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# OPTIMIZED DESIGN OF MULTI-LEVEL LOW-CARBON LOGISTICS DISTRIBUTION SCHEME BASED ON TWO STAGES

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## *Abstract:*

*The logistics network, as a key component of commodity distribution, has a direct impact on carbon emissions and resource utilization. Its main objective is to optimize the distribution process of commodities in order to improve efficiency, reduce costs, ensure timely delivery of commodities, and simultaneously satisfy customers' needs. The problem of multiple factors in the optimal allocation of logistics network objectives leading to decision-making difficulties is addressed. The complex multilevel logistics network optimization problem is decomposed into two stages. The first stage determines the selection of cargo transit points and the distribution of cargo flow between nodes, starting with the establishment of a Comprehensive Modal Emission Model (CMEM) taking into account the speed of the vehicle, the amount of cargo loaded, the road surface conditions and the characteristics of the vehicle itself. Secondly, the carbon emission cost generated from the flow of goods, together with the transportation cost, distribution cost and fixed cost at the transit point, constitute the comprehensive cost, and establish a multi-objective optimization model of low-carbon logistics network with the goal of minimizing the comprehensive cost and transportation time. The Non-dominated Sorted Genetic Algorithm with Elite Strategies (NSGA-II) is used for the solution. Finally, MATLAB software was used to numerically analyze the two schemes of "Considering Carbon Tax Levy" and "Not Considering Carbon Tax Levy". The results show that the government's imposition of an environmental tax on companies will change the distribution of transit points and flows within the logistics network, reducing CO2 emissions by 226.5 kg and saving 257.65 CNY in comprehensive costs. The second stage determines the order and path of distribution from each transit point to its own customers, establishes a low-carbon logistics network distribution path optimization model with the goal of minimizing the cost of carbon emissions, and solves the problem using Genetic Algorithm (GA). Through the coordinated use of the two-stage optimization model, it provides enterprises with a network distribution solution that takes into account the low-carbon goal and logistics efficiency, and provides the government with a basis for carbon tax levy and a reference for the tax rate.*

**Keywords:** *low-carbon logistics network, carbon tax, distribution scheme, NSGA-II algorithm*

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## 1. Introduction

With the vigorous development of economic globalization and the rapid growth of cargo transportation, logistics industry has become one of the important pillars to promote national economic development. However, the traditional logistics methods have problems such as waste of resources and environmental pollution, which not only affect the sustainable development of logistics industry, but also cause irreversible damage to the ecological environment of human society. China's logistics industry's high energy consumption, high emissions, high pollution, high costs and low timeliness problems need to be addressed. The government's commitment to carbon emissions per unit of GDP in the 14th Five-Year Plan period has also accelerated the transformation of China's logistics industry into a low-carbon industry.

The impact of the logistics activities of enterprises on the environment has received widespread attention from the society. In order to meet the environmental protection requirements of customers and the government, enterprises need to take up the social responsibility of environmental protection and take measures to reduce the negative impact of logistics activities on the environment. Logistics and distribution plan design usually requires determining elements such as facility location, transportation mode, transportation path, logistics flow and inventory. Most logistics and distribution program designs rely on facility location theory to establish mathematical models, including several categories ranging from linear deterministic models to nonlinear stochastic models (Li,2015). Low-carbon logistics and distribution solution design is to fully consider the factors of environmental protection and carbon emission, balance the economic and environmental objectives, minimize facility construction costs, transportation and distribution costs and inventory costs, reduce environmental pollution, and improve logistics efficiency on the basis of meeting customer needs.

In summary, the paper will study a three-tier logistics network designed to address facility selection, demand allocation and route selection in the flow involving factories, transit points and customers.

## 2. Literature review

Several types of research methods and models are covered regarding the optimization of low-carbon logistics and distribution scheme. In terms of multi-objective optimization, (Li et al, 2020) developed a multi-objective optimization model with the objectives of minimizing carbon emissions, distance traveled and number of vehicles used and solved it using a genetic algorithm, which showed that the overall solution of the improved algorithm outperformed the original algorithm, and the computation time was reduced by 37% compared to the original algorithm. In addition, (Masoud H et al., 2023) developed a multi-objective mixed integer linear programming model containing three dimensions of economic, environmental and social responsibility for solving open and closed route problems. The three objective functions of the model include minimization of total cost and greenhouse gas emissions, maximization of employment and economic development, and a small problem instance was solved using the Augmented Epsilon Constraint (AEC) method of the CPLEX optimization solver. In cold chain logistics, (Zhang et al.,2022) constructed low-carbon cold chain logistics distribution system optimization decision model using a two-layer planning method and solved the model with chaotic particle swarm algorithm. (Bao et al.,20 18) established a joint distribution path optimization model for cold chain logistics considering time window, carbon emission cost and cargo damage cost, transformed the multi-distribution center problem into a single distribution center problem by introducing a virtual yard, and solved the path optimization problem by using an improved genetic algorithm. In terms of linear programming, (Ji et al., 2021) found that scholars paid less attention to the cost of carbon emissions through the study of cold chain inventory paths and established a linear programming (LP) model, which mainly considered vehicle transportation costs, time windows, and carbon emission costs. Although the LP model is relatively simple, it is more innovative to develop the LP model into three low-carbon robust optimization models. (Elhedhli S et al., 2012) modeled the relationship between CO2 emissions and vehicle weight through a concave function, thus posing a concave minimization problem. Since it was not possible to solve the obtained model directly, a Lagrangian relaxation method was used to solve the problem. (Yang et al.,2016) proposed a new planning model for urban logistics distribution network under carbon emission tax constraints, which was simplified to a purely linear mixed integer programming by linearization. (Li et al.,2 017) used robust optimization method to build a robust hybrid linear programming model for remanufacturing logistics network with the objective of minimizing the sum of carbon trading revenue and expenditure and logistics cost and verified the feasibility of the robust model by case study.

In addition, (Zhu et al.,2021) considered the cost factor, time window, deterioration rate of agricultural products, inventory and distribution capacity, carbon trading mechanism, etc. to construct a low-carbon and environmentally friendly logistics site-path optimization model, introduce adaptive operator and disaster operator to improve the Genetic Algorithm (GA), and use it to solve the site path optimization problem in green logistics. (Liu et al., 2023) established a multi-objective optimization model based on dynamic train information, converted the multi-objective problem into a single-objective problem by weighting method, and designed a k-short-circuit optimization algorithm based on genetic algorithm.

In vehicle route optimization studies, different research teams have used different optimization methods and models to solve specific problems. For example, (Ren et al.,2022) constructed a mathematical model for route optimization with the objective of minimising total expenditure costs for individual customers, ecommerce business customers and the transport sector. (Büşra O et al., 2021) investigated the Green Vehicle Routing Problem for Simultaneous Pickup and Delivery (G-VRPSPD) with the goal of minimizing fuel consumption costs while meeting customer pickup and delivery needs. To solve the problem effectively, the researchers developed a hyper-heuristic (HH-ILS) algorithm based on iterative local search and variable neighborhood descent heuristics. The results show that the green objective function has a significant effect on the total fuel consumption cost. (Guo et al.,2022) established a time-dependent green vehicle routing problem with time windows model for cold chain logistics. This model aims to minimize the total cost, including the transportation cost, refrigeration cost, carbon emission cost, and labor cost. (Liu,2022) investigated the dual-objective hybrid fleet vehicle path problem with a time window, considering mainly the total operating costs incurred in the distribution process (including vehicle immobilization, transportation, charging, and carbon emission costs) as well as the time penalty costs. (Li et al.,2020) developed a multi-objective low carbon vehicle path optimization model with the objective of achieving the lowest total system cost and minimum vehicle turnaround time. (Yuan et al.,2021) proposed a set of coverage formulations for the generalized vehicle routing problem with time windows (GVRPTW) and provided a heuristic solution based on column generation.

In solving these problems, the research team used a variety of heuristic and meta-heuristic algorithms. For example, (Peng et al., 2021) solved the passenger travelling path problem by Genetic Algorithm (GA) and Monte Carlo simulation with the constraints of travelling cost and the number of interchanges, and the objective of the shortest total travelling time. (Tong,2022) established a two-layer model, the upper layer is the optimization model of the distribution centre location problem, which is solved by Quantum Particle Swarm Optimization (QPSO) algorithm. The lower layer is the optimization model of distribution path layout, which is solved by Ant Colony Optimization (ASO) algorithm. (Zhang et al.,2021) developed a multi-objective model based on low carbon and stochastic demand and designed a multi-objective genetic algorithm based on Pareto optimality. (Vincent F. Yu et al.,2023) investigated the vehicle routing problem with cross-docking distribution under demand uncertainty (VRPCD-DU) and proposed an efficient adaptive large neighborhood search (ALNS) algorithm for solving large instances. (Zhang et al., 2019) established a cold chain logistics path optimization model including carbon emission cost. Through the combination of nucleic acid calculation and ant colony optimization, the effect of unreasonable parameter selection on the performance of the algorithm is avoided. (Song et al.,2020) considered a canonical vehicle routing problem (VRP) in the cold chain logistic system, which includes three special constraints, namely a scheduling time window for each customer, different types of vehicles, and different energy consumption and capacity for each vehicle. The objective is to minimize the total cost and an Improved Artificial Fish Swarm (IAFS) algorithm is proposed to solve the model. In addition, some scholars have also studied multi-type green vehicle path optimization, (He et al., 2018) introduced the approximate calculation method of fuel consumption and carbon emission, established the Green Multi-type Vehicle Routing Problem with

Time Windows (GMVRPTW) to find environmentally friendly green paths, and meanwhile designed an improved taboo search algorithm to solve the problem.
In summary, the research results on the optimization of low-carbon logistics and distribution schemes mainly have the following shortcomings:

1. Most of the existing studies only consider one of the two, namely, the determination of the distribution scheme and the selection of vehicle paths, and seldom consider these two issues together, thus forming a more comprehensive and practical research framework.
2. The calculation of carbon emissions fails to take into account a variety of factors, such as load capacity, vehicle speed, road gradient, engine, windward area of the vehicle and fuel type.

Proper facility selection avoids wasted resources, optimized demand allocation improves transport efficiency, and route optimization reduces energy consumption. By addressing these issues, the logistics network can be made more environmentally friendly and cost-effective, while adapting to policy and social needs. To this end, this paper will study a three-tier logistics network, fully considering the combined effect of multiple influencing factors on carbon emissions, making the assessment of environmental benefits more accurate and comprehensive. Organic integration of two key aspects, the determination of distribution schemes and the selection of vehicle paths, achieves a more comprehensive and efficient optimization. The design includes issues such as facility selection, demand allocation and route selection in the flow of goods from factories, transit points and customers.

## 3. Problem Description

This paper focuses on the optimization of a multi-level logistics network based on a low-carbon perspective. The problems related to the selection of transit points, the distribution of transport and distribution volumes and the determination of transport routes in the whole multi-tier logistics network are optimally designed according to the different demands of customers for goods, taking into account the cost and time.

### 3.1. Problem Assumptions

The problem studied in this paper has the following six hypotheses:

1. The goods transported between factories, transit points, and customers are of the same type and do not take into account the time value of the goods.
2. The transportation cost, distribution cost, distance and time from the factory to the transit point and from the transit point to the customer are known values.
3. Transit points have capacity constraints, and their fixed costs, unit land value, area, and capacity are all known values.
4. The factory has a maximum supply capacity limit and the distribution vehicle has a maximum load limit.(Lv,2013).
5. Carbon emissions is a general term or abbreviation for greenhouse gas emissions, which include carbon dioxide, methane, nitrous oxide, hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and so on, and this paper calculates the emissions of carbon dioxide, which is the most abundant among them.
6. Transportation companies lack sensitivity to the carbon tax levy and the carbon tax rate.

### 3.2. Cost of Carbon Emissions

There are two sources of carbon emissions generated throughout the process of goods moving from the factory through the transit point and then to the final customer, one is generated by the logistics process and the other is generated by the transit point.

#### 3.2.1. Carbon Cost of Logistics Process

When calculating the carbon emissions caused by the logistics process, there are two main methods, the first is to use the amount of fuel consumed to calculate the carbon emissions with the following formula: Carbon emissions = fuel consumption × carbon emission factor. The second one is to monitor freight vehicles in real time and calculate the carbon emissions of different types of vehicles. The carbon emissions from vehicle travel are affected by various factors such as cargo capacity, vehicle speed, road gradient, engine, windward area of the vehicle and fuel type. The model used in this paper is the CMEM (Comprehensive Modal Emission Model) microscopic model which is applicable to multiple vehicle models (Leng,2021).
Fuel consumption rate *FCR* calculation method is shown in formula (1)

$$FCR = \varphi(\lambda N V_s + P/\eta)/\mu \quad (1)$$

Where: ***P*** is the total vehicle traction power, the calculation method is shown in the formula (2)

$$P = P_{tract}/\varepsilon + P_{acc} \quad (2)$$

Where: $\boldsymbol{P_{acc}}$ is the power demand associated with the operation of vehicle accessories (e.g., air conditioners, freezers), usually taken as 0; $\boldsymbol{P_{tract}}$ is the tractive power of the engine, calculated as in formula (3)

$$P_{tract} = \frac{Ma + Mg\sin\theta + 0.5C_d A\rho v^2 + MgC_r\cos\theta}{1000/v} \quad (3)$$

Where: ***M*** is the total weight of the vehicle, the calculation method is shown in the formula (4)

$$M = \omega + x_{ij} \quad (4)$$

Where: $\boldsymbol{\omega}$ is the weight of empty vehicle (kg); $\boldsymbol{x_{ij}}$ is the weight of cargo (kg).
The average speed of the vehicle is ***v*** over a distance $\boldsymbol{d_{ij}}$ from logistics node ***i*** to ***j***. The calculation of fuel consumption (L) is given in formula (5)

$$F_{ij} = \frac{FCR \cdot d_{ij}}{v\psi} = \frac{\tau(\lambda N V_S + P/\eta)d_{ij}}{v} \quad (5)$$

Where: $\tau = \varphi/\mu\psi$. Let $\gamma = 1/1000\varepsilon\eta$ , $\alpha = a + g\sin\theta + g C_r\cos\theta$, $\beta = 0.5C_d\rho A$ be obtained from logistics node ***i*** to transport $\boldsymbol{x_{ij}}$ units of goods to logistics node ***j***. The fuel consumption of the vehicle is shown in formula (6)

$$F_{ij} = \frac{\tau(\lambda N V_S + \gamma\omega\alpha v + \gamma x_{ij}\alpha v + \gamma\beta v^3)d_{ij}}{v} \quad (6)$$

A carbon emission factor is the amount of carbon emissions produced per unit of energy or activity (e.g., electricity generation or transportation). It is usually measured in kilograms or tons of carbon emissions, and its magnitude depends on the type of energy used and the technology, with different fuels and technologies producing different carbon emissions.
The carbon emission factor is calculated as follows: Carbon emission factor = Default value of net heating value (TJ/Gg) × Default value of effective carbon emission factor (Kg/TJ). According to the data published by *the Intergovernmental Panel on Climate Change* (*IPCC*), the default value of net heating value of gasoline/diesel is 43(TJ/Gg) and the default value of effective carbon emission factor is 74100(Kg/TJ), and the calculated carbon emission factor $\boldsymbol{e_0}$=2.67( kg/L). The carbon tax rate, a constant, is also added to the model to convert the carbon emissions throughout the transportation process into a corresponding carbon tax, which can also be referred to as the cost of carbon emissions
The cost of carbon emissions generated by a freight vehicle carrying $\boldsymbol{x_{ij}}$ units of cargo traveling between logistics nodes ***i*** and ***j*** is shown in formula (7)

$$E_{co_2}(x_{ij}) = c_0 e_0 F_{ij} \quad (7)$$

Where: $\boldsymbol{c_0}$ is the carbon tax rate (CNY/kg), taken as 0.1; $\boldsymbol{e_0}$ is the carbon emission factor (kg/L), taken as 2.67; $\boldsymbol{F_{ij}}$ is the fuel consumption (L).
The time spent by freight vehicles traveling between logistics nodes ***i*** and ***j*** is shown in formula (8)

$$T(x_{ij}) = t_{ij} f(x_{ij}) \quad (8)$$

Where: $\boldsymbol{t_{ij}}$ is the time generated by a single vehicle fully loaded traveling between logistics nodes ***i*** and ***j*** (h); $\boldsymbol{f(x_{ij})}$ is the number of trips, which is calculated as shown in formula (9)

$$f(x_{ij}) = \begin{cases} 1 & x_{ij} \le Q \\ 2 & x_{ij} > Q \end{cases} \quad (9)$$

The parameters used in the calculation and their values are shown in Tables 1 and 2.

Table 1. Common parameters of vehicles

| Parameters | Definition (unit) | Value |
|---|---|---|
| $\varphi$ | Mass ratio of fuel to air | 1 |
| $\eta$ | Efficiency of diesel engines | 0.45 |
| $\mu$ | Heat value of diesel fuel (kj/g) | 44 |
| $\varepsilon$ | Drive train efficiency | 0.4 |
| $a$ | Acceleration (m/s$^2$) | 0 |
| $\theta$ | Road slope | 0 |
| $\rho$ | Air density (kg/m$^3$) | 1.2041 |
| $g$ | Gravitational acceleration (m/s$^2$) | 9.81 |
| $\psi$ | Conversion parameter to convert fuel units from g/s to ls | 737 |
| $C_d$ | Air resistance coefficient | 0.7 |
| $C_r$ | Rolling resistance coefficient | 0.01 |

Table 2. Relevant parameters of freight vehicles

| Parameters | Definition (unit) | Value |
|---|---|---|
| $\omega$ | Empty vehicle weight(kg) | 6000 |
| $v$ | Vehicle speed (m/s) | 13.89 |
| $\lambda$ | Engine friction factor (kj/r/l) | 0.2 |
| $N$ | Engine speed (r/s) | 33 |
| $A$ | Windward area of the vehicle (m$^2$) | 8.16 |
| $Q$ | Maximum vehicle weight (kg) | 10000 |
| $V_s$ | Engine displacement(L) | 5 |

### 3.2.2. Cost of Carbon Emissions at Transit Points

The carbon emissions generated at a staging point depend on a number of factors, including the size of the facility, the type and energy efficiency of the energy used, the type of cargo and its volume, and the mode of transportation. Storage facilities consume significant amounts of electricity to keep goods in proper condition, as well as to maintain facilities such as lighting and ventilation systems.

The cost of carbon emissions generated at transit point $j$ transit point is shown in formula (10)

$$e_{co_2} = c_0 \delta g_j S_j \tag{10}$$

Where: $\boldsymbol{c_0}$ is the carbon tax rate (CNY/kg), taken as 0.1; $\boldsymbol{\delta}$ is the carbon emission factor (kg/kW·h) under the coal generation method, taken as 0.8; $\boldsymbol{g_j}$ is the amount of energy required per area of the transit point $\boldsymbol{j}$ (kW·h/m$^2$); $\boldsymbol{S_j}$ is the area of the transit point $\boldsymbol{j}$ (m$^2$).

## 4. Low-Carbon Logistics Network Optimization Model

### 4.1. Low-Carbon Logistics Network Multi Objective Optimization Model (Model-1)

In the optimization of low-carbon logistics network, delivery cost, delivery time and carbon emission become the three directions of optimization. Delivery cost optimization is an important way for enterprises to reduce operating expenses and improve economic efficiency, delivery time optimization is a necessary condition to meet customer demand and improve delivery efficiency, and carbon emission optimization is an important means for enterprises to fulfill their social responsibility and protect the environment. The carbon emission can be obtained by the product of fuel consumption and carbon emission factor, and further multiplied by the carbon tax rate to calculate the carbon emission cost, see formula (7), the carbon emission cost has the same magnitude as the transportation cost and the fixed cost of the transit point (CNY), and the three are combined into the comprehensive cost. So far the three optimization directions are converted into two optimization objectives, i.e. the lowest comprehensive cost and the smallest delivery time.

#### 4.1.1. Variable setting and meaning

The variables in the multi-objective optimization model of low-carbon logistics network and the meanings they represent are shown in Table 3.

Table 3. Variables and their significance in the model-1

| Variable Name | Meaning |
|---|---|
| $m(i=1\sim m)$ | Number of factories in the logistics network |
| $n(j=1\sim n)$ | Logistics Number of transit points in the network |
| $p(k=1\sim p)$ | Number of customers in the logistics network |
| $U_j$ | Maximum capacity of the $j^{th}$ transit point |
| $C_j$ | Opening cost of the $j^{th}$ transit point |
| $V_i$ | Maximum supply of factory $i$ |
| $d_k$ | Demand from customer $k$ |
| $c_{ij}^1$ | Unit transportation cost of transporting goods from factory $i$ to transit point $j$ |
| $c_{jk}^2$ | Unit delivery cost of delivering goods from transit point $j$ to customer $k$ |
| $t_{ij}^1$ | Transportation time of a fully loaded bicycle from factory $i$ to transit point $j$ |
| $t_{jk}^2$ | Delivery time of a fully loaded bicycle from transit point $j$ to customer $k$ |
| $x_{ij}$ | Volume of goods delivered from factory $i$ to transit point $j$ |
| $y_{jk}$ | Volume of goods delivered from transit point $j$ to customer $k$ |
| $z_j$ | Is 1 means open transit point $j$, otherwise 0 |

#### 4.1.2. Multi-Objective Optimization Model

Objective function:

$$\begin{aligned} min\, F_1 = &\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}^1 x_{ij} + \\ &\sum_{j=1}^{n}\sum_{k=1}^{p} c_{jk}^2\, y_{jk} + \sum_{j=1}^{n} C_j z_j + \\ &\sum_{j=1}^{n} e_{co_2}\, z_j + \sum_{i=1}^{m}\sum_{j=1}^{n} E_{co_2}(x_{ij}) + \\ &\sum_{j=1}^{n}\sum_{k=1}^{p} E_{co_2}(y_{jk}) \end{aligned} \tag{11}$$

$$min\, F_2 = \sum_{i=1}^{m}\sum_{j=1}^{n} T_{ij}(x_{ij}) + \sum_{j=1}^{n}\sum_{k=1}^{p} T_{jk}(y_{jk}) \tag{12}$$

Constraints:

$$\sum_{i=1}^{m} x_{ij} \leq U_j z_j \quad j = 1 \sim n \tag{13}$$

$$\sum_{k=1}^{p} y_{jk} \leq U_j z_j \quad j = 1 \sim n \tag{14}$$

$$\sum_{j=1}^{n} x_{ij} \leq V_i \qquad i = 1 \sim m \tag{15}$$

$$d_k \leq \sum_{j=1}^{n} y_{jk} \quad k = 1 \sim p \tag{16}$$

$$\sum_{k=1}^{p} y_{jk} \leq \sum_{i=1}^{m} x_{ij} \quad j = 1 \sim n \tag{17}$$

$$z_j \in \{0,1\}; x_{ij}, y_{jk} \geq 0 \tag{18}$$

The formula (11) is the objective function $\boldsymbol{F_1}$, the first two items represent the transportation cost from the factory to the transit point and the distribution cost from the transit point to the customer, and the third item represents the fixed cost of choosing the transit point; the fourth, fifth, and sixth items represent the carbon emissions generated by the energy consumption of the transit point, the carbon emissions from the transportation from the factory to the transit point, and the carbon emissions from the distribution from the transit point to the customer, respectively; The formula (12) is the objective function $\boldsymbol{F_2}$, and these two terms represent the transportation time from the plant to the transit point and the delivery time from the transit point to the customer, respectively. (Wang,2020). The formula (13) and (14) represent constraints on the capacity of the transit point, i.e., the flow of goods through a node cannot exceed the upper limit of the capacity of that node; The formula (15) indicates that the plant has a supply capacity constraint; The formula (16) ensures that the customer's demand is met; and the formula (17) ensures that the inflow of goods to the transit point is greater than or equal to the outflow of goods from it.

## 4.2. Low-Carbon Logistics Network Distribution Path Optimization Model (Model-2)

The purpose of this model is to find the sequence of delivery from the transit points to their customers in the low-carbon logistics network, i.e., the optimal solution of the distribution path, on the basis of meeting the needs of the customers, so as to minimize the carbon emission cost of the logistics network in the distribution stage. It is assumed that each transit point uses one delivery vehicle to fulfill the delivery task to its customers, and the delivery vehicle starts from the transit point and finally returns to the original transit point.

### 4.2.1. Variable Setting and Meaning

The variables in the distribution path model of the low-carbon logistics network and the meanings they represent are shown in Table 4

Table 4. Variables and their significance in the model

| Variable Name | Meaning |
|---|---|
| $s$ | Number of customers in the logistics network |
| $d_{ij}$ | Denotes the distance between logistics nodes *i* and *j* |
| $D_i$ | Denotes the demand of the $i^{th}$ customer |
| $q_{ij}$ | The cargo capacity of the vehicle en route from logistics node *i* to *j* |
| $g_{ij}$ | A value of 1 indicates that the route from logistics node *i* to *j* is selected, otherwise 0 |

### 4.2.2. Distribution Path Optimization Model

Objective function:

$$min\, f = \sum_{i=0, j\neq i}^{s} \sum_{j=0, j\neq i}^{s} E_{co_2}(q_{ij}) g_{ij} \tag{19}$$

Constraints:

$$\sum_{j=0, j\neq i}^{s} g_{ij} - \sum_{j=0, j\neq i}^{s} g_{ji} = 0 \quad i = 0 \sim s \tag{20}$$

$$\sum_{j=0, j\neq i}^{s} q_{ji} - \sum_{j=0, j\neq i}^{s} q_{ij} = D_i \quad i = 1 \sim s \tag{21}$$

$$\sum_{j=0, j\neq i}^{s} g_{ij} = 1 \quad i = 1 \sim s \tag{22}$$

$$d_k \leq \sum_{j=1}^{n} y_{jk} \quad k = 1 \sim p \tag{23}$$

$$q_{ij} \geq 0, g_{ij} \in \{0,1\} \quad i,j = 0 \sim s \tag{24}$$

The formula (19) is the objective function indicating that the carbon cost of the transportation process is minimized; The formula (20) indicates that the vehicle arrives at a customer and must leave from that customer; The formula (21) indicates the flow balance; The formula (22) indicates that each customer can be served by one vehicle; and the formula (23) indicates the maximum load limit.

## 5. Algorithm Design

This paper studies the problems related to transit point selection, capacity allocation and transportation path in multi-level logistics networks. For the optimization model Model-1, the model belongs to the multi-objective mixed integer programming problem, which is difficult to be solved quickly by traditional algorithms, and is mostly solved by applying heuristic optimization algorithms. Usually, the multi-objective optimization problem is transformed into a single-objective problem to solve. Although this method can simplify the calculation, only one optimal solution can be obtained, and the multi-objective optimal solution set cannot be obtained, nor can the solution be flexibly adjusted according to different transportation demands. In addition, single objective planning cannot cope with the diversity of decision objectives in realistic situations, so a more integrated approach is needed to solve such problems, which will be solved in this paper using the nondominated ranking genetic algorithm with elite strategy (NAGA-II). The superiority of the NSGA-II algorithm is verified by comparing it with the conventional Paretosearch Algorithm in solving the Pareto frontier. For the optimization model Model-2, this path optimization problem is solved using genetic algorithm (GA) in combination with the above problem feature analysis.

### 5.1. NSGA-II Algorithm

In 2000, Deb proposed an improved algorithm of NSGA, the Non-dominated Sorting Genetic Algorithm with Elite Strategy (Non-dominated Sorting Genetic Algorithm-II, NSGA-II),(Gao, 2006). The specific flow of the algorithm is shown in Fig. 1.

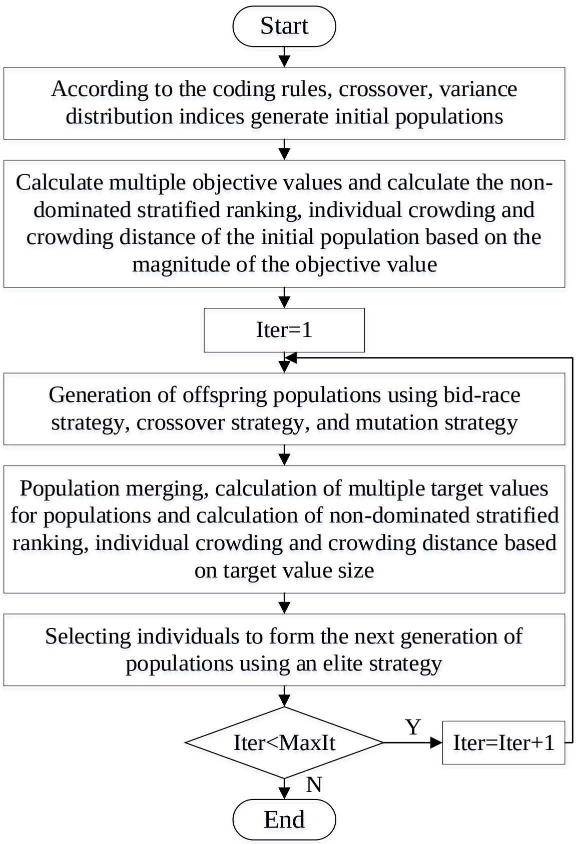


Fig. 1. NSGA-II algorithm flow chart

The detailed algorithm design of this paper is as follows.

**Step1:** Initial population generation, chromoso-mes are coded using real numbers, and their numbers are determined by the decision variables $x_{ij}$, $y_{jk}$ , $z_j$ and the constraints $i \times j + j \times k + j$, and the specific chromosome coding is shown in Fig. 2

**Step2:** Find the individuals in the initialized population that cannot be dominated by other individuals and the corresponding set of individuals dominated by these individuals and put them into the first layer.

**Step3:** Excluding the individuals in the first level, continue to find the remaining individuals that cannot be dominated by other individuals and the corresponding set of individuals dominated by these individuals and put them into the second level until each individual is attributed to the corresponding level.

**Step4:** Calculate individual crowding degree and crowding distance (Li,2022). The crowding degree of the $i^{th}$ individual is defined as the side length of the rectangle formed by the two nearest individuals $i$-1 and $i$+1 in the nondominated solution set at its level, as shown in Fig. 3. The two sets of crowding degrees $f_1$ , $f_2$ in the same individual are summed to the crowding distance.

There are $d$ individuals in a layer, and these individuals are arranged from largest to smallest according to the objective function value $f_1$ , so that $q = f_1^{max_1^{min}}$; similarly, these individuals are arranged from largest to smallest according to the objective function value $f_2$ , so that $p = f_2^{max_2^{min}}$ , then the crowding degree of the $i^{th}$ individual about the direction of $f_1$ is shown in formula (23), and the crowding degree about the direction of $f_2$ is shown in formula (24), and the denominator terms $q$ and $p$ serve to normalize.

$$C_{f_1} = [f_1(i+1) - f_1(i-1)]/q \\ i = 2, \cdots, d-1 \tag{23}$$

$$C_{f_2} = [f_2(i+1) - f_2(i-1)]/p \\ i = 2, \cdots, d-1 \tag{24}$$

**Step5:** Use the bidding race strategy: randomly select two individuals $i$ and $j$ from the parent $N$ individuals, and compare the non-dominance ranking level of the two in preference to the individual with high non-dominance ranking level. That is, $i_{rank} < j_{rank}$, then the $i^{th}$ individual is retained; if the non-dominance ranking levels of the two are the same, then the individual with the higher crowding degree crowding distance is selected in preference. i.e. $i_{rank} = j_{rank}$ and $i_d > j_d$ then the $i^{th}$ individual is retained. Execute $N$/2 bidding tournament selection to get $N$/2 individuals.

**Step6:** Select the crossover probability $P_c$ =0.8, choose two individuals randomly from $N$/2 indi-viduals, this paper uses simulated binary crossover to get two new individuals. After $N$/2 cycles, $Q$ new children individuals are finally obtained.

The calculation using simulated binary crossover (SBX) to generate two offspring individuals can be calculated by formula (24) (Bao,2023)

$$\begin{cases} x_i^{new} = 0.5 \times [(1+\beta)x_i + (1-\beta)y_i] \\ x_i^{new} = 0.5 \times [(1-\beta)x_i + (1+\beta)y_i] \end{cases} \tag{24}$$

Among them

$$\beta = \begin{cases} (r \times 2)^{\frac{1}{1+\eta}} & r \le 0.5 \\ (\frac{1}{2-r\times 2})^{\frac{1}{1+\eta}} & \text{otherwise} \end{cases} \tag{25}$$

$\boldsymbol{r}$ is a random number and $r \in [0,1]$ , usually $\boldsymbol{r} \le \boldsymbol{P_c}$, $\boldsymbol{\eta}$ is a custom parameter value, the larger the value, the closer the resulting offspring individuals are to the parent individuals, in this paper we take 20.

**Step7:** Select the variation probability $P_m$ =0.8 , choose an individual randomly from $N$/2 individuals, and use polynomial variation method in this paper to get a new individual. Finally, $R$ new offspring individuals are obtained.

The procedure to calculate the generation of offspring individuals $x_i^{new}$ from parent individuals $\boldsymbol{x_i}$ using the polynomial variation method is shown in formula (26)

$$x_i^{new} = x_i + \beta_i \tag{26}$$

Among them

$$\beta_i = \begin{cases} (2u_i)^{\frac{1}{\eta_u+1}} - 1 & u_i < 0.5 \\ 1 - [2(1-u_i)]^{\frac{1}{\eta_u+1}} & u_i \ge 0.5 \end{cases} \tag{27}$$

$\boldsymbol{u_i}$ is a random number and $\boldsymbol{u_i} \in [0,1]$ , $\boldsymbol{\eta_u}$ is a custom non-negative real number, this paper takes 20.

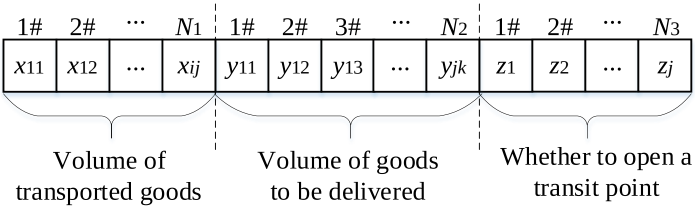

Fig. 2. Chromosome coding

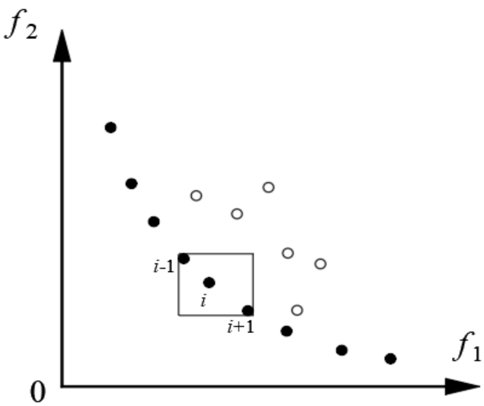

Fig. 3. Individual crowding degree

**Step8:** The parent and child populations are merged to form a population size of $N+Q+R$ individuals. This new population is then subjected to non-dominated hierarchical sorting and crowding calculation.

**Step9:** Use the elite strategy to select $N$ individuals from $N+Q+R$ individuals to form the next generation of new populations, giving preference to individuals with high hierarchical ranking, and if the ranking is the same, giving preference to individuals with large crowding distances, as shown in Fig. 4.

**Step10:** See if the maximum number of iterations 500 is reached, if not, return to **Step4**, if it is reached, end and output the Pareto optimal solution.

### 5.2. Genetic Algorithm

Genetic algorithm (GA) is an optimization algorithm inspired by natural evolutionary theory. It simulates the basic operations of selection, crossover and mutation in biological evolution, and searches the candidate solutions in the solution space iteratively to find the optimal solution or a solution close to the optimal solution step by step. The detailed process of the genetic algorithm is relatively simple compared with the NSGA-II algorithm, and will not be repeated in this paper.

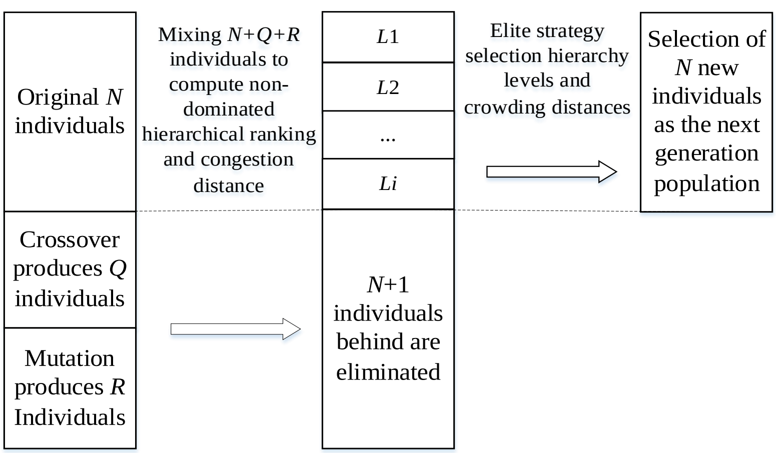

Fig. 4. Elite selection strategy

## 6. Example analysis

The modeling solution in this paper is a three-level logistics network containing three factories, four transit points and six customers, as shown in Fig. 5

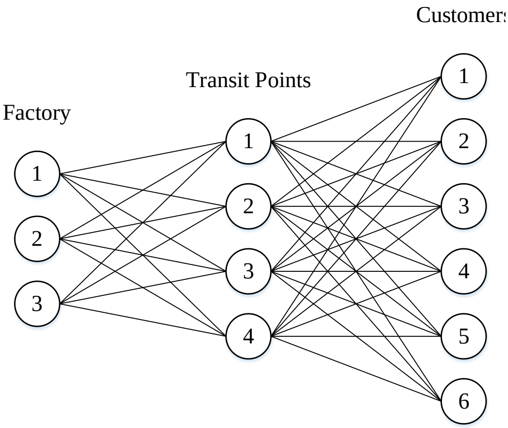


Fig. 5. Actual logistics network

According to the data shown in Tables 5 to 13, it is possible to know the customer's demand, the data about the transit points, and the unit freight, distance and time between each logistics node.

Table 5. Customer demand

| **Customers** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| **Demand(t)** | 7 | 5 | 3 | 4 | 6 | 5 |

Table 6 Factory supply capacity

| **Factory** | **1** | **2** | **3** |
|---|---|---|---|
| **Supply capacity(t)** | 12 | 15 | 12 |

Table 7. Data related to transit points

| **Transit Points** | **1** | **2** | **3** | **4** |
|---|---|---|---|---|
| **Capacity(t)** | 18 | 16 | 15 | 15 |
| **Opening fee (CNY)** | 150 | 130 | 125 | 125 |
| **Area ($m^2$)** | 675 | 600 | 575 | 550 |
| **Amount of energy required per area ($kW{\cdot}h/m^2$)** | 0.5 | 0.5 | 0.5 | 0.5 |

Table 8. Unit transportation cost from factory to transit point (CNY/t)

| **Factory** | **Transit Points** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| **1** | 3 | 7 | 1 | 5 |
| **2** | 4 | 9 | 6 | 4 |
| **3** | 4 | 4 | 7 | 2 |

Table 9. Unit distribution cost from transit point to customer (CNY/t)

| **Transit Points** | **Customers** | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| **1** | 3 | 3 | 7 | 4 | 7 | 5 |
| **2** | 5 | 10 | 5 | 2 | 8 | 9 |
| **3** | 3 | 5 | 4 | 6 | 7 | 8 |
| **4** | 5 | 5 | 8 | 9 | 5 | 8 |

Table 10. Distance from transit point to customer (km)

| **Transit Points** | **Customers** | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| **1** | 59 | 50 | 72 | 49 | 67 | 76 |
| **2** | 70 | 31 | 34 | 51 | 64 | 61 |
| **3** | 42 | 39 | 66 | 74 | 69 | 51 |
| **4** | 49 | 69 | 63 | 52 | 70 | 68 |

Table 11. Time from factory to transit point (h)

| **Factory** | **Transit Points** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| 1 | 1.26 | 1.10 | 1.14 | 1.12 |
| 2 | 1.36 | 0.96 | 1.12 | 1.30 |
| 3 | 1.24 | 1.06 | 1.04 | 1.20 |

Table 12. Distance from factory to transit point (km)

| **Factory** | **Transit Points** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| 1 | 63 | 55 | 57 | 56 |
| 2 | 68 | 48 | 56 | 65 |
| 3 | 62 | 53 | 52 | 60 |

Table 13. Transit point to customer time (h)

| **Transit Points** | **Customers** | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** |
| 1 | 1.18 | 1.00 | 1.44 | 0.98 | 1.34 | 1.52 |
| 2 | 1.40 | 0.62 | 0.68 | 1.02 | 1.28 | 1.22 |
| 3 | 0.84 | 0.78 | 1.32 | 1.48 | 1.38 | 1.02 |
| 4 | 0.98 | 1.38 | 1.26 | 1.04 | 1.40 | 1.36 |

### 6.1. Low-Carbon Logistics Network Multi-Objective Optimization Model Solution

The NSGA-II algorithm program is written using the model in Section 4.1 in conjunction with Ma-tlab software running on a computer with an Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz. Input the data in Table 5~13, encode the parameters of the actual problem of goods going from the factory to the customer via the transit point, generate the initial population, then perform the calculation of hierarchical sorting and congestion, perform the operation of crossover, variation, etc. in turn, and then generate new populations according to the elite strategy until the termination condition is satisfied and exit the ou-tput result. Let the carbon tax rate be $c_0$ = 0, 0.1 (CNY /kg), respectively, and compare the distribution scheme when carbon emissions are considered with and without carbon emissions.

#### 6.1.1. Results Solving

The program was set with the parameters: population size of 200, iteration number of 500, crossover probability of 0.8, and variation probability of 0.1, and computed in Matlab R2021b environment.

(1) Not considering carbon tax levy

The average Pareto distances between individuals and the Pareto frontiers of the distribution schemes are shown in Figures 6 and 7. A set of Pareto optimal solutions is selected for analysis and the results are obtained by solving using Matlab software as:

$X$=[3,9,0,0,0,6,0,0,0,0,0,12,0]

$Y$=[3,0,0,0,0,0,0,0,5,3,4,0,3,4,0,0,0,6,2,0,0,0,0,0,0,0]

$Z$=[1,1,1,0]

Distribution scheme I was obtained after chromosome decoding, as shown in Figure 10.

(2) Considering carbon tax levy

The average Pareto distances between individuals and the Pareto frontiers of the distribution schemes are shown in Figures 8 and 9. A set of Pareto optimal solutions is selected for analysis and the results are obtained by solving using Matlab software as:

$X$=[12,0,0,0,6,0,0,0,0,0,0,12,0]

$Y$=[0,5,3,4,1,5,0,0,0,0,0,0,7,0,0,0,5,0,0,0,0,0,0,0,0]

$Z$=[1,0,1,0]

Distribution scheme II was obtained after chromosome decoding, as shown in Figure 11.

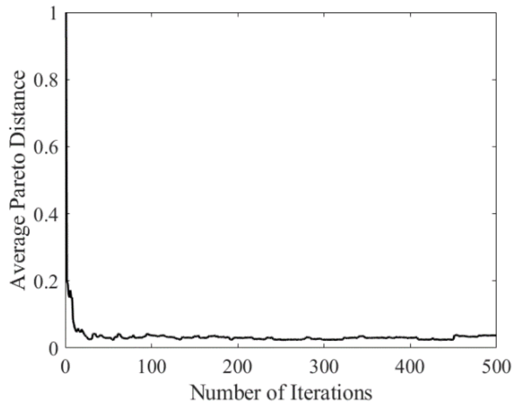


Fig. 6. Average Pareto distance between individuals when the carbon tax rate is zero

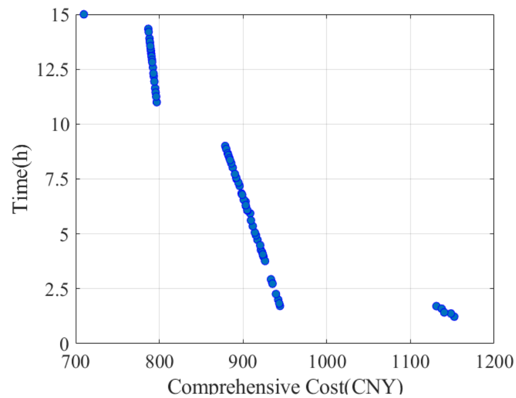


Fig. 7. Pareto frontier when carbon tax rate is zero

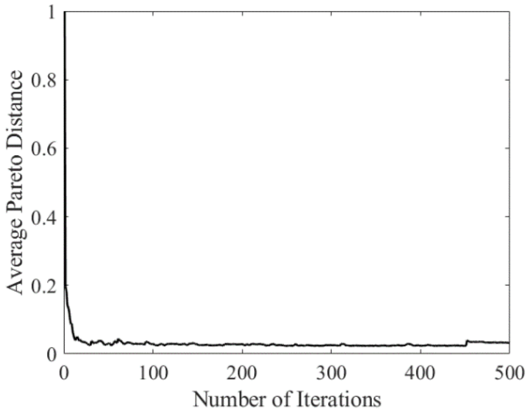


Fig. 8. Average Pareto distance between individuals when the carbon tax rate is 0.1

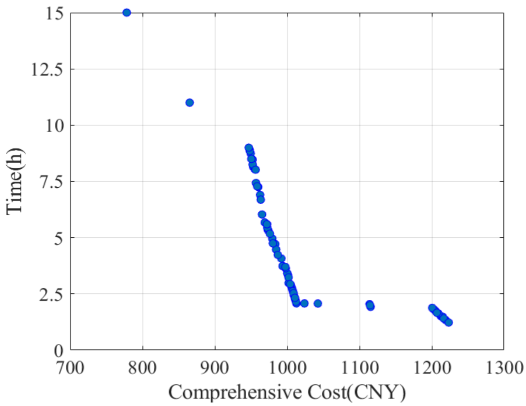


Fig. 9. Pareto frontier when carbon tax rate is 0.1

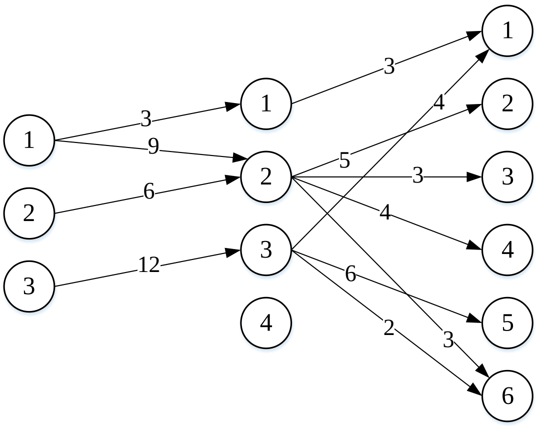


Fig. 10. Optimal solution when carbon tax rate is zero

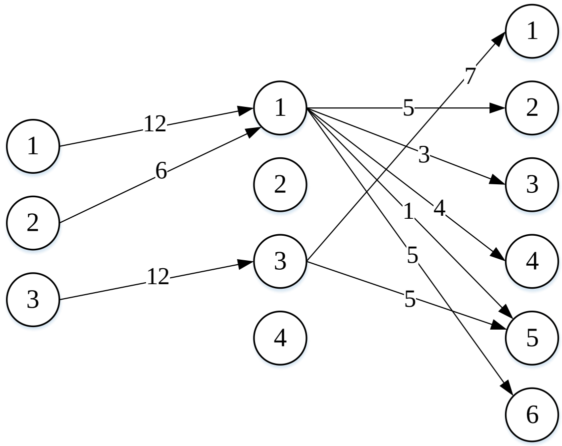


Fig. 11. Optimal solution when carbon tax rate is 0.1

### 6.1.2. Algorithm Performance Analysis

In terms of solving multi-objective planning models for logistics networks, while the built-in traditional solution function algorithms provided by the MATLAB software perform well in many contexts, however, when compared to the meta-heuristic algorithms, they clearly present some noteworthy shortcomings. This comparison highlights the limitations of traditional solver algorithms when dealing with complex or highly nonlinear problems, whereas metaheuristic algorithms are better suited to cope with these challenging tasks. Therefore, when selecting a problem solving method, the advantages and disadvantages of both methods need to be weighed against the nature and requirements of the particular problem in order to obtain the best solution. The Pareto front is obtained by solving using Paretosearch Algorithm, a built-in function algorithm of MATLAB software is shown in Figures 12, 13.

The Pareto front obtained using the solution function algorithm that comes with the MATLAB software contains only 4 sets of solutions, whereas the Pareto front obtained through the NSGA-II algorithm contains 70 sets of solutions, which clearly indicates that the NSGA-II algorithm exhibits higher performance and potential in multi-objective optimization problems. This discrepancy highlights the limitations of traditional solution methods when dealing with multi-objective optimization and the capability of meta-heuristic algorithms, especially when dealing with complex problems. The NSGA-II algorithm is able to provide a richer set of solutions, which helps the decision maker to make a more comprehensive choice between different trade-offs and trade-offs. Therefore, it is more reasonable to choose the NSGA-II algorithm for multi-objective optimization problems of logistics networks in order to better explore the problem space and obtain more potential optimization solutions.

### 6.1.3. Analysis of Results

The heuristic algorithm explores the solution space through a series of strategies and rules and tries to find a more superior solution in an acceptable time. Observe the trend of the curve of average Pareto distance between individuals and the number of iterations, the curve begins to decline faster, indicating that the algorithm has found some solutions in a shorter period of time; with the increase in the number of iterations, the decline of the curve slows down, and eventually the curve tends to stabilize, indicating that the distance of the solutions in the solution set that the algorithm has found with respect to the Pareto front is no longer changing significantly and the algorithm's search in the solution space has stabilized and no more big fluctuations.

The specific cost and time for the two schemes are shown in Table 14.

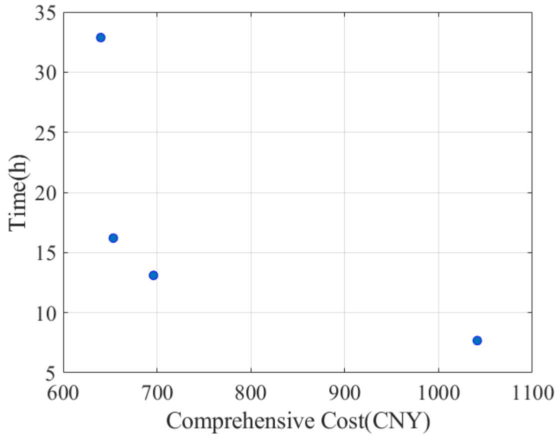

Fig. 12. Pareto frontier solved by the Paretosearch when the carbon tax rate is zero

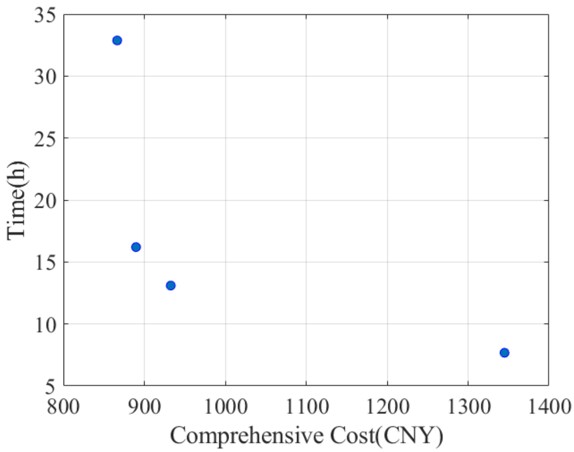

Fig. 13. Pareto frontier solved by the Paretosearch when the carbon tax rate is 0.1

Table 14. Pareto optimal solution

| | | **Scheme I ($c_0$=0)** | **Scheme II ($c_0$=0.1)** |
|---|---|---|---|
| **Cost(CNY)** | Transportation | 210.00 | 144.00 |
| | Distribution | 179.00 | 140.00 |
| | Fixed costs at transit points | 405.00 | 275.00 |
| | Total | 794.00 | 559.00 |
| **Carbon emissions (kg)** | Transit point carbon emissions | 740.00 | 500.00 |
| | Transportation, distribution carbon emissions | 613.00 | 626.50 |
| | Total | 1353.00 | 1126.50 |
| **Total carbon cost (CNY)** | | 0 | 112.65 |
| **Time(h)** | Transportation | 5.40 | 4.92 |
| | Distribution | 7.96 | 8.50 |
| | Total | 13.36 | 13.42 |

When the government has not levied environmental protection tax on the enterprise, Scheme I is the optimal distribution plan for the enterprise, although the carbon tax rate is 0, but the vehicle will still produce carbon emissions in the distribution process, when the carbon tax rate is 0.1 CNY/kg, the cost of carbon emissions from the transit point of Scheme I and the cost of carbon emissions from transportation and distribution total 135.3 CNY (carbon emissions are 1353 kg). When the government levies an environmental tax on the enterprise, the optimization scheme changes, abandoning transit point 2, and the enterprise's distribution scheme changes from the original scheme I to scheme II, and the carbon emission cost of the transit point as well as the carbon emission cost of transportation and distribution of scheme II totals 112.65 CNY (carbon emissions of 1126.5 kg). Comparing the two schemes, it can be seen that although the total time increases by 0.06 hours, the change in the scheme reduces the carbon emissions and the overall cost, and the change in the specific distribution route reduces the carbon dioxide emissions by 226.5 kg and saves 257.65 CNY in the overall cost.

### 6.2. Low-Carbon Logistics Network Distribution path optimization model solving

Using the scheme obtained in Section 6.1.1, the distance data between the required customers are shown in Table 15.

#### 6.2.1. Vehicle Distribution Routes for Scheme I

(1) Solution based on transit point 1

For transit point 1, 3t of goods need to be delivered to customer 1.

The optimal route is to deliver 3t of cargo from transit point 1 to customer 1, unload 3t and then return from customer 1 to transit point 1. The specific route is shown in Table 16.

(2) Solution based on transit point 2

For transit point 2, 5t, 3t, 4t and 3t of goods need to be delivered to customers 2, 3, 4 and 6, respectively. the iterative process is shown in Fig 14.

The optimal distribution route is divided into two stages. The specific routes are shown in Table 17.

The first stage is: 5t of cargo is delivered from transit point 2 to customer 2, 5t is unloaded and then returned to transit point 2 from customer 2. The second stage is: 10t of cargo is delivered from transit point 2 to customer 3, 3t of cargo is unloaded and 7t of cargo is delivered from customer 3 to customer 4, 4t of cargo is unloaded and 3t of cargo is delivered from customer 4 to customer 6, 3t of cargo is unloaded and then returned to transit point 2 from customer 6.

(3) Solution based on transit point 3

For transit point 3, 4t, 6t and 2t of goods need to be delivered to customers 1, 5 and 6 respectively. the iterative process is shown in Fig. 15.

The optimal distribution route is divided into two stages. The specific routes are shown in Table 18.

The first stage is: delivery of 4t cargo from transit point 3 to customer 1, unloading of 4t and then return to transit point 3 from customer 1. The second stage is: 8t of cargo is transported from transit point 3 to customer 6, 2t is unloaded and then 6t of cargo is transported from customer 3 to customer 5, 6t is unloaded and then returned to transit point 3 from customer 5.

Table 15. Distance between customers (km)

| customer | customer | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| 1 | 0 | 19 | 32 | 21 | 27 | 18 |
| 2 | 19 | 0 | 28 | 25 | 24 | 24 |
| 3 | 32 | 28 | 0 | 15 | 20 | 25 |
| 4 | 21 | 25 | 15 | 0 | 16 | 20 |
| 5 | 27 | 24 | 20 | 16 | 0 | 17 |
| 6 | 18 | 24 | 25 | 20 | 17 | 0 |

Table 16. Optimal route for transporting goods at transit point 1

| Stage | Transit point 1 | | | |
|---|---|---|---|---|
| | **Route** | $q_{ij}$ | $d_{ij}$ | $E_{co_2}(q_{ij})$ |
| 1 | Transit point 1 $\overset{3t0t}{\rightleftarrows}$ Customer 1 | 3 | 118 | 6.08 |
| Delivering 3t of goods with a distance of 118km, the carbon emission cost is 6.08 CNY | | | | |

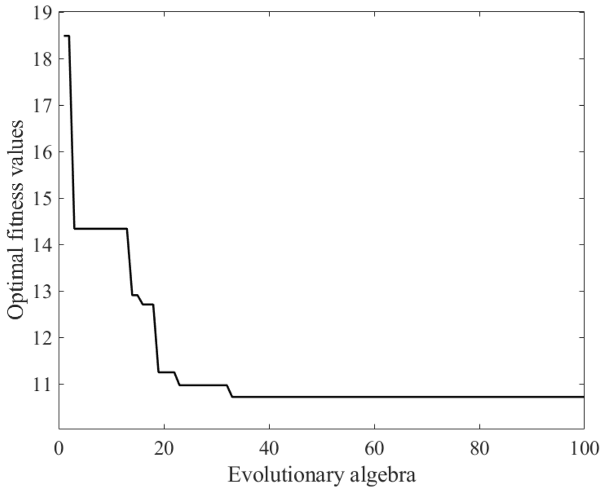


Fig. 14. Iteration process of transit point 2

Table 17. Optimal route for transporting goods at transit point 2

| Stage | Transit point 2 | | | |
|---|---|---|---|---|
| | **Route** | $q_{ij}$ | $d_{ij}$ | $E_{co_2}(q_{ij})$ |
| 1 | Transit Point 2 $\overset{5t0t}{\rightleftarrows}$ Customer 2 | 5 | 62 | 3.33 |
| 2 | Transit Point 2 $\xrightarrow{10t}$ Customer 3 | 10 | 34 | 2.40 |
| | Customer 3 $\xrightarrow{7t}$ Customer 4 | 7 | 15 | 0.95 |
| | Customer 4 $\xrightarrow{3t}$ Customer 6 | 3 | 20 | 1.09 |
| | Customer 6 $\xrightarrow{0t}$ Transit Point 2 | 0 | 61 | 2.94 |
| Delivering 15t of goods with a distance of 192km, the carbon emission cost is 10.71 CNY | | | | |

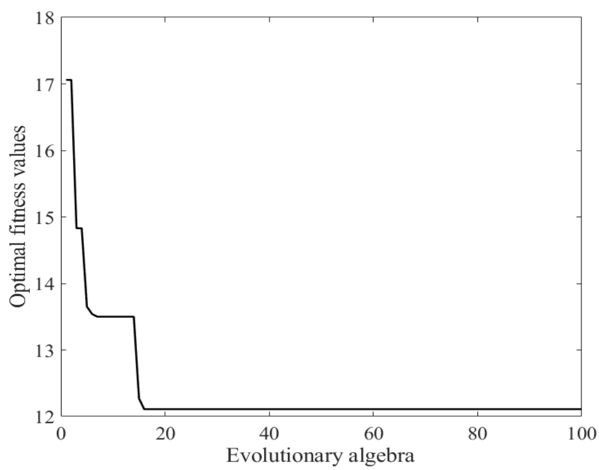


Fig. 15. Iteration process of transit point 3

Table 18. Optimal route for transporting goods at transit point 3

| Stage | Transit point 3 | | | |
|---|---|---|---|---|
| | Route | $q_{ij}$ | $d_{ij}$ | $E_{co_2}(q_{ij})$ |
| 1 | Transit point 3 $\overset{4t0t}{\rightleftarrows}$ Customer 1 | 4 | 84 | 4.40 |
| 2 | Transit point 3 $\xrightarrow{8t}$ Customer 6 | 8 | 51 | 3.33 |
| | Customer 6 $\xrightarrow{6t}$ Customer 5 | 6 | 17 | 1.05 |
| | Customer 5 $\xrightarrow{0t}$ Transit point 3 | 0 | 69 | 3.32 |
| Delivering 15t of goods with a distance of 221km, the carbon emission cost is 12.10 CNY | | | | |

### 6.2.2. Vehicle Distribution Routes for Scheme II

The program sets the parameters as follows: population size of 50, maximum evolutionary generation of 100, crossover probability of 0.8, and v-ariation probability of 0.1.

(1) Solution based on transit point 1

In Scheme I, transit point 1 needs to deliver 5t, 3t, 4t, 1t and 5t of goods to customers 2, 3, 4, 5 and 6, respectively. the iterative process is shown in Fig 16.The optimal distribution route is divided into two stages. The specific routes are shown in Table 19.

The first stage is: 10t of cargo is delivered from transit point 1 to customer 2, 5t is unloaded and then 5t of cargo is delivered from customer 2 to customer 6, 5t is unloaded and then returned to transit point 1 from customer 6.The second stage is: 8t of cargo from transit point 1 to customer 4, 4t of cargo from customer 4 to customer 3 after unloading, 1t of cargo from customer 3 to customer 5 after unloading 3t, and 1t of cargo from customer 5 back to transit point 1 after unloading.

(2) Solution based on transit point 3

In Scheme I, transit point 3 needs to deliver 7t and 5t of goods to customers 1 and 5, respectively. the optimal distribution route is divided into two stages. The specific routes are shown in Table 20.The first stage is: 7t of cargo is delivered from transit point 3 to customer 1, 7t is unloaded and then returned from customer 1 to transit point 3. The second stage is: transporting 5t of cargo from transit point 3 to customer 5, unloading 5t and then returning to transit point 3 from customer 5.

### 6.2.3. Analysis of Results

The specific carbon costs and vehicle distances traveled for the vehicle distribution paths of the two Schemes are shown in Table 21. As can be seen from the table above, although the total carbon cost of Scheme I is 28.89 CNY, which is slightly lower than Scheme II's 29.02 CNY, the difference between the two is so slight that it is difficult to have a significant impact on the environment. However, Scheme II has a clear advantage in terms of the distance traveled by the vehicle, which is only 523 kilometers, compared to the 531 kilometers that Scheme II needs to travel. This suggests that Scheme II is able to accomplish the delivery task in a shorter distance traveled, which may lead to better customer satisfaction.

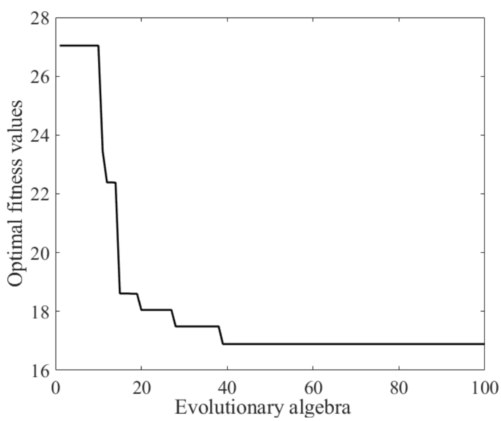


Fig. 16. Iteration process of transit point 1

Table 19. Optimal route for transporting goods at transit point 1

| Stage | Transit point 1 | | | |
|---|---|---|---|---|
| | **Route** | $q_{ij}$ | $d_{ij}$ | $E_{co_2}(q_{ij})$ |
| 1 | Transit Point 1 $\xrightarrow{10t}$ Customer 2 | 10 | 50 | 3.53 |
| | Customer 2 $\xrightarrow{5t}$ Customer 6 | 5 | 24 | 1.43 |
| | Customer 6 $\xrightarrow{0t}$ Transit Point 1 | 0 | 76 | 3.66 |
| 2 | Transit Point 1 $\xrightarrow{8t}$ Customer 4 | 8 | 49 | 3.24 |
| | Customer 4 $\xrightarrow{4t}$ Customer 3 | 4 | 15 | 0.81 |
| | Customer 3 $\xrightarrow{1t}$ Customer 5 | 1 | 20 | 1.01 |
| | Customer 5 $\xrightarrow{0t}$ Transit Point 1 | 0 | 67 | 3.23 |
| Delivering 18t of cargo with a distance of 301km, the carbon emission cost is 16.91 CNY | | | | |

Table 20. Optimal route for transporting goods at transit point 3

| Stage | Transit point 3 | | | |
|---|---|---|---|---|
| | **Route** | $q_{ij}$ | $d_{ij}$ | $E_{co_2}(q_{ij})$ |
| 1 | Transit Point 3 $\overset{7t0t}{\rightleftarrows}$ Customer 1 | 7 | 84 | 4.70 |
| 2 | Transit Point 3 $\overset{5t0t}{\rightleftarrows}$ Customer 5 | 5 | 138 | 7.41 |
| Delivering 13t of cargo with a distance of 222km, the carbon emission cost is 12.11 CNY | | | | |

Table 21. Carbon costs and vehicle distance traveled

| | **Scheme I** | **Scheme II** |
|---|---|---|
| Cost of carbon emissions (CNY) | 28.89 | 29.02 |
| Distance traveled by vehicle (km) | 531 | 523 |

## 7. Conclusions

Aiming at the typical logistics process of goods going from factories to customers through transit points, focusing on the carbon emissions generated by the transportation and distribution process of freight vehicles, and adding the carbon emission cost on top of the traditional logistics cost, we constructed a multi-objective planning model with the minimum logistics cost and the shortest transportation and distribution time, and a distribution path optimization model with the minimum carbon emissions, and respectively adopted the non-dominated with elite strategy Genetic Algorithm (NSGA-II) (Martinez-puras, A,2016) and Genetic Algorithm (GA) were used to solve the examples respectively. The analysis results of the examples are as follows:

1. The proposed multi-objective planning model and distribution path optimization model better meet the logistics and distribution needs, while also more in line with environmental protection requirements, showing a high degree of practicality.
2. Based on the nature of the problem to be solved, the characteristics of the model, the size of the data, and the computational resources, the more robust and reliable NSGA-II is selected as the solution algorithm.
3. The scheme considering carbon emission reduces the carbon emission of the whole logistics network and saves cost; the distribution path considering carbon emission shortens the traveling distance of vehicles. The low carbon optimization idea for multilevel logistics network is demonstrated and the effectiveness and feasibility of the algorithm is verified, which can provide a reference for decision makers to choose a reasonable logistics and distribution plan.

However, the thesis only considers a single model and a single cargo for modeling, and the link between the two models is not strong enough. The direction of subsequent research is:

1. Optimization of low-carbon logistics network distribution scheme with multiple car models and multiple cargo categories.
2. Considering the decision-making reaction in the second stage when designing the network in the first stage, and constructing the model of two-layer planning; or in the second stage, with the updating of the network information, determining the distribution scheme and optimizing the vehicle paths at the same time, so as to make the model more holistic and the results more persuasive.

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