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A novel robust fuzzy mean-UPM model for green closed-loop supply chain network design under distribution ambiguity

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ABSTRACT

Green closed-loop supply chain (GCLSC) is a supply chain that encompasses forward and reverse flows of components and products in logistic networks with a focus on economic and environmental performance. In the decision-making process of GCLSC, the presence of uncertainty and risk originating from the size and complexity of network is crucial to consider, and the distribution of uncertain parameter may be ambiguous. To characterize the ambiguity caused by distributional perturbation, a novel ambiguity distribution set is proposed, and further a new upside risk: upper partial moment with power q is introduced to quantify the economic risk in the GCLSC. Subsequently, a distributionally robust fuzzy GCLSC network design model which attempts to optimize the worst-case performance of the network is developed with the perspective of a trade-off between upside risk and expectation of economic cost. To format a sustainable GCLSC paradigm, the policy of carbon cap is adopted to control carbon emissions in terms of environmental constraints. Furthermore, the tractable counterpart of the proposed model is obtained by transforming distributionally robust credibility objective and constraints into their equivalent forms under ambiguous distribution of uncertain parameter. Finally, a case study on Coca-Cola Company in Northeast China is investigated to test and verify the proposed model. The advantage of proposed model is demonstrated through comparative study on distribution ambiguity free and without environmental constraint problem. Computational results reveal that the proposed model has superior capability of immunity against the risk of distribution ambiguity.

1. Introduction

Environmental concerns in supply chain (SC) activities have attracted increasing attention of academic researchers and industrial practitioners over the last decade [1,2]. Governments around the world have established numerous legislations and administrative rules to impel industry to take care of environmental issues [3]. Generally, adding a reverse flow and controlling greenhouse gas emissions can be regarded as two effective environmental strategies in SC management [4]. Therefore, how to formulate a closed-loop supply chain network with the control of carbon emissions becomes a crucial problem of green closed-loop supply chain (GCLSC) management.

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The sheer size and complexity of GCLSC have led to the presence of uncertainty and risk, which becomes a critical reality to be dealt with [5]. Accordingly, some optimization methods, such as robust optimization, stochastic programming and fuzzy programming, are presented to resist the ambiguity of uncertain parameters. Robust optimization can address uncertainty with limited distributional information. Its ambiguity-averse nature makes it a popular framework recently and has been utilized in designing of GCLSC network [6–8]. Stochastic programming is an optimization tool to deal with uncertainty in which probability distribution of uncertain parameter is exactly known, and a variety of stochastic models have been presented and promote more GCLSC researches [9,10].

Fuzzy optimization can effectively model the parameter influenced by epistemic uncertainty [11]. Numerous achievements have been obtained and practiced by company and institution in real-life, which strongly suggest fuzzy optimization is a choice for decision making problem under uncertainty. For example, the performance of IT projects in a Turkish company was evaluated by an integrated fuzzy method [12], since the key performance indicators of projects commonly depended heavily on IT experts' opinions; Due to unavailability or lack of sufficient reliable historical data of rare neurological disorders, Iranian food and drug administration employed a credibility-based fuzzy programming approach to handle the scarce drugs rationing problem [13]; An authorized dismantling center in Istanbul utilized an intuitionistic fuzzy approach to evaluate various alternatives for location selection [14], because they thought the fuzzy approach can capture more degrees of uncertainty and account multiple conflicting evaluation criteria; Especially, a real-life company: SPAPCO in Iran used a flexible fuzzy approach for evaluating supplier's sustainability [15]. The sustainability of 25 suppliers was measured based on real dataset, and a comparison on deterministic and fuzzy output was conducted. Authors remarked that dealing with vague and unknown information and performance evaluation with routine deterministic methods may make mistakes in the decision making process.

In GCLSC management field, fuzzy optimization method has been verified useful in constructing the supply chain network model and analyzing the realistic case. Soleimani et al. [16] addressed a design problem of a closed-loop supply chain regarding product, component and raw material recycling. A fuzzy three-objective sustainable and green closed-loop supply chain network was constructed. Fazli-Khala et al. [17] designed a green supply chain network with a bi-objective optimization formulation to minimize the total cost and harmful gas emissions, and a case on lead-acid battery supply chain was analyzed. Yu and Solvang [18] presented a fuzzy-stochastic multi-objective sustainable CLSC network design model to balance the trade-off between cost effectiveness and environmental performance. From the practical implementation perspective, a new solution approach was proposed and tested the performance of the model over different uncertain environments.

The majority of existing GCLSC studies require the full distributional information of uncertain input data. This means the complete distributions of uncertain parameter should be fixed in advance, and are perfectly clear. However, since the GCLSCs are often suffered with diverse types and dimensions of uncertainty that originate from unanticipated situations or experience judgment limitations, a notable issue of GCLSCs under uncertainty is the distributions of uncertain parameters could be ambiguous. In this case, the misusing of an incorrect distribution has a damaging impact [19]. Therefore, there is a necessity to study GCLSC network design problem under partial fuzzy distribution information of model parameters. Specifically, in this study, transportation cost, demand and carbon emissions are considered to suffer with the influences of distribution ambiguity.

Fuzzy possibility theory [20] is a useful tool to model the ambiguity on perturbation of fuzzy possibility distribution, where parametric interval-valued (PIV) fuzzy variable has been used to many application areas due to its computational advantages [21]. In the existing studies, two types of variable interval on fuzzy possibility distribution are defined according to different fluctuation modes. For example, researchers proposed a definition of PIV fuzzy variable, in which the changeable interval on distribution ambiguity is determined by the smaller fluctuation in two distinct directions of nominal distribution [21]. By contrast, in [22], the parametric possibility distribution is not necessarily normalized, and its perturbations are directly scaled with nominal distribution. Motivated by these researches, this study presents a novel characterization method for distribution ambiguity, in which the variable distribution fluctuates in a linear perturbation mode around nominal possibility distribution. This proposed definition on PIV fuzzy variable is more generalized compared with the existing literature [21,22]. Furthermore, a new ambiguity distribution set of PIV fuzzy variable is formulated based on the proposed definition.

Additionally, this paper investigates GCLSC network design problem from a perspective of the risk control on economic cost. To be specific, a novel fuzzy upside risk measurement: upper partial moment (UPM) with power q is presented, which can effectively measure the upside risk of economic cost in GCLSC network. It generalizes fuzzy measurement of upper side risk, and the commonly used upper semi-deviation and second order semi-deviation can be viewed as its two special cases. To address the issue of limited distribution information, we employ the framework of distributionally robust fuzzy optimization, where fuzzy distribution of demand, transportation cost and carbon emissions is assumed to lie in a certain ambiguity set instead of being known perfectly, and manager chooses a decision that performs the best against the worst possible distribution within ambiguity distribution set. Further, a new mean-UPM GCLSC network design model with environmental constraint is proposed. When uncertain parameters belong to our new ambiguity distribution sets, the derived equivalent forms of the proposed model are computational tractable. Finally, a realistic case study on GCLSC network design problem of Coca-Cola Company in northeast China is conducted. The computational results show the reliability of outcome decisions.

The contributions in this study are mainly summarized as the following four aspects:

- Theory: This paper defines the perturbation of possibility distributions in a linear mode, then gives a new expression on distributional perturbation. Based on this new observation, three commonly used PIV fuzzy variables are introduced, and further a new definition of ambiguity distribution set is given. The new definition can link the fuzzy and robust optimization and provide a tractable characterization of distributional ambiguity.
- Model: To measure upside risk of economic cost, a new deviation risk measure: upper partial moment with power q is presented. Further, a mean-risk modeling criterion is employed based on the new measure, and a distributionally robust fuzzy mean-UPM GCLSC network design model is constructed. The uncertain carbon emissions in transportation is also included into GCLSC network decision system in the form of environmental constraint.
- Solvability: Since the possibility distribution of uncertain parameter has linear perturbation structure, thus the proposed model is hard to solve. To obtain its tractable formulation, we deal with the objective and constraints separately. To be specific, some theoretical results on upper partial moment are derived, and further the equivalent forms of distributionally robust objective are obtained. Then we transform the ambiguous credibility constraints under some ambiguity distribution sets. Finally, the tractable framework of the proposed model is deterministic and represented with analytical piecewise functions, which can be solved efficiently by commercial-grade solvers.
- Application: To demonstrate the proposed model and approach, a practical case of GCLSC network design problem about Coca-Cola Company in northeast China is addressed. In particular, the specific method on how to generate ambiguity distribution set of uncertain parameter from the real data is illustrated. The sensitivity analysis of different parameters on location strategy and economic cost is discussed. Moreover, two comparisons on distribution ambiguity free and absence of environmental constraint are conducted to show the advantage of our approach.

The remainder of the study is organized as follows: Section 2 reviews the related literature. A detailed background of the presented problem is described in Section 3, and a new distributionally robust mean-risk GCLSC model is formulated based on a new risk measurement. Section 4 introduces a new expression on perturbation mode of fuzzy possibility distribution, and a definition of ambiguity distribution set is provided. Section 5 derives the equivalent forms of distributionally robust objective and constraints to prove the tractability of the problem-solving. Section 6 introduces the background and data of a realistic case, and how to generate the ambiguity distribution set from the real data. The computational results are discussed in Section 7. Section 8 do a analysis on parameters' sensitivity. Section 9 compares the difference on results under distribution perturbation with distribution ambiguity free and absence of environmental constraint. Section 10 draws some management implications. The conclusions are presented in the final section. The proofs and deterministic parameter values are summarized in Appendix A and Appendix B, separately.

2. Literature review

This work is related to **two** distinct areas of GCLSC research: environmental concerns in GCLSC, uncertainty in GCLSC. In this section, we briefly review previous studies in these areas and eventually explain the motivation and our work.

2.1. Environmental concerns in GCLSC

In the past decade, along with the increasingly prominent environmental problems, numerous SC studies in the literature are interested in the reverse logistic, and publications on recycling of end-of-life products have shown a strong and continuous growth [23]. To design the closed-loop supply chain (CLSC) network more realistically, several studies use different recycling schemes to collect and remanufacture end-of-life products and raw materials [10,24–26]. More specifically, Huynh et al. [24] addressed an inventory replenishment and capacity planning problem, and recycling happened between customer points and second-class warehouses. In [10], five levels were designed in the reverse logistic (collection centers, recycle centers, disposal centers, redistribution centers and second markets). All these products, as raw materials, were recycled from the recycling centers to suppliers or re-distribution centers, and regularly provided to the second group of customers. Hasanov et al. [25] considered a four-level CLSC with remanufacturing. The remanufacturer reused recoverable parts from buyers and placed an order with tier-1 suppliers to remanufacture. As'ad et al. [26] used two stage optimization model to formulate a CLSC decision. In this study, the vendor not only transformed the procured raw materials (RMs) from supplier into finished products, but processed the returned products, received from buyer, into finished products.

To mitigate environmental consequences of CLSC network, many more green and sustainable efforts have been made from different aspects. Some researchers concern on carbon control associated with product life cycles and referred to as carbon footprint [27]. Specifically, Krikke [28] proposed a framework concerning the carbon footprint of a copier CLSC, whereas Tiwari et al. [29] considered a GCLSC network design problem in semiconductor industries from the perspective of minimizing the carbon footprints.

In the meantime, numerous reduction policies of carbon emissions have been introduced (e.g. carbon cap, carbon tax, carbon trade, carbon offset and carbon subsidy) to improve climate change effectively [30]. In these policies, the carbon cap policy was used by Mohajeri & Fallah [31] to limit the carbon emissions for formulating GCLSC network design model; Haddad-sisakht & Ryan [32] proposed a three-stage GCLSC model with uncertain carbon tax rate and stochastic demand; The carbon trade policy provides an option for low-emission enterprises to profit by sharing their quota through carbon trading system, and Samuel et al. [33] constructed two mathematical models to investigate the effects of the quality of returns on the CLSC network under it; Aldoukhi & Gupta [34] designed a new CLSC network with considering a downward

Table 1
Review and analysis of the related Green CLSC literature.

Researches	Problem	Uncertainty			Distribution	Carbon control		Risk
	type	Costs	Demands	Carbon emissions	information	Objective	Constraint	attitude
Saedinia et al. [6]	robust	*	*		free		*	–
Ma et al. [7]	robust	*	*		imprecise			mean-CVaR
Ahmadi et al. [9]	stochastic		*		known			mean
Hajipour et al.[10]	stochastic	*	*		known			mean
Fazli-Khalaf et al. [17]	robust fuzzy	*	*	*	known	*		–
Krikke et al. [28]	determinate				–	*		–
Tiwari et al. [29]	determinate				–	*		–
Haddad-sisakht et al. [32]	robust stochastic		*	*	imprecise		*	mean
Darbari et al. [44]	fuzzy		*		known	*		–
Karimi et al. [45]	fuzzy	*	*		known		*	–
Talaei et al. [50]	robust fuzzy	*	*		known	*		mean
Ghahremani-Nahr et al. [51]	robust fuzzy	*	*		known			–
Dehghan et al. [53]	robust stochastic/fuzzy	*	*		imprecise			mean
Pourjavad et al. [54]	fuzzy		*		known	*		–
This paper	distributionally robust fuzzy	*	*	*	imprecise		*	mean-UPM

product substitution policy under four carbon emissions regulation policies including carbon offset; Wu et al. [35] established a variational inequality model of the CLSC network multiphase equilibrium, and the optimal technology decision of green supply chain under different government subsidy rates was obtained. In particular, several researches focused on the designing and planning CLSC problem under more than one carbon policy, and studied their effects on the economic and environmental performance [30,34].

Additionally, in the environmental concerns, some other useful eco-indicators have been utilized in SC management. For example, to evaluate the environmental impacts, Eco-indicator 99 is employed by studies [36–38], and all of them have constructed multi-objective programming model to balance the economic and environmental issues. The difference among them is in their consideration of the uncertainty. Eco-innovation (EI) has been defined as an useful eco-indicator and emphasised as a core driver for change in the transition to sustainability. Jabbour et al. [39] qualitatively analysed three cases of low-carbon eco-innovation, and analyse how certain human critical success factors were related to specific EI in some sustainable supply chains. An ecosilient index [40] are suggested to assess the greenness and resilience of SC, and its application is illustrated via case study of an upstream automotive supply chain.

2.2. Fuzzy in GCLSC

Complex nature of GCLSC has led to uncertainty of various parameters. Among the optimization approaches under uncertainty, fuzzy programming approach is more practical in non-deterministic models due to its capability to handle both epistemic and vague uncertainty [41], and has been widely applied for GCLSC design and management [42,43]. In the recent studies, Darbari et al. [44] presented a mixed integer linear programming model with fuzzy goals of minimizing environmental impact and maximizing net profit and social impact, in which the demand and capacity were uncertain and estimated with fuzzy numbers. Karimi et al. [45] designed a fuzzy GCLSC model with the price consideration, in which the membership function for recovery product was used to find satisfaction degrees of DCs and customers. Some important benefits are identified from five aspects to verify the effectiveness of fuzzy programming in [46,47]. However, in situation where the fuzzy distribution is difficult to predict due to the lack of *good enough* data, or the assumed distribution deviates from the actual distribution, the conventional fuzzy programming becomes invalid in some real-world problems.

An important breakthrough on incorporating robust ideology into fuzzy programming is achieved in [48]. Robust fuzzy programming method can effectively address uncertainty with limited fuzzy distributional information [49], and the last decade has witnessed its quick development and application in GCLSC problem. Talaei et al. [50] and Ghahremani-Nahr et al. [51] both designed their GCLSC networks with robust fuzzy programming approach, but the considered uncertain parameters were distinct. Furthermore, Farrokh et al. [52] employed a robust fuzzy stochastic programming approach to deal with the CLSC network design problem in a hybrid uncertain environment. Similarly, Dehghan et al. [53] presented a robust stochastic-possibilistic programming model based on Me measure. They gave a comparative study and found their model was better than the model of [52]. For more recent robust fuzzy programming studies on GCLSC design and management, the interested readers may refer to [17,51,54].

To review the previous mentioned studies on GCLSC management, and specify the distinctiveness of this paper, we classify the related literature in Table 1. As shown in Table 1, some model properties are categorized for easily finding the research gap and our motivation.

2.3. Motivation and our work

From the summarized studies in Table 1, we obtain the following observations that can motivate the present study: (*i*) A large portion of literature on environmental management in GCLSC measured total carbon dioxide emissions by environmental objective, while few models adopt the form of environmental constraints. (*ii*) Most of uncertainty are related with the impact of economic aspect, and originated from uncertain nature of supply chain network, such as price and demand [4]; production cost and demand [45]; transportation cost and remanufacturing capacity [50]; cost, demand and returned products [55]. Only a few consider the uncertainty of carbon emissions with fuzzy optimization method [17,32]. (*iii*) Most of the efforts in GCLSC network mentioned above are conducted under the assumption that the crisp fuzzy distribution is known, and very few researches considered the ambiguity in distribution information. That means the noted uncertainty caused by distributional perturbation is disregarded in the most of relevant literature. However, in reality the distributional information is often unavailable or partially known. Accordingly, it is necessary to present a proper expression for perturbation mode of fuzzy distribution, and further model and optimize the GCLSC network from a realistic perspective.

In this paper, we employ a novel distributionally robust optimization approach that can utilize fuzzy distribution information to construct an ambiguity set. We further illustrate how to formulate a new ambiguity set via nominal possibility distribution. The new expression for distribution ambiguity is constructed with a linear perturbation mode, and three special ambiguity distribution set, including trapezoidal, triangular and uniform, are obtained. In addition, the policy of carbon cap to control the fuzzy uncertainty of carbon emissions in the form of environmental constraint is employed. To measure the upward risk of total economic cost, a novel fuzzy upside risk measurement is proposed. We analyze a GCLSC network design problem, and a new mean-UPM GCLSC network design model with environmental constraint is proposed. A realistic case study on GCLSC network design problem of Coca-Cola Company in Chinese northeast region is conducted. The computational results show the effectiveness and reliability of outcome decisions. The resulting distributionally robust optimization problem is tractably solved.

It should be noted that the proposed optimization approach in our paper is distinguished from the ones in the existing literature (such as [17], [49]), and the main differences are summarized as follows:

- Although our approach and the ones in existing studies both belong to robust fuzzy programming method, there are obvious distinctions between them. First, the different combination of robustness and fuzziness directly determines the difference of modeling way. The studies [17,49] consider the robustness of uncertain parameter in a fuzzy programming, where fuzzy parameter and robust parameter can be separated. In contrast, the robustness and fuzziness in our paper are concentrated in a variable distribution which belong to an ambiguity distribution set. Here the robustness and fuzziness are inseparable. The modeling way determines the type of the model, i.e., the former is a robust fuzzy programming, and our model is actually a distributionally robust fuzzy programming.
- The distinction of model between our study and others directly leads to different solving methods. In [17,49], authors dealt with fuzzy parameters in the model firstly, and then the robustness is analyzed. By contrast, the robustness and fuzziness are treated simultaneously in our study. Specifically, we select a special distribution: parametric selection distribution from the ambiguity distribution set, and solving the model based on the “worst-case” orientation.
- The last difference is the utilized fuzzy measures. The fuzzy possibility measure is used in [17], while the possibility and necessity measures are used to cope with imprecision parameters in [49]. In our study, the credibility measure [56] with self duality is employed, and further define the upper partial moment based on it.

3. Problem statement

3.1. Assumption and notation

In this section, an investigated GCLSC network is a single-period, multiple-product, multiple-part and six-echelons network. The forward flow includes suppliers, plants, distribution centers and customer zones, while return flow includes recycling centers and disposal centers. The proposed six-echelons network is sketched in Fig. 1.

In the setting of proposed GCLSC network problem, decision makers want to obtain the following four aspects of objectives. (1) In the forward and return logistic network, they need to determine the optimal locations of supplier, distribution center, recycling center and disposal center. Then the entire GCLSC network is formulated. (2) They design the GCLSC network with the main concern of control the total economic cost, and make a trade-off between the risk of cost fluctuation and average economic cost to balance the performance of the entire GCLSC network. (3) To protect the environment, they design the GCLSC network in a way that set a carbon emissions cap for the entire chain in the form of constraint. (4) They want to ensure the level of satisfied customer demand reaches to a great extent, and reduce the disruption risk of supply chain.

To specify the study scope, some assumptions involved in our GCLSC network model are described below.

(A.1) The locations of plants and customer zones are known and existed, whereas the potential locations of supplier, distribution center, recycling center and disposal center are also known in the GCLSC network.

(A.2) Carbon emissions from suppliers are out of consideration for the complexity of green supplier selection. In addition, carbon emissions from other facilities are fixed and predetermined.

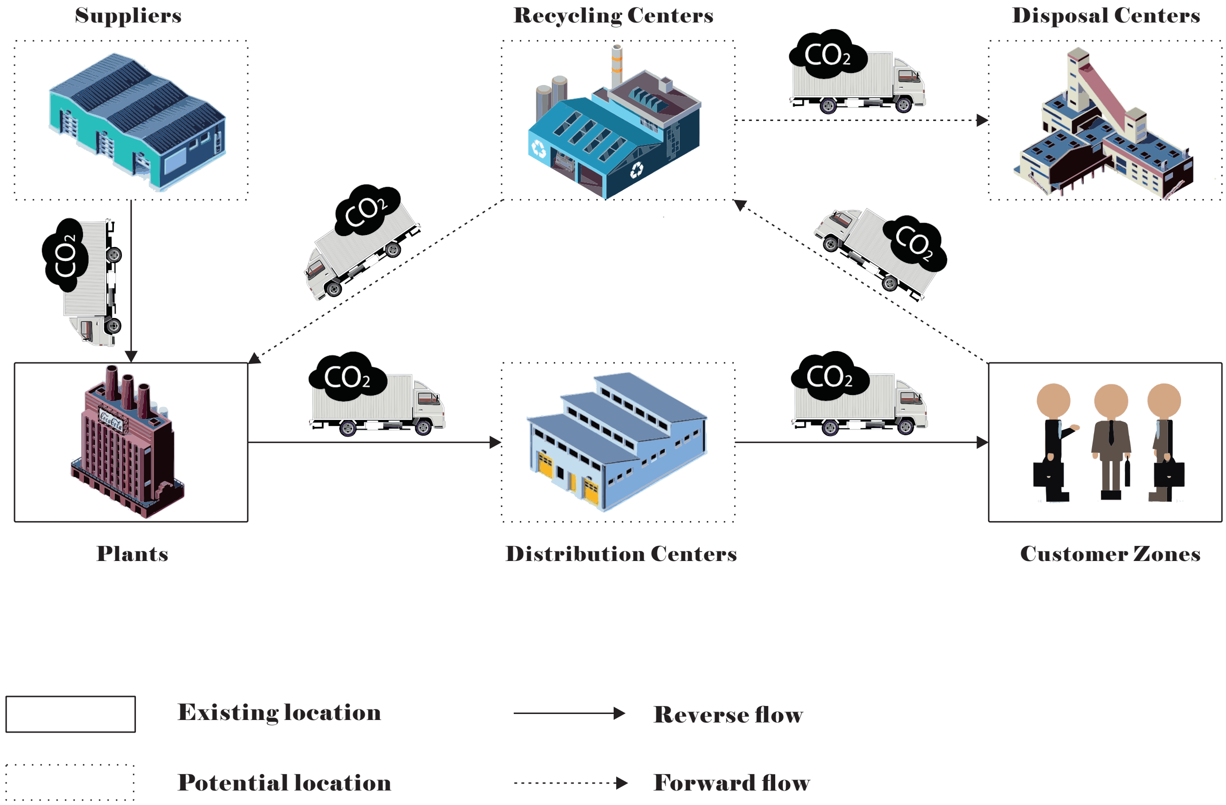


Fig. 1. The structure of the investigated GCLSC network.

(A.3) The total carbon emissions in logistic activities require no more than a carbon cap which is fixed and predetermined.
(A.4) All returned products from customer zones are fully shipped to recycling centers to protect environment.
(A.5) The quantity of transportation costs, customers' demands and carbon emissions in transportation are uncertain and their variable distributions belong to some ambiguity distribution sets.

In the proposed GCLSC network, the potential locations of supplier, distribution center, recycling center and disposal center need to be selected, and are indexed by $i \in \{1, \ldots, I\}$, $k \in \{1, \ldots, K\}$, $m \in \{1, \ldots, M\}$ and $n \in \{1, \ldots, N\}$; While the locations of plant and customer zones are fixed in advance, and indexed by $j \in \{1, \ldots, J\}$ and $l \in \{1, \ldots, L\}$. In addition, consider a set $p \in \{1, \ldots, P\}$ of products are produced in the proposed network, and a set $r \in \{1, \ldots, R\}$ of components included in every product.

3.2. Constraints

The GCLSC network is a complex product flow system, in which the following four aspects of constraints need to be considered:

- **Constraints on service level**

The demands of all customer zones are satisfied, which is represented as

$$\sum_{k=1}^{K} z_{klp} + \tau_{lp} \geq \xi_{lp}, \ \forall\, l, p,$$

where ξ_{lp} denotes demand of product p for customer zone l, decision variable z_{klp} denotes quantity of product p posted from distribution center k to customer zone l, and τ_{lp} denotes quantity of non-satisfied demand of product p for customer zone l. Due to numerous realistic influences, it is difficult to ensure this constraint hold when customers' demands are quite uncertain. The variable distribution of uncertain demand ξ_{lp} is denoted as $\mu_{\xi_{lp}}$. The credibility of the service level constraint is higher than a given level $\beta_{lp} \in (0, 1)$, which can be expressed as follows:

$$\mathrm{Cr}_{\mu_{\xi_{lp}}} \left\{ \sum_{k=1}^{K} z_{klp} + \tau_{lp} \geq \xi_{lp} \right\} \geq \beta_{lp}, \ \forall\, l, p. \tag{1}$$

- **Constraints on carbon emissions**

Carbon emissions from facilities and transportation between facilities are computed by:

$$
\begin{aligned}
\mathrm{CE} &= \mathrm{CaE}^0 + \mathrm{CaE}(\boldsymbol{\eta}) \\
&= \left(\sum_{j=1}^{J}\sum_{p=1}^{P} E_{jp}^{p} + \sum_{k=1}^{K}\sum_{p=1}^{P} E_{kp}^{d} v_k + \sum_{m=1}^{M}\sum_{p=1}^{P} E_{mp}^{c} c_m + \sum_{n=1}^{N}\sum_{r=1}^{R} E_{nr}^{D} w_n \right) \\
&\quad + \left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} \eta_{ijr}^{sp} x_{ijr} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} \eta_{jkp}^{pd} y_{jkp} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P} \eta_{klp}^{dc} z_{klp} \right. \\
&\quad \left. + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P} \eta_{lmp}^{cc} \kappa_{lmp} + \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R} \eta_{mjr}^{cp} t_{mjr} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R} \eta_{mnr}^{cn} \varpi_{mnr} \right),
\end{aligned}
$$

where E_{jp}^{p} denotes carbon emissions in *kg* due to production of one unit of product p at the plant j, E_{kp}^{d} denotes carbon emissions in *kg* due to storing and distributing of one unit of product p at the distribution center k, E_{mp}^{c} denotes carbon emissions in *kg* due to recycling of one unit of returned product p at the recycling center m, E_{nr}^{D} denotes carbon emissions in *kg* due to disposal of one unit of unusable returned part r at disposal center n; Decision variable x_{ijr} denotes quantity of component r bought from supplier i to plant j, y_{jkp} denotes quantity of product p sent from plant j to distribution center k, κ_{lmp} denotes quantity of product p returned from customer zone l to recycling center m, t_{mjr} denotes quantity of recycled component r shipped from recycling center m to plant j, ϖ_{mnr} denotes quantity of unrecoverable components r shipped from recycling center m to disposal center n, τ_{lp} denotes quantity of non-satisfied demand of product p for customer zone l; While binary variable $v_k \in \{0,1\}$ indicates if a distribution center is opened at location k, $c_m \in \{0,1\}$ indicates if a recycling center is opened at location m, and $w_n \in \{0,1\}$ indicates if a disposal center is opened at location n.

Here CaE^0 is the total carbon emissions from facilities, whereas $\mathrm{CaE}(\boldsymbol{\eta})$ is from transportation between facilities, in which uncertain carbon emissions vector $\boldsymbol{\eta} = (\eta_{ijr}^{sp}, \eta_{jkp}^{pd}, \eta_{klp}^{dc}, \eta_{lmp}^{cc}, \eta_{mjr}^{cp}, \eta_{mnr}^{cn})$, and its components are uncertain carbon emissions in transportation. Specifically, uncertain carbon emissions η_{ijr}^{sp} denotes carbon emissions in *kg* due to shipping one unit of part r from supplier i to plant j, η_{jkp}^{pd} denotes carbon emissions in *kg* due to shipping one unit of product p from plant j to distribution center k, η_{klp}^{dc} denotes carbon emissions in *kg* due to shipping one unit of product p from distribution center k to customer zone l, η_{lmp}^{cc} denotes carbon emissions in *kg* due to shipping one unit of product p from customer zone l to recycling center m, η_{mjr}^{cp} denotes carbon emissions in *kg* due to shipping one unit of part r from recycling center m to plant j, and η_{mnr}^{cn} denotes carbon emissions in *kg* due to shipping one unit of part r from recycling center m to disposal center n. The sum of carbon emissions from facilities and transportation is required not to exceed a carbon cap, which is modelled as

$$\mathrm{CaE}^0 + \mathrm{CaE}(\boldsymbol{\eta}) \le C^{cap},$$

where C^{cap} denotes a carbon cap on emissions over the entire planning horizon. $\mathrm{CaE}(\boldsymbol{\eta})$ is a linear combination of uncertain carbon emissions, and it is also uncertain. Denote its variable distribution as μ_{CaE}. Constraint (2) shows that the restriction on carbon emissions should be satisfied with a credibility level $\gamma \in (0,1)$, i.e.,

$$\mathrm{Cr}_{\mu_{\mathrm{CaE}}}\{\mathrm{CaE}(\boldsymbol{\eta}) + \mathrm{CaE}^0 \le C^{cap}\} \ge \gamma. \tag{2}$$

- **Constraints on movement equilibrium**

Constraint (3) ensures returned products are totally collected from customer zone.

$$\sum_{m=1}^{M} \kappa_{lmp} = \pi_{lp}, \ \forall\, l, p, \tag{3}$$

where π_{lp} denotes the amount of return of the used product p from customer zone l. Constraint (4) expresses that components required by products of plant can be satisfied by supplier and recycling center.

$$\sum_{i=1}^{I} x_{ijr} + \sum_{m=1}^{M} t_{mjr} = \sum_{k=1}^{K}\sum_{p=1}^{P} \delta_{rp} y_{jkp}, \ \forall\, j, r, \tag{4}$$

where δ_{rp} denotes the quantity of component r required to produce one unit of product p. Constraint (5) indicates all products from plant can be sent to customer zone.

$$\sum_{j=1}^{J} y_{jkp} = \sum_{l=1}^{L} z_{klp}, \ \forall\, k, p. \tag{5}$$

Constraints (6)-(7) ensure returned products from customer zone are totally disassembled and sent to plant or disposal center.

$$\sum_{j=1}^{J} t_{mjr} = \vartheta_r \sum_{l=1}^{L}\sum_{p=1}^{P} \kappa_{lmp}\delta_{rp},\ \forall\, r, m, \tag{6}$$

$$\sum_{n=1}^{N} \varpi_{mnr} = (1-\vartheta_r) \sum_{l=1}^{L}\sum_{p=1}^{P} \kappa_{lmp}\delta_{rp},\ \forall\, r, m, \tag{7}$$

where ϑ_r denotes the average disposal fraction of component r.

- **Constraints on capacity**

Constraints (8)-(14) are about the capacity restriction for all the facilities in GCLSC network. Firstly, constraint (8) ensures that component r shipped from supplier i should not exceed its supply capacity, i.e.

$$\sum_{j=1}^{J} x_{ijr} \le S^s_{ir} u_i,\ \forall\, i, r, \tag{8}$$

where S^s_{ir} denotes the capacity of storing component r for supplier i, and $u_i \in \{0, 1\}$ indicates if a supplier is selected at location i. Constraints (9)-(10) guarantee that product p from plant to distribution center neither exceed the storing capacity of plant j, nor the capacity of distribution center k, i.e.

$$\sum_{k=1}^{K} y_{jkp} \le S^p_{jp},\ \forall\, j, p, \tag{9}$$

$$\sum_{j=1}^{J} y_{jkp} \le v_k S^d_{kp},\ \forall\, k, p, \tag{10}$$

where S^p_{jp} denotes the capacity of storing product p for plant j, and S^d_{kp} denotes the capacity of storing product p for distribution center k. Constraint (11) shows that product p from distribution center to customer zone does not exceed the capacity of distribution center k, i.e.

$$\sum_{l=1}^{L} z_{klp} \le v_k S^d_{kp},\ \forall\, k, p. \tag{11}$$

Constraint (12) is to ensure that product p from customer zone to recycling center should not exceed the capacity of recycling center m, i.e.

$$\sum_{l=1}^{L} \kappa_{lmp} \le c_m S^r_{mp},\ \forall\, m, p, \tag{12}$$

where S^r_{mp} denotes the capacity of handling product p for recycling center m. Constraint (13) expresses that component r from recycling center to disposal center can not exceed the capacity of disposal center n, i.e.

$$\sum_{m=1}^{M} \varpi_{mnr} \le w_n S^D_{nr},\ \forall\, n, r, \tag{13}$$

where S^D_{nr} denotes the capacity of handling component r for disposal center n. Constraint (14) guarantees that component r transported from recycling center to plant and disposal center should not exceed the capacity of components removed at recycling center m, i.e.

$$\sum_{j=1}^{J} t_{mjr} + \sum_{n=1}^{N} \varpi_{mnr} \le c_m \sum_{p=1}^{P} S^r_{mp}\delta_{rp},\ \forall\, m, r. \tag{14}$$

In view of the reality of GCLSC problem, decision variables must satisfy the following two constraints,

$$u_i, v_k, c_m, w_n \in \{0, 1\},\ \forall\, i, r, k, m, n, \tag{15}$$

$$x_{ijr}, y_{jkp}, z_{klp}, \kappa_{lmp}, t_{mjr}, \varpi_{mnr} \ge 0,\ \forall\, i, j, r, k, p, l, m, n. \tag{16}$$

3.3. Objective

The GCLSC network design problem studied in this paper seeks to minimize the total economic cost in GCLSC, which consists of mainly five aspects:

• Transportation cost (TC) between the different facilities and centers for each forwarded and collected product is depicted as

$$TC=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R}\zeta^{I}_{ijr}x_{ijr}+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\zeta^{J}_{jkp}y_{jkp}+\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P}\zeta^{K}_{klp}z_{klp}$$
$$+\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P}\zeta^{L}_{lmp}\kappa_{lmp}+\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R}\zeta^{M}_{mjr}t_{mjr}+\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R}\zeta^{N}_{mnr}r_{mnr},$$

where ζ^{I}_{ijr} denotes transportation cost of component r from supplier i to plant j, ζ^{J}_{jkp} denotes transportation cost of product p from plant j to distribution center k, ζ^{K}_{klp} denotes transportation cost of product p from distribution center k to customer zone l, ζ^{L}_{lmp} denotes transportation cost of product p from customer zone l to recycling center m, ζ^{M}_{mjr} denotes transportation cost of component r from recycling center m to plant j, and ζ^{N}_{mnr} denotes transportation cost of component r from recycling center m to disposal center n.

• Investment cost required to open facilities including supplier, distribution center, recycling center and disposal center, which depends on whether the facilities open. Denoted the category of cost as IC and formulate it as follows:

$$IC=\sum_{i=1}^{I}C^{s}_{i}u_i+\sum_{k=1}^{K}C^{d}_{k}v_k+\sum_{m=1}^{M}C^{r}_{m}c_m+\sum_{n=1}^{N}C^{D}_{n}w_n.$$

where C^{s}_{i} denotes fixed cost of selecting supplier i, C^{d}_{k} denotes fixed cost of opening distribution center k, C^{r}_{m} denotes fixed cost of opening recycling center m, and C^{D}_{n} denotes fixed cost of opening disposal center n.

• Production cost (PC_{I}) consists of manufacturing cost in supplier and plant and processing cost in distribution center.

$$PC_{\mathrm{I}}=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R}C^{m}_{ir}x_{ijr}+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}C^{M}_{jp}y_{jkp}+\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P}C^{P}_{kp}z_{klp}.$$

where C^{m}_{ir} denotes the manufacturing cost of unit component r by supplier i, C^{M}_{jp} denotes the manufacturing cost of unit product p at plant j, and C^{P}_{kp} denotes the processing cost of unit product p at distribution center k.

• Dismantling cost (DC) contains collection/disassembly and recycling cost in recycling center, shredding and disposal cost in disposal center.

$$DC=\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P}C^{C}_{mp}\kappa_{lmp}+\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R}C^{R}_{mr}t_{mjr}+\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R}Cd_{nr}r_{mnr}.$$

where C^{C}_{mp} denotes the processing cost of unit returned product p at the recycling center m, C^{R}_{mr} denotes the recycling cost of unit component r sent to production center from recycling center m, and Cd_{nr} denotes the disposal cost of unit unusable returned component r at disposal center n.

• Penalty cost (PC_{II}) occurs in case of customer's demand of product cannot be satisfied and it can be expressed as

$$PC_{\mathrm{II}}=\sum_{l=1}^{L}\sum_{p=1}^{P}P_{lp}\tau_{lp},$$

where P_{lp} denotes the penalty cost per unit of non-satisfied demand of product p for customer zone l. Combining these costs, we can get the total economic cost (EC) function of GCLSC network problem as follows:

$$EC=\mathrm{TC}+\mathrm{IC}+\mathrm{PC}_{\mathrm{I}}+\mathrm{DC}+\mathrm{PC}_{\mathrm{II}}.$$

3.4. GCLSC Network model with new risk measure

Many realistic factors, such as the fuel price, weather and vehicle load, have a significant impact on transportation cost, so transportation cost is commonly uncertain. Therefore, in this paper the uncertainty of EC is assumed to only stem from transportation cost TC and the other costs are precise. For simplicity, denote the sum of the other costs as $\Pi_C=IC+PC_{\mathrm{I}}+DC+PC_{\mathrm{II}}$. The average performance of CLSC network is an important and common concern, and the expected value of total economic cost is expressed as follows:

$$\mathbb{E}[EC]=\mathbb{E}[TC]+\Pi_C.$$

Additionally, the uncertainty in transportation cost is considered as one of main sources of risk in GCLSC network design. Usually, positive and negative deviations from the expected value are considered as equally risky which need be treated by dispersion measures. However, for the risk of economic cost in GCLSC, the only direction need punishment is the upper side. In this paper we therefore present a novel upper side risk measure to quantify the uncertain risk of total economic cost, and call it upper partial moment.

Definition 1 [57]**.** The upper partial moment with power q of total economic cost EC is defined as

$$\mathrm{UPM}^q[EC] = \left\{\mathbb{E}\left[(EC - \mathbb{E}[EC])^+\right]^q\right\}^{\frac{1}{q}},$$

where $\mathbb{E}[EC]$ is the finite expected value of EC, and $(EC - \mathbb{E}[EC])^+$ is computed by

$$(EC - \mathbb{E}[EC])^+ = \begin{cases} EC - \mathbb{E}[EC], & if\ EC \geq \mathbb{E}[EC] \\ 0, & if\ EC < \mathbb{E}[EC]. \end{cases}$$

As mentioned above, the upward risk of EC stems from the uncertainty of transportation cost, and EC is a linear function of transportation costs. Thus, computing the UPM^q of EC actually equals to computing the UPM^q of TC, i.e., $\mathrm{UPM}^q[EC] = \mathrm{UPM}^q[TC]$. Based on L-S integral [58], the UPM^q of TC can be computed with the following definition.

Definition 2. If TC is a fuzzy variable with finite expected value m, then the UPM^q of TC is computed with the following integral

$$\begin{aligned}\mathrm{UPM}^q[TC] &= \left\{\int_{(-\infty,+\infty)} [(TC-m)^+]^q \mathrm{d}(\mathrm{Cr}\{TC \leq r\})\right\}^{\frac{1}{q}} \\ &= \left\{\int_{(m,+\infty)} (TC-m)^q \mathrm{d}(\mathrm{Cr}\{TC \leq r\})\right\}^{\frac{1}{q}},\end{aligned} \tag{17}$$

where $\mathrm{Cr}\{TC \leq r\}$ is credibility distribution of TC.

The credibility distribution of TC can be computed by [56,59]

$$\mathrm{Cr}\{TC \leq r\} = \frac{1}{2}\Big(1 + \sup_{t \leq r} \mu_{TC}(t;\theta) - \sup_{t > r} \mu_{TC}(t;\theta)\Big).$$

The main challenge in some practical problems is that fuzzy distribution is unknown. Obtaining an accurate estimate of the distribution from data record can be very difficult due to the complexity of the problem. While in many cases with observable information, the predictability of distribution set can be greatly improved through perturbation parameters. Facing such a case of limited information, we formulate a new ambiguity distribution set of variable possibility distribution to obtain efficient and robust decisions. Thus, based on the above description, a distributionally robust fuzzy GCLSC network model with minimizing the upper partial moment and expected value of total economic cost is formulated as:

$$\begin{array}{ll} \min & \max\limits_{\mu_{TC} \in \mathscr{P}_{TC}} \mathrm{UPM}^q[TC] + \varrho(\mathbb{E}[TC] + \Pi_C) \\ \text{s. t.} & \min\limits_{\mu_{\xi_{lp}} \in \mathscr{P}_{\xi_{lp}}} \mathrm{Cr}\{\sum_{k=1}^K z_{klp} + \omega_{lp} \geq \xi_{lp}\} \geq \beta_{lp},\ \forall\, l, p \\ & \min\limits_{\mu_{\mathrm{CaE}} \in \mathscr{P}_{\mathrm{CaE}}} \mathrm{Cr}\{\mathrm{CaE}(\boldsymbol{\eta}) + \mathrm{CaE}^0 \leq C^{cap}\} \geq \gamma, \\ & \text{constraints (3)-(16).} \end{array} \tag{18}$$

In model (18), μ_{TC} is variable distribution of uncertain transportation cost TC; whereas $\mathscr{P}_{TC}$, $\mathscr{P}_{\xi_{lp}}$ and $\mathscr{P}_{\mathrm{CaE}}$ are the corresponding ambiguity distribution sets that μ_{TC}, $\mu_{\xi_{lp}}$ and μ_{CaE} belong to, respectively. The solving of model (18) is directly related to these uncertain distribution sets. Additionally, $\varrho \geq 0$ is a relative weight of components in objective function. It represents a trade-off between upper side risk and average performance of cost function and is decided with the attitude of decision maker.

Note that fuzzy mean-UPM GCLSC network model (18) is a semi-infinite optimization problem, since the computation of objective function and constraints are related to ambiguity distribution sets. The solving attempt based on conventional optimization method is difficult to achieve for the distributions of fuzzy uncertain parameters are changeable and belong to some distribution sets. To solve model (18), it is necessary to determine the type and structural feature of fuzzy parameters with the changeable distribution. In the next section, according to the mode of distributional perturbation, a novel definition on the changeable possibility distribution and its ambiguity distribution set will be presented.

4. Ambiguity distribution set of PIV fuzzy variable

4.1. Novel definition of ambiguity distribution set

In fuzzy supply chain decision system, the uncertain parameter is often assumed to be a fuzzy variable with known possibility distribution, for instance, the customer demand ξ can be represented as a triangular fuzzy variable [60] and its fixed possibility distribution $\mu_\xi(r)$ was depicted in Fig. 2(a).

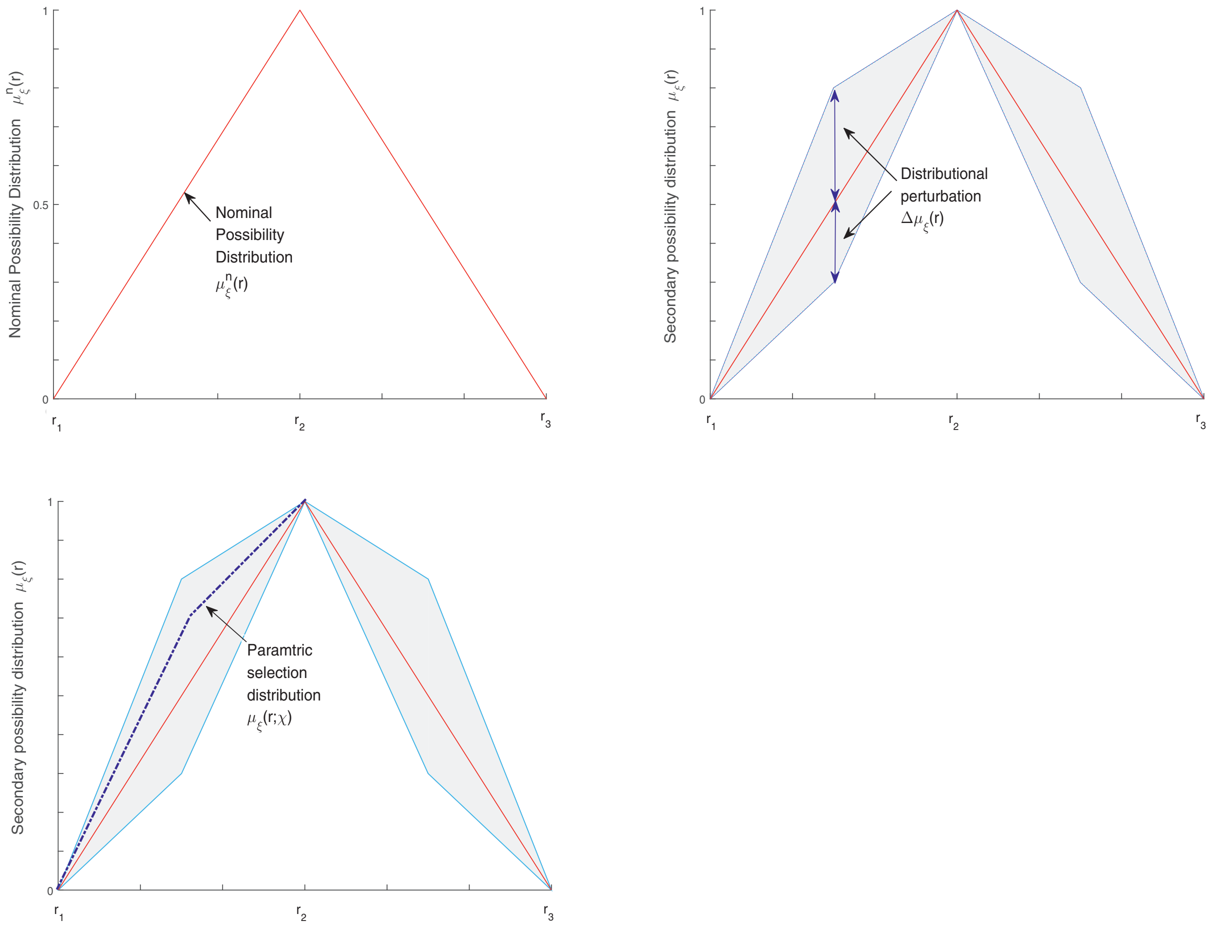


Fig. 2. The nominal possibility distribution, distributional perturbations and parametric selection distribution of PIV triangular fuzzy variable.

It is, however, difficult and challenged to obtain the fully distributional information of fuzzy uncertain parameter from today's complicated and changeable world. It is relatively easy to determine a changeable range of possibility distribution. When the possibility distribution changed from a line to a belt, the type of corresponding variable is also generalized from type-1 to type-2 [20].

A parametric interval-valued (PIV) fuzzy variable [21] is a kind of type-2 fuzzy variable and its secondary possibility distribution is a family of possibility distributions (the shaded part in Fig. 2-(b)). In the family of possibility distributions, a possibility distribution is termed nominal (or principle) possibility distribution which corresponds to the distribution of fuzzy variable shown in Fig. 2(a). A bounded collection of distributions is formed with some fluctuating distributions centred with the nominal possibility distribution. The formulation of fluctuating possibility distribution in a *unknown-but-bounded* mode can be expressed as follows:

$$\mu_\xi(r) = \mu^n_\xi(r) + \epsilon\Delta\mu_\xi(r),$$

where $\mu^n_\xi(r)$ is the nominal possibility distribution of ξ, $\Delta\mu_\xi(r)$ is the perturbation of possibility distribution on the nominal distribution $\mu^n_\xi(r)$, and ϵ is a given magnitude.

Furthermore, to distinguish two distinct kinds of perturbation directions, we set parameters θ_l and θ_r as lower and upper perturbation coefficients. Based on the above linear expression, we can have the following definition:

Definition 3. If ξ is a PIV fuzzy variable, then its secondary possibility distribution $\tilde{\mu}_\xi(r)$ is a subinterval of [0,1], specifically, $\tilde{\mu}_\xi(r) = [\mu^n_\xi(r) - \theta_l\Delta\mu_\xi(r), \mu^n_\xi(r) + \theta_r\Delta\mu_\xi(r)]$.

Specially, when $\theta_l = \theta_r = 0$, the corresponding secondary possibility distribution is the nominal (or principle) possibility distribution of ξ.

Note that the kind of PIV fuzzy variables is determined by the corresponding nominal possibility distribution. In addition, when the definition mode of distributional perturbation $\Delta\mu_\xi(r)$ is different, we can derive diverse PIV fuzzy variables. For example, in [21], the distributional perturbation $\Delta\mu_\xi(r)$ is defined as $\min\{\mu_\xi^n(r), 1-\mu_\xi^n(r)\}$. In contrast, the distributional perturbation is directly scaled with the value of nominal distribution in [22].

Next, we introduce three common PIV fuzzy variables that are important and useful in practical fuzzy decision system.

• **Trapezoidal & Triangular distribution.** If $\xi = \mathrm{Tra}(r_1, r_2, r_3, r_4; \theta_l, \theta_r)$ is a PIV trapezoidal fuzzy variable, then its secondary possibility distribution $\tilde{\mu}_\xi(r) = [\mu_\xi^n(r) - \theta_l\Delta\mu_\xi(r), \mu_\xi^n(r) + \theta_r\Delta\mu_\xi(r)]$, in which the nominal possibility distribution of ξ is

$$\mu_\xi^n(r) = \begin{cases} \frac{r-r_1}{r_2-r_1}, & \text{if } r \in [r_1, r_2] \\ 1, & \text{if } r \in (r_2, r_3] \\ \frac{r_4-r}{r_4-r_3}, & \text{if } r \in (r_3, r_4]. \end{cases}$$

Particularly, if $r_2 = r_3$, then ξ is called a PIV triangular fuzzy variable and usually denoted by $\mathrm{Tri}(r_1, r_2, r_3; \theta_l, \theta_r)$. Its secondary possibility distribution $\tilde{\mu}_\xi(r) = [\mu_\xi^n(r) - \theta_l\Delta\mu_\xi(r), \mu_\xi^n(r) + \theta_r\Delta\mu_\xi(r)]$, in which the nominal possibility distribution of ξ is

$$\mu_\xi^n(r) = \begin{cases} \frac{r-r_1}{r_2-r_1}, & \text{if } r \in [r_1, r_2] \\ \frac{r_3-r}{r_3-r_2}, & \text{if } r \in (r_2, r_3]. \end{cases}$$

• **Uniform distribution.** If $\varsigma = \mathrm{Uni}[a^\varsigma, b^\varsigma; \theta_l]$ is a PIV uniform fuzzy variable, then its secondary possibility distribution $\tilde{\mu}_\varsigma(r)$ is $[\mu_\varsigma^n(r) - \theta_l\Delta\mu_\varsigma(r), \mu_\varsigma^n(r) + \theta_r\Delta\mu_\varsigma(r)]$, in which the nominal possibility distribution of ς is

$$\mu_\varsigma^n(r) = \begin{cases} 1, & \text{if } r \in [a^\varsigma, b^\varsigma] \\ 0, & \text{otherwise.} \end{cases}$$

Note that, for $\mu_\varsigma^n(r) \le 1$, so parameter $\theta_r = 0$. The distributional perturbation $\Delta\mu_\varsigma(r) = \mu_\varsigma^n(r)$, and its secondary possibility distribution $\tilde{\mu}_\varsigma(r)$ actually is $[(1-\theta_l)\mu_\varsigma^n(r), 1]$.

Assume that ξ is a PIV fuzzy variable with the secondary possibility distribution $\tilde{\mu}_\xi(r) = [\mu_\xi^n(r) - \theta_l\Delta\mu_\xi(r), \mu_\xi^n(r) + \theta_r\Delta\mu_\xi(r)]$. Define a variable distribution in the distributional interval as *parametric selection distribution* (PSD), which is the convex combination of two extreme distributions of the distributional interval $[\mu_\xi^n(r) - \theta_l\Delta\mu_\xi(r), \mu_\xi^n(r) + \theta_r\Delta\mu_\xi(r)]$. To be specific, for any $\lambda \in [0, 1]$, the parametric selection distribution $\mu_\xi(r; \chi)$ of ξ is

$$\mu_\xi(r; \chi) = \mu_\xi^n(r) - \chi\Delta\mu_\xi(r), \tag{19}$$

where parameter $\chi = \lambda\theta_r - (1-\lambda)\theta_l$. As shown in Fig. 2-(c), the PSD can run over the entire family of possibility distribution of PIV fuzzy variable when the values of parameter χ changes, therefore, it can be viewed as a representation of variable distributions.

Furthermore, if we define the family of possibility distribution as ambiguity distribution set of PIV fuzzy variable, then it can be formulated as follows:

$$\mathscr{P}_\xi = \left\{ \mu_\xi(r; \chi) \,\middle|\, \begin{array}{l} \mu_\xi(r; \chi) = \mu_\xi^n(r) - \chi\Delta\mu_\xi(r) \\ \chi = \lambda\theta_r - (1-\lambda)\theta_l \\ \lambda \in [0, 1],\ \theta_r, \theta_l \in [0, 1] \end{array} \right\},$$

where $\mu_\xi^n(r)$ is the nominal distribution of ξ, $\Delta\mu_\xi(r)$ is the perturbation of possibility distribution with respect to nominal distribution $\mu_\xi^n(r)$.

4.2. Ambiguity distribution sets of uncertain parameters in GCLSC model

Assume uncertain parameters in GCLSC model be PIV fuzzy variables. Based on the novel formulation of ambiguity distribution set of PIV fuzzy variable, in this subsection, we will give the concrete forms of ambiguity distribution sets under some specific PIV fuzzy parameters.

Assume uncertain transportation costs from one facility to another are PIV trapezoidal fuzzy variables. To be specific,

$$\zeta_{ijr}^I = \mathrm{Tra}(r_1^I, r_2^I, r_3^I, r_4^I; \theta_l^I, \theta_r^I),\ \zeta_{jkp}^J = \mathrm{Tra}(r_1^J, r_2^J, r_3^J, r_4^J; \theta_l^J, \theta_r^J),\ \zeta_{klp}^K = \mathrm{Tra}(r_1^K, r_2^K, r_3^K, r_4^K; \theta_l^K, \theta_r^K),$$

$$\zeta_{lmp}^L = \mathrm{Tra}(r_1^L, r_2^L, r_3^L, r_4^L; \theta_l^L, \theta_r^L),\ \zeta_{mjr}^M = \mathrm{Tra}(r_1^M, r_2^M, r_3^M, r_4^M; \theta_l^M, \theta_r^M),\ \zeta_{mnr}^N = \mathrm{Tra}(r_1^N, r_2^N, r_3^N, r_4^N; \theta_l^N, \theta_r^N).$$

As previous mentioned, TC is a linear combination with respect to these PIV fuzzy variables, so TC is also a PIV trapezoidal fuzzy variable [21]. Then ambiguity distribution set of TC is denoted as

$$\mathscr{P}_{TC} = \left\{ \mu_{TC}(r; \chi) \,\middle|\, \begin{array}{l} \mu_{TC}(r; \chi) = \mu_{TC}^n(r) - \chi\Delta\mu_{TC}(r) \\ \chi = \lambda\theta_r^{TC} - (1-\lambda)\theta_l^{TC} \\ \lambda \in [0, 1],\ \theta_r^{TC}, \theta_l^{TC} \in [0, 1] \end{array} \right\},$$

in which nominal possibility distribution of TC is

$$\mu^n_{TC}(r) = \begin{cases} \frac{r-r_1}{r_2-r_1}, \text{ if } r \in [r_1, r_2] \\ 1, \quad\quad \text{if } r \in (r_2, r_3] \\ \frac{r_4-r}{r_4-r_3}, \text{ if } r \in (r_3, r_4], \end{cases}$$

and, following [21], the distributional perturbation $\Delta\mu_{TC}(r) = \min\{\mu^n_{TC}(r),\ 1-\mu^n_{TC}(r)\}$. Here, for any s, parameters r_s in nominal possibility distribution of TC are computed by

$$r_s = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} r^I_s x_{ijr} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} r^J_s y_{jkp} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P} r^k_s z_{klp}$$
$$+ \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P} r^L_s \kappa_{lmp} + \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R} r^M_s t_{mjr} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R} r^N_s r_{mnr}. \tag{20}$$

Moreover, we have lower perturbation coefficient $\theta^{TC}_l = \max\{\theta^I_l, \theta^J_l, \theta^K_l, \theta^L_l, \theta^M_l, \theta^N_l\}$, and upper perturbation coefficient $\theta^{TC}_r = \min\{\theta^I_r, \theta^J_r, \theta^K_r, \theta^L_r, \theta^M_r, \theta^N_r\}$.

Similarly, ambiguity distribution set of demand $\xi_{lp} = \text{Tri}[r^{lp}_1, r^{lp}_2, r^{lp}_3; \theta^{lp}_l, \theta^{lp}_r]$ on product p for customer zone l is defined as

$$\mathscr{P}_{\xi_{lp}} = \left\{ \mu_{\xi_{lp}}(r; \chi^{lp}) \;\middle|\; \begin{array}{c} \mu_{\xi_{lp}}(r; \chi^{lp}) = \mu^n_{\xi_{lp}}(r) - \chi^{lp}\Delta\mu_{\xi_{lp}}(r) \\ \chi^{lp} = \lambda\theta^{lp}_r - (1-\lambda)\theta^{lp}_l \\ \lambda \in [0,1],\ \theta^{lp}_r, \theta^{lp}_l \in [0,1] \end{array} \right\},$$

in which nominal possibility distribution is

$$\mu^n_{\xi_{lp}}(r) = \begin{cases} \frac{r-r^{lp}_1}{r^{lp}_2-r^{lp}_1}, \text{ if } r \in [r^{lp}_1, r^{lp}_2] \\ \frac{r^{lp}_3-r}{r^{lp}_3-r^{lp}_2}, \text{ if } r \in (r^{lp}_2, r^{lp}_3], \end{cases}$$

and the distributional perturbation $\Delta\mu_{\xi_{lp}}(r) = \min\{\mu^n_{\xi_{lp}}(r),\ 1-\mu^n_{\xi_{lp}}(r)\}$.

On the other hand, assume the carbon emissions in transportation from one facility to anther be PIV uniform fuzzy variables. To be specific, one has

$$\eta^{sp}_{ijr} = \text{Uni}[a^{sp}_{ijr}, b^{sp}_{ijr}; \theta^{sp}_l],\ \eta^{pd}_{jkp} = \text{Uni}[a^{pd}_{jkp}, b^{pd}_{jkp}; \theta^{pd}_l],\ \eta^{dc}_{klp} = \text{Uni}[a^{dc}_{klp}, b^{dc}_{klp}; \theta^{dc}_l],$$

$$\eta^{cc}_{lmp} = \text{Uni}[a^{cc}_{lmp}, b^{cc}_{lmp}; \theta^{cc}_l],\ \eta^{cp}_{mjr} = \text{Uni}[a^{cp}_{mjr}, b^{cp}_{mjr}; \theta^{cp}_l],\ \eta^{cn}_{mnr} = \text{Uni}[a^{cn}_{mnr}, b^{cn}_{mnr}; \theta^{cn}_l].$$

Thus, as a linear combination with respect to these PIV uniform fuzzy variables, $\text{CaE}(\boldsymbol{\eta})$ is still a PIV uniform fuzzy variable. Then ambiguity distribution set of $\text{CaE}(\boldsymbol{\eta})$ is as follows:

$$\mathscr{P}_{\text{CaE}} = \left\{ \mu_{\text{CaE}}(r; \chi') \;\middle|\; \begin{array}{c} \mu_{\text{CaE}}(r; \chi') = \mu^n_{\text{CaE}}(r) - \chi'\Delta\mu_{\text{CaE}}(r) \\ \chi^{lp} = (\lambda-1)\theta^{\text{CaE}}_l \\ \lambda \in [0,1],\ \theta^{\text{CaE}}_l \in [0,1] \end{array} \right\},$$

in which the nominal possibility distribution of $\text{CaE}(\boldsymbol{\eta})$ is

$$\mu_{\text{CaE}}(r) = \begin{cases} 1, \quad \text{if } r \in [a^{\text{CaE}}, b^{\text{CaE}}] \\ 0, \quad \text{otherwise.} \end{cases}$$

Here, parameters a^{CaE} and b^{CaE} in nominal possibility distribution are computed by

$$a^{\text{CaE}} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} a^{sp}_{ijr} x_{ijr} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} a^{pd}_{jkp} y_{jkp} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P} a^{dc}_{klp} z_{klp}$$
$$+ \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P} a^{cc}_{lmp} \kappa_{lmp} + \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R} a^{cp}_{mjr} t_{mjr} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R} a^{cn}_{mnr} r_{mnr}, \tag{21}$$

and

$$b^{\text{CaE}} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} b^{sp}_{ijr} x_{ijr} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P} b^{pd}_{jkp} y_{jkp} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{p=1}^{P} b^{dc}_{klp} z_{klp}$$

$$+\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{p=1}^{P} b^{cc}_{lmp}\kappa_{lmp} + \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{r=1}^{R} b^{cp}_{mjr}t_{mjr} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{r=1}^{R} b^{cn}_{mnr}r_{mnr}. \tag{22}$$

Moreover, following [21], we have lower perturbation coefficient $\theta_l^{\mathrm{CaE}} = \max\{\theta_l^{sp}, \theta_l^{pd}, \theta_l^{dc}, \theta_l^{cc}, \theta_l^{cp}, \theta_l^{cn}\}$.

5. Model analysis

In this section, we will discuss how to convert objective function and constraints into their equivalent forms, and reformulate the above mean-UPM GCLSC network model as a computational tractable model.

There is a notable property of model (18) to be discussed. In the case of distribution ambiguity-free, the distributional perturbation is set to zero. The distributionally robust mean-UPM GCLSC network model (18) reduces to its counterpart, in which fuzzy transportation costs, demands and carbon emissions are only characterized by their nominal possibility distributions. The ambiguity-free model can be named as *fuzzy nominal problem*, that is, type-1 fuzzy programming model.

5.1. Analysis on distributionally robust objective function

This subsection discusses the computational issue on the distributionally robust objective function. We firstly try to find the equivalent form of the upper side risk UPM^q of transportation cost.

Theorem 1. *Let TC be PIV trapezoidal fuzzy variable* $\mathrm{Tra}(r_1, r_2, r_3, r_4; \theta_l, \theta_r)$ *and its finite expected value m.*

(i) If $m \in [\frac{r_1+r_2}{2}, r_2]$, *then*

$$\mathrm{UPM}^q[TC] = \left\{\frac{(1-\chi)(r_2-m)^{q+1}}{2(1+q)(r_2-r_1)} + \frac{(1+\chi)(r_4-m)^{q+1} - 2^{-q}\chi[(r_4-m)+(r_3-m)]^{q+1} - (1-\chi)(r_3-m)^{q+1}}{2(1+q)(r_4-r_3)}\right\}^{\frac{1}{q}}.$$

(ii) If $m \in (r_2, r_3]$, *then*

$$\mathrm{UPM}^q[TC] = \left\{\frac{(1+\chi)(r_4-m)^{q+1} - 2^{-q}\chi[(r_4-m)+(r_3-m)]^{q+1} - (1-\chi)(r_3-m)^{q+1}}{2(1+q)(r_4-r_3)}\right\}^{\frac{1}{q}}.$$

(iii) If $m \in (r_3, \frac{r_3+r_4}{2}]$, *then*

$$\mathrm{UPM}^q[TC] = \left\{\frac{(1+\chi)(r_4-m)^{q+1} - 2^{-q}\chi[(r_4-m)+(r_3-m)]^{q+1}}{2(1+q)(r_4-r_3)}\right\}^{\frac{1}{q}}.$$

Next, we will deal with the distributionally robustness of the objective function. For simplicity, we obtain the theoretical results and conduct the experiments under $q = 1$. In this case, the UPM^1 is actually the upside semideviation, which also be termed as upper partial mean used in [61]. For notational simplicity, when $q = 1$, we denote UPM^1 as UPM. The theoretical results are summarized as the following theorem.

Theorem 2. *Let TC be PIV trapezoidal fuzzy variable* $\mathrm{Tra}(r_1, r_2, r_3, r_4; \theta_l, \theta_r)$ *and its finite expected value m. Then the distributionally robust objective function*

$$\max_{\mu_{TC}\in\mathscr{P}_{TC}} \mathrm{UPM}[TC] + \varrho\mathbb{E}[TC] + \varrho\Pi_C$$

is equivalent to $\mathbb{M}(\mathbf{r}) + \varrho\Pi_C$, *where*

(i) If $m \in [\frac{r_1+r_2}{2}, r_2]$, *then*

$$\mathbb{M}(\mathbf{r}) = \begin{cases} a(\theta_r^{TC})^3 + b(\theta_r^{TC})^2 + c\theta_r^{TC} + d, & \text{if } \Delta > 0 \\ a(-\theta_l^{TC})^3 + b(-\theta_l^{TC})^2 - c\theta_l^{TC} + d, & \text{if } \Delta \le 0 \end{cases}$$

(ii) If $m \in (r_2, r_3]$, *then*

$$\mathbb{M}(\mathbf{r}) = \begin{cases} \frac{[(2\varrho-1)(r_1+r_2)+(2\varrho+1)(r_3+r_4)]}{8} + \frac{(2\varrho+1)(r_4-r_3)-(2\varrho-1)(r_2-r_1)}{16}\theta_r^{TC}, & \text{if } (2\varrho+1)(r_4-r_3) \ge (2\varrho-1)(r_2-r_1) \\ \frac{[(2\varrho-1)(r_1+r_2)+(2\varrho+1)(r_3+r_4)]}{8} - \frac{(2\varrho+1)(r_4-r_3)-(2\varrho-1)(r_2-r_1)}{16}\theta_l^{TC}, & \text{if } (2\varrho+1)(r_4-r_3) < (2\varrho-1)(r_2-r_1) \end{cases}$$

(iii) If $m \in (r_3, \frac{r_3+r_4}{2}]$, *then*

$$\mathbb{M}(\mathbf{r}) = \begin{cases} \tilde{a}(\theta_r^{TC})^3 + \tilde{b}(\theta_r^{TC})^2 + \tilde{c}\theta_r^{TC} + \tilde{d}, & \text{if } \tilde{\Delta} > 0 \\ \tilde{a}(-\theta_l^{TC})^3 + \tilde{b}(-\theta_l^{TC})^2 - \tilde{c}\theta_l^{TC} + \tilde{d}, & \text{if } \tilde{\Delta} \le 0 \end{cases}$$

in which components r_s *of parameters vector* $\mathbf{r} = r_s, s = 1, \ldots, 4$ *are determined by Eq. (20). Moreover, parameter* $a, b, c, \Delta, \tilde{a}, \tilde{b}, \tilde{c}$ *and* $\tilde{\Delta}$ *are shown in Proof.*

5.2. Analysis on distributionally robust credibility constraints

In this subsection, we will discuss how to handle the distributionally robustness in credibility constraints. First, we deal with the computational issue on credibility of fuzzy event in robust service level constraint

$$\min_{\nu_{\xi_{lp}}\in\mathscr{P}_{\xi_{lp}}} \mathrm{Cr}\left\{\sum_{k=1}^{K} z_{klp}+\tau_{lp}\ge \xi_{lp}\right\}\ge \beta_{lp},\ \forall\, l,p$$

and derive its analytical expression. The computational results are shown in the following theorem.

Theorem 3. *Let uncertain demand of product p for customer zone l be PIV triangular fuzzy variable* $\xi_{lp}=\mathrm{Tri}[r_1^{lp},r_2^{lp},r_3^{lp};\theta_l^{lp},\theta_r^{lp}]$. *Then the distributionally robust credibility service level constraint*

$$\min_{\nu_{\xi_{lp}}\in\mathscr{P}_{\xi_{lp}}} \mathrm{Cr}\left\{\sum_{k=1}^{K} z_{klp}+\tau_{lp}\ge \xi_{lp}\right\}\ge \beta_{lp},\ \forall\, l,p$$

is equivalent to the following deterministic constraint

$$\mathbb{F}(\mathbf{r}_{lp},t_{lp})\ge \beta_{lp},\ \forall\, l,\, p,$$

where

$$\mathbb{F}(\mathbf{r}_{lp},t_{lp})=\begin{cases}0, & t_{lp}\in(0,r_1^{lp}]\\ \frac{(t_{lp}-r_1^{lp})(1+\theta_r^{lp})}{2(r_2^{lp}-r_1^{lp})}, & t_{lp}\in(r_1^{lp},\frac{r_1^{lp}+r_2^{lp}}{2}]\\ \frac{(t_{lp}-r_1^{lp})+(r_2^{lp}-t_{lp})\theta_r^{lp}}{2(r_2^{lp}-r_1^{lp})}, & t_{lp}\in(\frac{r_1^{lp}+r_2^{lp}}{2},r_2^{lp}]\\ \frac{t_{lp}-2r_2^{lp}+r_3^{lp}-(r_2^{lp}-t_{lp})\theta_l^{lp}}{2(r_3^{lp}-r_2^{lp})}, & t_{lp}\in(r_2^{lp},\frac{r_2^{lp}+r_3^{lp}}{2}]\\ \frac{t_{lp}-2r_2^{lp}+r_3^{lp}-(t_{lp}-r_3^{lp})\theta_l^{lp}}{2(r_3^{lp}-r_2^{lp})}, & t_{lp}\in(\frac{r_2^{lp}+r_3^{lp}}{2},r_3^{lp}],\\ 1, & t_{lp}\in(r_3^{lp},+\infty),\end{cases}$$

with parameter $t_{lp}=\sum_{k\in\mathcal{K}} z_{klp}+\tau_{lp}$ *and* $\mathbf{r}_{lp}=(r_1^{lp},r_2^{lp},r_2^{lp})$.

Similar to distributioanlly robust service level constraint, an analytical expression for robust credibilistic carbon emissions constraint can be achieved by the following theorem.

Theorem 4. *Let uncertain carbon emissions of transportation be PIV uniform fuzzy variable* $\mathrm{CaE}(\boldsymbol{\eta})=\mathrm{Uni}[a^{\mathrm{CaE}},b^{\mathrm{CaE}};\theta_l^{CaE}]$. *Then the distributionally robust credibility carbon emissions constraint*

$$\min_{\nu_{\mathrm{CaE}}\in\mathscr{P}_{\mathrm{CaE}}} \mathrm{Cr}\{\mathrm{CaE}(\boldsymbol{\eta})+\mathrm{CaE}^0\le C^{cap}\}\ge\gamma$$

is equivalent to the following deterministic constraint

$$\mathbb{G}(a^{\mathrm{CaE}},b^{\mathrm{CaE}};C^{cap})\ge\gamma,$$

where

$$\mathbb{G}(a^{\mathrm{CaE}},b^{\mathrm{CaE}};C^{cap})=\begin{cases}\frac{\theta_l^{CaE}}{2}, & C^{cap}-\mathrm{CaE}^0\in(0,a^{\mathrm{CaE}})\\ \frac{1}{2}, & C^{cap}-\mathrm{CaE}^0\in[a^{\mathrm{CaE}},b^{\mathrm{CaE}}]\\ 1-\frac{\theta_l^{CaE}}{2}, & C^{cap}-\mathrm{CaE}^0\in(b^{\mathrm{CaE}},+\infty)\end{cases}$$

with parameters a^{CaE} *and* b^{CaE} *are separately determined by Eqs. (21) and (22).*

5.3. Equivalent form of distributionally robust fuzzy GCLSC model

Based on the above Theorems (2)-(4), the distributionally robust fuzzy mean-UPM GCLSC optimization problem (18) is equivalent to the following mix-integer nonlinear programming:

$$\begin{cases}\min & \mathbb{M}(\mathbf{r})+\varrho\,\Pi_C\\ \text{subject to} & \mathbb{F}(\mathbf{r}_{lp},\sum_{k=1}^{K} z_{klp}+\tau_{lp})\ge\beta_{lp},\ \forall\, l,p\\ & \mathbb{G}(a^{\mathrm{CaE}},b^{\mathrm{CaE}};C^{cap})\ge\gamma\\ & \text{constraints (3)-(16).}\end{cases}\tag{23}$$

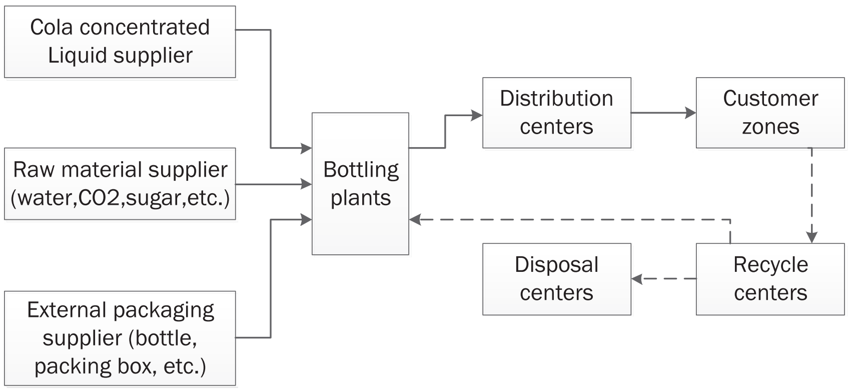


Fig. 3. The schematic process of GCLSC network of Coca-Cola.

Table 2
The number and locations of potential facilities in case study.

Facilities	Counter	Cities
Supplier	9	$C_2, C_8, C_9, C_{14}, C_{16}, C_{20}, C_{28}, C_{31}, C_{34}$
Bottling Plant	4	$C_{11}, C_{15}, C_{26}, C_{36}$
Distribution center	9	$C_3, C_7, C_{10}, C_{14}, C_{17}, C_{20}, C_{27}, C_{29}, C_{32}$
Customer zone	36	$C_1, C_2, \ldots, C_{36}$
Recycling center	7	$C_5, C_{12}, C_{14}, C_{17}, C_{20}, C_{29}, C_{34}$
Disposal center	4	$C_{12}, C_{22}, C_{24}, C_{31}$

In model (23), the objective and constraints are deterministic and represented with analytical piecewise function. Because the piecewise functions in objective have generically exponential size, this means the equivalent programming is hard to solve. However, we can easily verify model (23) can be effectively solved in the case that q equals to one. For example, when $m \in (r_2, r_3]$, the objective and constraints of the equivalent programming (23) are linear, and the equivalent programming (23) becomes a tractable conic optimization problem. Otherwise, we need to seek some heuristic algorithms for making optimal strategy.

6. Case study

As early as 1927, Coca-Cola Company entered China and now China becomes its the largest overseas market. In case study, Coca-Cola is chosen to apply our GCLSC network framework. The selection was motivated by the fact that Coca-Cola Company is a leader in CLSC and sustainable development [62].

6.1. Background description

The Coca-Cola company has 30 factories in China, including 28 Coca-Cola bottling plants, an enterprise producing concentrated liquid in Shanghai and a production base of Chinese brand in Tianjin now. The schematic process of CLSC network of Coca-Cola is depicted in Fig. 3. Note that water is their primary input to manufacturing. They need the number of liters of water to produce the same number of liters of product. So water supplier is commonly located in the local of bottling plants. The cola concentrated liquid is directly delivered from Shanghai. Other raw material suppliers (such as CO_2 and sugar etc.) are carefully selected in the surrounding cities. In the packaging, their products are all delivered in bottles. So the supply on bottle and outer packaging box is also necessary. In particular, ninety-eight percent of their product is delivered in bottles that are recyclable, and reusable. The recycling plants are developed in the same area that make it easier to bottle and outer box recovery.

Coca-Cola has divided China into 7 major regional market. The northeast area includes Liaoning, Jilin and Heilongjiang province. To illustrate the effectiveness of the proposed model and approach, the northeast distribution area of Coca-Cola was chosen to apply the distributionally robust fuzzy mean-UPM GCLSC framework. Fig. 4 shows the locations of potential cities in whole supply chain network of northeast area of Coca-Cola, and the number and locations of facilities in case study are shown in Table 2.

In this area, 4 plants produce Coca-Cola bottled beverages, which are located in Dalian, Shenyang, Changchun and Harbin. There are 36 cities in three provinces of northeast area, and these cities are fixed as 36 customer zones. Transportation cost between two facilities is assumed mainly to be affected by the distance and route. The farther the straight distance between the two cities is, the higher the transportation cost is. In the aspect of route selection, the motorway cost is often higher

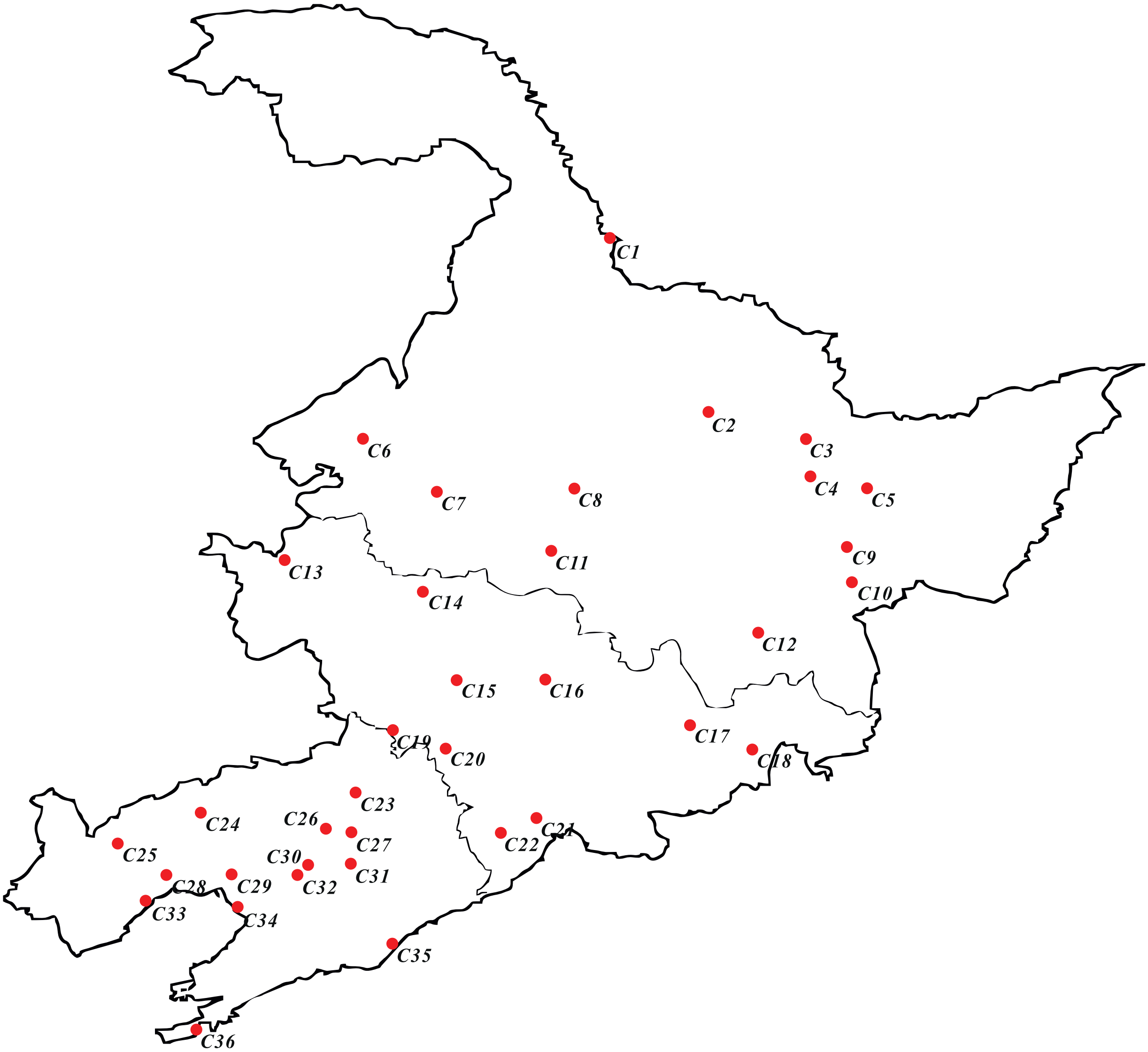


Fig. 4. Location of facilities in northeast area of Coca-Cola.

Table 3
Problem size for case study.

Network structure						Variables			Constraints	CPU
SU	BP	DC	CZ	RC	DC*	Binary	Integer	Other		time(s)
9	4	9	36	7	4	29	1570	4781	367	(0.67, 1.92)

SU=supplier, BP=bottling plant, DC=distribution center, CZ=customer zone, RC=recycling center, DC*=disposal centers.

than that of the common grade highway, but selecting motorway can save transit time. Here we obtain the distance among different facilities from a Chinese navigation APP (Amap. com) with the motorway priority mode, and the data on distance of 36 cities are listed in Tables 18–22 in Appendix B.

6.2. Generating ambiguity distribution set

Suppose transportation cost between two arbitrary facilities be trapezoidal PIV fuzzy variable, and it's a linear function of distance. Next taking transportation cost from supplier to plant ζ^l_{ijr} as an example, we will show how to formulate ambiguity distribution set of PIV fuzzy transportation cost $\mathrm{Tra}(r^l_1, r^l_2, r^l_3, r^l_4; \theta^l_l, \theta^l_r)$.

Table 4
The computational results of location strategy under different parameter values.

	Optimal location strategy				
Parameter	Values	Supplier	Distribution center	Recycling center	Disposal center
ϱ	3×10^{-3}	$C_2, C_8, C_9, C_{16}, C_{34}$	$C_3, C_{14}, C_{20}, C_{27}, C_{32}$	C_{12}, C_{29}, C_{34}	$C_{12}, C_{22}, C_{24}, C_{31}$
	5×10^{-2}	$C_2, C_8, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{27}, C_{29}, C_{32}$	C_{20}, C_{29}	$C_{12}, C_{22}, C_{24}, C_{31}$
	3×10^{-1}	$C_2, C_8, C_9, C_{16}, C_{28}, C_{31}, C_{34}$	$C_{14}, C_{17}, C_{27}, C_{29}, C_{32}$	C_{20}, C_{29}	$C_{12}, C_{22}, C_{24}, C_{31}$
β	0.9	C_9, C_{16}, C_{34}	$C_{14}, C_{17}, C_{27}, C_{29}, C_{32}$	$C_{12}, C_{14}, C_{29}, C_{34}$	$C_{12}, C_{22}, C_{24}, C_{31}$
	0.8	$C_2, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{20}, C_{27}, C_{32}$	$C_{12}, C_{14}, C_{29}, C_{34}$	$C_{12}, C_{22}, C_{24}, C_{31}$
	0.7	$C_2, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{20}, C_{27}, C_{32}$	$C_{12}, C_{14}, C_{29}, C_{34}$	$C_{12}, C_{22}, C_{24}, C_{31}$
C^{cap}	10000	C_{16}, C_{31}, C_{34}	$C_7, C_{14}, C_{20}, C_{27}, C_{32}$	C_{12}, C_{20}, C_{29}	$C_{12}, C_{22}, C_{24}, C_{31}$
	11100	$C_2, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{20}, C_{27}, C_{32}$	C_{12}, C_{20}, C_{29}	$C_{12}, C_{22}, C_{24}, C_{31}$
	13500	$C_2, C_8, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{27}, C_{29}, C_{32}$	C_{12}, C_{29}, C_{34}	$C_{12}, C_{22}, C_{24}, C_{31}$
ϑ_r	0.4	$C_2, C_8, C_9, C_{16}, C_{20}, C_{28}, C_{31}, C_{34}$	C_{14}, C_{29}, C_{32}	C_{12}, C_{20}, C_{29}	$C_{12}, C_{22}, C_{24}, C_{31}$
	0.6	$C_2, C_9, C_{16}, C_{31}, C_{34}$	$C_3, C_{14}, C_{27}, C_{32}$	C_{12}, C_{20}, C_{34}	C_{12}, C_{22}, C_{31}
	0.8	C_9, C_{16}, C_{34}	$C_3, C_{14}, C_{20}, C_{27}, C_{32}$	C_{12}, C_{20}, C_{34}	C_{12}, C_{31}

The coefficients of trapezoidal quadruple $(r_1^l, r_2^l, r_3^l, r_4^l)$ can be gained with the similar approach in [63]. Specifically, we set a multiplier $\iota = (\iota_1, \iota_2, \iota_3, \iota_4)$. The coefficient r_i^l is a linear function of distance, i.e. $r_i^l = \iota_i \cdot dist$, where ι_i is a reduction or amplification factor, and *dist* is the distance between supplier and plant. Then nominal possibility distribution of PIV fuzzy transportation cost is obtained. In addition, many factors, such as the fuel price, weather and vehicle load, have an appreciable effect on transportation cost. Thus, the perturbation of nominal possibility distribution caused by these factors cannot be neglected. Usually, perturbation coefficient θ_l^l and θ_r^l can be generated randomly from a subinterval of [0, 1], or determined with experts' judgments. In this paper, without loss of generality, we set all lower and upper perturbation coefficients of uncertain transportation costs are identical. For computational simplicity, the maximal lower and minimal upper perturbation coefficients are set to be 0.7 and 0.3, respectively. According to Subsection 4.2, ambiguity distribution set of PIV fuzzy transportation cost can be constructed.

Uncertain demands of 36 customer zones are assumed to be PIV fuzzy triangular variables, and estimated by the number of population. More specifically, the coefficient of triangular triple $(r_1^{lp}, r_2^{lp}, r_3^{lp})$ of uncertain demand ξ^{lp} is assumed to be a linear function of population of customer zone. The coefficient of triangular triple $r_i^{lp} = h_i^{lp} \cdot D_{lp}$, where h_i^{lp} is the proportion of population in each customer zone, and the population statistics data D_{lp} are drawn from the National Bureau of Statistics of China [64]. Similarly, for simplicity, the lower and upper perturbation coefficients θ_l^{lp} and θ_r^{lp} are assumed to be 0.3 and 0.5. Further ambiguity distribution set of PIV fuzzy triangular demand is obtained.

Any movement in GCLSC, from transfer of raw materials between plants to movement of products in warehouses or other facilities, consumes energy and directly generates carbon emissions. Energy consumption is different depending on the mode of transportation, distance and weight. In this paper we assume uncertain carbon emissions are estimated with three aspects of these factors. As mentioned above, the mode of transportation is motorway priority; The distance between each pair of two facilities is listed in Tables 18–22 in Appendix B; The weight of the product is measured per box. Assume carbon emissions be PIV fuzzy uniform variable, and every PIV fuzzy carbon emissions fluctuates within a possible band $[a, b]$. The coefficients of every PIV fuzzy carbon emissions are 0.01 kg per box per km, then $a(\text{or } b) = 0.01 \cdot num_{box} \cdot dist$. The perturbation coefficient θ_l^{CaE} is derived by the similar way with uncertain transportation cost. Finally, we have ambiguity distribution set of PIV fuzzy carbon emissions.

7. Computational results

In this section, the computational results of the distributionally robust fuzzy mean-UPM GCLSC network design model will be presented. The proposed model of case study is coded by IBM ILOG CPLEX 12.6.3 Academic Version, and solved on a personal computer with Inter(R) Core i5-6500, 24.0 GB RAM and Windows 10 operating system. The complexity of proposed GCLSC network on GCLSC network structure, variables, constraints and computational time is summarized as Table 3, in which the interval of CPU times is the actual computational time in case study. Note that the model dimension is not affected by selected parameters, but CPU time varies slightly with the values of model parameters.

Firstly, we will show briefly how the locations of facilities in GCLSC network are affected by four kinds of parameter. For conciseness, we omit the marks of four bottling plants in the following table and figures on optimal location strategy because they are always located in fixed positions in reality. The obtained location strategies are shown in Table 4.

Furthermore, take the case of $\vartheta_r = 0.6$ in Table 4 as example, a detailed presentation of quantity decision on components and products provided by every selected facilities is given in Tables 5,6,7, 8.

Table 5
Quantity of component 1 and 2 from supplier to plant.

Supplier	Plant			
	C_{11}	C_{15}	C_{26}	C_{36}
C_2	(380, 310)	-	-	-
C_9	(450, 70)	-	-	-
C_{16}	(290, 180)	(100, 50)	-	-
C_{31}	-	-	(320,160)	-
C_{34}	-	-	-	(360,180)

Table 6
Quantity of product from plant to distribution center.

Plant	Distribution center			
	C_3	C_{14}	C_{27}	C_{32}
C_{11}	1441	1039	-	-
C_{15}	-	435	1262	-
C_{26}	-	-	160	-
C_{36}	-	-	186	1974

Table 7
Quantity of product from distribution center to customer zone.

Distribution center	Customer zone
	$C_1 - C_{36}$
C_{11}	C_3: 74, C_4: 208, C_5: 120, C_8: 399, C_{10}: 149, C_{11}: 263, C_{12}: 228
C_{15}	C_6: 507, C_{11}: 803, C_{13}: 164
C_{26}	C_{18}: 28, C_{19}: 294, C_{20}: 93, C_{22}: 193, C_{26}: 803, C_{27}: 151, C_{31}: 46
C_{36}	C_{24}: 151, C_{25}: 179, C_{29}: 103, C_{31}: 79, C_{32}: 318, C_{33}: 254, C_{34}: 218, C_{36}: 672

Table 8
Quantity of component 1 and 2 from recycling center to plant and disposal center.

Recycling center	Plant			
	C_{11}	C_{15}	C_{26}	C_{36}
C_{12}	(3840, 1920)	-	-	-
C_{20}	-	(3294, 1647)	-	-
C_{29}	-	-	-	(3960, 1980)
Recycling center	Disposal center			
	C_{12}	C_{22}	C_{24}	C_{31}
C_{12}	(2500, 1280)	-	-	-
C_{20}	-	(2196, 1098)	-	-
C_{29}	-	-	-	(2640, 1320)

8. Sensitivity analysis

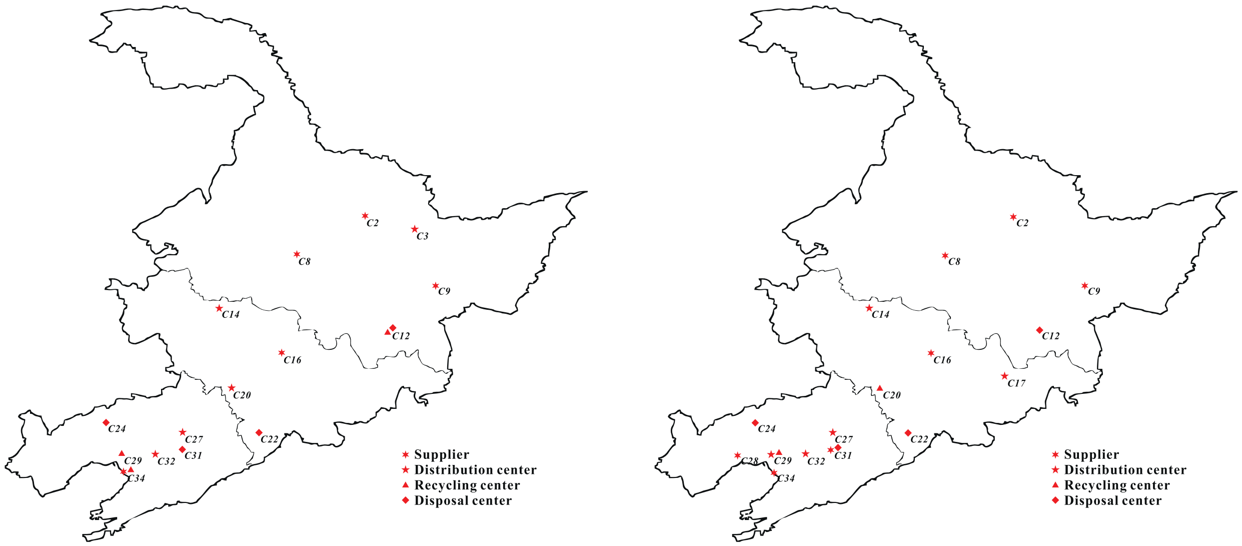
In this section, the effects of trade-off parameter ϱ, customer demand level β and carbon emissions cap C^{cap} on the performance of the distributionally robust fuzzy mean-UPM GCLSC network design model are analyzed, which is mainly carried out from two aspects: location policy and economic cost.

8.1. The effect of trade-off parameter ϱ

8.1.1. The effect of ϱ on optimal decision

In this subsection, we set parameter $\beta = 0.8$ and $C^{cap} = 18500$ and do the numerical experiments. Fig. 5 depicts the location strategies for parameter $\varrho = 3 \times 10^{-3}$ and 3×10^{-1}, respectively. By comparing site selection scheme, we find that the selections of disposal center under these two cases are identical. The reason for this is the requirement of high recovery for products needs four potential disposal center should be all opened. In contrast, the location strategies of supplier, distribution center and recycling center are significantly distinct.

It can be seen from Figs. 5(a) and (b) that the numbers of selected supplier and distribution center are different. For example, when parameter $\varrho = 3 \times 10^{-3}$, five suppliers, i.e., $C_2, C_8, C_9, C_{16}, C_{34}$, are opened; While seven suppliers, with the cities' numbers $2, 8, 9, 16, 28, 31, 34$, are opened if parameter $\varrho = 3 \times 10^{-1}$. Even though the numbers of selected distribution



(a) under $\varrho = 3 * 10^{-3}$ (b) under $\varrho = 3 * 10^{-1}$

Fig. 5. Optimal location strategy of facilities in GCLSC under different ϱ.

center are same, the site selections differ significantly. In the former case, five distribution centers should be located in city $C_3, C_{14}, C_{20}, C_{27}$ and C_{32}. On the contrary, in the latter case, five distribution centers should be opened in city $C_{14}, C_{17}, C_{27}, C_{29}$ and C_{32}. From the analysis we can see that the location strategy is sensitive to parameter ϱ, and the proposed modelling formulation is effective to handle the location problem for GCLSC network design in case study.

8.1.2. The effect of ϱ on economic cost

Fig. 6 depicts the trade-off between the upside risk UPM[EC] and average performance $\mathbb{E}[EC]$ for different values of parameter ϱ. Note that, if trade-off parameter $\varrho = 0$, decision makers only concern about risk control of cost function, and ignore the influence of own feature of cost function. In this case there is minimal upper side risk to economic cost of GCLSC network. The computational results show that the proposed fuzzy mean-UMP GCLSC model can make a good trade-off between the risk and average performance of economic cost in objection function.

Figs. 7(a) and (b) depict the variation tendency of UPM[EC] and $\mathbb{E}[EC]$ with respect to trade-off parameter ϱ, respectively. As shown in figures, UPM[EC] is monotonic nondecreasing and $\mathbb{E}[EC]$ is monotonic nonincreasing in ϱ, and the values of these two indices change significantly in initial stage and then tend to be stable.

8.2. The effect of demand level β

8.2.1. The effect of β on optimal decision

In this subsection, we set parameter $\varrho = 4 \times 10^{-3}$ and $C^{cap} = 16500$ and do the numerical experiments. According to site selection scheme, we know that the selections of recycling center and disposal center under $\beta = 0.9$ and $\beta = 0.8$ are identical. In the meantime, the location strategies of supplier and distribution center are significantly distinct. From Table 4, the numbers of selected supplier and distribution center are obviously different. Concretely, when parameter $\beta = 0.9$, only three supplier C_9, C_{16}, C_{34} are opened; While five suppliers, with numbers $2, 9, 16, 31, 34$, are opened if parameter $\beta = 0.8$. Similar to supplier, the location strategies of distribution centers under the two cases are different on location. In the case of $\beta = 0.9$, five distribution centers should be located in city $C_{14}, C_{17}, C_{27}, C_{29}$ and C_{32}. But when $\beta = 0.8$, five distribution centers should be opened in city $C_3, C_{14}, C_{20}, C_{27}$ and C_{32}.

In the computational process, we note that, if $0.9 < \beta \leq 1$, the location strategies is exactly the same; While when $\beta \leq 0.9$, the location strategies also have no difference. This fact shows location strategy is not sensitive in parameter β. The major reason leading to the above conditions is that the values of customers' demand level β_{lp} are assumed to be the same one β for computational simplicity. Validated by some numerical experiments, the location strategies are distinct when the value of β_{lp} differ from each other. Thus, decision makers can set different values of customers' demand level by the reality, and obtain more sensitive location decisions.

8.2.2. The effect of β on economic cost

Fig. 8 depicts the change in objective value of fuzzy mean-UPM GCLSC network model with respect to credibility level β. It shows that the objective value of the proposed fuzzy GCLSC network design model is monotone increasing in β. The

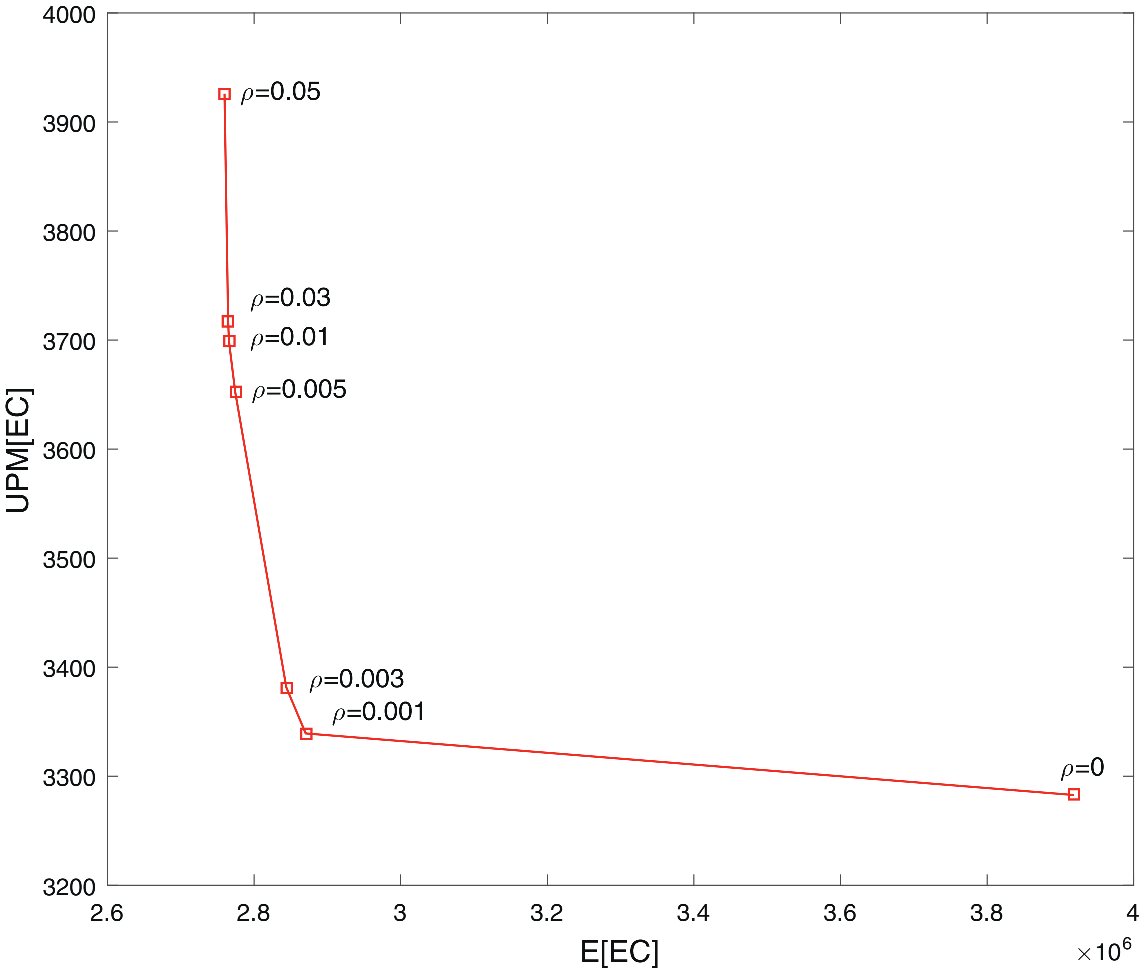
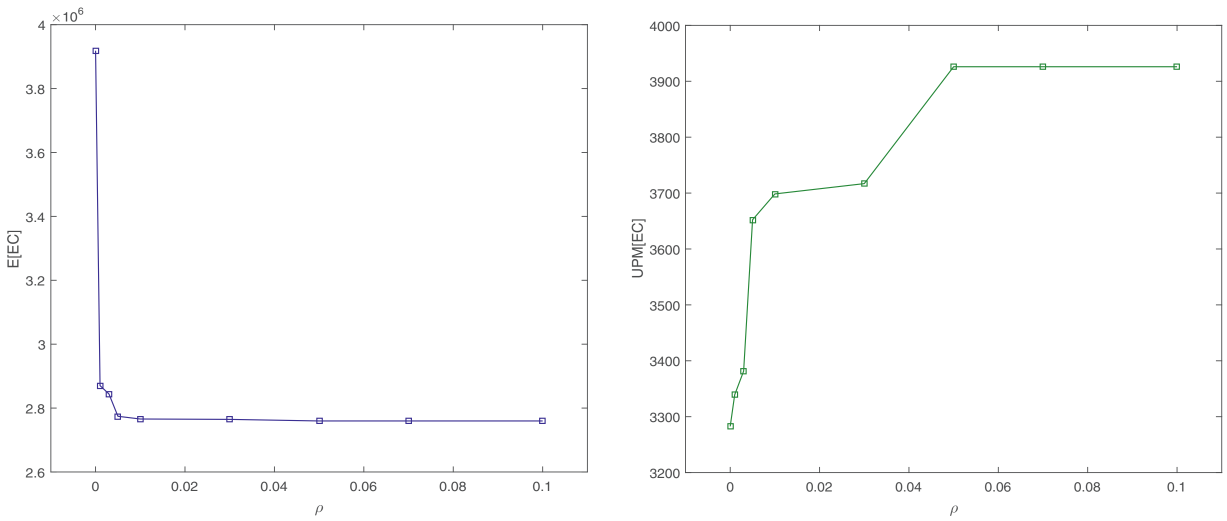


Fig. 6. Trade-off between $\mathbb{E}[EC]$ and UPM$[EC]$ in GCLSC network of Coca-Cola.



(a) $\mathbb{E}$[EC] under parameter ϱ. (b) UPM[EC] under parameter ϱ.

Fig. 7. Variation trends of $\mathbb{E}[EC]$ and UPM$[EC]$ w.r.t. ϱ.

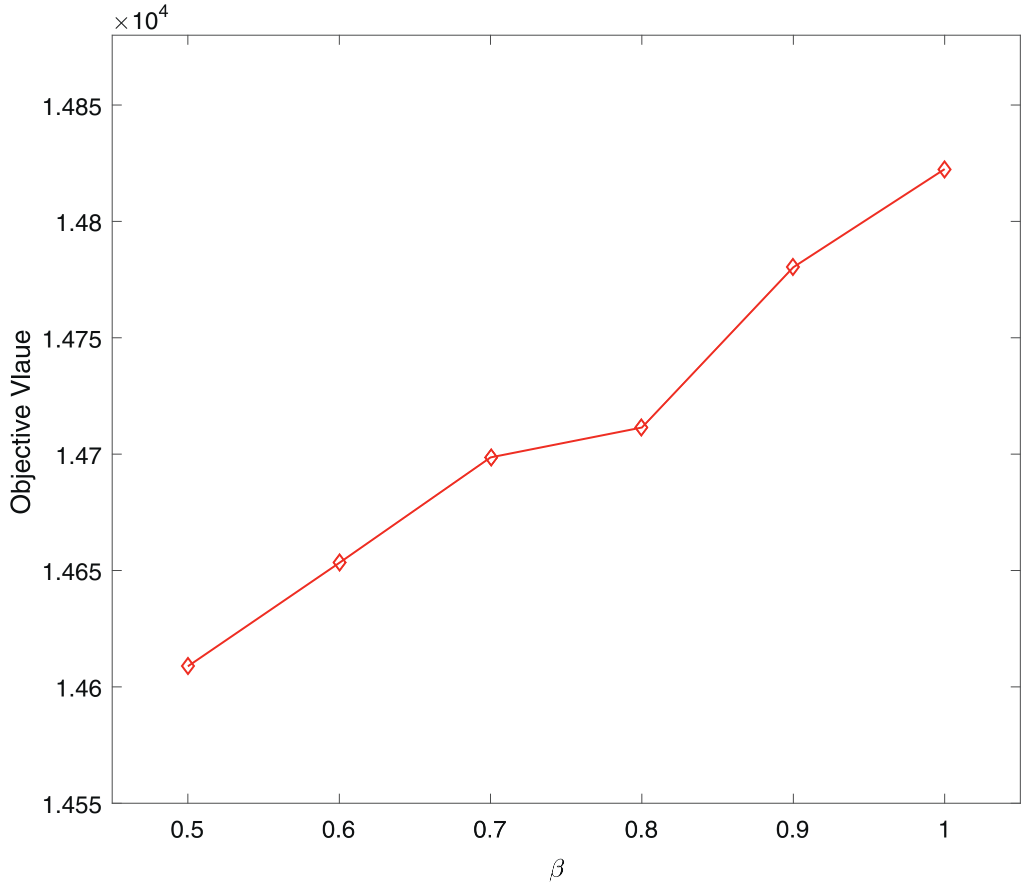


Fig. 8. Change in objective value of fuzzy GCLSC network model w.r.t. β.

computational results are consistent with reality that the level of customers' demand is higher, the total cost of GCLSC network is greater.

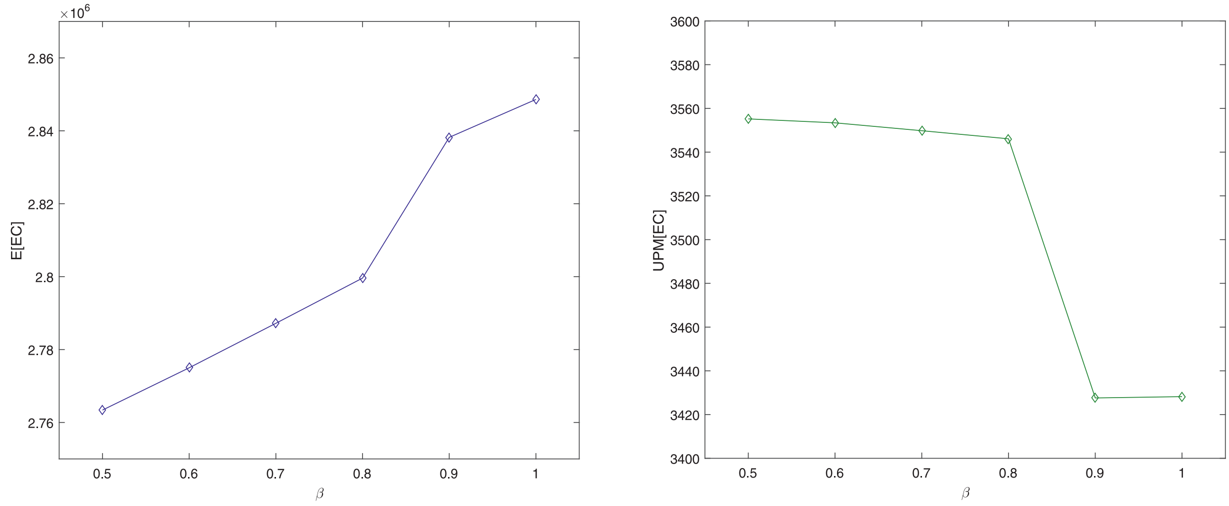
We make the following observations with respect to demand level: (i) From Fig. 9(a), the demand level β has a positive impact on the expected value of economic cost, which means the average cost increases monotonically in β. Thus, a high requirement of demand level β will lead to a large expected value of economic cost. This fact reveals an insight that satisfying high requirement of customer demand will be costly and in this moment decision makers need to make some efforts on the control of cost. (ii) Fig. 9-(b) tells us that the upper side risk of economic cost is different with the average performance of economic cost. The satisfied level of customer demand β has a negative impact on the upper partial moment of economic cost. The UPM[EC] has a slow reduction initially, and then reduces sharply as β crosses the value 0.8. This figure reveals an insight that demand level β has the positive consequence of risk reduction. The higher satisfied level of customer demand is, the lower upside fluctuation risk of economic cost is. In addition, the variation trends of the expected value and upper partial moment of economic cost are opposite, so a better trade-off between them is needed.

8.3. The effect of carbon emissions cap C^{cap}

8.3.1. The effect of C^{cap} on optimal decision

In this subsection, we set parameter $\varrho = 3 \times 10^{-2}$ and $\beta = 0.9$ and perform the numerical experiments. According to site selection scheme under different C^{cap}, we learn about that although the selections of disposal center under different C^{cap} are same, the location strategies of supplier, distribution center and recycling center are significantly distinct.

By Table 4, the numbers and selections of selected supplier, distribution center and recycling center are different. Specifically, when the cap of carbon emissions $C^{cap} = 10000$, three suppliers C_{16}, C_{31}, C_{34} are selected. When $C^{cap} = 11100$ and $C^{cap} = 13500$, the numbers of suppliers are five and six respectively. Moreover, in the former case, they are $C_2, C_9, C_{16}, C_{31}, C_{34}$; While in the later case, they are $C_2, C_8, C_9, C_{16}, C_{31}, C_{34}$. Similarly, although the number of selected distribution centers is same, the location strategies under three cases are different. For example, when $C^{cap} = 10000$, six distribution centers should be located in city $C_7, C_{14}, C_{20}, C_{27}$ and C_{32}; While $C^{cap} = 11100$, the city C_7 is replaced by city C_3; And if $C^{cap} = 13500$, the location decision has a different city C_{29} with both of the formers.



(a) $\mathbb{E}$[EC] under parameter β.

(b) UPM[EC] under parameter β.

Fig. 9. Variation trends of $\mathbb{E}[EC]$ and UPM$[EC]$ w.r.t. β.

8.3.2. The effect of C^{cap} on economic cost

Fig. 10 depicts the change in objective value of fuzzy GCLSC network model with respect to C^{cap}. It shows that the optimal value of the proposed distributionally robust fuzzy GCLSC network model has a dramatically cut initially, then tends to be stable. In general, the cost decreases with the increasing of carbon emissions cap C^{cap}.

Fig. 11 reveals the following two insights: (i) The cap on carbon emissions C^{cap} has a negative impact on the expected value of economic cost initially, and it decreases rapidly before C^{cap} reaches the value 1.3×10^4. As C^{cap} crosses this value, the expected value of economic cost $\mathbb{E}[EC]$ still change but tends to be stable. That means we can reduce economic cost as the cap on carbon emissions increases. Moreover, the computational results show that the unrestricted increasing of carbon emissions cap is unnecessary, because even if the value is increasing, the expected value of economic cost $\mathbb{E}[EC]$ will not cut down. (ii) The cap on carbon emissions C^{cap} has a positive impact on the upside risk of fluctuation of economic cost and UPM$[EC]$ increases rapidly initially. When C^{cap} reaches the value 1.3×10^4, the upward risk of economic cost run up to maximal value. Later, the upward risk of economic cost decreases and tends to be stable. Note that the variation trends of the expected value and upper partial moment of economic cost are opposite, so a better trade-off between them is necessary and important.

8.4. The effect of disposing fraction rate ϑ_r

8.4.1. The effect of ϑ_r on optimal decision

The recycling rate is defined differently in each geographical region and each course of time [65], but commonly means a percentage of recyclable parts available for each product. In this study, we use the term: disposing fraction rate and remark that the higher the disposing fraction rate, the more parts can be recycled and reused. Since there are two recyclable components per product, for simplicity, these two disposing fraction rates are set as $\vartheta_1 = \vartheta_2$. In this subsection, we set parameter $\varrho = 3 \times 10^{-2}$, $\beta = 0.95$ and $C^{cap} = 9900$ then do the numerical experiments.

According to Table 4, the numbers and selections of selected supplier, distribution center, recycling center and disposal center under different ϑ_r are all distinct. As the disposing fraction rate increases from 0.4 to 0.8, the number of selected distribution center increases from 3 to 5, but conversely, the numbers of selected suppliers and disposal center decrease. The number of recycling center remains the same, however the selection site changes. For example, when $\vartheta_1 = \vartheta_2 = 0.4$, the recycling center, i.e., C_{12}, C_{20}, C_{29} are opened; But when $\vartheta_1 = \vartheta_2 = 0.6$ or 0.8, the recycling center C_{12}, C_{20}, C_{34} are selected.

Furthermore, a comparison is conducted to figure out the impact of changing ϑ_r on the quantity of components provided by suppliers and recycling centers. From Tables 9 and 10, when $\vartheta_r = 0.4$, eight suppliers provide the component for plant, and the sum of the components is $(2790, 1395)$; when $\vartheta_r = 0.8$, only three suppliers are needed, and now the total number of components provided is $(1188, 594)$. Additionally, by comparing the components from recycling center to plant, we know that the number of returned components has nearly doubled when ϑ_r changes from 0.4 to 0.8. A higher disposing fraction rate means the recycling center can return more reusable parts, so the change of these computational results are reasonable and intuitive.

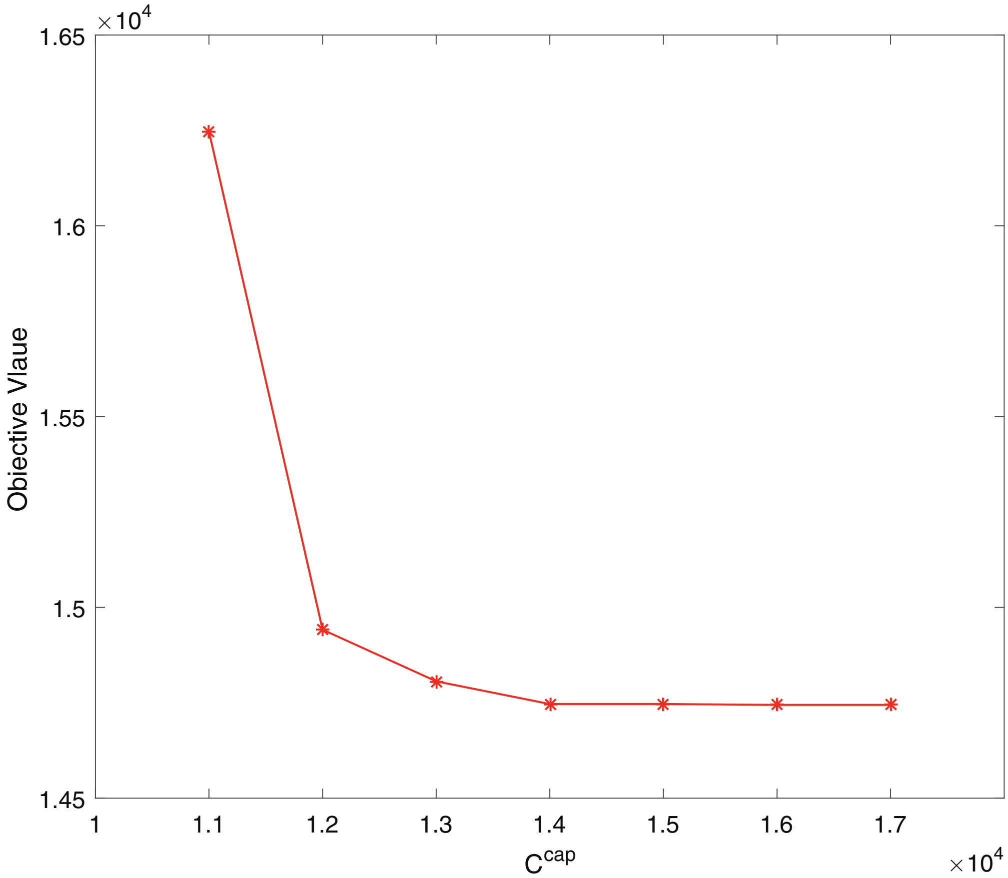
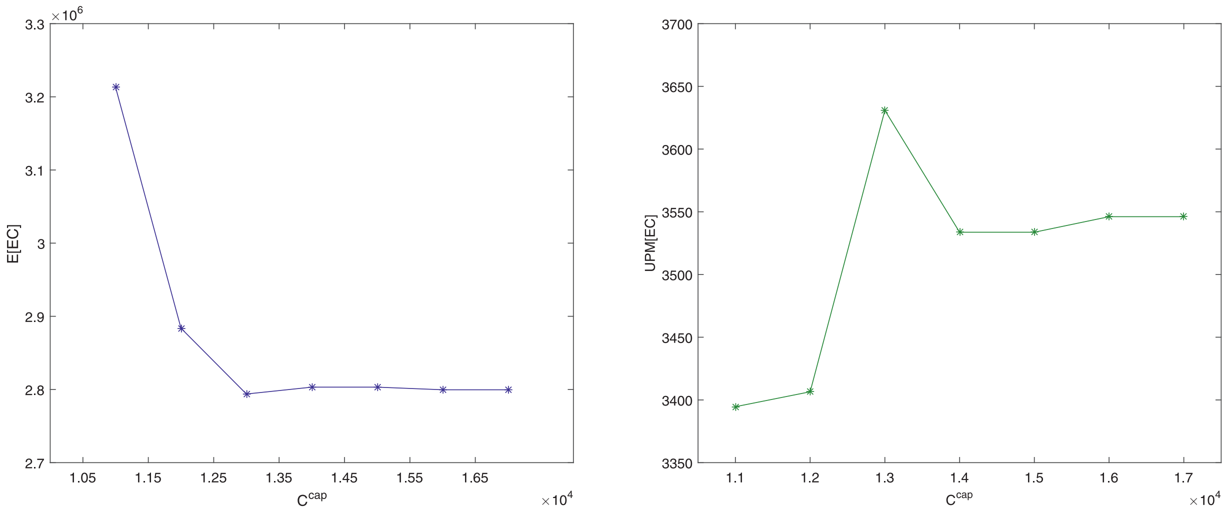


Fig. 10. Change in objective value of fuzzy GCLSC network model w.r.t. C^{cap}.



(a) $\mathbb{E}[\mathrm{EC}]$ under C^{cap}.

(b) UPM[EC] under C^{cap}.

Fig. 11. Variation trends of $\mathbb{E}[EC]$ and UPM$[EC]$ w.r.t. C^{cap}.

Table 9
The comparison on quantity of component from supplier to plant.

Supplier	Plant			
	C_{11}	C_{15}	C_{26}	C_{36}
$\vartheta_r = 0.4$				
C_2	(380, 65)	-	-	-
C_8	(300, 350)	-	-	-
C_9	(450, 0)	-	-	-
C_{16}	(0, 150)	(390, 80)	-	-
C_{20}	-	(290, 260)	-	-
C_{28}	-	-	(300,0)	-
C_{31}	-	-	(320,170)	-
C_{34}	-	-	-	(360,320)
$\vartheta_r = 0.8$				
C_9	(112, 44)	(326, 0)	-	-
C_{16}	(0, 12)	(390, 218)	-	-
C_{34}	-	-	-	(360,320)

Table 10
Quantity of component from recycling center to plant.

Recycling center	Plant			
	C_{11}	C_{15}	C_{26}	C_{36}
$\vartheta_r = 0.4$				
C_{12}	(3560, 1280)	-	-	-
C_{20}	-	(1004, 502)	-	-
C_{29}	-	-	(3552, 1916)	(280, 0)
$\vartheta_r = 0.8$				
C_{12}	(4848, 2424)	-	-	-
C_{20}	-	(3884, 2082)	(780, 250)	-
C_{29}	-	-	(3420, 1850)	(1860, 790)

8.4.2. The effect of ϑ_r on economic cost

Fig. 12 depicts the change in objective value of fuzzy GCLSC network model with respect to ϑ_r. It shows that the optimal value of the proposed distributionally robust fuzzy GCLSC network model decreases with the increasing of disposing fraction rate ϑ_r, which also means a less cost. Figs. 13(a) and (b) depict the variation tendency of UPM[EC] and $\mathbb{E}[EC]$ with respect to disposing fraction rate ϑ_r, respectively. As shown in figures, $\mathbb{E}[EC]$ is monotonic decreasing and UPM[EC] is monotonic increasing in ϑ_r. The variation tendency of objective value and $\mathbb{E}[EC]$ is consistent, and both of them reflect a fact about cost system, i.e., increasing the disposing fraction rate can reduce the cost. In general, heightening disposing fraction rate is considered beneficial to both environment and cost system. But the variation of UPM[EC] enlightens us that it has a negative effect on the risk of economic cost. When we want to improve the environment and reduce the cost via adjusting the disposing fraction rate, it is significant to pay more attention to the upside risk of economic cost.

9. Comparative study

9.1. Comparative study with distribution ambiguity free

In the case of distribution ambiguity-free, that is, when the lower and upper perturbation coefficients θ_l and θ_r is set to zero, the distributionally robust fuzzy mean-UPM GCLSC network model (18) reduces to a fuzzy model under nominal possibility distribution. We conduct the numerical experiments without distributional perturbation via IBM ILOG CPLEX software, and obtain the computational results on different values of trade-off parameter. For simply and intuitively display, the optimal value, average performance and upside risk on economic cost of two programming model are presented in Figs. 14–15.

Fig. 14 shows a comparison on the optimal values of distributionally robust model and nominal distribution model. Accordingly, we call the optimal value of distributionally robust model (18) as distributionally robust optimal economic cost, while the optimal value of nominal distribution model as nominal optimal economic cost. From Fig. 12, we know that the nominal optimal economic cost is always lower than distributionally robust optimal economic cost. Fig. 15 depicts the variation tendencies of average performance on economic cost $\mathbb{E}[EC]$ and upside risk on economic cost UPM[EC]. In Figs. 15(a) and (b), the average performances $\mathbb{E}[EC]$ and upside risk UPM[EC] under two optimization models present out the same change trend, and the computational results under nominal distribution model are always lower than that under distributionally robust model.

The difference of computational results between distributionally robust model and nominal distribution model is called the price of robustness. Distributionally robust model pays a certain price of economic cost to ensure variable distributions

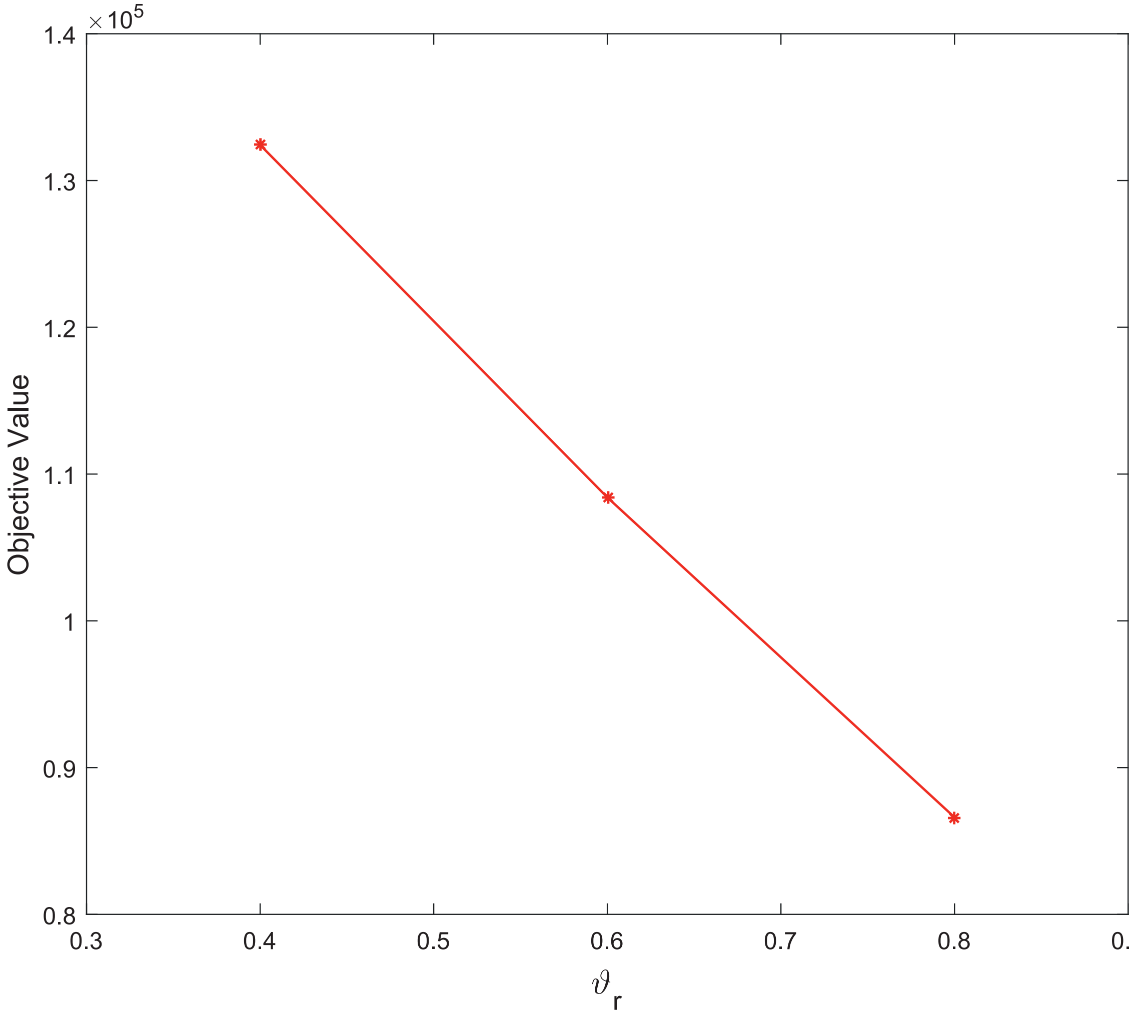
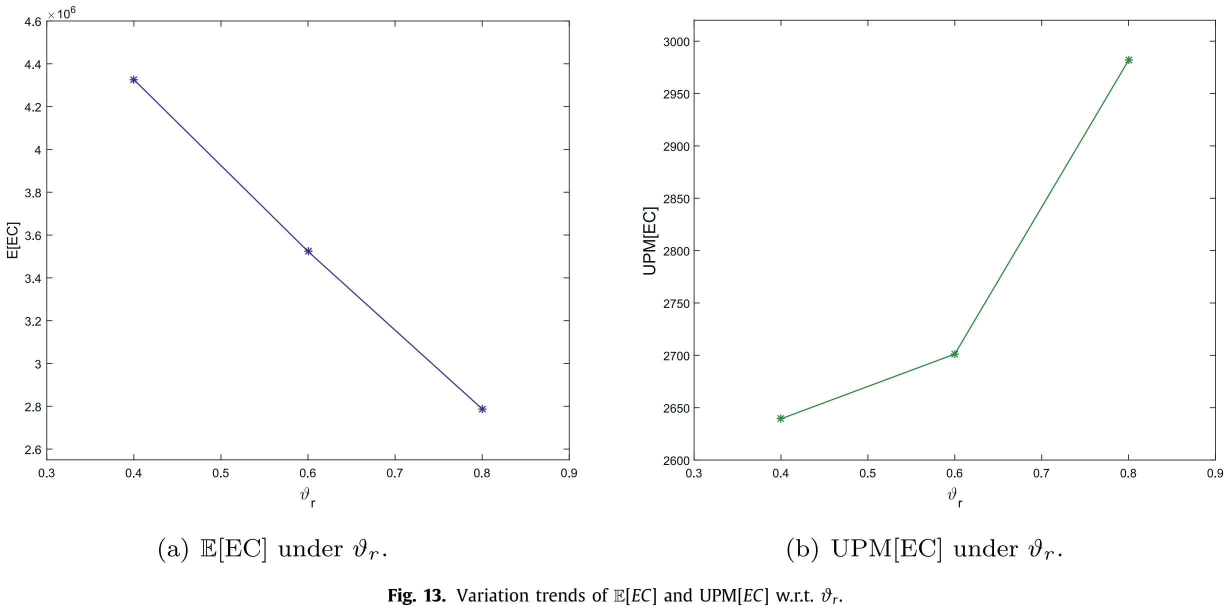


Fig. 12. Change in objective value of fuzzy GCLSC network model w.r.t. ϑ_r.



(a) $\mathbb{E}$[EC] under ϑ_r.

(b) UPM[EC] under ϑ_r.

Fig. 13. Variation trends of $\mathbb{E}[EC]$ and UPM$[EC]$ w.r.t. ϑ_r.

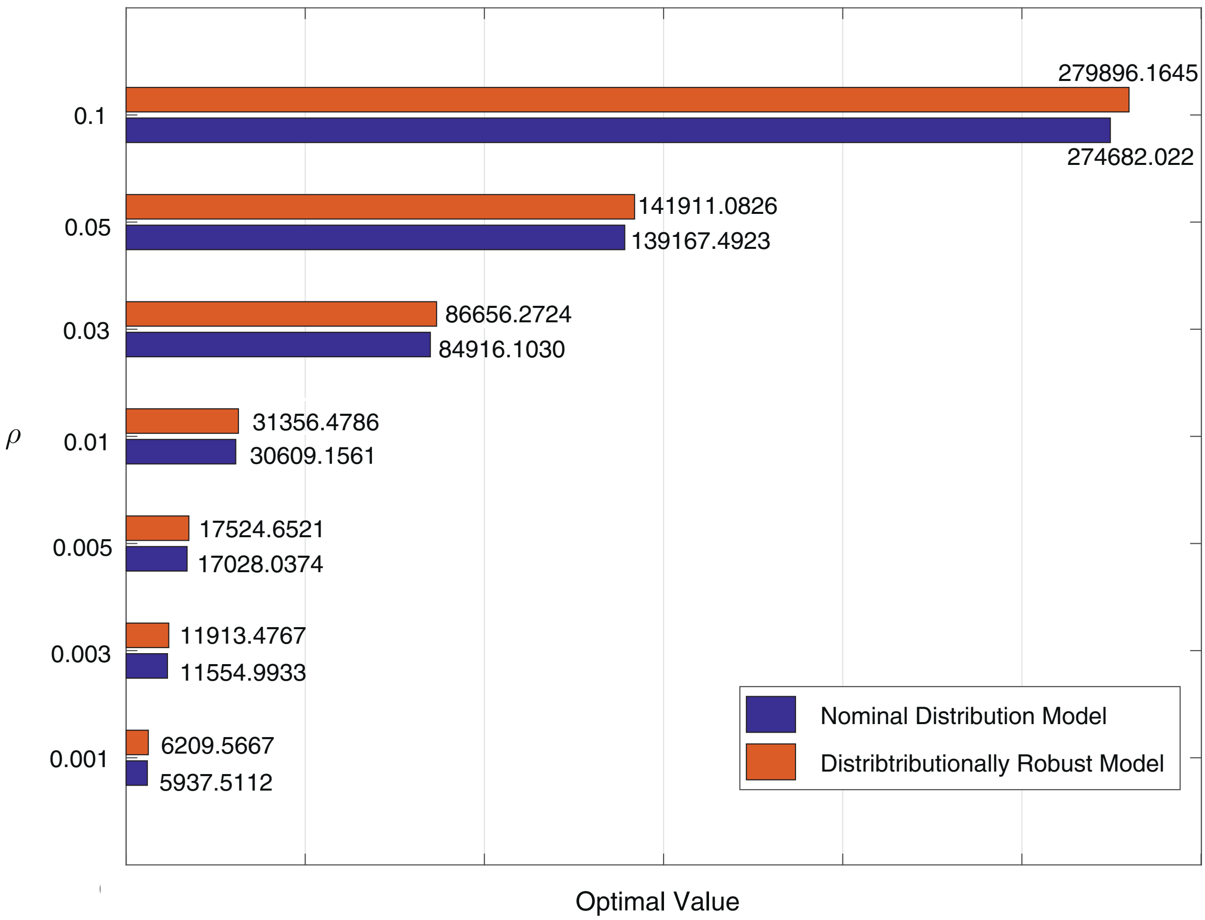
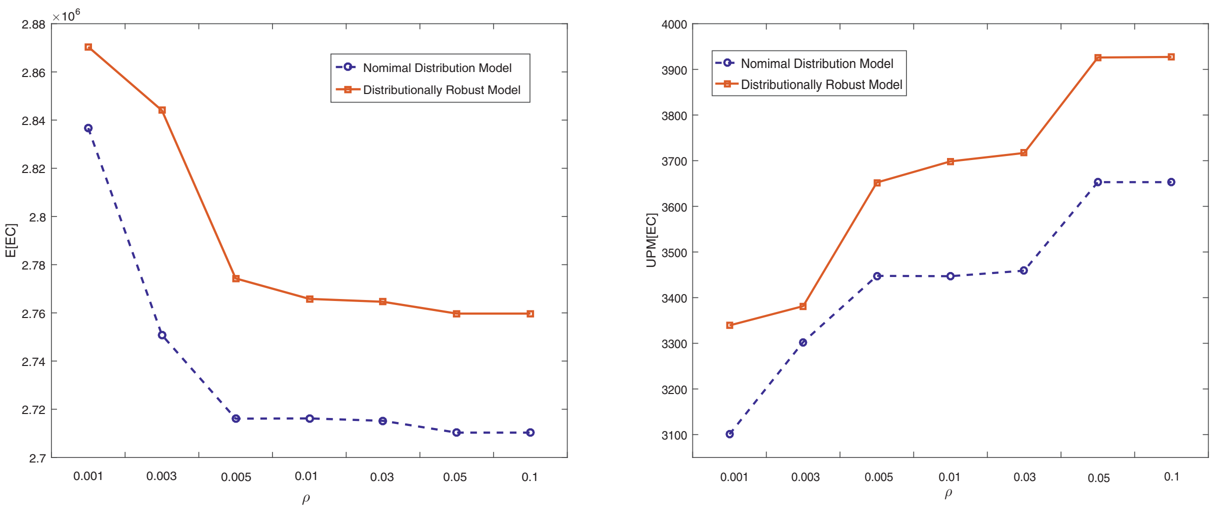


Fig. 14. Comparison on optimal values of two optimization models w.r.t. ϱ.



(a) Comparison on $\mathbb{E}$[EC] w.r.t. ϱ.	(b) Comparison on UPM[EC] w.r.t. ϱ.

Fig. 15. Comparison on $\mathbb{E}[EC]$ and UPM$[EC]$ of two optimization models w.r.t. ϱ.

Table 11
The comparison of results on environmental concerns.

Location	With environmental constraint	Without environmental constraint
Supplier	C_{16}, C_{31}, C_{34}	$C_2, C_8, C_9, C_{16}, C_{31}, C_{34}$
Distribution center	$C_7, C_{14}, C_{20}, C_{27}, C_{32}$	$C_3, C_{14}, C_{27}, C_{29}, C_{32}$
Recycling center	C_{12}, C_{20}, C_{29}	C_{12}, C_{14}, C_{29}
Disposal center	$C_{12}, C_{22}, C_{24}, C_{31}$	$C_{12}, C_{22}, C_{24}, C_{31}$
Indices		
Objective value	97763.9881	94573.2438
$\mathbb{E}[EC]$	3.1447×10^6	3.0337×10^6
UPM[EC]	3423.6	3562.1

in ambiguity distribution set are feasible, which can immune the uncertainty caused by distributional perturbation. In particular, if the circumstance of decision making is full of uncertainty of distributional perturbation, decision makers should employ the distributionally robust optimization method. Otherwise, they will face enormous decision-making risks, because the solution of nominal distribution model may be infeasible in reality.

9.2. Comparative study with absence of environmental constraint

Many researchers have considered carbon emissions as a separate objective to do the trade-off analysis, because optimizing the total cost and carbon emissions may have conflict with each other. In the proposed model, the carbon emissions are considered as an environmental constraint. However, it's also crux to identify that how much cost systems may incur when carbon emissions are reduced. Therefore, in this subsection, we solve the problem regardless of such environmental constraint to figure out the impact of carbon cap policy on designing the GCLSC network.

The comparative results are summarized in Table 11. It can be inferred that the configurations of GCLSC network with and without environmental constraint are markedly different. More facilities are incorporated into GCLSC network without environmental constraint, such as suppliers $C_2, C_8,$ and C_9. These facilities participate in the GCLSC activities, which increases the quantity of products and components in the supply chain. An intuition is that the total cost of GCLSC should be significantly enhanced, since following the increase of products and components, various costs experienced in transportation and processing are all rising. However, the expected value of economic cost $\mathbb{E}[EC]$ actually decreases. The reason for this is here we meet the needs of customers fully without considering the adverse impact on the environment, so we don't have to bear any penalty cost of customer unmet demand. As far as the environmental importance was concerned, this practice is clearly not desirable. Another interesting observation is that the risk of the cost system UPM[EC] is not reduced but increased without environmental constraints, which means this constraint has a positive effect on both the environmental and economic aspects of GCLSC management.

10. Management implications

Based on the analysis of computational results, this paper provides some significant implications for supply chain managers to incorporate proper design and management into their uncertain green closed-loop supply chain.

For every SC management practitioner, it's a reality that uncertainty make GCLSC network complicated and exposed to risk. When the uncertainty relies heavily on expert's judgment, fuzzy optimization is recommended by operation researchers. However, the noise data from expert's judgment cause the possibility distribution of uncertain parameter fluctuating. For practitioner with limited operation research knowledge, the misusing of incorrect distribution has a damaging impact. Therefore, one of the advantages of our model is that if the accurate possibility distributions of uncertain parameters are unavailable in realistic GCLSC network, decision makers should employ the proposed distributionally robust fuzzy optimization model to design their GCLSC network. When decision makers neglect the impact of small fluctuations in nominal distribution on the quality of nominal solution, they can obtain a nominal solution under distribution ambiguity free. But from the comparative analysis on computational results in Section 8, our proposed model can help decision makers take more intelligent and robust decisions under knowing partial distribution.

Another advantage of our model is that the impact of risk on SC network design is discussed based on UPM. In the paper, a mean-UPM GCLSC network formulation is developed to deal with the risk of uncertainty in complex economic situation and logistics network. It is worth noting that many decision makers often overlook the direction of risk on economic cost in real-world. To better control the upward risk, they can use the UPM to quantify the uncertain risk of economic cost.

The computational results demonstrate that the change of two indices of cost system: $\mathbb{E}[EC]$ and UPM[EC] are opposite with respect to four important parameters. Thus, by the degrees of managers' preferences and aversions, a most suitable value should be set for different parameter in the GCLSC network model. In particular, according to the degree of risk-averse and the computational results, decision-makers should select an appropriate trade-off parameter ρ to balance upper side risk and average performance of cost function.

Our model is easy to implement in practice, because, according to the obtained theoretical results, managers can generate ambiguity distribution set of uncertain parameter, and then formulate their own GCLSC logistic network. Moreover, the GCLSC network model has been transformed into an equivalent form which can be solved with existing commercial optimization software. These efforts are all helpful for the application of this model.

11. Conclusions

Green closed-loop supply chain, as an important realistic problem, is discussed in the paper. The following four aspects of main results are obtained.

Considering the risk control of economic cost, a novel fuzzy upward risk measure: UPM with power q was presented, which is more generalized and some common used fuzzy measurements are its special cases. Based on this new measure, a distributionally robust fuzzy mean-UPM model had been established. The objective function of proposed model was to find a trade-off relation between the UPM and expected value of economic cost. The satisfaction level of customer and control of carbon emissions were ensured in the form of robust credibility constraints.

A notable property of proposed model is the possibility distribution of uncertain parameter contains distributional ambiguity. Concretely, the possibility distribution is always fluctuating center with its nominal distribution, and meanwhile the distribution perturbation is bounded. To cope with complex ambiguity in distribution perturbation, a new definition of PIV fuzzy variable was proposed, and three common PIV fuzzy variable had new characterizations with the proposed definition. Following this, three ambiguity distribution sets of uncertain transportation cost, customer demand and carbon emissions were obtained.

To find the computational tractable form of propose model, it is required to handle distributionally robust objective and credibility constraints. The ambiguity distribution set of uncertain model parameter was a collection of possibility distributions having bounded perturbation center with nominal distribution. We chose the parametric selection distribution as the representation of variable distributions, and finally, the tractable framework of the proposed model was deterministic and represented as analytical piecewise functions, which can be solved efficiently by commercial-grade solvers.

Due to the leadership in sustainable development and GCLSC management, a realistic case on Coca-Cola Company in northeast China was addressed. A crux issue in case study is how to generate ambiguity distribution set of uncertain parameter based on the real data set, and it had been explained in detail. We also analyzed the influences of diverse model parameters on location strategy and economic cost in GCLSC network. The conclusion shed light on us some implications that empowered managers and decision makers to seek the best network design and cost control strategy. The comparison with the case of distribution ambiguity free verified the advantage of the proposed model and method.

Some opportunities can be considered for future research: *i*) Several uncertainty sets on fuzzy possibility distribution have been presented in recent years. However, it seems that no consensus on which type of set can be regarded as a " better" one. If an ambiguity set can be viewed as better than another alternative, what are the evaluation criteria? What is the relationship between performance and tractability of an ambiguity set? They are all interesting topics deserved to be investigated. *ii*) Many different carbon policies, such as carbon cap, carbon tax, carbon trade and carbon offset, have been discussed in supply chain management in the literature. However, the investigation on the integration and comparison study of carbon policies needs a further discussion. Additionally, some carbon strategies, e.g. carbon sink and carbon source, only have been applied to biology and environment fields. Their combination with GCLSC management is also a future research direction. *iii*) As noted by [66], to develop a stronger theoretical frameworks, some limitations on strategic aspects of our model can be extended. Some tactical decisions such as inventory strategy and vehicle routing design can be considered. Additionally, supplier selection and pricing decision can enhance the applicability of our model. The extended formulations will be our aims of future research and application.

Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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Appendix A. Proof of Theorems

Proof of Theorem 1

Proof. We only prove the case: $(r_1 + r_2)/2 < m \le r_2$, the other cases can be proved similarly.

Let $TC = [r_1, r_2, r_3, r_4; \theta_l^{TC}, \theta_r^{TC}]$ be a PIV trapezoidal fuzzy variable. Then the parametric selection distribution of TC is the following piecewise linear function

$$\mu_{TC}(r;\chi) = \begin{cases} \frac{(1+\chi)(r-r_1)}{r_2-r_1}, & r_1 \le r \le \frac{r_1+r_2}{2} \\ \frac{(1-\chi)r+\chi r_2-r_1}{r_2-r_1}, & \frac{r_1+r_2}{2} < r \le r_2 \\ 1, & r_2 < r \le r_3 \\ \frac{(\chi-1)r-\chi r_3+r_4}{r_4-r_3}, & r_3 < r \le \frac{r_3+r_4}{2} \\ \frac{(1+\chi)(r_4-r)}{r_4-r_3}, & \frac{r_3+r_4}{2} < r \le r_4, \end{cases}$$

where $\chi = \lambda\theta_r^{TC} - (1-\lambda)\theta_l^{TC}$.

From the expression of $\mu_{TC}(r;\chi)$, the credibility distribution function of TC is the following nondecreasing function

$$\mathrm{Cr}\{TC \le r\} = \begin{cases} 0, & r \le r_1 \\ \frac{(1+\chi)(r-r_1)}{2(r_2-r_1)}, & r_1 < r \le \frac{r_1+r_2}{2} \\ \frac{(1-\chi)r+\chi r_2-r_1}{2(r_2-r_1)}, & \frac{r_1+r_2}{2} < r \le r_2 \\ \frac{1}{2}, & r_2 < r \le r_3 \\ \frac{(1-\chi)r+(\chi-2)r_3+r_4}{2(r_4-r_3)}, & r_3 < r \le \frac{r_3+r_4}{2} \\ \frac{(1-\chi)r_4+(1+\chi)r-2r_3}{2(r_4-r_3)}, & \frac{r_3+r_4}{2} < r \le r_4 \\ 1, & r \ge r_4. \end{cases}$$

If $(r_1+r_2)/2 < \mathrm{E}[TC] = m \le r_2$, then UPM of TC is computed by the following integral

$$\begin{aligned} \mathrm{UPM}^q[TC] &= \left\{ \int_{(m,+\infty)} (r-m)^q \mathrm{d}(\mathrm{Cr}\{TC \le r\}) \right\}^{\frac{1}{q}} \\ &= \left\{ \int_{(m,r_2)} (r-m)^q \mathrm{d}\left(\frac{(1-\chi)r+\chi r_2-r_1}{2(r_2-r_1)} \right) + \int_{(r_2,r_3)} (r-m)^q \mathrm{d}\left(\frac{1}{2}\right) \right. \\ &\quad \left. + \int_{(r_3,\frac{r_3+r_4}{2})} (r-m)^q \mathrm{d}\left(\frac{(1-\chi)r+(\chi-2)r_3+r_4}{2(r_4-r_3)} \right) + \int_{(\frac{r_3+r_4}{2},r_4)} (r-m)^q \mathrm{d}\left(\frac{(1-\chi)r_4+(1+\chi)r-2r_3}{2(r_4-r_3)} \right) \right\}^{\frac{1}{q}} \\ &= \left\{ \frac{(1-\chi)(r_2-m)^{q+1}}{2(1+q)(r_2-r_1)} + \frac{(1+\chi)(r_4-m)^{q+1}}{2(1+q)(r_4-r_3)} - \frac{2^{-q}\chi\left[(r_4-m)-(r_3-m)\right]^{q+1} + (1-\chi)(r_3-m)^{q+1}}{2(1+q)(r_4-r_3)} \right\}^{\frac{1}{q}}. \end{aligned}$$

It follows that

$$\mathrm{UPM}^q[TC] = \left\{ \frac{(1-\chi)(r_2-m)^{q+1}}{2(1+q)(r_2-r_1)} + \frac{(1+\chi)(r_4-m)^{q+1} - 2^{-q}\chi\left[(r_4-m)-(r_3-m)\right]^{q+1} - (1-\chi)(r_3-m)^{q+1}}{2(1+q)(r_4-r_3)} \right\}^{\frac{1}{q}}.$$

The proof of theorem is complete. □

Proof of Theorem 2

Proof. We only prove the case: $(r_1+r_2)/2 < m \le r_2$, the other cases can be proved similarly.

For $TC = [r_1, r_2, r_3, r_4; \theta_l^{TC}, \theta_r^{TC}]$ is a PIV trapezoidal fuzzy variable, according to Theorem (1),

$$\mathrm{UPM}[TC] = \frac{(1-\chi)(r_2-m)^2}{4(r_2-r_1)} + \frac{(1+\chi)(r_4-m)^2 - 2^{-1}\chi\left[(r_4-m)-(r_3-m)\right]^2 - (1-\chi)(r_3-m)^2}{4(r_4-r_3)}.$$

Furthermore, according to [21], the formula of expected value of uncertain transportation cost TC is

$$\mathbb{E}[TC] = m = \frac{r_1+r_2+r_3+r_4}{4} + \frac{(r_1-r_2-r_3+r_4)}{8}\chi.$$

For computational simplicity, let $m = u + v\chi$, then we have

$$\mathrm{UPM}[TC] + \varrho\mathbb{E}[TC] = a\chi^3 + b\chi^2 + c\chi + d,$$

where parameter

$$a = -\frac{v^2}{4(r_2-r_1)}, \quad b = \frac{2(r_2-u)v+v^2}{4(r_2-r_1)},$$

$$c = \frac{2(r_1-u)^2 + 2(r_2-u)v + 4v - (r_4-r_3) + 8\varrho v(r_2-r_1)}{8(r_2-r_1)}$$

and

$$d = \frac{(r_2 - r_1)((r_3 + r_4 - 2u + 4\varrho u)) + 4\varrho u + (r_2 - u)^2}{4(r_2 - r_1)}.$$

Assume $A = b^2 - 3ac, B = bc - 9ad, C = c^2 - 3bd$. Since $a < 0$, if $\Delta = B^2 - 4AC > 0$, then

$$\max_{\mu_{TC} \in \mathscr{P}_{TC}} \mathrm{UPM}[TC] + \varrho \mathbb{E}[TC] = a(\theta_r^{TC})^3 + b(\theta_r^{TC})^2 + c\theta_r^{TC} + d,$$

In contrast, if $\Delta = B^2 - 4AC \le 0$, then

$$\max_{\mu_{TC} \in \mathscr{P}_{TC}} \mathrm{UPM}[TC] + \varrho \mathbb{E}[TC] = a(-\theta_l^{TC})^3 + b(-\theta_l^{TC})^2 - c\theta_l^{TC} + d,$$

On the other hand, when $r_3 < m \le (r_3 + r_4)/2$, parameter

$$\tilde{a} = -\frac{\nu^2}{4(r_4 - r_3)}, \quad \tilde{b} = \frac{(1 + 2r_3 - 2u)\nu^2}{4(r_4 - r_3)},$$

$$\tilde{c} = \frac{(r_4 - u)^2 - 2(r_2 - u)\nu - 2(\frac{r_4 + r_3}{2} - u)^2 + 4\varrho \nu(r_4 - r_3)}{4(r_4 - r_3)}$$

and

$$\tilde{d} = \frac{4\varrho u(r_4 - r_3) + (r_4 - u)^2}{4(r_4 - r_3)}.$$

Similarly, we also have $\tilde{A} = \tilde{b}^2 - 3\tilde{a}\tilde{c}, \tilde{B} = \tilde{b}\tilde{c} - 9\tilde{a}\tilde{d}, \tilde{C} = \tilde{c}^2 - 3\tilde{b}\tilde{d}$, and $\tilde{\Delta} = \tilde{B}^2 - 4\tilde{A}\tilde{C}$.

The proof of theorem is complete. □

Proof of Theorem 3

Proof. For notational simplicity, denote $t_{lp} = \sum_{k \in \mathcal{K}} z_{klp} + \tau_{lp}$.

Let $\xi_{lp} = \mathrm{Tri}[r_1^{lp}, r_2^{lp}, r_3^{lp}; \theta_l^{lp}, \theta_r^{lp}]$ be PIV triangular fuzzy variables, then its parametric selection distribution $\mu_{\xi_{lp}}(t_{lp}; \chi^{lp})$ is

$$\mu_{\xi_{lp}}(t_{lp}; \chi^{lp}) = \begin{cases} \frac{(1+\chi^{lp})(t_{lp} - r_1^{lp})}{r_2^{lp} - r_1^{lp}}, & r_1^{lp} < t_{lp} \le \frac{r_1^{lp} + r_2^{lp}}{2} \\ \frac{(1-\chi^{lp})t_{lp} + \chi r_2^{lp} - r_1^{lp}}{r_2^{lp} - r_1^{lp}}, & \frac{r_1^{lp} + r_2^{lp}}{2} < t_{lp} \le r_2^{lp} \\ \frac{(\chi^{lp} - 1)t_{lp} - \chi r_2^{lp} + r_3^{lp}}{r_3^{lp} - r_2^{lp}}, & r_2^{lp} < t_{lp} \le \frac{r_2^{lp} + r_3^{lp}}{2} \\ \frac{(1+\chi^{lp})(r_3^{lp} - t_{lp})}{r_3^{lp} - r_2^{lp}}, & \frac{r_2^{lp} + r_3^{lp}}{2} < t_{lp} \le r_3^{lp}, \end{cases}$$

where parameters $\chi^{lp} = \lambda\theta_r^{lp} - (1 - \lambda)\theta_l^{lp}$.

Further we can obtain the following credibility distribution function

$$\mathrm{Cr}\{\xi_{lp} \le t_{lp}\} = \begin{cases} 0, & t_{lp} \le r_1^{lp} \\ \frac{(1+\chi^{lp})(t_{lp} - r_1^{lp})}{r_2^{lp} - r_1^{lp}}, & r_1^{lp} < t_{lp} \le \frac{r_1^{lp} + r_2^{lp}}{2} \\ \frac{(1-\chi^{lp})t_{lp} + \chi r_2^{lp} - r_1^{lp}}{2(r_2^{lp} - r_1^{lp})}, & \frac{r_1^{lp} + r_2^{lp}}{2} < t_{lp} \le r_2^{lp} \\ \frac{(1-\chi^{lp})t_{lp} + (\chi - 2)r_2^{lp} + r_3^{lp}}{2(r_3^{lp} - r_2^{lp})}, & r_2^{lp} < t_{lp} \le \frac{r_2^{lp} + r_3^{lp}}{2} \\ \frac{(1+\chi^{lp})t_{lp} + (1-\chi^{lp})r_3^{lp} - 2r_2^{lp}}{2(r_3^{lp} - r_2^{lp})}, & \frac{r_2^{lp} + r_3^{lp}}{2} < t_{lp} \le r_3^{lp} \ r_3^{lp} < t_{lp}. \end{cases}$$

According to the definition of uncertain distribution set, the PIV possibiity distribution $\mu_{\xi_{lp}} \in \mathscr{P}_{\xi_{lp}}$ means $\lambda \in [0, 1]$ and $\theta_r^{lp}, \theta_l^{lp} \in [0, 1]$. Since $\chi^{lp} = \lambda\theta_r^{lp} - (1 - \lambda)\theta_l^{lp}$, we can have $\chi^{lp} \in [-\theta_l^{lp}, \theta_r^{lp}]$.

It follows that

$$\min_{\mu_{\xi_{lp}} \in \mathscr{P}_{\xi_{lp}}} \mathrm{Cr}\{\xi_{lp} \le t_{lp}\} = \min_{\chi^{lp} \in [-\theta_l^{lp}, \theta_r^{lp}]} \mathrm{Cr}\{\xi_{lp} \le t_{lp}\}.$$

Denote $\mathbb{F}(\mathbf{r}_{lp}, t_{lp}) = \min_{\chi^{lp} \in [-\theta_l^{lp}, \theta_r^{lp}]} \mathrm{Cr}\{\xi_{lp} \le t_{lp}\}$. Thus the credibility constraint is equivalent to the following deterministic form

$$\mathbb{F}(\mathbf{r}_{lp}, t_{lp}) \ge \beta_{lp}, \ \forall\, l \in \mathcal{L}, p \in \mathcal{P},$$

where

$$\mathbb{F}(\mathbf{r}_{lp}, t_{lp}) = \begin{cases} 0, & t_{lp} \in (0, r_1^{lp}] \\ \frac{(t_{lp}-r_1^{lp})(1+\theta_r^{lp})}{2(r_2^{lp}-r_1^{lp})}, & t_{lp} \in (r_1^{lp}, \frac{r_1^{lp}+r_2^{lp}}{2}] \\ \frac{(t_{lp}-r_1^{lp})+(r_2^{lp}-t_{lp})\theta_r^{lp}}{2(r_2^{lp}-r_1^{lp})}, & t_{lp} \in (\frac{r_1^{lp}+r_2^{lp}}{2}, r_2^{lp}] \\ \frac{t_{lp}-2r_2^{lp}+r_3^{lp}-(r_2^{lp}-t_{lp})\theta_l^{lp}}{2(r_3^{lp}-r_2^{lp})}, & t_{lp} \in (r_2^{lp}, \frac{r_2^{lp}+r_3^{lp}}{2}] \\ \frac{t_{lp}-2r_2^{lp}+r_3^{lp}-(t_{lp}-r_3^{lp})\theta_l^{lp}}{2(r_3^{lp}-r_2^{lp})}, & t_{lp} \in (\frac{r_2^{lp}+r_3^{lp}}{2}, r_3^{lp}], \\ 1, & t_{lp} \in (r_3^{lp}, +\infty). \end{cases}$$

The proof of theorem is complete. □

Proof of Theorem 4

Proof. The proof of Theorem 4 is similar to that of Theorem 3. □

Appendix B. The related parameters in case study

In addition, set δ_{rp}=[2,1].

Table 12
Selecting-manufacturing cost and storing capacity of suppliers.

Parameters		Values								
		$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$
C_i^s		35,000	**35,000**	**35,000**	**35,000**	**35,000**	**35,000**	**35,000**	**35,000**	**35,000**
C_{ir}^m	$r=1$	38	31	31	31	31	31	31	31	31
	$r=2$	35	36	36	36	36	36	36	36	36
S_{ir}^s	$r=1$	380	300	450	200	390	290	300	320	360
	$r=2$	310	350	400	290	230	260	310	290	320

Table 13
Manufacturing cost, storing capacity and carbon emission of bottling plants.

Parameters	Values			
	$j=1$	$j=2$	$j=3$	$j=4$
C_{jp}^M	22	26	34	31
S_{jp}^P	2480	2300	2100	2200
E_{jp}^P	2.1	2.2	2.2	2.3

Table 14
Opening-processing cost, storing capacity and carbon emission of distribution centers.

Parameters	Values								
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$
C_k^d	65,000	65,000	65,000	65,000	65,000	65,000	65,000	65,000	67,000
C_{kp}^P	23	26	30	26	30	35	26	30	30
S_{kp}^d	1441	1108	1474	1474	1541	1541	1608	1675	1975
E_{kp}^d	0.6	0.7	0.8	0.7	0.8	0.7	0.8	0.9	0.9

Table 15
Opening-processing-recycling cost, handling capacity and carbon emission of recycling centers .

Parameters		Values						
		$m=1$	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$
C_m^r		55,000	55,000	55,000	55,000	55,000	55,000	60,000
C_{mp}^C		10	12	11	12	18	12	11
C_{mr}^R	$r=1$	4.3	4.3	4.3	4.3	4.3	4.3	6
	$r=2$	5.3	5.3	5.3	5.3	5.3	5.3	4.5
S_{mp}^r		2800	3200	4600	2900	6500	5300	3300
E_{mp}^r		0.9	0.8	0.7	0.8	0.7	1.1	0.7

Table 16
Opening-disposal-recycling cost, handling capacity and carbon emission of disposal centers .

Parameters		Values			
		$n=1$	$n=2$	$n=3$	$n=4$
C_n^D		30,351	35,000	35,000	35,000
Cd_{nr}	$r=1$	5	4.3	4.3	4.3
	$r=2$	8	5.3	5.3	5.3
S_{nr}^D	$r=1$	0.7	0.6	0.7	0.8
	$r=2$	0.8	0.8	0.8	0.9
E_{nr}^D	$r=1$	2500	2850	3000	2750
	$r=2$	3000	3650	2650	2500

Table 17
Values of general parameters .

Parameters	Values								
π_{lp}	257	156	305	145	269	274	266	359	264
	224	225	220	243	248	313	212	268	279
	198	258	357	278	234	287	213	229	257
	260	369	228	325	267	250	217	239	252
P_{lp}	475	490	560	572	574	580	460	524	490
	560	574	572	580	460	524	490	500	574
	524	580	460	524	490	560	524	574	580
	460	524	490	560	574	524	580	460	524

Table 18
The distance between suppliers and bottling plants (km) .

Suppliers	Bottling Plants			
	C_{11}	C_{15}	C_{26}	C_{36}
C_2	328	595	916	1284
C_8	112	379	699	1086
C_9	430	791	1001	1286
C_{14}	215	187	458	815
C_{16}	256	252	416	787
C_{20}	390	112	245	613
C_{28}	792	514	236	380
C_{31}	650	373	62	383
C_{34}	765	488	180	22

Table 19
The distance between bottling plants and distribution centers (km) .

Bottling Plants	Distribution centers								
	C_3	C_7	C_{10}	C_{14}	C_{17}	C_{20}	C_{27}	C_{29}	C_{32}
C_{11}	446	155	478	215	455	390	567	755	688
C_{15}	681	344	632	187	392	112	327	447	411
C_{26}	1002	629	940	458	682	245	55	162	82
C_{36}	1370	986	1225	815	966	613	426	278	300

Table 20
The distance between distribution centers and customer zones (km) .

Distribution centers	Customer zones																																			
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}	C_{28}	C_{29}	C_{30}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}
C_3	631	145	10	65	148	622	581	364	202	264	446	402	826	642	681	596	676	731	935	955	1127	1103	1033	1138	1259	1104	1105	1264	1226	1154	1158	1184	1315	1261	1322	1461
C_7	518	464	581	521	596	160	10	186	571	620	155	491	367	183	344	410	609	665	458	456	638	610	557	662	784	629	619	788	751	678	682	720	839	797	847	986
C_{10}	887	401	264	212	253	775	620	562	87	10	478	166	863	676	632	521	439	494	738	734	620	691	851	1015	1131	940	880	1136	1091	1001	934	1032	1186	1109	927	1225
C_{14}	659	524	642	579	655	337	183	309	628	676	215	463	192	10	187	252	534	552	281	279	461	433	381	486	608	458	454	607	580	507	512	538	668	615	676	815
C_{17}	1028	782	676	618	693	765	609	567	502	439	455	273	690	534	392	263	10	71	480	476	312	426	593	752	873	682	622	878	816	743	676	774	928	851	672	966
C_{20}	955	710	796	735	810	610	456	492	796	734	390	569	462	279	112	201	476	530	81	10	207	178	155	348	470	245	215	447	389	306	303	337	484	413	424	613
C_{27}	1105	1003	972	914	987	773	619	720	942	880	567	715	523	454	327	356	622	676	183	215	276	211	58	237	358	55	10	277	202	118	88	146	314	226	262	426
C_{29}	1226	1092	1160	1103	1175	898	751	858	1153	1091	755	925	644	580	447	550	816	870	358	389	470	405	236	135	192	162	202	89	10	126	189	95	138	60	296	278
C_{32}	1184	1050	1094	1036	1109	860	720	791	1093	1032	688	866	607	538	411	508	774	828	305	337	423	358	183	201	307	82	146	196	95	26	82	10	236	100	217	300

Table 21
The distance between customer zones and recycling centers (km) .

Customer zones	Recycling centers						
	C_5	C_{12}	C_{14}	C_{17}	C_{20}	C_{29}	C_{34}
C_1	770	909	659	1028	955	1226	1261
C_2	285	540	524	782	710	1092	1085
C_3	148	402	642	676	796	1160	1171
C_4	81	345	579	618	735	1103	1113
C_5	10	419	655	693	810	1175	1185
C_6	743	645	337	765	610	898	937
C_7	596	491	183	609	456	751	797
C_8	505	448	309	567	492	858	868
C_9	200	228	628	502	796	1153	1170
C_{10}	253	166	676	439	734	1091	1109
C_{11}	461	329	215	455	390	755	765
C_{12}	419	10	463	273	569	925	943
C_{13}	841	710	192	690	462	644	684
C_{14}	655	463	10	534	279	580	615
C_{15}	696	466	187	392	112	447	488
C_{16}	611	355	252	263	201	550	585
C_{17}	693	273	534	10	476	816	851
C_{18}	749	264	552	71	530	870	905
C_{19}	813	572	281	480	81	358	384
C_{20}	810	569	279	476	10	389	413
C_{21}	847	454	461	312	207	470	505
C_{22}	940	520	433	426	178	405	440
C_{23}	926	685	381	593	155	236	260
C_{24}	1086	844	486	752	348	135	189
C_{25}	1208	966	608	873	470	192	255
C_{26}	1017	774	458	682	245	162	180
C_{27}	987	715	454	622	215	202	226
C_{28}	1212	970	607	878	447	89	148
C_{29}	1175	925	580	816	389	10	60
C_{30}	1087	836	507	743	306	126	121
C_{31}	1070	768	512	676	303	189	184
C_{32}	1109	866	538	774	337	95	100
C_{33}	1263	1020	668	928	484	138	183
C_{34}	1185	943	615	851	413	60	10
C_{35}	1184	765	676	672	424	296	258
C_{36}	1385	1059	815	966	613	278	22

Table 22
The distance between recycling centers and disposal centers (km).

Recycle centers	Disposal centers			
	C_{12}	C_{22}	C_{24}	C_{31}
C_5	419	940	1086	1070
C_{12}	10	520	844	768
C_{14}	463	433	486	512
C_{17}	273	426	752	676
C_{20}	569	178	348	303
C_{29}	925	405	135	189
C_{34}	943	440	189	184

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