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Research on Optimizing Logistics and Distribution Paths Considering Carbon Emissions

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Abstract: With the intensification of global climate change, reducing carbon emissions has become an urgent task for various industries. The logistics industry has high carbon emissions, and traditional path planning ignores environmental impacts. The current hot topic is to study the optimization of logistics paths that consider carbon emissions, in order to achieve a win-win situation for both the economy and the environment. This article aims to explore relevant theories and methods, propose solutions to reduce logistics carbon emissions, and promote sustainable development. Taking the optimization of logistics distribution paths in a certain enterprise as the research object, starting from the global background of energy conservation and emission reduction, this paper proposes to take the total cost (including time window penalty, transportation, carbon emissions, and fixed costs) as the optimization objective, construct a carbon emission logistics distribution path optimization model with time window, solve it using the improved grey wolf optimization algorithm, and compare it with the original plan. The results showed that after optimization, the cost was significantly reduced, verifying the effectiveness of the model, reducing delivery costs, and improving the economic benefits of the enterprise. Not only does it solve the problems of the enterprise, but it also provides reference for related industries.

Keywords: Path optimization, Carbon emission, Grey wolf algorithm.

1. Introduction

The intensification of global warming, melting of Antarctic glaciers, and frequent haze in the north are all related to excessive carbon dioxide emissions. The concept of energy conservation, emission reduction, and low-carbon development has deeply penetrated people's hearts. The logistics industry, as a pillar of the national economy, increases costs and pollutes the environment due to unreasonable transportation routes. Therefore, there is an urgent need to develop low-carbon logistics. After the epidemic, a new economic pattern has emerged, and national policies emphasize green and low-carbon economy. The government will increase research investment, leverage the advantages of logistics companies, reduce energy consumption and greenhouse gas emissions, and achieve the goal of green and low-carbon development. The low-carbon economy is characterized by low emissions, low pollution, and low energy consumption, with efficient and rational use of energy as the foundation. Controlling carbon emissions is a major global issue, and many countries have implemented policies such as carbon caps, carbon emissions trading mechanisms, and carbon taxes. Green logistics has become an important development direction for logistics enterprises, which requires the integration of low-carbon concepts throughout the entire logistics process, maintaining a balance between economic growth and low-carbon economy, and promoting harmonious coexistence between humans and nature. This article introduces carbon emission cost as the objective function and establishes a vehicle routing optimization model. Scientifically and reasonably arranging delivery plans can improve customer satisfaction, corporate image, and reduce costs. The development of the Internet has led to bionic intelligent algorithms, such as longicorn beetle whiskers, artificial bee colonies, wolves, etc., which play an important role in solving optimal problems, especially in vehicle path planning.

Mazzarino (2000) attempted to use a static comparison method to demonstrate that the main factor contributing to climate change is the carbon emissions from the transportation industry [1]. Friedl's (2003) survey found an "N" - shaped relationship between carbon emissions and economic development, with the economy and per capita income directly proportional to carbon emissions [2]. Dagoumas et al. (2010) used a mixed model to analyze the carbon pollution problem in the UK, proposed solutions to improve low-carbon logistics, and emphasized that addressing energy and environmental hazards is crucial for achieving sustainable economic development [3]. Moghaddam et al. (2012) analyzed the fuzzy demand VRP problem to help companies determine suitable transportation routes and increase customer satisfaction. On this basis, research on low-carbon VRP with time windows has also begun to emerge when considering distance and fuel factors [4]. Some scholars such as Viktor (2019) have conducted research on this and developed a method based on an improved ant algorithm for solving [5]. At the same time, some scholars have also begun to pay attention to green logistics and low-carbon economy, such as Qin (2019) who took into account the cost of carbon emissions and constructed a green path optimization model with the minimum total cost as the objective function [6]. Krishna et al. (2023) conducted research on multiple vehicle delivery problems with maximum capacity constraints and no time constraints, and used multiple optimization algorithms to solve and compare the constructed last mile perishable goods delivery path optimization model. Finally, they concluded that taboo search algorithm was superior to other methods [7]. Siti Fatimah et al. (2020) solved the vehicle routing problem with load constraints based on an improved ant colony algorithm [8].

In summary, this article proposes to take the total cost (including time window penalties, transportation, carbon emissions, and fixed costs) as the optimization objective, construct a carbon emission logistics distribution path optimization model with time windows, solve it using an improved grey wolf optimization algorithm, and calculate it with a case study of a certain enterprise in Chengdu, and compare and verify it with the existing solutions of the enterprise.

2. Problem Description and Model Building

2.1. Problem Description and Parameter Description

The problem studied in this paper can be described as sending the same type of vehicles from a distribution center of an enterprise to multiple fixed distribution points in a certain area. The load of each distribution vehicle is certain, and the maximum distance of a single trip is also certain. The location and demand of each distribution point in the area are known, and each distribution point has its specified delivery time window limit. All vehicles must return to the distribution center after completing the distribution task. All vehicles can serve all distribution points. In order to meet the store demand and vehicle load limit and within the store constraint time, we should comprehensively consider the fixed cost, transportation cost, time window penalty cost and carbon emission cost of vehicles used in the distribution process, reasonably arrange the distribution route of vehicles, build an enterprise logistics distribution route optimization model with the optimal comprehensive cost and carbon emission, and obtain the vehicle distribution scheme with the minimum carbon emission, that is, the determination of the number of distribution vehicles and distribution routes.

In order to facilitate the abstraction of the vehicle distribution route optimization model into a mathematical model and facilitate the research needs, the following assumptions are set for the distribution model:

(1) The location of the distribution center is fixed and there is only one, and the geographical location is known;

(2) There is no shortage, and it can meet the needs of all customer points;

(3) The demand and geographical location of all distribution points are known, and the demand of any distribution point is not greater than the maximum load capacity of the distribution vehicle;

(4) All delivery vehicles have the same model, the same load capacity and mileage limit, and can meet the needs of delivery;

(5) All distribution vehicles drive at the same speed and uniform speed, start from the distribution center, and return to the distribution center after completing the distribution;

(6) A single distribution vehicle can provide distribution services for multiple distribution points, but a distribution point can only be served by a single distribution vehicle, only once;

(7) Vehicles arriving at all distribution points have time window constraints, and failure to arrive at the agreed time will result in penalty costs;

(8) The distribution road is smooth, regardless of road congestion and other conditions;

(9) The total length of distribution routes for all distribution vehicles shall not exceed their maximum mileage.

Table 1. Symbol and variable description

symbol	Interpretation	unit
N	Location aggregation, 0 represents the distribution center node, and other nodes represent customer demand points, $N = (0, 1, 2, 3, \dots, N)$	one
K	Collection of delivery vehicles, $K = (0, 1, 2, 3, \dots, N)$	one
P	Unit value of product	yuan
Q	Maximum vehicle load	kg
Q_i	Demand of distribution point i	kg
t_0^k	Time of departure of vehicle k from the distribution center	
t_i^k	Time when vehicle k arrives at distribution point i	
d_{ij}	Distance between distribution point i and distribution point j	km
F_c	Fixed vehicle costs	yuan
P_l	Fuel consumption cost per unit distance	yuan
v	Vehicle running speed	km/h
w	Carbon emissions per unit driving distance	
P_c	Carbon tax price	yuan/kg
$[s_i, e_i]$	The time window at which the customer i expects to be served, s_i is the time at which the time window at the distribution point i starts, and e_i is the time at which the time window at the distribution point i ends	
x_{ijk}	0-1 variable, if vehicle k accesses from distribution point i to distribution point j, take 1, otherwise take 0	
y_{ik}	0-1 variable, if vehicle k is the service of distribution point i, take 1, otherwise take 0	
ε_1	Penalty cost per unit time of early arrival	yuan
ε_2	Penalty cost per unit time of lateness	yuan

2.2. Cost Analysis

The cost involved in the model in this paper includes four parts: fixed cost, transportation cost, time window penalty cost and carbon emission cost.

2.2.1. Fixed Cost

The distribution vehicles used in this paper are the same kind of vehicles, and the fixed cost is usually a constant, which has nothing to do with the mileage of the vehicles. It is only related to the number of distribution vehicles used, including the fixed loss of vehicles, the driver's salary and other costs related to the use of vehicles. This paper only includes the daily depreciation value of vehicles and the average daily salary of drivers. Its function is defined as C_1, and the expression is:

$$C_1 = \sum_{j=1}^{N}\sum_{k=1}^{K} x_{0ij} \cdot F_C \tag{1}$$

2.2.2. Transportation Cost

Transportation cost refers to the transportation related expenses incurred in the process of goods distribution. In this model, it is assumed that the vehicle is running at a uniform speed, and the impact of running speed and distribution sequence on the transportation cost is not considered temporarily. It is proportional to the driving distance, and its function is defined as C_2, and the expression is:

$$C_2 = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=0}^{K} d_{ij} \cdot x_{ijk} \cdot p_l \tag{2}$$

2.2.3. Time window penalty cost

Time window penalty cost refers to the additional cost incurred in the process of logistics distribution or service provision due to the failure of distribution vehicles or service personnel to arrive or provide services within the time window specified by the customer. This time window is the time range within which customers can receive services, usually including the earliest and the latest time of receiving services. Considering the business hours of stores and the working hours of employees, each distribution point has a corresponding time range for acceptable services. If it cannot be delivered within the specified time window, early arrival or late arrival will result in penalty costs. The function is defined as C_3, and the expression is:

$$C_3 = \varepsilon_1 \sum_{k=1}^{K} \sum_{i=0}^{N} max\{s_i - t_i, 0\} + \varepsilon_2 \sum_{k=1}^{K} \sum_{i=0}^{N} max\{t_i - e_i, 0\} \tag{3}$$

2.2.4. Carbon emission cost

The carbon emission cost calculated in this paper mainly refers to the CO2 emission cost generated by fuel consumption during transportation. Among them, the fuel consumption is not only related to the transportation distance, but also related to the transportation load. If the total vehicle weight is divided into the vehicle weight Q_0 and the cargo capacity X, the fuel consumption per unit distance $\rho\ (X)$ is:

$$\rho(X) = a(Q_0 + X) + b \tag{4}$$

The maximum load capacity of the vehicle is Q, the fuel consumption per unit distance at full load is ρ^*, and the fuel consumption per unit distance at no load is ρ_0, which can be calculated as follows:

$$\rho_0 = aQ_0 + b \tag{5}$$

$$\rho^* = a(Q_0 + Q) + b \tag{6}$$

$$a = \frac{\rho^* - \rho_0}{Q} \tag{7}$$

The fuel consumption per unit distance $\rho(X)$ can be expressed as:

$$\rho(X) = \rho_0 + \frac{(\rho^* - \rho_0)}{Q} \cdot X \tag{8}$$

In the process of enterprise product distribution, if the products of Q_{ij} are transported from distribution point i to distribution point j, the carbon emissions generated during distribution between the two distribution points are expressed as:

$$E_1 = w \cdot \rho(Q_{ij}) \cdot d_{ij} \tag{9}$$

Where w is the carbon emission coefficient, Q_{ij} is the load capacity of the vehicle when driving from customer i to customer j, and $\rho(Q_{ij})$ is the fuel consumption per unit distance when the vehicle is driving between $(i,\ j)$. If the carbon tax price is P_c, the carbon emission cost function can be defined as C_4, and the expression is:

$$C_4 = P_c \cdot \omega\left(\sum_{k=0}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} x_{ijk} \cdot d_{ij} \cdot \rho(Q_{ij})\right) \tag{10}$$

2.3. Model Establishment

Through the above analysis, the objective function of the lowest total cost is as follows for the logistics distribution path optimization problem considering carbon emissions:

$$MinZ = C_1 + C_2 + C_3 + C_4 \tag{11}$$

The constraints are as follows:

$$\sum_{k=1}^{K} \sum_{i=0}^{N} x_{ijk} = 1, i = 1,2,3,\cdots,N \tag{12}$$

$$\sum_{i=1}^{N} y_{ik} q_i \leq Q, k = 1,2,3,\cdots,K \tag{13}$$

$$\sum_{k=1}^{K} y_{0k} = K, \sum_{i=1}^{N} x_{i0k} = 1,\ \ i = 1,2,3,\cdots,N; k = 1,2,3,\cdots,K \tag{14}$$

$$\sum_{k=1}^{K} x_{ijk} = y_{jk}, \sum_{i=1}^{N} x_{ijk} = y_{jk},\ i,j \in (1,2,3,\cdots,N); k = 1,2,3,\cdots,K \tag{15}$$

$$x_{ijk} \in \{0,\ 1\},\ i,j = 1,2,\cdots,n;\ k = 1,2,3,\cdots,K \tag{16}$$

$$y_{ik} \in \{0,\ 1\},\ i = 1,2,\cdots,n;\ k = 1,2,3,\cdots,K \tag{17}$$

$$t_i^k \in [s_i, e_i] \tag{18}$$

Formula (12) indicates that each distribution point is served by at most one distribution vehicle; Formula (13) indicates that the total demand of vehicle service customers is not greater than the maximum load capacity of the vehicle; Formula (14) indicates that each vehicle needs to return to the distribution center after completing the distribution task; Formula (15) indicates that the distribution service of each distribution point is completed by only one vehicle; Formula (16) and formula (17) represent the 0-1 constraint of decision variables; Formula (18) indicates the acceptable time window range of the distribution point.

3. Algorithm Solution

Gray wolf optimization algorithm has strong applicability in solving VRP, and can solve complex VRP problems well. Because of its good performance, it is widely used by scholars at home and abroad in various fields, including vehicle routing problem. Therefore, combined with the characteristics of research examples, this paper selects gray wolf optimization algorithm to solve the model.

3.1. Gray Wolf Algorithm

Grey Wolf Optimizer (GWO) is an optimization algorithm inspired by the behavior of gray wolves in nature, which was proposed by Iranian researcher mirjalili and others in 2014. The algorithm simulates the social level and hunting strategy of gray wolves, and finds the optimal solution through the cooperation of gray wolves. The optimal three groups of wolves are α, β and δ, and the rest are called ω. In the process of wolf pack optimization, ω wolves update their positions around α, β and δ, and the gray wolf in the upper layer will be replaced by the gray wolf with better fitness until the global optimal solution appears.

In the process of hunting, the behavior of gray wolf hunting prey is defined as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_P(t) - \vec{X}(t)\right| \tag{19}$$

$$\vec{X}_{(t+1)} = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \tag{20}$$

In formulas (19) and (20), t is the current iterative algebra, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_P$ and $\vec{X}$ are the position vectors of prey and gray wolf respectively. The calculation formulas of $\vec{A}$ and $\vec{C}$ are as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{21}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{22}$$

$$|\vec{a}| = 2 \cdot \left(1 - \frac{t}{T_{max}}\right) \tag{23}$$

In formulas (21), (22) and (23), $\vec{a}$ is the convergence factor. With the number of iterations decreasing linearly from 2 to 0, $\vec{r}_1$ and $\vec{r}_2$ take a random number between [0, 1]. Therefore, the value range of A is [-2, 2], and the value range of C is [0, 2].

$$\begin{cases} \vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \end{cases} \tag{24}$$

In formula (24), $\vec{D}_\alpha, \vec{D}_\beta$ and $\vec{D}_\delta$ represent the distance between α, β and δ and other individuals, respectively; $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$ represent the current positions of α, β and δ, respectively; $\vec{C}_1$, $\vec{C}_2$, $\vec{C}_3$ are random vectors, and $\vec{X}$ is the current gray wolf position.

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - A_1 \cdot \left(\vec{D}_\alpha\right) \\ \vec{X}_2 = \vec{X}_\beta - A_2 \cdot \left(\vec{D}_\beta\right) \\ \vec{X}_3 = \vec{X}_\delta - A_3 \cdot \left(\vec{D}_\delta\right) \end{cases} \tag{25}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{26}$$

Formula (25) defines the step size and direction of ω individuals in the wolf pack towards α, β and δ; Equation (26) defines the final position of ω.

3.2. Solution Design

The main flow of this algorithm is as follows:

Step 1: initialize the parameters, make the current iteration times t=0, and randomly generate the position of gray wolf individuals within the search range.

Step 2: calculate the individual fitness function value of gray wolf, and save the three best gray wolf positions as alpha wolf, beta wolf and delta wolf.

Step 3: judge whether the algorithm iteration termination conditions are met. If yes, go to step 6. Otherwise, go to step 4.

Step 4: update the coefficient vector and update the positions of alpha wolf, beta wolf and delta wolf of the leadership according to the formula.

Step 5: determine whether the maximum number of iterations has been reached. If the conditions are met, execute step 6; If the conditions are not met, proceed to step 4.

Step 6: output the global optimal solution and the optimal distribution path, that is, the final spatial location and fitness function value of the gray wolf, and the algorithm iteration ends.

4. Case Analysis

4.1. Data Acquisition and Parameter Setting

This paper is based on the background that a distribution center of an enterprise in Chengdu provides a logistics distribution service for a total of 56 stores in Chengdu. The following is the basic information of some distribution stores, including longitude and latitude, demand, expected time window and service time.

Table 2. Partial distribution store information data

number	longitude	latitude	Demand (kg)	Expected time window	Service Time (min)
1	104.07873	30.664697	440	5:30-6:30	8
2	104.141	30.678845	470	5:30-6:30	8
3	104.08472	30.657545	160	5:30-6:30	3
4	104.10179	30.647128	480	5:30-6:30	9
5	104.07047	30.660804	360	5:30-6:30	7
6	104.04585	30.666265	150	5:30-6:30	3
7	104.06745	30.646155	220	5:30-6:30	4
8	104.03584	30.736334	330	5:30-6:30	6
9	104.04994	30.674731	490	5:30-6:30	9
10	104.244038	30.601521	500	5:30-6:30	9
11	104.18981	30.657766	170	5:30-6:30	3
12	104.08035	30.650015	500	5:30-6:30	9
13	104.14847	30.644706	490	5:30-6:30	9
14	104.08676	30.656727	300	5:30-6:30	6
15	104.12925	30.614586	430	5:30-6:30	8
16	104.05586	30.632086	170	5:30-6:30	3
17	104.14752	30.78637	280	5:30-6:30	5
18	104.0507	30.707937	480	5:30-6:30	9
19	104.07823	30.664496	430	5:30-6:30	8
20	104.26797	30.583908	490	5:30-6:30	9

The parameters in the model set in this paper are as follows: the number of vehicles is 8, the vehicle speed is 40km/h, the vehicle load is 3000kg, the fixed cost of each vehicle is 300 yuan, the unit distance distribution cost is 3 yuan/km, the early arrival penalty coefficient is 40 yuan/h, the late penalty coefficient is 60 yuan/h, the carbon emission coefficient is 2.63kg/l, the carbon tax price is 0.171 yuan/kg, the full load fuel consumption is 0.4l/km, and the no-load fuel consumption is 0.6l/km. According to the theoretical basis of internalization of external costs, the amount of carbon tax should offset the tax caused by CO2 emissions and external social costs. The social cost of carbon dioxide emissions in China is $24 per ton [9], and the carbon tax is set through exchange rate conversion.

4.2. Model Solution and Analysis

In this paper, matlab2021a programming software is used to solve the problem. The population size is set to 150 and the number of iterations is set to 1000. Figure 1 shows the convergence of the gray wolf algorithm. The x-axis represents the number of iterations, and the y-axis represents the best target value.

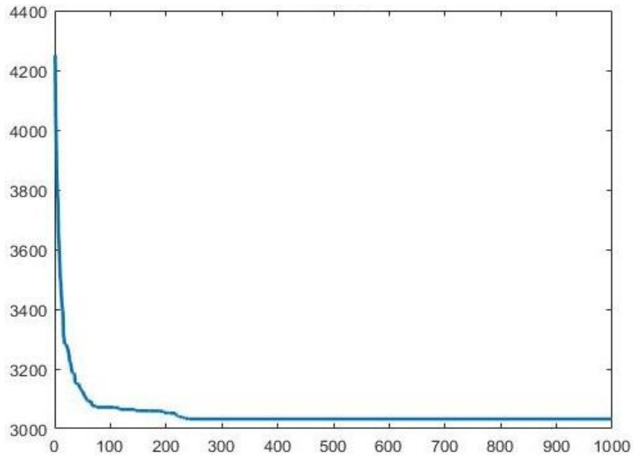

Figure 1. Iteration diagram of Grey Wolf algorithm

After the model calculation, this paper compares the optimization results with the existing logistics distribution costs of the enterprise, and compares the results before and after the optimization of the enterprise logistics distribution path. The comparison results are shown in Table 3 and table 4.

Table 3. Cost comparison and analysis of two schemes

index	Cost of existing scheme	Optimized scheme cost	Reduction ratio
fixed cost	2400	2100	12.5%
transportation cost	1221.81	881.11	27.9%
Time penalty cost	178.4	47.22	73.5%
Carbon emission cost	50.45	38.39	23.9%
total cost	3850.71	3066.72	20.4%

Table 4. Comparison of results before and after optimization of enterprise logistics distribution path

Indicators	Before optimization	After optimization	Reduction ratio
Total delivery mileage (km)	407.27	293.7	27.9%
Total delivery time (h)	15.9	13.06	17.9%
Total delivery cost (yuan)	3850.71	3066.72	20.4%
Total number of vehicles delivered (one)	8	7	12.5%
Average loading rate	76.8%	87.8%	-11%

First, in terms of the total distribution mileage, it was 407.27 kilometers before optimization, while the total distribution mileage optimized by the improved gray wolf algorithm was 293.7 kilometers, which was reduced by 113.57 kilometers before and after optimization, with a reduction rate of 27.9%. Secondly, in terms of the total distribution duration, it was 15.9 hours before optimization, while the total distribution duration optimized by the improved gray wolf algorithm was 13.06 hours, which was reduced by 2.84 hours before and after optimization, with a reduction rate of 17.9%. Moreover, in terms of the total distribution cost, it was 3850.71 yuan before optimization, while the total distribution time optimized by the improved gray wolf algorithm was 3066.72 yuan, which was reduced by 783.99 yuan before and after optimization, with a reduction rate of 20.4%. In addition, in terms of the total number of distribution vehicles, the first 8 vehicles were optimized, while the total number of distribution vehicles optimized by the improved gray wolf algorithm was 7, which was reduced by 1 vehicle before and after optimization, with a reduction rate of 12.5%. Finally, in terms of average loading rate, the average loading rate before optimization was 76.8%, while the average loading rate after improved gray wolf algorithm optimization was 87.8%, which increased by 11% before and after optimization.

After comparing the total mileage, total time, total cost and total number of vehicles, it can be concluded that the optimized logistics distribution path considering carbon emissions has great advantages over the original logistics distribution path.

5. Conclusion

In this paper, when constructing the logistics distribution path optimization model considering carbon emissions, a variety of cost factors are deeply considered to ensure that the model is closer to the actual operation. The mathematical model of total cost minimization not only considers fixed costs, such as vehicle depreciation costs, but also carefully includes time window penalty costs, transportation costs and carbon emission costs. The penalty cost of time window reflects the additional costs incurred due to failure to deliver or delay at the agreed time, which helps to improve customer satisfaction and service level. Transportation cost is directly related to the driving distance, and it is an important part of logistics distribution that can not be ignored. Through the verification of specific examples, the model shows good rationality and practicability.

In view of the global urgent need for environmental protection and low carbon, this paper quantifies the carbon emissions generated in the process of vehicle distribution into carbon emission costs through carbon tax. Finally, the carbon emission costs are incorporated into the total distribution costs. This measure not only helps enterprises better evaluate and control the environmental impact in the distribution process, but also provides strong support for enterprises to achieve win-win results in economic benefits and environmental protection. Finally, an optimization model of logistics distribution path considering carbon emissions considering economic benefits and environmental protection is constructed.

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