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Research on Green Logistics Network Planning and Carbon Emission Control Strategy Based on Internet of Things Technology

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Abstract In this paper, on the background of Internet of Things (IoT) technology, a three-level logistics network consisting of multiple suppliers, manufacturers, and distribution centers is established, and multiple decision-making problems of material collection, logistics generation, transportation modes, and transportation routes in the logistics network are solved by setting up a mixed-integer nonlinear planning model that minimizes the operation cost and carbon emission cost of the logistics network. After that, the optimization is carried out by max-min ant system and ant colony algorithm, so that the improved ant colony algorithm sets the solution equations of the specific model targeted to the specific problems. The results show that the algorithm in this paper can effectively optimize the logistics distribution problem, and its transportation distance is significantly reduced (6.38%) compared with the traditional ant colony algorithm, and the algorithm in this paper can solve the logistics path optimization problem faster, which controls the cost of transportation to a certain extent. Under the multiple conflicting objectives of simultaneously considering transportation cost, carbon emission and cargo loss rate, the government can increase the market share of railroad cold chain transportation by giving appropriate tariff subsidy policy or by increasing the travel speed of railroad cold chain liner. In enhancing the competitiveness of railroad cold chain logistics transportation, the tariff subsidy and the cold chain train can be substituted to a certain extent.

Index Terms nonlinear planning model, ant colony algorithm, urban transfer technology, logistics network, carbon emission control

I. Introduction

With the development of the global economy and the growing demand for logistics, the carbon emissions of the logistics industry have gradually increased and become one of the important sources of global greenhouse gas emissions [1], [2]. In order to realize the goal of sustainable development, the concept of green logistics has emerged, aiming to reduce the impact of logistics activities on the environment [3], [4].

Carbon emissions from logistics activities originate from three main sources, including energy consumption generated during transportation, manufacturing and use of logistics equipment, and waste generated during logistics [5]. The fuel required in the transportation process directly leads to an increase in carbon emissions from logistics activities [6]. For example, gasoline or diesel used in motor vehicles and fuel used in ship transportation release large amounts of carbon emissions, and the increase in carbon emissions leads to global warming and affects the ecological balance of the environment [7]-[9]. Similarly, the manufacture and use of logistics equipment the production and use of logistics equipment is also an important cause of carbon emissions [10], [11]. The production process of logistics equipment consumes a large amount of resources and energy, while the use of equipment also consumes a large amount of fuel [12], [13].

In addition, with the upgrading of logistics equipment, the disposal of used equipment also generates a large amount of waste, which further increases carbon emissions [14]. And the waste generated during transportation, such as packaging waste and used equipment, which are either incinerated and disposed of or transported to landfills, all contribute to a large amount of carbon emissions [15]-[17]. In the era of Internet of Things (IoT), IoT technology provides technical support for realizing green logistics [18], [19]. The green logistics network planning and carbon emission control strategy based on IoT technology is to use IoT technology architecture to realize the intelligent regulation and carbon emission dynamic management of the whole logistics process, through the integration of transportation efficiency optimization, energy structure transformation and carbon footprint tracking, so as to form a quantifiable and verifiable carbon reduction system [20]-[23].

In this study, a two-level supply chain network including upstream suppliers and downstream customers is centered on a storage-based distribution center. A bi-objective stochastic planning model considering network cost and CO_2 emission equivalent is proposed, including an economic objective to minimize the total network cost and an environmental objective to minimize the CO_2 emission of the transportation process. Under the premise of considering the carbon emission cost and satisfying the demand of each distribution center, the optimal design of the manufacturer's purchasing decision, production arrangement, distribution mode, distribution route and other problems is carried out to minimize the manufacturer's operation cost and carbon emission cost. Then drawing on the improvement ideas of max-min ant system and adaptive ant colony algorithm, the basic ant colony algorithm is improved in terms of parameter adaptation, pheromone updating technology, and city transfer technology to get the specific solution algorithm of the model. Finally, the solution results of the model logistics path optimization and the sensitivity of the model are analyzed.

II. Low-carbon logistics network optimization model based on improved genetic algorithm

II. A. Description of the problem

II. A. 1) Supply chain structure

This study takes a storage-based distribution center as the core of a two-level supply chain network that includes both its upstream suppliers and downstream customers. Physical flow is top-down in the supply chain and information flow is bottom-up. The suppliers transport their products to the distribution center according to the customers' demands, and then the distribution center completes the delivery to the customers. The following scientific assumptions are made for the constructed model.

(1) It is assumed that the customer's demand per cycle is uncertain, described by different scenarios, and the demand is fed back to the distribution center at the beginning of each cycle.

(2) Only the remaining products returned at the end of each weekly period incur an inventory holding cost, which is related to the amount of inventory and is given in the form of a segmented function.

(3) When a shortage occurs at the distribution center, it is assumed that a portion α of the shortage is allowed to be delayed for distribution until the next cycle, and the remainder does not reach the customer.

(4) The initial inventory of the distribution center can be zero or positive.

(5) It is assumed that all levels of transportation are performed by a variety of vehicles with different transportation costs, capacities, and emission capabilities.

(6) Assume that CO_2 emissions from transportation are used as a measure of the environmental element.

(7) It is assumed that the total cost of the network includes the cost of replenishment at the distribution center, the cost of product purchase, the cost of vehicle transportation, the cost of inventory holding at the distribution center, the cost of backorders at the distribution center, and the cost of out-of-stock losses.

The objective of this study is to find the optimal ordering, inventory and vehicle scheduling plan that minimizes the total network cost and environmental pollution under the uncertainty of customer demand.

II. A. 2) Measurement of environmental objectives

In this study, greenhouse gases generated during transportation are used as a measure of environmental factors. Based on the IPCC Guidelines for National Greenhouse Gas Inventories database and its measurement methodology, IPCC national emission factors will be selected to calculate CO_2 equivalent as follows. In particular, the raw emission factors, Chinese calorific values and carbon oxidation factors of various fuels can be obtained from the IPCC Guidelines for National Greenhouse Gas Inventories database:

$$\begin{aligned} &CO_2 \text{ emissions} = CO_2 \text{ emission factor} \\ &\times \text{intensity of source activity} \left(\text{i.e. fuel consumption}\right) \end{aligned} \tag{1}$$

$$\begin{aligned} &CO_2 \text{ emission factor} = \text{raw emission factor} \\ &\times \text{our calorific value} \times \text{carbon oxidation factor} \end{aligned} \tag{2}$$

In addition, CO_2 emissions during transportation are related to vehicle type, travel speed, and load conditions.

II. A. 3) Uncertainty characterization

For the uncertainty of customer demand in each cycle, this study uses the situation tree method to describe it. In a scenario tree, each stage represents the time required to update the information obtained by the decision maker once. Therefore, in a multi-period stochastic planning problem, the stages in the situation tree do not necessarily correspond exactly to the periods. Each phase consists of a series of nodes and branches: each node represents a stochastic state that may occur in that phase, and the root node represents the current state; each branch represents a situation that may occur in the next phase with a certain probability. The probability of each node is equal to the product of the probabilities of all the branches connecting the root node and the node, and the sum of the probabilities of all the nodes in each stage is 1. Therefore, a path from the root node to a leaf node represents a possible situation from the current state to a certain cycle.

II. B.Problem assumptions

(1) Basic Assumptions

For the purpose of analysis, the following conditional assumptions are made in this paper for the problem: the locations of raw material suppliers and distribution centers have been determined; the location of the manufacturer's plant as well as its production capacity are known; one unit of production capacity is required for each unit of product regardless of the type of product; the cost of producing the same product in each plant is the same; and the demand of each distribution center is known and should be met.

(2) Composition of Logistics Network Operation Costs

Raw material procurement costs, i.e., the cost of purchasing raw materials from suppliers at each of the manufacturer's factories, including the cost of the raw materials themselves as well as transportation costs; production costs, including the cost of producing products at each of the manufacturer's factories; and transportation costs, with the transportation costs in this section only taking into account the costs from each factory to each distribution center.

(3) Calculation of carbon emission cost

The carbon emission cost in this paper is measured on the basis of carbon tax. The carbon emissions triggered in the logistics network mainly come from the carbon emissions generated by the consumption of materials in the production process and the carbon emissions generated in the transportation process. Based on this, this paper mainly focuses on the transportation process and the production process to account for the carbon emissions, and the formula for the carbon emission cost is as follows: Carbon Emission Cost=Carbon Tax×(Carbon Emissions from the Production Process+Carbon Emissions from the Transportation Process).

II. C.Low-carbon logistics network modeling

Before the model is constructed, the relevant variables and symbols are defined as follows: the supplier number is $j \in J$; the number of the manufacturer's factory is $k \in K$; the number of the distribution center is $l \in L$; the number of raw materials required for the manufacturer's production is $m \in M$; and the number of the product is $i \in I$.

MC_{mjk} denotes the manufacturer's cost of purchasing raw material m from supplier j to factory k;

SC_{mj} denotes the capacity limit of raw material m produced by supplier j;

R_{mi} denotes the quantity of raw material m required to produce a unit of product i;

CP_k denotes the k capacity limit of the plant;

PC_{ik} denotes the production cost per unit of product for plant k;

TC_{ikl} denotes the transportation cost per unit of product i transported from factory k to distribution center l;

LC_{ik}, UC_{ik} denote the lower and upper limits of the production capacity of factory k to produce product i, respectively;

CO_{2ik} denotes the carbon emission of product i produced by factory k;

CO_{2r} denotes the carbon emissions per unit of distance per unit of weight of the product under the transportation mode r;

W_m is the unit weight of raw material m;

W_i is the unit weight of product i;

G_{mjk} denotes the total quantity of raw material m purchased by the manufacturer from supplier j to factory k;

H_{ikl} denotes the total quantity of product i transported from factory k to distribution center l;

TD_{mr} denotes the transportation distance of raw material m transported by transportation mode r;

TD_{ir} denotes the transportation distance for transportation mode r to transport product i;

SCR_{co_2} denotes the carbon tax rate.

Based on the above description and assumptions, the mixed integer nonlinear programming model [24], [25] is constructed as follows:

$$MinZ = Min\left[\sum_{m,j,k} MC_{mjk}G_{mjk} + \sum_{i,k,l} PC_{ik}H_{ikl} + \sum_{i,k,l} TC_{ikl}H_{ikl} + \left(\sum_{i,k,l} CO_{2ik}H_{ikl} + \sum_{m,j,k,r} CO_{2r}W_m G_{mjk}TD_{mr} + \sum_{i,k,l,r} CO_{2r}W_i H_{ikl}TD_{ir}\right)SCR_{co_2}\right] \tag{3}$$

The constraints are:

$$\sum_{i,l} H_{ikl}R_{mi} < \sum_{j} G_{mjk} \quad \forall k,m \tag{4}$$

$$\sum_{k} G_{mjk} < SC_{mj} \quad \forall m \tag{5}$$

$$LC_{ik} \le \sum_{l} H_{ikl} < UC_{ik} \quad \forall i \tag{6}$$

$$\sum_{i,l} H_{ikl} \le CP_k \tag{7}$$

In the above model, the objective function Eq. (3) represents the minimization of operating costs and carbon emission costs. The first term represents the purchasing cost of the manufacturer, the second term represents the sum of the manufacturing cost of all the factories of the manufacturer, the third term represents the transportation cost, and the last term is the carbon emission cost, which mainly takes into account the carbon emission generated by the processes of producing products, transporting raw materials, and transporting products. Eq. (4) represents the demand limit for raw material m; Eq. (5) is set up for the production capacity limit of the supplier; Eq. (6) is set up for the production capacity limit of the manufacturer's factory k to produce the product i; and Eq. (7) indicates that the factory k to produce the product i does not exceed its total production capacity.

II. D.Algorithm for solving the model

II. D. 1) Flaw Analysis of Basic Ant Colony Algorithm

The basic ant colony algorithm suffers from the defects of slow solution speed and prone to stagnation phenomenon, which ultimately leads to the loss of solution diversity and the search falls into the phenomenon of local convergence. In addition, from the perspective of the optimization problem of the single-cycle transportation path optimization model (RSTRO) based on risk analysis, there are more parameters and the objective function calculation is more complicated, which makes the algorithm as a whole take up less resources to complete the model solving work in a shorter period of time.

II. D. 2) Improvements to the basic ACO algorithm

(1) Parameter Adaptation

In this paper, the α, β parameter adaptation [26] adjustment strategy is introduced, which takes the median value of the number of iterations as the critical value, and takes the small value of α in the early stage of searching, so as to strengthen the guiding effect of heuristic factors, so that the search enters the order as soon as possible, and takes the small value of β in the later stage of search, so as to weaken the resistance of heuristic factors to convergence, so that the ant colony algorithm has better balance performance in the whole search cycle, improves the cooperation ability between ant colony individuals, and improves the probability and efficiency of finding the optimal solution, α, β adaptive adjustment strategy is as follows:

$$\alpha = \begin{cases} \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) \cdot \dfrac{N}{N_{mid}} & 1 \le N \le N_{mid} \\ \alpha_{\max} & N_{mid} \le N \le N_{\max} \end{cases} \tag{8}$$

$$\beta=\begin{cases}\beta_{\max} & 1\le N\le N_{mid}\\ \beta_{\max}-(\beta_{\max}-\beta_{\min})\cdot\dfrac{N-N_{mid}}{N_{mid}} & N_{mid}\le N\le N_{\max}\end{cases} \tag{9}$$

where $\alpha_{\min},\alpha_{\max},\beta_{\min},\beta_{\max}$ denote the minimum and maximum values of α,β, respectively, and $N,N_{mid},N_{\max}$ denote the current number of iterations, the intermediate value of iterations, and the maximum number of iterations.

(2) Pheromone updating technique

In this paper, the pheromone updating technique of the basic ACO algorithm is improved as follows.

a) In each iteration, the pheromone is updated only when the optimal path searched by all ants is better than the current global optimal path, i.e., the pheromone updating link is triggered at most once in each iteration, and the pheromone is not updated when no better solution is found in a certain iteration.

b) In order to avoid the over-enhancement of the positive feedback effect, the pheromone strength of each route is limited to a range of values $[\tau_{\min},\tau_{\max}]$, and at the same time, in order to expand the search space as much as possible, the initial value of the pheromone strength is set to $\tau_{\max}$.

c) Set the pheromone update rule as relative enhancement and proportional attenuation, i.e., when a channel between node i and node j belongs to the current optimal path, the pheromone intensity of the channel will be enhanced to a multiple of the maximum value of all the feasible channels from node i, and then all channels in the road network will be attenuated proportionately after all the sub-channels of the optimal paths have been enhanced. This updating strategy is designed in this paper as follows:

$$\begin{cases}\tau_{ijk}(N)=\max\left\{\tau_{ijk}(N)\middle|j\in allowed,k\in K\right\}\cdot\xi & L_{ijk}(N)\in L_{Mostly}\\ \tau_{ijk}(N+1)=\rho\cdot\tau_{ijk}(N) & i\in I,j\in J,k\in K\end{cases} \tag{10}$$

where $\tau_{ijk}(N)$ denotes the pheromone strength of the channel using the kth mode of transportation between node i and node j after the Nth iteration; $allowed$ denotes the set of all accessible next nodes from node i; ξ denotes the pheromone strength enhancement coefficient; $L_{ijk}(N)\in L_{Mostly}$ denotes the channel between node i and node j using the kth mode of transportation on the current optimal path; $\tau_{ijk}(N+1)$ denotes the pheromone intensity of the channel between node i and node j using the kth mode of transportation before the $N+1$th iteration; ρ denotes the pheromone intensity decay coefficient.

(3) Urban transfer techniques

In addition to the pheromone update [27] can be compensated by the way, but also through the improvement of the city transfer strategy, to ensure that there is always a part of the ants to explore new paths, in order to enhance the ability to search for the global optimal solution, this paper's improved city transfer strategy is as follows:

$$P_{ijk}^{m}=\begin{cases}\dfrac{\tau_{ijk}\cdot\alpha+\eta_{ijk}\cdot\beta}{\sum\limits_{x\in allowed}\tau_{ixk}\cdot\alpha+\eta_{ijk}\cdot\beta} & j\in allowed\ And\ L_{ijk}\notin L_{Mostly}\\ & Or\ j\in allowed\ And\ q>q_0\\ 0 & j\in allowed,L_{ijk}\in L_{Mostly}\ And\ q\le q_0\\ & Or\ j\notin allowed\end{cases} \tag{11}$$

where P_{ijk}^{m} denotes the probability that the mth ant chooses the kth mode of transportation channel between node i and node j; η_{ijk} denotes the heuristic factor for adopting the kth mode of transportation channel between node i and node j; $allowed$ denotes the set of the next nodes that the mth ant is allowed to pass through ; q_0 is a parameter on $[0,1]$ denoting the upper limit of the probability threshold for the activation of the ants' special no-travel rule, and q is a random number on $[0,1]$ with $q\le q_0$ when the ants are forbidden to choose the current optimal path.

II. D. 3) Improvement of the design of the algorithm's solution operator

(1) Path encoding

In this paper, the permutation of all the elements in the set I is used as the encoding mode of the algorithm path, the first element of the path encoding must be O, the position of s is uncertain, the ants searching process, encountering s means that the search stops, and the encoding of its path encoding after the s element does not affect the path representation.

(2) Heuristic factor

In this paper, we apply ACO algorithm to solve the path optimization problem, and design the heuristic factors by integrating the attributes of transportation distance, transportation rate and transportation mode as follows:

$$\begin{aligned}&\eta_{ijk}=\frac{1}{d_{ijk}\cdot f_{c}^{k}}+\frac{1}{\min\left\{d_{ijk}\cdot f_{c}^{k}\,\middle|\,j\in allowed,k\in K\right\}}\cdot flag\\&j\in allowed\end{aligned} \tag{12}$$

where η_{ijk} denotes the heuristic factor for adopting the kth transportation mode channel between node i and node j; d_{ijk} denotes the transportation distance between node i and node j adopting the kth transportation mode channel; f_{ijk}^{t} denotes the transportation rate corresponding to d_{ijk}; $allowed$ denotes the set of all accessible next nodes from node i; $flag$ denotes the transportation mode consistency test parameter with value:

$$flag=\begin{cases}1 & k_{\text{Current}}=k_{ijk}\\0 & k_{\text{Current}}\neq k_{ijk}\end{cases} \tag{13}$$

where k_{Current} denotes the transportation mode of the ant's currently selected channel, and in particular, its value is set to 4 when the ant departs from point O before; and k_{ijk} denotes the transportation mode that will be used between node i and node j.

(3) Optimal path judgment rule

In this paper, the starting and ending point constraints of the RSTRO model are satisfied by the path encoding method, the spatial relationship constraints are satisfied by the $allowed$ set and equation, and the operation mode constraints are satisfied by the taboo table of the ant colony algorithm. The optimality of the path can be measured by whether the integrated cost is minimized.

(4) Ant search stopping rule

In this paper, the RSTRO model of the spatial relationship constraint formula to strengthen the taboo, in addition to the normal situation, the ants search to the end of the end s search ends, there may be not reached the end of the end, but $allowed$ set has been empty, this time, the search is caught in the stop, but the path is infeasible, and is not compared as a feasible solution.

(5) Iteration stopping rule

In this paper, the maximum number of iterations is chosen as the iteration stopping rule.

III. Analysis of solution results based on green logistics network optimization and carbon emission

III. A. Logistics path optimization solution results and analysis

III. A. 1) Research hypothesis

This paper takes the logistics network in Henan Province as an example for logistics path optimization. In order to verify the effectiveness of the improved ant colony algorithm, this paper adopts the relevant data of J Logistics Company in Henan Province for research. The logistics company has its own warehouse in Zhengzhou, the specific transportation process that is: assuming that at a certain point in time in the cities of Henan Province have orders, the goods in the warehouse in Zhengzhou City, loaded on the car, Zhengzhou City as the starting point, through the various regions of Henan Province's second-tier logistics services, and then finally return to the initial point of Zhengzhou City.

The research objective of this paper is to find the optimal transportation route for J Logistics in Henan Province in order to realize the transportation cost reduction. In building the model, the following three issues need to be considered:

First: only consider the case of one vehicle distribution, which is a simplified treatment of the model.

Second: the location of centralized distribution points can be represented by latitude and longitude data in Baidu map. This paper utilizes the 2000 national geodetic coordinate system based on Gaussian positive and negative arithmetic, through the conversion of 3° projection band plane right-angle coordinates (X, Y) conversion formula, the relevant latitude and longitude data are processed to obtain the corresponding right-angle coordinates, which can effectively reduce the gap with the actual distance.

Third: Assuming that at a certain point in time, there are distribution tasks in all 18 regions of the selected Henan Province.

III. A. 2) Data substitution

The 18 selected urban areas in Henan Province include Zhengzhou, Kaifeng, Shangqiu and so on. The latitude and longitude data of these 18 areas, as well as the coordinates of each transportation service point are collected, and the latitude and longitude data are converted into right-angle coordinates according to the coordinate conversion formula, with Zhengzhou City as the receiving and shipping center for each service area. The 18 distribution points are numbered with the numbers 1-18 respectively. Assuming that at a certain point in time the goods need to be distributed throughout the province, and by a car distribution, J Logistics first from the warehouse in Zhengzhou City to distribute the goods in the province, J Logistics 18 regions in Henan Province, the coordinates of each service point as shown in Table 1.

Table 1: J logistics company, 18 regions of Henan province

Projection point number	Latitude			Longitude			Coordinate (x, km)	The coordinate (y,km)
	Degree	Min	Second	Degree	Min	Second		
1 Zhengzhou city	35	43	22	114	52	54	3847.41	38495.39
2 Kaifeng city	35	33	35	114	45	46	3821.87	38564.13
3 Shangqiu city	35	24	29	114	40	12	3811.86	39379.69
4 luoyang city	33	41	38	112	21	53	3849.04	37624.73
5 Sanmenxia city	30	47	32	112	12	34	3839.7	37519.4
6 Nanyang city	36	59	23	109	39	58	3654.47	38376.63
7 Hebi city	35	34	41	116	13	31	3935.72	38524.22
8 Puyang city	35	50	50	117	29	26	3969.28	38635.1
9 Xinxiang city	33	18	9	113	45	54	3901.75	38565.6
10 Zhumadian city	34	46	45	115	52	28	3624.69	38593.19
11 Jiyuan demonstration area	35	6	57	113	33	39	3892.74	38372.82
12 Zhoukou city	35	4	41	114	24	25	3763.09	38534.99
13 xinyang city	34	37	51	114	53	18	3495.2	38574.25
14 Jiaozuo city	34	53	40	114	51	8	3856.55	38385.16
15 Luohe city	32	28	20	112	36	18	3703.34	38459
16 Pingdingshan city	33	43	43	113	17	17	3730.62	38434.2
17. Xu chang city	34	14	42	115	53	32	3794.38	38489.95
18 anyang city	32	7	56	116	14	45	4033.05	38554.31

III. A. 3) Solution results and analysis

In matlab software, the number of ants m=105, the pheromone importance factor α=1, the heuristic function importance factor β=6, the pheromone volatility factor ρ=0.01, the number of iterations of the algorithm is 250, and the distribution center is Zhengzhou city. The planning study of 18 areas in the province was carried out by using the ant colony algorithm, and after the analysis of matlab software, the path planning distance using the basic ant colony algorithm was about 1927 km, and the transportation routes were: 1-2-3-12-17-16-15-10-13-6-5-4-11-14-7-18-8-9-1. The path routes of the basic ACO algorithm are shown in Fig. 1 and the iteration curve of the basic ACO algorithm is shown in Fig. 2. The basic ant colony algorithm finds the optimal path at the 115th generation.

After analysis by matlab software, using the improved ant colony algorithm, 18 regions in Henan Province are planned with a path distance of about 1804 km, and the specific routes are: 1-2-12-3-8-18-7-9-14-11-4-5-6-13-10-15-16-17-1. The path line of the improved ACO algorithm is shown in Fig. 3, and the iteration curve of the improved ACO algorithm is shown in Fig. 4. From the figure, it can be seen that the optimal path is obtained in the 43rd generation, which indicates that the improved ant colony algorithm can significantly reduce the convergence time of the algorithm.

Comparing the results of the basic ant colony algorithm and the improved ant colony algorithm, the improved ant colony algorithm reduces the transportation distance by about 123km, i.e., the distribution distance of the optimal path is reduced by about 6.38% compared with the previous one. The improved ACO algorithm reduces the distance of vehicle transportation to some extent and reduces the transportation cost of J Logistics.

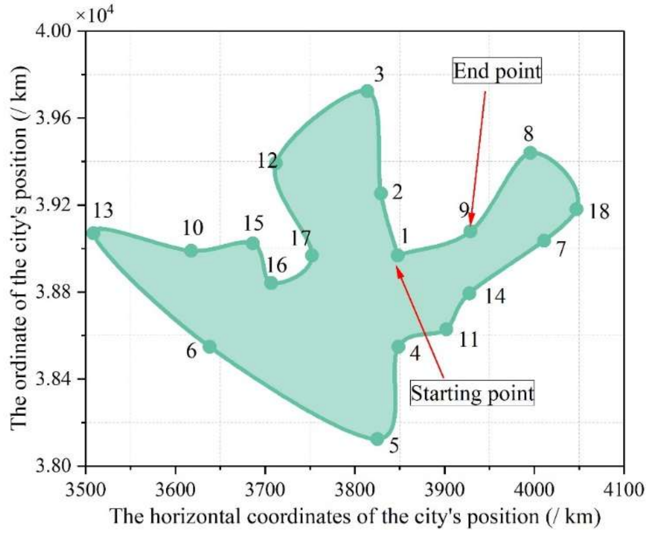

Figure 1: Path diagram of basic ant colony algorithm

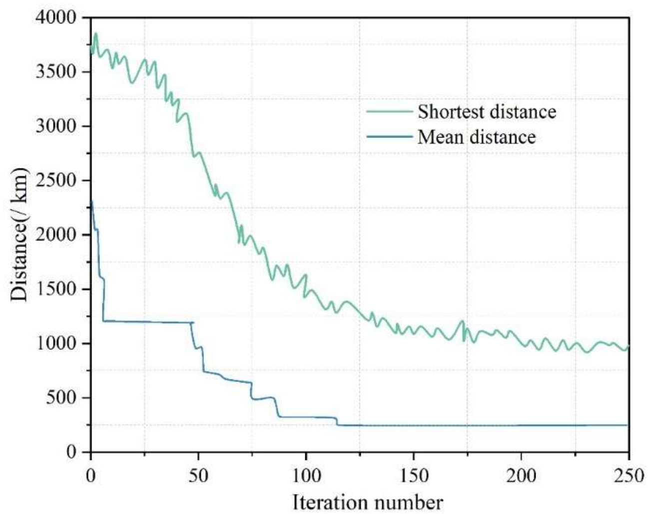

Figure 2: The iterative graph of the basic ant colony algorithm

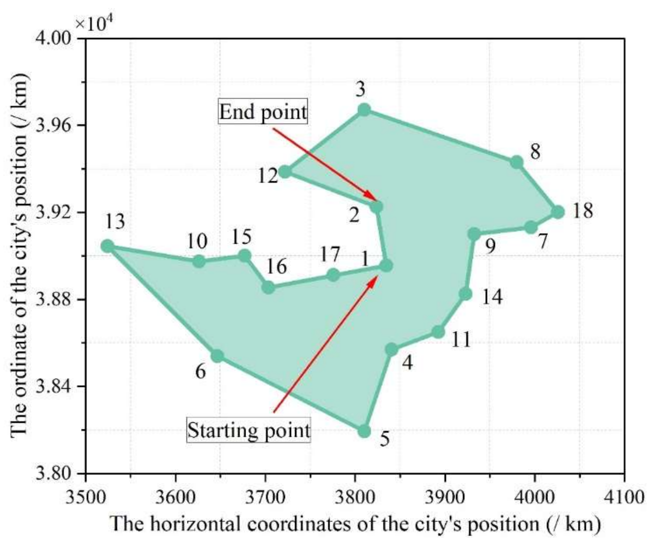

Figure 3: The path diagram of the improved ant colony algorithm

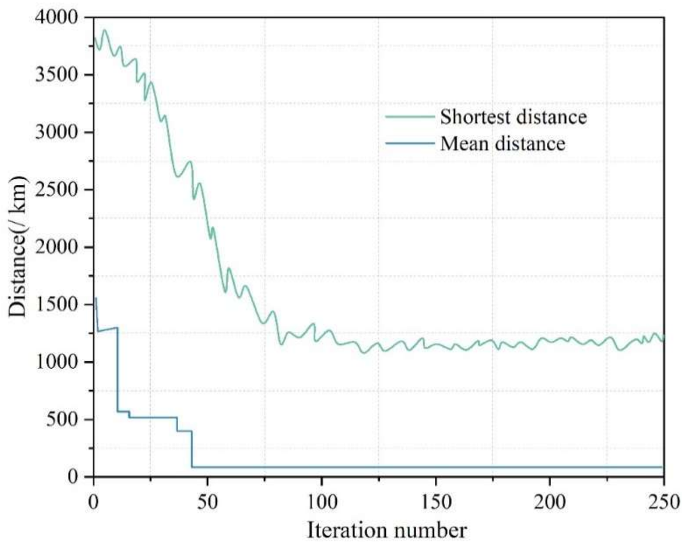

Figure 4: An iterative diagram of ant colony algorithm

III. A. 4) Tests of the effectiveness of the algorithm

The improved ant colony algorithm proposed in this paper has ideal convergence effect. In order to prove that the improved algorithm of this paper has certain advantages, based on the genetic algorithm, particle swarm algorithm and the improved ant colony algorithm (RSTRO) proposed in this paper, and at the same time, the data of the logistics network of Henan Province of the above J Logistics Company are run to solve the problem, and the results of the three algorithms are shown in Table 2. It can be seen that for the planning of logistics transportation path, the improved ACO algorithm designed in this paper has better convergence effect and faster convergence time, and the optimal path is smaller than that of the genetic algorithm and particle swarm algorithm. This proves that the improved ant colony algorithm has obvious advantages and solves the logistics path planning problem more satisfactorily.

Table 2: The calculation of the 3 algorithms

Algorithm	Mileage/km	Running time/s
Genetic algorithm	1935.7815	3.77
Particle swarm algorithm	2042.8291	5.86
RSTRO	1914.8879	2.15

III. B. Analysis of model sensitivity and carbon emission control strategies

III. B. 1) Sensitivity analysis of freight subsidies

In order to improve the competitiveness of railroad cold chain transport, tariff subsidy is usually used as an effective way to guide cold chain cargo transport from public to railway and to rationalize the transport structure. In the case of fixed train travel speed of 60 km · h^{-1}, by changing the share ratio of railroad tariff subsidy (0-30%), referring to the limitation of the tariff subsidy of the China-European liner train by the Ministry of Finance, and adopting the adaptive genetic-simulated annealing algorithm, the relationship between the market share of railroads and tariff subsidy is calculated, and the influence of tariff subsidy on railroads' market share is shown in Figure 5. The influence of freight subsidy on railway market share is shown in Figure 5. From the figure, it can be concluded that with the tariff subsidy gradually increased from 0 to 30%, the railroad market share shows a gradual increase in the phenomenon of fluctuations from 19.23%~24.68% when there is no subsidy to 25.13%~27.73% when the maximum subsidy. When the share of railroad tariff subsidy is 5%, the increase of railroad market share in the calculated transportation scenario is more significant. At 10% and 20% subsidy, the lower bounds of the rail market share decrease compared to 5% and 15% subsidy, respectively, mainly due to the fact that the optimal set of scenarios takes into account the impacts of cost, carbon emission and cargo loss rate at the same time. Under the railroad tariff subsidy, the cost of adopting railroad transportation mode decreases, while there is no change in the indicators of carbon emission and cargo loss rate, so this paper gives the interval of railroad market share in the optimal set of solutions to obtain a high growth of railroad market share with the least subsidy as possible.

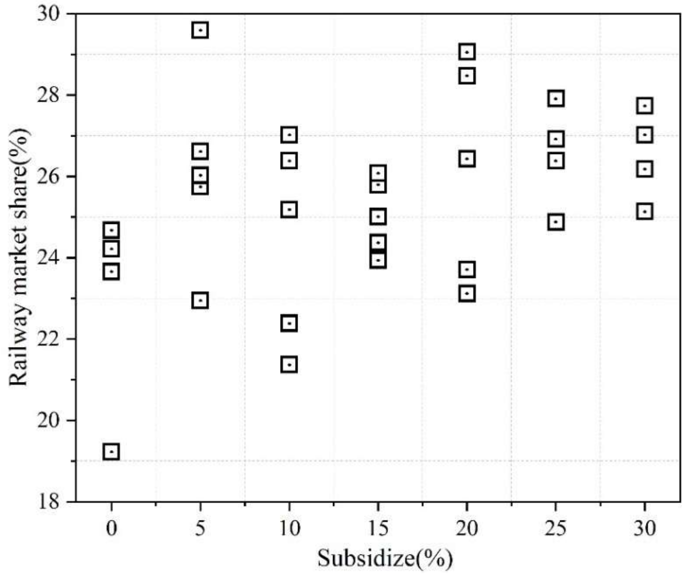

Figure 5: The impact of tariff subsidies on railway market share

III. B. 2) Sensitivity analysis of train travel speeds

As the travel speed of railroad cold chain transport trains is improved, the impact of train travel speed on the market share of the railroad by increasing the travel speed (60~120 km · h^{-1}) without tariff subsidy is shown in Figure 6. As can be seen from the figure, as the travel speed increases from 60 km · h-1 to 120 km · h^{-1}, the railroad market share increases gradually, with fluctuations ranging from 19.23% to 24.68% to 27.23% to 32.66%. In the case of higher travel speed, it is possible to shorten the in-transit time of the railroad cold chain train, thus reducing the indicator of cargo loss rate. The results of the set of optimal transportation scenarios at a confidence level of 90% show that the increase in the market share of the railroad is significant when the travel speed is increased from 60 to 70 km · h^{-1}, which is comparable to the results for a travel speed of 120 km · h^{-1}.

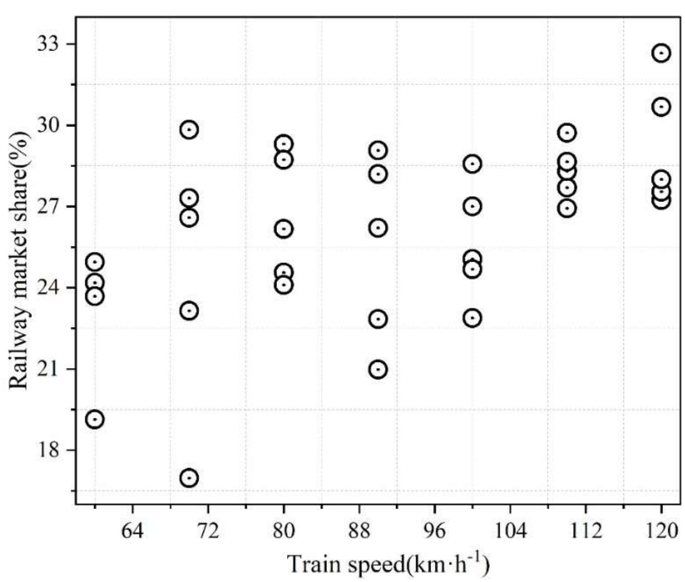

Figure 6: The impact of train travel on railway market share

III. B. 3) Sensitivity analysis of cold chain cargo categories

There are different kinds of cargoes in the cold chain transport cargoes with different requirements on transport time, and under the conditions of random OD, no subsidy, and no increase in railroad speed, the influence of cargoes with different sensitivity to transport time on the cold chain logistics of the railroad in the cold chain transport network is determined by taking different values of activation energy E_a (106~115 kJ · mol^{-1}). Where the smaller the value of E_a is taken, the higher the sensitivity to transportation time is, and the influence of cargo category on cargo loss rate is shown in Figure 7. As can be seen from the figure, in terms of the cargo loss rate indicator, there is a great difference between different cargo categories, and its fluctuation range gradually decreases from 23.25% to 25.35% to about 0.52% as the value of E_a increases.

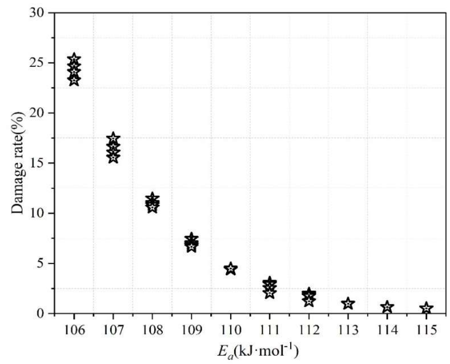

Figure 7: The effect of the goods category on the loss rate

The influence of cargo categories on railroad market share is shown in Figure 8. It can be seen that the initial value of railroad market share corresponding to different cargo categories fluctuates because the model simultaneously considers three conflicting objectives of transportation cost, carbon emission and cargo loss rate for optimization solution. Since the railroad market share is obtained based on solving the transportation scheme of cold chain network, the change of cargo loss rate is only one of the objectives when solving the transportation scheme, and when the above three conflicting objectives are considered at the same time in the model, the change of the cargo loss rate indicator of different transportation time-sensitive cargoes doesn't directly determine the increase or decrease of the railroad market share. Therefore, in the Pareto-optimal solution set obtained under the opportunity constrained planning model, cargoes with different transportation time sensitivities directly affect the change of cargo loss rate index and the initial value of railroad market share.

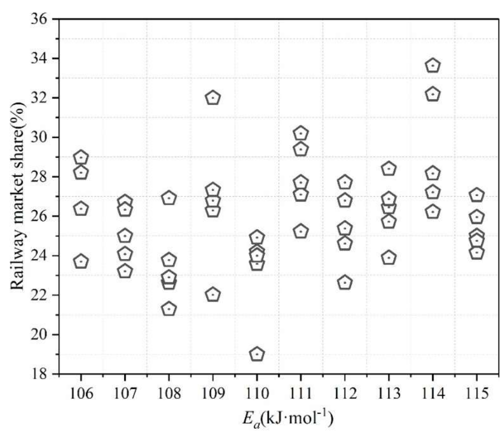

Figure 8: The impact of goods category on railway market share

IV. Conclusion

In this study, the green logistics network and carbon emission control problem under multi-period uncertainty is investigated, and a single-period logistics network optimization model is proposed and solved based on an improved basic ant colony algorithm. The following research conclusions are drawn:

(1) The improved ACO algorithm can effectively optimize the logistics distribution problem in Henan Province, and the optimized transportation distance is reduced by 6.38% compared with the traditional ACO algorithm. Meanwhile, according to the effectiveness test of the algorithm, it can be seen that the improved ACO algorithm can solve the logistics path optimization problem in a more ideal way than other algorithms.

(2) When adopting 5% freight subsidy, or only increasing the train travel speed to 70 km · h^{-1}, the effect of railroad market share increase is obvious. For regions with limited transport conditions, the tariff subsidy can be adopted to promote the rationalization of cold chain transport structure; for regions with better transport conditions, the tariff subsidy can be abolished when the expected competitiveness of the railroad cold chain can be achieved by

increasing the train travel speed. Cargoes with different levels of transport time sensitivity have a direct impact on the change of the cargo loss rate indicator and the initial value of the railroad's market share.

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