3	12	8	

The inexact-fuzzy-stochastic mathematical programming model for designing CLSC network is to achieve a maximized satisfaction degree for objective function and constraints under uncertainty.

Table 2
Sources of discrete intervals and random generation values in each scenario

Parameters	Problem 1			Problem 2			Problem 3		
	Scenario 1 (π_1 = 0.5)	Scenario 2 (π_2 = 0.3)	Scenario 3 (π_3 = 0.2)	Scenario 1 (π_1 = 0.5)	Scenario 2 (π_2 = 0.3)	Scenario 3 (π_3 = 0.2)	Scenario 1 (π_1 = 0.5)	Scenario 2 (π_2 = 0.3)	Scenario 3 (π_3 = 0.2)
$F_b{}^{\pm}$	[2000,500]	[2000,500]	[2000,500]	[3500,7000]	[3500, 7000]	[3500, 7000]	[4500, 8000]	[5500, 9000]	[5900, 9600]
$F'_{tp}{}^{\pm}$	[2600,5300]	[2600,5300]	[2600,5300]	[4400, 8300]	[4400, 8300]	[4400, 8300]	[5400, 9300]	[6400, 10300]	[6900, 11300]
$F''_{lp}{}^{\pm}$	[3000,6000]	[3000,6000]	[3000,6000]	[4000,9000]	[4000,9000]	[4000,9000]	[5000,10000]	[5000,11000]	[6000,12000]
$C_{aq\theta}$	[20, 50]	[30, 60]	[40, 70]	[35, 55]	[45, 65]	[50, 75]	[45, 65]	[55, 75]	[75, 95]
$\eta_{bp\theta}$	[40, 60]	[45, 65]	[50, 70]	[50, 75]	[55, 80]	[60, 90]	[60, 85]	[65, 90]	[85, 110]
$\eta'_{tp\theta}$	[50, 80]	[55, 90]	[60, 95]	[65, 100]	[70, 110]	[65, 105]	[75, 200]	[90, 150]	[90, 150]
$\rho_{bp\theta}$	[15, 30]	[18, 35]	[20, 40]	[20, 35]	[30, 40]	[35, 50]	[30, 45]	[60, 70]	[60, 70]
$\varepsilon_{lp\theta}{}^{\pm}$	[25, 40]	[30, 58]	[40, 65]	[50, 75]	[60, 80]	[65, 90]	[60, 85]	[90, 100]	[90, 100]
DE_{ip}	[500,1500]	[600,1700]	[750,1600]	[800,2000]	[850,2100]	[900,2200]	[900,3000]	[1050,2500]	[1350,2800]
$\beta_{lp\theta}$	[15, 30]	[20, 40]	[30, 60]	[30, 75]	[40, 80]	[55, 100]	[40, 85]	[50, 90]	[50, 90]
CAP_l	[1000,3000]	[1100,3100]	[1200,3200]	[1500,3500]	[1450,3600]	[1300,3700]	[2500,4500]	[3450,5600]	[3950,5900]
CAP'_t	[600,1500]	[700,1600]	[650,1750]	[800,1600]	[850,1700]	[900,2000]	[900,2600]	[950,2700]	[950,2700]

The expected objective function (cost) would range from 31.56×10^5 to 43.15×10^5 with the degree of overall satisfaction ($\lambda^{\pm}$) being [0.17, 0.83] for test problem 1 (Table 3). For test problem 2, the expected objective function (cost) would range from 59.07×10^6 to 67.47×10^6 with the degree of overall satisfaction ($\lambda^{\pm}$) being [0.14, 0.79] (Table 3). For test problem 3, the expected objective function (cost) would range from 72.08×10^9 to 79.06×10^9 with the degree of overall satisfaction ($\lambda^{\pm}$) being [0.19, 0.8] (Table 3).The lower objective function value represents an alternative with a lower variety of costs, demands, capacities etc; the higher one corresponds to an alternative with a higher variety of costs, demands, capacities etc.

Table 3
Solution for the objective function and satisfaction degree

Problem	Objective function ($Z^{\pm}$)	Satisfaction degree($\lambda^{\pm}$)
1	$[31.56 \times 10^5, 43.15 \times 10^5]$	[0.17, 0.83]
2	$[59.07 \times 10^6, 67.47 \times 10^6]$	[0.14, 0.79]
3	$[72.08 \times 10^9, 79.06 \times 10^9]$	[0.19, 0.8]

The obtained results reveal that the proposed model has notable efficiency and usefulness for the facility location of CLSC networks. Moreover, these results reiterate that the proposed model is able to constructively capture and include the uncertainties involved in the various parameters of the model comprising of different types of costs, demands, capacities etc. Furthermore, it can be concluded that the proposed solution approach is well suited to solve the inexact-fuzzy-stochastic mathematical programming problem.

5. Conclusions

The objective of this paper was to develop and demonstrate an optimization model that can be utilized as a decision making tool for different members of supply chain for investigating the target values of the objectives they try to achieve. To this end, an inexact-fuzzy-stochastic mathematical programming model is proposed which minimizes the total costs including the fixed costs associated with locating the product-specific bidirectional facilities, disposal centers and hybrid metal manufacturing facilities and transportation costs between various facilities. Furthermore, to cope with the issue of uncertainty in the CLSC network design, since most of the parameters in the problem are presented with an imprecise nature, a solution methodology is developed by combining inexact programming, fuzzy programming and stochastic programming.

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