Green Logistics Delivery Path Optimization Considering Deliveryman Satisfaction under Time-Varying Road Networks

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Abstract. With the rise of green logistics and the continuous development of urban transportation networks, in order to solve the problems of high carbon emissions and low satisfaction of delivery personnel in logistics distribution. This article focuses on the optimization problem of green logistics distribution paths under time-varying road networks. With the satisfaction of delivery personnel as a constraint, carbon emission costs are considered in the distribution problem. A green logistics distribution model with the minimum comprehensive cost is established, and an improved ant colony algorithm integrating particle swarm algorithm ideas is designed. The effectiveness and feasibility of the proposed method are verified through numerical experiments. The research results indicate that green logistics delivery path optimization considering the satisfaction of delivery personnel can significantly reduce carbon emissions and improve delivery efficiency.

Keywords: green logistics, deliveryman satisfaction, time-varying road network

1 INTRODUCTION

With global climate change, carbon dioxide emissions have attracted widespread attention worldwide. According to the report "Carbon Dioxide Emissions from Fuel Burning: Overview" released by the International Energy Agency, CO2 emissions from transportation account for 1/4 of the total global emissions, while road transportation accounts for 3/4 of the total emissions from transportation activities. Therefore, studying green logistics transportation is of great significance.[1]

In order to adapt to the development of green logistics, Erdogan et al. first proposed the green VRP problem, with minimizing fuel consumption as the optimization objective[2], Rauniyar et al. constructed a multi-objective optimization model that minimizes the total cost of fuel consumption and carbon emissions, as well as the total driving distance, based on vehicle capacity constraints[3].In terms of constructing a logistics distribution path optimization model under time-varying conditions, Xiao et

V. Vasilev et al. (eds.), *Proceedings of the 2024 5th International Conference on Management Science and Engineering Management (ICMSEM 2024)*, Advances in Economics, Business and Management Research 306,
https://doi.org/10.2991/978-94-6463-570-6_100

al. reflected the impact of transportation on distribution by dividing time periods and constructed a low-carbon vehicle path optimization model with a time window[4], Zulvia et al. considered customer satisfaction when constructing the model and constructed the GVRP model with the lowest total cost and the highest customer satisfaction[5].

However, as an intermediate link between enterprises and customers, existing research rarely considers how the satisfaction of delivery personnel can have a significant impact on enterprise costs and customer satisfaction when the transportation environment changes. This article considers the satisfaction of delivery personnel as a constraint in a time-varying road network environment, constructs a green logistics distribution model with the minimum total cost, and designs an improved genetic algorithm that integrates the idea of particle swarm optimization to solve the model.

2 OPTIMIZATION MODEL ESTABLISHMENT

2.1 Problem Description

The distribution network system includes a distribution center and multiple customer demand points. The customer demand is known, and ordinary trucks are used. Each distribution vehicle departs from the distribution center, delivers to different customer demand points, and finally returns to the distribution center. Considering the satisfaction of the delivery personnel as the constraint and the goal of minimizing the total distribution cost, a scientific and reasonable distribution path is planned. When constructing the model, the following assumptions need to be made: (1) There are K vehicles in the distribution center, and one delivery person corresponds to one vehicle. (2) The maximum load capacity of the vehicle is known, and the total demand of customers on each route does not exceed the maximum load capacity of the vehicle. (3) All customer needs must be met, and each customer can only be visited once. (4) The driving speed of vehicles varies at different time periods. (5) The service time of the vehicle at the customer's location is negligible.

2.2 Parameter Symbols

According to the needs of model establishment, the parameter symbols in this article are set as follows:

N: Fresh delivery center and customer point collection, where i is the customer number,, i=1,2,3,...n, Distribution center number is 0; q_i: The demand for customer i; K: Vehicle Collection, $K = \{k|k=1,2,3,...,m\}$, The total number of vehicles in the fresh food distribution center is m; f_k: Fixed usage cost of vehicle k; f_o: Unit fuel consumption cost of vehicles; f_i: Partial fixed penalty cost for lateness; Q_k: Rated load capacity of vehicle k; t_{ki}: The time when delivery vehicle k arrives at customer i; Et_i: The earliest time customer i can tolerate being served; Lt_i: The latest time customer i can tolerate being served; et_i: The earliest expected service time for customer i; lt_i: The latest expected service time for customer i;

ε_1: Engine module coefficient; ε_2: Speed module coefficient; ε_3: Load module coefficient; c_1: Carbon emission coefficient; T: Expected normal working hours of carbon emission coefficient delivery personnel; T_{max}: Maximum acceptable overtime hours for delivery personnel; k_1: The salary of delivery personnel during normal working hours; ρ_1: Penalty cost for early arrival of vehicles; ρ_2: Penalty cost for delayed arrival of vehicles; g: Truck self weight; β: Cost per unit carbon emissions; T_c: Traffic congestion time period; T_f: Normal traffic time period; v_f: Vehicle speed during traffic congestion periods; v_c: Vehicle speed during normal traffic hours;

2.3 Related Factor Analysis

（1）Analysis of time-varying road network

In a time-varying network, due to different road congestion situations and vehicle speeds at different time periods, the speed function at each time period can be expressed as:

$$v_{ij}^k = \begin{cases} v_f & t \in T_f \\ v_c & t \in T_c \end{cases} \tag{1}$$

（2）Analysis of fuel consumption and carbon emissions

To make the calculation of vehicle fuel consumption more realistic, This article uses the comprehensive mode emission model CMEM proposed by Barth [6] to calculate vehicle fuel consumption:

$$c(Q_{ik}) = \varepsilon_1 d_{ij}/v_{ij}^k + \varepsilon_2 d_{ij}(v_{ij}^k)^2 + \varepsilon_3(g + Q_{ik})d_{ij} \tag{2}$$

The carbon emissions of vehicles are directly proportional to fuel consumption, and the calculation formula for vehicle carbon emissions :

$$c_{ij} = c_1 c(Q_{ik}) \tag{3}$$

（3）Satisfaction analysis of delivery personnel

This article evaluates the satisfaction of delivery personnel from two aspects: work intensity and salary, and takes into account their psychological state. Unlike the traditional method of using delivery distance[7], this study describes work intensity through working hours and finds that the longer overtime, the faster the decrease in satisfaction. Salary consists of basic salary and overtime pay. As salary increases, satisfaction increases rapidly at low wages, slows down at high wages, and reaches its highest level when the expected highest salary P_{emax} is reached. The salary and salary satisfaction function for improving the work intensity of delivery personnel in the design is shown in Figure 1:

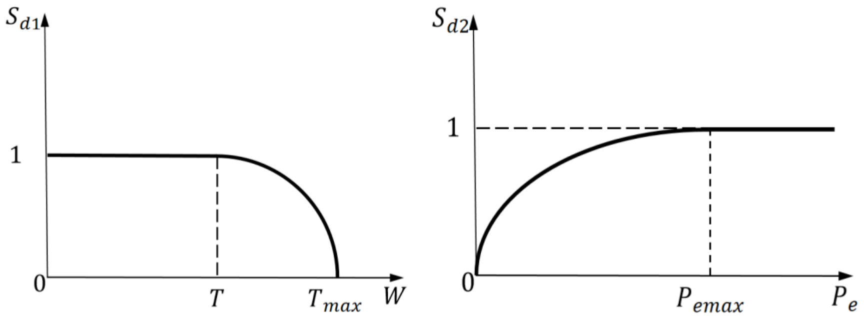

Fig. 1. Function of improved the job intensity satisfaction and salary for delivery personnel

The functional relationship between the satisfaction of delivery personnel with work intensity and work time can be expressed as:

$$S_{d1} = \begin{cases} 1 & W \in [0, T) \\ \sqrt{(T_{max} - T)^2 - (W - T)^2} & W \in [T, T_{max}) \\ 0 & W \in [T_{max}, +\infty] \end{cases} \tag{4}$$

$$W = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} \frac{d_{ij}}{v_{ij}^{k}} \tag{5}$$

The satisfaction of delivery personnel with salary and compensation as a function of salary and compensation can be expressed as:

$$S_{d2} = \begin{cases} 1 & P_e \in [P_{emax}, +\infty) \\ \log_{P_{emax}}(P_e + 1) & P_e \in [0, P_{emax}] \end{cases} \tag{6}$$

The salary of delivery personnel is as follows:

$$P_e = \begin{cases} k_1 W & W \in [0, T) \\ k_1 W + 1.5 k_1 (W - T) & W \in [T, +\infty] \end{cases} \tag{7}$$

In summary, this article empowers delivery personnel with job intensity satisfaction and salary satisfaction, and adds them up to obtain the comprehensive satisfaction of delivery personnel, expressed as:

$$S_d = \mu_1 S_{d1} + \mu_2 S_{d2} \tag{8}$$

In the above equation, μ_1, μ_2 is the weight, and the initial values will be set to 0.5, 0.5.

（4）Time Penalty Analysis

This article designs an improved hybrid time window function for the timeliness of goods delivery, as shown in Figure 2, to represent the cost due to time deviation. Using maximum value to indicate customer rejection of goods.

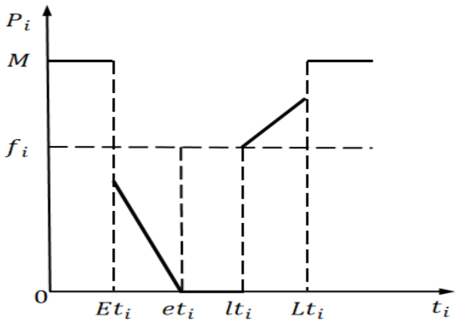

Fig. 2. Function of improved hybrid time window

The time penalty cost for violating time window constraints at the customer's location i during the delivery process can be expressed as:

$$P_i = \begin{cases} M & t_{ki} \in [0, Et_i) \cup (Lt_i, +\infty) \\ \rho_1(t_i - et_i) & t_{ki} \in [Et_i, et_i) \\ \rho_2(lt_i - t_i) + f_i & t_{ki} \in (lt_i, Lt_i] \\ 0 & t_{ki} \in [et_i, lt_i] \end{cases} \tag{9}$$

2.4 Model establishment

The final established model is as follows:

$$minZ = \sum_{k=1}^{m}\sum_{j=1}^{n} x_{oj}^{k} f_k + \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}^{k} c(Q_{ik}) f_o + $$

$$\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} \beta x_{ij}^{k} c_{ij} + \sum_{i=1}^{n} P_i + P_e \tag{10}$$

$s.t.$

$$\frac{1}{a}\sum_{d=1}^{a} S_d \geq T \tag{11}$$

$$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{0j}^{k} \leq m \quad \forall k \in K, j \in N \tag{12}$$

$$\sum_{j=1}^{n} x_{0j}^{k} = \sum_{j=1}^{n} x_{j0}^{k} \leq 1 \quad \forall k \in K, j \in N \tag{13}$$

$$\sum_{k=1}^{m}\sum_{i=1}^{n} y_i^k = 1 \quad i \in N \tag{14}$$

$$\sum_{i=1}^{n} y_i^k q_i \leq Q_k \quad \forall k \in K \tag{15}$$

$$Et_i \leq t_{ki} \leq Lt_i \quad i \in N \tag{16}$$

$$t_{kj} = \sum_{k=1}^{m}\sum_{i=0}^{n} x_{ij}^{k} [max(t_{ki}, et_i) + \frac{d_{ij}}{v_{ij}^{k}}] \quad j \in N \tag{17}$$

$$x_{ij}^{k} \in [0,1], y_i^k \in [0,1] \tag{18}$$

Equation (10) represents the minimization of total delivery costs, including fixed costs, fuel consumption costs, carbon emissions costs, time penalty costs, and delivery worker wages. Equation (11) represents the average satisfaction of delivery personnel; Equation (12).The distribution center has sufficient vehicles. Equation (13) indicates that each vehicle departs from the refrigeration center and finally returns to the refrigeration center. Equation (14) indicates that each customer can only be served once.Equation (15) represents the capacity constraint of the vehicle. Equation (16) indicates that the arrival time of the vehicle is within the allowable range of the customer point.Equation (17) represents the time when the vehicle arrives at the customer's location. Equation (18) represents the decision variable.

3 ALGORITHM DESIGN

This article uses ant colony algorithm to solve the model, and addresses the problem of premature convergence and local optimization in traditional ant colony algorithm. By introducing the idea of partial particle swarm algorithm and improving the traditional ant colony algorithm from the perspectives of ant aggregation and pheromone concentration.

3.1 Weight Adaptive Formula

Adjust the speed of ants by setting weights, and the formula for calculating the speed of ants with added weights is shown in formula (19):

$$v_i(t+1) = \omega v_i(t) + \delta_1 r\big(P_i - x_i(t)\big) + \delta_2 r\big(L_{best} - x_i(t)\big) \tag{19}$$

In the formula: t represents the number of iterations, $x_i(t)$ represents the position of ant i in the t-th iteration; $v_i(t)$ represents the speed of ant i in the t-th iteration ; r representing random numbers that follow a uniform distribution , $r \in (0, 1)$; δ_1、δ_2 representing self factors and social factors.

This article introduces adjustment factors and clustering factors to improve the weights and improve the ant colony algorithm

The adjustment factor E_{TZ} is shown in equation (20)

$$E_{TZ} = \frac{F\big(L_{best}(t+1)\big)}{F\big(L_{best}(t)\big)} \tag{20}$$

Ant aggregation $Ag(i)$ is shown in formula (21)

$$Ag(i) = \left[\sum_{j=1}^{n} \left(\frac{m}{n} - a_j\right)^2\right]^{\frac{1}{2}} \tag{21}$$

In the formula: i represents the starting point of ants,m represents the number of ants,n represents the number of paths and destinations,a_j represents the number of ants that have not passed through the optimal path at this time.

The final weight value ω is Equation (22):

$$\omega = f(E_{TZ}, \ Ag) = \omega_0 - E_{TZ}\omega_1 + Ag\omega_2 \tag{22}$$

Generally speaking, ω_0 takes a value of 1, ω_1 is the weight under the action of E_{TZ}, and ω_2 is the weight under the action of Ag.

3.2 Formula for Updating Pheromone Concentration

This article improves the pheromone concentration strategy of the traditional ant colony algorithm. Before 20 iterations, the conventional pheromone concentration strategy is adopted. After 20 iterations, the pheromone concentration released by ants in paths with less ant aggregation is appropriately increased. After improvement, the pheromone update strategy for paths with less ant aggregation is shown in formula (23):

$$\begin{gathered} C_n(t+1) = (1-\alpha)\cdot C_n(t) + \Delta C_n + \Delta\rho \\ \Delta C_n = \sum C_n^k \end{gathered} \tag{23}$$

In the formula: $C_n(t+1)$ represents the concentration of pheromones on the path n during the $t+1$iteration,α representing the degree of evaporation of pheromones; ΔC_n represents the total increase in pheromones along the path n; C_n^k represents the pheromone evaporation of the path n, $\Delta\rho$ represents the increase in pheromones released by paths with low ant aggregation.

3.3 Steps to Improve Ant Colony Optimization Algorithm

Step 1: Initialize the parameters related to the ant colony algorithm.

Step 2: Initialize the number of ants, randomly initialize the speed and starting point of ants, and calculate the fitness value of ants. Mark the path of the ant in the first iteration result as the best path P_i for individual ants, and mark the fitness value of individual ants as the best fitness value. Select the minimum fitness value generated by all ants in the ant colony as the global best fitness value, and the path of the ant with the minimum fitness value generated as the global best path L_{best}.

Step 3: Update the speed of ants according to formulas (19) , and update the pheromone concentration strategy of ants through formulas (23).

Step 4: Compare the fitness values of each ant with the best individual fitness value, retain the best search results of both parties, and update the strategy.

Step 5: Compare the fitness values of individual ants and ant colonies with the optimal fitness values of ant colonies, retain the best search results of both parties, and update the strategy.

Step 6: Compare the current iteration count with the upper iteration count. If the iteration count has reached the upper limit, end the optimization process and output the optimal solution. Otherwise, return to step 3.

4 EXPERIMENTAL SIMULATION AND ANALYSIS

4.1 Parameter Settings

This study uses the R101 example from Solomon's benchmark suite as the base case and selects the first 30 customer points for experiments. Appropriate modifications were made according to the characteristics of the model, and both the traditional ant colony algorithm and the optimized algorithm proposed in this paper were used to solve the model. Each method was tested ten times, with the best-performing instance from each method selected as the final result.

The model parameter settings as show in Table 1 and algorithm parameter settings as the follows：

Table 1. Model parameter table

symbol	Parameter values	symbol	Parameter values	symbol	Parameter values	symbol	Parameter values
f_k	200yuan	ε_1	$1.5*10^{-3}$	T_c	[7:00,9:00]	k_1	60yuan/h
f_o	7yuan/L	ε_2	$4.3*10^{-7}$	v_c	50	ρ_1	40yuan/h
f_i	100	ε_3	$1.05*10^{-8}$	T	8h	ρ_2	50yuan/h
P_{emax}	1400yuan	c_1	2.4kg/L	T_{max}	12h	β	1yuan/kg

Algorithm parameter settings:Ant quantity M=50, iteration times 200, pheromone evaporation factor: 0.3, ant pheromone concentration: 1， δ_1： 2， δ_2： 1.5.ant movement speed limit V_{max}： 10，lower limit V_{min}： -10， ω_1： 0.45， ω_2： 0.0138，$\Delta\rho$：0.1.

4.2 Sensitivity Analysis and Algorithm Comparison

（1）Sensitivity analysis of satisfaction function weight

In order to explore the various costs that enterprises need to invest under different levels of satisfaction, this article sets three different levels for the constraint T of average deliveryman satisfaction, which are 70%, 80%, and 90%, respectively. The delivery routes for each situation are shown in Figure 3.

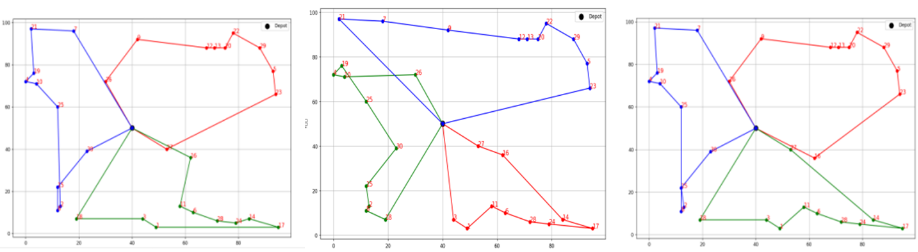

Fig. 3. Paths under different average deliveryman satisfaction constraints

By comparing the changes in the objective function values at different levels of satisfaction by assigning different weights to the satisfaction function, the obtained objective function values are shown in Table 2:

Table 2. Sensitivity Analysis of Customer Satisfaction Function Weights

Satisfaction weight （μ_1， μ_2）	T=70%	T=80%	T=90%
（0.9，0.1）	2075.32	2093.28	2135.38
（0.7，0.3）	2053.12	2080.82	2103.64
（0.5，0.5）	2053.12	2069.56	2088.44
（0.3，0.7）	2053.12	2053.12	2053.12
（0.1，0.9）	2053.12	2053.12	2053.12

From the table, it can be seen that as the satisfaction of delivery personnel increases, the cost required by the enterprise also increases. When=0.3, the enterprise can achieve a satisfaction level of 90 by spending 2053.12 yuan. It can be seen that when the salary satisfaction is low, the enterprise can obtain a delivery plan with higher satisfaction from delivery personnel at lower delivery costs.

（2）Algorithm comparison

To verify the effectiveness of the improved algorithm in this article, traditional ant colony algorithm (ACA) and improved ant colony algorithm were used to solve the above model, and the results are as show in Table 3:

Table 3. Comparison of Algorithm Results

Satisfaction constraint	IM-ACO		ACO	
	total cost	Actual satisfaction	total cost	Actual satisfaction
T=70%	2053.12	73.36%	2134.25	71.86%
T=80%	2069.56	84.16%	2186.72	82.64%
T=90%	2088.44	90.69%	2376.49	90.23%

It can be found that the total cost obtained by the improved genetic algorithm is less than that obtained by traditional genetic algorithms under the same level of satisfaction constraints, reducing by 3.7%, 5.3%, and 12% respectively. The actual customer satisfaction is also higher. Compared with ACO algorithm, IM-ACO can achieve better optimization results.

5 CONCLUSION

This article focuses on the optimization problem of green logistics delivery paths under time-varying road networks. With the satisfaction of delivery personnel as a constraint, an optimization model with the goal of minimizing comprehensive costs is constructed, and an improved ant colony algorithm integrating particle swarm algorithm ideas is designed to solve it. The experimental results show that the new algorithm can effectively reduce carbon emissions, improve delivery efficiency, and is superior to traditional methods in terms of cost and delivery staff satisfaction. Research has shown that path optimization considering the satisfaction of delivery personnel is of great significance for improving the efficiency of green logistics, and provides practical applications for green logistics distribution path planning.

ACKNOWLEDGMENT

Financial support：University-local government scientific and technical cooperation cultivation project of Ordos Institute-LNTU, (YJY-XD-2024-B-013)

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