

Retraction

Retracted: Path Optimization Model for Urban Transportation Networks under the Perspective of Environmental Pollution Protection

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] C. Liu, Z. Li, and Y. Li, "Path Optimization Model for Urban Transportation Networks under the Perspective of Environmental Pollution Protection," *Journal of Advanced Transportation*, vol. 2021, Article ID 8952123, 11 pages, 2021.

Research Article

Path Optimization Model for Urban Transportation Networks under the Perspective of Environmental Pollution Protection

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In view of the lack of consideration of environmental protection performance in the traditional path optimization model, a path optimization model for urban traffic networks from the perspective of environmental pollution protection is proposed. Firstly, the urban real-time traffic condition is expressed by the road traffic state index, and an integer programming model is established to optimize the route with the goal of low carbon and shortest distribution time. Then, a hybrid particle swarm optimization algorithm combined with adaptive disturbance mechanism based on variable neighborhood descent is designed, which can better carry out adaptive disturbance according to the situation that the population falls into local extreme value, and the 2-opt local search method is introduced to improve the quality of solution. Finally, the improved particle swarm optimization algorithm is used to solve the two-objective model to obtain the Pareto front solution set, that is, the path scheme under real-time traffic conditions. The experimental demonstration of the proposed model based on two application scenarios shows that its distribution cost, distribution time, and carbon emission are 1975 yuan, 27 h, and 213 kg, respectively, which are better than other comparison models and have high application value.

1. Introduction

With the increasingly prominent ecological and environmental protection issues and the implementation of related policies, the carbon emission problem in the urban transportation process has gradually attracted people's attention [1]. The carbon emissions generated during the driving of a vehicle are affected by factors such as vehicle type, driving time, and speed. Studies have shown that path planning with optimized speed can reduce more carbon emissions and total costs than path planning with fixed speeds [2, 3]. However, in traffic jams, the speed of the vehicle is determined by the actual road conditions. Therefore, it is more

practical to optimize low-carbon vehicle paths under time-varying traffic conditions [4].

Based on the current development of monitoring information technology, real-time monitoring of urban road traffic networks has been roughly achieved. This provides a good road condition data basis for vehicle path planning (VPP) [5, 6]. From the perspective of environmental pollution protection, green transportation needs to consider the impact of logistics activities on the environment. The main goal is to reduce energy consumption and pollutant emissions [7], specifically, the carbon emissions of vehicles. The road traffic index can be used to get the speed of the vehicle and then calculate the delivery time and carbon emissions

based on this. Finally, the vehicle path optimization strategy under time-varying traffic conditions is obtained [8]. Vehicle green path planning is of great significance for reducing CO₂ emissions. It helps to achieve the strategic goal of “carbon neutrality and carbon peak” in advance.

At present, there have been many studies on VPP issues. It not only considers that the actual vehicle speed will be affected by many factors but also considers the impact of vehicle travel time on users. Traditional VPP methods mainly include heuristic algorithm, simulated annealing algorithm, genetic algorithm, ant colony algorithm, tabu search, quantum evolution algorithm, and hybrid algorithm [9]. Reference [10] proposed a vehicle path planning scheme with a specified length. The maximum length of coverage can be generated under different scenarios and different conditions, and an expected path with arbitrary topological classification can be generated according to curvature constraints and obstacle constraints. However, the impact of the real-time status of the urban traffic network on the route plan is not considered. In Reference [11], a new heuristic algorithm for heterogeneous vehicle path planning based on primitive dual technology was proposed for the task assignment and routing problems of two heterogeneous unmanned vehicles located in different warehouses and a set of targets to be visited. High-quality feasible solutions can be obtained in a short time, but the solution efficiency is difficult to meet actual needs. Reference [12] proposed an optimal maneuvering destination and constraint conditions under the condition of no connected graph to realize military amphibious vehicle path planning. Among them, the area theory is used to solve the problem of amphibious vehicle simulation and maneuvering path planning on unconnected graphs. But it does not apply to civil vehicle path planning. Reference [13] designed a global path planning algorithm to optimize the generation of sparse waypoints with clear constraints. In order to deal with the dynamic and unpredictable environment, fuzzy decision-making and fine dynamic window layer establish a local hierarchical structure. By controlling the yaw speed, it is responsible for avoiding collision guidance signals in a large range and close range. However, the algorithm overhead is large and the real-time performance is poor. Reference [14] proposed a Bezier curve optimization method to optimize the path plan of the automatic driving process, especially the automatic obstacle avoidance. The obstacle avoidance problem is transformed into an optimization problem under equality constraints, and the Lagrangian method is combined to solve it. However, the issue of carbon emissions is not considered, and it lacks environmental protection. In Reference [15], in order to analyze the interaction between real-time planning and tracking control of intelligent vehicles, based on the improved rapid exploration random tree algorithm and linear time-varying algorithm, a new intelligent vehicle path planning and tracking control architecture was proposed, which effectively improves the efficiency of path planning. Reference [16] proposed a vehicle path planning scheme that considers fuel consumption and carbon emissions based on the dynamic

traffic network structure. Among them, the traditional path planning Dijkstra algorithm is improved, and the vehicle fuel consumption and emission measurement model are combined to realize the vehicle green path planning. However, it did not consider the problems of increased fuel consumption and increased carbon emissions under traffic congestion.

In view of the lack of consideration of traffic conditions and low environmental protection in most path planning models, a path optimization model for urban transportation networks from the perspective of environmental pollution protection is proposed. Compared with the traditional model, its innovations are summarized as follows:

- (1) Since most of the route optimization models are not comprehensive enough to consider environmental protection, the proposed model quantifies the speed through the road traffic index. And combining the two goals the lowest carbon emissions and the shortest delivery time, a route optimization model for urban transportation networks is designed. Ensure to reduce carbon emissions under the premise of less delivery time.
- (2) In order to prevent particle swarm optimization (PSO) from falling into the local optimum and losing the best searched solution due to disturbance, the proposed model optimizes PSO, combining the adaptive perturbation mechanism with variable neighborhood descending search as the main body, adopting adaptive neighborhood selection strategy, and applying a variable number of cycles in each neighborhood search, so as to improve the detection ability and search of the solution space efficiency.

2. Model Building

2.1. Definition of Vehicle Routing Problem. The VPP issue was raised by Dantzig and Ramser in 1959. By studying this problem, it is possible to reasonably plan the driving path of the vehicle, so as to achieve the purpose of reducing cost and improving efficiency [17].

The cold chain logistics distribution path optimization problem of multiple distribution centers is a highly complex vehicle routing problem. Combining the characteristics of cold chain logistics, the VPP problem can be defined: the location of the cold chain distribution center, the location of the store, and the demand for cold chain products are known. On the basis of considering the maximum load capacity of cold chain delivery vehicles, the time window requirements for the store to accept order delivery services, carbon emissions, and other constraints, use cold chain delivery vehicles to provide cold chain order delivery services to stores and plan the driving route of cold chain delivery vehicles reasonably, So as to achieve the shortest vehicle driving distance, the lowest total cost of cold chain logistics and distribution, and the highest vehicle utilization rate [18]. The driving path of the cold chain logistics distribution vehicle facing the urban transportation network is shown in Figure 1.

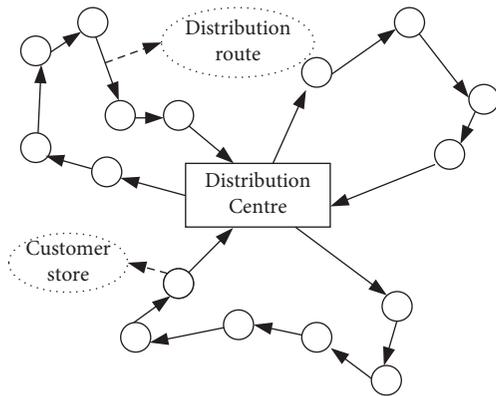


FIGURE 1: Schematic diagram of driving path of cold chain logistics distribution vehicles.

As can be seen from Figure 1, the vehicle routing problem of cold chain logistics includes the following elements:

- (1) Cold chain distribution center: the cold chain distribution center is the starting and ending point of all cold chain distribution services. In a closed-loop cold chain logistics distribution system, the cold chain distribution vehicles need to return to the cold chain distribution center from which they started after completing the store order distribution task. In a cold chain logistics distribution system, according to the geographical location of the distribution store and the complexity of the distribution task, one or more cold chain distribution centers will be arranged for distribution and delivery services.
- (2) Store: stores are an important node in the cold chain logistics distribution network. Information such as the location of the store, the time window requirements for accepting order delivery services, and the demand for cold chain products will affect the path selection of cold chain delivery vehicles in their delivery process.
- (3) Cold chain products: cold chain products are perishable. And because of their different attributes (volume, quantity, quality, price, etc.) and different store order requirements, it is necessary to select a reasonable delivery method and delivery vehicle to complete the delivery task.
- (4) Delivery vehicles: the delivery vehicle is an important tool to complete the delivery task. Due to the perishability of cold chain products, professional refrigerated trucks need to be used in the order distribution service of cold chain products. Choosing a cold chain delivery vehicle needs to consider the characteristics of the cold chain vehicle such as the vehicle model, the maximum load of the vehicle, the cost of the vehicle, fuel consumption, and the number of vehicles.
- (5) Constraints: constraints are the factors that need to be considered when planning the order delivery route of cold chain delivery vehicles. Such as the

maximum load capacity of cold chain delivery vehicles, carbon emissions, and the time window within which stores can accept order delivery services.

- (6) Objective function: the objective function is the ultimate goal of planning the cold chain logistics distribution path. For example, the total cost of cold chain logistics and distribution is the smallest, and the driving distance of cold chain distribution vehicles is the shortest.
- (7) Vehicle distribution route network: the vehicle distribution path network is composed of network nodes and arcs. In the cold chain logistics distribution path network, the network nodes are cold chain distribution centers and stores. Arcs represent transportation roads, and their weights represent time, distance, cost, and so on.

2.2. Model Building. The low-carbon vehicle routing optimization problem considering the urban transportation network can be described as follows: in a distribution center, a group of homogeneous fleets are responsible for the distribution tasks of multiple customers; the maximum load of the vehicle is W , and the demand of customers is Q ; the speed at which a vehicle travels varies with traffic conditions, which in turn affects the travel time of the vehicle and the amount of carbon emissions produced; and to solve the vehicle path with the shortest time and the lowest carbon emissions as the goal [19, 20].

The assumptions of the path optimization model are as follows:

- (1) There is only one distribution center in the logistics distribution network, facing multiple customers, and the location is known.
- (2) The demand of each customer is known, and the vehicle must not exceed its load capacity during delivery.
- (3) There is only one vehicle in the fleet, and the load capacity is known.
- (4) Each customer's needs must be met and can only and must be visited once.
- (5) Vehicles are not allowed to stop on the way, regardless of the cargo loading and unloading time.
- (6) The time period of all delivery activities is divided into several time periods. The driving speed of a vehicle on a certain route during a certain period of time is determined by the average value of the road traffic index on the route during this period of time. And the speed of the vehicle does not change in each time period, regardless of the speed change process across the time period [21].

2.2.1. Solution of Transportation Time. Urban Road Traffic State Index (TSI) uses a quantified value to indicate the degree of road traffic congestion, with a value between 0 and

100. The larger the value, the more congested the road [22]. The relationship between the road traffic index and speed is expressed as follows:

$$\text{TSI} = \left(\frac{v_{\max} - v}{v_{\max}} \right) \times 100\%, \quad (1)$$

where TSI is the road traffic index; v_{\max} is the maximum vehicle speed allowed on the road; and v is the real-time vehicle speed.

In order to facilitate qualitative understanding, the transportation department divides the index from 0 to 100 into four intervals. The four levels of traffic congestion are unblocked, relatively unblocked, congested, and congested. The traffic conditions in the city during the morning rush hour are generally smoother. Therefore, the proposed model will solve the problem within this time period.

$$t_{ij} = \begin{cases} \frac{d_{ij}}{v_{ijr}}, & \tau_{ij} \leq T_{r+1} - \frac{d_{ij}}{v_{ijr}}, \\ \frac{d_{ij}}{v_{ijr}} + t_{ij}^s, & \frac{T_{r+1} - d_{ij}}{v_{ijr}} \leq \tau_{ij} \leq T_{r+1}, \end{cases} \quad t_{ij}^s = \frac{(d_{ij}/v_{ij(r+1)}) - (d_{ij}/v_{ijr})}{T_{r+1} - (T_{r+1} - d_{ij}/v_{ijr})} (T_{r+1} - \tau_{ij}), \quad (3)$$

where d_{ij} is the distance from point i to point j ; v_{ijr} is the speed of the vehicle from point i to point j in the r time period; t_{ij} indicates that the time point when the vehicle arrives at point j is within $[T_r, T_{r+1}]$; and t_{ij}^s indicates that the time point when the vehicle arrives at point j is in the next time period.

2.2.2. Solving Carbon Emissions. The carbon emission calculation uses the carbon emission calculation function given by the European Commission in the MEET (Methodologies for Estimating air Pollutant Emissions from Transport) report, which is calculated as follows:

$$C = P + av + bv^2 + cv^3 + \frac{d}{v} + \frac{e}{v^2} + \frac{f}{v^3}, \quad (4)$$

where C represents the carbon emissions of a vehicle traveling 1 km at a speed of v , and the unit is g. The value of the parameter (P, a, b, c, d, e, f) is related to the type of vehicle. The cold chain vehicle used in this study is a heavy-duty truck. The value of the parameter (P, a, b, c, d, e, f) is (1765, -17.8, 0, 0.00114, 0, 36076, 0).

Assuming that the speed of the vehicle is constant in each time period, the carbon emissions of the vehicle between any two points are the sum of the carbon emissions generated during the time the vehicle is traveling at a constant speed.

The time period of all delivery activities is divided into R time periods, which are represented by $[T_1, T_2], [T_2, T_3], \dots, [T_R, T_{R+1}]$. The speed of vehicles on the route between any two customer nodes is a piecewise function of time. The corresponding travel time is a piecewise function of the start time. Assuming that the departure time τ_{ij} of the vehicle from point i to point j is in the time period $[T_r, T_{r+1}]$, the corresponding delivery time t_{ij} is calculated as follows:

$$t_{ij} = \phi_{ij}(\tau_{ij}), \quad (2)$$

where ϕ_{ij} is a function of time from point i to point j .

When the distance between two points and the division of road conditions are different, the specific form of formula (2) will be different. The situation that the delivery of vehicles between two nodes will only span one time segment is shown as follows:

Suppose τ_{ij} is in the time period $[T_g, T_{g+1}]$, $\tau_{ij} + t_{ij}$ is the time point when the vehicle arrives at the point j , and $\tau_{ij} + t_{ij}$ is in the time period $[T_h, T_{h+1}]$. The carbon emissions of a vehicle traveling from point i to point j are calculated as follows:

$$C_{ij} = C_{ijg} \cdot (T_{g+1} - \tau_{ij})v_{ijg} + C_{ijh} \cdot (\tau_{ij} + t_{ij} - T_h)v_{ijh} + \sum_{g+1}^{h-1} C_{ijr} \cdot (T_{r+1} - T_r)v_{ijr}, \quad (5)$$

$$\begin{aligned} C_{ijg} &= P + av_{ijg} + bv_{ijg}^2 + cv_{ijg}^3 + \frac{d}{v_{ijg}} + \frac{e}{v_{ijg}^2} + \frac{f}{v_{ijg}^3}, \\ C_{ijh} &= P + av_{ijh} + bv_{ijh}^2 + cv_{ijh}^3 + \frac{d}{v_{ijh}} + \frac{e}{v_{ijh}^2} + \frac{f}{v_{ijh}^3}, \\ C_{ijr} &= P + av_{ijr} + bv_{ijr}^2 + cv_{ijr}^3 + \frac{d}{v_{ijr}} + \frac{e}{v_{ijr}^2} + \frac{f}{v_{ijr}^3}, \end{aligned} \quad (6)$$

where C_{ij} is the carbon emissions produced by the vehicle from point i to point j . The first part of formula (5) is the carbon emissions generated by the vehicle driving in $[T_g, T_{g+1}]$. The second part represents the carbon emissions generated by the vehicle driving in $[T_h, T_{h+1}]$. The third part

represents the carbon emissions generated by the vehicle during the time period between these two time periods.

2.2.3. Two-Objective Integer Programming Model. According to the analysis and calculation of transportation time and carbon emissions, the dual-objective function of the route optimization problem is obtained as follows:

$$\begin{aligned} \min T &= \sum_{(i,j) \in N} \sum_{k \in K} t_{ij} x_{ij}^k, \\ \min C &= \sum_{(i,j) \in N} \sum_{k \in K} C_{ij} x_{ij}^k. \end{aligned} \quad (7)$$

The constraints are

$$\sum_i q_i \sum_j x_{ij}^k \leq Q, \quad \forall k \in K, \quad (8)$$

$$\sum_k \sum_j x_{ij}^k = 1, \quad \forall i \in Q, \quad (9)$$

$$\sum_i x_{i0}^k = 1, \quad \forall k \in K, \quad (10)$$

$$\sum_i x_{oi}^k = 1, \quad \forall k \in K, \quad (10)$$

$$\tau_j = \tau_j + t_{ij}, \quad (11)$$

$$\sum_i x_{im}^k - \sum_j x_{jm}^k = 0, \quad \forall m \in Q, \forall k \in K, \quad (12)$$

$$x_{ij}^k \in \{0, 1\}, \quad \forall i, j \in Q, \forall k \in K,$$

where T is the delivery time of all vehicles; C is the total carbon emissions; $x_{ij}^k = \begin{cases} 1 & \text{if vehicle } k \text{ passes customer } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$; N is a

collection of network nodes (including distribution centers and customer points); and K is the collection of vehicles. Equation (8) represents the capacity limit of the vehicle; equation (9) means that each customer has one and only one car to provide service; equation (10) means that all vehicles can only depart from the distribution center once and finally return to the distribution center; equation (11) represents the time relationship; and equation (12) indicates that the vehicle must leave after completing the service.

3. Model Solving

3.1. Two-Objective Solution. PSO cannot be directly used to solve biobjective problems. The proposed model adopts the ε -constraint method (epsilon constraint method, ECM) for biobjective solutions. First, find the optimal solution for a goal. Then, use the goal of the optimal solution as a constraint to solve the second goal and save the noninferior solution. Then, gradually let go of the constraints on the first goal. Finally, the noninferior solutions are merged to obtain the Pareto front [23].

When solving the proposed dual-objective model, the solution is first based on the shortest total delivery time. Take

the total time as the constraint condition, and then solve the problem with the lowest vehicle carbon emission as the goal. The specific solution process is as follows:

$$\begin{cases} \text{if } T \leq T_{\min} + n\varepsilon, \\ C = \sum_{k \in K} C_k, \\ \text{else } C = \sum_{k \in K} C_k + M, \\ \text{END,} \end{cases} \quad (13)$$

where M is a sufficiently large positive integer; n is the number of iterations for biobjective solutions; and T_{\min} is the shortest delivery time for all vehicles.

3.2. Encoding. For the vehicle path optimization problem model, the coding method is as follows: define the particle position $L = (l_1, l_2, \dots, l_i, \dots, l_n)$, $l_i \in [1, k]$ in the population. The i position of the particle represents the i customer position. If $k-1 < l_i \leq k$ indicates that the i customer is delivered by the k car, the velocity of the particle $V = \{v_1, v_2, \dots, v_i, \dots, v_n\}$, $v_i \in [1, k]$. The initial solution L represents the order of customer locations that the delivery vehicle passes, and the first one is 0.

Assuming there are 3 cars and 8 customers, one solution of the proposed model is $L = (4, 2, 6, 7, 1, 8, 9, 10)$. First, the elements of L are divided into k sets. Then, they were sorted in descending order according to the size of l_i , that is, customers with a large l_i value prioritize vehicle delivery. Finally, the distribution center is removed, that is, a distribution route plan for each vehicle is generated. The encoding process is shown in Figure 2.

As can be seen from Figure 2, after grouping, they are $\{1,2\}$, $\{4,6,7\}$, $\{8,9,10\}$, and after sorting, they are $\{2,1\}$, $\{7,6,4\}$, $\{10, 9, 8\}$. The corresponding optimized paths are vehicle 1: 0 2 5 0; vehicle 2: 0 4 3 1 0; and vehicle 3: 0 8 7 6 0.

3.3. Population Initialization and Location Update. In the population initialization, the speed and position of the particles are randomly generated according to the encoding method and the set range. Then, half of the particles are converted into real numbers according to the nearest neighbor method to generate new positions [24, 25]. Since the PSO algorithm uses real number coding, the following mapping method is proposed. Map the solution generated by the nearest neighbor method to the real number form, namely, in the set of nodes visited by the same vehicle, suppose there are N nodes in total, and the vehicle number is k , then for the i node on the path, its position size is $i \times 0.99 / (N + 1) + k$.

In the PSO algorithm, g_{best} records the optimal state experienced by the current population and affects the change process of all individual position states. If you blindly accept a better solution, it is likely that the search of the algorithm will gradually gather near the best solution, and the exploration ability will be weakened. Therefore, in order to improve the above-mentioned problem, the adaptive disturbance is carried out based on the algorithm search

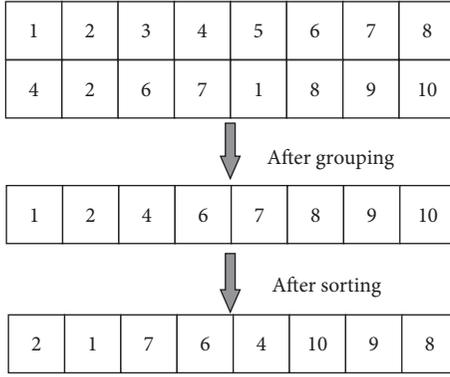


FIGURE 2: Encoding process.

process with the variable neighborhood descent (VND) as the main body. Not only can the search space be expanded, but inferior solutions can be accepted according to the set threshold in order to get out of the superior [26, 27]. At the same time, in order to prevent the loss of the best solution searched due to disturbances, G_{best} is taken as the optimal solution searched in history, and g_{best} is taken as the population extremum.

Regarding the perturbation mechanism, one is the timing of perturbation, which can effectively balance the search advantage between PSO and VND. The other is that the perturbation part adopts a variable neighborhood structure. Both of these play a key role in the effect of the disturbance.

3.3.1. Linear Start Criterion. In order to make better use of the global search capability of PSO, it also provides a better quality perturbation solution for the adaptive perturbation mechanism (APM) process. Therefore, a linear starting criterion is proposed. The mathematical expression is as follows:

$$\text{via} = \text{noimprove}_{\max} - (\hat{\vartheta}_{\max} - \hat{\vartheta}_{\min}) \times \frac{\vartheta}{\vartheta_{\max}}, \quad (14)$$

where ϑ and ϑ_{\max} , respectively, represent the number of iterations and the maximum number of iterations of PSO; $\hat{\vartheta}_{\max}$ and $\hat{\vartheta}_{\min}$, respectively, represent the maximum and minimum allowable historical optimal solution G_{best} unimproved times. If G_{best} is not improved in successive generations, it is considered that the algorithm has fallen into a local extremum. So only when G_{best} 's unimproved times noimp_times is greater than via , APM is started.

3.3.2. Neighborhood Structure. Before VND search, it is necessary to define a set of neighborhood structures. The proposed model uses common neighborhood structures such as between paths and within paths to perform disturbances. In order to improve the effectiveness of the execution operation, in the neighborhood transformation between paths, a path is first randomly selected. By calculating the distance between this path and the center of gravity of other paths in the solution, the ratio of each

distance to the sum of all distances is used as the selection probability. Another path λ_2 is chosen according to the rules of roulette.

- (1) **Cross1:** since the number of customers contained in the two selected routes is different, the intersection points are randomly selected, respectively. The intersection divides the path into two parts, and the first part of path λ_1 is combined with the second part of λ_2 to form a new path. In the same way, the remaining two parts of λ_1 and λ_2 are combined into another new path. See Figure 3.
- (2) **Cross2:** this crossover operation is similar to Cross1, except that the first part of path λ_1 is combined with the first part of λ_2 to form a new path. In the same way, the remaining two parts of λ_1 and λ_2 are combined to form another new path. The order of λ_1 nodes remains unchanged, and the order of λ_2 nodes needs to be reversed. See Figure 4.

First, one or two points in λ_1 are chosen to insert into λ_2 , and then one or two points in λ_1 are exchanged with one point in λ_2 . At the same time, a path λ is selected from the solution set in the neighborhood structure within the path. Finally, the positions of any two points in λ are swapped, and any one or two points in λ are inserted into another position in the path.

3.3.3. Adaptive Selection Neighborhood Strategy. The proposed model uses an adaptive selection strategy to select a certain neighborhood structure between paths to search. Compared with randomly selecting a neighborhood for change, the neighborhood structure that has been searched for a better solution has a greater chance of being selected, and the blindness of the search is reduced.

In the initial stage of location update, the weight of the neighborhood structure between each path is assigned as 1. The number of disturbances is updated every 35 generations, and the number of uses and scores are reset. The weights are updated as follows:

$$\omega_{u,t+1} = \omega_{u,t} \times (1 - \mu) + \mu \times \frac{\sigma_{u,t}}{\pi_{u,t}}, \quad (15)$$

where t represents the update cycle; $\omega_{u,t}$ represents the weight of the u neighborhood in the t cycle and is selected according to the roulette rules. Its selection probability is $\omega_{u,t} / \sum_i \omega_{i,t}$; $\sigma_{u,t}$ represents the score of the u -th neighborhood structure in the last update cycle; $\pi_{u,t}$ represents the number of times the u -th neighborhood structure was used in the last update cycle. The value range of μ is $[0,1]$, which is 0.1.

$\sigma_{u,t}$ calculation criteria: in the same cycle, after the neighborhood structure changes between paths, if its fitness value is better than the optimal solution G_{best} found in the history, 30 points are added to the neighborhood structure, and noimp_times is set to 0. Update G_{best} and g_{best} at the same time; if the solution obtained does not further improve G_{best} but is better than $G_{\text{best}} + G_{\text{best}} \times \delta$, δ is the coefficient of deviation, $\delta \in (0,1)$, then 12 points are added. And

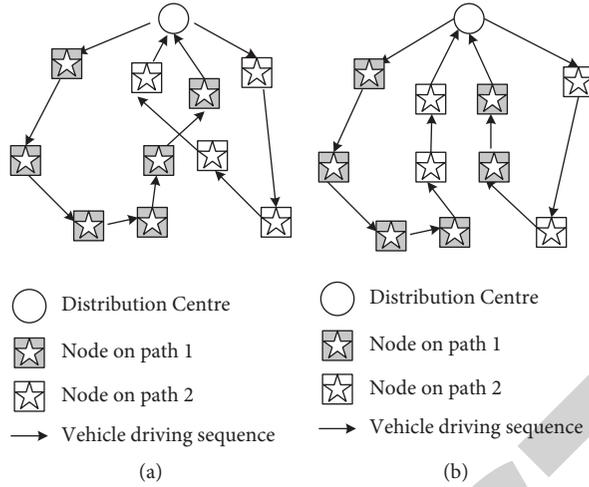


FIGURE 3: Cross1 neighborhood structure.

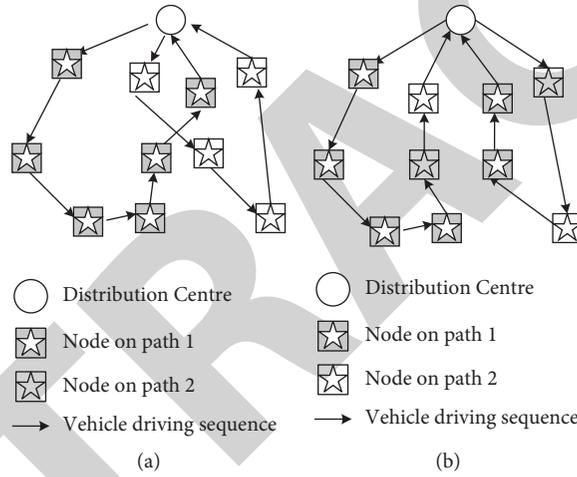


FIGURE 4: Cross2 neighborhood structure.

accumulate $noimp_times$, G_{best} remains unchanged, but update g_{best} which plays the role of disturbing PSO. If neither of the above two conditions is satisfied, but a solution that satisfies the constraint is obtained, 5 points are added and the worst particle in the population is replaced. Otherwise, the score remains unchanged. In the solution of the proposed model, δ takes 0.1.

3.3.4. Perturbing the Search Process. The proposed model solving algorithm is mainly composed of interpath VND and intrapath VND, which are represented by inter-VND and intra-VND, respectively. The perturbation search process is shown in Figure 5.

Among them, the intra-VND and inter-VND change steps in the neighborhood change process within the path are the same. The difference is that the input initial solution is Ω_1 , which uses the neighborhood change structure within the path and the number of neighborhoods included. And when searching for the local optimization of the solution set Ω in a certain neighborhood structure, it is easier to ignore

the set number of cycles. Therefore, in order to better improve the search efficiency, the change of the number of adaptive cycles is added in the disturbance search process. The number of cycles can be adjusted according to the quality of the solution found in this kind of neighborhood structure.

Assuming that the current neighborhood structure is \tilde{N} , the input initial solution is Ω , and the number of cycles p_{max} is initially set. First, obtain a perturbation solution Ω' randomly in the neighborhood. The neighborhood change itself is random, so in the search process, the quality of the neighborhood solution obtained is different. Its quality determines the number of searches in the current neighborhood. If the searched solution Ω'' is better than the current Ω' , it will replace the current solution. On this basis, if the set conditions are met, the number of cycles is increased by 1. If it is not better than the solution Ω' , the loop counter p is accumulated. If the set conditions are not met on this basis, the number of cycles is reduced by one. The set condition is to satisfy the constraint. At the same time, in order to further control the process of the cycle, calculate the

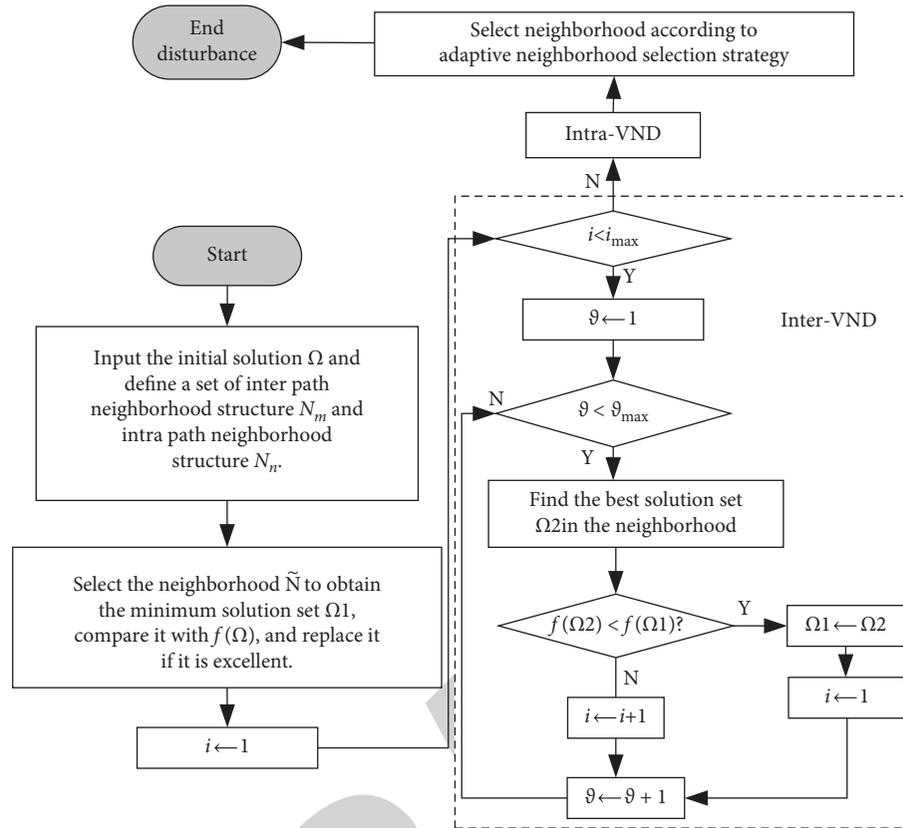


FIGURE 5: Disturbance search process.

number of consecutive occurrences of feasible or infeasible solutions in the same neighborhood. If it is not less than ε , change the number of cycles.

3.4. Local Search. In order to speed up the convergence speed of the PSO algorithm and improve the quality of the solution, a 2-opt local search method is introduced. That is, after each update of the particle swarm, a local search is performed on each particle of the swarm. The neighborhood of the particle is obtained by exchanging every element in the particle pair by pair. Then, select the optimal value as the new particle in the neighborhood, that is, update the population again.

4. Experimental Results and Analysis

4.1. Experiment One. Suppose a distribution center arranges 3 vehicles for 9 customers, and the maximum load capacity of each vehicle is 165 kg. The customer point numbers are 1, 2, ..., 10, respectively. The coordinate position of the customer, the demand of each customer point, and the distribution center are shown in Table 1. The unit transportation cost and speed are set to 1, where 0 represents the serial number of the distribution center.

The proposed model is used to optimize the distribution path of 9 customers, and the optimal path diagram is shown in Figure 6.

As can be seen from Figure 6, the three paths are car 1: 0-7-2-3-0; car 2: 0-8-6-4-0; and car 3: 0-5-9-1-0. Distribution

according to this route scheme can not only meet the minimum distribution cost but also minimize the comprehensive time consumption, so as to achieve a win-win situation for both sides of distribution.

In the experiment, the population number of PSO algorithm is 50 and the maximum iteration number is 2000. In order to compare the effects of different methods more scientifically, each method runs 35 times independently, and the average value of 35 experiments is taken as the final result. In order to demonstrate the performance of the proposed model, it is compared with Reference [11, 14, 15]. The results are shown in Table 2, that is, the minimum cost and success rate of finding the best route for distribution vehicles, where iteration rate = the number of iterations required to find the best route/the total number of iterations.

As can be seen from Table 2, compared with other models, the transportation cost of the proposed model is the smallest, which is 1975 yuan, and the iteration rate is the lowest, which is only 0.02. The proposed model comprehensively considers the situation of urban traffic network and improves the PSO algorithm through adaptive disturbance mechanism to improve the global convergence speed, so the iteration rate is lower. At the same time, the improved PSO algorithm is used to solve the double-objective optimization problem, and the economy and environmental protection are guaranteed. Reference [11] proposed a heterogeneous vehicle routing model based on primal dual technology. The solution obtained by this technology may be locally optimal, so the

TABLE 1: Customer information and distribution center.

No.	Customer coordinates	Demand	No.	Customer coordinates	Demand
0	(88,50)	0	5	(28,9)	76
1	(63,57)	24	6	(155,0)	89
2	(21,98)	85	7	(89,76)	22
3	(57,79)	40	8	(172,15)	31
4	(118,18)	32	9	(25,47)	56

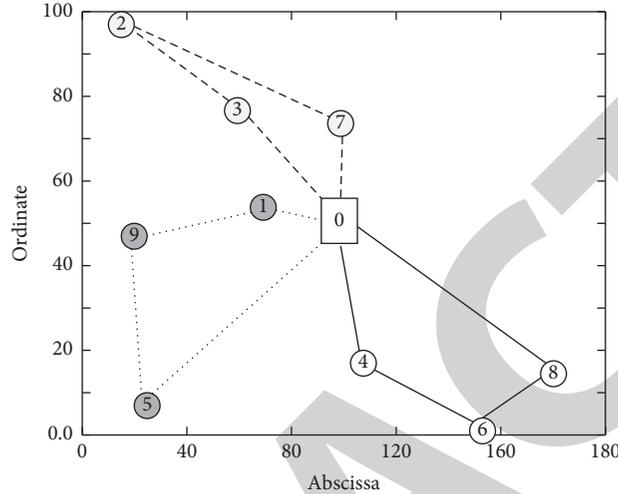


FIGURE 6: Optimal path graph of the proposed method.

TABLE 2: Test results of different models.

Model	Minimum cost/yuan	Iteration rate
Reference [11]	3152	0.24
Reference [14]	2618	0.13
Reference [15]	2321	0.05
Proposed method	1975	0.02

distribution cost is high, which is 3125 yuan. Reference [14] used the Bessel curve optimization model to realize the path planning in the process of automatic driving. The Lagrange solution method is more traditional. So, compared with the improved PSO algorithm, its performance is poor, so the iteration rate exceeds 0.1. Meanwhile, based on the improved fast exploration random tree algorithm and linear time-varying algorithm, Reference [15] proposed an intelligent vehicle path planning and tracking control model. The integration of the algorithm improved the performance of the model, and its iteration rate was only 0.03 higher than that of the proposed model. However, due to the lack of environmental protection considerations, it consumed more energy, and the transportation cost was 2321 yuan.

4.2. Experiment Two. The proposed model is simulated and verified in the running environment of Windows 10 operating system and MATLAB 2016b. Taking the actual cold chain distribution data of a fresh food supplier in a market in Chongqing as an example, the supplier implements cold chain distribution for 28 distribution points in Chongqing. Given the demand and time window requirements of each distribution point, the distribution path and minimum cost

obtained by the proposed model are shown in Figure 7, where 0 represents the distribution center.

As can be seen from Figure 7, there is a reasonable path planning for 28 distribution points, and when the number of iterations is 450, the proposed model tends to be stable. At this time, the total distribution time is the smallest, and the value is about 27 h.

In order to demonstrate the effectiveness and stability of the proposed model, it is compared with References [11, 14, 15]. The carbon emission results of each model are shown in Figure 8.

As can be seen from Figure 8, the proposed model converges fastest. When the number of iterations is close to 500, the resulting carbon emission is the smallest, about 213 kg. The proposed model designs the double-objective optimization function with the minimum carbon emission and the shortest delivery time and uses the improved PSO algorithm to obtain the high-quality solution, so the convergence speed is fast and the overall performance is the best. The other three models lack environmental protection considerations in path optimization, so the carbon emission is high, no less than 400 kg. However, Reference [15] combined the improved fast exploration random tree algorithm and linear time-varying algorithm for path optimization, which shortens the optimization time to a certain extent, and the path scheme consumes less energy, so the carbon emission is about 400 kg. The optimization algorithm used in the models of References [14] and [11] are more traditional. Both of them tend to be stable after the number of iterations exceeds 1000, and the path scheme is not globally optimal. The overall carbon emission of the two schemes exceeds 500 kg.

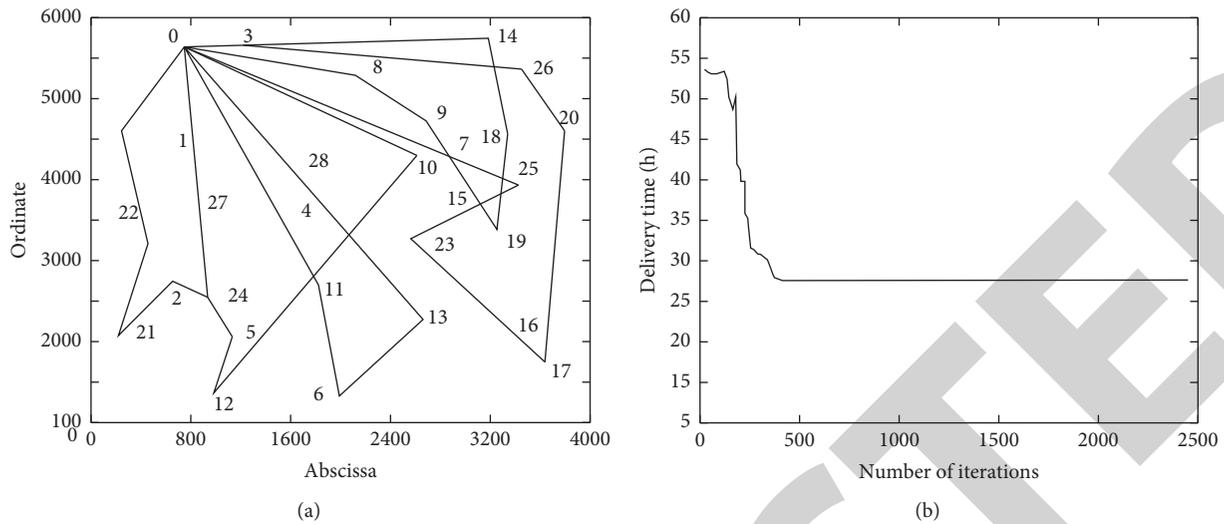


FIGURE 7: Operation results of the proposed model. (a) Optimization path. (b) Minimum cost of optimized path.

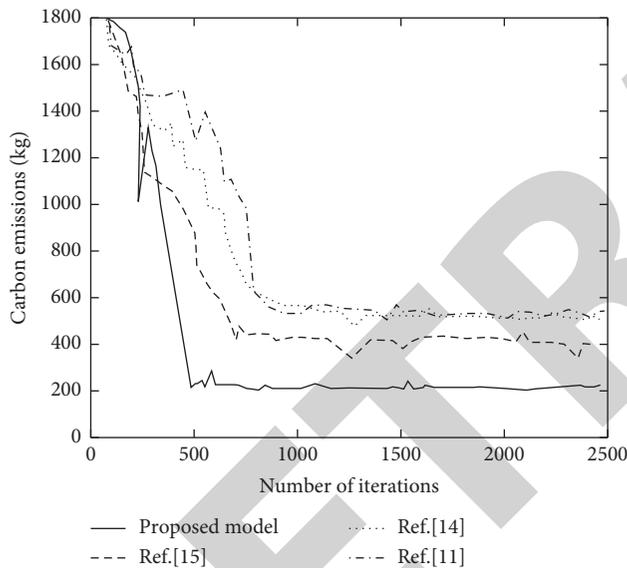


FIGURE 8: Carbon emissions of different models.

5. Conclusion

With the state's attention to environmental pollution, logistics enterprises should also bear more responsibilities for energy conservation and emission reduction. In addition to improving distribution efficiency and ensuring customer satisfaction, logistics enterprises should also reduce the impact of logistics activities on the environment. Therefore, this paper proposes a path optimization model for urban traffic network from the perspective of environmental pollution protection. This paper constructs a double-objective optimization model with the lowest carbon emission and the shortest delivery time and uses the hybrid PSO algorithm based on adaptive disturbance mechanism to search the optimal solution of the model, so as to obtain the path optimization scheme under real-time traffic conditions. Experiments are carried out in two application scenarios.

The experimental results show that when the route distribution cost, distribution time, and carbon emission of the model are 1975 yuan, 27 h, and 213 kg, respectively, and the iteration rate is 0.02, the optimization speed is fast, and the optimized route scheme is more in line with the actual target requirements, which provides a good theoretical basis for the popularization and application of the proposed model in the field of logistics distribution. Since only one distribution model is considered in the proposed model, the current single model is extended to multimodel in the next research. In the actual logistics distribution, different types of goods need to be distributed by different types of vehicles. It is of universal significance to study the multivehicle routing optimization problem.

Data Availability

The data contained in this article can be found in this article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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