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# Research on Vehicle Scheduling Method in Logistics Distribution

Xiaofan Shi *

College of Management, Shanghai University, Shanghai, China
* Corresponding Author: Xiaofan Shi

## ABSTRACT

Vehicle distribution is a critical link in logistics activities that directly connects with customers, and distribution costs account for a significant proportion of overall logistics operations. This paper aims to solve the vehicle scheduling problem faced by logistics enterprises in practice and proposes an optimization model for the Capacitated Vehicle Routing Problem based on the Ant Colony Algorithm. The main purpose of the study is to improve vehicle utilization efficiency and reduce operating costs by optimizing distribution paths. The experimental results show that the Ant Colony Algorithm has high efficiency and feasibility in solving the vehicle scheduling problem with capacity constraints, effectively reducing logistics distribution costs and providing a viable solution for practical logistics vehicle scheduling.

## KEYWORDS

Vehicle Scheduling Problem; Logistics Distribution; Ant Colony Algorithm.

## 1. INTRODUCTION

With the rapid development of the global economy and the continuous progress of society, the logistics industry plays an increasingly important role in the national economy. As a key component of the logistics system, the Vehicle Routing Problem (VRP), first proposed by Dantzig and Ramser in 1959 [1], plays a vital role in improving logistics efficiency, reducing operating costs, and optimizing resource allocation. Especially against the background of booming e-commerce, consumers have put forward higher requirements for fast and punctual delivery services, which further promotes the research and application of efficient logistics vehicle scheduling methods.

Traditional logistics vehicle scheduling methods mainly rely on experience and rules, leading to randomness and uncertainty that hinder overall efficiency improvement. In response, academia and industry have conducted extensive research on various VRP variants. Foreign scholars have explored different constraints and algorithms: Gheysens et al. [3] utilized branch-and-bound methods to determine optimal fleet size and composition; Gendreau et al. [4] applied parallel tabu search to solve dynamic vehicle routing problems; Ninikas and Minis [5] studied load transfer operations for dynamic VRP with mixed backhauls; and Rasku et al. [6] investigated automatic algorithm configuration for VRP solvers. Domestic scholars have also made significant contributions in recent years, with research covering aspects such as integrated loading and unloading operations, fuzzy time windows, and O2O real-time delivery . The Ant Colony Algorithm, originally proposed by Dorigo and Gambardella for the traveling salesman problem, has been widely applied to VRP due to its distributed computation and positive feedback characteristics, with recent studies further improving it for specific logistics scenarios .

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## 2. VEHICLE SCHEDULING MODEL WITH CAPACITY CONSTRAINTS

The vehicle scheduling problem in logistics can be described as follows: delivery vehicles depart from the distribution center and deliver goods to customers along appropriate routes and travel times. During this process, various constraints such as vehicle utilization and delivery time must be observed to achieve optimization objectives such as minimizing travel distance, reducing transportation costs, and fully utilizing delivery vehicles.

This paper studies a Capacitated Vehicle Routing Problem (CVRP) within a certain area. There is one distribution center with multiple vehicles of a single type, each having the same capacity limit. Within this area, there are *n* service objects, each at a fixed location waiting for vehicle service. Each customer has only one type of service demand, namely distribution, and the demand quantity is a known fixed value. The demand weight of each node differs, and the goods weight of any single node is less than or equal to the maximum cargo capacity of the distribution vehicle. Each customer can only be served by one vehicle. Vehicles departing from the distribution center must eventually return to the center.

To facilitate modeling and solving, the following assumptions are made: when a batch of goods for the same customer is transported, only one vehicle can be used for single-batch operation, and goods cannot be transported in separate batches; the vehicles operate at a constant average speed regardless of urban node changes or climate changes; all transportation costs depend on route distance and the number of vehicles used; only the transportation stage is considered, excluding costs from other logistics links such as packaging, warehousing, and processing; and losses during transportation due to natural causes, improper storage, theft, or damage are not considered.

The parameters in the model are defined as follows: $L$ represents the total number of customers served; $Q$ represents the maximum load capacity of delivery vehicles; $q_i$ represents the goods demand quantity of customer *i*;$d_{ij}$represents the distance between customer *i* (or distribution center) and customer *j*; $K$ represents the total number of vehicles; $w_p$represents the dispatch cost per vehicle; $C_p$represents the total vehicle dispatch cost; and $TD$ represents the total vehicle travel distance.

The decision variables are defined as:

$$x_{ijk} = \begin{cases} 1, \text{if vehicle travels from customer i to j} \\ 0, \text{otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1, \text{if vehicle serves customer i} \\ 0, \text{otherwise} \end{cases}$$

The model is subject to the following constraints. First, the capacity constraint requires that the sum of demands of all customers served by a vehicle on its distribution route must be less than or equal to the vehicle's maximum load capacity:

$$\sum_{i=1}^{n_k} q_i y_{ik} \leq Q_k, n_k \neq 0$$

Second, the single-visit constraint ensures that each customer is served by exactly one vehicle:

$$\sum_{i=1}^{L} \sum_{k}^{K} y_{ik} = 1$$

Third, the closed-route constraint requires that vehicles must return to the distribution center after completing their delivery tasks:

$$\sum_{i=1}^{N}\sum_{j=1}^{K} x_{1ik} = \sum_{j=1}^{N}\sum_{k=1}^{K} x_{j1k}$$

Fourth, the number of customers served by each vehicle must not exceed the total number of demand points:

$$0 \leq L_k \leq L$$

The objective is to minimize the total transportation cost. The total cost consists of two components: the vehicle dispatch cost and the vehicle travel cost. The vehicle dispatch cost is a fixed cost per vehicle used, set at 1000 units per vehicle. The total dispatch cost is:

$$Cp = \Sigma W_p$$

The vehicle travel cost is proportional to the total distance traveled, with the unit distance cost set to 1. The overall objective function is:

$$Z = min\{C_p + 1 * TD\}$$

This formulation ensures that the optimization simultaneously considers both the number of vehicles deployed and the total distance traveled, seeking the most cost-effective solution that satisfies all customer demands while respecting vehicle capacity limits.

## 3. VEHICLE SCHEDULING ALGORITHMS

Logistics distribution vehicle scheduling essentially comes down to solving vehicle route optimization problems, which can be tackled by exact algorithms, classical heuristics, and modern heuristics [1]. Exact algorithms like integer programming and dynamic programming can find optimal solutions but struggle with large-scale problems due to computational complexity. Classical heuristics, such as the Saving Algorithm [1], usually start from an original solution and improve it through local search, being suitable for small to medium-sized problems.

Modern heuristic algorithms have gained prominence for VRP due to their ability to find satisfactory solutions within reasonable time. Genetic Algorithms have been successfully applied to various VRP variants: Zhou and Shen [7] proposed an adaptive parallel genetic algorithm for integrated loading and unloading VRP; Fan et al. [8] developed a hybrid genetic algorithm for VRP with fuzzy demands and time windows; and Fan et al. [12] further designed a hybrid genetic algorithm for multi-depot joint distribution routing. Huang et al. [11] proposed an adaptive genetic grey wolf optimizer for CVRP that enhances convergence capability. Shang et al. [14] developed an improved simulated annealing algorithm with reheating operation for CVRP, designing a random neighborhood transformation strategy to enhance initial solution quality.

Classical heuristic algorithms usually start from an original solution and improve it through approximate search and generalization strategies. Common methods include the Sweep Algorithm, Saving Algorithm, Two-phase Method, and Insertion Algorithm. The Saving Algorithm has good scalability and can more fully utilize vehicles, but its solution quality for large-scale VRP is relatively poor. The Sweep Algorithm can be combined with insertion algorithms to solve problems but has a slow solving process. These methods are suitable for small-scale VRP solving.

The Ant Colony Algorithm, inspired by the collective foraging behavior of ants [2], operates by simulating the pheromone-laying and following mechanism. Initially, ants randomly explore paths, depositing pheromone on routes between nodes. The amount of pheromone influences subsequent ants' path choices, with higher concentrations attracting more ants. Over time, pheromone evaporates at a constant rate, preventing premature convergence. The algorithm iteratively constructs solutions using a probabilistic transition rule, updates local and global pheromone, and converges to optimal

or near-optimal solutions. Recent domestic studies have applied and improved the Ant Colony Algorithm for specific logistics contexts: Xu [20] researched vehicle routing optimization for an electronics company using an improved ant colony algorithm, while Wu [21] studied quick-frozen food logistics distribution route optimization based on the same approach.

The mathematical model of the Ant Colony Algorithm includes key parameters: *m* represents the number of ants in the colony; $\alpha$ is the pheromone heuristic factor measuring the influence of environmental information on ant decision-making; $\tau_{ij}$(*t*) represents the residual pheromone amount on path *i* to *j* at time *t*; $\beta$ is the expectation heuristic factor reflecting ants' sensitivity to visibility between nodes; $\eta_{ij}$ (*t*) represents the visibility of path (*i*, *j*) at time *t*; $d_{ij}$ represents the distance between location *i* and *j*; and $\rho$ represents the pheromone volatilization coefficient with (1-$\rho$) being the pheromone residual coefficient.

The probability of ant *k* selecting the next location is:

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{s \in allowed_k}[\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}}, j \in allowed_k$$

After completing path construction, pheromone updating is performed:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, 0 < \rho < 1$$

In the ant-cycle model used in this paper, the pheromone increment is $\Delta\tau_{ij}^{k} = Q/L_k$ when ant *k* has traversed path *i* to *j*, where $L_k$ is the total distance traveled by the ant and $Q$ is the total pheromone amount. Through this mechanism, the algorithm progressively converges toward optimal solutions by reinforcing shorter paths with higher pheromone concentrations.

## 4. EXPERIMENT AND ANALYSIS

To verify the application effect of the Ant Colony Algorithm for the Capacitated Vehicle Routing Problem, this paper conducted simulation experiments using MATLAB R2023b on a computer with Intel Core i5-10300H CPU, 4.50GHz, RTX2060 GPU, and 16GB memory running Windows 11.

The algorithm parameters were determined through extensive experimentation. Six parameters needed to be optimized: ant quantity *m*, total pheromone $Q$, number of iterations $N$, pheromone concentration control parameter $\alpha$, visibility weight control parameter $\beta$, and pheromone volatilization factor $\rho$. Initial parameter values were set as *m*=100, $\alpha$=1, $\beta$=5, $\rho$=0.5, $Q$=50, and $N$=100. However, from the initial results, the average path length remained unstable in the final stages, indicating unsatisfactory convergence, so further experiments were conducted to determine optimal parameters.

Through systematic experimentation adjusting one parameter at a time while keeping others constant, with each parameter value tested for no fewer than ten simulations, the optimal parameter combination was determined as $\alpha$=0.9, $\beta$=8, $\rho$=0.50, *m*=180, $N$=150, and $Q$=70. Compared with the initial parameter combination, the optimized parameters achieved smaller minimum path lengths with more stable convergence characteristics.

Simulation experiments were conducted sequentially with 20, 40, and 65 randomly generated customer nodes. The first node served as the logistics distribution center. Customer demand quantities were also randomly generated.

For the 20-customer case, the Ant Colony Algorithm produced a result with a total cost of 3753.91, using 3 vehicles with a total travel distance of 753.91, and a running time of 11.41 seconds. Three

distribution routes were generated, each starting from and returning to the distribution center after serving customers along the route.

For the 40-customer case, the Ant Colony Algorithm produced a result with a total cost of 7278.67, using 6 vehicles with a total travel distance of 1278.67, and a running time of 26.21 seconds. The six routes demonstrated well-organized distribution paths covering all customer points efficiently.

For the 65-customer case, the Ant Colony Algorithm produced a result with a total cost of 10904.24, using 9 vehicles with a total travel distance of 1904.24, and a running time of 53.35 seconds. The solution routes demonstrated well-organized distribution paths with minimal path crossings.

To better verify the effectiveness of the Ant Colony Algorithm, this paper also implemented the Saving Algorithm for the same model. For the 20-customer case, the Saving Algorithm achieved a total cost of 3837.50 with a travel distance of 837.50 and a running time of 0.041 seconds. For the 40-customer case, it achieved a total cost of 7302.44 with a travel distance of 1302.44 and a running time of 0.21 seconds. For the 65-customer case, it achieved a total cost of 11118.70 with a travel distance of 2118.70 and a running time of 0.71 seconds.

The comparison results clearly demonstrate that the vehicle scheduling scheme based on the Ant Colony Algorithm has a lower total cost than that of the Saving Algorithm across all test cases. The cost advantage becomes more pronounced as the problem scale increases. The solutions from the Saving Algorithm exhibit more path crossings, resulting in increased total vehicle travel distance and higher distribution costs. The Ant Colony Algorithm can find lower-cost vehicle scheduling schemes while satisfying vehicle capacity constraints, effectively improving vehicle utilization efficiency and reducing logistics company operating costs. However, due to the need for multiple iterations, the Ant Colony Algorithm requires a longer running time compared to the Saving Algorithm, which is an inherent trade-off between solution quality and computational efficiency.

## 5. CONCLUSION

This paper focuses on the method of logistics distribution vehicle scheduling. Due to the relatively backward decision-making process of vehicle scheduling, which in many cases relies on the personal experience of responsible persons, logistics efficiency has not reached an optimal state, potentially leading to greatly reduced customer satisfaction. On the other hand, insufficiently rigorous vehicle scheduling decisions may also result in higher costs for distribution enterprises.

Through in-depth analysis of the vehicle route planning problem with vehicle capacity constraints, this paper designed an algorithm using the Ant Colony Algorithm in MATLAB that can effectively solve relatively complex problems, thereby improving the decision-making process and enabling more reasonable and efficient arrangement of vehicle route selection. A CVRP optimization model was constructed that comprehensively considers customer locations, demand quantities, and vehicle capacity limits, with the objective of minimizing total transportation cost including both fixed vehicle dispatch costs and variable travel costs. The model incorporates constraints on vehicle capacity, single-visit service, closed routes, and customer count limits per vehicle.

The experimental results demonstrate that the Ant Colony Algorithm applied to the CVRP problem can effectively solve the vehicle scheduling problem with capacity constraints, improve the decision-making efficiency of vehicle scheduling, and reduce the distribution costs of logistics companies. Comparative analysis with the Saving Algorithm further confirms the superiority of the proposed method in terms of solution quality. The cost improvements, while modest in per-unit terms in the simplified model, would translate to significant savings in real-world applications where actual distribution costs are substantially higher.

Future research directions include considering more realistic factors such as dynamic customer demands, time window constraints, multiple distribution centers, and real-time traffic conditions.

Additionally, hybrid approaches incorporating other optimization techniques could be explored to address the limitations of the Ant Colony Algorithm when dealing with very large numbers of nodes, particularly the increasing computational complexity and running time. The integration of the scheduling algorithm with practical distribution center operations to better reflect actual conditions and achieve optimal logistics vehicle scheduling remains an important area for future work.

## REFERENCES


[1] Dantzig G B, Ramser J H. The Truck Dispatching Problem [J]. Management Science, 1959, 6(1): 80-91.

[2] Dorigo M, Gambardella L M. Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem [J]. IEEE Transactions on Evolutionary Computation, 1997, 1(1): 53-66.

[3] Gheysens F, Golden B, Assad A. A New Heuristic for Determining Fleet Size and Composition [J]. Mathematical Programming Study, 1986, 26: 233-236.

[4] Gendreau M, Guertin F, Potvin J Y, et al. Parallel Tabu Search for Real-Time Vehicle Routing and Dispatching [J]. Transportation Science, 1999, 33(4): 381-390.

[5] Ninikas G, Minis I. Load Transfer Operations for a Dynamic Vehicle Routing Problem with Mixed Backhauls [J]. Journal on Vehicle Routing Algorithms, 2019, 2(1-4): 45-60.

[6] Rasku J, Musliu N, Kärkkäinen T. On Automatic Algorithm Configuration of Vehicle Routing Problem Solvers [J]. Journal on Vehicle Routing Algorithms, 2019, 2(1-4): 1-22.

[7] Zhou R, Shen W L. Adaptive Parallel Genetic Algorithm for Integrated Loading and Unloading Vehicle Routing Problem [J]. China Mechanical Engineering, 2018, 29(22): 2740-2749.

[8] Fan H M, Wu J X, Geng J, et al. Vehicle Routing Problem with Fuzzy Demands and Time Windows and Hybrid Genetic Algorithm [J]. Journal of Systems & Management, 2020, 29(1): 107-118.

[9] Wu T Y, Chen J J, Jian J, et al. Real-Time Pickup and Delivery Route Selection for O2O Delivery Vehicles [J]. Systems Engineering – Theory & Practice, 2018, 38(11): 2885-2891.

[10] Li M M, Lu J, An Y. Bi-Objective Vehicle Routing Problem with Time Window Assignment Considering Customer Preferences [J]. Journal of Southeast University (Natural Science Edition), 2018, 48(3): 568-575.

[11] Huang G W, Cai Y G, Qi Y H, et al. Adaptive Genetic Grey Wolf Optimizer Algorithm for Capacitated Vehicle Routing Problem [J]. Acta Electronica Sinica, 2019, 47(12): 2602-2610.

[12] Fan H M, Xu Z L, Li Y, et al. Hybrid Genetic Algorithm for Multi-Depot Joint Distribution Routing Problem [J]. Journal of Shanghai Jiao Tong University, 2019, 53(8): 1000-1009.

[13] Zhang J L, Liu J L, Zhao Y W, et al. Time-Dependent Simultaneous Pickup and Delivery VRP and Hyper-Heuristic Algorithm [J]. Computer Integrated Manufacturing Systems, 2020, 26(7): 1905-1917.

[14] Shang Z Y, Gu J N, Wang J P. Improved Simulated Annealing Algorithm for Capacitated Vehicle Routing Problem [J]. Computer Integrated Manufacturing Systems, 2021, 27(8): 2260-2269.

[15] Li D C, Chen Y R, Zhang Z C. Electric and Fuel Vehicle Hybrid Routing Problem Based on Branch-and-Price Algorithm [J]. Systems Engineering – Theory & Practice, 2021, 41(4): 995-1009.

[16] Zhang Y Z, Zhang Z W. A Solution Method for Material Distribution Problem Considering Dynamic Customer Demands [J]. Journal of Xi'an Jiaotong University, 2020, 54(8): 124-131.

[17] Ren T, Chen Y, Xiang Y C, et al. Low-Carbon Cold Chain Vehicle Routing Optimization Considering Customer Satisfaction [J]. Computer Integrated Manufacturing Systems, 2020, 26(4): 1108-1117.

[18] Xia Y K, Deng Y D, Pang Y, et al. Fresh Food Vehicle Routing Problem with Customer Classification and Splittable Demands [J]. Computer Integrated Manufacturing Systems, 2021, 27(4): 1238-1248.

[19] Zhou X C, Lv Y, He C H, et al. Multi-Depot Green Vehicle Routing Model with Time-Varying Speed and Optimization Algorithm [J]. Control and Decision, 2022, 37(2): 473-482.

[20] Xu H. Research on Vehicle Routing Problem Optimization of F Company Based on Improved Ant Colony Algorithm [D]. Changchun: Changchun University of Technology, 2023.

[21] Wu X Q. Research on Quick-Frozen Food Logistics Distribution Route Optimization Based on Ant Colony Algorithm [D]. Dalian: Dalian Jiaotong University, 2023.