Vehicle logistics path optimization based on ant colony and particle hybrid algorithm

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Abstract. In the actual vehicle logistics distribution process, the number of vehicles and the choice of distribution path determine the logistics cost. Aiming at the problem of high logistics cost, this paper establishes a multi-objective vehicle logistics path optimization mathematical model considering the distribution process and the number of vehicles. In order to solve the model, a hybrid ant colony particle swarm optimization algorithm is proposed. The algorithm integrates the particle swarm algorithm into the ant colony algorithm, which makes the ant colony algorithm have the characteristics of "particles", speeds up the search speed of the ant colony algorithm, and reduces the defect of falling into local convergence. The simulation results show that the path optimization model and its hybrid algorithm have fast convergence, can effectively reduce the distribution process and the number of vehicles, and can reduce a large number of vehicle logistics costs, which provides a valuable reference for the whole vehicle logistics path planning.

Keywords: Vehicle logistics; ant colony algorithm; particle swarm optimization; path optimization.

1. Introduction

Vehicle logistics refers to the logistics activity in which finished vehicles are transported to designated places according to customer order requirements [1]. Road transportation as its main transportation mode, the corresponding costs also account for the largest proportion of vehicle logistics costs. In addition, the high logistics cost is mainly caused by the unreasonable transportation path and loading method. Therefore, in order to reduce the cost, it is necessary to choose a reasonable transportation route and improve the loading efficiency.

The vehicle logistics transportation problem is a typical vehicle routing problem (VRP). The main purpose of the vehicle transportation path optimization is to improve the loading rate and decrease the number of transport vehicles and driving mileage via reasonably dispatching the transportation vehicles to optimize the transportation path and the order of the delivery points [3]. Much effort has been conducted on the optimization model of vehicle logistics transportation. Hu Yuan et al. [4] considered three transportation modes of road, railway and waterway, and established a vehicle transportation model with time constraints. Li Ying et al. [5] proposed a two-level order distribution model based on
the order distribution problem in vehicle logistics services, and established a two-level planning model with the goal of punctual delivery and minimal logistics procurement. Guan Chao et al. [6] established a planning model considering the economic benefits of vehicle transportation and other factors.

In terms of the method about solving the optimal path, Yannis Marinakis et al. [7] established an optimization model with the shortest path as the goal, and proposed a hybrid variable domain search strategy to guide the particle position update, and combined local and global expansion domain topology to solve the particle update speed, which enhanced the search efficiency of the algorithm. Li Jinfu et al. [8] combined greedy algorithm and genetic algorithm to solve the optimal path through an adaptive control strategy. Ma Guiping et al. [9] solved the optimal path by improving the traditional ant colony algorithm. Specifically, they improved the update method of the traditional ant colony pheromone. Viktor Danchuk et al. [10] selected the logistics path according to the traffic flow speed in the logistics path, and also improved the pheromone update process, so that the ants can run synchronously and asynchronously, thereby increasing the search speed. Kannan Govindan et al. [11] proposed three hybrid group algorithms in the process of solving vehicle path optimization, and used response surface method and multi-objective decision-making method to adjust the parameters to improve the quality of the solution.

In summary, it can be seen that most of the studies only focus on the improvement of a single parameter, while the cost of the entire vehicle logistics is often multi-faceted. Thus, the algorithm should reflect the common effect of multiple parameters. In this study, two aspects including the vehicle transportation path and transportation vehicle combination are simultaneously taken into consideration to establish the optimization model. Furthermore, in order to improve the accuracy of the solution, the particle swarm integrated ant colony algorithm is used to solve the logistics path optimization problem.

2. Establishment of vehicle logistics model

2.1. Problem description

In this study, the vehicle logistics transportation path refers to the route that the finished vehicles are sent out from the automobile manufacturer's general warehouse to each sales node by road transportation. Path optimization means that after receiving the exact transportation volume and distribution point, the logistics enterprise chooses the most reasonable path between the nodes to deliver the goods to the destination. When building the model, it is assumed that the following conditions are true: the distribution company has K distribution vehicles of the same specification, and distributes to n (n ≥ K) customers. Each vehicle starts from the general warehouse of the automobile manufacturer to each node based on the transportation network. At the same time, the following conditions should be satisfied:

1) The transportation volume of each vehicle cannot exceed the maximum carrying capacity;
2) Each transportation vehicle can serve multiple distribution points, but each distribution point can only have one vehicle for distribution.
3) The transportation transport vehicle k immediately goes to the next node or returns to the distribution center after serving at the node i.

The goal of the solution can be described as: obtaining the distribution path of k transport vehicles under the condition of using the minimum number of transport vehicles and the shortest total travel distance.

| Parameter definition | Explanation |
|----------------------|-------------|
| K={1,2,3,⋯,k}        | Collection of all delivery vehicles |
| N={1,2,3,⋯,n}        | Collection of all delivery nodes |
| d_{ij}               | Distance between node i and node j |
| Cap                  | Maximum transport volume of vehicle k |
| r_i                  | Demand for node i |
| P_k                  | Node set of service of vehicle k |
Decision variables:

\[ x_{ijk} = \begin{cases} 
1, & \text{Vehicle } k \text{ completes customer } i \text{ and then serves } j, \quad i, j \in N \\
0, & \text{otherwise}
\end{cases} \quad (1) \]

\[ x_{ik} = \begin{cases} 
1, & \text{Customer } i \text{ is served by vehicle } k, \quad i \in N, \quad k \in K \\
0, & \text{otherwise}
\end{cases} \quad (2) \]

### 2.2. Mathematical model

In the mathematical model of vehicle distribution [12], formulas (3) and (4) are the optimized objective functions [13], \( C_1 \) and \( C_2 \) means the number of transport vehicles and the total mileage is the least, respectively; in the constraint condition s.t., Equation (5) restricts that the delivery vehicle can not deliver to multiple nodes at the same time; Equation (6) restricts the maximum load of delivery vehicle \( k \); Equation (7) restricts that each node can be delivered only by one delivery Vehicles ; Equation (8) restricts that all delivery vehicles start from the distribution center and return to the starting position after delivering goods; Equation (9) restricts that vehicle \( k \) should start from node \( i \) to the next node after finishing the delivery at node \( i \), which restricts the continuity of the delivery process; Equation (10) restricts the delivery vehicle to a closed loop in the delivery path, and there is no sub-loop in the middle.

\[ C_1 = \min \sum_{j=1}^{N} \sum_{i=1}^{N} x_{ijk} \quad (3) \]

\[ C_2 = \min \sum_{j=1}^{N} \sum_{i=1}^{N} x_{ijk} d_e \quad (4) \]

\[
\begin{align*}
\sum_{j=1}^{N} \sum_{i=1}^{N} x_{ijk} &= 1, \quad j \in N \\
\sum_{i=1}^{N} r_i x_{ik} &\leq Cap, \quad k \in K \\
\sum_{i=1}^{N} x_{ik} &= 1, \quad i \in N \\
\sum_{i=1}^{N} x_{ik} &= \sum_{j=1}^{N} x_{jik}, \quad k \in K \\
\sum_{i=1}^{N} x_{ik} &= \sum_{j=1}^{N} x_{ijk}, \quad k \in K \\
\sum_{i,j,k} x_{ijk} &= |P_k| - 1, \quad k \in K 
\end{align*}
\]
s.t.

### 3. Path optimization method based on ant colony and particle swarm hybrid algorithm

#### 3.1. Ant colony optimization method

The ant colony algorithm [14] simulates the process of the ant colony foraging from randomly selecting a path to finally approaching an optimal path, as shown in Figure 1. Ant colony algorithm mainly includes selection transition probability \( P_{ijk}(t) \), pheromone update and update rule. In the initial path search process \( T=0 \), when the ant colony encounters an obstacle at \( B \), they will choose the path \( B-C \) or \( B-D \) according to the selection probability \( P_{ijk}(t) \). \( P_{ijk}(t) \) depends on the length of the route and the concentration of pheromone on the path, as illustrated in formula (11). When the optimal path \( A-B-C-E-F \) is found \( T=2 \), the pheromone concentration on this path will be continuously superimposed, and thus the ant colony will be induced to choose this path not the path of \( A-B-D-E-F \).
Fig. 1 Scheme of searching for the shortest path using ant colony algorithm

\[
p_{ij}^k(t) = \begin{cases} 
\frac{\tau_{ij}^k(t) \cdot \eta_{ij}^k(t)}{\sum_{j \in \text{allowed}_i} \tau_{ij}^k(t) \cdot \eta_{ij}^k(t)}, & j \in \text{allowed}_i \\
0, & \text{others}
\end{cases} \quad (11)
\]

In formula (11): \( p_{ij}^k(t) \) — the transition probability; \( \tau_{ij}^k(t) \) — the concentration of pheromone; \( \eta_{ij}^k(t) \) — the reciprocal of the distance between path nodes; \( \alpha \) — the information heuristic factor; \( \beta \) — the expected heuristic factor.

Pheromone left by the ant colonies has two same characteristics [15]: one is easy to volatilize and the other one is easy to be superimposed. When the ant colony completes a comprehensive path search, the pheromone should be updated.

\[
\tau_{ij}^k(t+1) = (1-\rho) \tau_{ij}^k(t) + \Delta \tau_{ij}^k(t) \quad (12)
\]

\[
\Delta \tau_{ij}^k(t) = \sum_{i=1}^{m} \Delta \tau_{ij}^k(t) \quad (13)
\]

\[
\Delta \tau_{ij}^k(t) = \frac{Q}{L_k} \quad (14)
\]

In the formula: \( \rho \) — volatility coefficient; \( (1-\rho) \tau_{ij}^k(t) \) — the remaining concentration of pheromone after volatilization; \( \Delta \tau_{ij}^k(t) \) — pheromone increment generated between nodes \( (i, j) \); \( Q \) — a constant, indicating the content of pheromonal — the moving distance of ant \( k \).

3.2. Optimization method of particle swarm optimization

Particle Swarm Optimization [16] (PSO) is an optimization algorithm based on bird swarms searching for food, which uses shared information between swarms in the search process. The flight path depends on the intending flight direction of itself and the group. Each particle changes its speed and position according to formula (15, 16).

\[
v_{k+1} = w v_k + c_1 r_1 (P_{\text{best}} - x_k) + c_2 r_2 (G_{\text{best}} - x_k) \quad (15)
\]

\[
x_{k+1} = x_k + v_{k+1} \quad (16)
\]

In the formula: \( v_k \) — the velocity vector; \( x_k \) — the position vector; \( c_1, c_2 \) — learning factors; \( r_1, r_2 \) — mutually independent random numbers between \( [0,1] \); \( w \) — a non-negative number, used to adjust the current speed.

3.3. Hybrid algorithm of ant colony and particle swarm

In the logistics path optimization, the particle swarm algorithm changes the flight direction of the particles to guide their speed and position in the next iteration vector, and the corresponding optimization calculation is mainly according to the individual extreme value, the overall extreme value and the individual position of the particle. Although this algorithm has strong global search ability and fast solution speed, the optimization result is often not the global optimal value. On the other hand, the ant colony algorithm determines the selection path according to the probability during the solution process. Its advantage is that the pheromone is updated after each iteration, which makes the algorithm have the
characteristics of positive feedback and makes the solution result closer to the optimal solution, but the solution time is long. [17]

In order to effectively combine the advantages of these two algorithms, a new hybrid ant colony and particle swarm algorithm is proposed in this study. This hybrid algorithm can not only combine the advantages of the two algorithms, but also can effectively avoid the above-mentioned drawbacks. The key of the hybrid algorithm is to accelerate the optimization speed of the ant colony, so that the ants have the "particle" nature of the particle algorithm [18]. The implementation steps are as follows:

Step 1: Initialize each parameter in the hybrid algorithm and determine the global iteration number Ncmax of the algorithm and the iteration number N of the local particle swarm algorithm.

Step 2: Establish the initial pheromone of the hybrid algorithm, calculate the fitness value and individual extreme value of each ant, and calculate the selection probability according to formula (11), make the ant determine the moving path by choosing the largest probability.

Step 3: The ant colony optimization result obtained in step 2 is subjected to the particle cross operation, and the Pbest and Gbest of the particles are calculated.

Step 4: If the particle reaches the specified number of iterations and obtain the current internal global extremum, otherwise return to step 3.

Step 5: If the obtained global extremum includes all nodes, that is, all nodes have been allocated, update the pheromone on the global path using formula (12-14), otherwise return to calculating the fitness value and individual extremum of ants value.

Step 6: When the maximum number of iterations is calculated, output the global optimal result, otherwise return to step 2.
4. Example verification

4.1. Research object and data collection

The research object of this paper is the optimization of logistics path selection for a certain automobile sale in Chongqing. The problem can be described as follows: according to the ordering situation, the automobile manufacturer arranges the transportation vehicles to transport the finished vehicles to each automobile sales store via the highway transportation mode, and in the transportation process, it should minimize the transportation vehicles and the total mileage. In the process of research, 14 sales nodes in Chongqing are selected for path optimization, and the order quantity of each sales store in a week is obtained through questionnaire survey, as shown in Table 2. According to Google map, the distance symmetry matrix between the automobile manufacturer and each sales store is obtained, as shown in Table 2. According to Google map, the distance symmetry matrix between the automobile manufacturer and each sales store is obtained, as shown in Table 3. According to the requirements of Vehicle Transportation Management work Plan, the full carrying capacity of vehicle transportation is 7 crew commercial vehicles.

| Distribution point | Demand / vehicle | Serial number | Demand / vehicle |
|--------------------|------------------|---------------|------------------|
| Nanchuan 4S store  | 6                | 8             | Qijiang 4S store  | 4               |
| Jiulongpo 4S shop  | 3                | 9             | Yunyang 4S store  | 2               |
| Yuzhong 4S store   | 4                | 10            | Tongnan 4S store  | 5               |
| Chongqing 4S store | 9                | 11            | Yubei 4S store    | 10              |
| Wanzhou 4S store   | 3                | 12            | Rongchang 4S store| 1               |
| Banan 4S store     | 2                | 13            | Bishan 4S store   | 3               |
| Fuling 4S store    | 1                | 14            | Fengjie 4S store  | 2               |

Table 2. Demand scale

Table 3. The distance matrix between each distribution point

| Distance symmetric matrix | Logistics Center | Nanchuan 4S store | Jiulongpo 4S shop | Yuzhong 4S store | Chongqing 4S store | Wanzhou 4S store | Banan 4S store | Fuling 4S store | Qijiang 4S store | Yunyang 4S store | Tongnan 4S store | Yubei 4S store | Rongchang 4S store | Bishan 4S store | Fengjie 4S store |
|---------------------------|------------------|------------------|-------------------|-----------------|-------------------|------------------|----------------|----------------|-----------------|-----------------|-----------------|---------------|-----------------|----------------|----------------|
| Demand / vehicle          | 0                | 98               | 89                | 103             | 274               | 16               | 26             | 281            | 103             | 278             | 289             | 283            | 283             | 273            | 273            |
| 1                         | 12               | 278              | 95                | 103             | 274               | 16               | 281            | 103            | 278             | 96              | 101             | 88             | 103             | 13             | 12             |
| 2                         | 12               | 96               | 11                | 278             | 75                | 108              | 281            | 103            | 274             | 82              | 101             | 73             | 289             | 109            | 73             |
| 3                         | 12               | 278              | 95                | 274             | 90                | 108              | 288            | 109            | 274             | 90              | 102             | 75             | 281             | 107            | 75             |
| 4                         | 12               | 82               | 11                | 273             | 103               | 108              | 282            | 107            | 279             | 101             | 102             | 88             | 288             | 104            | 88             |
| 5                         | 12               | 273              | 103               | 274             | 126               | 108              | 283            | 107            | 278             | 96              | 289             | 283            | 289             | 109            | 89             |
| 6                         | 12               | 278              | 103               | 283             | 95                | 104              | 288            | 109            | 274             | 89              | 289             | 283            | 289             | 113            | 90             |
| 7                         | 12               | 82               | 11                | 273             | 278               | 108              | 283            | 110            | 279             | 96              | 288             | 107            | 289             | 107            | 90             |
| Total demand              | 12               | 55               |                   | 12              |                   |                 | 12             |                | 12              | 12              | 12              | 12             | 12              |                | 12             |

According to Table 2, since it is set in the hybrid algorithm that each node can only arrange one delivery vehicle for service, for node 4 (Chongqing 4S store) and node 11 (Yubei 4S store), an additional delivery vehicle is added for delivery. As a result, the adjusted demand data is shown in Table 3.
4.2. Parameter setting
In this paper, the hybrid algorithm for solving vehicle logistics is under Windows 10 environment, Intel (R) Core (TM) i5-1035G4 CPU @1.10GHz, running memory 16G, implemented on Matlab 2019a software, and set relevant parameters [19].

4.3. Calculation results and analysis
Randomly run 10 times with Matlab 2019a, the average running time is 2s and the results obtained are shown in Table 4. The optimal path obtained is: 0→4→13→6→0; 0→2→8→0; 0→3→11→0; 0→1→7→0; 0→10→12→0; 0→14→9→5→0; 0→4→0; 0→11→0 The minimum total delivery mileage is 1744.5km, and the delivery path is shown in Figure 2.

In the solution process, the average mileage for 10 random runs is 1761.7km, only with 17.2km increase compared with the minimum mileage. Moreover, the total demand is 55 finished vehicles, so at least 8 transportation vehicles are required. Only 8 delivery vehicles are used, and the full loading rates are: 100%, 100%, 100%, 100%, 85.7%, 100%, 100%, 100%. It can be seen that 7 vehicles are fully loaded. The results obtained meet the requirement of minimum delivery vehicles and delivery mileage, suggesting that high accuracy and fast convergence of the hybrid algorithm in solving the logistics route optimization problem.

| Times | Distance /km | Path optimization results |
|-------|--------------|---------------------------|
| 1     | 1754.5       | 0-11-3-0; 0-4-2-6-0; 0-8-13-0; 0-7-1-0; 0-12-10-0; 0-5-9-14-0; 0-4-0; 0-11-0 |
| 2     | 1781.3       | 0-11-3-0; 0-4-13-6-0; 0-1-7-0; 0-2-8-0; 0-14-9-5-0; 0-10-12-0; 0-4-0; 0-11-0 |
| 3     | 1780.5       | 0-4-8-12-0; 0-3-2-0; 0-6-10-0; 0-11-7-13-0; 0-1-0; 0-5-9-14-0; 0-4-0; 0-11-0 |
| 4     | 1753.5       | 0-4-10-0; 0-6-8-12-0; 0-3-2-0; 0-11-7-13-0; 0-1-0; 0-14-9-5-0; 0-4-0; 0-11-0 |
| 5     | 1744.5       | 0-4-13-6-0; 0-2-8-0; 0-3-11-0; 0-1-7-0; 0-10-12-0; 0-14-9-5-0; 0-4-0; 0-11-0 |
| 6     | 1778.5       | 0-11-3-0; 0-4-2-6-0; 0-8-13-0; 0-7-1-0; 0-12-10-0; 0-14-9-5-0; 0-4-0; 0-11-0 |
| 7     | 1744.5       | 0-2-8-0; 0-3-11-0; 0-1-7-0; 0-10-12-0; 0-14-9-5-0; 0-4-13-6-0; 0-4-0; 0-11-0 |
| 8     | 1781.3       | 0-11-3-0; 0-1-7-0; 0-2-8-0; 0-14-9-5-0; 0-10-12-0; 0-14-3-6-0; 0-4-0; 0-11-0 |
| 9     | 1744.5       | 0-3-11-0; 0-1-7-0; 0-10-12-0; 0-2-8-0; 0-14-9-5-0; 0-4-13-6-0; 0-4-0; 0-11-0 |
| 10    | 1753.5       | 0-6-8-12-0; 0-3-2-0; 0-4-10-0; 0-11-7-13-0; 0-1-0; 0-14-9-5-0; 0-4-0; 0-11-0 |

Fig. 3 Optimal vehicle distribution route

Table 4. Path optimization results
5. Conclusion
This paper optimizes the vehicle logistics path and combines the actual vehicle logistics operation mode to establish a mathematical constraint model with the minimum number of vehicles and the minimum mileage as the goal. In order to accurately solve the model, a new ant colony and particle swarm hybrid algorithm is designed. The algorithm integrates the characteristics of the particles in the particle swarm algorithm into the ant colony algorithm, which can effectively improve its search speed and reduce the localization convergence. The calculation results show that the loading efficiency is high and the total mileage is the shortest, and the algorithm shows high solving efficiency and good convergence. In summary, the proposed optimization algorithm is an effective method to reduce the delivery cost of the whole vehicle.

References
[1] JIANG Yanning, XU Qi, REN Han, et al. Vehicle logistics path optimization under resource sharing mode [J]. Highway transportation technology, 2017, 34 (06): 114-121.
[2] ZHANG Yuan, YU Yi. Application of simulated annealing algorithm in vehicle logistics problem [J]. Logistics technology, 2016, 39 (12): 81-84.
[3] Reza Eshtehadi, Emrah Demir, Yuan Huang. Solving the vehicle routing problem with multi-compartment vehicles for city logistics [J]. Elsevier Ltd, 2020, 115-130.
[4] HU Yuan, SHUAI Yuhong. Study on multimodal transportation and route optimization of vehicle logistics transportation [J]. Journal of transportation engineering and information, 2019, 17 (01): 13-18.
[5] LI Liying, FU Hanmei. Order allocation problem of vehicle logistics service supply chain considering multiple transportation modes [J]. Computer applications, 2019, 39 (06): 1836-1841.
[6] GUAN Chao, DING Jie. Research on vehicle logistics network planning considering production economic benefits [J]. Logistics technology, 2015, 38 (08): 148-153.
[7] Yannis Marinakis, Athanasios Migdalas, Angelo Sifaleras. A hybrid Particle Swarm-Optimization Variable Neighborhood Search Algorithm for Constrained Shortest Path Problems [J]. European Journal of Operational Research, 2017, 14(6): 134-160.
[8] LI Jinfu, TUO Xianguo, LIU Yong, et al. Research on vehicle routing optimization design of vehicle logistics transportation [J]. Computer simulation, 2016, 33 (04): 184-188.
[9] MA Guiping, PAN Feng. Study on logistics transportation path based on improved ant colony algorithm [J]. Computer engineering and science, 2020, 42 (03): 523-528.
[10] Viktor Danchuk, Olena Bakulich, Vitaliy Svatko. An Improvement in ant Algorithm Method for Optimizing a Transport Route with Regard to Traffic Flow [J]. Transportation Science and Technology, 2017, 18: 425-434.
[11] Kannan Govindan, Ahmad Jafarian, Vahid Nourbakhsh. Designing a sustainable supply chain network integrated with vehicle routing: a comparison of hybrid swarm intelligence metaheuristics [J]. Computers and Operations Research, 2018, 20: 121-152.
[12] GUO Yinan, CHENG Jian, LUO Sha, et al. Robust dynamic multi-objective vehicle routing optimization method [J]. IEEE—Acm Transactions on Computational Biology and Bioinformatics, 2018, 15(6): 1891-1903.
[13] GUO Sen, QIN Guihe, ZHANG Jindong, et al. Research on particle swarm optimization algorithm for multi-objective vehicle routing problem [J]. Journal of Xi'an Jiaotong University, 2016, 50 (09): 97-104.
[14] QIN Yuannian, LIANG Zhonghua. New progress in research and application of ant colony algorithm [J]. Computer engineering and science, 2019, 41 (01): 173-184.
[15] JIANG Li, WANG Jing, LIANG Changyong, et al. Research on the distribution path of crowdsourcing based on improved ant colony algorithm [J]. Computer engineering and application, 2019, 55 (08): 244-249.
[16] JIA Huiqun, WEI Zhonghui, HE Xin, et al. Path planning based on improved particle swarm
optimization [J]. Journal of agricultural machinery, 2018, 49 (12): 371-377.

[17] WANG Xiufan, LIANG Feng. A novel PSO-ACO fusion algorithm for logistics distribution vehicle routing optimization [J]. Machine Tool & Hydraulics, 2020, 48(12): 155-160.

[18] HOU Yangqiang, WANG Tianqi, LI Liangyu, et al. Path planning of BIW side wall spot welding robot based on ant colony algorithm particle swarm optimization algorithm [J]. China Mechanical Engineering, 2017, 28 (24): 2990-2994.

[19] HAN Yan, XU Yan, ZHOU Jianping. Robot path planning based on particle swarm optimization and ant colony algorithm [J]. Modular machine tool and automatic machining technology, 2020 (02): 47-50.