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# Construction of Green Supply Chain Network Optimization Models for Textiles with Carbon Neutrality Goals

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**ABSTRACT**

*Given the high carbon intensity and complex supply chains in the textile industry, this paper investigates emission reduction and the trade-off between cost and carbon mitigation under carbon neutrality goals. A multi-objective mixed-integer linear programming (MOMILP) model is developed, integrating carbon trading mechanisms and dynamic demand response. High-carbon activities, including printing and dyeing and chemical fiber production, are considered, while decisions on raw material procurement, green process selection, facility location, production capacity allocation, and logistics routing are coordinated to achieve chain-wide emission reduction. Carbon price fluctuations are incorporated to dynamically model carbon trading, and green incentive constraints encourage the internalization of carbon externalities. The model is solved using an improved Non-dominated Sorting Genetic Algorithm II (NSGA-II), with the entropy weight-TOPSIS method applied for multi-attribute decision analysis on the Pareto frontier. Experiments show that the model can reduce costs by approximately 18.6–25.8% and carbon emissions by 22.3–33.2% across various carbon price scenarios. A combined carbon tax + green subsidy policy effectively reduces costs, and the improved algorithm outperforms others in convergence speed and solution diversity. This study provides a quantitative tool for textile enterprises to balance cost and emission reduction and offers theoretical support for policymakers to design green incentive mechanisms, providing practical guidance for advancing the industry's carbon-neutral transformation.*

**KEYWORDS**

*carbon neutrality, textile supply chain, multi-objective mixed-integer linear programming model, improved NSGA-II algorithm*

## INTRODUCTION

As a key area of global resource consumption and carbon emissions, the textile industry has a supply chain network covering multiple links, such as raw material planting, spinning and weaving, printing and dyeing, chemical fiber production, and logistics and transportation. This network is characterized by a long industrial chain, high carbon emission intensity, and multiple participating entities. According to research, chemical fiber production and printing and dyeing are typical high-carbon emission links, with high energy consumption and heavy pollution, becoming key bottlenecks in achieving the goal of carbon neutrality [1,2]. With the deepening of the dual carbon strategy, textile enterprises face increasingly stringent environmental regulations, such as carbon quota allocation, expansion of carbon trading pilots, and potential carbon tariff pressure. It is urgent to promote the green transformation of the entire industrial chain.

Existing research has carried out multi-dimensional exploration around green supply chain optimization. In terms of model construction, scholars mostly use single-objective or dual-objective planning methods, focusing on carbon emission control in single links, such as production layout and transportation routes [3]. Asha et al. [4] reviewed the latest literature on the application of multi-objective optimization techniques in green supply chain management, focusing on green supply chain structure, model building techniques that consider multiple objectives simultaneously, and solutions to multi-objective optimization problems. Tang et al. [5] constructed a multi-objective optimization model for machining based on an improved particle swarm optimization (PSO) algorithm, with the goal of minimizing carbon emissions and production costs. Su [6] explored the decision-making and coordination issues of a low-carbon supply chain under the influence of consumer preferences, established an operation optimization model with carbon constraints covering production, inventory, and transportation, and proposed a strategy suitable for a green market environment. In terms of policy mechanism integration, some studies have applied static policy parameters, such as carbon tax and carbon subsidy, to analyze their impact on corporate emission reduction decisions. Li [7] used a stochastic optimal control model to construct a dynamic decision-making mechanism for enterprises under carbon tax and emission reduction subsidy policies. The results showed that only by applying carbon tax and subsidy policies simultaneously could a balance between carbon reduction targets and profit maximization be achieved, considering capital uncertainty [7]. Ran [8] constructed a supply chain coordination model under the joint action of carbon tax and government subsidies. Through revenue sharing contracts, enterprises were encouraged to reduce emissions while taking into account economic benefits and carbon emission control, to achieve low-carbon coordinated operation of the entire supply chain [8]. However, carbon price fluctuations are affected by many factors, and it is necessary to apply dynamic carbon price simulation to improve the applicability of the model and evaluate its impact on green supply chain optimization and emission reduction.

In addition, the application of intelligent algorithms in supply chain optimization has also made progress. Multi-objective optimization algorithms, such as Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), are widely used to solve the conflict between cost and carbon emissions, providing technical support for multi-link collaborative optimization. Kabiri [9] established a dual-objective optimization model for maximizing profits and minimizing greenhouse gas emissions for production and distribution planning problems in a closed-loop supply chain. The NSGA-II algorithm was combined with Monte Carlo simulation to solve the problem and generate the Pareto frontier to support strategy selection [9]. Zhang [10] performed NSGA-II optimization on the layout of garment production lines and material distribution paths to balance operating costs and carbon emissions generated during transportation. Yaghin [11] applied carbon emission targets and uncertain demand modeling and optimized the procurement and production scheduling of the textile supply chain through fuzzy multi-objective mathematical programming to realize a trade-off between cost and carbon emissions. Chen [12] sorted out the practical path and framework for using multi-objective or intelligent optimization methods to achieve carbon emission reduction in various links of the textile supply chain. However, for the high-dimensional, multi-level network and dynamic carbon price response requirements of the textile supply chain, the standard NSGA-II is prone to local convergence and lacks adaptability, and it is urgently needed to enhance the solution efficiency and solution quality.

The contribution of this paper is that, targeting the characteristics of high-carbon links in the textile supply chain and the dynamic fluctuations of carbon prices, a multi-objective mixed-integer programming model is constructed that integrates the carbon trading mechanism with the coordinated optimization of the entire chain, and incorporates key links unique to industries, such as chemical fiber production and printing and dyeing processing, into the optimization system. By designing a weighted dynamic crowding distance calculation, neighborhood perturbation, and dynamic variation coupling mechanism, an improved NSGA-II algorithm is formed that is adapted to high-dimensional decision variables in the textile supply chain. It significantly outperforms existing algorithms in terms of convergence speed and solution diversity. At the same time, the optimal range of the carbon tax + green subsidy combination policy and the gradient of the impact of carbon price fluctuations on various links in the supply chain are quantified, achieving a breakthrough from static single-link optimization to dynamic full-chain coordination, providing more targeted quantitative tools and theoretical support for textile companies to balance emission reduction and costs and for policymakers to design incentive mechanisms.

## MOMILP (MULTI-OBJECTIVE MIXED-INTEGER LINEAR PROGRAMMING) MODEL DESIGN

### Improved NSGA-II Algorithm Design

In the solution process of MOMILP, traditional mathematical programming methods are inefficient in handling the large-scale variable characteristics of the textile multi-level network. This paper adopts the improved NSGA-II as the core solution algorithm. This algorithm applies a local search mechanism and a dynamic mutation strategy based on the standard NSGA-II, which significantly improves the convergence speed and the quality of the Pareto front distribution [13,14].

First, regarding local search, this paper designs a strategy based on neighborhood perturbation, aiming to improve the algorithm's refined search ability in later iterations [15]. After each generation of evolution is completed, the elite individuals in the current generation are subjected to neighborhood perturbation operations to generate several candidate solutions, which are compared with their original individuals, and the better solutions are retained to enter the next generation. Assuming that the best individual of the current generation is $x_{best}$, its neighborhood solution can be expressed as:

$$x' = x_{best} + \delta \cdot N(0,\sigma) \tag{1}$$

where $\delta$ represents the perturbation step size, and $N(0,\sigma)$ represents a normally distributed random number with a mean of 0 and a standard deviation of $\sigma$. By comparing candidate solutions with the original elite individuals, the better solutions are retained and entered into the next generation, thereby enhancing the algorithm's ability to mine high-quality solutions, avoiding premature convergence to local optimal solutions, and improving the refined search effect in later iterations.

Secondly, regarding mutation rate setting, a mutation rate adjustment strategy based on the number of iterations is adopted:

$$P_m(t) = P_{m\text{-}min} + (P_{m\text{-}max} - P_{m\text{-}min}) \cdot \frac{t}{T} \tag{2}$$

where $t$ is the current iteration number; $T$ is the maximum number of iterations; $P_{m\text{-}min}$ and $P_{m\text{-}max}$ are the minimum and maximum mutation rates, respectively. Notably, this paper employs a dynamic adjustment strategy in which the mutation rate gradually increases with the number of iterations, differing from the annealing approach used in traditional genetic algorithms to reduce the mutation rate. This design stems primarily from the high-dimensional, strongly constrained, and multimodal nature of the textile green supply chain network optimization problem. In the standard NSGA-II algorithm, while a low mutation rate in the later stages favors local convergence, it can also lead to a rapid decline in population diversity and trap the population on a local Pareto frontier. To avoid premature convergence and enhance the algorithm's ability to globally explore the complex solution space, this paper moderately increases the mutation rate in the later stages of iteration, coupled with a local search mechanism for elite individuals. This approach maintains solution quality while stimulating perturbations in underexplored areas.

In addition, to improve the uniformity of the Pareto front distribution, a weighted dynamic crowding distance calculation method is applied [16,17]. Compared with the traditional Euclidean distance calculation method, this method adds a target weight factor $w_k$ on the original basis to highlight the importance of the key target:

$$d_i = \sum_{k=1}^{K} w_k \cdot |f_k(i+1) - f_k(i-1)| \tag{3}$$

where $K$ is the number of targets; $f_k(i)$ represents the function value of the $i$-th solution on the $K$-th target; $w_k$ is the corresponding weight coefficient. In this way, the distribution quality and representativeness of the Pareto front in the multi-target space can be effectively improved.

Finally, this paper defines the objective function applicable to the textile green supply chain network optimization problem. The model contains two core optimization objectives: total operating cost $C$ and total carbon emissions $E$, which are specifically expressed as follows:

$$F(x) = \{minC(x), minE(x)\} \tag{4}$$

Among them, there are:

$$C(x) = \sum_{i=1}^{N_8} c_i^s x_i^s + \sum_{j=1}^{N_p} c_j^p x_j^p + \sum_{k=1}^{N_t} c_k^t x_k^t \tag{5}$$

$$E(x) = \sum_{i=1}^{N_8} e_i^s x_i^s + \sum_{j=1}^{N_p} e_j^p x_j^p + \sum_{k=1}^{N_t} e_k^t x_k^t \tag{6}$$

where $C(x)$ is the total operating cost of the textile green supply chain network, $N_s$ is the number of potential suppliers, $c_i^s$ is the unit fixed cost of selecting the *i*-th supplier, $x_i^s$ is the binary decision variable for selecting the *i*-th supplier, $x_i^s = 1$ indicates selecting this supplier, and $x_i^s = 0$ indicates not selecting it. $N_p$ is the total number of potential production bases, $c_j^p$ is the unit operating cost of the $j$-th production base, $x_j^p$ is the binary decision variable for the $j$-th production base, $N_t$ is the total number of potential logistics transportation routes, $c_k^t$ is the unit transportation cost of the *K*-th logistics transportation route, and $\mathrm{x}_\mathrm{k}^\mathrm{t}$ is the binary decision variable for the *K*-th logistics transportation route. $E(x)$ is the total carbon emissions of the textile green supply chain network, $e_i^s$ is the unit carbon emissions of the *i*-th supplier in the raw material production and processing links, $e_j^p$ is the unit carbon emissions of the $j$-th production base in the production and processing links, $e_k^t$ is the unit carbon emissions of the k-th logistics transportation route.

Let $q_{ij}$ be the amount of raw materials purchased from supplier *i* at production base j, $p_{jk}$ be the amount of finished products shipped from production base $j$ to distribution center *K*, and $t_{kl}$ be the amount of products distributed from distribution center *K* to demand market *i*. $s_j$ is the proportion $(0 \le s_j \le 1)$ of green processes used in production base $j$, and $r_{jk}$ is the proportion $(0 \le r_{jk} \le 1)$ of low-carbon transportation methods used from production base $j$ to distribution center k.

The constraints are as follows:

Raw material supply and demand balance constraints: $\sum_j q_{ij} \le Q_i \cdot x_i^s$, where $Q_i$ is the maximum supply of supplier *i*, ensuring that the supply capacity of the selected supplier can meet production demand; at the same time, $\sum_i q_{ij} \ge \sum_k p_{jk}/\eta_j$, $\eta_j$ are the raw material conversion rates of production base $j$, ensuring that the raw material input quantity matches the finished product output demand.

Production and distribution connection constraints: $\sum_j p_{jk} \le \sum_l t_{kl}$, which ensures that the input and output of the distribution center are balanced to avoid inventory backlogs or shortages; and $p_{jk} \le P_j \cdot y_j^p$, $P_j$ are the maximum production capacity of production base $j$, limiting the transportation volume of finished products to not exceed production capacity.

Logistics path constraints: $c_{jk}^t = (1 - r_{jk}) \cdot c_{jk0}^t + r_{jk} \cdot c_{jk1}^t$ , $e_{jk}^t = (1 - r_{jk}) \cdot e_{jk0}^t + r_{jk} \cdot e_{jk1}^t$ , where

$c_{jk0}^{t}$, $c_{jk1}^{t}$ and $e_{jk0}^{t}$, $e_{jk1}^{t}$ represent the unit cost and carbon emissions of traditional and low-carbon transportation, respectively. Logistics costs and carbon emissions are linked by the transport mode ratio.

The model in this paper aims to achieve the long-term sustainable development of the textile green supply chain. To this end, the model not only pursues the dual-objective optimization of operating costs and carbon emissions, but also explicitly incorporates the future-oriented carbon neutrality target constraints. This constraint is based on the long-term emission reduction path set at the enterprise or regional level, requiring that the cumulative net carbon emissions of the supply chain network during the planning period must not exceed the preset carbon budget limit. The constraint expression is as follows:

$$\sum_{t\text{-}1}^{T}(E_t\text{-}S_t)\leq B \tag{7}$$

where $E_t$ represents the total carbon emissions in period $t$; $S_t$ represents the carbon removal or offset achieved in period $t$ through carbon sinks, green certificate purchases, or Carbon Capture, Utilization, and Storage (CCUS) technologies; $B$ is the total carbon budget allowed in the entire planning period $T$.

**Integration of Multi-Attribute Decision Support Methods**

In multi-objective optimization problems, the Pareto front usually contains a large number of non-inferior solutions. How to select feasible solutions that take into account both economic and environmental benefits is a key challenge facing decision-makers. To this end, this paper uses the entropy weight-TOPSIS method to sort and optimize the Pareto front solution set [18,19].

First, the entropy weight method is used to determine the weight of each objective. Assuming that the normalized matrix of m solutions under n targets is $R = [r_{ij}]_{m\times n}$, the entropy value $H_j$ of each target is calculated as follows:

$$H_j=-\frac{1}{ln\ m}\sum_{i=1}^{m} r_{ij} ln\ r_{ij} \tag{8}$$

Then, the weight $w_j$ of each target is calculated:

$$w_j=\frac{1\text{-}H_j}{\sum_{j=1}^{n}(1\text{-}H_j)} \tag{9}$$

This method can automatically identify the amount of information of each target and assign it a corresponding weight, thereby avoiding the subjective bias caused by human weighting [20,21].

Next, the TOPSIS method is used to screen the compromise solution. It is assumed that the positive ideal solution $A^+$ and the negative ideal solution $A^-$ are:

$$A^+ = (\max_i r_{i1}, \max_i r_{i2}, ..., \max_i r_{in}) \tag{10}$$

$$A^- = (\min_i r_{i1}, \min_i r_{i2}, ..., \min_i r_{in}) \tag{11}$$

For any solution $i$, its distance to the positive and negative ideal solutions is:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} w_j (r_{ij} - a_j^+)^2} \tag{12}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} w_j (r_{ij} - a_j^-)^2} \tag{13}$$

The closeness $C_i$ is defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{14}$$

The one with the largest $C_i$ is the optimal compromise solution.

Through the entropy weight-TOPSIS method, this paper can quickly locate feasible solutions that take into account both economic and environmental benefits from a large number of Pareto solutions, enhancing the practicality and interpretability of the model results.

**Model Parameter Setting and Encoding Method**

In terms of chromosome structure design, this paper adopts a real number and binary mixed encoding strategy to meet the needs of various types of decision variables in the supply chain network [22,23]. The chromosome consists of three parts: supplier selection, production location layout, and transportation route allocation. The overall form is as follows:

$$X = [x_1^s, x_2^s, ..., x_i^s; y_1^p, y_2^p, ..., y_j^p; z_1^t, z_2^t, ... z_{k_t}^t] \tag{15}$$

where $x_i^s \in \{0,1\}$ indicates whether to select the $i$-th supplier; $y_j^p \in \{1,2,...,M\}$ indicates the location of the $j$-th factory; $z_k^t \in S_n$ indicates the node arrangement of the $K$-th transportation route.

To ensure that the generated solution satisfies the model constraints, this paper designs a feasibility repair mechanism, which is a correction strategy designed for situations where the solution violates the constraints during the model-solving process. When a solution violates the constraints, it is corrected in the following way:

$$x_i' = \begin{cases} x_i, & if\, g(x) \leq 0 \\ x_i - \alpha \cdot \nabla g(x), & otherwise \end{cases} \tag{16}$$

where $g(x)$ is the constraint function; $\alpha$ is the correction step; Here, $\nabla g(x)$ is actually defined as the integer variable differential gradient, which is used to adapt to the requirements for repairing feasible solutions in integer programming scenarios. Its specific calculation logic is as follows: For solutions that violate constraints, first identify the key decision variables, use the unit change of the variable value from 0 to 1 or 1 to 0 as the differential step size, and calculate the magnitude and direction of the impact of this change on the constraint function $g(x)$. If a unit change in a variable causes $g(x)$ to approach the direction that satisfies the constraint ($g(x) \leq 0$), then this change direction is the actual direction of $\nabla g(x)$. In formula (16), the correction step size $\alpha$ is simultaneously adjusted to a positive integer (1 or 2) to ensure that the adjusted variable still meets the integer or binary value requirements. Ultimately, through the logic of identifying key variables—calculating the differential direction—integer step size correction, the infeasible solution is repaired to the feasible domain.

Through the above parameter setting and encoding method, the model in this paper has good operability and scalability, and is suitable for textile green supply chain scenarios of different scales.

## EXPERIMENTAL DESIGN

The data source for this experiment is centered on the China Emission Accounts and Datasets (CEADs), which provides basic data on carbon emissions in different links and regions of the textile industry, providing authoritative support for the quantification of carbon emissions in the model. Carbon emission coefficients for key links, such as chemical fiber production, printing and dyeing processing, and logistics and transportation, are extracted from CEADs for the calculation of total carbon emissions. At the same time, combined with the public operation information of the textile industry cluster in the Yangtze River Delta region, economic parameters such as green raw material procurement costs and low-carbon technology transformation costs are supplemented to ensure the authenticity of the total operating cost accounting. The carbon trading-related data refers to the price fluctuation characteristics of the carbon market analysis module in CEADs, simulates the carbon price range of the national carbon market pilot from 2020 to 2023, and generates dynamic carbon price factors through time series processing to form a multi-scenario combination. All data are standardized. The specific time series construction process is as follows: First, based on the daily carbon price data of the national carbon market pilot from 2020 to 2023 in the CEADs carbon market analysis module, the data stationarity is verified by the Augmented Dickey-Fuller (ADF) unit root test; secondly, the ARIMA model is used to construct a dynamic carbon price series—the autoregressive term (AR) coefficient is set to 0.62 (reflecting the short-term continuity of carbon prices), the difference order d = 1, and the moving average term (MA) coefficient is set to -0.35. At the same time, the GARCH model is introduced to characterize the clustering of carbon price fluctuations; the model parameters are calibrated by the maximum likelihood estimation method, and finally five types of scenario dynamic carbon price factors are generated, including low carbon prices (40–50 CNY/ton), medium carbon prices (50–70 CNY/ton), high carbon prices (70–90 CNY/ton), fluctuating carbon prices (40–90 CNY/ton), and extremely high carbon prices (90–110 CNY/ton). Some data are described in Table 1:

Table 1. Part of CEADs Data

| Data Category | Specific parameters | Numerical range |
|---|---|---|
| Carbon emission coefficient | Chemical fiber production unit carbon emissions | 1.2-1.5 $kgCO_2e/kg$ |
| | Carbon emissions per unit of printing and dyeing processing | 6-9 $kgCO_2e/m^2$ |
| | Road transport carbon emission factors | 180-220 $gCO_2e/km{\cdot}t$ |
| Economic cost parameters | Price difference between recycled fiber and native fiber | 15%-25% |
| | Investment in printing and dyeing wastewater recycling equipment | 800,000-1.2 million CNY/set |
| Carbon trading parameters | Carbon price fluctuation range | 40-80 CNY/ton |
| Policy parameters | Green production subsidy ratio | 10%-15% |
| | Initial allocation coefficient of carbon quota | 0.8-1.0 |

To fully verify the performance of the improved NSGA-II algorithm proposed in this paper, three representative algorithms are selected for comparison: the first is the standard NSGA-II algorithm, which is the basic version of the improved algorithm in this paper and is used to verify the optimization effect of local search and dynamic mutation strategies; the second is the MOEA/D algorithm, which is a decomposition-based multi-objective algorithm commonly used in the field of supply chain optimization and is used to compare the solution performance of different algorithm frameworks under high-dimensional constraints; the third is the single-objective optimization algorithm, in which the minimum cost method focuses on minimizing operating costs and the minimum emission method focuses on minimizing carbon emissions. The two are used to highlight the irreplaceable role of multi-objective optimization in balancing the “cost-emission” conflict.

## RESULTS

### Multi-Dimensional Verification of Model Optimization Effect

To verify the actual optimization efficiency of the constructed MOMILP model in the textile green supply chain, the core indicators before and after optimization and the contribution of each link are analyzed, and the outcomes are displayed in Figure 1.

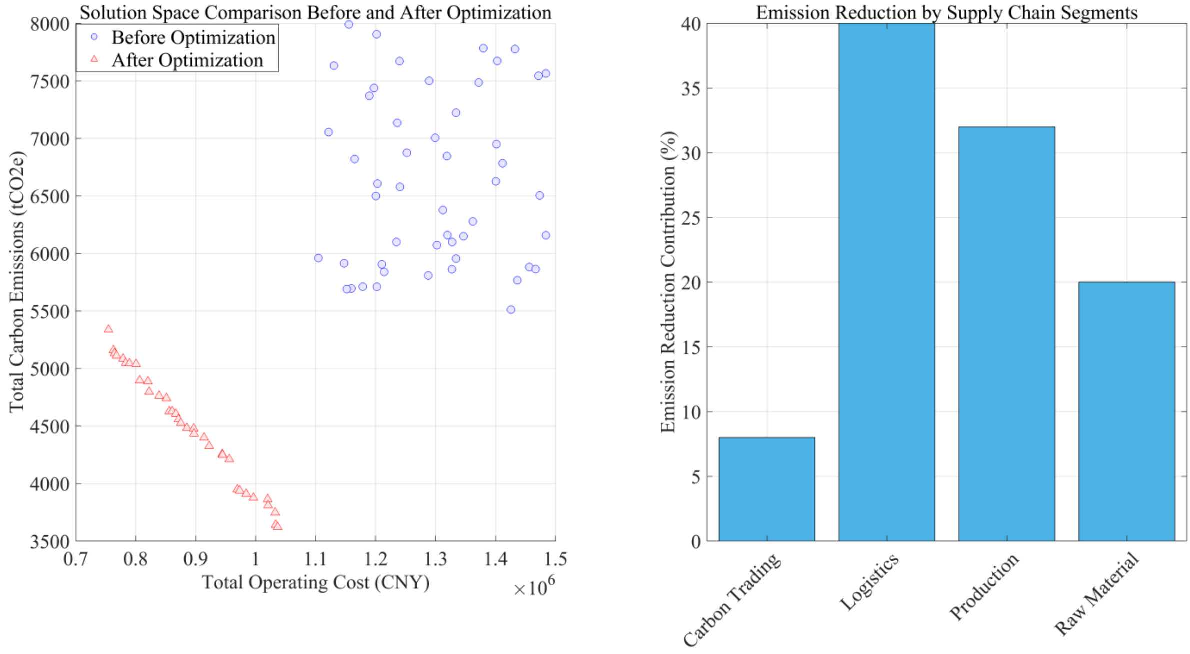


Figure 1. Core Indicators and Contribution of Each Link

In Figure 1, the optimized Pareto frontier solutions are all located at the lower left of the solutions before optimization, forming an obvious double-reduction area, and the cost is significantly reduced compared with before optimization, verifying the model's ability to coordinate optimization of cost and carbon emissions. Among the contributions of each link, the logistics and transportation link contributes the most to the total emission reduction, which is 40%, followed by the production and processing link, which is 32%. This indicates that transportation route optimization and production process transformation are the core means of emission reduction in the textile supply chain. Carbon quota trading refers to the process by which textile supply chain companies adjust their carbon quotas by buying and selling them through the carbon emissions trading market. Carbon quota trading has a relatively low contribution to overall emissions reductions, reflecting that, amidst the current volatility of carbon prices, companies are adopting a more conservative approach to adjusting their carbon quotas, relying more on direct emission reduction measures such as logistics optimization and production process improvements, rather than indirect emissions reductions through carbon market trading.

To further verify the adaptability of the model in different scenarios, Table 2 quantifies the optimization effect under different carbon price scenarios:

Table 2. Optimization Effect Under Different Carbon Price Scenarios

| Carbon Price Scenario (CNY/ton) | Cost Reduction Rate (%) | Carbon Emission Reduction Rate (%) | Number of Effective Solutions (pieces) | Algorithm Convergence Generation |
|---|---|---|---|---|
| Low (40–50) | 18.6 ± 1.2 | 22.3 ± 1.8 | 35 | 120 |
| Medium (50–70) | 21.5 ± 1.5 | 26.8 ± 2.1 | 38 | 150 |
| High (70–90) | 24.2 ± 1.8 | 30.5 ± 2.4 | 32 | 180 |
| Volatility (40–90) | 20.3 ± 2.0 | 25.1 ± 2.6 | 30 | 200 |
| Extremely High (90–110) | 25.8 ± 2.2 | 33.2 ± 2.8 | 28 | 220 |

The data in Table 2 show that the higher the carbon price, the more significant the cost and carbon emission reduction rate, reaching 24.2% and 30.5%, respectively, in the high carbon price scenario, indicating that the driving effect of carbon price increases on corporate emission reduction decisions has increased. However, in the scenario of carbon price fluctuations, the number of effective solutions decreases to 30, and the number of convergence generations increases to 200, reflecting that the uncertainty of carbon prices increases the difficulty of algorithm solution. Overall, the model can generate stable optimization solutions under various carbon price scenarios, verifying its adaptability to carbon market fluctuations.

**Comparative Algorithm Performance Evaluation**

The performance comparison results of the improved NSGA-II algorithm proposed in this paper and different algorithms are shown in Figure 2.

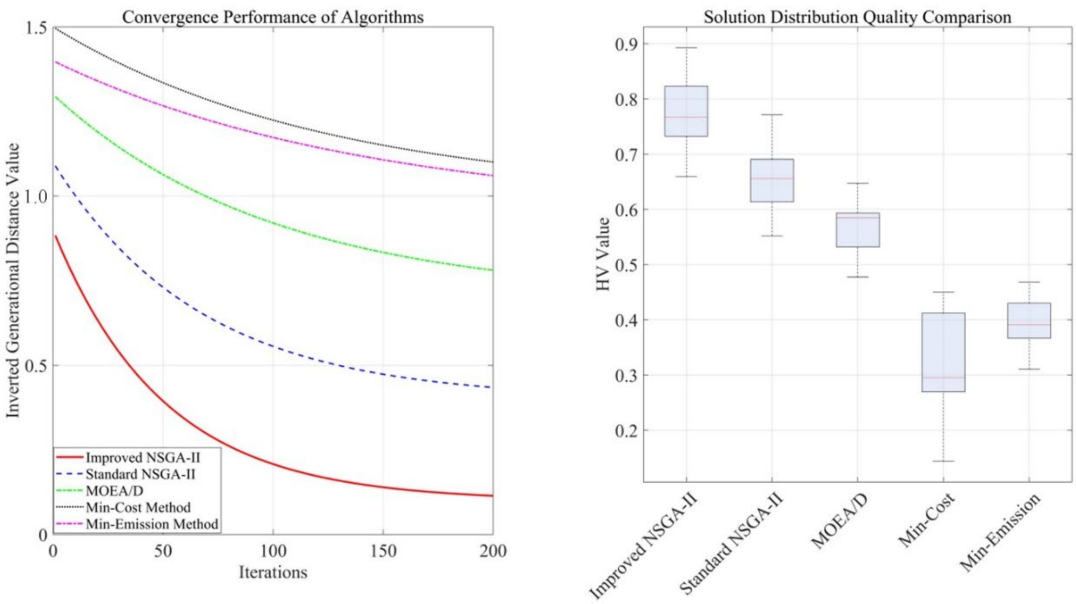


Figure 2. Performance Comparison of Different Algorithms

It can be seen that the Inverted Generational Distance (IGD) value of the improved NSGA-II drops to 0.18 after 100 iterations and tends to be stable, which is significantly lower than other algorithms. The standard NSGA-II lacks a local search mechanism, so it converges slowly and is prone to falling into local optimality. The decomposition efficiency of MOEA/D decreases when dealing with high-dimensional variables in the supply chain, resulting in high IGD values. Because the two single-objective algorithms focus solely on a single objective and fail to balance the constraints of the other objective, they achieve the highest IGD values and the worst convergence. The minimum emission method, while lower in emissions, results in uncontrolled costs, while the minimum cost method, while lower in costs, exceeds emission standards. Both algorithms struggle to adapt to practical decision-making needs. This result demonstrates the effectiveness of the proposed algorithm's local search for improved convergence accuracy and the dynamic mutation strategy for escaping local optima.

The median Hypervolume (HV) value of the improved NSGA-II is 0.75, which is significantly higher than that of other algorithms. The standard NSGA-II is 0.62; MOEA/D is 0.55; the HV values of the minimum cost method and the minimum emission method in the single-objective algorithm are 0.35 and 0.38, respectively. This shows that the solutions generated by the multi-objective algorithm are more evenly distributed and cover a wider range. In particular, the improved NSGA-II can find a better compromise solution in the cost-emission target space; the single-objective algorithm ignores the conflict of targets, and the diversity and practicality of the solution are obviously insufficient.

To quantify the performance differences of the algorithms, Table 3 compares the core indicators of each algorithm.

Table 3. Differences in Indicators of Different Algorithms

| Algorithm | Average IGD Value | Average HV Value | Solution Diversity Index | Calculation Time Taken (s) | Optimal Solution Proportion (%) |
|---|---|---|---|---|---|
| Improved NSGA-II | 0.18 | 0.75 | 0.82 | 58.6 | 78 |
| Standard NSGA-II | 0.35 | 0.62 | 0.68 | 52.3 | 62 |
| MOEA/D | 0.5 | 0.55 | 0.59 | 65.8 | 51 |
| Minimum Cost Method | 0.7 | 0.35 | 0.12 | 22.5 | 35 |
| Minimum Emission Method | 0.68 | 0.38 | 0.15 | 24.1 | 38 |

The data in Table 3 further confirm the performance differences of the algorithms. The improved NSGA-II performs best in terms of average IGD value, average HV value, and solution diversity index. In particular, the solution diversity index is 5–7 times that of the single-objective algorithm, indicating that it can generate more feasible solutions that take into account both cost and emissions. Although the standard NSGA-II takes less time to calculate, the proportion of optimal solutions is 16 percentage points lower than that of the algorithm in this paper, highlighting the necessity of improved strategies. Although the two single-objective algorithms have fast calculation speeds, they cannot balance the conflict between the two objectives, and the proportion of optimal solutions is less than 40%, which further illustrates the core value of multi-objective optimization in textile green supply chain decision-making.

### Synergistic Effect of Policy Tools

Four policy combination scenarios (no policy, carbon tax only, subsidy only, and carbon tax + subsidy) are set to analyze the impact of policy tools on supply chain optimization results, as displayed in Figure 3.

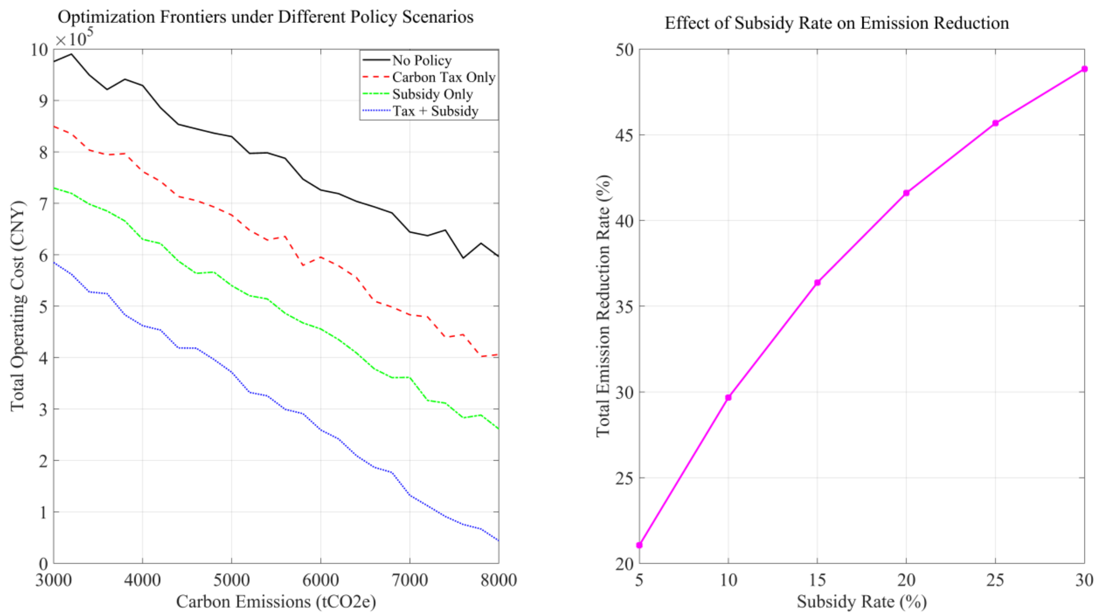


Figure 3. Supply Chain Optimization Results Under Different Policies

In Figure 3, the optimization frontier of the "carbon tax + subsidy" policy combination is the most to the lower left. Under the same carbon emission level, the cost is significantly lower than in other scenarios, which verifies the synergistic effect of the policy combination. Carbon tax forces enterprises to reduce emissions by increasing high emission costs, while subsidies encourage enterprises to transform by lowering the threshold for low-carbon transformation. The combination of the two forms a driving mechanism that emphasizes both rewards and punishments. When the subsidy intensity is higher than 5%, the emission reduction rate increases significantly with the increase of subsidies; after exceeding 15%, the marginal benefit decreases, suggesting that the policy needs to set an optimal subsidy range of 10%–15% to balance fiscal input and emission reduction benefits.

To further analyze the impact of the policy on each link, Figure 4 compares the link cost and emission changes under different policy scenarios:

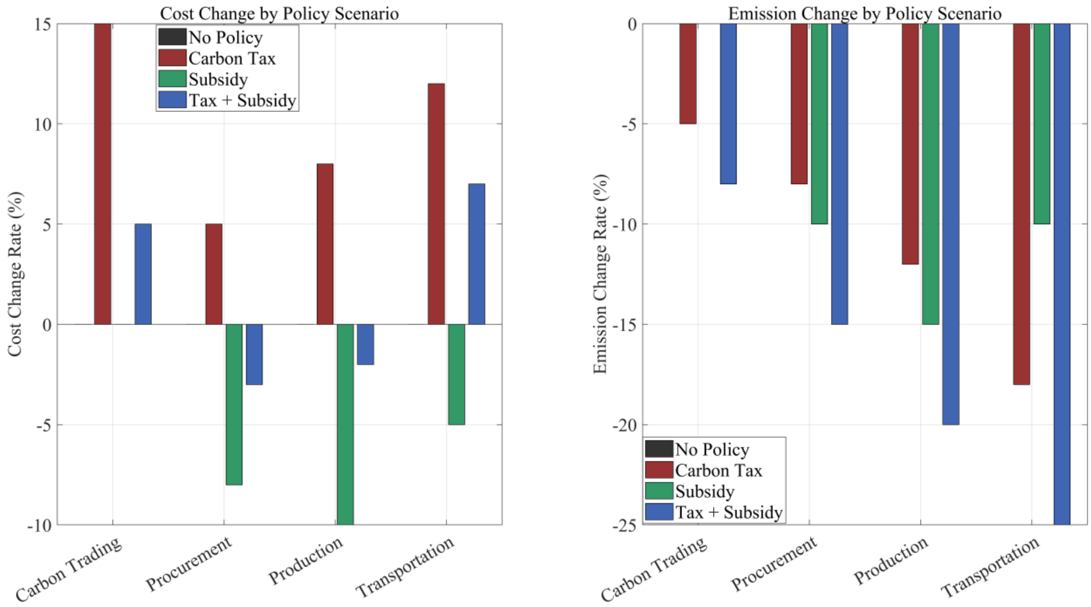


Figure 4. Link Cost and Emission Changes Under Different Policy Scenarios

In Figure 4, under the carbon tax scenario alone, the cost of transportation and carbon trading links has increased significantly, forcing companies to optimize transportation routes; under the subsidy scenario alone, the costs of production and procurement drop by 8%–10%, encouraging companies to choose green raw materials and low-carbon processes. Under the combined policy, the cost fluctuations of each link are small, ranging from -3% to 7%, achieving a balance between cost and emissions. In terms of emissions, the emission reduction of each link is the largest under the combined policy, with the transportation link reaching -25% and the production link reaching -20%, verifying the driving effect of the policy on emission reduction in the entire chain.

**Impact of Carbon Price Fluctuations on Supply Chain Resilience**

Carbon price fluctuations are a key variable that affects textile green supply chain decisions. To explore the cost and emission response of the supply chain under different fluctuations, three types of fluctuation scenarios of ±10%, ±20%, and ±30% are simulated based on CEADs carbon price data to analyze the dynamic impact of carbon price fluctuations on supply chain resilience. The results are shown in Figure 5.

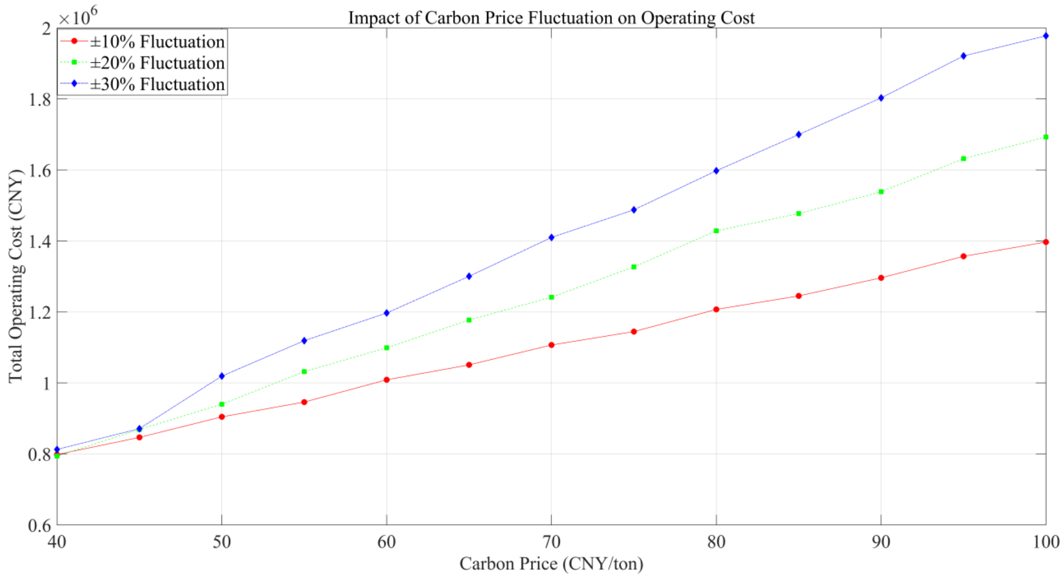


Figure 5. Relationship Between Carbon Price Fluctuations and Total Operating Costs and Carbon Emissions

Figure 5 shows that total operating costs increase linearly with rising carbon prices, and the greater the fluctuation, the more sensitive the costs are to carbon prices. When the carbon price increases from 40 CNY/ton to 100 CNY/ton, costs increase by 120,000 CNY under the ±30% fluctuation scenario, a significant increase compared to the ±10% fluctuation scenario. This is because companies must frequently adjust their carbon quota trading strategies under such high fluctuations, incurring additional transaction costs.

To further analyze the impact of carbon price fluctuations on various links in the supply chain, Figure 6 compares the changes in link costs and emissions under different fluctuation scenarios:

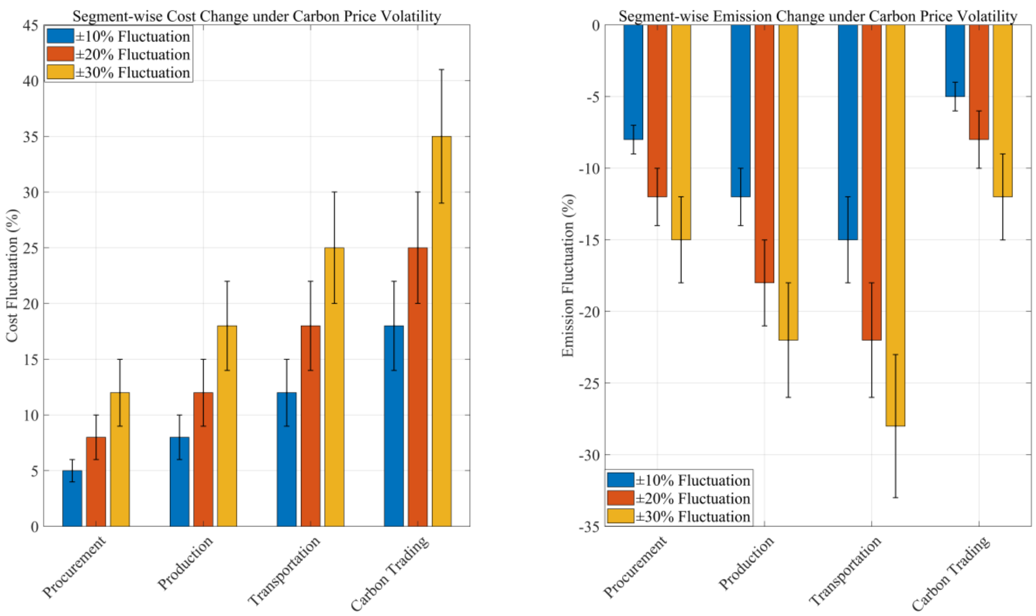


Figure 6. Changes in Link Costs and Emissions Under Different Volatility Scenarios

In Figure 6, the carbon trading link is most affected by volatility. Under the ±30% scenario, the cost fluctuation reaches 35%, far exceeding the second-ranked transportation link, because the carbon price directly determines the profit and loss of quota trading, followed by cost fluctuations in the production link, which is due to the rigid investment in low-carbon technology transformation. In terms of carbon emissions, the emission fluctuation in the transportation link is the most significant, at -28%; while the emission fluctuation in the procurement link is relatively stable, because the raw material selection decision cycle is long, and the sensitivity to short-term carbon price fluctuations is low.

**Sensitivity Analysis**

To further explore the impact of fluctuations in key parameters such as raw material costs, production costs, transportation costs, and green subsidy ratios on the model optimization results, the control variable method was used to simulate the variation of each parameter within the range of ±30%, and its dynamic effect on the total operating cost reduction rate and carbon emission reduction rate was analyzed. The results are shown in Figure 7.

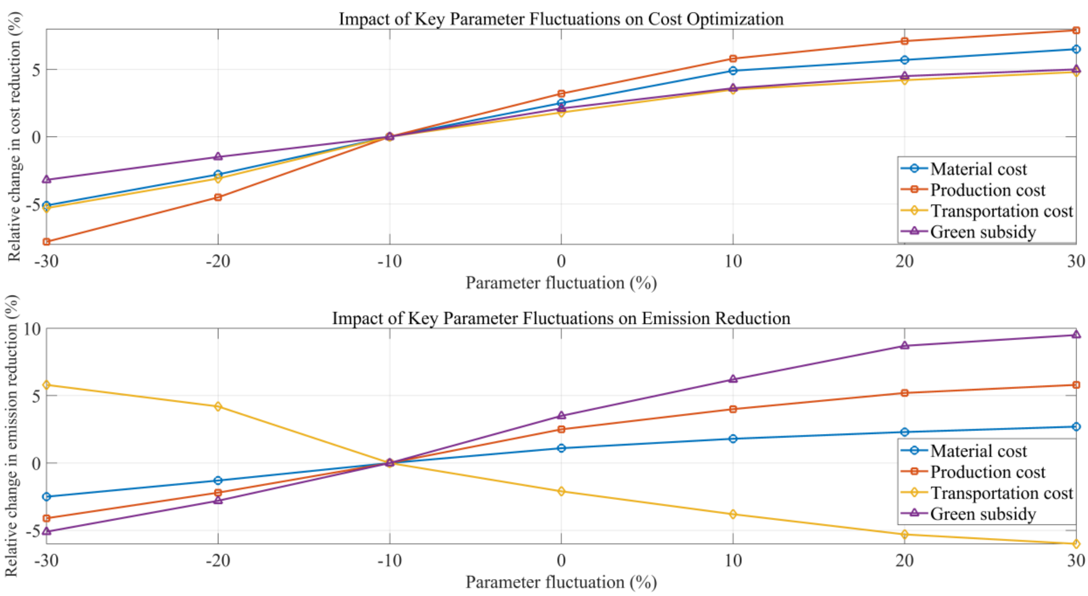


Figure 7. Impact of Key Parameter Changes on Model Optimization Results

Figure 7 clearly demonstrates the correlation between the fluctuations of various parameters and the cost reduction rate and carbon emission reduction rate. In terms of cost optimization, fluctuations in production costs have the most significant impact. When costs are reduced by 30%, the cost reduction rate increases by 7.1% relative to the baseline, demonstrating the critical role of production cost control in overall optimization. Transportation costs and the green subsidy ratio have relatively modest impacts, and the positive effect of subsidies remains stable. Regarding emissions reduction, an increase in the green subsidy ratio yields the most significant gains. These trends demonstrate the model's high sensitivity to production costs and green subsidy policies, providing a targeted reference for corporate decision-making and policy formulation.

## CONCLUSIONS

This paper aims at the emission reduction and cost balance problem of the textile green supply chain under the carbon neutrality goal, constructs a MOMILP that integrates the dynamic mechanism of carbon trading and multi-link collaborative optimization, and proposes a solution and decision-making framework of the improved NSGA-II algorithm combined with the entropy weight-TOPSIS method. The research results show that by applying carbon price volatility factors and combined policy tools, the model effectively depicts the impact of carbon market dynamics on supply chain decisions, and realizes the collaborative optimization of the entire chain—raw material procurement, production layout, transportation routes, and carbon quota trading. Experimental verification shows that the model can generate a stable Pareto optimal solution under different carbon price scenarios. Policy synergy analysis shows that the combination of carbon tax and green subsidy can significantly reduce costs, and the optimal subsidy range is 10%–15%. The research provides a quantitative tool for textile companies to cope with carbon market fluctuations and balance emission reduction and costs. It also provides theoretical support for policymakers to design green incentive mechanisms, which has practical significance for promoting the carbon-neutral transformation of the textile industry.

*Author Contributions*

All work in this study was independently completed by Renyi Qiu.

*Conflicts of Interest*

The author declares no conflict of interest.

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Not applicable.

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