



Research article

Optimal route selection for supporting lines in logistics companies

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Abstract: In this study, the challenges faced by logistics companies in daily route planning were investigated under complex and dynamic operational conditions. Using a Taiwanese logistics company as a real-world case, the problem involved planning dozens of delivery routes each day while complying with fixed primary routes, time windows, vehicle capacity limits, and heterogeneous store demands. To address these challenges, Rule-Based Reasoning and optimization algorithms were utilized to develop an intelligent route planning system. The rule-based component formalized domain-specific operational constraints to ensure feasibility, while Ant Colony Optimization was applied to refine route sequencing within the constrained solution space. Rather than fully replacing manual planning, the proposed hybrid framework was designed as a decision-support tool to provide structured, reproducible reference routes and assist planners in efficiently handling complex real-world logistics settings. The results demonstrated that the proposed framework could substantially reduce planning time while offering consistent and explainable routing baselines to support informed decision-making in practical logistics operations.

Keywords: routing optimization; ant colony optimization; capacitated vehicle routing problem

Mathematics Subject Classification: 90B06, 90C27, 90C35, 68T05

1. Introduction

In the global logistics landscape, the rapid growth of e-commerce and the increasing diversity of consumer demands have introduced unprecedented complexity into distribution networks. Logistics enterprises must continuously innovate and optimize their operational strategies to remain competitive, ensure service reliability, and enhance customer satisfaction. Among the critical operational challenges,

efficient and precise route planning plays a decisive role in determining overall performance. QuanTai Logistics, a subsidiary of FamilyMart, exemplifies these challenges within the Taiwanese retail distribution system. The nation is divided into seven regional logistics centers, each responsible for the design and management of delivery routes. For instance, the Linkou Distribution Center (DC) serves approximately 800 retail outlets, operating 30–40 vehicle routes daily, covering 10–15 stores. This logistical configuration corresponds directly to the classical Vehicle Routing Problem (VRP), a well-established yet computationally challenging optimization problem in operations research. The effective resolution of such issues necessitates advanced scheduling methods and algorithmic approaches that can potentially impact cost efficiency and service quality in large-scale retail logistics systems.

In practice, logistics companies often operate according to predetermined delivery schedules, referred to as main routes. These routes characterize a fixed sequence of customer locations, scheduled arrival times, predefined geographic positions, estimated driving distances, and associated delivery time windows. Such main routes form the backbone of daily distribution operations, ensuring consistency and reliability across the supply chain.

Nevertheless, fluctuations in daily order volumes can occur, introducing significant variability into this otherwise stable structure. On days with elevated delivery demand, the capacity of main routes alone may not be sufficient, necessitating the deployment of support vehicles. The allocation of stores to these support vehicles is a dynamic process that must be performed each day. The assignment depends primarily on store-level order volumes and must consider operational constraints, including scheduled arrival times, geographic distribution, route distances, and delivery working hours. As a result, the final delivery plan varies by dynamically generated support routes.

However, QuanTai Logistics has encountered several operational challenges despite adopting fixed main routes supplemented by dynamically assigned support vehicles. Specifically, the company's prior routing solutions had the following limitations:

1. Delivery personnel felt that the routes were not practical.
2. Cross-region deliveries resulted in extended working hours.
3. Imbalances occurred in the delivery areas, distances, and number of stores assigned to each route.
4. Some stores preferred (or required) fixed delivery routes without arbitrary changes.
5. The loading rate of each vehicle could exceed 100% only slightly; otherwise, the vehicle could not accommodate the load.

Route planning at QuanTai Logistics is predominantly performed manually. After receiving daily delivery data, planners must allocate orders and construct delivery routes through manual decision-making. Such reliance on human judgment substantially increases the planning workload and exposes operations to the risk of inefficiency, as human planners often struggle to consistently achieve near-optimal solutions.

In this study, we propose a hybrid route planning methodology that integrates Rule-Based Reasoning with Ant Colony Optimization to overcome the limitations above. The rule-based component provides domain-specific heuristics to guide initial decision-making, whereas the metaheuristic optimization process explores the solution space to refine routing configurations and enhance overall efficiency. Furthermore, the proposed approach is validated through real-world case applications, as this study was conducted in close collaboration with logistics companies, thereby ensuring theoretical rigor and practical relevance.

This study is organized as follows: In Section 2, we review the related literature and background knowledge, particularly on optimization algorithms, metaheuristic approaches in logistics, and

advanced route planning techniques. In Section 3, we outline the research methodology, including the research objectives, dataset characteristics, and the proposed model architecture. In Section 4, we present the results and a detailed analysis of the findings. Finally, in Section 5, the key contributions of this study are summarized, and potential directions for future research are discussed.

2. Related work

2.1. Vehicle routing problem (VRP)

The Vehicle Routing Problem (VRP) is a fundamental challenge in logistics and transportation optimization, where it appears in many real-life applications such as logistics, transportation, manufacturing, retail distribution, waste collection, and delivery planning [1]. The problem involves determining efficient allocation and scheduling of a fleet of vehicles to service a set of geographically dispersed customers to minimize total travel distance or distribution cost while satisfying operational constraints, such as vehicle capacity, delivery time windows, and service requirements. Due to its computational complexity and extensive real-world applications, VRP has been the focus of operations research and combinatorial optimization.

2.1.1. Basic vehicle routing problem

Basic VRP involves determining a set of vehicle routes with minimum total travel distance or cost, subject to vehicle capacity limitations and customer demand requirements. Each customer location (the endpoint) must be visited exactly once by a single vehicle, and all routes must start and end at a central depot. This problem can be formulated as an Integer Linear Programming model, in which the objective function minimizes the overall routing cost, whereas the constraints ensure vehicle capacities are not exceeded and guarantee that each customer is served exactly once. Methods reported in past surveys [2] include constructive heuristics, improvement heuristics, and metaheuristics.

Constructive heuristics build routing solutions from scratch using predefined heuristic rules. Owing to their simplicity and computational efficiency, they are widely applied to VRP variants. Although these methods can quickly generate feasible solutions, their suboptimal nature generally results in a performance gap between the optimal and the obtained solution [3,4]. Hence, constructive heuristics are often used to generate initial solutions for subsequent improvement through local search or metaheuristic optimization.

Improvement heuristics iteratively enhance routing solutions through local neighborhood search procedures, such as λ -opt (2-opt, 3-opt) methods. These methods can effectively refine routes and achieve locally optimal solutions. However, they are prone to being trapped in local minima, and the final solution is often highly dependent on the initial starting solution of the search process [1].

Metaheuristics differ from constructive and improvement heuristics in that they rely on general algorithmic frameworks rather than problem-specific structures. They provide high-level search strategies and are less dependent on the characteristics of a specific problem [5]. Many metaheuristics are inspired by natural phenomena or physical processes, such as evolution or thermodynamics. Examples include Genetic Algorithms and Simulated Annealing, which are typically efficient and possess strong global search capabilities, enabling them to minimize the risk of being trapped in local optima and effectively explore the solution space.

2.1.2. Capacitated vehicle routing problem (CVRP)

CVRP builds upon basic VRP by introducing vehicle capacity constraints. In this problem, each endpoint has a specific demand, and vehicles must serve customers without exceeding their capacity limits. The mathematical model, therefore, includes constraints for customer demand and vehicle capacity to minimize total travel distance or cost. CVRP is often discussed alongside other VRP models, particularly the VRP time windows (VRPTW) mentioned in Section 2.1.3. Altabeeb et al. [6] proposed a solution for CVRP using a Firefly Algorithm combined with local search and genetic operators. Lysgaard and Wøhlk [7] also studied a cumulative version of CVRP, focusing on minimizing total arrival time rather than total travel distance, and proposed a Branch-and-Cut-and-Price algorithm to achieve optimal solutions.

2.1.3. Vehicle routing problem with time windows (VRPTW)

VRPTW incorporates time constraints into basic VRP. In this variant, each endpoint must be visited within a specified time window. The model considers vehicle capacity constraints and adds constraints related to time-windows and arrival times to ensure that deliveries occur within the designated time. VRPTW is one of the most frequently studied variants of VRP, leading to extensive research on algorithmic solutions for this problem type. Ghoseiri and Ghannadpour [8] treated this problem as a multi-objective optimization problem, minimizing total distance and the number of vehicles used. They proposed a genetic algorithm combined with economic principles to find the optimal solution. Lei et al. [9] introduced an adaptive large neighborhood heuristic algorithm. Later, Vidal et al. [10] proposed a hybrid genetic algorithm with controllable high-order diversity to address the VRPTW problem comprehensively on a large scale. Yassen et al. [11] developed a method combining Harmony Search and local search algorithms, balancing global exploration and local refinement to solve VRPTW. Hu et al. [12] developed a two-stage method based on a modified neighborhood search heuristic algorithm, thereby minimizing the number of vehicles in the first stage and total distance in the second stage. Moreover, Zong et al. [13] proposed a reinforcement learning framework to solve VRPTW. The model aims to generate high-quality routing solutions within a limited inference time while addressing three major challenges: direct optimization under complex constraints, efficient management of time window limitations, and effective modeling of vehicle cooperation.

The problem investigated in this study shares many similarities with VRPTW while integrating characteristics of CVRP. Therefore, to fully understand the issues, we have given special attention to the features and solutions of these two VRP variants.

2.2. *Ant colony optimization (ACO)*

2.2.1. Algorithm introduction

ACO, proposed by Marco Dorigo in 1992, is an evolutionary algorithm inspired by the behavior of ants in search for food. Ants use pheromone concentrations to guide their colony toward their shortest paths, and this biological behavior has been successfully applied to optimization problems [14]. In 2025, Shi et al. [15] proposed that the development of multi-agent systems (MASs) has led to the multi-agent traveling

salesperson problem (MATSP), which aims to find multiple routes with minimal total cost through agent cooperation. To address MATSP, we propose a Distributed Ant Colony System (DACS) with pheromone transfer. In this system, each agent operates independently with partial data and resolves conflicts through consensus. A bidding-based cooperation mechanism is used to coordinate city allocation to agents. DACS employs two pheromone transfer strategies to enhance search efficiency. Extensive experiments conducted across nine datasets demonstrate the effectiveness and efficiency of DACS, even in complex environments.

Despite its advantages, the classical ACO algorithm possesses limitations, including slow convergence and premature stagnation. To address these issues, Sun et al. [16] proposed a novel Emergency Path-planning Improved ACO (EPIACO) algorithm. This algorithm incorporates six enhanced mechanisms: An uneven initial pheromone distribution, a heuristic function with directional judgment, an adaptive pheromone volatility factor, a differentiated pheromone update rule, an improved state transition probability strategy, and path smoothing. The results demonstrate that EPIACO outperforms classical ACO by reducing total path length, minimizing the number of turns, and accelerating convergence.

Building on these developments, the fundamental principles of Ant Colony Optimization are outlined as follows:

Basic principles

1. The construction phase:

Ants construct solutions based on state transition rules, considering pheromone levels, a greedy rule, and the set of unvisited cities. Random numbers and parameters control the relative importance of pheromone concentration and the greedy rule. A probability distribution is then used to make reasonable choices. Then, the construction functions as follows:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \in a_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta} & , j \in a_k \\ 0 & , otherwise \end{cases} \quad (1)$$

where:

- τ_{ij} is the pheromone on edge (i, j).
- $\eta_{ij} = \frac{1}{d_{ij}}$ is the heuristic desirability of moving from city i to city j.
- a_k is the set of cities that ant k is allowed to visit.
- The parameters α and β determine the relative importance of pheromone versus distance.

2. Local pheromone update:

Ants immediately update the pheromone levels along the paths they traverse to avoid other ants getting trapped in local optima. The initial pheromone level is an important parameter, and all paths begin with the same pheromone concentration.

3. Global pheromone update:

During path selection, ants consider the pheromone concentration and the distance between points, adopting a random local search strategy. This results in higher pheromone concentrations on shorter edges, increasing the probability of subsequent ants choosing

the same path. Each ant is restricted to valid routes (visiting each point exactly once), a constraint controlled by a tabu list. The function is as follows:

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k(t) \quad (2)$$

where:

- ρ is the pheromone evaporation coefficient, $0 < \rho \leq 1$.
- $\Delta\tau_{ij}^k(t)$ is the pheromone released by ant k on edge (i, j) , and is defined as:

$$\Delta\tau_{ij}^k(t) = \begin{cases} 1/d_{ij}, & \text{if edge}(i, j) \text{ is in the path } T^k \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

4. Termination step:

In this step, the algorithm determines if the iteration count has reached a preset value or if stagnation occurs (all ants choose the same path and the solution no longer changes). If either condition is met, the algorithm is stopped; otherwise, the iteration count is updated, and the process is repeated, as shown in Figure 1.

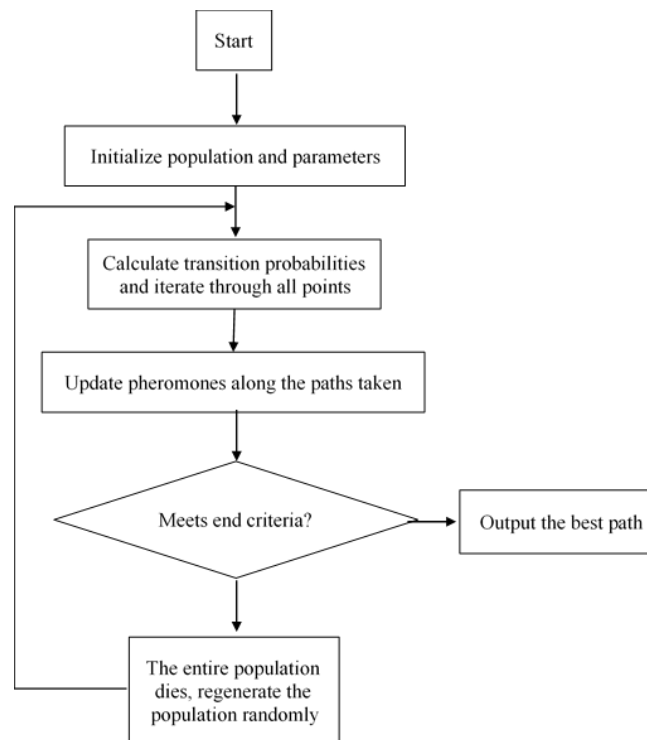


Figure 1. The Ant Colony algorithm flowchart.

Parameters include the number of ants, the rate of pheromone evaporation, the initial pheromone amount, relative importance of the greedy rule, and parameters controlling the equilibrium between exploration and exploitation. This algorithm is inspired by social behavior in nature and uses multi-point search, with positive and negative feedback mechanisms guiding the ant colony to an optimal solution. Pheromone levels and heuristic rules guide the search direction for the next iteration.

2.2.2. Comparison with other optimization algorithms

Besides ACO, other commonly used path optimization algorithms include Simulated Annealing (SA) and Genetic Algorithms (GA), often used to solve VRP.

SA is inspired by the annealing process in metals, in which heating and slow cooling alter physical properties. In the algorithm, this process is simulated by changing the temperature variable, initially set high and gradually cooled. At high temperatures, the algorithm accepts worse solutions to escape local optima. As the temperature decreases, the probability of accepting worse solutions decreases, thereby focusing the search on regions near the global optimum.

GA is an evolutionary computation approach based on Darwinian evolution. This algorithm optimizes a population of solutions through genetic operations such as selection, crossover, and mutation. The algorithm starts by assessing a random population of solutions and selects the fittest individuals for genetic functions, hoping that the new generation will perform better than the previous one. This process is repeated until a stopping condition is met. According to researchers [17], SA performs best in execution time (<1 s); however, it is second-best in finding the shortest path, next only to ACO. However, ACO has the longest execution time. The performance of GA falls between the two.

Within the resulting feasible solution space, ACO is employed to refine route sequences under multiple interacting constraints. ACO is well suited for path-construction and shortest path-oriented combinatorial problems, as its solution construction mechanism and pheromone-based adaptive search process corroborate the structural characteristics of route sequencing and path optimization. Compared with general-purpose metaheuristics, such as SA and GA, ACO has been reported to be effective at identifying high-quality shortest-path solutions, although this is typically associated with increased computational time. In the studied logistics setting, solution quality and operational feasibility of route sequences are prioritized over computational efficiency, because daily planning is conducted in an offline or semi-offline manner. Accordingly, ACO is adopted to emphasize path quality and structural compatibility with routing problems, whereas the Rule-Based Reasoning component restricts the search space to solutions that are operationally feasible and implementable.

3. The proposed approach

3.1. Approach framework

We investigated optimization approaches for logistics route planning in two major directions. Each part applied distinct methodologies to address the planning problem, enabling a comprehensive analysis and comparative evaluation of the effectiveness of different optimization techniques.

In the first part, rule-based programming was employed for route planning without incorporating machine learning algorithms. The goal here was to understand the performance of routes under traditional programming and provide a benchmark for subsequent comparisons. In the second part, heuristic algorithms were introduced to explore their application in route planning. These algorithms included constructive, reinforcement, and meta-heuristics. Through these, the contribution of heuristic algorithms to route optimization was evaluated.

Next, a rule-based combination method was established by integrating these two research components and ensuring that logistics route planning complies with company regulations. Two

methods were used to solve the route planning problem: Rule-Based Reasoning and ACO, as shown in Figure 2.

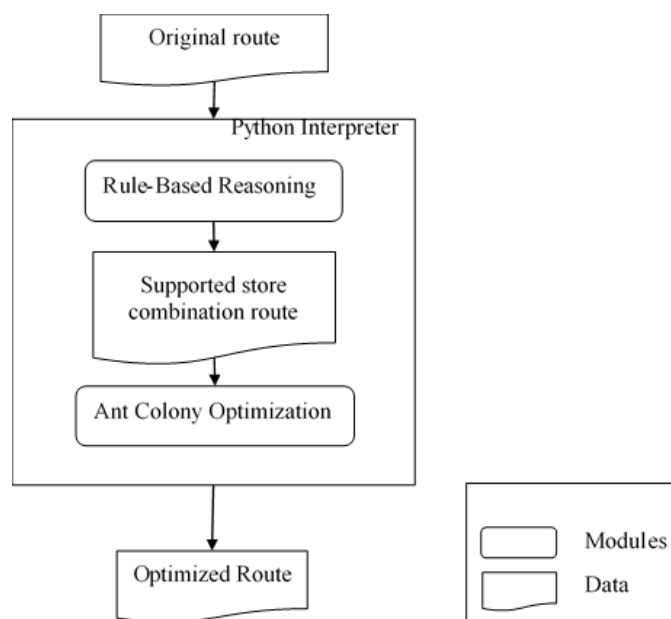


Figure 2. Research framework diagram.

The structure of this study is as follows: First, the daily shipping data, including the pre-planned primary routes from the vendor, were obtained. Next, using the rules of Rule-Based Reasoning, support stores were selected from the primary routes and combined to form support store routes. Finally, these routes were optimized using ACO, and the nearly optimal routes served as the output for the vendor's review.

The integration of Rule-Based Reasoning and ACO is motivated by their complementary strengths. Rule-Based Reasoning was employed to encode domain knowledge and operational constraints provided by logistics practitioners, ensuring that generated routes were operationally feasible and compliant with company policies. However, rule-based systems alone are limited in their ability for global optimization of route sequences and may result in suboptimal travel distances. ACO is therefore applied as a secondary optimization layer to refine the sequencing of stores within each generated route. In this integrated framework, Rule-Based Reasoning provides feasibility and structural guidance, while ACO facilitates local route optimization, enabling the system to balance practical constraints and computational optimization.

3.2. Rule-based reasoning

3.2.1. Route planning rules

The rules were derived from interviews on “Taiwan’s Logistics Demand” and historical route planning data, and from organizing manual planning steps and constraints for the support lines.

1. Manual planning steps:

- (1) Candidate selection: Excess stores were selected from fixed primary lines to form candidate support store routes.

- (2) Additional support: Checked whether other primary lines could assist the candidate support stores.
 - (3) Grouping: The remaining stores were grouped to form support routes.
 - (4) Regional clustering: The stores were grouped by area (areas were not fixed administrative regions but determined by daily conditions).
 - (5) Sequencing: Routing was initiated from the farthest store and proceeded toward the center. Any remaining stores were adjusted as if they were centrally located.
 - (6) Left-to-right sequencing:
 - (6a) Within the same area, stores were sequenced from left to right geographically, considering a stair-step pattern in terms of time and road order.
 - (6b) Alternatively, larger stores were scheduled first (reducing the number of stores per support vehicle), then stores to the left and right were selected to form support routes.
2. Constraints:
- (1) Vehicle number calculation: The number of support vehicles was calculated based on the excess cargo volume, dividing the excess by the maximum load capacity of each vehicle.
 - (2) Store arrival time: Store visits were required to comply with the specified arrival times.
 - (3) Route working hours: Each route was limited to a maximum of 5 hours.
 - (4) Primary route integrity: Primary routes could support candidate support stores, but the original store sequence was not altered.
 - (5) Load rate limit: The maximum load rate was 100%, with occasional exceptions based on experience.
 - (6) Regional and time constraints: Store regions and arrival times were critical factors.

The decision rules were derived from historical route planning data of the logistics company and complemented by interviews with practitioners and consideration of relevant operational constraints. Specifically, past planning records were analyzed to identify key challenges and practical issues encountered in daily operations. Furthermore, insights and experiential knowledge were obtained through interviews with the company's planners, thereby capturing the general procedures and considerations guiding the route planning process.

Then, a set of rules and steps was further organized and summarized.

1. Exceed cargo volume judgment:
 - (1) It was determined whether each primary line exceeded the cargo volume limit (provided by the logistics company).
 - (2) If exceeded, stores with smaller cargo volumes were selected from the primary line to form the candidate store set until the primary line no longer exceeded the cargo volume limit. If not exceeded, that primary line was ignored, and the focus moved on to the next one.
2. Administrative area segmentation:

The selected stores were segmented based on their administrative regions.
3. Regional support line prioritization:

Grouping stores within the same region was prioritized to form support lines, listing all possible routes after segmentation.
4. Near area distribution:

If candidate stores were within a 3 km radius of the logistics center, they were categorized as near area stores. After entering this range, directions were not considered; all stores in this area could be delivered.

5. Mid-area distribution:

If candidate stores were within a 3–5 km radius, they were categorized as mid-area stores. After entering this range, directions were not considered; all stores in this area could be delivered.

6. Far area distribution:

If the candidate stores were neither near nor mid-area stores:

- (1) If the first store planned was to the north of the center, subsequent stores could not be south of the center; the same applies to east and west.
- (2) The planned arrival time had to be within 30 minutes to 1 hour after the scheduled time.
- (3) The total route duration could not exceed 5 h.

7. Route confirmation:

Google Maps API was used to confirm the time for each route combination, updating the order, time, and route length in the original combination.

8. Rearranging candidate stores:

If candidate stores could not be grouped within the same region, they were placed back into the primary lines and other selection methods were reconsidered (e.g., larger cargo volumes and times) for reselecting candidate stores, then rearranging using rules 1–7.

These rules are represented here in a mathematical model:

(1) Variable definitions:

N : Number of all primary lines.

M : Number of all stores.

T_i : Cargo volume of primary line i .

C_i : Cargo volume limit of primary line i .

P_j : Cargo volume of store j .

D_{jk} : Distance between store j and store k .

L : Location of the logistics center.

$dist(L,j)$: Distance between logistics center L and store j .

t_{jk} : Travel duration between store j and store k .

(2) Set definitions:

S_i : Set of stores on primary line i .

R : Set of candidate stores.

N_z : Subset of candidate stores for support lines.

R_{near} : Set of near area stores ($dist(L,j) \leq 3$ KM).

R_{mid} : Set of mid-area stores (3 KM $< dist(L,j) \leq 5$ KM).

R_{far} : Set of far area stores ($dist(L,j) > 5$ KM).

(3) Constraints:

- Cargo volume exceedance:

For each primary route i , the total cargo volume T_i must satisfy the capacity constraint:

$$T_i = \sum_{j \in S_i} P_j \leq C_i, \forall i \in \{1, \dots, N\}$$

If the constraint is violated ($T_i > C_i$), a subset of stores is removed from S_i (specifically those with smaller cargo volumes) and reassigned to the candidate set

R until the constraint is satisfied.

$$\sum_{j \in S_i \setminus R} P_j \leq C_i$$

If not violated, the primary line was ignored and moved to the next.

- Administrative area segmentation:
Selected stores were segmented based on administrative areas.
- Regional support line prioritization:
Candidate stores were categorized based on their distance from the logistics center:

$$j \in R_{near} \Rightarrow \text{dist}(L, j) \leq 3$$

$$j \in R_{mid} \Rightarrow 3 < \text{dist}(L, j) \leq 5$$

$$j \in R_{far} \Rightarrow \text{dist}(L, j) > 5$$

- Same region support lines:
Selecting $j, k \in N_z$ was prioritized if j, k were in the same region.
- Delivery scope:
 - $j \in R_{near} \Rightarrow$ Deliver to all nearby stores
 - $j \in R_{mid} \Rightarrow$ Deliver to all mid-area stores
- Route planning constraints:
 $j \in R_{far}, k \in R_{far} \Rightarrow$ If the first store was north of the center, subsequent stores must not have been south, and vice versa.
- Planned arrival time:
The planned arrival time for each store must fall within a window of 30 minutes before to 1 hour after the scheduled time.
- Route duration constraint:
Let the sequence of stores in route S_i be $(v_0, v_1, \dots, v_{|S_i|})$, where v_0 represents the logistics center. The total travel time must not exceed 5 hours:

$$t_{S_i} = \sum_{j=0}^{|S_i|-1} t_{v_j v_{j+1}} \leq 5 \text{ hours}$$

- Route confirmation:
Google Maps API was used to confirm and update each combination's time, order, and route length.
- Rearranging candidate stores:
If candidate stores could not be grouped within the same region, candidate stores were reselected based on other criteria (e.g., larger cargo volumes and time) and rearranged using rules 1–7.

(4) Objective function:

Let E be the set of edges (j, k) belonging to all routes S_i . The objective is to minimize the total travel time and total travel distance:

$$\min \sum_{(j,k) \in E} t_{jk} + \sum_{(j,k) \in E} D_{jk}$$

Through these variables, sets, and constraints, the logistics route optimization problem could be transformed into a mixed-integer programming problem and a program written to solve it.

3.3. Ant colony optimization

After planning the combined routes according to the rules mentioned in the previous section, the sequence of routes generated by Rule-Based Reasoning may not be optimal. To address this issue, the ACO algorithm was employed to optimize the routes. Each store's coordinates (X, Y) were marked in the ACO algorithm. The Euclidean distance between two stores was used to calculate the distance, which was then applied to the D_{jk} distance in the ACO formula. The ACO steps were then initiated and iterated, simulating the ants walking along the routes, leaving a fixed number of pheromones on the paths. Since the route lengths varied, the pheromone concentration on each route differed. The subsequent ants chose the routes based on the pheromone concentration.

This study represents the latitude and longitude information of all stores in the routes planned by Rule-Based Reasoning as X and Y coordinates, as shown in Figure 3.

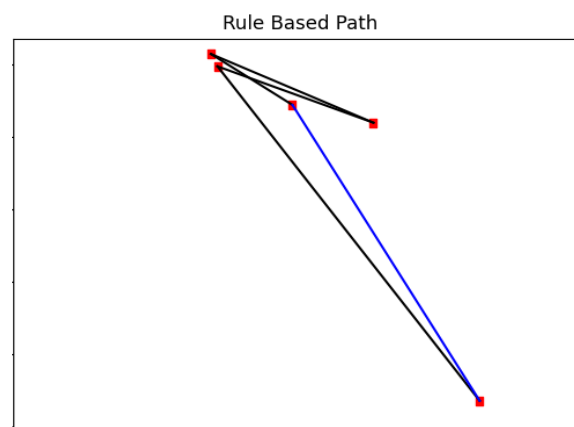


Figure 3. Path generated by Rule-Based Reasoning.

Figure 3 shows that the preliminary route planned by Rule-Based Reasoning has instances of back-and-forth movements, indicating potential detours. At this point, this route was optimized using the ACO algorithm. The algorithm simulated several ants traversing the path. The concentration of pheromones left by the ants between the stores (represented by red dots in Figure 3) was higher on shorter routes and lower on longer ones. The ants selected their paths based on the pheromone concentrations, resulting in an optimized route.

The final optimized route, obtained after applying the proposed algorithm, is illustrated in Figure 4. The figure contrasts the initial route generated by the Rule-Based Reasoning approach to the optimized route produced by the ACO algorithm. The original route included multiple back-and-forth

movements, potentially leading to detours and reduced efficiency. In contrast, the ACO-based optimization eliminated these redundant movements, yielding a smoother and more efficient route structure. This finding highlights the effectiveness of the ACO algorithm in enhancing route efficiency and reducing unnecessary travel.

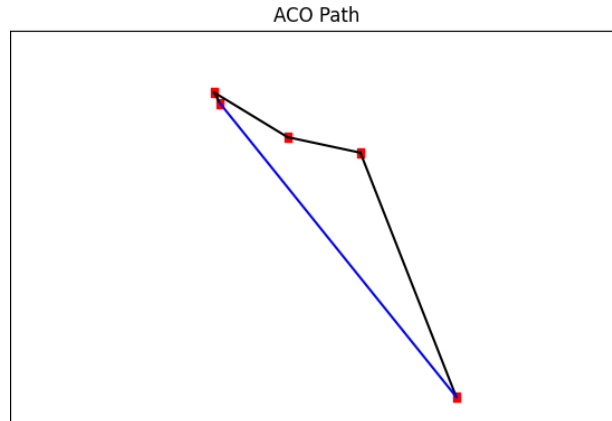


Figure 4. The path generated by Rule-Based Reasoning and optimized further by the Ant Colony Optimization (ACO).

4. Experiments

4.1. Experimental equipment

The specifications of the experimental equipment used in this study are shown in Table 1.

Table 1. Experimental equipment specifications.

Component	Specification
CPU	Intel® Core™ i7-8700 @ 3.20 GHz
RAM	24GB
GPU	NVIDIA GeForce RTX 2080 Ti
HDD	256GB SSD
OS	Windows 10 22H2

4.2. Evaluation criteria

The routes, after being generated using the proposed methods, were reviewed by the logistics company to assess their practical reasonableness. As such assessments are inherently subjective, they cannot be regarded as comprehensive evaluation criteria. Therefore, in this study, the total number of routes, the average route loading rates, and the planning times were compared to the corresponding data provided by the logistics company. As the company did not provide actual route execution data, discrepancies could arise in terms of time and distance, potentially reducing the accuracy of the comparison. Nevertheless, these measures still enabled a meaningful evaluation, particularly in determining whether ACO yielded better effectiveness than Rule-Based Reasoning alone.

Each logistics vehicle dispatched by the company incurred an approximate cost of 2000 TWD. Accordingly, the total number of routes directly influenced the overall cost of vehicle deployment: A larger number of routes implied lower effectiveness, whereas a smaller number of routes reflected higher effectiveness. With respect to loading rates, at a fixed cost of 2000 TWD per vehicle, higher loading rates represented more efficient utilization of cargo capacity. Thus, higher loading rates are considered more effective, whereas lower loading rates indicate reduced efficiency.

In addition, at the time of this study, the logistics company relied on manual planning methods, which may have led to variability in planning time compared with automated, computer-based approaches. From an efficiency perspective, shorter planning durations were considered more effective, whereas longer planning durations suggested reduced effectiveness. Similarly, in terms of travel distance, shorter routes for each vehicle were considered more efficient, whereas longer routes indicated fewer desirable outcomes.

4.3. Dataset

In this study, route and store data obtained from a nationwide logistics company were employed. The dataset comprised original routes representing the company's established primary delivery routes, each consisting of 3 to 15 stores. The data table recorded detailed information, including the route number, the sequence of stores within each route, the store name, the scheduled and estimated times, the cargo volume associated with each store, and the vehicle loading rate for that route. Several key data attributes are explained in detail below.

1. Route number and store sequence number:
The table label "route number" refers to the identifier for each main route, formatted as a number paired with a letter. Stores along each main route were sequentially numbered within the route and identified in the "route number" column as the main route number followed by the store sequence.
2. Scheduled time:
This is when the logistics company required delivery to each store. Deliveries were permitted between 30 minutes and 1 hour after this scheduled time.
3. Estimated time:
This time represents the planned arrival time at each store based on the route planning system of the logistics company for original routes. As the original data did not include planned support lines and used the logistics company's system for route planning, this field in the original data is the same as that for the scheduled time.

4.4. Experimental method

This study was conducted in close collaboration with a nationwide logistics company to evaluate the effectiveness of proposed route planning strategies. The primary objective was to generate routes that optimally satisfy operational constraints. Through this partnership, the logistics company provided professional expertise and recommendations to refine the route-planning algorithm, enhancing operational performance. This collaborative approach enabled the development of route plans that were efficient and practically implementable. By applying the rules established in this study, a subset of the resulting route plans is presented in Table 2.

Table 2. Partial route planning results.

ID	Store Name
101	
5J09	Jinyuan Store
5I10	Wanguo Store
102	
7P09	Xinbei Lin Store
7N05	Xinfu Store
8E01	Shuanglin Store
103	
7J01	Zhongshan Jieyun Station Store
7N07	Changtong Store
7I08	Xin Mackay Store
104	
5O04	Nanyang Store
5H06	Nanhai Store
5N05	Shuiyuan Store
5N07	Wensheng Store
105	
4I05	Xin Zhuang Shucheng Store
3M06	Xin Zhuang Super Store
4I08	Xin Zhuang Taipei Medical Store
106	
5A09	Sanchong Darong Store
5B06	Sanchong Chelutou Store
5C08	Sanchong Daqiao Store
TM5B09	Sanchong Xintian Store
107	
2U05	Tamsui Haidu 2nd Store
3B02	Tamsui Jia Zhou Store
108	
6B03	Guishan Lunghwa Store
6B04	Guishan Shanying Store
109	
4F03	Luzhou Jixian Store
4H05	Luzhou Minghua Store
4G04	Luzhou Xin'an Store
4H08	Luzhou Zhengyuan Store
110	
3C02	Taipei Veterans General Hospital Store
3D07	Zhongyang South Store
111	
8O02	Yonghe Dafu Store
8O04	Yonghe Yongfu Store
8N07	Yonghe Yulin Store
8L06	Yonghe Weiyuan Store
112	
7E01	SheZheng Store
7G09	Shilin Store
7E03	Shishang Store
113	
3D10	SheZiDao Store
5L07	SheZhong Store
7D03	XinHudong Store
114	
7J03	NingXia Store
7L03	Yongle Store
...	...

After applying the proposed route-planning methods, the results were initially evaluated using objective metrics, such as the total number of routes, average vehicle loading rates, planning times, and travel distances. To further validate the practical applicability of the routes and for further refinements, the collaborating logistics company provided feedback and suggestions. Their recommendations included reassigning stores between routes and adjusting delivery sequences to improve operational efficiency. Figure 5 and Figure 6 illustrate examples of the company’s feedback based on the results presented in the preceding table.



Figure 5. Feedback from the logistics company (example 1).



Figure 6. Feedback from the logistics company (example 2).

Based on this feedback, the program was modified to generate revised route-planning results. The logistics company subsequently reviewed the updated results to ensure that all routes were comprehensively assessed in terms of feasibility and practical applicability. This iterative process enabled both quantitative evaluation and qualitative validation, ensuring efficiency and operational feasibility of the optimized routes.

The results of Rule-Based Reasoning and the logistics company's planning are compared in Table 3. The average time column reflects actual delivery data provided by the logistics company, while the Rule-Based Reasoning column presents the estimated times using Google Maps API. The logistics company provided only store sequence and schedule information, and not the original route details; this information is marked as not available.

Table 3. Comparison between route planning by rule-based approach and logistics company planning.

	Rule-Based Reasoning	Manual Planning
Total route count	118	102
Avg. load rate	0.733581	0.843235
Avg. time (hour)	4.42	3.48
Avg. length (km)	52.644	No data
Total store num	717	
Planning Time	2–5 minutes	1–3 hours

Note: Here, the planning time is reported in minutes for algorithm-based methods and in hours for manual planning, reflecting computational time and human labor time, respectively.

As shown in Table 3, the results indicate that compared with the company's manual planning, rule-based planning produced a larger total number of routes and slightly lower loading rates. When total route count and average loading rate were considered evaluation criteria, the rule-based approach performed less effectively than manual planning. However, Rule-Based Reasoning demonstrated a clear advantage in planning efficiency, achieving substantially shorter computation times than manual methods.

4.5. Results with ant colony optimization integration

Based on the logistics company's recommendations, specific routes in the aforementioned planning results exhibited inefficiencies or unnecessary detours. To address this, two illustrative examples are presented here, comparing the same set of stores on Google Maps before and after optimization using ACO. The parameter settings for ACO are shown in Table 4. Table 5 reports the performance results under different ant populations (3, 10, and 30). The results indicated that the configuration with ant population = 3 achieved the best overall performance, whereas larger ant populations did not provide additional improvements and mainly increased computational cost. Therefore, ant = 3 was adopted for subsequent analysis and discussions.

Table 4. Ant Colony Optimization parameter settings.

Parameter	Value
Ant populations	3, 10, 30
Store amount per iteration	3~6 (Different by each combination)
Pheromone factor- a	1
Activation function factor- b	5
Pheromone volatility	0.1
Iteration	200

Table 5. Performance under different ant populations.

Performance metric	3 ants	10 ants	30 ants
Ant populations	3	10	30
Total route count	117	119	119
Avg. load rate	0.742515	0.726937	0.726937
Avg. time (hour)	4.41	4.39	4.39
Avg. length (km)	50.732	51.06	51.107
Total store number	717		

Table 6. The route table for route 106 without Ant Colony Optimization.

Route 106	
Store number	Store name
5A09	Sanchong Darong Store
5B06	Sanchong Chelutou Store
5C08	Sanchong Daqiao Store
5B09	Sanchong Xintian Store
Total Length	46.1 km

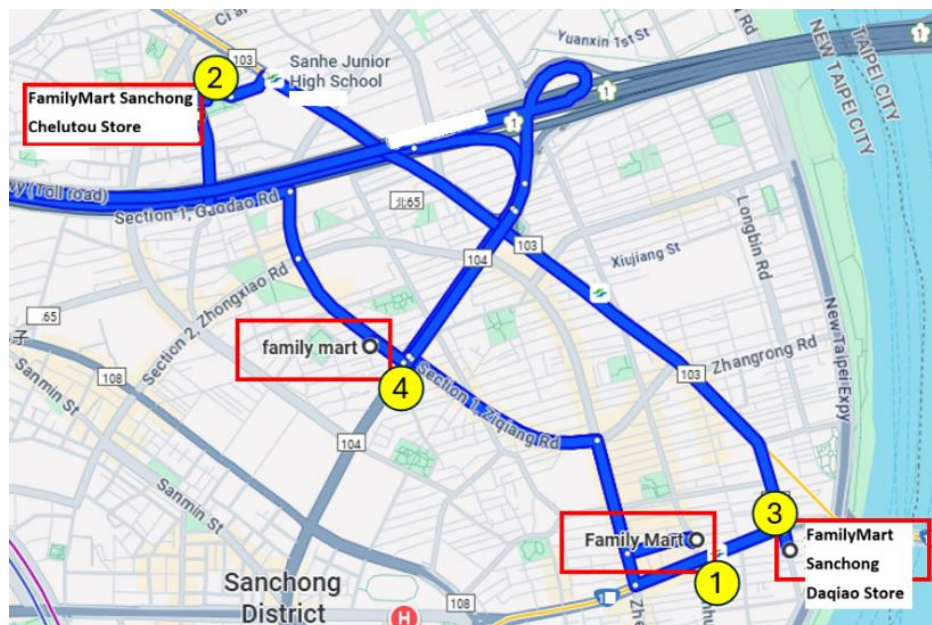
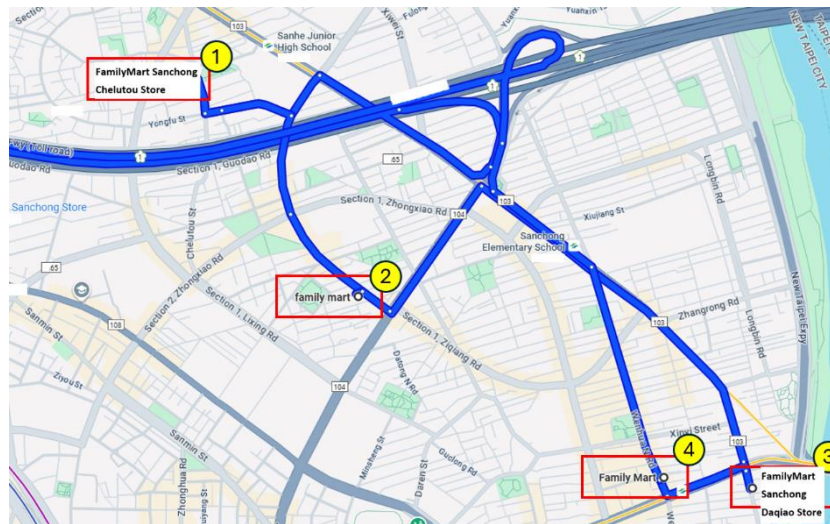
**Figure 7.** The route map through Google Maps for route 106 without Ant Colony Optimization.

Table 7. The route table for route 106 with Ant Colony Optimization.

Route 106	
Store number	Store name
5B06	Sanchong Chelutou Store
5B09	Sanchong Xintian Store
5C08	Sanchong Daqiao Store
5A09	Sanchong Darong Store
Total Length	29.7 km

**Figure 8.** The route map through Google Maps for route 106 with Ant Colony Optimization.

After setting the parameters and running planning rules with ACO, we obtained the results with and without ACO. Taking Route 106 as an example, the ACO significantly improved the initial inefficient path. As shown in Table 6 and Table 7, the total route length was reduced from 46.1 km to 29.7 km, enhancing overall efficiency. In the original plan shown in Figure 7, the route departed from the Da Rong store, proceeded north to the Che Lu Tou store, and then traveled south to the Da Qiao store, causing unnecessary back-and-forth movements. After ACO optimization, a more efficient sequence was identified, as shown in Figure 8: Starting from the Che Lu Tou store, which is closer to the logistics center, proceeding southeast to the Da Qiao store, then visiting the Da Rong store, and finally returning to the logistics center. This revised route effectively eliminated redundant detours and substantially improved route efficiency.

A comparison of Rule-Based Reasoning, Rule-Based Reasoning combined with ACO, and manual planning conducted by the logistics company is presented in Table 8. The average time column presents actual delivery times provided by the logistics company. In contrast, the times for Rule-Based Reasoning and Rule-Based Reasoning combined with ACO were estimated using the Google Maps API. As the logistics company provided information only about store sequences and scheduled times without detailed original route information, the corresponding data are indicated as not available.

Table 8. Comparison of Rule-Based Reasoning, ACO-enhanced planning, and manual planning.

	Rule-Based	Rule-Based +ACO	Manual Planning
Total route count	118	117	102
Avg. load rate	0.733581	0.742515	0.843235
Avg. time (hour)	4.42	4.41	3.11
Avg. length (km)	52.644	50.732	No data
Total store num	717		
Planning Time	2–5 minutes	3–10 minutes	1–3 hours

Note: Planning time is reported in minutes for algorithm-based methods and in hours for manual planning, presenting computational time and human labor time, respectively.

After optimizing routes and combinations with ACO, we found that the route count was 117, less than that obtained using only Rule-Based Reasoning, but still greater than the number obtained through manual planning by the logistics company. The average route loading rate showed a slight increase compared to that obtained using only Rule-Based Reasoning, indicating an improvement in cargo volume per route, although the value was still lower than that obtained through manual planning by the logistics company. Regarding route time, the average time slightly decreased after ACO optimization compared to using only Rule-Based Reasoning. Additionally, the average route length decreased by approximately 2 km after applying ACO, showing a positive effect of ACO on route length optimization.

Overall, the ACO showed particular effectiveness in optimizing route lengths, though there is room for improvement in other aspects, such as route combinations. Additionally, route count and loading rate were used as proxies for operational cost and resource utilization, with each additional vehicle incurring an approximate fixed cost of 2,000 TWD, providing practical insight despite the absence of fuel or real-time flexibility data.

4.6. Discussion of experimental results

This study primarily provides a structured, computationally efficient decision-support framework that translates domain rules into executable planning logic and generates actionable reference routes for real-world logistics operations.

Manual planning by experienced logistics personnel yielded better performance in route count and average loading rate (Table 3 and Table 8), highlighting the key role of human expertise and experiential knowledge in generating efficient route combinations. Experienced planners use tacit knowledge to apply flexible, context-dependent packing strategies and pragmatic operational adjustments that are difficult to formalize in algorithms. In practice, manual planning sometimes achieves load utilization beyond 100% of capacity, whereas the proposed method applies strict capacity constraints and standardized loading rules. Consequently, these implicit practices were not fully captured by the current rule-based and optimization framework, partly explaining the observed performance gap. This gap can be further explained by the following structural and modeling-related factors:

1. Complexity and limitations of rule settings:
Rule-Based Reasoning depends on predefined rule settings, and the complexity and applicability of these rules directly influence the results. The logistics company's business

processes and requirements are complex and variable. Even with interview data and constraints provided by the logistics company, it may not be possible to comprehensively cover all possibilities or exceptional cases, which may result in suboptimal routes.

2. Lack of human experience and flexibility:

Although manual planning has limitations, route planners can adjust or plan routes based on their experience and real-time conditions. This flexibility and ability to adapt in real-time are difficult to replicate in Rule-Based Reasoning. Route planners can respond swiftly to emergencies or specific needs, whereas algorithms may require more data or time to adapt accordingly.

3. Inability to incorporate logistics officers' preferences as rules:

Logistics officers often develop unique working methods and route-selection criteria based on their experiences and preferences over time. For example, they may adjust delivery routes according to traffic conditions, road characteristics in certain areas, specific customer needs, and preferences. These personalized preferences and experiences are dynamic and context-specific, making them challenging to formalize and quantify as algorithmic rules.

4. Heterogeneity of performance data sources:

Some differences observed in Table 8 are partly due to manual planning being based on real delivery data, which reflects drivers' familiarity with routes, their ability to adapt to traffic, and other contextual factors that the rule-based models cannot capture. In contrast, the rule-based and ACO methods were evaluated using travel times estimated by the Google Maps API, ensuring a consistent and controlled environment that does not capture these real-world advantages.

Consequently, performance differences between Rule-Based Reasoning and ACO reflect improvements in route structure and sequencing. The fact that the ACO approach demonstrates better performance than rule-based planning under the same evaluation conditions indicates that the optimized routes have the potential to provide valuable references for human planners, thereby supporting more efficient real-world planning while remaining compliant with business rules and operational constraints.

5. Conclusion and future work

5.1. Conclusion

In this study, we explored the optimal route selection problem of logistics companies, utilizing the ACO algorithm for improved route planning. Focusing on the CVRP, we propose a method combining Rule-Based Reasoning and ACO for route planning.

Through collaboration with logistics companies and real-world case applications, the proposed approach was validated in this study by generating feasible reference routes, improving route-structure consistency, and substantially reducing planning time under complex operational constraints. The outcomes pertaining to daily logistics planning indicated that although manual planning continues to achieve superior performance in terms of route count and average loading rate, the proposed approach provides stable, explainable baseline solutions that can effectively support human decision-making. Future research directions include optimizing algorithm performance, expanding to additional application scenarios, and exploring other advanced route planning technologies.

To summarize, this study demonstrates that combining structured Rule-Based Reasoning with metaheuristic optimization offers a practical approach for integrating algorithmic support into real-world logistics operations, particularly in settings where feasibility, transparency, and planning efficiency are critical.

5.2. Future work

In future research, we will focus on exploring directions to enhance the practicality and effectiveness of solutions to vehicle routing problems and support innovation and sustainable development in the logistics industry. One such promising direction is improving ACO, where advanced strategies such as hybrid metaheuristic approaches and dynamic parameter adaptation mechanisms can be investigated to develop more robust and adaptive route planning. Another potential direction is the application of deep learning to analyze historical logistics data to generate or optimize routes with higher precision and adaptability. By exploring these directions, researchers can further improve vehicle routing performance and contribute to the advancement of intelligent, efficient, and cost-effective logistics systems.

Author contributions

Jong-Yih Kuo and Hui-Chi Lin design the methodology; Jong-Yih Kuo and Hui-Chi Lin realize the system; Jong-Yih Kuo and Ti-Feng Hsieh make the validation; Jong-Yih Kuo and Hui-Chi Lin write the original draft; Ti-Feng Hsieh review and edit the manuscript.

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Where in the article is the information located: Throughout the manuscript, primarily for linguistic polishing and formatting consistency.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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