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A robust multi-objective optimization model for sustainable closed-loop supply chain network design under demand uncertainty

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ABSTRACT. *At this stage, the clothing logistics industry still has some shortcomings in terms of rapid response performance and warehouse integration, and the operation of reverse logistics network planning is also in the primary development stage. Therefore, on the basis of considering the forward garment logistics, the return and replacement process of garments should be taken into account to achieve a win-win situation for economic, environmental and social benefits. In addition, the impact of the existence of uncertain factors on the network planning is considered to establish a scientific and reasonable clothing closed-loop supply chain network system. Based on the distribution characteristics of clothing enterprises and supporting facilities, the location model was proposed to determine the optimal location and quantity of the corresponding facilities. At the same time, taking into account the carbon emissions in the construction, manufacturing and transportation process and the social responsibility of the enterprise, the environmental and social risk assessment targets are added on the basis of maximizing the profit of the enterprise, and a multi-objective planning model of transportation vehicle path optimization is established. According to the characteristics of the model, a two-stage algorithm is designed. The first stage obtains the optimal initial solution through the greedy algorithm, and the second stage solves the bi-level programming model by the particle swarm optimization algorithm. Finally, based on the data of a certain city, the parameter assignment of the model is carried out, and the problem is solved by CPLEX optimization software. The feasibility and correctness of the model and algorithm are verified by several numerical examples and sensitivity analysis of model parameters.*

KEYWORDS: *clothing logistics industry, closed-loop supply chain, sustainable network, robust optimization, hybrid algorithm*

1. Introduction

With the continuous acceleration of the process of globalization and industrialization, environmental pollution, ecological destruction and social problems have received extensive attention from countries all over the world. The 2015 United Nations Development Summit adopted the "the 2030 Agenda for Sustainable Development", which systematically planned 17 global goals for sustainable development by 2030, involving economic development, social progress, and environmental protection [1]. As a labor-intensive network chain structure, the supply chain (SC) is also one of the important sources of energy consumption and environmental pollution. In recent years, the public and the government have attached great importance to the sustainable development of SC companies, requiring companies to reduce environmental pollution in actual production. And assume the corresponding social responsibilities, making the traditional SC management gradually shift to the direction of sustainable SC management.

SC network design is an extremely important strategic decision in SC management. In recent years, academia has combined SC network design with sustainable development strategies in order to achieve a balanced development of economy, environment and society [2]. An important part of any SC is its Reverse Logistics (RL). RL is “the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for recapturing value or proper disposal. Remanufacturing and refurbishing activities also may be included in the definition of RL” [3]. With the progress of society and economic development, clothing has become an indispensable part of people's daily lives. At present, with the rapid development of the internet industry and e-commerce business, more and more consumers are choosing online shopping, which is accompanied by the emergence of large quantities of returns. Therefore, the optimization of the network design and operation of the RL in the apparel industry is essential to improve the competitiveness of enterprises. To address this issue, a part of literature is focused on the configuration of a closed-loop supply chain (CLSC) network design because of the existing legal requirements, environmental protection and related economic benefits.

In the actual CLSC network design, parameters such as customer demand, recycling quantity and quality are difficult to determine, which affects the effectiveness of CLSC decision-making and the reliability of operations. The solution obtained through the uncertain model can more flexibly deal with unexpected and uncertain situations that may occur in practice. The stochastic programing is an efficient tool used for considering the uncertain parameters. However, with the advancement of industrial upgrading and global production, it is difficult to obtain sufficient historical data, and thus it is impossible to construct an accurate parameter distribution function. At the same time, the computational complexity of random programming is relatively high, and it has certain limitations in practical applications. A robust optimization (RO) can be considered as an alternative approach for dealing with the uncertain parameters in the case where there is no enough historical data to estimate the probability distribution of the uncertain parameters.

In summary, the existing literature mainly conducts CLSC network design from the economic and environmental perspectives, and less considers the impact of social factors. At the same time, the existing literature uses stochastic programming to solve the parameter uncertainty in CLSC network design, but this method is relatively insufficient in terms of feasibility and flexibility. Therefore, in order to construct a sustainable CLSC network to solve the recycling of fast fashion clothing, in addition to the economic goal, this research also considers the minimum carbon emissions in the process of logistics facility construction and product processing, and proposes the visual pollution index as a social goal to minimize the impact on regional populations. The RO approach is applied to deal with model parameters' uncertainty.

The paper is organized as follows. In Section 2, the literature in this area of research is reviewed. Section 3 discusses the problem definition, the multi-objective model related to the CLSC in apparel industry is formulated. The solving methodology is presented in Section 4. The performance of the proposed model, which is validated with numerical experimentations, the sensitivity analysis and some managerial implications are provided in Section 5. Finally, concluding remarks are discussed in Section 6.

2. Literature review

In this paper, we attempt to propose a model for a CLSC network design problem, regarding sustainability and uncertainty issues and use a hybrid algorithm to solve the model. Consequently, the focus of the literature survey in this study is subdivided into three sections: sustainability, parameter uncertainty and heuristic algorithms.

The sustainability is an evolving area of research, and the modelling of RL and SC network design with multiple objectives is gaining interest of the researchers. The optimization in cost function of model when coupled with additional goals like environmental, social, enhancing service performance helps to have a more robust and sustainable network design. Perez-Fortes et al. [4] designed a biomass energy system multi-objective mixed integer programming model considering the three main goals of sustainability. Varsei et al. [5] proposed a general model for wine SC network design, and explored the social impact of feasible solutions by introducing social influence coefficients. Chaabane et al. [6] adopted the principle of life cycle assessment (LCA) to integrate the SC in each link, designed a multi-objective mixed integer programming model that considers economic and environmental impacts, and analyzes the impact of different environmental policies on SC strategies. Sahebjamnia et al. [7] studied the tire CLSC network design problem considering sustainable development strategies, and developed a variety of hybrid meta-heuristic algorithms to solve the model.

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All activities in both RL and SC are clearly subject to remarkable uncertainties. To deal with uncertainties, Lee and Dong [8] introduce a two stage stochastic programming to take uncertainty into account in a dynamic reverse logistics. A sample average approximation with a simulated annealing-based heuristic algorithm is adopted to solve the problem. Pishvaee et al. [9] proposed a scenario-based stochastic programming for an integrated forward–reverse logistics network design under demand, quantity and quality return rate and variable cost uncertainty. As it can be seen, stochastic programing is the most widely tool that is used to design a robust supply chain network. However, limited researches employ robust optimization approach to tackle the existing uncertainties in supply chain network design. For example, Hasani et al. [10] used a robust optimization approach to design closed-loop logistics networks.

The CLSC network design problem is an NP-hard problem. With the increase of problem scale and system complexity, traditional accurate algorithms are no longer applicable, and heuristic algorithms are needed to solve them. Kim et al. [11] introduced a route-finding program for vehicles in South Korea transporting electronic material wastes that were at the end of their life cycle. Their aim was to minimize the transportation routes by identifying the four main areas of recycling centers. In order to solve this problem, tabu search algorithm was employed. Diabat et al. [12] designed a multi-step RL network problem in order to determine the quantity and positions of primary facilities, and maximum keeping time for small volumes of returned products. They proposed a model to reduce the total costs in RL network designing problem, including the costs of keeping, preparation, transportation, etc. To solve this problem, they used genetic and artificial immune system algorithms. Soleimani and Govindan (2015) developed a model to improve CLSC network. This model determined the design and planning in location and allocation of the proposed network. Then, they presented a methodology based on particle swarm optimization and a genetic algorithm to solve the model. The results showed that the proposed hybrid algorithm outperforms the single genetic algorithm and single particle swarm optimization.

According to the mentioned literature, limited researches have been done on the sustainability and uncertainty issues to design CLSC networks. This is the first research that considers both sustainability and robustness issues to design a CLSC network for the apparel industry.

3. Problem definition and model formulation

3.1 Problem definition

We consider a single period, single product, multi-echelon CLSC network consisting of raw material supplier, yarn manufacturer, fabric manufacturer, apparel manufacturer and customer. As it can be seen in Fig. 1, the forward SC needs to meet customer demands by manufacturing clothing stepwise. The CLSC also involves collecting end-of-life products from customers, classifying them, and

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providing recovered products to various manufacturers in supply chain. The collected end-of-life products are classified by recovery options, in apparel industry such as repair, remanufacturing and recycling, and then sent to the corresponding apparel manufacturer, fabric manufacturer and yarn manufacturer.

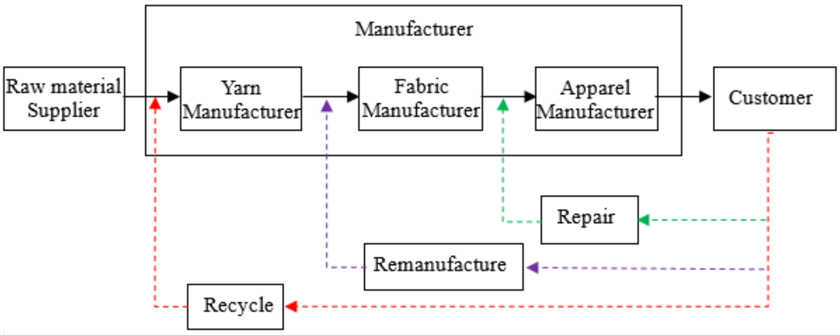

Figure. 1 CLSC network structure in apparel industry.

Among them, recycling can be regarded as a dismantling process, dismantling waste garments of lower value after sorting, and using them as yarn. Restructuring is actually a repair process, which enables waste clothing to be used as a raw material for weaving into the finished product manufacturing. Finally, repairing can be regarded as a repackaging process, allowing the clothing supplier to repack the returned seasonal clothing without quality problems to reduce inventory. By proposing a multi-objective model that considers the uncertainty of customer demands, where seeks to maximize profits, minimize carbon emissions, and maximize social benefits, we can decide on a reasonable number and locations of raw material suppliers and various manufacturers, recycling relationships, and recycling intervals.

3.2 Indices, parameters, and variables of the model

In this section, the problem is formulated by mixed integer programming. The indices, parameters and decision variables used to formulate the problem mathematically are described below.

Indices:

I : index of candidate locations for raw material suppliers $i = 1,...,I$;

J : index of candidate locations for yarn manufacturers $j = 1,...,J$;

K : index of candidate locations for fabric manufacturers $k = 1,...,K$;

L : index of candidate locations for apparel manufacturers $l = 1,...,L$;

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Parameters:

p : price of final products;

ω : regional population;

Pe : unit penalty cost of over-production;

$\widetilde{De}$: customer demands of the final products;

$InvCo$: unit inventory cost;

$ShortCo$: unit shortage cost;

GHG : unit carbon emission amount of per distance transportation;

ε : influence radius of facility location;

α : rate of recyclable materials;

c_1 , c_2 , c_3 : unit handling cost at yarn manufacturers, fabric manufacturers and apparel manufacturers;

c^c : unit transportation cost of the final products;

β_i^s , β_j^1 , β_k^2 , β_l^3 : unit cost of products from raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

α_i^s , α_j^1 , α_k^2 , α_l^3 : fixed cost of opening raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

Q_i^s , Q_j^1 , Q_k^2 , Q_l^3 : supply capacity of raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

D_i , D_j , D_k , D_l : transport distance of raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

w_i , w_j , w_k , w_l : unit carbon emissions amount of handling at raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

W_i , W_j , W_k , W_l : carbon emissions amount of opening raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

φ_i , φ_j , φ_k , φ_l : visual pollution factor of raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

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τ_i , τ_j , τ_k , τ_l : location impact factor of raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

γ_i , γ_j , γ_k , γ_l : recovery amount at raw material supplier i , yarn manufacturer j , fabric manufacturer k and apparel manufacturer l ;

Decision variables:

s_i : order amount from raw material supplier i ;

r_j^1 : order amount from yarn manufacturer j ;

r_k^2 : order amount from fabric manufacturer k ;

r_l^3 : order amount from apparel manufacturer l ;

S_i : a binary variable that equals one if raw material supplier i is opened and zero otherwise;

R_j^1 : a binary variable that equals one if yarn manufacturer j is opened and zero otherwise;

R_k^2 : a binary variable that equals one if fabric manufacturer k is opened and zero otherwise;

R_l^3 : a binary variable that equals one if apparel manufacturer l is opened and zero otherwise;

I_f : shortage amount of products in period f ;

I_0 : inventory amount of products in last period;

3.3 Model formulation

In terms of the above notations, the considered CLSC network design problem can be formulated as follows.

$$\begin{aligned}\max z_1 = &\sum_i (p - c_1 - c_2 - c_3 - \beta_i^s - c^c) s_i + \sum_j (p - c_1 - c_2 - c_3 - \beta_j^1 - c^c) r_j^1 \\ &+ \sum_k (p - c_2 - c_3 - \beta_k^2 - c^c) r_k^2 + \sum_l (p - c_3 - \beta_l^3 - c^c) r_l^3 \\ &- \max\{Pe(I_0 + \sum_i s_i Q_i^s + \sum_j r_j^1 Q_j^1 + \sum_k r_k^2 Q_k^2 + \sum_l r_l^3 Q_l^3 - \tilde{D}e - I_f), 0\} \\ &- InvCoI_0 - ShortCoI_f \\ &- \sum_i \alpha_i^s S_i - \sum_j \alpha_j^1 R_j^1 - \sum_k \alpha_k^2 R_k^2 - \sum_l \alpha_l^3 R_l^3 \end{aligned} \tag{1}$$

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$$\begin{aligned}\min z_2 &= \sum_i s_i (D_i GHG + w_i) + \sum_j r_j^1 (D_j GHG + w_j) \\ &+ \sum_k r_k^2 (D_k GHG + w_k) + \sum_l r_l^3 (D_l GHG + w_l) \\ &+ \sum_i S_i W_i + \sum_j R_j^1 W_j + \sum_k R_k^2 W_k + \sum_l R_l^3 W_l\end{aligned} \tag{2}$$

$$\begin{aligned}\min z_3 = \max\{\omega[\sum_i \frac{\phi^i (\sum_i S_i \gamma_i \tau_i}{(D_i + \varepsilon)^2} + \sum_j \frac{\phi^j (\sum_j S_j \gamma_j \tau_j}{(D_j + \varepsilon)^2} + \\ \sum_k \frac{\phi^k (\sum_k S_k \gamma_k \tau_k}{(D_k + \varepsilon)^2} + \sum_l \frac{\phi^l (\sum_l S_l \gamma_l \tau_l}{(D_l + \varepsilon)^2}]\}\end{aligned} \tag{3}$$

s.t.

$$s_i \leq Q_i^s S_i \ \forall i \tag{4}$$

$$r_j^1 \leq Q_j^1 R_j^1 \ \forall j \tag{5}$$

$$r_k^2 \leq Q_k^2 R_k^2 \ \forall k \tag{6}$$

$$r_l^3 \leq Q_l^3 R_l^3 \ \forall l \tag{7}$$

$$I_0 + \sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 - I_f \geq \tilde{De} \tag{8}$$

$$\sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 \geq \alpha \tilde{De} \tag{9}$$

$$s_i, r_j^1, r_k^2, r_l^3 \geq 0 \ \forall i, j, k, l \tag{10}$$

$$S_i, R_j^1, R_k^2, R_l^3 \in \{0,1\} \ \forall i, j, k, l \tag{11}$$

The objective function (1) maximizes the average profit, including sales profit, facility construction cost, shortage penalty cost and overproduction penalty cost. The environmental objective function (2) minimizes the carbon emissions of the entire CLSC system. The social objective function (3) minimizes the maximum visual pollution index in each region under all scenarios to reduce the impact of the RL network on community life. Constraints (4)-(7) is the constraint on the operation capability of each facility in the network. Constraints (8) is the demand constraint of the end customer, that is, to meet the current demand on the basis of supplementing the shortage of customers in the previous period. Constraints (9) is the constraint on the collection target of the enterprise, where α represents the percentage of recycled materials used by the enterprise. Constraints (10) and Constraints (11) define the domain for decision variables.

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4. Solution approach

4.1 The robust linear programming model with uncertain

This study takes into account the uncertainty of customer demands in the modeling process, assuming that there are several possibilities for customer demands, each possibility is called a scenario, and other parameters are deterministic values. In the absence of historical data, expert evaluation and RO theory are used to solve practical problems. At the same time, fuzzy numbers are used to represent customer demands, which can more truly reflect the uncertainty of customer demands. Since the commercial solver CPLEX cannot directly solve the uncertain model, the demand with box uncertainty is transformed through a robust optimization method:

$$\begin{aligned} &Min \quad z=\sum_j c_j x_j \,, \\ &s.t.: \\ &\sum_j a_{ij} x_j \le \tilde{b}_i \quad \forall i \,, \\ &x_j \ge 0 \quad \forall j \,, \end{aligned} \tag{12}$$

Where $\widetilde{b_i}$ is the right coefficient of the uncertainty, that is, $\widetilde{b_i} \in [\overline{b_{is}} - \widehat{b_{is}}\ , \overline{b_{is}} + \widehat{b_{is}}\ ]$, and $\overline{b_{is}}$ is the nominal value of the box uncertainty set. Converting formula (12), we can get:

$$\sum_j a_{ij} x_j \le \tilde{b}_i = \sum_{s=1}^{\tau_i} \tilde{b}_{is} = \sum_{s=1}^{\tau_i} b_{is} - \beta(\tau_i\ , \Gamma_i) \tag{13}$$

The parameter Γ_i is defined for each constraint, similar to the constraint defined by Bertsimas and Sim. In addition, Γ_i is not necessarily an integer, and can take a value in the interval $[0\ , |J_i|]$ (J_i is the set of uncertain parameters in the i-th constraint). The protection function $\beta(\tau_i\ , \Gamma_i)$ of each constraint i is defined as:

$$\beta(\tau_i\ , \Gamma_i) = \underset{\{S_i \cup t_i | \ S_i \subseteq \tau_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in \tau_i \setminus S_i\}}{Max} \{\sum_{s \in \tau_i} \hat{b}_{is} + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{b}_{it_i} \tag{14}$$

Then formula (13) can be completely transformed as follow:

$$\sum_j a_{ij} x_j \le \sum_{s=1}^{\tau_i} b_{is} - \beta(\tau_i\ , \Gamma_i) \Rightarrow \sum_j a_{ij} x_j + \beta(\tau_i\ , \Gamma_i) \le \sum_{s=1}^{\tau_i} b_{is} = b_i \tag{15}$$

4.2 The ε-constraint method

This model considers the economic, environmental and social objectives at the same time, in order to design a sustainable CLSC system. In the processing of the multi-objective model, we refer to the method used by Mavrotas [8], and employ the ε-constraint method to perform the model conversion. Some of its merits are as follows:

(1) The ε-constraint method alters the original feasible region, thus a different efficient solution can be exploited with a change in ε. As a consequence, with the ε-constraint method we may obtain non-extreme efficient solutions.

(2) The ε-constraint method can produce unsupported efficient solutions in MOMP [40] and has good performance in solving non-convex problems.

(3) An additional advantage of the e-constraint method is that we can control the number of the generated efficient solutions by properly adjusting the number of grid points in each one of the objective function ranges [39].

The following equation shows the reformed model:

$$\begin{aligned} & Min\ z = z_1 \\ & s.t. \\ & z_2 \le f_2^* + k\Delta\varepsilon_2 \\ & z_3 \le f_3^* + k\Delta\varepsilon_3 \end{aligned} \tag{16}$$

$$\sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 \ge \tilde{D}e * \alpha \quad \tilde{D}e \in [(1-\omega)De, (1+\omega)De] \tag{17}$$

$$I_0 + \sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 - I_f \ge \tilde{D}e \quad \tilde{D}e \in [(1-\omega)De, (1+\omega)De] \tag{18}$$

Eq. (4) - (7), (10) and (11)

4.3 Hybrid algorithm design

Due to the large scale of the studied problem, it is difficult to find a satisfactory solution within a limited time just using CPLEX. Therefore, we introduce the Particle Swarm Optimization (PSO) algorithm and Greedy algorithm in the solution process to solve the proposed model. The PSO algorithm is a meta-heuristic algorithm, and it belongs to a category of algorithms used to find the optimal or near-optimal solutions of numerical problems. First, starting from the random solution, the quality of the solution is evaluated according to the fitness, and the optimal solution is found through iteration. The PSO algorithm has attracted the attention of academia due to its advantages such as easy implementation, high accuracy, and fast convergence, and has demonstrated its superiority in solving practical problems. Greedy algorithm is a quick and simple method to solve

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optimization problems. In the process of problem solving, it always makes the most satisfying choice for the current situation.

In this study, the PSO algorithm is used to obtain the best location plan for each facility in the network, and then the Greedy algorithm is used to quickly obtain the best recovery area division plan under the determined location plan. By combining these two algorithms, the complete optimal solution can be quickly obtained. The specific algorithm process is as follows:

(1) initialize particle swarm, including swarm size N , position x_i and velocity v_i of each particle.

(2) calculate the fitness value $F_{it}[i]$ of each particle, which is the value of the objective function. Generally, the choice of objective function is determined by specific issues.

(3) for each particle, compare its fitness value $F_{it}[i]$ with the individual optimal $p_{best}(i)$. If $F_{it}[i] > p_{best}(i)$, replace $p_{best}(i)$ with $F_{it}[i]$.

(4) for each particle, compare its fitness value $F_{it}[i]$ with the global optimal g_{best} . If $F_{it}[i] > g_{best}$, replace g_{best} with $F_{it}[i]$.

(5) the formula for updating the velocity v_i and position x_i of the particle is as follows:

$$v_{id} = wv_{id} + c_1 r_1 \left(p_{best}(id) - x_{id} \right) + c_2 r_2 \left(g_{best}(d) - x_{id} \right)$$

$$x_{id} = x_{id} + v_{id}$$

w is the weight of inertia, which shows the tendency of particle to remain in its previous exploration direction. c_1 and c_2 are cognitive and social factors, respectively; r_1 and $r_2 \in [0,1]$ are random numbers, and d shows the number of iterations.

(6) if the termination condition is met (the error value is small enough or the maximum iterative number is reached), then exit; otherwise return to step (2).

For this model, the decoded information of the each particle obtains the location plan S_i, R_j^1, R_k^2, R_l^3 and the corresponding transportation quantity s_i, r_j^1, r_k^2, r_l^3 , and uses formula (16) to calculate the profit under the current plan. Greedy algorithm is to always choose the most profitable flow plan under the determined location plan. In order to make the solution meet the maximum capacity constraints of facilities, that is formulas (4)-(7), we introduce two larger parameters *ShortCo* and *InvCo* as the stock-out penalty factor and over-production penalty factor. The calculation formula of penalty costs C_{p1} and C_{p2} are as follows:

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$$C_{p1} = ShortCo * \sum_i \sum_j \sum_k \sum_l f_p * \left| \min\{\tilde{De} - \sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3, 0\} \right| \tag{19}$$

$$C_{p2} = * \sum_i \sum_j \sum_k \sum_l f_p * \max\{\sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 - \tilde{De}, 0\} \tag{20}$$

$$f_p(\sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3, \tilde{De}) = \begin{cases} C_{p1} & \sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 \geq \tilde{De} \\ C_{p2} & \sum_i s_i + \sum_j r_j^1 + \sum_k r_k^2 + \sum_l r_l^3 \leq \tilde{De} \end{cases} \tag{21}$$

5. Implementation and evaluation

5.1 Instances

This section mainly verifies the performance of the proposed model through numerical experiments. The detailed data used in this study are shown in Table 1 - 5. Since the objective of this model is to maximize profit, the penalty cost of over-production is needed to limit production. At the same time, an inventory target similar to safety stock is introduced, that is, if the customer's demand is not met, it will incur stock-out penalty costs.

Table 1 Manufacturer-related parameters.

parameters	c_1	c_2	c_3	c^c	p	α
value	40	80	150	50	700	0.3
parameters	Pe	$InvCo$	$Invtarloss$	$DisCo$	$ShortCo$	De
value	750	200	300	400	140	800

Table 2 Parameters related to raw material suppliers.

raw material suppliers i	α_i^s	β_i^s	Q_i^s
1	1000	2000	200
2	1000	1900	200
3	1000	1800	200

Table 3 Parameters related to the yarn manufacturers.

yarn manufacturers j	α_j^1	β_j^1	Q_j^1
1	1000	1500	100
2	1000	1200	100
3	1000	1000	100

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Table 4 Parameters related to the fabric manufacturers.

fabric manufacturers k	α_k^2	β_k^2	Q_k^2
1	1500	4500	55
2	1500	4000	55
3	1500	3500	55

Table 5 Parameters related to the apparel manufacturers.

apparel manufacturers l	α_l^3	β_l^3	Q_l^3
1	3000	12000	25
2	3000	11000	25
3	3000	10000	25

5.2 Results and implications

In this section, we assess the effectiveness of the proposed decision model and the efficiency of our hybrid algorithms through experimenting with the instances obtained above. We have coded the mathematical modeling and algorithm in C#. All experiments were done on a PC with 5 cores of CPUs, 2.3 GHz processing speed and 8 GB of memory, and running under the Visual Studio 2015 and CPLEX library version 12.5.1.

First, in order to explore the relationship between economic, environmental and social goals, this study adopts the ε-constraint method to study the relationship between different objectives. It can be seen from Fig. 2 that as carbon emissions decrease, the average profit increases, and vice versa. In other words, there is a negative correlation between profit and the carbon emission objective function. On the other hand, the visual pollution index increases as the average profit increases, which means that there is a positive correlation between the profit and the visual pollution objective function. Therefore, it can be concluded that an increase in carbon emissions also corresponds to a decrease in visual pollution, and vice versa. Therefore, in order to reduce visual pollution, it is necessary to build returned clothing processing and recycling facilities far away from densely populated areas, but the vehicle transportation distance is longer, resulting in higher total costs and higher carbon emissions. This conflict between goals highlights the important role of multi-objective optimization, which allows decision makers to trade-off between economic, environmental, and social goals and manage the system according to specific conditions.

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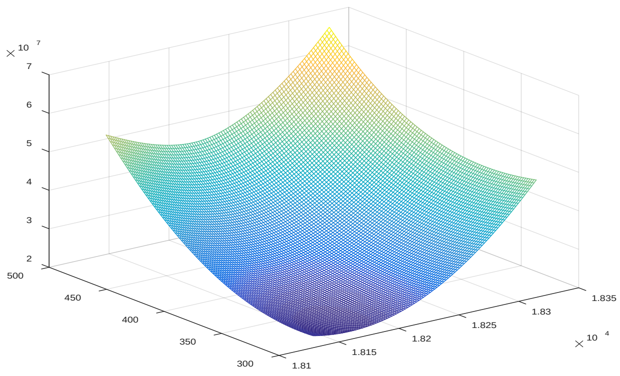

Figure. 2 Pareto solution set of economic, environmental and social objectives

As mentioned before, the uncertain customer demand of the proposed model can be solved with robust optimization modeling to enhance the network design and management of reverse logistics. The effect of uncertainty is studied by changing the parameter of Γ_i.We can easily compute the compatibility index and the degree of balance of each solution. The values of the economic, environmental and social objective functions are shown in Table 6.

Table 6 Objectives result of uncertain customer demand-Robust model.

Γ_i	economic objective function value (z_1)	Environmental objective function value (z_2)	social objective function value (z_3)
Γ_i=0.0	964900.2064	420432.260	2363592.545
Γ_i=0.2	948448.5098	424615.110	2363638.448
Γ_i=0.4	932152.7316	427754.345	2363727.701
Γ_i=0.6	893925.7166	551618.887	4283687.508
Γ_i=0.8	877341.6666	555118.965	4283745.670
Γ_i=1.0	861036.9841	559799.501	4283838.076

The results of applying the CLSC network that the three objectives function value deteriorate when the protective parameter of Γ_i increases. As shown in Fig. 3, the average profit decrease and the carbon emissions increase dramatically with capacity increases up to $\Gamma_i = 0.6$, above which it does not change significantly. This change trend is particularly evident in the visual pollution index as shown in Fig. 4. This may be because more facilities are opened under this level of uncertainty, some of which are difficult to avoid crowded areas, leading to a sharp increase in the visual pollution index, and also a certain increase in total costs and carbon emissions.

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The main advantage of the proposed Robust model is that it can minimize the impact of uncertainty, thereby ensuring the flexibility and quality of the solution.

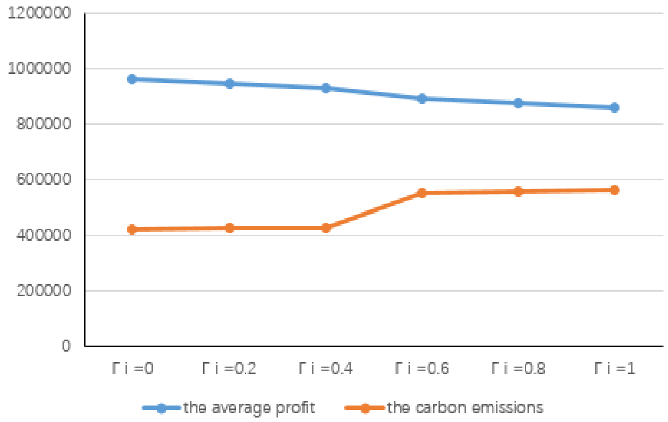

Figure. 3 Economic and environmental objectives of uncertain customer demand-Robust model.

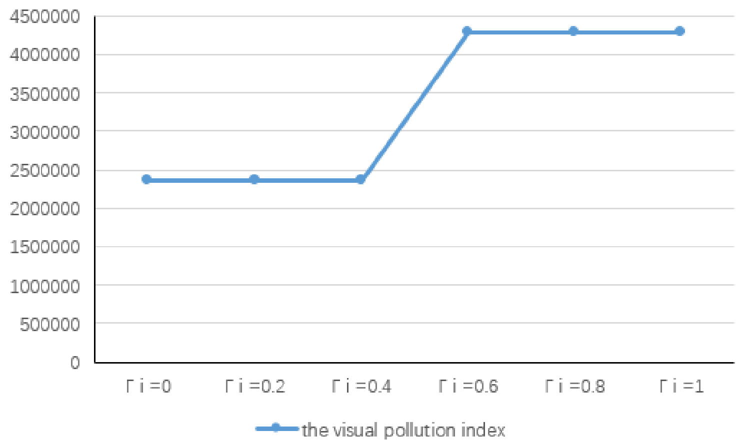

Figure. 4 Social objective of uncertain customer demand-Robust model.

To sum up, in order to design and manage a sound and flexible CLSC system for the apparel industry, we must pay attention to reducing the negative impact on the environment and society while focusing on profits. In other words, in order to achieve sustainability, companies have to increase a certain cost to open facilities in remote places far away from the crowd, which can avoid disturbing residents' lives. Regarding the uncertainty in CLSC, it is recommended to open more facilities to flexibly respond to changing customer demands, although this is accompanied by more facility opening costs.

6. Conclusions

Based on the actual situation, this study took into account the uncertainty of customer demands, and aimed at maximizing economic profits, minimizing negative environmental benefits, and minimizing social impact. A dynamic decision-making model for the apparel industry CLSC was proposed, which can dynamically determine the location of various facilities and flow distribution plan during the planning period. We used the ε-constraint method to solve the trade-off problem between the goals in the multi-objective programming model, and applied RO to deal with the uncertain customer demand in the model, and finally obtain an environmentally and socially friendly and flexible solution. The effectiveness of the proposed model and hybrid algorithm is verified by numerical examples. The numerical examples will help to identify the trade-offs between the three objectives and obtain a compromise solution. When economic objective is maximized and environmental objective is minimized, terrible solutions are obtained in terms of social impact. On the contrary, when the social goal is minimized, a solution is obtained that opens up facilities farther away from the crowd and minimizes the impact on residents' lives. However, the solution causes a significant increase in costs and carbon emissions due to longer transportation distances. In addition, through the sensitivity analysis of the uncertainty level, we gave some management suggestions to enhance the flexibility of CLSC.

As future research and also the limitation of this paper, more factors related to environmental and social benefits can be considered, such as the impact of noise on the environment, the impact of increased job opportunities on social benefits, etc. Moreover, the application of the proposed model and solution procedures in other recyclable products can be an interesting research topic. In addition, more uncertain factors can be considered, such as recovery rate, recovery quality and unit cost, etc.

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