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An environmental supply chain network under uncertainty

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1. Environmental protection is considered in a closed-loop supply chain network.
2. Two different multi-objective environmental uncertain supply chain models are developed.
3. A quantitative environmental impact assessment method based on LCA is used to evaluate the environment effects.
4. The inverse distribution method is used to transform uncertain models into equivalence crisp models.

An environmental supply chain network under uncertainty

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Abstract

In the present study, a closed-loop supply chain network for production and recovery of button batteries is investigated under uncertainty. The environmental impact of button batteries is taken into account in the design of the supply chain network. Since there are many uncertainties in reality, the demand, cost and capacity are considered uncertain variables. To explore the impact of these uncertainties on the supply chain network, two multi-objective mixed integer programming models under uncertainty are developed, i.e., the expected value model and the chance-constrained model. The aim is to reduce the multiple environment effects on the total cost and weigh the pros and cons. A method based on life cycle assessment is proposed to evaluate the environment effects on the supply chain network. The two models can be converted into crisp models by the uncertainty theory. Lastly, numerical experiments are used to verify the feasibility of the proposed models and method.

Keywords: Environmental protection; Multi-objective; Uncertain environment; Supply chain network; Life cycle assessment.

1 Introduction

An efficient supply chain network is the embodiment of an enterprise's ability, which makes it competitive in today's market. The impact of commercial activities on the environment has led to government legislation and the enhancement of consumer awareness of environmental protection. Therefore, the people and government exert pressure on enterprises to reduce the impact of production and operation on the environment. In recent years, supply chain management with environmental protection has attracted great attention from researchers and scholars owing to these factors. This kind of supply chain incorporates environmental pollution into the design process, from product design to scrap.

Obviously, supply chain network design plays an important role in the environment. For instance, scrapped products have a significant impact on the environment, numerous literature were devoted to the management of these products. Research showed that it is necessary to establish reverse supply chain model. It involves determining the number of required collection, recycling, recycling and disposal centers, their location and capacity, and the material flow. Mathematical models were used to studied this issue. Mutha and Pokharel (2009) developed a mathematical model for the design of a reverse logistics network, and the application of the model is illustrated by a numerical example. Paksoy and Özceylan (2014) considered both economic and environmental performances in a supply chain network, and proposed an environmentally conscious optimization model. Zolfagharinia *et al.* (2014) modeled a two-stock inventory system with backordering option for a reverse supply chain, and designed a simulation-based hybrid variable neighborhood search to solve the model. Giri and Bardhan (2015) studied models under both linear and iso-elastic demand patterns, and used wholesale-price-discount contract to coordinate the chain. Moreover, many literatures have been conducted on the closed-loop supply chain problem. Wang *et al.* (2017) investigated wage contract models in different scenarios, and the results showed that the company benefits from the worker's observable effort under full information. Altmann and Bogaschewsky (2014) proposed a multi-objective closed-loop supply chain model, which supports decision makers to better understand the influence of parameters. Allevi *et al.* (2018) investigated a multitiered closed-loop supply chain network, and used a variational inequality approach to analyze the effects of environmental policies. Rabbani *et al.* (2019) considered a closed-loop supply chain (CLSC) including a manufacturer, a distributor, and third-party logistics provider. To investigate whether a manufacturer should do remanufacturing or sets a fee for technology licensing of distributors and cooperate with them in remanufacturing, three multi-level leader-follower Stackelberg game models were proposed.

The dynamic and uncertain nature of the scrapped product leads to the uncertainty of the supply chain network. Numerous researchers studied supply chain problems in random environments. Based on this hypothesis, probability theory is introduced into the supply chain to cope with the uncertainty. Listes (2013) studied a generic stochastic model for supply-and-return network, and a integer L-shaped method was proposed for the model. Sazvar *et al.* (2014) developed a stochastic centralized supply chain model, and proposed a new replenishment policy for deteriorating items. Modak and Kelle (2019) considered dual-channel supply chain under price and delivery-time dependent stochastic customer demand, and the results suggested that demand uncertainty affect the optimal price and lead time. Fuzzy set theory, first stated by Zadeh (1965), has been widely applied to supply chain Pishvaee and Torabi (2013) proposed a bi-objective possibilistic model for closed-loop supply chain network, and developed an interactive fuzzy solution approach. Ramezani *et al.* (2014) studied a multi-product, multi-period, closed-loop supply chain network, and used a fuzzy optimization approach to convert the fuzzy model into an equivalent crisp model. Badhotiya *et al.* (2019) considered a novel fuzzy multi-objective mixed integer programming model, and used an example inspired from an automobile industry to demonstrate analytical results.

In addition, a part of the literatures studied the influence on the environment of the supply chain, which aims to incorporate environment effects into this issue. A life cycle assessment (LCA) based biofuel supply chain model with 3E criteria was proposed by Liu (2007), and a Pareto-optimal solution surface of this multi-objective problem was obtained. A new energy and carbon LCA model for vehicle energy supply infrastructure was developed by Lucas *et al.* (2013). The results suggested that 37% Normal charging and car/H2 station ratio are close to conventional one. An advanced life cycle assessment was used to analyze environmental impacts on particular food supply chains Goucher *et al.* (2017), and the results suggested that the greenhouse effect of an 800-gram bread during its whole life cycle was equivalent to 0.589 kg of carbon dioxide. Qualitative properties of the dynamic trajectories were obtained under suitable assumptions. A bi-objective programming model for green closed-loop supply chain was proposed by Ghomi-Avili *et al.* (2018), and KKT conditions and the possibilistic method were used to solve the fuzzy model.

As everyone knows, probability distributions are often based on historical data. In a supply chain, the data of these parameters cannot be always exactly determined and known. There are always some reasons why data is not available, such as information unavailable, fluctuating nature of parameters, poor statistical analysis, uncertainty in judgment, etc. However, when statistics are unreliable or unavailable, probability theory is not the best choice. The general possible values of these parameters are provided by the experts at approximate intervals, language terms, etc. For example, the unit transportation cost is “about 50”, the demand of customer is ”about 300”, etc. In such a situation, we have no choice but to invite domain experts to evaluate the belief degree that whether uncertain events will occur.

It is inappropriate to model belief degrees with probability theory, because it may lead to the result of violating intuition. Consider a counterexample. Suppose a vehicle passes 50 bridges. The weight of the vehicle is 90 tons, and the bearing capacity of the bridge obeys the iid uniform distribution [95,110]. Suppose a bridge collapses when its load-bearing capacity is less than the weight of a vehicle. Obviously, the probability that this vehicle will pass 50 bridges is 1. However, when there are no samples of bridge bearing capacity observed at present, we must invite some bridge engineers to assess their belief degrees. As we stated before, because of conservatism, people usually estimate a wider range of values than the actual load-bearing capacity of bridges. Assume that the belief degree function is

$$\Phi(x) = \begin{cases} 0, & \text{if } x < 80 \\ (x-80)/40, & \text{if } 80 \le x \le 120 \\ 1, & \text{if } x > 120 \end{cases}$$

What happens if the belief degree function is considered a probability distribution? Firstly, we must consider the strength of 50 bridges as iid uniform random variable over [80,120] tons. If we let the vehicle cross 50 bridges one by one, then we have

$$\Pr\{\text{"the truck can cross over the 50 bridges" }\} = 0.75^{50} \approx 0$$

As a result, it is almost impossible for the vehicle to cross 50 bridges successfully. Unfortunately, the results are at opposite poles. This example shows that the improper use of probability theory makes the inevitable event impossible.

The uncertainty theory was initiated by Liu (2007) and refined by Liu (2010) to address personal belief degrees rationally. It is a useful tool for solving such problems in uncertain environments. The uncertainty theory is a branch of axiomatic mathematics for modeling human uncertainty, which have many research results such as uncertain programming (Wen *et al.* (2014); Zhang *et al.* (2014); Shen and Zhu (2017, 2018, 2019); Gao *et al.* (2017); Gao and Kar (2017); Gao *et al.* (2018)), uncertain supply chain (Lan *et al.* (2017, 2018); Wang *et al.* (2017); Feng *et al.* (2017)), uncertain risk analysis (Liu and Dan (2017); Zhou *et al.* (2017); Chen *et al.* (2018)), uncertain uncertain calculus (Chen and Ralescu (2013); Yao *et al.* (2014); Chen (2015); Yang *et al.* (2016)), uncertain differential equation (LiuH (2013); Wang (2013); Yao *et al.* (2013)).

The concerned problem in this paper is motivated by a button battery production supply chain network. With the development of social economy, the number of batteries used in production and life has increased dramatically, and the battery has penetrated into every corner of our life and work. However, the battery in daily life is harmful to us unconsciously. Since the pollution of used batteries is very secretive, its harm has not yet been fully recognized by the public. According to the experts' assessment, a small button cell can pollute 600,000 liters of water, which can not be consumed by one person all one's life. Every year, more than 32 billion used batteries worldwide are discarded into the natural environment, and its impact on the environment can be imagined. Even more frightening is that the battery contains three substances that are harmful to the natural environment: mercury, lead, and cadmium. If waste batteries are mixed with domestic waste for landfill, the infiltration of mercury and heavy metals will infiltrate the soil, contaminate groundwater, and then enter fish and crops, destroying environment and indirectly threatening human health. To reduce the environmental impact of waste batteries, there are generally three treatment methods: solidification deep buried, stored in waste mine, recycling. Waste batteries are generally shipped to specialized toxic and hazardous landfills, but this is not only costly but also wasteful, as there are many useful substances that can be used as raw materials. The recovery and reuse of waste batteries mainly adopts fire method, hydrometallurgy process and solid electrolytic reduction technology. Moreover, the plastic casing can be regenerated without secondary pollution to the environment.

In this paper, a closed-loop supply chain network with economic and environmental factors is studied. The aim is to study the effects of uncertainties on supply chain, and to find the optimal solution in the face of multiple objective functions. The demand, cost and capacity are considered uncertain variables. Two practical and tractable multi-objective uncertain programming models are developed for the supply chain network with environmental protection. The economic and environmental objective functions are considered simultaneously. To simulate the effects of different configurations on the environment, a quantitative environmental impact assessment method based on LCA is integrated into the design of closed-loop supply chain. The uncertainty theory is used to characterize the epistemic uncertainty in reality. Under different decision criteria, the expected value model and chance-constrained model are employed to address the problem. The equivalence of the models is discussed base on the inverse distribution method. Furthermore, this paper presents an effective solution method to address the models.

The main innovations of this paper are as follows. (1) The demand, cost and capacity are considered uncertain variables, which differ from that of random variables. In a real supply chain network, it would be more reasonable to regard these factors as uncertain variables. (2) Due to the complexity of the uncertain scenario, the conventional algorithm is no longer applicable, so we use inverse distribution method to transform uncertain models into crisp models. (3) Numerical experiments suggest that the proposed method can effectively solve the optimal solution.

The rest of this study is structured as follows. In Section 2, basic definitions and properties regarding uncertainty theory are introduced. In Section 3, the problem and notations are presented, and two multi-objective uncertain mathematical models are constructed. The equivalence of the models is investigated in Section 4. In Section 5, computational experiments are presented to verify the modeling idea and the effectiveness of the proposed method.

2 Uncertainty theory

To describe an uncertain variable which refers to human uncertainty, Liu (2007) established the uncertainty theory and has been developed well up to now. Some concepts in uncertainty theory will be introduced.

Let Γ be a nonempty set, and let $\mathcal{L}$ be a σ-algebra over Γ. Each element $\Lambda \in \mathcal{L}$ is called an event. A set function $\mathcal{M}$ from $\mathcal{L}$ to $[0,1]$ is called an uncertain measure if it satisfies the normality axiom, duality axiom, subadditivity axiom and product axiom:
Axiom I (normality axiom). $\mathcal{M}\{\Gamma\} = 1$ for the universal set Γ;
Axiom II (duality axiom). $\mathcal{M}\{\Lambda\} + \mathcal{M}\{\Lambda^c\} = 1$ for any event Λ;
Axiom III (subadditivity axiom). $\mathcal{M}\left\{\bigcup_{i=1}^{\infty} \Lambda_i\right\} \leq \sum_{i=1}^{\infty} \mathcal{M}\{\Lambda_i\}$ for every countable sequence of events $\Lambda_1, \Lambda_2, \cdots$.

Besides, the product uncertain measure on the product σ-algebra $\mathcal{L}$ was defined by Liu (2009) as follows: Let $(\Gamma_k, \mathcal{L}_k, \mathcal{M}_k)$ be uncertainty spaces for $k = 1, 2, \cdots$. The product uncertain measure $\mathcal{M}$ is an uncertain measure satisfying $\mathcal{M}\left\{\prod_{i=1}^{\infty} \Lambda_k\right\} = \bigwedge_{i=1}^{\infty} \mathcal{M}_k\{\Lambda_k\}$, where Λ_k are arbitrarily chosen events from $\mathcal{L}_k$ for $k = 1, 2, \cdots$, respectively. (Product axiom)

An uncertain variable is a measurable function ξ from an uncertainty space $(\Gamma, \mathcal{L}, \mathcal{M})$ to the set R of real numbers, i.e., for any Borel set B of real numbers, the set $\{\xi \in B\} = \{\gamma \in \Gamma | \xi(\gamma) \in B\}$ is an event. The uncertain distribution Φ of an uncertain variable ξ is defined by $\Phi(x) = \mathcal{M}\{\xi \leq x\}$ for any real number x. The uncertain variables $\xi_1, \xi_2, \cdots, \xi_m$ are said to be independence (Liu (2009)) if

$$\mathcal{M}\left\{\bigcap_{i=1}^{m} (\xi_i \in B_i)\right\} = \min_{1 \leq i \leq m} \mathcal{M}\{\xi_i \in B_i\}$$

for any Borel sets $B_1, B_2, \cdots, B_n$ of real numbers.

Definition 1 *Liu (2007) An uncertain distribution $\Phi(x)$ is said to be regular if its inverse function $\Phi^{-1}(x)$ exists and is unique for each $\alpha \in (0,1)$. Then the inverse function Φ^{-1} is called the inverse uncertainty distribution of ξ.*

Theorem 1 *Liu (2010) Assume $\xi_1, \xi_2, \cdots, \xi_n$ are independent uncertain variables with regular uncertainty distributions $\Phi_1, \Phi_2, \cdots, \Phi_n$, respectively. If $f(x_1, x_2, \cdots, x_n)$ is strictly increasing with respect to $x_1, x_2, \cdots, x_m$ and strictly decreasing with respect to $x_{m+1}, x_{m+2}, \cdots, x_n$, then the uncertain variable $\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$ has an expected value*

$$E[\xi] = \int_0^1 f(\Phi_1^{-1}(\alpha), \cdots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1-\alpha))\mathrm{d}\alpha$$

provided that $E[\xi]$ exists.

For any real numbers a and b, we have $E[a\xi + b\eta] = aE[\xi] + bE[\eta]$, where ξ and η are independent to each other.

Theorem 2 *Liu (2010) Assume the constraint function $g(x, \xi_1, \xi_2, \cdots, \xi_n)$ is strictly increasing with respect to $\xi_1, \xi_2, \cdots, \xi_k$ and strictly decreasing with respect to ξ_{k+1}, $\xi_{k+2}, \cdots, \xi_n$. If $\xi_1, \xi_2, \cdots, \xi_n$ are independent uncertain variables with uncertainty distributions Φ_1, Φ_2, $\cdots$, Φ_n, respectively, then the chance constraint*

$$\mathcal{M}\left\{g(x, \xi_1, \xi_2, \cdots, \xi_n) \leq 0)\right\} \geq \alpha$$

holds if and only if

$$g(x, \Phi_1^{-1}(\alpha), \cdots, \Phi_k^{-1}(\alpha), \Phi_{k+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1-\alpha)) \leq 0.$$

3 Models

3.1 Problem description

A multi-echelon closed-loop supply chain is considered in this paper. New products produced by the manufactory are distributed to customers through the forward network. In the closed-loop supply chain, scrapped products are transported to the recycling center. Customers' demands should be satisfied and returned products will be collected.

The aim of the proposed supply chain network to minimize the total cost and the total environmental impact simultaneously in an uncertain scenario. Therefore, it is necessary to make a reasonable tradeoff between the two objectives. An environment effect assessment method is employed to assess the second objective function. The LCA is a common method for environment effect assessment, and it has been widely used in the past twenty years. However, the process of LGA is expensive, time-consuming and complex, and usually requires professional knowledge of environmental management. Eco-indicator 99 (Goedkoop and Spriensma (2000)) is one of the most advanced environment effect assessment methods in the world. The method can reduce the life cycle analysis process of the designed product greatly.

3.2 Mathematical models under uncertainty

Before constructing the mathematical models, parameters and variables are introduced as follows.

Indexes

i the candidate locations of manufactories, $i = 1, 2, \cdots, I$

j the index of customer, $j = 1, 2, \cdots, J$

k the candidate locations of collection centers, $k = 1, 2, \cdots, K$

l the index of recycling center for metal, $l = 1, 2, \cdots, L$

m the index of recycling center for plastic, $m = 1, 2, \cdots, M$

Parameters

d_j the demand of customer j

r_j the return rate of customer j

f_i the cost of opening manufactory i

g_k the cost of opening collection center k

c_{ij} unit shipping cost from manufactory i to customer j

a_{jk} unit shipping cost of scrapped products from customer j to collection center k

b_{kl} unit shipping cost of scrapped products from collection center k to recycling center l for metal

h_{km} unit transportation cost of scrapped products from collection center k to recycling center m for plastic

ρ_i unit manufacturing cost of product at manufactory i

σ_k unit process cost of scrapped products at collection center k

β_l unit process cost of scrapped products at recycling center l for metal

τ_m unit process cost of scrapped products at recycling center m for plastic

π_i the capacity of manufactory i

η_k the capacity of collection center k

δ_l the capacity of recycling center l for metal

ς_m the capacity of recycling center m for plastic

ei^{pro} environmental impact of a unit of product

ei_{ij}^{tpc} environment effect of transporting a unit of product from manufactory i to customer j

ei_{jk}^{tcc} environment effect of transporting a unit of scrapped product from customer j to collection center k

ei_{kl}^{tcs} environment effect of transporting a unit of scrapped product from collection center k to recycling center l for metal

ei_{km}^{tcp} environment effect of transporting a unit of scrapped product from collection center k to recycling center m for plastic

ei^{col} environment effect handling a unit of used product at a collection center

ei^{src} environment effect of recycling the metal part of a unit of scrapped product

ei^{prc} environment effect of recycling the plastic part of a unit of scrapped product

Decision variables

u_{ij} the number of products transported from manufactory i to customer j

q_{jk} the number of scrapped products transported from customer j to collection center k

v_{kl} the number of metal part of scrapped products transported from collection center k
to recycling center l

w_{km} quantity of plastic part of scrapped products transported from collection center k to recycling center m

x_i 1, if a manufactory is opened at position i; 0, otherwise

y_k 1, if a collection center is opened at position k; 0, otherwise

The demands d_j, rates of return percentage r_j, fixed charges (f_i, g_k), transportation costs (c_{ij}, a_{jk}, b_{kl},h_{km}), manufacturing costs ρ_i, process costs (σ_k, β_l, τ_m) and capacities (π_i, η_k, δ_l, ς_m) are considered uncertain variables and independent of each other.

The first objective function of the supply chain network includes the opening costs, process and shipping costs.

$$W_1 = \sum_i f_i x_i + \sum_k g_k y_k + \sum_i \sum_j (\rho_i + c_{ij}) u_{ij} + \sum_j \sum_k (\sigma_k + a_{jk}) q_{jk} + \sum_k \sum_l (\beta_l + b_{kl}) v_{kl} + \sum_k \sum_m (\tau_m + h_{km}) w_{km}. \tag{1}$$

The environment effect of different supply chain network configurations is estimated by the Eco-indicator 99 approach. The system boundary and functional unit should be first identified. Next, the life cycle should be determined. The life cycle stages include: (1) produce, (2) shipping from manufactories to customers, (3) shipping from customers to collection centers, (4) handling the scrapped products at collection centers, (5) shipping from collection centers to recycling centers for metal, (6) metal recycling, (7) shipping from collection centers to recycling centers for plastic and (8) plastic recycling.

Three different perspectives (hierarchist, individualist, egalitarian) based on the cultural theory are provided by Eco-indicator 99 method. The second objective function is as follows.

$$W_2 = \sum_i \sum_j (ei^{pro} + ei^{tpc}_{ij}) u_{ij} + \sum_j \sum_k (ei^{col} + ei^{tcc}_{jk}) q_{jk} + \sum_k \sum_l (ei^{src} + ei^{tcs}_{kl}) v_{kl} + \sum_k \sum_m (ei^{prc} + ei^{tcp}_{km}) w_{km} \tag{2}$$

For the total cost and overall environmental impact, the optimal value cannot be obtained at the same time because the two objective functions conflict with each other. To coordinate the conflict, the decision maker should establish a hierarchy between two incompatible objectives to find a satisfactory solution. In reality, the decision maker will be more inclined to consider minimizing the total cost. Accordingly, reducing the total cost will be given priority. Secondly, it is to reduce the overall environmental impact. The total cost W_1 must be less than a preset value C,

$$W_1 + d_1^- - d_1^+ = C,$$

where d_1^- and d_1^+ are the positive and negative deviations from the preset value C, respectively.

Similarly, the overall environmental impact must be less than a preset value E,

$$W_2 + d_2^- - d_2^+ = E,$$

where d_2^- and d_2^+ are the positive and negative deviations from the preset value E, respectively.

The supply chain network problem can be modeled in many ways according to different objectives. The expected value is the average value of uncertain variable in the sense of uncertain measure, which can represent the size of uncertain variables. An expected value model is conducted as follows:

$$\begin{aligned}
&\operatorname{lexmin}\{\mathrm{d}_1^+, \mathrm{d}_2^+\} \\
&\text{subject to:} \\
&E[W_1] + d_1^- - d_1^+ = C \\
&W_2 + d_2^- - d_2^+ = E \\
&E\left[d_j - \sum_i u_{ij}\right] \le 0, \ \forall j
\end{aligned} \tag{3}$$

$$E\left[d_j r_j - \sum_k q_{jk}\right] \leq 0,\ \forall j \tag{4}$$

$$E\left[\sum_j u_{ij} - x_i \pi_i\right] \leq 0,\ \forall i \tag{5}$$

$$E\left[\sum_j q_{jk} - y_k \eta_k\right] \leq 0,\ \forall k \tag{6}$$

$$E\left[\sum_k v_{kl} - \delta_l\right] \leq 0,\ \forall l \tag{7}$$

$$E\left[\sum_k w_{km} - \varsigma_m\right] \leq 0,\ \forall m \tag{8}$$

$$d_1^-, d_1^+, d_2^-, d_2^+ \geq 0,$$

$$x_i, y_k \in \{0,1\}, \forall i, k$$

$$u_{ij}, q_{jk}, v_{kl}, w_{km} \geq 0, \forall i, j, k, l, m$$

where lexmin means to minimize the objective vectors in dictionary order.

The model attempts to minimize the positive deviations. Formulation (3) ensure that the demands of all customers must be met. Formulation (4) ensure that all used products are collected from the customers. Constraints (5)-(8) ensure that capacity constraints are met. The above constraints are established under the expected value criterion.

In practice, the decision maker always considers the risk and finds an upper bound so as to design an optimal plan. That is, the decision maker's aim may include the condition of satisfying some chance constraints under some preset confidence levels. Under other conditions, given confidence levels α. Accordingly, a chance-constrained model is conceived.

The decision maker needs determine a budget target $\overline{f}$ such that there exists a solution x^* satisfies $\mathcal{M}\{f(x) \leq \overline{f}\} \geq \alpha$. For example, let $\alpha = 0.9$, the decision maker can determine a budget target $\overline{f}$ and then choose a solution x that satisfies $\mathcal{M}\{f(x) \leq \overline{f}\} \geq 0.9$. If the decision maker chooses the solution x, the total cost will be lower than $\overline{f}$ at least 90%. Hence, the problem can be conducted as the following chance-constrained model according to Definition 1:

$$\text{lexmin}\{\mathrm{d}_1^+, \mathrm{d}_2^+\}$$

subject to

$$\mathcal{M}\{W_1 - d_1^+ - C \leq 0\} \geq \alpha, \tag{9}$$

$$W_2 - d_2^+ - E \leq 0, \tag{10}$$

$$\mathcal{M}\left\{d_j \leq \sum_i u_{ij}\right\} \geq \alpha_1,\ \forall j \tag{11}$$

$$\mathcal{M}\left\{d_j r_j \leq \sum_k q_{jk}\right\} \geq \alpha_2,\ \forall j \tag{12}$$

$$\mathcal{M}\left\{\sum_j u_{ij} \leq x_i \pi_i\right\} \geq \alpha_3,\ \forall i \tag{13}$$

$$\mathcal{M}\left\{\sum_j q_{jk} \leq y_k \eta_k\right\} \geq \alpha_4,\ \forall k \tag{14}$$

$$\mathcal{M}\left\{\sum_k v_{kl} \leq \delta_l\right\} \geq \alpha_5,\ \forall l \tag{15}$$

$$\mathcal{M}\left\{\sum_k w_{km} \leq \varsigma_m\right\} \geq \alpha_6,\ \forall m \tag{16}$$

$$d_1^+, d_2^+ \geq 0,$$

$$x_i, y_k \in \{0,1\}, \forall i, k$$

$$u_{ij}, q_{jk}, v_{kl}, w_{km} \geq 0, \forall i, j, k, l, m$$

where α, $\alpha_i, i = 1, 2, \cdots, 6$ are preset confidence levels.

The model attempts to minimize the pessimistic value to W_1 and W_2 (9,10). Constraints (11) and (16) ensure that the conditions hold under confidence levels $\alpha_i, i = 1, 2, \cdots, 6$.

Two multiobjective programming models are built to cope with an uncertain closed-loop supply chain network. It is generally known that because of the multi-type of uncertainty information, the decision maker will face the problem of multi-dimensional decision variables. In a random environment, it is generally known that this multidimensional decision problem leads to multiple integration problems, thereby making the calculation more difficult to achieve. Fortunately, the problem of multiple integration was avoided by the operation law of inverse uncertainty distribution. Thus, the proposed uncertainty model outperforms the stochastic model in many types of uncertain facility location problems.

4 Equivalence proof of uncertain models

Since uncertain variables are included in the two models, it is difficult to solve them directly. In many uncertain programming literatures, various optimization methods are used to find the approximate optimal solution of the uncertain model. Although the feasibility of these methods is often illustrated by numerical experiments, the preciseness and generality of these methods are not satisfactory. Fortunately, with the help of uncertainty theory, the two uncertain models can be converted into crisp forms.

Theorem 3 *The expected value model can be converted into the following model equivalently:*

$$
\begin{aligned}
&\mathrm{lexmin}\{\mathrm{d}_1^+, \mathrm{d}_2^+\} \\
&\textit{subject to:} \\
&E[W_1] + d_1^- - d_1^+ = C \\
&W_2 + d_2^- - d_2^+ = E \\
&\int_0^1 \Phi_{d_j}^{-1}(\alpha)\mathrm{d}\alpha \le \sum_i u_{ij},\ \forall j \\
&\int_0^1 \Phi_{d_j}^{-1}(\alpha)\Phi_{r_j}^{-1}(\alpha)\mathrm{d}\alpha \le \sum_k q_{jk},\ \forall j \\
&\sum_j u_{ij} \le x_i \int_0^1 \Phi_{\pi_i}^{-1}(\alpha)\mathrm{d}\alpha,\ \forall i \\
&\sum_j q_{jk} \le y_k \int_0^1 \Phi_{\eta_k}^{-1}(\alpha)\mathrm{d}\alpha,\ \forall k \\
&\sum_k v_{kl} \le \int_0^1 \Phi_{\delta_l}^{-1}(\alpha)\mathrm{d}\alpha,\ \forall l \\
&\sum_k w_{km} \le \int_0^1 \Phi_{\varsigma_m}^{-1}(\alpha)\mathrm{d}\alpha,\ \forall m \\
&d_1^-, d_1^+, d_2^-, d_2^+ \ge 0, \\
&x_i, y_k \in \{0,1\}, \forall i, k \\
&u_{ij}, q_{jk}, v_{kl}, w_{km} \ge 0, \forall i, j, k, l, m
\end{aligned}
$$

where Φ_f^{-1} denotes the inverse uncertainty distribution of f.

Proof: According to the nature of expected value, it yields

$$E[d_j] \le \sum_i u_{ij}. \tag{17}$$

And because

$$E[d_j] = \int_0^1 \Phi_{d_j}^{-1}(\alpha)\mathrm{d}\alpha, \tag{18}$$

it yields

$$\int_0^1 \Phi_{d_j}^{-1}(\alpha)\mathrm{d}\alpha \le \sum_i u_{ij}. \tag{19}$$

Likewise, the equivalent forms of other constraints can be obtained.

Besides,

$$
\begin{aligned}
E[W_1] = & \sum_i x_i \int_0^1 \Phi_{f_i}^{-1}(\alpha)\mathrm{d}\alpha + \sum_k y_k \int_0^1 \Phi_{g_k}^{-1}(\alpha)\mathrm{d}\alpha \\
& + \sum_i \sum_j u_{ij} \left(\int_0^1 \Phi_{\rho_i}^{-1}(\alpha)\mathrm{d}\alpha + \int_0^1 \Phi_{c_{ij}}^{-1}(\alpha)\mathrm{d}\alpha \right) \\
& + \sum_j \sum_k q_{jk} \left(\int_0^1 \Phi_{\sigma_k}^{-1}(\alpha)\mathrm{d}\alpha + \int_0^1 \Phi_{a_{jk}}^{-1}(\alpha)\mathrm{d}\alpha \right) \\
& + \sum_k \sum_l v_{kl} \left(\int_0^1 \Phi_{\beta_l}^{-1}(\alpha)\mathrm{d}\alpha + \int_0^1 \Phi_{b_{kl}}^{-1}(\alpha)\mathrm{d}\alpha \right) \\
& + \sum_k \sum_m w_{km} \left(\int_0^1 \Phi_{\tau_m}^{-1}(\alpha)\mathrm{d}\alpha + \int_0^1 \Phi_{h_{km}}^{-1}(\alpha)\mathrm{d}\alpha \right) \qquad (20)
\end{aligned}
$$

The theorem is proved.

Theorem 4 *The chance-constrained model can be converted into the following model equivalently:*

$\mathrm{lexmin}\{\mathrm{d}_1^+, \mathrm{d}_2^+\}$

subject to:

$\Psi_{W_1}^{-1}(\alpha) - d_1^+ - C \leq 0$

$W_2 - d_2^+ - E \leq 0$

$\Phi_{d_j}^{-1}(\alpha_1) \leq \sum_i u_{ij}, \ \forall j$

$\Phi_{d_j}^{-1}(\alpha_2)\Phi_{r_j}^{-1}(\alpha_2) \leq \sum_k q_{jk}, \ \forall j$

$\sum_j u_{ij} \leq x_i \Phi_{\pi_i}^{-1}(1-\alpha_3), \ \forall i$

$\sum_j q_{jk} \leq y_k \Phi_{\eta_k}^{-1}(1-\alpha_4), \ \forall k$

$\sum_k v_{kl} \leq \Phi_{\delta_l}^{-1}(1-\alpha_5), \ \forall l$

$\sum_k w_{km} \leq \Phi_{\varsigma_m}^{-1}(1-\alpha_6), \ \forall m$

$d_1^+, d_2^+ \geq 0,$

$x_i, y_k \in \{0,1\}, \forall i, k$

$u_{ij}, q_{jk}, v_{kl}, w_{km} \geq 0, \forall i, j, k, l, m$

where Ψ_f^{-1} *and* Φ_f^{-1} *denote the inverse uncertainty distributions.*

Proof: According to the definition, it yields

$$\mathcal{M}\{W_1 - d_1^+ - C \leq 0\} \geq \alpha \tag{21}$$

is equivalent to

$$\Psi_{W_1}^{-1}(\alpha) - d_1^+ - C \leq 0, \tag{22}$$

where

$$\begin{aligned}\Psi_{W_1}^{-1}(\alpha) = &\sum_i x_i \Phi_{f_i}^{-1}(\alpha) + \sum_k y_k \Phi_{g_k}^{-1}(\alpha)\\ &+ \sum_i \sum_j u_{ij}[\Phi_{\rho_i}^{-1}(\alpha) + \Phi_{c_{ij}}^{-1}(\alpha)]\\ &+ \sum_j \sum_k q_{jk}[\Phi_{\sigma_k}^{-1}(\alpha) + \Phi_{a_{jk}}^{-1}(\alpha)]\\ &+ \sum_k \sum_l v_{kl}[\Phi_{\beta_l}^{-1}(\alpha) + \Phi_{b_{kl}}^{-1}(\alpha)]\\ &+ \sum_k \sum_m w_{km}[\Phi_{\tau_m}^{-1}(\alpha) + \Phi_{h_{km}}^{-1}(\alpha)].\end{aligned} \tag{23}$$

According to the definition of uncertain distribution, it yields

$$\mathcal{M}\left\{d_j \leq \sum_i u_{ij}\right\} = \Phi\left(\sum_i u_{ij}\right) \geq \alpha_1. \tag{24}$$

Take inverse distribution on both sides, it yields

$$\Phi_{d_j}^{-1}(\alpha_1) \leq \sum_i u_{ij}. \tag{25}$$

According to the inverse distribution property of product of uncertain variables Liu (2007),

$$\mathcal{M}\left\{d_j r_j \leq \sum_k q_{jk}\right\} \geq \alpha_2 \tag{26}$$

is equivalent to

$$\Phi_{d_j}^{-1}(\alpha_2)\Phi_{r_j}^{-1}(\alpha_2) \leq \sum_k q_{jk}. \tag{27}$$

Because

$$\mathcal{M}\left\{\sum_j u_{ij} \leq x_i \pi_i\right\} = 1 - \mathcal{M}\left\{x_i \pi_i < \sum_j u_{ij}\right\}, \tag{28}$$

then

$$\mathcal{M}\left\{\sum_j u_{ij} \le x_i\pi_i\right\} \ge \alpha_3 \tag{29}$$

is equivalent to

$$\mathcal{M}\left\{x_i\pi_i < \sum_j u_{ij}\right\} = \Phi\left(\sum_j u_{ij}\right) \le 1-\alpha_3. \tag{30}$$

Take inverse distribution on both sides, it yields

$$\sum_j u_{ij} \le x_i\Phi^{-1}_{\pi_i}(1-\alpha_3). \tag{31}$$

Likewise, the equivalent forms of other constraints can be obtained.

The theorem is proved.

5 Numerical experiments

To assess the performance of the proposed mathematical models, numerical experiments are performed. LINGO 11.0 will be used in the examples to solve the supply chain network models.

A button battery supply chain network involving 15 customers, 6 candidate locations for opening new manufactories, 10 candidate locations for collection centers, 4 metal and plastic recycling centers is considered. The demands and return percentages are list in Table 1. The costs of opening manufactories and collection centers are list in Tables 2-3. Assume that all uncertain variables follow the zigzag distribution.

Table 1: The demands and return percentages

Customer	Demand	Return percentage
1	$(250, 270, 290)$	$(0.55, 0.75, 0.95)$
2	$(230, 260, 280)$	$(0.65, 0.7, 0.85)$
3	$(180, 210, 260)$	$(0.5, 0.7, 0.8)$
4	$(220, 250, 270)$	$(0.55, 0.75, 0.85)$
5	$(100, 110, 130)$	$(0.45, 0.65, 0.75)$
6	$(90, 105, 150)$	$(0.6, 0.7, 0.8)$
7	$(85, 95, 105)$	$(0.5, 0.65, 0.85)$
8	$(50, 70, 90)$	$(0.55, 0.7, 0.75)$
9	$(130, 150, 160)$	$(0.65, 0.75, 0.8)$
10	$(300, 320, 330)$	$(0.5, 0.7, 0.8)$
11	$(150, 180, 210)$	$(0.5, 0.65, 0.85)$

12	$(120, 130, 140)$	$(0.55, 0.75, 0.85)$
13	$(190, 200, 210)$	$(0.45, 0.65, 0.75)$
14	$(100, 105, 110)$	$(0.65, 0.7, 0.85)$
15	$(60, 80, 100)$	$(0.55, 0.75, 0.95)$

Table 2: The fixed costs and capacities of manufactories

Location	Fixed cost	Capacity
1	$(120000, 150000, 180000)$	$(2000, 2200, 2400)$
2	$(150000, 160000, 170000)$	$(1750, 1900, 2050)$
3	$(130000, 150000, 180000)$	$(1800, 2000, 2200)$
4	$(145000, 150000, 165000)$	$(1650, 1800, 2000)$
5	$(135000, 140000, 155000)$	$(1900, 2100, 2300)$
6	$(155000, 165000, 175000)$	$(2100, 2300, 2500)$

Table 3: The fixed costs and capacities of collection centers

Location	Fixed cost	Capacity
1	$(15000, 16000, 18000)$	$(2300, 2400, 2500)$
2	$(15500, 17000, 19000)$	$(2350, 2450, 2550)$
3	$(17000, 18000, 20000)$	$(2200, 2300, 2400)$
4	$(16000, 18000, 19000)$	$(2500, 2600, 2700)$
5	$(17500, 18500, 19500)$	$(2250, 2300, 2500)$
6	$(17000, 19000, 20000)$	$(2400, 2500, 2600)$
7	$(18500, 19500, 20000)$	$(2500, 2650, 2700)$
8	$(17000, 17500, 18500)$	$(2250, 2450, 2550)$
9	$(17500, 18000, 19500)$	$(2100, 2200, 2500)$
10	$(18000, 18500, 19000)$	$(2400, 2600, 2700)$

$c_{ij} \sim Z(30, 40, 50), a_{jk} \sim Z(35, 45, 55), b_{kl} \sim Z(25, 30, 35), h_{km} \sim Z(20, 25, 30),$
$\rho_i \sim Z(12, 15, 18), \sigma_k \sim Z(3, 4, 5), \beta_l \sim Z(8, 9, 10), \tau_m \sim Z(5, 6, 7),$
$\delta_l \sim Z(2000, 2200, 2400), \varsigma_m \sim Z(2100, 2150, 2200),$
$ei^{pro} = 5, ei^{tpc}_{ij} = 3, ei^{tcc}_{jk} = 2, ei^{tcs}_{kl} = 3, ei^{tcp}_{km} = 2, ei^{col} = 4, ei^{src} = 1, ei^{prc} = 2.$

5.1 Case study of the expected value model

Take preset values $C = 810000$ and $E = 31025$. The expected Value model is as follows.

$\text{lexmin}\{\mathrm{d}_1^+, \mathrm{d}_2^+\}$

subject to:

$E[W_1] + d_1^- - d_1^+ = 810000$

$W_2 + d_2^- - d_2^+ = 31025$

$\int_0^1 \Phi_{d_j}^{-1}(\alpha)\mathrm{d}\alpha \le \sum_{i=1}^{6} u_{ij},\ j = 1, 2, \cdots, 15$

$\int_0^1 \Phi_{d_j}^{-1}(\alpha)\Phi_{r_j}^{-1}(\alpha)\mathrm{d}\alpha \le \sum_{k=1}^{10} q_{jk},\ j = 1, 2, \cdots, 15$

$\sum_{j=1}^{15} u_{ij} \le x_i \int_0^1 \Phi_{\pi_i}^{-1}(\alpha)\mathrm{d}\alpha,\ i = 1, 2, \cdots, 6$

$\sum_{j=1}^{15} q_{jk} \le y_k \int_0^1 \Phi_{\eta_k}^{-1}(\alpha)\mathrm{d}\alpha,\ k = 1, 2, \cdots, 10$

$\sum_{k=1}^{10} v_{kl} \le \int_0^1 \Phi_{\delta_l}^{-1}(\alpha)\mathrm{d}\alpha,\ l = 1, 2, \cdots, 4$

$\sum_{k=1}^{10} w_{km} \le \int_0^1 \Phi_{\varsigma_m}^{-1}(\alpha)\mathrm{d}\alpha,\ m = 1, 2, \cdots, 4$

$d_1^-, d_1^+, d_2^-, d_2^+ \ge 0,$

$x_i, y_k \in \{0, 1\}, i = 1, 2, \cdots, 6; k = 1, 2, \cdots, 10$

$u_{ij}, q_{jk}, v_{kl}, w_{km} \ge 0, i = 1, 2, \cdots, 6; j = 1, 2, \cdots, 15; k = 1, 2, \cdots, 10; l = 1, 2, \cdots, 4;$
$m = 1, 2, \cdots, 4.$

The objective function can be rewritten as

$$\min P_1 d_1^+ + P_2 d_2^+,$$

where P_1 and P_2 denote weight factors, $P_1 = 0.9, P_2 = 0.1$. The optimal solution (0,1.8722) of the objective function is obtained by Lingo, and the corresponding decision variables $x_1 = x_5 = x_6 = 1, x_2 = x_3 = x_4 = 0,\ y_k = 1, k = 1, 2, \cdots, 10$. This result suggests that the first aim can be achieved, while the second aim cannot be achieved. After adjusting the factors, the results are reported in Table 4. As the environmental impact is emphasized, the total cost of the supply chain network will increase. This results remind decision makers to make the most reasonable decision after weighing the pros and cons.

Table 4: The relationship between weight factors and the optimal solution (expected value model)

P_1	P_2	Optimal solution
0.9	0.1	$(0, 1.8722)$
0.7	0.3	$(217, 1.3116)$
0.5	0.5	$(401, 0.9803)$

To further explore the feasibility of the proposed models, the problem is investigated in a large scale. $P_1 = 0.9, P_2 = 0.1$. A part of the uncertain variables are randomly generated in table 5. Suppose the number of potential factories is 8, 10, 15, 20, 30, the number of potential collection centers is 12, 15, 20, 25, 30, and the number of recycling centers is 8.

Table 5: Ranges of the uncertain variables

d_j	r_j	f_i	π_i	g_k	η_k
[50,300]	[0.45,0.95]	[120000,180000]	[1600,2500]	[15000,20000]	[2100,2700]

Table 6: Large-scale cases (the expected value model)

No	Mfy(opened)	Collection center(opened)	(C, E)	(d_1^+, d_2^+)
1	4	12	(9.0E+5,3.3E+4)	(302,50.343)
2	6	13	(11.0E+5,3.6E+4)	(455,60.253)
3	9	17	(16.0E+5,4.0E+4)	(627,80.766)
4	14	20	(20.0E+5,4.5E+4)	(925,125.22)
5	16	22	(26.0E+5,5.3E+4)	(1223,377.83)

As can be seen from Table 6, the larger the scale, the greater the deviation.

5.2 Case study of the chance-constrained model

Assume that the decision maker should determine a budget target under confidence level $\alpha = 0.9$, $\alpha_i = 0.9, i = 1, 2, \cdots, 6$.

$\text{lexmin}\{\text{d}_1^+, \text{d}_2^+\}$

subject to:

$\Psi_{W_1}^{-1}(0.9) - 810000 \leq d_1^+$

$W_2 - 31025 \leq d_2^+$

$\Phi_{d_j}^{-1}(0.9) \leq \sum_i u_{ij},\ j = 1, 2, \cdots, 15$

$\Phi_{d_j}^{-1}(0.9)\Phi_{r_j}^{-1}(0.9) \leq \sum_k q_{jk},\ j = 1, 2, \cdots, 15$

$\sum_j u_{ij} \leq x_i \Phi_{\pi_i}^{-1}(0.1),\ i = 1, 2, \cdots, 6$

$\sum_j q_{jk} \leq y_k \Phi_{\eta_k}^{-1}(0.1),\ k = 1, 2, \cdots, 10$

$\sum_k v_{kl} \leq \Phi_{\delta_l}^{-1}(0.1),\ l = 1, 2, \cdots, 4$

$\sum_k w_{km} \leq \Phi_{\varsigma_m}^{-1}(0.1),\ m = 1, 2, \cdots, 4$

$d_1^+, d_2^+ \geq 0,$

$x_i, y_k \in \{0, 1\}, i = 1, 2, \cdots, 6; k = 1, 2, \cdots, 10$

$u_{ij}, q_{jk}, v_{kl}, w_{km} \geq 0, i = 1, 2, \cdots, 6; j = 1, 2, \cdots, 15; k = 1, 2, \cdots, 10; l = 1, 2, \cdots, 4;$
$m = 1, 2, \cdots, 4.$

Similar to the above, the objective function can be rewritten as

$$\min P_1 d_1^+ + P_2 d_2^+,$$

where P_1 and P_2 are weight factors, $P_1 = 0.9, P_2 = 0.1$. The optimal solution (0,19.22274) of the objective function is gotten by Lingo, the corresponding decision variables $x_1 = x_3 = 1, x_2 = x_4 = x_5 = x_6 = 0, y_1 = y_2 = y_3 = y_4 = y_5 = y_7 = y_8 = y_{10} = 1, y_6 = y_9 = 0$. This result reveals that the first aim can be achieved, while the second aim cannot be achieved. Similar to the expected value model, the total costs of the supply chain network will deviate significantly from the predetermined value when the environmental impact is taken seriously.

Table 7: The relationship between weight factors and the optimal solution (chance-constrained model)

P_1	P_2	Optimal solution
0.9	0.1	$(0, 19.22274)$
0.7	0.3	$(569, 16.0495)$
0.5	0.5	$(933, 10.75661)$

Table 8: Large-scale cases (the chance-constrained model)

No	Mfy(opened)	Collection center(opened)	(C, E)	(d_1^+, d_2^+)

1	2	9	(9.0E+5,3.3E+4)	(583,82.209)
2	5	12	(11.0E+5,3.6E+4)	(747,105.22)
3	6	13	(16.0E+5,4.0E+4)	(961,139.63)
4	11	17	(20.0E+5,4.5E+4)	(1275,163.82)
5	14	17	(26.0E+5,5.3E+4)	(1560,445.33)

The results from large-scale cases for the chance-constrained model are list in Table 8.

To investigate the sensitivity of the confidence levels α and $\alpha_i, i = 1, 2, \cdots, 6$ in the chance-constrained model, another supplementary test is performed and the results are shown in Fig.1. When the sensitivity of a confidence level is tested, other confidence levels are taken as 0.9. The step size of the confidence level is taken as 0.2. Fig.1 implies that the objective value is nondecreasing with respect to the confidence level α, $\alpha_i, i = 1, 2, \cdots, 6$. The result of the sensitivity analysis allows decision makers to make the most reasonable judgment based on the degree of understanding of actual problems in an uncertain environment. In other words, when the decision maker handles the uncertainty at a higher confidence level, the environmental load also increases.

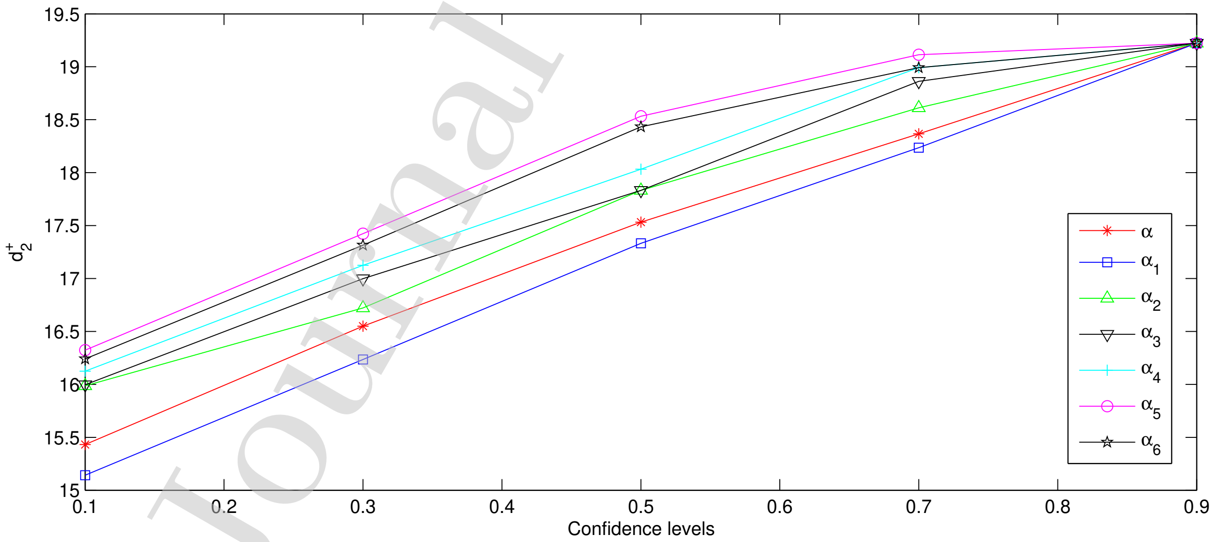

Figure 1: The sensitivity analysis of confidence levels

The results of two numerical examples also reveal the conflict between the two objective functions (i.e., total cost minimization and total environmental impact minimization), because the reduction of total environmental impact leads to the increase of total cost, and vice versa. The expect value model tends to decentralize networks to minimize the overall environmental impact. The environmental impact of decentralized networks is reduced, more manufactories are opened than centralized structures, so there are more or possibly shorter paths for transporting products from source to destination. Less number of manufactories and collection centers is opened in the chance-constrained model. This suggests that the chance-constrained model tends to centralize supply chain network.

Enterprises and decision makers can use these models as quantitative and transparent indicators to demonstrate their efforts to protect the environment to stakeholders. In the proposed solution, the decision maker can adjust the scope of the goal throughout the process. Therefore, the whole Pareto optimal solution from a rough hypothesis (For example, the values of C and E) can be obtained. However, in further solving, the decision maker may be interested in adjusting initial assumptions.

The expected value model and chance-constrained model are used to cope with the uncertain closed-loop supply chain network. The results of the examples suggest that there is a relative difference between the two models. This is primarily because the two models are built from different perspectives, thereby resulting in different optimal solutions. In fact, which model is more suitable is determined by the preference of the decision maker and the mastery of the actual situation.

6 Conclusions

Environmental protection has become an important issue in recent years. An uncertain environmental supply chain network for button batteries was investigated in this paper. In addition to considering the environment effect of the supply chain, it also combines the design of closed-loop supply chain. To make the research more realistic, the demand, cost and capacity were considered uncertain variables owing to lack of observed data. To address these empirical data in the problem, two novel multi-objective mixed integer programming models that rely on different criteria were developed. Besides, positive and negative deviations were introduced into the objective functions. A method based on LCA was proposed to evaluate the environment effects. The equivalent forms of these models were obtained in accordance with the uncertainty theory. Numerical experiments suggested that the expected value model tends to be decentralized while the chance-constrained model tends to be centralized. The effectiveness and efficiency of the proposed models and solution method was verified.

Furthermore, it is an interesting research to develop some efficient heuristic algorithms to solve the problem in large scale. Besides, other factors affected by human activities in the supply chain network can also be considered uncertain variables, and this modeling idea may also be suitable for solving other supply chain network design problems.

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