

Green closed-loop supply chain network design considering cost control and CO₂ emission

Lufei Huang

School of Management, Shanghai University, Shanghai, China

Liwen Murong

School of Engineering, The University of Tokyo, Tokyo, Japan, and

Wencheng Wang

School of Management, Shanghai University, Shanghai, China

Abstract

Purpose – Environmental issues have become an important concern in modern supply chain management. The structure of closed-loop supply chain (CLSC) networks, which considers both forward and reverse logistics, can greatly improve the utilization of materials and enhance the performance of the supply chain in coping with environmental impacts and cost control.

Design/methodology/approach – A biobjective mixed-integer programming model is developed to achieve the balance between environmental impact control and operational cost reduction. Various factors regarding the capacity level and the environmental level of facilities are incorporated in this study. The scenario-based method and the Epsilon method are employed to solve the stochastic programming model under uncertain demand.

Findings – The proposed stochastic mixed-integer programming (MIP) model is an effective way of formulating and solving the CLSC network design problem. The reliability and precision of the Epsilon method are verified based on the numerical experiments. Conversion efficiency calculation can achieve the trade-off between cost control and CO₂ emissions. Managers should pay more attention to activities about facility operation. These nodes might be the main factors of costs and environmental impacts in the CLSC network. Both costs and CO₂ emissions are influenced by return rate especially costs. Managers should be discreet in coping with cost control for CO₂ emissions barely affected by return rate. It is advisable to convert the double target into a single target by the idea of “Efficiency of CO₂ Emissions Control Reduction.” It can provide managers with a way to double-target conversion.

Originality/value – We proposed a biobjective optimization problem in the CLSC network considering environmental impact control and operational cost reduction. The scenario-based method and the Epsilon method are employed to solve the mixed-integer programming model under uncertain demand.

Keywords Closed-loop supply chain network, Mixed-integer programming, Uncertainty, Stochastic programming, Epsilon method, CO₂ emissions

Paper type Research paper

1. Introduction

Supply chains are growing and becoming more complex as demands increase. Moreover, consumers tend to require higher quality of products. This leads to a large number of returns, translating directly to increased environmental impacts. Thus, the urgent need to



reduce those impacts has aroused broad attention from governments, academia, and industries. Various measures are developed to meet the trade-off between environmental protection and cost reduction by many large economic entities. Long-term measures, such as product distribution and facility allocation, have more profound influences on the development of sustainable supply chain networks than short-term measures, such as power options and equipment transformation. The fact that more and more stakeholders realize the importance of long-term measures promotes the in-depth study in this field. Since more attention has been put into this field, related studies have increased correspondingly (Govindan *et al.*, 2017).

The purpose of a closed-loop supply chain (CLSC) network design is to find the optimal long-term strategy for the product life cycle management via all forward/reverse logistics activities (Guide and Van Wassenhove, 2009). Unlike traditional supply chain networks, the CLSC networks increase the overall added value of the supply chain by collecting and reusing the returned (used or unused) products. The performance of environmental protection will be enhanced by those reusing activities accordingly. Among many environmental factors, the concept of CO₂ emissions has been widely discussed by scholars on not only traditional supply chain networks but also CLSC networks. For instance, Elhedhli and Merrick (2012) proposed a supply chain network design problem, taking into consideration carbon emission costs alongside fixed and variable location and production costs. Bazan *et al.* (2017) developed a two-level CLSC network model that integrated greenhouse gas emissions and energy computations. To cope with the complex supply chain system, a joint assessment of the economy and the environment can greatly improve the overall performance of the supply chain. However, uncertainty in demands and returns is another major obstacle in the practical market. Considering uncertain factors can make the proposed model more practical (Snyder *et al.*, 2016).

Environmental issues have become an important concern in modern supply chain management. The structure of CLSC networks, which considers both forward and reverse logistics, can greatly improve the utilization of materials and enhance the performance of the supply chain in coping with environmental impacts and cost control. Existing research paid less attention to integrated models that consider both environmental and economic objectives on logistics facility environmental level option decisions and transportation activities under uncertain demand. In this study, a biobjective MIP of CLSC-related optimization problems in case of facility environmental level option and transportation activities is discussed to contribute to the stream of related research. The factors of CO₂ emissions and uncertain demand are considered in the proposed model simultaneously.

To develop a well-designed CLSC network, this paper proposes a stochastic MIP model aiming to control carbon dioxide emissions, and factors in both environmental levels and facilities capacity levels are integrated. The scenario-based method and the Epsilon method are proposed to solve the problem. The numerical experiments are conducted to verify the proposed method and the MIP model. Managerial advice in the green CLSC network is also discussed in this study. The results show that the presented MIP model with uncertain demand is an effective way of formulating and solving CLSC network design problem. The Epsilon method is tested effectively based on the numerical experiments. Multiobjective model can achieve the trade-off between cost control and environmental concerns. Compared with transportation activities, managers should pay more attention to activities related to facility operations.

The study is organized as follows: Section 1 presents the induction of this study. Section 2 lists the review of related literature studies. Section 3 describes the research background. Section 4 proposes the stochastic MIP model. Section 5 develops a corresponding Epsilon method. Section 6 discusses numerical experiments and analyzes the reliability of the proposed model. The last section is the conclusions of the study.

2. Related studies

In this study, a stochastic MIP model regarding economical control and environmental impact in a green CLSC network design is proposed. This section is divided into two parts, which are green supply chain management and the CLSC network design problem.

2.1 Green supply chain management

Considerable attention is put on the development of green supply chain (GSC) due to the worse environment. Many scholars present the review studies of the GSC theory. Several scholars put the emphasis on the framework of GSC. [Dubey et al. \(2015\)](#) focused on the investigation of relationship among participants in the GSC, and a theoretical system considering total quality was developed. [Hussain et al. \(2016\)](#) provided a useful measure for supply chain managers to develop a green service supply chain. The evaluation method they proposed incorporated environmental factors, social factors, customer relationships, and risk evaluation.

Research in green activities is also an important issue in this field. [Zhu and He \(2017\)](#) put emphasis on evaluating the influence of product design and found that price competition has positive effect on the sustainable development. [Matsumoto et al. \(2018\)](#) analyzed the characteristic of auto parts remanufacturing market regarding carbon dioxide emissions and found that price strategy is a stimulus to the purchase intention. [Liu et al. \(2016\)](#) provided supply chain-oriented analyses to identify both the important emission drivers and sources in Chinese exports. [Ji et al. \(2017\)](#) analyzed the behavior of carbon dioxide emissions from various channel members by the Stackelberg game model. They found the importance of low carbon sensitivity in supply chain. [Acquaye et al. \(2018\)](#) proposed an environmental performance evaluation model based on the concept of life cycle.

Supply chain network design problems under uncertain demand have been received weighty concern in the last decade. [Pasandideh et al. \(2015\)](#) developed a multiperiod three-echelon supply chain problem under uncertain environments where the internal parameters such as production demands, production time, and setup and operation times are subject to a certain probability distribution. [Chen et al. \(2017\)](#) analyzed the pricing decisions of a supply chain with one pair of manufacturer and retailer, which considered the consumer demand, the manufacturing cost, and the sales effort cost as uncertain variables.

Numerous solution methods are developed in the research of GSC management. [Govindan et al. \(2015\)](#) proposed a multiobjective stochastic model for GSC. They applied a metaheuristic approach to solve this problem. When it comes to performance optimization, the MIP model is usually adopted in this field. [Altmann \(2015\)](#) associated the MIP model with a demand function regarding green factors. The improved model could do good to sustainable development of companies and actual interests. A fuzzy MIP model was developed by [Jindal and Sangwan \(2014\)](#) to optimize the profits in a reverse logistics supply chain. [Rezaee et al. \(2017\)](#) proposed a two-stage mathematical programming model to establish a GSC in a carbon-trading environment.

2.2 Closed-loop supply chain network design problem

CLSC network problems are the hinge in the field of GSC network. A systemic literature review of CLSC network design problems is presented by [Govindan et al. \(2017\)](#).

The facility allocation problem is generally involved in the CLSC network design problem, and there is also much discussion in the structure design of a CLSC network. [Pishvae and Torabi \(2010\)](#) presented a biobjective possibilistic MIP model to handle the uncertain and imprecise parameters in the CLSC network problem. [Özkar and Başlıgil \(2013\)](#) considered three factors — trade satisfaction, customer satisfaction, and total interests — in a CLSC network model under uncertain demand. [Soleimani et al. \(2017\)](#) proposed a multihierarchy CLSC network model and put emphasis on the return options. [Zeballos et al. \(2018\)](#) developed

an MIP model combining the conditional value at risk (CVaR) with the construct of a CLSC network. The proposed method could improve the economic performance by controlling the returned products. Taleizadeh *et al.* (2018) investigated the influence of marketing performance on decision-making process of stakeholders. They conducted the research for the dual-channel CLSC network by the application of the Stackelberg game theory.

Various solution methods are developed for the numerous studies in the CLSC network area.

As the vital environmental factor in the CLSC network, the impact of CO₂ emissions has been widely discussed. Tosarkani and Amin (2018) developed a fully fuzzy programming method to determine the possible upper, middle, and lower ranges of profit for a multiechelon battery CLSC with multicomponents and multiproducts in multiperiod under imprecise information. Guo *et al.* (2019) developed a multiperiod CLSC model with the consideration of supply disruption and government subsidy.

Similar to traditional supply chain network research, uncertainty is also an important factor that concerns the CLSC network. Pishvaei *et al.* (2011) presented a robust mathematical model to deal with the uncertainty for a CLSC design problem. Bai and Sarkis (2013) proposed the term of reverse logistics flexibility into the CLSC research. A third-party reverse logistics provider performance assessment application of the reverse logistics framework was illustrated. A multiobjective mathematical model was presented for a CLSC network under uncertainty demand by Zhen *et al.* (2019). A Lagrangian relaxation method was developed to solve the model. Prakash *et al.* (2018) developed a generic CLSC network based on MIP formulation with direct shipping to the customer from manufacturing plants as well as shipping through distribution centers under supply risks, transportation risk, and uncertain demand using a robust optimization (RO) approach.

Several viewpoints about the related research can be derived from above review of references. (1) Multiobjective optimization and MIP method are widely employed for both GSC and closed-loop supply network design. (2) Carbon emission factors are the focus of research in GSCs and CLSCs. (3) As far as we know, there has been little in-depth research for the optimization problem in the CLSC network considering integrated uncertain demand CO₂ emission control on facilities and transportations. The proposed optimization model in this study integrates environmental factors and factors of CLSC design issues, including facility allocation, facility capacity, and environment-level, uncertain demand and channel flow decision, which is rather useful for decision-makers. Thus, differences between this study and other studies in the literature are revealed. The proposed stochastic MIP model regarding CO₂ emissions incorporates the uncertainty of product demand, forward/reverse logistics, and different types of facilities and products. Insightful opinions and research findings are of great significance to the improvement of a green CLSC network.

3. Problem description

CLSC research has been introduced in vary industries, such as battery recycling (Kannan *et al.*, 2010), textile products (Fahimnia *et al.*, 2013), and e-commerce (Prakash *et al.*, 2018). This study presents a multiechelon CLSC network regarding environmental levels and facility capacities. The structure of the CLSC network and flow of logistic activities are illustrated in Figure 1.

In the proposed CLSC network, product demands generated from customer points, product types, and product quantities vary. Therefore, appropriate capacity for facilities is necessary to cope with uncertain demand. New products are transported from the manufacture firms to customer points via multiple distribution points. A return flow becomes the reverse channel through which return products are gathered, sorted, and distributed back to the manufacture firms for further repairing and disassembling.

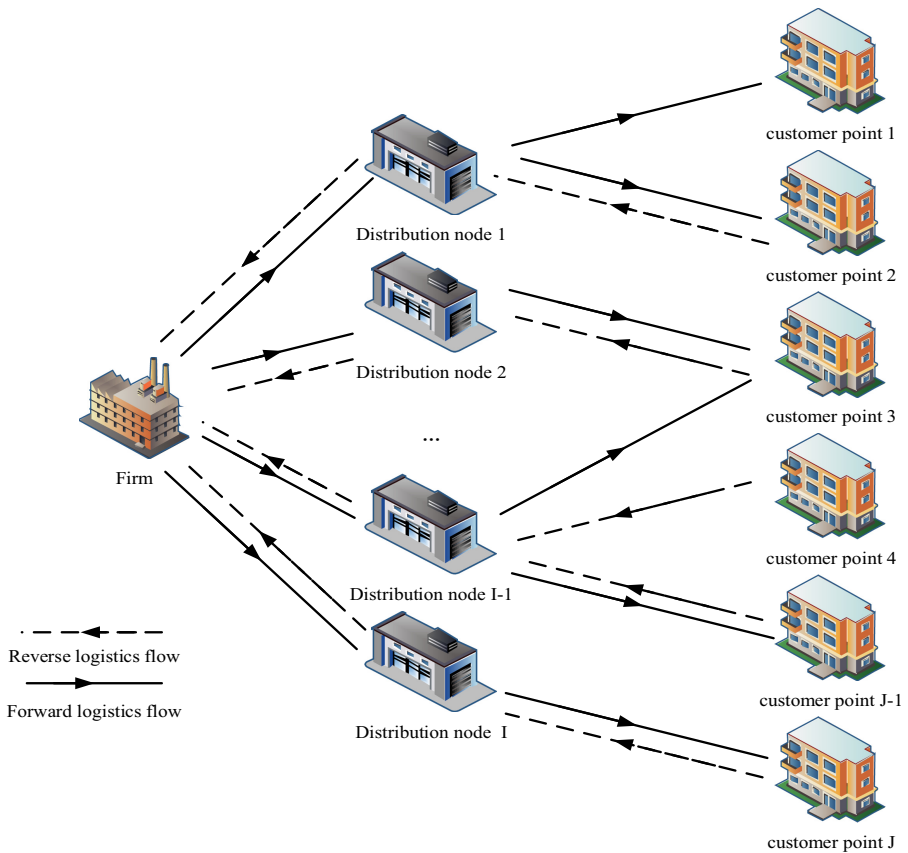


Figure 1.
General structure of a
closed-loop supply
network

One core element of the green CLSC network is the environmental concern. According to the literature review, the fact that CO₂ emissions are generally mentioned by scholars is revealed. In this study, the green factor is exclusively represented by CO₂ emissions. The transportation process is the main source of CO₂ emissions. In this study, the environmental protection level of the distribution point facility, which means, the carbon dioxide emission level, has been specifically considered together with the capacity level of the facility. The operating costs of the facility increase as capacity or environmental protection levels increase. Thus, a stochastic MIP model that considers capabilities and environmental levels of facilities is proposed to balance environmental impacts with economic factors.

The influence of environmental levels on facilities depends on various factors, such as power options for facilities and building material options. In this paper, the environmental level is presented as discrete forms. Three environmental protection grades are set in this proposed model, and hence, there are three emissions ranges. Managers can evaluate the environmental level of facilities based on the practical situation of enterprises and analyze the CO₂ emissions from energy options. Specifically, for the level of environmental level, the numerals “1,” “2,” or “3” can be used to indicate the CO₂ emission levels of facilities “30000 g,” “50000 g,” or “70000 g.” The boundary of CO₂ emissions needs to be clarified corresponding to the environmental levels. The CO₂ emissions emitted by manufacturing companies are rather

larger than CO₂ emissions emitted by service organizations. Similarly, capacity levels can be listed depending on some elements, such as the weight and volume of products. All candidate distribution points have the same attributes for capacity-level decisions and environment-level decisions.

The factor “uncertain demand” makes the CLSC network model more complex. In traditional CLSC network studies, the emphasis is put on the uncertain demand in the forward logistics process. In the reverse channel, the amount of returned product is uncertain due to the uncertain demand for new products. Therefore, a scenario-based method is adopted in this paper to deal with the uncertainty.

In order to ensure the accuracy of the CLSC model, a series of assumptions are proposed as follows: (1) Background information of elements in the green CLSC network, such as locations of involved points, options for facilities in environmental levels and capacity levels, the unit cost of logistics activities, and the unit emission emitted during logistics activities, is known; (2) uncertain demand of different customer segments can be met by an alternative facility; (3) attributes of products remain the same during the logistic activities, and hence, capacity constraints in the reverse phase remain the same as in the forward phase.

4. Model formulation

This section specifies the process of formulating the stochastic MIP model. The notations used in the model are listed as follows:

4.1 Notations

4.1.1 Indices and sets.

I = index set of customer points, $\{1, 2, \dots, |I|\}$

J = index set of potential distribution nodes, $\{1, 2, \dots, |J|\}$

P = index set of product types, $\{1, 2, \dots, |P|\}$

C = index set of technology selection options of emissions control level for facilities, $\{1, 2, \dots, |C|\}$

G = index set of capacity-level options, $\{1, 2, \dots, |G|\}$

S = index set of scenarios, $\{1, 2, \dots, |S|\}$

4.1.2 Parameters.

\dot{d}_j = distance from the firm to node j (in kilometers)

\ddot{d}_{ji} = distance between node j and customer point i (in kilometers)

f_{cg} = fixed running cost with emissions control level c and capacity level g for opening potential nodes

e_{cg} = fixed CO₂ emissions (in g) per unit capacity with emissions control level c and capacity level g for opening potential nodes

h_g = capacity (in K/m³) of potential distribution nodes with capacity level g

a_p = handling cost for distributing or collecting a unit of product p

D_{pis} = demand of product p at customer segment i under scenario s

w_s = probability of scenario s

- r_{ips} = return rate at of product p customer segment i under scenario s
 x_p = vehicle capacity occupied by a unit of (return) product p
 y_p = factor for converting a unit of (return) product p to the unit capacity at facilities
 \dot{t} = unit cost of shipping one truck-load products per kilometer
 \ddot{t} = unit CO₂ emissions (in g) of shipping one truck-load of products per kilometer

4.1.3 Decision variables.

- α_{pjs} = volume of product p shipped from the production/recovery firm to distribution node j under scenario s
 β_{pjs} = volume of recoverable product p shipped from node j to the production/recovery firm under scenario s
 η_{pjis} = volume of product p shipped from node j to i under scenario s
 μ_{pijs} = volume of return product p shipped from node i to j under scenario s
 ψ_{cgj} = binary variable equals “1” if the distribution point with emissions control level c is open at node j , and “0” otherwise

4.2 Objective functions

Formulation process of the proposed MIP model is described in this subsection. In order to develop a green CLSC network, the objective of this model is to estimate the CO₂ emissions and operation cost. The detailed process of formulating the green forward–backward CLSC network model is shown as follows:

Objective 1: Minimizing the total cost of the entire network is the first objective function, including the shipping cost for delivering products, the fixed operating costs of the opening facility, the variable cost of products processing, and the inventory cost of temporarily holding products. The equations of the four subitems involved in objective 1 are shown as follows.

- (1) The function of the transporting cost for delivering products via forward and reverse channels is formulated as

$$TC = \sum_{s \in S} w_s \left\{ \sum_{j \in J, p \in P} \dot{d}_j \dot{t} (\alpha_{pjs} + \beta_{pjs}) x_p + \sum_{j \in J, i \in I, p \in P} \ddot{d}_{ji} \ddot{t} (\eta_{pjis} + \mu_{pijs}) x_p \right\}$$

- (2) The fixed cost of facilities is formulated by

$$FC = \sum_{g \in G, c \in C, j \in J} \psi_{cgj} f_{cg}$$

- (3) The variable cost of manufacturing, recovery, distribution, collection, and disassembling is calculated by

$$VC = \sum_{s \in S, i \in I, j \in J, p \in P} w_s a_p (\alpha_{pjs} + \beta_{pjs} + \eta_{pjis} + \mu_{pijs})$$

Objective 2: Measuring the impact of emission control factors on the frequent transit network (FTN) is the second objective of this model. This expression aims to minimize the total amount of CO₂ emissions due to transport flow and facility operations.

The formulations of the two subparts involved in objective 2 are shown as follows. The following expression is proposed to minimize the CO₂ emissions during transportation and operation activities.

The formulations involving three subparts are shown as follows.

(1) CO₂ emissions during transportation are calculated by

$$TE = \sum_{s \in S} w_s \left\{ \sum_{p \in P, j \in J} \dot{d}_j \ddot{t} (\alpha_{pjs} + \beta_{pjs}) x_p + \sum_{j \in J, p \in P, i \in I} \ddot{d}_{ji} \ddot{t} (\eta_{pjis} + \mu_{pjis}) x_p \right\}$$

(2) The fixed CO₂ emissions of facilities are calculated by

$$FE = \sum_{g \in G, c \in C, j \in J} \psi_{cgj} \ell_{cg}$$

The objective function of the presented model is described as follows:

Objective 1: Min $F_1 = TC + FC + VC$

Objective 2: Min $F_2 = TE + FE$

4.3 Mathematical model

The mathematical optimization model is constructed as follows:

$$\text{Min } F_1 = TC + FC + VC \tag{1}$$

$$\text{Min } F_2 = TE + FE \tag{2}$$

$$\sum_j \eta_{pjis} = D_{pis} \quad \forall p \in P, \forall i \in I, \forall s \in S \tag{3}$$

$$\sum_j \mu_{pjis} = D_{pis} r_{ips} \quad \forall p \in P, \forall i \in I, \forall s \in S \tag{4}$$

$$\alpha_{pjs} = \sum_i \eta_{pjis} \quad \forall p \in P, \forall j \in J, \forall s \in S \tag{5}$$

$$\beta_{pjs} = \sum_i \mu_{pjis} \quad \forall p \in P, \forall j \in J, \forall s \in S \tag{6}$$

$$\sum_p \sum_j \beta_{pjs} \leq \sum_p \sum_j \alpha_{pjs} \quad \forall s \in S \tag{7}$$

$$\sum_p \sum_i \sum_j \mu_{pjis} \leq \sum_p \sum_i \sum_j \eta_{pjis} \quad \forall s \in S \tag{8}$$

$$\sum_i \sum_p y_p (\alpha_{pjs} + \beta_{pjs} + \eta_{pjis} + \mu_{pjis}) \leq \sum_c \sum_g h_g \psi_{cgj} \quad \forall j \in J, \forall s \in S \tag{9}$$

$$\sum_g \sum_c \psi_{cgj} \leq 1 \quad \forall j \in J \tag{10}$$

$$\sum_j \sum_g \sum_c \psi_{cgj} \geq 1 \tag{11}$$

$$\alpha_{pjs}, \beta_{pjs}, \eta_{pjis}, \mu_{pjis} \geq 0 \quad \forall p \in P, \forall i \in I, \forall s \in S, \forall j \in J \tag{12}$$

$$\psi_{cgj} \in \{1, 0\} \quad \forall j \in J, g \in G, \forall c \in C \tag{13}$$

Eqs. (1–2) represent the overall CO₂ emissions. Constraints (3–4) ensure that demands from customer segments are met and all return products are collected. Constraints (5–8) ensure that product flows at facilities are uniform during transportation. Constraint (9) describes the capacity constraints of facilities. Constraint (10) ensures that one and only capacity level and environmental levels are set to each facility. Constraint (11) ensures that each point has one and only set of environmental levels and capacity levels. Constraints (12–13) ensure that non-negativity variables and binary variables meet the requirements of proposed model.

A facility location problem with certain demand is an NP-hard problem (Boland *et al.*, 2017; Min *et al.*, 2006). The model this study investigates is under the condition of uncertain demand, and it is also an NP-hard problem, but under more complex condition.

5. Solution method

The motivation for formulating a multiobjective optimization problem is to optimize different objective functions simultaneously. In studies regarding minimization, the Epsilon-constraint method can be generally applied. This approach is applicable for solving multiobjective problems and getting feasible solutions. This technique iteratively solves the model, which, in each step, converts all the objective functions, except one, to appropriate Epsilon-based constraints (Tosarkani and Amin, 2018). For instance, the following holds (Eqn (14)):

$$\min(f_1(x), f_2(x), \dots, f_n(x)) \tag{13}$$

subject to

$$x \in S$$

In this approach, for each replication, one objective function is taken as the only objective function, while the others are set as constraints using appropriate epsilons, i.e.,

$$\min f_1(x), f_2(x) \leq \varepsilon_2, f_3(x) \leq \varepsilon_3, \dots, f_n(x), \leq \varepsilon_n x \in S \tag{14}$$

The solutions on the Pareto frontier in the multiobjective models are a set of nondominated solutions. Ultimately, the decision-maker chooses the best or feasible solution with respect to the objective and the Pareto solutions.

Compared with stochastic opportunity constraint programming (Schön and König, 2018; Rijpkema *et al.*, 2016), the scenario-based method is more convenient for dealing with the uncertain environment (Freeman *et al.*, 2015; Vrakopoulou *et al.*, 2019). Therefore, we employ the scenario-based method to cope with the uncertain demand. The probability of each discrete scene is defined as the reciprocal of the number of discrete scenes. The number of scenes is set to 100, which can eliminate the effects of uncertainty.

6. Model analysis

6.1 Case description and experiment setting

We assume the following problem scale in the proposed CLSC network, that there are a firm, six potential distribution nodes and ten customer points, as illustrated in Figure 2.

The main parameters mentioned in the model are presented in Tables I–IV.

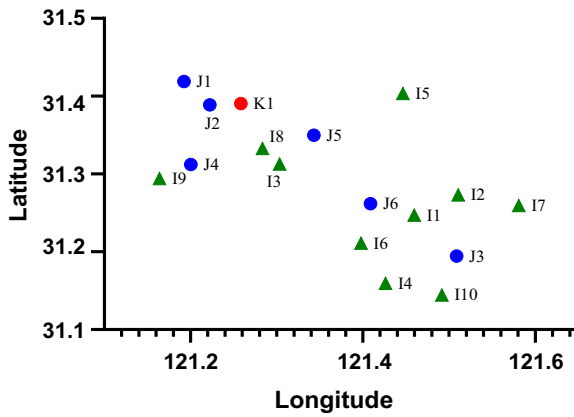


Figure 2. Layout of the proposed problem

Facility type	Environmental level	Capacity level	Fixed cost/RMB
Distribution/Collection point	1	1	200,000
	1	2	220,000
	1	3	240,000
	2	1	300,000
	2	2	330,000
	2	3	360,000
	3	1	400,000
	3	2	440,000
	3	3	480,000

Table I. Fixed costs of facilities

Product type	Capacity level	Process cost/RMB
1	1	0.8
1	2	1.3
1	3	1.8
1	4	0.8
1	5	1.4
1	6	1.9
2	1	0.8
2	2	1.3
2	3	1.5
2	4	0.6
2	5	1
2	6	1.5
2	1	0.6
2	2	1.1
2	3	2
2	4	0.6
2	5	1.1
2	6	1.8

Table II. Process costs of facilities

6.2 Numerical experiment result

Numerical experiments are conducted in this section, based on the case study, aiming to compare the proposed Epsilon method with CPLEX, to confirm the reliability of the introduced stochastic MIP model and support-related practitioners in the process of decision-making.

The proposed model is solved by the solver, CPLEX 12.9. The C# programming language is applied for coding. The solving process is conducted by Visual Studio 2015 IDE, on a Lenovo laptop (4 Intel(R) Core (TM) i7-6500U processors, @ 2.5 GHz and 8 GB memory), under the Windows 10 operation system.

The proposed Epsilon-constraint model of this paper is represented as follows:

$$\text{Min } F_1(x) \tag{15}$$

subject to

$$F_2(x) \leq \varepsilon_2$$

and Constraints (3–12).

The presented model in Eqn (15) is solved for the following situation: With F_2 as the objective function and eliminating F_1 to find the optimum value of F_2 which is termed as ω here. To find the Pareto optimal solutions, the epsilons associated with F_2 are assigned based on the values of ω , which is 1539154.40 g of CO₂ emissions. The values related to the epsilons are illustrated in Table V.

From Table V, clearly, $\varepsilon_2 \in (1616112.12, 2462647.04)$. In each instance of Table V, the two objective functions can lead to a Pareto solution and the final computations can present a schematic of the Pareto frontier and likewise for the nondominated solutions, as Figure 3 shown. The details of the numerical validation of the model and the solution methodology are discussed next.

Facility type	Environmental level	Capacity level	Fixed emission/g
Distribution/Collection point	1	1	400,000
	1	2	440,000
	1	3	480,000
	2	1	300,000
	2	2	330,000
	2	3	360,000
	3	1	200,000
	3	2	220,000
	3	3	240,000

Table III.
Fixed emissions emitted by facilities

Parameters	Setting
Handling product capacity of different distribution/collection points	$h_g = 4000, 4500, \text{ and } 5000 \text{ K m}^3$ for level $g = 1, 2, \text{ and } 3$, respectively
Struck capacity of unit product	$x_p = 0.5, 1.2, \text{ and } 2 \text{ ton}$ for $p = 1, 2, \text{ and } 3$, respectively
Unit capacity of different products	$y_p = 10, 15, \text{ and } 20 \text{ m}^3$ for $p = 1, 2, \text{ and } 3$, respectively
Unit transportation cost per ton · km	$t = 0.5 \text{ RMB/ton} \cdot \text{km}$
Unit CO ₂ emissions per ton · km	$\dot{i} = 0.3 \text{ g/ton} \cdot \text{km}$
Return rate	$r_{ips} = \text{U}[0,0.05]$
Demand	$D_{pis} = \text{U}[2000,3000]$

Table IV.
Input parameters of disparate facilities and products

Table V. Values of epsilons and results of objective functions

ϵ_2	Value of ϵ_2	F_1 [/¥]	F_2 [CO ₂ g]
0.05 * $\omega + \omega$	1616112.12	3785204.02	1556462.08
0.10 * $\omega + \omega$	1693069.84	3665195.78	1675752.52
0.15 * $\omega + \omega$	1770027.56	3562770.21	1770027.55
0.20 * $\omega + \omega$	1846985.28	3545195.78	1795752.54
0.25 * $\omega + \omega$	1923943.00	3435195.78	1905752.54
0.30 * $\omega + \omega$	2000900.72	3331677.20	2000900.72
0.35 * $\omega + \omega$	2077858.44	3325204.02	2016462.08
0.40 * $\omega + \omega$	2154816.16	3225195.78	2115752.54
0.45 * $\omega + \omega$	2231773.88	3125195.78	2215752.42
0.50 * $\omega + \omega$	2308731.60	3125195.78	2215752.36
0.55 * $\omega + \omega$	2385689.32	3125195.78	2215752.54
0.60 * $\omega + \omega$	2462647.04	3125195.78	2215752.37

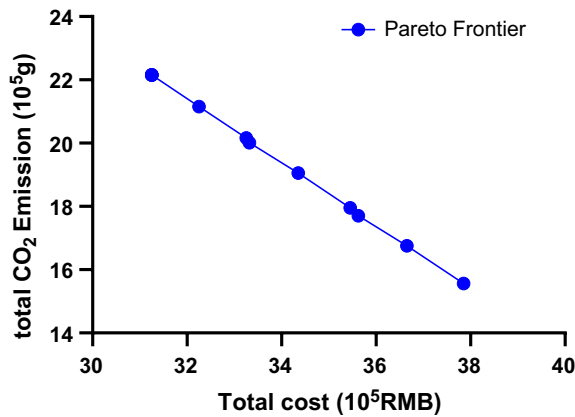


Figure 3. Pareto frontier of the proposed problem

For the Epsilon-constraint method, the change in ϵ means the acceptability of the entire CLSC network to environmental objective. In terms of cost objectives, cost from distribution and cost from transportation are barely influenced by different values of ϵ . With the increase in the value of ϵ , cost from facility operation grows inversely. The sudden shift of the smallest share from cost from distribution activities to cost from facilities operation is rather remarkable when the value of ϵ is over 1.25. The results of the analysis are shown in Figure 4. Consequently, the control of cost from facilities operation is an important concern for the practical operation of the CLSC network.

In terms of environmental impact, CO₂ emissions from transportation activities are quite stable regardless of the value of ϵ . With the growth of the value of ϵ , CO₂ emissions from facility operation increase. When the value of ϵ is over 1.1, the share of CO₂ emissions from facility operation occupies the major part of the total emissions. The results of the analysis are shown in Figure 5. Consequently, it is necessary to pay more attention to the set of environmental levels in the CLSC network design.

The emphasis of the CLSC network design is on the control of costs from facilities operation and the set of environmental levels. When the value of ϵ ranges from 1.05 to 4.45, costs and CO₂ emissions are varied regularly with the change of it. However, the regular change shifts into a stable status, when the value of ϵ is over 1.45. This finding suggests that

Figure 4.
Cost subobjective value change under different ϵ values

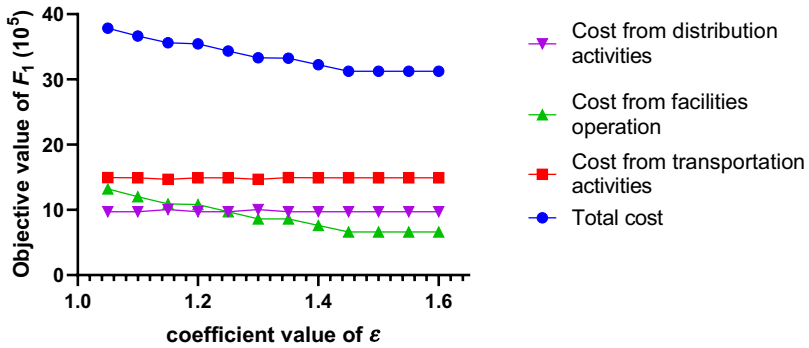
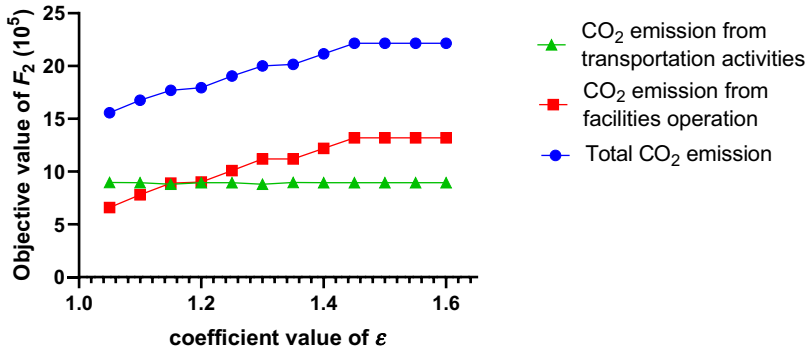


Figure 5.
Environment subobjective value change under different ϵ values



managers should decide the extent of toleration for emissions from a scientific perspective. Otherwise, higher level of toleration will not make a difference and will be a waste on costs and time.

The idea of “Efficiency of CO₂ Emissions Control Reduction” is employed to present the effectiveness of CO₂ emissions change, which is calculated by the ratio of the “declining volume of CO₂ emissions between two adjacent cases” to the “increment of cost between the two adjacent cases,” as Eqn (16) stated. Base on the formulation of efficiency (Δ) in controlling CO₂ emissions, the specific value of ϵ for the biobjective optimization problem can be decided. Apparently, the optimal value of ϵ for the proposed model is 1.35, according to Figure 6.

$$\Delta = \frac{F_1^{\epsilon_{N-1}} - F_1^{\epsilon_N}}{F_1^{\epsilon_N} - F_1^{\epsilon_{N-1}}} \times 100\% \quad (16)$$

6.3 Sensitivity analysis result

Return rate is the major index in the CLSC network design. In order to explore the changes in the values of the objective functions based on the return ratio, a set of sensitivity analysis based on three kinds of return rate is applied on the presented model.

As illustrated in Figure 7, the Pareto frontier curve is moved to the right with the increase in return rate. It implies that CO₂ emissions are influenced adversely by return rate, so are costs.

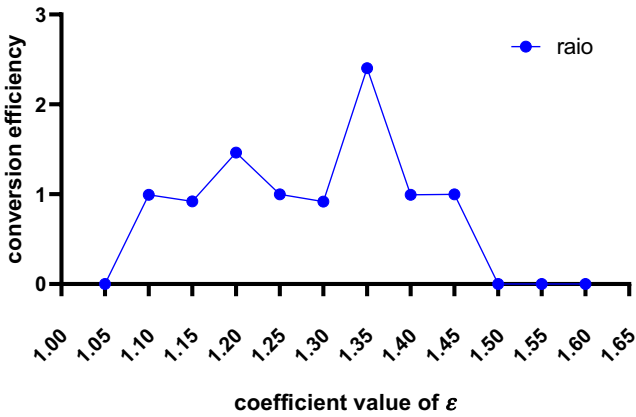


Figure 6. Efficiency of CO₂ emissions control reduction under different ϵ values

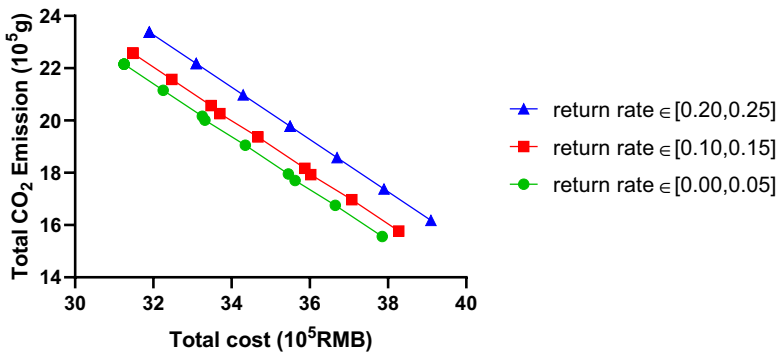


Figure 7. Pareto frontiers with different return rates

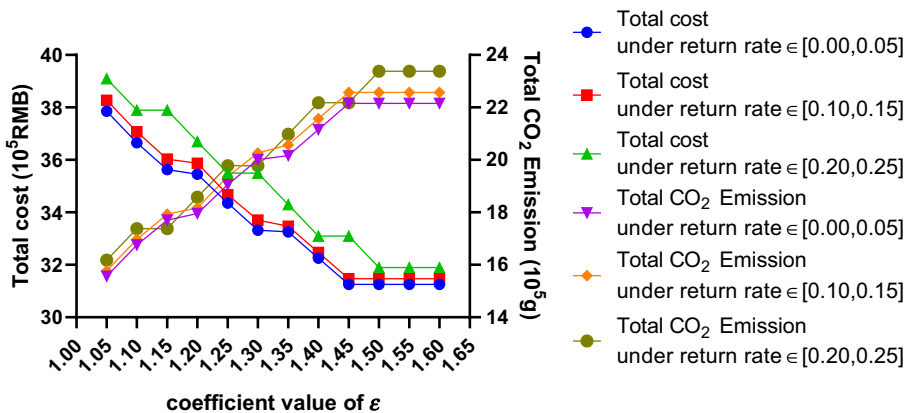


Figure 8. Economic and environmental subobjective under different ϵ values

The changes in the economic and environmental subobjective under different values have been compared, as shown in [Figure 8](#).

With the reduction in requirement on environmental levels, costs are declining, while CO₂ emissions are increased, as presented in [Figure 8](#). Meanwhile, the influence on costs is greater than that on emissions. Under different requirement on environmental levels, costs will increase uniformly as the return rate increases. However, there is no consistent change in CO₂ emissions.

7. Conclusions

A multiechelon model regarding cost reduction and emission control is proposed in this paper for the CLSC network under the multiproduct and uncertain demand environment. A stochastic MIP model is introduced to estimate the minimum carbon dioxide emission and operational cost in the CLSC network. A corresponding Epsilon method is proposed to solve the multiobjective model. There are several findings derived from the experiments.

- (1) The proposed stochastic MIP model is an effective way of formulating and solving the CLSC network design problem.
- (2) The reliability and precision of the Epsilon method are verified based on the numerical experiments. Conversion efficiency calculation can achieve the trade-off between cost control and CO₂ emission.
- (3) Managers should pay more attention to activities about facilities operation. These nodes might be the main factors in cost and environmental impact changes on the CLSC network.
- (4) Both costs and CO₂ emissions are influenced by return rate, especially costs. Managers should be discreet in coping with cost control, for CO₂ emissions barely affected by return rate.
- (5) It is advisable to convert the double target into a single target by the idea of "Efficiency of CO₂ Emissions Control Reduction." It can provide managers with a way to double-target conversion.

There are some limitations in this study. Because of the limitations of decision variables, the influence of the multiperiod on the CLSC network is neglected. In future study, the decision variables regarding production economies and diseconomies ([Zhen et al., 2017](#)), transportation mode ([Etemadnia et al., 2015](#)), and recovery efficiency ([De Giovanni et al., 2016](#)) can be improved for the practicality of the solution method.

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Corresponding author

Liwen Murong can be contacted at: liwen.murong@gmail.com

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