A Fuzzy Robust Programming Model for Sustainable Closed-Loop Supply Chain Network Design with Efficiency-Oriented Multi-Objective Optimization

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Abstract: Sustainable closed-loop supply chain (SCLSC) network design and decision-making is a critical problem for enterprises and organizations' operations because of its excellent economic, environmental, and social performance. This article proposes a multi-objective mixed-integer programming model with targets for minimum total cost, reduction in environmental damage, and maximum social responsibility. In order to deal with the uncertainty caused by the dynamic business environment, a fuzzy robust programming (FRP) approach is applied. Furthermore, an efficiency-oriented optimization methodology, hybridizing meta-heuristics and efficiency evaluation, is proposed to solve the developed multi-objective model and functions as auxiliary decision-making. Data envelopment analysis is applied to evaluate the sustainability performance of feasible solutions and calculate their efficiency. The efficiency can comprehensively reflect the sustainability performance and guide the evolution process of meta-heuristic algorithms. A numerical case validates the proposed FRP model and efficiency-oriented optimization methodology. The results demonstrate that with the proposed methodology, decision-makers not only can obtain a set of efficient schemes but also can determine the optimal scheme with the best sustainability performance.

Keywords: sustainable supply chain; closed-loop supply chain; fuzzy robust programming; meta-heuristic; data envelopment analysis

1. Introduction

With the increasing awareness of environmental problems, social responsibility, and the competitive market environment, organizations and enterprises focus on taking the sustainability paradigm into supply chain network design [1,2]. The connotation of sustainable development is very extensive. As illustrated in the published report The 2030 Agenda for Sustainable Development by the World Commission on Environment and Development (WCED), energy crisis, employment difficulties, and resource shortage are matters of significant importance in sustainable development. The tendency to design a sustainable supply chain (SSC) network has several motivations including: (1) achieving competitive advantages, following the tide of globalization and maintaining customer loyalty [3]; (2) promoting the conservation and sustainable use of energy and other resources [4]. In the scope of SSC network design, the sustainability paradigm can be considered an integrated paradigm including economic, environmental, and social dimensions [5,6]. Sustainability design in the supply chain contains the concepts of green development and social responsibility, which requires supply chain managers to systematically take environmental and social objectives as strategic considerations [7,8]. Based on the sustainability concept, the SSC network design in this article comprehensively considers an increase in economic benefit and a reduction in environmental damage and social responsibility. The closed-loop supply chain (CLSC) design has drawn more and more attention in dealing with environmental damage and resource shortage [9,10]. The government has published some regulations which require the original equipment manufacturers to recycle, collect,
and reuse end-of-life (EOL) products [11]. Furthermore, the recycling and reuse of EOL products have significant economic potential for enterprise performance [12,13]. This article considers the recycling and remanufacturing of EOL products in configuring the sustainable closed-loop supply chain (SCLSC) network.

The SCLSC network is configured by integrating forwarding supply chain and reverse logistics in which economic, environmental, and social issues are considered simultaneously. The forwarding supply chain is responsible for meeting the product demand of the customer market and component demand for repairing recycled EOL products [14]. Reverse logistics control the recycling, collection, sorting, repair, and other issues for dealing with EOL products from the customer market [15,16]. Designing an efficient SCLSC network can significantly improve sustainability performance by using efficient transportation systems and applying recycled components for remanufacturing products [17,18]. Furthermore, the tendency to configure SCLSC is to enhance customer loyalty and achieve an excellent enterprise image [1,19]. When integrating economic, environmental, and social paradigms in the supply chain network, supply chain management is converted to the SCLSC management.

Another critical issue is the uncertainty in the operation of SCLSC network. The dynamic business environment and complex network construct cause high uncertainty and significantly influence the performance of the supply chain [20]. Decision-making in a dynamic and uncertain environment is difficult. If the uncertainty and dynamics are ignored at the strategic and operational levels, unreliable decisions could cause huge damage to the supply chain system [21,22]. Designing a reliable SCLSC network that can continuously function under uncertain business environments and parameter perturbation is necessary [23]. The uncertainty caused by the business-as-usual operation environment mainly functions in the product market, production activities, and transportation activities [24,25]. Customer demand, transportation cost, and facility capacity are some typical examples influenced by uncertainty in the supply chain network [1,26]. An efficient and reliable technique to cope with uncertainty is critical and essential for outputting reliable solutions and improving the supply chain performance. Most of the studies have focused on the appropriate methods to control the ambiguity and uncertainty of parameters. Stochastic programming can efficiently deal with uncertain parameters whose probability distribution can be precisely estimated according to the historic data [27,28]. Possibility programming can efficiently cope with the parameters with epistemic uncertainty [29]. If there is a lack of historic data for estimating the distribution of parameters, fuzzy programming can estimate the possible distribution of uncertain parameters according to the knowledge and experience of decision-makers or experts. In the SCLSC network, the measurement of social factors is an uncertain factor. It is difficult to obtain sufficient and effective data for modeling the lost work. Hence, fuzzy sets are essential for modeling uncertain parameters lacking sufficient data. Furthermore, robust programming is an effective method to obtain risk-aversion solutions [6,30,31]. This method can adjust the risk-aversion level and the conservation level of output decisions. Considering the complexity and diversity of uncertainty in the SCLSC network, researchers have attempted to combine multiple uncertainty techniques to obtain more efficient models. In this article, a fuzzy robust programming (FRP) approach is applied to cope with the uncertainty in demand and transportation activities.

In general, this article proposes a generic framework for designing an SCLSC network considering economic, environmental, and social paradigms under high uncertainty. The strategic and operational decisions are considered. The strategic decision includes raw material, supplier selection, and facility location, while the operational decision includes the number of component flows and product flows between nodes at all levels of the SCLSC network. To achieve this goal, a multi-objective mixed-integer programming model is developed, which aims to minimize the total cost, reduce environmental damage, and reduce the negative influence on social responsibility.

The decision-making of the SCLSC network design is another important aspect. The main purpose of decision-making is to select the optimal solution by evaluating the per-
formance of feasible solutions obtained by solving the multi-objective model. The critical issues of performance evaluation are to select appropriate indicators and efficient evaluation methods. The indicators should comprehensively reflect the economic, environmental, and social paradigms and could be measured quantitatively. The evaluation approach should be able to quantitatively calculate and describe the sustainability performance of feasible solutions so that the optimal solution can be selected according to performance sorting. Multi-criteria decision-making (MCDM) is widely used in the comprehensive evaluation of sustainable performance. Şenel et al. apply the concept of octahedron sets to multi-criteria decision-making problems and validate the improved MCDM method [32]. The data envelopment analysis (DEA) method, as a quantitative multi-criteria decision method, is widely applied in evaluating sustainability performance [33–35]. Hence, an efficiency-oriented optimization methodology is proposed to solve the multi-objective model and select the optimal solution. In this methodology, multi-objective optimization and performance evaluation are performed in parallel. Meta-heuristic algorithms are utilized to obtain feasible solutions and output them as the decision-making units (DMU) of performance evaluation. The DEA method evaluates DMUs, calculates their efficiency, and selects the optimal solution according to their efficiency sorting.

In general, this study provides a framework for designing a sustainable closed-loop supply chain network under uncertainty, which minimizes net cost and pollution emission and maximizes social performance. The research problem considers both strategic decisions and planning decisions. Strategic decisions involve supplier selection and location of facilities. Planning decisions conclude the quantity of raw material that should be bought from each supplier and the amount of product that exists in each part of the network. Furthermore, for coping with uncertain parameters, we adopt the fuzzy robust programming approach to derive a crisp equivalent model of a certain type. Finally, we propose an efficiency-sorting-based multi-objective optimization algorithm. In this algorithm, the optimization process and the evaluation process are performed in parallel. The individual with the best sustainability performance obtained by the evaluation process can guide the next iteration of the optimization process.

The following research is organized as follows. Section 2 reviews the corresponding literature. The proposed multi-objective mixed-integer programming model and the fuzzy robust counterpart form are developed in Section 3. Section 4 presents the multi-objective intelligent optimization algorithm as the solution method. Section 5 provides a numerical case and corresponding results analyses. Conclusions are represented in Section 6.

2. Literature Review

Due to the importance of excellent designing of sustainable closed-loop supply chain networks, many papers are conducted in this area and the research on the uncertainty of the supply chain has become deeper. This section is dedicated to conducting a review of papers involving SCLSC network design with uncertainty. Multi-objective optimization has been an efficient method for solving the problem of supply chain network design in the case of seeking multi-objective performance. Wang et al. considered economic performance and environmental influence in designing a green supply chain network. The multi-objective model is solved by the normalized normal constraint approach [18].

On the other hand, uncertainty is another important aspect of the supply chain network. Govindan et al. reviewed the studies relating to supply chain network design under uncertainty [36]. They pointed out that designing a reliable supply chain network can efficiently deal with high uncertainty. Pishvaee et al. developed a robust optimization model for coping with a closed-loop supply chain including customers in the first and second markets [37]. Recently, most of the research takes into consideration multi-objective optimization and uncertainty optimization. Talaei et al. firstly proposed fuzzy robust optimization approach for dealing with uncertain cost and demand rates in a carbon-efficient green closed-loop supply chain network [21]. The fuzzy robust model can obtain the optimal solutions which incur a cost increase named “robustness price” compared with
the determined model. On the basis of the fuzzy robust optimization method, Nayeri et al. solved a multi-objective FRO model for designing a sustainable closed-loop tire supply chain network by the goal programming approach [38]. Soleimani et al. proposed a fuzzy multi-objective model for designing a sustainable green supply chain with social consideration [39]. The mathematical model was solved by the \( \varepsilon \)-constraint method and genetic algorithm. Safaei et al. adopted robust optimization for coping with uncertain scenarios in the cardboard closed-loop supply chain [40]. Setiawan et al. optimized a multi-objective mask closed-loop supply chain considering environmental impact [41]. The objective functions were defined by the fuzzy membership degree function and converted into a single-objective model by \( \varepsilon \)-constraint. Ghahremani-Nahr et al. applied robust fuzzy programming to address the effect of uncertainty in the closed-loop supply chain [42]. The multi-objective whale optimization algorithm is applied for solving the developed equivalent model. Zhang et al. developed a multi-objective robust fuzzy optimization model for coping with the inherent uncertainty in the closed-loop supply chain [5]. The uncertainty was divided into two categories: one was uncertainty parameters solved by fuzzy membership theory and the other was managed with the robust optimization method. Pourmehdi et al. adopted a scenario-based stochastic programming method for dealing with the uncertainty in the steel sustainable closed-loop supply chain [43]. The preemptive fuzzy goal programming, as a particle multi-objective method, was utilized to solve the mathematical model. Yu et al. designed and optimized a multi-objective hazardous waste network [44]. Stochastic programming was used to define uncertain parameters and a sample average approximation-based goal programming method was applied for solving the model. Goodarzian et al. developed a multi-objective fuzzy robust optimization model for designing a pharmaceutical supply chain network [26]. They applied several metaheuristic algorithms named MOSEO, MOSAM, MOKA, and MOFFA, for obtaining the optimal solution. Isaloo et al. developed a scenario-based multi-objective model with the targets of minimum cost and pollution emission for configuring the plastic injection supply chain network [45]. Fathollahi-Fard et al. proposed a multi-objective two-stage stochastic programming model for maximizing economic and social performance [46].

Furthermore, there are many uncertain factors in the sustainable closed-loop supply chain network, such as the quantification of social impact. Many studies focus on modeling these factors. Soleimani et al. adopted a fuzzy set to model the lost working days due to work damages for described social factors [39]. Lee et al. extended fuzzy sets and proposed Cubic sets [47]. Ma et al. adopted interval uncertainty sets, including box sets and polyhedron sets, to model uncertainty parameters in the shared cycle recycling supply chain [6].

Their results demonstrated that the proposed hybrid meta-heuristic algorithms had better solution efficiency than current methods.

From the aforementioned review:

- Most recent researches pay attention to multi-objective optimization for seeking an excellent trade-off between economic and environmental performance. Few take into consideration social performance.
- For different kinds of uncertainty in the supply chain network, there are targeted uncertainty technologies for coping with them.
- For solving the multi-objective mathematical model, firstly, some studies convert the multi-objective optimization problem into a single-objective problem by \( \varepsilon \)-constraint and other methods. Secondly, some exact solution methods are applied, such as goal programming. Thirdly, metaheuristic approaches are utilized which adopt the concept of the Pareto optimal solution. However, when solving multi-objective SCLSC network optimization problems, metaheuristic algorithms are rarely applied.
3. Model Formulation

3.1. Problem Description

This article configures the SCLSC network integrating forwarding supply chain and reverse logistics. In the forward supply chain, raw materials are delivered to manufacturing centers and the new products are accessed by customer markets through distribution centers which satisfy customer demands. In the reverse logistic, the EOL products are recycled, collected, tested, repaired, and dismantled. As shown in Figure 1, the proposed SCLSC network consists of a forwarding supply chain and reverse logistics, which is related to raw material suppliers, production centers, distribution centers, repair centers, recycling centers, and disposal centers. In recycling centers, the recycled EOL products are tested and the materials are dismantled. The obtained materials are divided into repairable products and irreparable products in recycling centers. Then, repairable materials are transited to repair centers and the materials needed to repair EOL products are relocated from raw material suppliers to repair centers. The repaired product has the same performance and quality as the new product. Furthermore, the irreparable materials are transported to the disposal center to be scrapped harmlessly.

![Figure 1. The generic network of sustainable closed-loop supply chain.](image)

Environmental pollution will happen in the process of transportation and operation involving production centers, repair centers, recycling centers, and disposal centers. In the real world, production, repair, recycling, disposal, and transportation activity lead to carbon emissions or solid waste emissions.

3.2. Social Factor Modeling

In this article, lost working days due to occupational accidents are adopted to evaluate social performance. This evaluation indicator is related to the facilities opening involving production centers, repair centers, and recycling centers. However, in the real world, prior information about lost working days is difficult to obtain due to different production technologies, staff equality, and so on. Hence, fuzzy programming is utilized to measure lost working days.

Figure 2 shows the fuzzy membership level of lost working days due to work damage. In Figure 2, LDideal represents the ideal number of lost working days, and LDmax is the maximum number. Then, the membership degree functions of lost working days involving the aforementioned facilities are calculated as Formula (1).

$$U_e = \begin{cases} \frac{G_{e}^{\max} - \sum_{e} G_{e} Y_{e}}{G_{e}^{\max}} & 0 \leq \sum_{e} G_{e} Y_{e} \leq G_{e}^{\max} \\ 0 & G_{e}^{\max} \leq \sum_{e} G_{e} Y_{e} \end{cases}, \quad e \in \{j, r, b\}$$ (1)
where $G_{m}^{\text{max}}$ represents the maximum mean of lost working days of production centers, repair centers, and recycle centers. $G_{e}$ indicates the number of lost working days of the abovementioned three facilities.

![Diagram](image)

**Figure 2.** Fuzzy membership function of lost working days.

### 3.3. Notations

Firstly, we present the indices, parameters, and decision variables involved to form the mathematical model.

#### Indexes
- $i$: Index of raw material suppliers, $i = 1, \ldots, I$
- $j$: Index of production centers, $j = 1, \ldots, J$
- $k$: Index of distribution centers, $k = 1, \ldots, K$
- $b$: Index of recycling centers, $b = 1, \ldots, B$
- $d$: Index of disposal centers, $d = 1, \ldots, D$
- $c$: Index of customers, $c = 1, \ldots, C$
- $m$: Index of products, $m = 1, \ldots, M$
- $n$: Index of raw materials, $n = 1, \ldots, N$

#### Parameters
- $\bar{DE}_{cm}$: Demands of customer $c$ for product $m$
- $\bar{RE}_{cm}$: Recycle quantity of customer $c$ for product $m$
- $\bar{DE}_{rm}$: Demands of repair center $r$ for raw material $n$
- $\bar{TC}_{ij}$: Transport cost of raw material per kg from raw material supplier $i$ to production center $j$
- $\bar{TC}_{jk}$: Transport cost of product per kg from production center $j$ to distribution center $k$
- $\bar{TC}_{kc}$: Transport cost of product per kg from distribution center $k$ to customer $c$
- $\bar{TC}_{ir}$: Transport cost of raw material per kg from raw material supplier $i$ to repair center $r$
- $\bar{TC}_{ic}$: Transport cost of product per kg from customer $c$ to recycling center $b$
- $\bar{TC}_{br}$: Transport cost of product per kg from recycling center $b$ to repair center $r$
- $\bar{TC}_{rk}$: Transport cost of product per kg from repair center $r$ to distribution center $k$
- $\bar{TC}_{bd}$: Transport cost of raw material per kg from recycling center $b$ to disposal center $d$
- $MC_{m}^{n}$: Manufacturing cost of producing unit new product $m$ in production center $j$
- $MC_{m}^{i}$: Repair cost of producing unit repaired product $m$ in production center $r$
- $IC_{i}^{r}$: Testing cost of testing unit material $n$ in recycling center $b$
- $AC_{b}^{i}$: Disassembly cost of disassembling unit recycled product $m$ in recycling center $b$
\( DC_d \) Disposal cost of disposing unit component \( n \) in disposal center \( d \)

\( PR_i \) Purchasing cost of unit component \( n \) from component supplier \( i \)

\( OC_j \) Opening cost of production center \( j \)

\( OC_k \) Opening cost of distribution center \( k \)

\( OC_r \) Opening cost of repair center \( r \)

\( OC_b \) Opening cost of recycling center \( b \)

\( OC_d \) Opening cost of disposal center \( d \)

\( Cap_i^n \) Capacity of raw material supplier \( i \) for material \( n \)

\( Cap_j^n \) Capacity of production center \( j \) for material \( n \)

\( Cap_k^n \) Capacity of distribution center \( k \) for material \( n \)

\( Cap_r^n \) Capacity of repair center \( r \) for material \( n \)

\( Cap_b^n \) Capacity of recycling center \( b \) for material \( n \)

\( Cap_m^n \) Capacity of production center \( j \) for product \( m \)

\( Cap_m^k \) Capacity of distribution center \( k \) for product \( m \)

\( Cap_m^r \) Capacity of repair center \( r \) for product \( m \)

\( Cap_m^b \) Capacity of recycling center \( b \) for product \( m \)

\( HE_j^m \) Solid waste emission of producing unit product \( m \) in production center \( j \)

\( HE_r^m \) Solid waste emission of repairing unit product \( m \) in repair center \( r \)

\( HE_b^m \) Solid waste emission of dismantling unit product \( m \) in recycling center

\( HE_d^n \) Solid waste emission of disposing unit material \( n \) in disposal center \( d \)

\( CE_{ij} \) Carbon emission of component per kg from raw material supplier \( i \) to production center \( j \)

\( CE_{jk} \) Carbon emission of component per kg from production center \( j \) to distribution center \( k \)

\( CE_{kc} \) Carbon emission of component per kg from distribution center \( k \) to customer \( c \)

\( CE_{ir} \) Carbon emission of component per kg from raw material supplier \( i \) to repair center \( r \)

\( CE_{cb} \) Carbon emission of component per kg from customer \( c \) to recycling center \( b \)

\( CE_{br} \) Carbon emission of component per kg from recycling center \( b \) to repair center \( r \)

\( CE_{rk} \) Carbon emission of component per kg from repair center \( r \) to distribution center \( k \)

\( CE_{bd} \) Carbon emission of component per kg from recycling center \( b \) to disposal center \( d \)

\( G_j \) Numbers of lost working days caused by work damages during the opening of distribution center \( j \)

\( G_r \) Numbers of lost working days caused by work damages during the opening of repair center \( r \)

\( G_b \) Numbers of lost working days caused by work damages during the opening of recycling center \( b \)

\( G_{ij}^{\text{max}} \) Maximum averages of lost working days caused by work damages during the opening of distribution center \( j \)

\( G_{jr}^{\text{max}} \) Maximum averages of lost working days caused by work damages during the opening of repair center \( r \)

\( G_{rb}^{\text{max}} \) Maximum averages of lost working days caused by work damages during the opening of recycling center \( b \)

\( W_m \) Weight of product \( m \)

\( W_n \) Weight of component \( n \)

\( \sigma_{mn} \) Utilization ratio of \( n \)th component per unit of product \( m \)

\( \theta_d^n \) Average disposal fraction of disposal center

\( PrJ_m \) Price of new product produced by production centers

\( PrR_m \) Price of repaired product produced by repair centers
3.4. Objective Functions

3.4.1. The First Objective Function: Economic Factor

The first objective function seeks to minimize the total net cost, which indicates the economic aspect of the SRCLSC network. The net cost consists of transportation costs between facilities, facility opening costs, procurement costs of components, production cost, repair cost, testing cost, disassembly cost, disposing cost, and revenue.

\[
\text{Min } Z_1 = \sum_{i,j} \left( P_{ij} \cdot X_{ij} \right) + \sum_{j} \left( C_{ij} \cdot Y_{ij} \right) + \sum_{k} \left( C_{ik} \cdot Y_{ik} \right) + \sum_{d} \left( D_{id} \cdot Y_{id} \right) \\
+ \sum_{j,m} \left( C_{jm} \cdot X_{jm} \right) + \sum_{k,m} \left( C_{km} \cdot X_{km} \right) + \sum_{d,k} \left( C_{dk} \cdot X_{dk} \right) \\
+ \sum_{j,m} \left( A_{jm} \cdot X_{jm} \right) + \sum_{b,m} \left( A_{bm} \cdot X_{bm} \right) + \sum_{b,d} \left( A_{bd} \cdot X_{bd} \right) \\
+ \sum_{i,n} \left( W_{in} \cdot \bar{T}_{ci} \cdot X_{in} \right) + \sum_{j,k,m} \left( W_{jk} \cdot \bar{T}_{cj} \cdot X_{jk} \right) + \sum_{k,c,m} \left( W_{km} \cdot \bar{T}_{ck} \cdot X_{km} \right) \\
+ \sum_{c,b,m} \left( W_{cm} \cdot \bar{T}_{bc} \cdot X_{cm} \right) + \sum_{b,r,n} \left( W_{br} \cdot \bar{T}_{cr} \cdot X_{br} \right) + \sum_{r,k,m} \left( W_{rk} \cdot \bar{T}_{rk} \cdot X_{rk} \right) \\
+ \sum_{i,r,n} \left( W_{in} \cdot \bar{T}_{ci} \cdot X_{in} \right) + \sum_{b,d,n} \left( W_{bd} \cdot \bar{T}_{bd} \cdot X_{bd} \right) - \sum_{j,k,m} \left( P_{jk} \cdot X_{jk} \right) - \sum_{r,k,m} \left( P_{rk} \cdot X_{rk} \right)
\]  

(2)

3.4.2. The Second Objective Function: Environmental Factor

The second objective function seeks to minimize pollution emissions for maximizing environmental performance. Two aspects make up the environment: carbon emission and solid waste emission. The former is produced by vehicle emission during transportation
between facilities. The latter is produced during the operation of the facilities, involving the process of production, repair, disassembly, testing, and disposal.

\[
\begin{align*}
\text{Min } Z_2 & = \sum_{i,m} HE_{ij} \sum_k X_{jk}^m + \sum_{r,m} HE_{ir} \sum_k X_{rk}^m + \sum_{b,m} HE_{ib} \sum_c X_{cb}^m \\
& + \sum_{b,n} HE_{bn} \left( \sum_r X_{br}^n + \sum_d X_{bd}^n \right) + \sum_{d,n} HE_{dn} \sum_p X_{pd}^n \\
& + \sum_{c,b} CE_{cb} \sum_{m} W_{cm} \cdot X_{cb}^m + \sum_{r,b} CE_{rb} \sum_{m} W_{mr} \cdot X_{rb}^m + \sum_{i,r} CE_{ir} \sum_{n} W_{in} \cdot X_{ir}^n \\
& + \sum_{b,r} CE_{br} \sum_{n} W_{bn} \cdot X_{br}^n + \sum_{b,d} CE_{bd} \sum_{n} X_{bd}^n \\
\end{align*}
\]

(3)

3.4.3. The Third Objective Function: Social Factor

The third objective function seeks to minimize the lost working days due to work damage by maximizing the membership degree of all corresponding facilities, which represents the social aspect.

\[
\begin{align*}
\text{Max } Z_3 & = \sum_j U_j + \sum_r U_r + \sum_b U_b
\end{align*}
\]

(4)

3.5. Objective Functions

3.5.1. Flow Balance Constraints

Constraint (9) guarantees that the number of raw materials should be transited from raw materials suppliers and that all of the raw materials are used to produce new products. Relation (10) ensures the quality of the inflow and outflow of new products for each distribution center. Equations (11) and (12) confirm the recycled products from customers to recycling centers are dismantled into various raw materials, which are transported to repair centers and disposal centers. Constraint (13) shows that the repair centers make all the raw materials for the new products from raw materials suppliers and recycling centers.

\[
\begin{align*}
\sum_{i} x_{ij}^n & = \sum_k \sigma_{mn} \cdot x_{jk}^m \forall j, n, m \\
\sum_k x_{kc}^m & = \sum_j x_{jk}^m + \sum_r x_{rk}^m \forall k, m \\
\sum_k \sigma_{mn} \cdot x_{rk}^m & = \sum_i x_{ir}^n + \sum_b x_{br}^n \forall r, n, m \\
\theta_n \sum_{c,b} \sigma_{mn} \cdot x_{cb}^m & = \sum_{b,d} x_{bd}^n \forall b, n, m \\
(1 - \theta_n) \sum_{c,b} \sigma_{mn} \cdot x_{cb}^m & = \sum_{b,r} x_{br}^n \forall b, n, m \\
\end{align*}
\]

(5) (6) (7) (8) (9)

3.5.2. Demand and Recycling Constraints

Equation (5) calculates the number of new products transported from distribution centers to customers and ensures that the demand for new products in customers is satisfied. Equation (6) calculates the number of recycled EOL products transited from customers to recycling centers. Expression (7) calculates the number of raw materials sent to the repair center from raw materials suppliers and calculates that raw material suppliers will satisfy the demand for components in repair centers.

\[
\sum_k x_{kc}^m \geq D_{mc} \forall c, m
\]

(10)
$\sum_{k} X_{mc}^{m} \geq \tilde{DE}_{mc} \forall c, m$  \hspace{1cm} (11)

$\sum_{k} X_{nc}^{m} \geq \tilde{DE}_{nc} \forall r, n$  \hspace{1cm} (12)

### 3.5.3. Carbon Cap Constraints

Formula (8) represents that the carbon emission of the SCLSC network should be less than or equal to the carbon emission capacity.

$$\sum_{i} \sum_{j} CE_{ij} \sum_{n} W_{n} \cdot X_{ij}^{n} + \sum_{j} \sum_{k} CE_{jk} \sum_{m} W_{m} \cdot X_{jk}^{m} + \sum_{k} \sum_{c} CE_{kc} \sum_{m} W_{m} \cdot X_{kc}^{m}$$

$$+ \sum_{c} \sum_{b} CE_{cb} \sum_{n} W_{n} \cdot X_{cb}^{n} + \sum_{r} \sum_{k} CE_{rk} \sum_{m} W_{m} \cdot X_{rk}^{m} + \sum_{r} \sum_{c} CE_{rc} \sum_{n} W_{n} \cdot X_{rc}^{n}$$

$$+ \sum_{b} \sum_{d} CE_{bd} \sum_{n} X_{bd}^{n} \leq \tilde{E}_{cap} \hspace{1cm} (13)$$

### 3.5.4. Capacity Constraints

Constraint sets (14)–(17) guarantee that the inflow and outflow cannot be more than the capacity of opened production centers and distribution centers. Constraint (18) shows that the recycled products flowing into recycling centers are less than or equal to the capacity of recycling centers for products. Formula (19) shows that the recycled products flowing out of recycling centers should not exceed the capacity of recycling centers for each raw material. Similarly, relation (20) and (21) separately indicate the capacity of repair centers for incoming raw materials and outgoing products. Constraint (22) ensures the products flowing into disposal centers cannot be more than the capacity for raw materials.

$\sum_{i} X_{ij}^{n} \leq Y_{j} \cdot \text{Cap}_{ij}^{m} \forall j, n$  \hspace{1cm} (14)

$\sum_{k} X_{jk}^{m} \leq Y_{j} \cdot \text{Cap}_{jk}^{m} \forall j, m$  \hspace{1cm} (15)

$\sum_{l} X_{lk}^{m} \leq Y_{k} \cdot \text{Cap}_{lk}^{m} \forall k, m$  \hspace{1cm} (16)

$\sum_{c} X_{kc}^{m} \leq Y_{k} \cdot \text{Cap}_{kc}^{m} \forall k, m$  \hspace{1cm} (17)

$\sum_{c} X_{cb}^{m} \leq Y_{b} \cdot \text{Cap}_{cb}^{m} \forall b, m$  \hspace{1cm} (18)

$\sum_{d} X_{bd}^{n} + \sum_{r} X_{br}^{n} \leq Y_{b} \cdot \text{Cap}_{bd}^{n} \forall b, n$  \hspace{1cm} (19)

$\sum_{k} X_{rk}^{m} \leq Y_{r} \cdot \text{Cap}_{rk}^{m} \forall r, m$  \hspace{1cm} (20)

$\sum_{b} X_{br}^{n} + \sum_{i} X_{ir}^{n} \leq Y_{r} \cdot \text{Cap}_{br}^{n} \forall r, n$  \hspace{1cm} (21)

$\sum_{b} X_{bd}^{n} \leq Y_{d} \cdot \text{Cap}_{bd}^{n} \forall b, n$  \hspace{1cm} (22)

### 3.5.5. Lost Working Days Constraints

Constraint sets (23)–(25) show the limitations of the fuzzy membership degree relating to the lost working days because of occupational involving production centers, repair centers and recycling centers.

$$G_{j}^{max} - \sum_{j} G_{j} \cdot Y_{j}$$

$$\geq U_{j} \forall j \hspace{1cm} (23)$$
\[
\frac{G_{r}^{\text{max}} - \sum G_{r} \cdot Y_{r}}{G_{r}^{\text{max}}} \geq U_{r} \forall r
\] (24)

\[
\frac{G_{b}^{\text{max}} - \sum G_{b} \cdot Y_{b}}{G_{b}^{\text{max}}} \geq U_{b} \forall b
\] (25)

3.5.6. Binary and Non-Negative
Constraint (26) and (27) indicate the characteristics of decision variables.

\[
Y_{i}, Y_{j}, Y_{k}, Y_{r}, Y_{b}, Y_{d} \in \{0, 1\} \forall i, j, k, r, b, d
\] (26)

\[
X_{ij}^{n}, X_{jk}^{m}, X_{ik}^{n}, X_{kr}^{m}, X_{br}^{n}, X_{bd}^{n}, U_{f}^{1}, U_{f}^{2}, U_{b}^{3} \geq 0 \forall i, j, k, r, b, c, d, n, m
\] (27)

4. Fuzzy Robust Optimization Model
To deal with the uncertainty parameters in the SCLSC network, the FRP approach proposed by Talaei et al., is employed in this article. FRP has an excellent performance in the problem including uncertainty parameters with epistemic characteristics [21]. The FRP approach is an extended form of the chance constraint fuzzy programming. For better understanding, the proposed model can be abstracted to the compacted form of the possibility linear programming problem as follows:

\[
\text{Min } Z = f_{1} y + \tilde{c}_{1} x
\] (28)

\[
s.t.
\]

\[
A x \geq \tilde{d}
\] (29)

\[
B x \leq \tilde{c}
\] (30)

\[
C x = 0
\] (31)

\[
S x \leq N y
\] (32)

\[
y \in \{0, 1\}, x \geq 0
\] (33)

where vector \(f\) and coefficient matrix \(B\) and \(N\) are crisp parameters, when vector \(\tilde{c}_{1}, \tilde{d}\) and \(\tilde{c}\) are uncertainty parameters. Formula (28) represents the membership function of the trapezoidal fuzzy member \(\tilde{r}\) by four sensitive spots \((r_{1}, r_{2}, r_{3}, r_{4})\).

Knowing that constraints (29) and (30) with uncertain parameters should be formulated with a satisfaction level of \(a_{k}\) means decision makers will be satisfied as to the necessity for each constraint. Therefore, the deterministic model can be formed as follows:

\[
\text{Min } E[Z] = f_{1} y + \left(\frac{c_{1}(1) + c_{1}(2) + c_{1}(3) + c_{1}(4)}{4}\right) x
\] (34)

\[
s.t.
\]

\[
A x \geq (1 - a_{k})d_{(3)} + a_{k}d_{(4)}
\] (35)

\[
B x \leq (1 - a_{k})c_{(2)} + a_{k}c_{(1)}
\] (36)

\[
C x = 0
\] (37)

\[
S x \leq N y
\] (38)

\[
0.5 \leq a_{k} \leq 1
\] (39)

\[
y \in \{0, 1\}, x \geq 0
\] (40)
According to the fuzzy robust optimization proposed by Talaei et al. [21], the FRP counterpart of Formula (40) can be presented as follows:

\[
\min E[Z] + \eta (Z_{\text{max}} - E[Z]) + \pi_1 \left( \sum_{i} (d_{ij} - (1 - a_k)d_{ij}) + a_k \sum_{j} d_{ij} \right) \\
+ \pi_2 \left( (1 - a_k') e_{ij} + a_k e_{ij} - c_{ij} \right)
\]

(41)

\[Z_{\text{max}}\] in Formula (41) is defined as follows:

\[Z_{\text{max}} = f_1 y + c_{1(4)} x\]

(42)

In Formula (41), the first expression indicates minimizing the expected value of the first objective function. The second expression measures the difference between the most pessimistic value and the expected value. \(\eta\) represents the weight of the second part of Formula (41). Moreover, \(\pi_k\) is the unit penalty for the possible deviation from each constraint with uncertain parameters. Equation (42) calculates the worst case of the first objective function.

Hence, the developed multi-objective FRP model for SCLSC network design can be written as follows.

\[
\min Z_1 = E[Z_1] + \eta (Z_{1\text{max}} - E[Z_1]) + \pi_1 \left( \sum_{i} D^{m}_{ij} - (1 - \phi) D^{n}_{ij} + \phi D^{w}_{ij} \right) \\
+ \pi_2 \left( (1 - \phi) D^{m}_{ij} + \phi D^{w}_{ij} \right) + \pi_3 \left( (1 - \phi) E_{ij} + \phi E_{ij} \right) \\
+ \pi_4 \left( (1 - \phi) E_{ij} + \phi E_{ij} \right)
\]

(43)

The second and third objective functions s.t.

\[
E[Z_1] = \sum_{i} \pi R^{i} X_{ij} + \sum_{j} \sum_{k} C_{ij} Y_{ik} + \sum_{j} \sum_{k} C_{ij} Y_{ik} \\
+ \sum_{j} \sum_{k} C_{ij} Y_{ik} + \sum_{j} \sum_{k} C_{ij} Y_{ik}
\]

(44)

\[
Z_{1\text{max}} = \sum_{i} \sum_{j} \sum_{k} X_{ij} + \sum_{j} \sum_{k} C_{ij} Y_{ik} + \sum_{j} \sum_{k} C_{ij} Y_{ik} \\
+ \sum_{j} \sum_{k} C_{ij} Y_{ik} + \sum_{j} \sum_{k} C_{ij} Y_{ik}
\]

(45)

\[
\sum_{k} X_{ij} \geq (1 - \phi) D^{m}_{ij} + \phi D^{n}_{ij} \\
\sum_{b} X_{ij} \leq (1 - \phi) E_{ij} + \phi E_{ij} \\
\sum_{i} X_{ij} \geq (1 - \phi) D^{m}_{ij} + \phi D^{n}_{ij}
\]

(46) (47) (48)
Because the proposed model is a multi-objective mixed-integer linear programming problem, objective functions conflict with each other and it is difficult to find the optimal solution. In general, a set of feasible solutions can be obtained by solving the multi-objective model. In this article, an efficiency-oriented optimization methodology is proposed to select the optimal solution according to the efficiency sorting of feasible solutions. This optimization methodology hybridizes multi-objective meta-heuristic algorithms and the DEA model. Meta-heuristic algorithms can obtain feasible solutions which are considered the input DMUs of the DEA method. The traditional CCR model can distinguish efficient DMUs and inefficient DMUs, while the second goals-based DEA model can further sort the input DMUs of the DEA method. The evaluation results of the DEA methods can guide the evolution process of the population in the final archive are considered feasible solutions and the best cross-efficiency is selected as the optimal solution. In this methodology, the Pareto optimal solutions in the final archive are considered feasible solutions and the best cross-efficiency is regarded as the optimal one.

Constraint (5)–(27) where \( \phi, \varphi, \varsigma, \varsigma \) are satisfaction levels for constraints with uncertain parameters and \( \eta \) is the weight of the deviation of excepted value and maximum value of the first objective function. Furthermore, \( \pi_1, \pi_2, \pi_3, \pi_4 \) are the unit penalty of deviation of constraints with uncertain parameters.

5. Efficiency-Oriented Multi-Objective Optimization

Because the proposed model is a multi-objective mixed-integer linear programming problem, objective functions conflict with each other and it is difficult to find the optimal solution. In general, a set of feasible solutions can be obtained by solving the multi-objective model. In this article, an efficiency-oriented optimization methodology is proposed to select the optimal solution according to the efficiency sorting of feasible solutions. This optimization methodology hybridizes multi-objective meta-heuristic algorithms and the DEA model. Meta-heuristic algorithms can obtain feasible solutions which are considered the input DMUs of the DEA method. The traditional CCR model can distinguish efficient DMUs and inefficient DMUs, while the second goals-based DEA model can further sort the efficient DMUs according to their cross-efficiency values. In this methodology, the evaluation results of the DEA methods can guide the evolution process of the population in meta-heuristic algorithms. The steps of the efficiency-oriented optimization methodology are presented in Figure 3.

![Flow chart of performance-oriented optimization methodology](image)

**Figure 3.** The flow chart of performance-oriented optimization methodology.

**Step 1:** Initialize algorithm parameters and generate the initial population.

**Step 2:** Perform the evolution process on the parent population based on the special evolution mechanism and generate offspring population. The offspring population will converge to the optimal solution with the best cross-efficiency.

\[
\sum_{i}^{j} \sum_{k}^{m} W_{n} \cdot X_{ij}^{n} + \sum_{i}^{j} \sum_{k}^{m} W_{m} \cdot X_{jk}^{m} + \sum_{i}^{j} \sum_{k}^{m} W_{n} \cdot X_{kc}^{m} \\
+ \sum_{c}^{b} \sum_{k}^{m} W_{n} \cdot X_{cb}^{m} + \sum_{r}^{k} \sum_{k}^{m} W_{m} \cdot X_{r}^{m} + \sum_{i}^{j} \sum_{r}^{k} W_{n} \cdot X_{ir}^{n} \\
+ \sum_{b}^{r} \sum_{k}^{m} W_{n} \cdot X_{br}^{n} + \sum_{b}^{r} \sum_{k}^{m} W_{n} \cdot X_{br}^{n} \\
\leq (1 - \xi) E_{cap}(2) + \xi E_{cap}(1)
\]
Step 3: Update the archive according to the dominant relationship of individuals and select the superior Pareto optimal solutions. The individuals in the archive are considered DMUs of DEA methods.

Step 4: On one hand, divide the Pareto optimal individuals into efficient individuals and inefficient individuals based on the CCR model. On the other hand, furtherly evaluate efficient DMUs, calculate their cross-efficiency values and sort them. The individual with the best cross-efficiency is selected as the optimal solution.

Step 5: Cycle from step 2 to step 4 until the maximum iteration number is met. Finally, the Pareto optimal solutions in the final archive are considered feasible solutions and the solution with the best cross-efficiency is regarded as the optimal one.

5.1. Meta-Heuristic Algorithms

5.1.1. Fast and Elite Non-Dominated Sorting Genetic (NSGA-II) Algorithm

The fast and elite non-dominated sorting genetic (NSGA-II) algorithm is a typical MOOA based on biological evolution mechanisms. The basic process of selection, crossover and mutation are similar to the traditional genetic algorithm. In NSGA-II, the offspring population is selected by the elite non-dominated sorting strategy. The individuals are divided into several Pareto fronts according to the number of times they are dominated. The individuals with the lowest time being dominated are put into the optimal front. Then, the elite individual in the first front is determined by crowding distance and the other individuals are sorted based on different crowding distances.

5.1.2. Multi-Objective Particle Swarm Optimization (MOPSO) Algorithm

MOPSO is a commonly used swarm intelligent optimization algorithm. Based on traditional particle swarm optimization, the non-dominated sorting mechanism and elite archive are introduced into MOPSO. The main characteristic is the updating process of position and velocity of particles which is calculated in Equations (50) and (51):

\[ v_i(k+1) = w \cdot v_i(k) + c_1 \cdot \text{rand} \cdot (p_{best}(k) - x_i(k)) + c_2 \cdot \text{rand} \cdot (g_{best}(k) - x_i(k)) \]  \hspace{1cm} (50)
\[ x_i(k+1) = x_i(k) + v_i(k+1) \]  \hspace{1cm} (51)

5.2. Efficiency Sorting Strategy

The DEA approach is applied to evaluate the feasible solutions obtained in each iteration and calculate their efficiency values. In the DEA method, the normalization and standardization of indicator values are not required. The traditional DEA model can divide the decision-making units (DMUs) into efficient units and inefficient units. For further evaluating and distinguishing the efficiency of efficient DMUs, some studies focus on the extended DEA model for quantitatively sorting objective data. In this article, based on the efficiency sorting multi-objective optimization framework proposed by Wang et al. (2020), the secondary goals-based DEA model is utilized to evaluate and sort the DMUs in an efficiency-oriented solution methodology. The principles of the traditional DEA model and secondary goals-based DEA model are presented as follows.

5.2.1. CCR Model

The traditional DEA model (i.e., CCR model) can calculate the self-evaluation efficiency values of DMUs. The CCR model with constant returns to scale is presented as follows.

\[ \max E_{dd} = \frac{\sum_{r=1}^{s} u_{rd} \cdot y_{rd}}{\sum_{i=1}^{m} v_{id} \cdot x_{id}} \]  \hspace{1cm} (52)
\[ \frac{\sum_{r=1}^{s} u_{rij} \cdot y_{rij}}{\sum_{i=1}^{m} v_{ij} \cdot x_{ij}} \leq 1, j = 1, 2, \ldots, n \]  \hspace{1cm} (53)
\[ u_{rf} \geq \epsilon, v_{ij} \geq \epsilon; r = 1, 2, \ldots, s; i = 1, 2, \ldots, m \]  \hspace{1cm} (54)
where $E_{dd}$ is the self-evaluation efficiency value of $d$th DMU, $y_{rd}$ is the value of $r$th output indicator of $d$th DMU and $u_{rd}$ is the corresponding weight, $x_{id}$ is the value of $i$th input indicator of $d$th DMU and $v$ is the corresponding weight. Relation (53) represents that the efficiency value of $v$ DMU should be smaller than or equal to 1. Expression (54) indicates the weights of output and input should be more than 0. $\varepsilon$ states a non-Archimedes number that is smaller than any positive number. If the $E_{dd}$ is equal to 1, the DMU is DEA efficient; otherwise, the DMU is inefficient.

5.2.2. Secondary Goals-Based DEA Model

The traditional CCR model can distinguish DMU sets by dividing them into DEA efficient units and inefficient units. However, when the self-evaluation efficiency values of multiple DMUs are equal to 1, the CCR model cannot distinguish and further sort them. In this article, the secondary goals-based DEA model proposed by Doyle et al. is utilized to further evaluate the cross-evaluation efficiency value of DMUs and sort them. Differently from the self-evaluation based CCR model, the secondary goals-based DEA model is based on cross-evaluation, which is shown as follows.

$$\min I_d = \sum_{j=1}^{n} z_{dj}$$  \hspace{1cm} (55)

$$\sum_{r=1}^{s} u_{rd} y_{rd} - \sum_{i=1}^{m} v_{id} x_{id} \leq 0, j = 1, 2, \ldots, n$$  \hspace{1cm} (56)

$$\sum_{d=1}^{n} v_{id} x_{id} = 1$$  \hspace{1cm} (57)

$$\sum_{r=1}^{s} u_{rd} y_{rd} = E_{dd}$$  \hspace{1cm} (58)

$$0 < h_{dj} + M z_{dj} < M + \varepsilon, j = 1, 2, \ldots, n$$  \hspace{1cm} (59)

$$\frac{\sum_{r=1}^{s} u_{rd} y_{rd}}{\sum_{i=1}^{m} v_{id} y_{id}} + h_{dj} = \frac{\sum_{r=1}^{s} u_{rd} y_{rd}}{\sum_{i=1}^{m} v_{id} y_{id}}, j = 1, 2, \ldots, n$$  \hspace{1cm} (60)

$$z_{dj} = \begin{cases} 0, & \text{if } j = 1, 2, \ldots, n \\ 1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (61)

$$h_{dj} \in R$$  \hspace{1cm} (62)

$$u_{ij} \geq \varepsilon; v_{ij} \geq \varepsilon; r = 1, 2, \ldots, s; i = 1, 2, \ldots, m$$  \hspace{1cm} (63)

where objective function (36A) aims to minimize $\sum_{j=1}^{n} z_{dj}$ (i.e., ensure $z_{dj}$ to be 0) for obtaining a set of optimal weights. Expressions (56)–(58) specify the calculation and definition of self-evaluation efficiency. The constraints (59) and (60) specify the comparison of cross-evaluation efficiency and self-evaluation efficiency of $d$th DMU. If $z_{dj} = 1$, $h_{dj} \leq 0$ according to constraint (59) and the cross-evaluation efficiency of $d$th DMU is greater than its self-evaluation efficiency according to constraint (60). Otherwise, $h_{dj} \geq 0$ and the cross-evaluation efficiency of $d$th DMU is smaller than its self-evaluation efficiency. Expression (63) specifies that the weights of input and output indicators should be more than 0. According to the cross-evaluation efficiency value obtained by the secondary goals-based DEA model, the efficient DMUs can be distinguished and sorted.

5.2.3. Indicator Selection

In order to evaluate the feasible solutions obtained in each iteration and calculate the efficiency, it is critical to select the appropriate input and output indicators. In the DEA model, the indicator selection should follow the principles below:

1. The indicators should be quantitative to avoid the influence of subjective preference.
2. The input indicators should be minimum indicators and the output indicators should be maximum indicators.
3. The indicators should comprehensively the supply chain performance including economic, environmental and social dimensions.
According to the abovementioned principles, the evaluation indicators are presented as follows:

The input indicators contain:

1. Cost indicators, including transportation cost, facility opening cost, ordering cost, and facility processing cost:

\[
\text{TransCost} = \sum_{i,j,n} W_{in} \cdot V_{in} \cdot X_{ij} + \sum_{j,k,m} W_{kn} \cdot V_{kn} \cdot X_{jk} + \sum_{k,l,m} W_{ln} \cdot V_{ln} \cdot X_{kl} + \sum_{m} W_{mm} \cdot V_{mm} \cdot X_{mm}
\]

\[
\text{OpenCost} = \sum_{j} O_{j} \cdot Y_{j} + \sum_{k} O_{k} \cdot Y_{k} + \sum_{r} O_{r} \cdot Y_{r} + \sum_{b} O_{b} \cdot Y_{b} + \sum_{d} O_{d} \cdot Y_{d}
\]

(65)

2. Social indicators, including the lost working days measured:

\[
\text{OrderCost} = \sum_{i,n} P_{in} \cdot Y_{ij}
\]

(66)

\[
\text{ProCost} = \sum_{j,m} MC_{jm} \cdot X_{jm} + \sum_{k,m} MC_{km} \cdot X_{km} + \sum_{n} IC_{jn} \left( \sum_{r} X_{br} + \sum_{d} X_{bd} \right)
\]

\[
+ \sum_{m} AC_{mn} \cdot X_{mn} + \sum_{d} DC_{dn} \cdot X_{bd}
\]

(67)

Environmental indicators, including carbon emission and solid waste emission:

\[
\text{CarEmi} = \sum_{i,j} CE_{ij} \cdot W_{in} \cdot X_{ij} + \sum_{j,k} CE_{jk} \cdot W_{kn} \cdot X_{jk} + \sum_{k,l} CE_{kl} \cdot W_{ln} \cdot X_{kl} + \sum_{l,m} CE_{lm} \cdot W_{mm} \cdot X_{lm}
\]

\[
+ \sum_{m} CE_{mm} \cdot W_{mm} \cdot X_{mm} + \sum_{n} CE_{mn} \cdot W_{nm} \cdot X_{nm} + \sum_{p} CE_{np} \cdot W_{pm} \cdot X_{pm} + \sum_{q} CE_{qq} \cdot W_{qq} \cdot X_{qq}
\]

(68)

\[
\text{SolEmi} = \sum_{j,m} HE_{jm} \cdot X_{jm} + \sum_{k} HE_{km} \cdot X_{km} + \sum_{b,m} HE_{bm} \cdot X_{bm}
\]

\[
+ \sum_{b,n} HE_{bn} \left( \sum_{r} X_{br} + \sum_{d} X_{bd} \right) + \sum_{d,n} HE_{dn} \cdot X_{dn}
\]

(69)

The output indicators contain:

1. Profit indicator:

\[
\text{Revenue} = \sum_{m} PR_{mn} \cdot X_{rn}
\]

(70)

2. Social indicators, including the lost working days measured:

\[
\text{LosDay} = \sum_{j} U_{j} + \sum_{r} U_{r} + \sum_{b} U_{b}
\]

(71)

6. Numerical Case

This section is dedicated to presenting a numerical example, and then the corresponding parameters are shown, and finally the analyses of the results are conducted.

6.1. Case Description

For exploring the application and validity of the proposed fuzzy robust optimization model and intelligent optimization algorithms, this section represents a numerical case. This model and solution were coded and tested on a laptop with windows 10 (Core(TM) i7-6700HQ CPU@2.60 Hz and 16.00 GB RAM). In this numerical case, the size of the problem is shown in Table 1. In this article, Table 2 represents five kinds of uncertainty parameters which are trapezoidal fuzzy numbers: demand for products in customers, demand for raw materials in remanufacturing centers, number of recycled products, carbon emission cap and transportation cost. Other parameters are generated by uniform distribution, as shown in Table 3.
Table 1. The problem size.

| Facility                  | Potential Nodes | Facility                  | Potential Nodes |
|---------------------------|-----------------|---------------------------|-----------------|
| Product                   | 1               | Raw material              | 3               |
| Raw materials supplier    | 4               | Recycling center          | 5               |
| Manufacturing center      | 3               | Disposal center           | 3               |
| Distribution center       | 6               | Customer                  | 11              |
| Remanufacturing center   | 3               |                           |                 |

Table 2. The other parameters subject to Uniform distribution in the SCLSC network.

| Parameters | $r_2$               | $r_3$               | $r_4$               |
|------------|---------------------|---------------------|---------------------|
| $DE_m^n$   | Unif (35, 40)       | Unif (40, 45)       | Unif (45, 50)       |
| $RE_m^n$   | Unif (15, 20)       | Unif (20, 25)       | Unif (25, 30)       |
| $DE_m^n$   | Unif (200, 250)     | Unif (250, 300)     | Unif (300, 350)     |
| $ECap$     | Unif (200, 240)     | Unif (240, 280)     | Unif (280, 320)     |
| $TC_{ij}$  | Unif (0.105, 0.110) | Unif (0.110, 0.115) | Unif (0.115, 0.120) |
| $TC_{jk}$  | Unif (0.120, 0.125) |                    |                    |
| $TC_{kc}$  |                    |                    |                    |
| $TC_{ir}$  |                    |                    |                    |
| $TC_{cb}$  |                    |                    |                    |
| $TC_{br}$  |                    |                    |                    |
| $TC_{rk}$  |                    |                    |                    |
| $TC_{bd}$  |                    |                    |                    |

6.2. Results and Discussion

Two efficiency-oriented solution methodologies are applied to solve the mathematical model developed in this article, which is secondary goals-based NSGA-II (SG-NSGA-II) and secondary goals-based MOPSO (SG-MOPSO), respectively. In an attempt to ensure the fairness of the experiments, the corresponding control parameters of NSGA-II and MOPSO are set as follows: maximum number of iterations = 100; population size = 200; variable dimension = 336; in NSGA-II, crossover percentage = 0.7; mutation possibility = 0.02; in MOPSO, inertia weight = 0.7298; personal learning coefficient = 1.4962; global learning coefficient = 1.4962.

Both efficiency-oriented solution methodologies were run 10 times. The Pareto front obtained by SG-NSGA-II and SG-MOPSO is shown in Figure 4. The x-axis indicates the total economic performance (the first objective function), the y-axis represents the environmental pollution emission (the second objective function), and the z-axis represents the social impact (the third function). In Figure 4 it can be seen that the distribution degree of feasible solutions obtained by SG-NSGA-II is higher than that obtained by SG-MOPSO. The aforementioned phenomenon indicates that the solution diversity is similar in the two efficiency-oriented solution methodologies. To further distinguish the quality and performance of obtained feasible solutions, Tables 4 and 5 present the self-evaluation values and cross-efficiency values of the feasible solutions obtained by SG-NSGA-2 and SG-MOPSO. In Tables 4 and 5, “self” indicates self-evaluation efficiency calculated by the traditional CCR model and “cross” represents cross-efficiency obtained by the secondary goals-based DEA model. Comparing the self-evaluation efficiency, the DMUs can
be divided into DEA efficient units and inefficient units. As presented in Tables 4 and 5, the values of input and output indicators are presented. According to self-evaluation efficiency, it can conclude that all obtained schemes are DEA relatively efficient. Furthermore, all feasible solutions can be distinguished and sorted based on cross-evaluation efficiency. As shown in Tables 4 and 5, the optimal schemes with the optimal cross-evaluation efficiency are in bold.

The important decisions relating to network configuration solved by SG-NSGA-II and SG-MOPSO are presented in Table 6. Table 6 presents the network configuration decision of the optimal scheme obtained by both efficiency-oriented solution methodologies. For example, according to the obtained schemes obtained by SG-NSGA-II, the raw material supplier 4 is selected. As can be seen in Table 6, production center 1 and 2 are opened, distribution center 2, 4, 5, and 6 are opened, repair center 1 and 3 are opened, recycling center 5 is opened, and disposal centers are opened in potential location 1 and 2.

![Figure 4. The space distribution of obtained Pareto optimal solutions.](image)

**Table 4.** Indicators and efficiency values calculated by SG-NSGA-II.

| DMU | Input | Output | Self | Cross |
|-----|-------|--------|------|-------|
|     | Transport Cost | Opening Cost | Order Cost | Process Cost | Carbon Emission | Solid Emission | Revenue | Lost Working Days |       |       |
| 1   | 493,833 | 48,694 | 72,342 | 500,588 | 490.42 | 157.33 | 4,143,000 | 8.7363 | 1.0000 | 0.3029 |
| 2   | 473,933 | 55,637 | 72,756 | 489,989 | 476.91 | 149.78 | 4,029,000 | 8.0063 | 1.0000 | 0.4018 |
| 3   | 449,958 | 43,683 | 66,858 | 447,033 | 464.84 | 144.61 | 3,882,000 | 8.6007 | 1.0000 | 0.3823 |
| 4   | 441,943 | 52,596 | 67,272 | 512,510 | 440.43 | 139.45 | 3,960,000 | 7.8232 | 1.0000 | 0.4448 |
| 5   | 492,450 | 44,425 | 71,065 | 493,695 | 481.11 | 133.60 | 3,936,000 | 6.1792 | 1.0000 | 0.9286 |
| 6   | 473,933 | 55,637 | 72,756 | 489,989 | 476.91 | 149.78 | 4,029,000 | 8.0063 | 1.0000 | 0.4018 |
| 7   | 449,958 | 43,683 | 66,858 | 447,033 | 464.84 | 144.61 | 3,882,000 | 8.6007 | 1.0000 | 0.3823 |
| 8   | 441,943 | 52,596 | 67,272 | 512,510 | 440.43 | 139.45 | 3,960,000 | 7.8232 | 1.0000 | 0.4448 |
| 9   | 492,450 | 44,425 | 71,065 | 493,695 | 481.11 | 133.60 | 3,936,000 | 6.1792 | 1.0000 | 0.9286 |
| 10  | 493,833 | 48,694 | 72,342 | 500,588 | 490.42 | 157.33 | 4,143,000 | 8.7363 | 1.0000 | 0.3029 |
| 11  | 452,111 | 48,808 | 66,688 | 493,070 | 453.01 | 144.21 | 3,585,000 | 7.9384 | 1.0000 | 0.9936 |
| 12  | 408,657 | 53,535 | 73,019 | 531,301 | 499.69 | 160.32 | 4,035,000 | 8.1373 | 1.0000 | 0.4049 |
| 13  | 470,983 | 50,411 | 62,587 | 452,363 | 464.57 | 144.52 | 3,990,000 | 8.6279 | 1.0000 | 0.3504 |
| 14  | 449,112 | 56,309 | 67,119 | 426,297 | 452.17 | 146.83 | 3,918,000 | 7.8681 | 1.0000 | 0.4737 |
Table 5. Indicators and efficiency values calculated by SG-MOPSO.

| DMU | Input Cost | Output Cost | Process Cost | Carbon Emission | Solid Emission | Revenue | Lost Working Days | Self | Cross |
|-----|------------|-------------|--------------|-----------------|----------------|---------|-------------------|------|-------|
| 1   | 659600     | 41706       | 90544        | 602750          | 662.05         | 178.82  | 5154000           | 8.000| 1.000 | 0.4783 |
| 2   | 660157     | 47820       | 80967        | 622465          | 654.91         | 192.03  | 5460000           | 5.000| 1.000 | 0.5215 |
| 3   | 668984     | 63755       | 89688        | 594961          | 658.19         | 185.84  | 5415000           | 5.000| 1.000 | 0.5546 |
| 4   | 647114     | 45897       | 89168        | 569337          | 648.26         | 184.04  | 5361000           | 4.000| 1.000 | 0.5762 |
| 5   | 637212     | 55192       | 81012        | 581502          | 658.19         | 185.84  | 5334000           | 4.000| 1.000 | 0.5907 |
| 6   | 629990     | 55464       | 78168        | 577766          | 634.30         | 170.93  | 5235000           | 7.000| 1.000 | 0.4919 |
| 7   | 634105     | 30294       | 81457        | 564696          | 625.68         | 181.94  | 5391000           | 5.000| 1.000 | 0.4904 |
| 8   | 636202     | 65939       | 87761        | 570562          | 637.24         | 178.48  | 5379000           | 4.000| 1.000 | 0.5941 |
| 9   | 650233     | 49591       | 89003        | 586320          | 648.95         | 178.53  | 5190000           | 1.000| 1.000 | 0.9286 |
| 10  | 663550     | 42467       | 90761        | 562545          | 660.41         | 172.19  | 5184000           | 7.000| 1.000 | 0.4995 |
| 11  | 604000     | 51161       | 89069        | 551701          | 645.92         | 177.46  | 5160000           | 3.000| 1.000 | 0.7086 |
| 12  | 657757     | 55069       | 89149        | 579980          | 666.43         | 171.38  | 5142000           | 6.000| 1.000 | 0.5684 |
| 13  | 470384     | 49496       | 61902        | 455024          | 472.66         | 144.42  | 3990000           | 8.6279| 1.000 | 0.7254 |
| 14  | 44346      | 60702       | 63633        | 455676          | 445.69         | 144.80  | 3918000           | 7.8681| 1.000 | 0.9826 |

Table 6. The results of strategic scheme of the SCLSC network.

| Facility          | SG-NSGA-II | SG-MOPSO |
|-------------------|------------|----------|
| Raw materials supplier | 4          | 1, 2, 3, 4 |
| Manufacturing centers | 1, 2      | 3        |
| Distribution centers | 2, 4, 5, 6 | 1, 4, 5, 6 |
| Remanufacturing centers | 1, 3      | 1        |
| Recycling centers      | 5          | 2        |
| Disposal centers       | 1, 2       | 2, 3     |

6.3. Comparison of Algorithms

This section performs a comparison of the solution performance of two efficiency-oriented solution methodologies and the sustainability performance of their solutions. Figure 5 shows the comparison of the values of objective functions obtained by SG-NSGA-II and SG-MOPSO. It can be seen that the net cost and the pollution emission solved by SG-NSGA-II are lower than that of SG-MOPSO. Furthermore, there are fewer lost working days in the case of SG-NSGA-II, which represents that the social performance of the scheme obtained by SG-MOPSO is better than SG-NSGA-II. Furthermore, Figure 6 presents the comparison of cross-efficiency values of feasible schemes obtained by two efficiency-oriented solution methodologies. It can be concluded that in total, the cross-efficiency values of all feasible solutions obtained by SG-MOPSO are better than that of SG-NSGA-II. On the other hand, the sustainability performance of the optimal scheme of SG-MOPSO is greater than that of SG-NSGA-II. Hence, SG-MOPSO has better solution performance than SG-NSGA-II.

Figure 5. The value of objective functions based on two of meta–heuristic algorithms.
6.4. Robustness Analyses

This section is dedicated to performing sensitivity analysis on FRO and the deterministic model. The results obtained by solving FRO and the deterministic model are compared. The uncertain parameters are defined as the expected value of the trapezoidal fuzzy member in the deterministic model. Figures 7 and 8 present the comparison of objective function values obtained by solving two models. In Figures 7 and 8, the “FRO” in the x-axis indicates the fuzzy robust optimization model and “Deterministic” represents the deterministic model. The “net cost” indicates the economic performance (the first objective function), the “pollution emission” represents the environmental (the second objective function), and “lost working days” is the social impact (the third objective function). The difference in the net cost between the fuzzy robust programming model and the deterministic model is defined as “robustness cost” which is the cost that incorporates into the supply chain to face the uncertain environment. Furthermore, the environmental and social performance obtained by the fuzzy robust programming model is better than that of the deterministic model. Based on the mentioned point, considering the fuzzy robust model in the real world may lead to better sustainable performance and economic performance in the long term.

Figure 6. Comparison of the efficiency values of the results.

Figure 7. The comparisons of objective functions based on FRO and deterministic model with NSGA-II.
Figure 7. The comparisons of objective functions based on FRO and deterministic model with NSGA-II.

Figure 8. The comparisons of objective functions based on FRO and deterministic model with MOPSO.

7. Conclusions

This article addresses a sustainable closed-loop supply chain network design and design problem under high uncertainty. A multi-objective mixed-integer programming model is developed for the purpose of the minimum total cost, reduction in environmental damage, and maximum social responsibility. The social issue is measured by lost working days caused by occupational accidents which are defined quantitatively by fuzzy programming. Furthermore, in order to cope with the uncertainty, a fuzzy robust programming approach is applied to convert the developed model. An efficiency-oriented optimization methodology is proposed to solve the multi-objective FRP model. Based on this methodology, decision-makers can obtain a set of feasible solutions, evaluate comprehensively their sustainability performance, and select the optimal solution according to cross-evaluation efficiency values. Meanwhile, decision-makers can distinguish efficient units and inefficient units of feasible solutions according to self-evaluation efficiency. In this efficiency-oriented optimization methodology, the cross-evaluation efficiency-sorting strategy can guide the evolution process of meta-heuristic algorithms. In summary, the numerical case validates the proposed FRP model and the efficiency-oriented optimization methodology. Finally, we perform sensitivity analyses on the robustness of FRP and the deterministic model. The results illustrate that the FRP model can efficiently deal with the uncertainty in the SCLSC network.

The main contributions are presented as follows:

1. This article proposes a multi-objective mixed-integer programming model with targets of the minimum total cost, reduction in environmental damage, and maximum social responsibility.
2. In order to deal with the uncertainty caused by the dynamic business environment, a fuzzy robust programming (FRP) approach is applied.
3. An efficiency-oriented optimization methodology, hybridizing meta-heuristics and efficiency evaluation, is proposed to solve the developed multi-objective model as auxiliary decision-making.

However, this study still has some limitations and can be extended by using the following ideas. Firstly, the uncertainty caused by random disruption can cause huge costs in transportation and production activities [47]. The abovementioned type of uncertainty can be modeled by a scenario-based approach such as robust programming. The second direction is to configure a responsive supply chain for improving delivery ability and customer loyalty. Furthermore, additional measures such as emergency shipment and...
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