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# Multi-Objective Genetic Algorithm-Based Optimization for Drop-and-Pull Transport Vehicle Scheduling

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***Abstract:*** *With the widespread adoption of container drop-and-hook transportation in port hinterland logistics, enhancing customer satisfaction while maintaining transport efficiency has become a critical issue. This paper addresses the tractor-trailer scheduling problem under a multi-enterprise alliance framework, and develops a multi-objective scheduling optimization model aiming to maximize both the total alliance profit and customer satisfaction. The model comprehensively considers practical factors such as vehicle operating costs, fixed costs, time window penalty costs, trailer storage fees, and carbon emission costs. To solve the model, an improved multi-objective genetic algorithm is proposed, integrated with simulated annealing and variable neighborhood perturbation mechanisms to enhance the search capability. Numerical experiments are conducted to verify the effectiveness of the algorithm and to compare the performance of two different scheduling strategies. Results demonstrate that the proposed method can effectively balance service quality and economic benefits, providing both theoretical support and practical guidance for alliance-based transport scheduling.*
***Keywords:*** *Drop-and-hook transportation; customer satisfaction; vehicle scheduling; multi-objective genetic algorithm*

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## I. INTRODUCTION

In the increasingly frequent container transportation activities between ports and inland hinterlands, efficient scheduling and organization have become key to ensuring the smooth operation of the logistics system. Traditional transport methods often face challenges such as low loading and unloading efficiency, slow scheduling response, and poor resource utilization when confronted with intensive tasks, complex routes, and strict time requirements. As a transport organization mode that separates trailers from tractors, drop-and-hook transportation offers advantages such as rapid loading, flexible operations, and low empty driving rates. It is particularly suitable for large-scale container dispatch scenarios between ports and inland yards. This mode demonstrates significant potential in improving overall loading efficiency, alleviating port congestion, and optimizing resource allocation, making it a vital development direction for enhancing container transport efficiency. A scientifically designed vehicle scheduling scheme can not only significantly reduce tractor idle time and waiting time, but also effectively lower logistics costs and improve overall transport efficiency.

In recent years, scholars at home and abroad have conducted extensive research on the optimization of tractor scheduling, primarily from three perspectives: optimization objectives, constraint considerations, and algorithm design. Regarding optimization objectives, researchers have focused on balancing transportation efficiency, costs, profitability, risks, and customer satisfaction. Wang et al.[1] constructed a tri-objective optimization model, systematically demonstrating how to achieve alliance stability and equitable profit distribution. Wang et al.[2] and Zhang et al.[3] developed dual-objective models based on customer satisfaction and transportation costs, respectively, employing genetic algorithms to balance customer demands with scheduling efficiency. Liang et al.[4] further proposed an improved ε-constraint method tailored to perishable goods distribution, validating the concurrent management of cost and satisfaction. Wu et al.[5] extended research into risk management by developing a replenishment model for multi-compartment tractors and trailers, balancing delivery costs and societal risks. In terms of constraints, studies have progressively moved toward greater complexity and specificity. Wang et al.[6] expanded their perspective to human factors engineering by incorporating driver work-rest constraints to enhance scheduling flexibility. Bjelić et al.[7] focused on multi-size trailer constraints, improving container loading efficiency through intelligent trailer-size matching. Regarding algorithm design, intelligent algorithms have increasingly become mainstream. Feng et al.[8] developed a two-stage truck-freight matching model, applying a genetic algorithm to achieve efficient resource matching. Campuzano et al.[9] proposed metaheuristic algorithms suitable for large-scale instances to handle tractor multi-stop transportation routing problems. Wen et al.[10] developed an adaptive large neighborhood search (ALNS) algorithm to effectively manage carbon emissions in multi-stop green tractor routing. Wang et al.[11] further integrated clustering analysis with adaptive genetic algorithms to tackle multi-stop pickup-and-delivery problems under dynamic demand, enhancing operational efficiency. Huber et al.[12] meticulously analyzed the impact of neighborhood operator design on solution performance for the Swap-Body problem. Du et al.[13] improved the simulated annealing algorithm by incorporating traffic congestion data, achieving reduced loss costs and enhanced customer satisfaction in cold-chain logistics.

As an effective means to improve logistics efficiency and reduce operational costs, container drop-and-hook transportation has attracted widespread attention in recent years. However, under a multi-enterprise alliance model, how to reasonably schedule tractors to achieve the coordinated optimization of overall alliance profit and customer satisfaction remains a complex and pressing challenge. Existing studies mainly focus on single-objective optimization, often overlooking the balance between customer satisfaction and economic returns, making it difficult to meet the increasingly diverse demands of real-world transportation. To address this issue, this paper develops an optimization model for tractor scheduling that aims to maximize both alliance-wide profit and customer satisfaction. Furthermore, an efficient multi-objective optimization algorithm is designed to provide decision-making support for the operational management of drop-and-hook transport alliances.

## II. PROBLEM DESCRIPTION

### 2.1 General description

In the container transportation network connecting port yards and inland hinterlands, there are multiple transport enterprises and customer locations. These enterprises form an alliance to collaboratively manage drop-and-hook transport vehicle scheduling. The objective is to complete all transportation tasks within the specified time by efficiently dispatching tractors and trailers, while minimizing transportation costs and maximizing overall profit and customer satisfaction. The transport demands are categorized into two types: loaded container transport and empty container transport. Within the constructed alliance transport network, multiple depots and transportation tasks exist, and any task can be handled by any drop-and-hook transport vehicle within the alliance. After completing a task, a vehicle may return to any depot within the alliance.

To facilitate the research, the following assumptions are made:

(1) All tractors and trailers have the same specifications, and trailers can be attached interchangeably among vehicles. Each tractor can only tow one trailer at a time.

(2) Information about transportation tasks and vehicle routes is predetermined. Tractors maintain constant speed during transportation, and factors such as traffic congestion and vehicle breakdowns are not considered.

(3) The time for attaching/detaching trailers and loading or unloading containers is negligible, and all transportation task details are known in advance.

(4) Tractors and trailers within the alliance are shared resources. Vehicles from different yards can be deployed across enterprises without corporate restrictions.

(5) The alliance platform assigns transportation tasks based on the shortest-path principle, allocating tasks to the nearest available tractor. Upon task completion, tractors return to the nearest yard within the alliance.

(6) Each enterprise within the alliance must earn at least as much revenue as it would operating independently, ensuring fairness in revenue distribution.

(7) Trailer storage fees at customer points are known in advance. Fees must be paid for trailers stored at customer locations, and the number of stored trailers cannot exceed the requirements at each customer point.

(8) The number of tractors available at each yard is limited.

### 2.2 Definition of Parameters

To facilitate modeling and analysis, the definitions of all sets, parameters, and decision variables are listed in Table 1.

**Table 1 Parameter Description**

| Parameter | Definition |
|---|---|
| $E$ | The empty container depot |
| $U$ | The loaded container depot |
| $S$ | The sets of vehicle yards |
| $N$ | The customer points |
| $R$ | The transportation tasks |
| $O$ | The tractor transportation statuses |
| $M_s$ | The set of tractors at yard $s$ |
| $Q_s$ | The total number of tractors at yard $s$ |
| $d_{ij}^{s}$ | The distance from node $i$ to node $j$ for tractors at yard $s$ |

| | |
|---|---|
| $T_{ij}^{s}$ | The travel time from node *i* to node *j* for tractors at yard *s* |
| $T_k$ | The maximum working duration of tractor *k* |
| $T_r^k$ | The start time of the drop-and-pull operation for task *r* |
| $T_j^t$ | The trailer storage duration at customer point *j* |
| $t_r$ | The start time for transportation task *r* |
| $[a_i, b_i]$ | The service time window for transportation task *r* |
| $e_i$ | The earliest and latest acceptable service times at customer point *i* |
| $l_i$ | The earliest and latest acceptable service times at customer point *i* |
| $t_{ij}$ | The travel time between customer points *i* and *j* |
| $K_j$ | The maximum empty trailer storage capacity at customer point *j* |
| $Q_o$ | The load capacity under transportation status *o* |
| $c_o$ | The fuel consumption per unit distance under transportation status *o* |
| $P$ | The fuel price |
| $H_j$ | The trailer storage cost per unit time at customer point *j* |
| $F_k$ | The daily fixed cost for tractor *k* at yard *s* |
| $y_j$ | The number of empty trailers stored at customer point *j* |
| $r_o$ | The unit revenue obtained by a tractor performing a transportation task under status *o* |
| $R$ | The total alliance revenue |
| $R_i$ | The revenue of enterprise *i* |
| $R_{task}$ | The revenue of a single transportation task |
| $\alpha$ | The carbon emission factor, |
| $\lambda$ | The carbon tax rate |
| $x_{ij}^{k,s}$ | Whether tractor *k* from yard *s* travels from node *i* to node *j* |
| $w_r$ | Whether transportation task *r* is delayed |
| $v_j$ | Whether trailer storage at customer point *j* is permitted |
| $x_{ijo}$ | Whether the tractor operates under transportation status *o* |

## III. MODEL FORMULATION

In the container drop-and-hook transportation network spanning port yards and nearby inland hinterlands, there exist supply and demand relationships for goods between customer points, as well as empty container demands between empty container yards and customer locations. When a tractor departs from a depot and the destination requires a trailer that is not currently available at the originating depot, the tractor must first travel to a customer site or another depot where trailers are stored for dispatching. If the transportation task requires an empty container, the tractor must first go to the empty container yard to retrieve one, deliver it to the customer point for loading, and then proceed with subsequent transport tasks.Within the alliance, revenue sources include: income generated when a tractor tows a loaded container with a trailer to complete a delivery task; income from returning empty containers to the empty container yard; and income from dispatching empty containers and trailers. The associated costs include: the fixed cost of tractors, travel costs under different driving states, penalty costs for exceeding customer service time windows, trailer storage fees at customer points, and carbon emission costs incurred during travel.

In actual transport operations, if a vehicle arrives too early, it must wait at the task location; if it arrives too late, it may delay the transport of other goods, resulting in losses. Therefore, this paper uses customer satisfaction to characterize the transportation company's requirements regarding vehicle arrival times. The customer satisfaction for vehicle arrival time is calculated as follows:

$$\mu_{ij}(t_{ij}) = \begin{cases} 0 & , t_{ij} < e_i \\ \dfrac{t_{ij} - e_i}{a_i - e_i} & , \mathrm{e}_i \le t_{ij} < a_i \\ 1 & , a_i \le t_{ij} < b_i \\ \dfrac{l_i - t_{ij}}{l_i - b_i} & , b_i \le t_{ij} < l_i \\ 0 & , t_{ij} \ge l_i \end{cases} \tag{1}$$

The average customer satisfaction is represented by the mean satisfaction across all customer points:

$$\mu(t) = \frac{\sum_{(i,j)\in N} \mu_{ij}(t_{ij})}{n} \tag{2}$$

Consequently, the mathematical model for the tractor scheduling optimization problem in container drop-and-pull transportation is formulated with the objective of maximizing alliance profitability and customer satisfaction, expressed as follows:

Objective Functions:

$$\max Z = \sum_{s\in S}\sum_{o\in O}\sum_{(i,j)\in A}(r_o \cdot d_{ij}^s \cdot Q_o \cdot x_{ijo}) - [P\sum_{s\in S}\sum_{o\in O}\sum_{(i,j)\in A}(c_o \cdot x_{ijo} \cdot Q_o \cdot d_{ij}^s) + C_5 \cdot \{\max[(e_i - T_r^k),0] + \max[(T_r^k - l_i),0]\} + \sum_{j\in N} H_j \cdot T_j^t \cdot y_j \cdot v_j + \lambda \cdot \alpha \cdot (\sum_{s\in S}\sum_{o\in O}\sum_{(i,j)\in A} P \cdot (c_o \cdot x_{ijo} \cdot Q_o \cdot d_{ij}^s)) + \sum_{s\in S}\sum_{k\in M_s} F_k] \tag{3}$$

Constraints:

$$\sum_{j\in N}\sum_{k\in M_s} x_{ij}^{k,s} \le Q_s, \quad \forall s \in S \tag{4}$$

$$\sum_{s\in S}\sum_{k\in M_s}\sum_{i\in N} x_{ij}^{k,s} = 1, \quad \forall j \in N \tag{6}$$

$$\sum_{(i,j)\in A} T_{ij}^s \cdot x_{ij}^{k,s} \le T_k, \quad \forall k \in M_s, s \in S \tag{7}$$

$$t_{j+1}^{k,s} \ge t_j^{k,s} + T_{ij}^s x_{ij}^{k,s}, \quad \forall j \in N, k \in M_s, s \in S \tag{8}$$

$$\sum_{k\in K} x_{ijk} = \sum_{k\in K} x_{jik}, \quad \forall i, j \in N \tag{9}$$

$$t_{ij} \ge e_i, \ \forall i, j \in N \tag{10}$$

$$\sum_{i\in I} R_i = R \tag{11}$$

$$R_i \ge R_{\text{single}}, \quad \forall i \in I \tag{12}$$

$$x_{ijk} + x_{ijl} \le 1, \ \ \forall i, j \in N, k \in K \tag{13}$$

$$y_j \le K_j, \quad \forall j \in N \tag{14}$$

Where constraint (4) ensures maximization of the total alliance revenue; (5) maximizes average customer satisfaction; constraint (6) limits the number of tractors departing from all yards to the total number available within the alliance; constraint (8) ensures each transportation task is completed by exactly one tractor, preventing duplication; constraint (7) restricts the daily working hours of each tractor; constraint (8) ensures sequential task scheduling for tractors; constraint (9) mandates tractors to return to the nearest yard after task completion according to the shortest path principle; constraint (10) specifies that tasks cannot start earlier than their earliest acceptable time; constraint (11) states that the sum of revenues of individual enterprises equals the total alliance revenue; constraint (12) guarantees that each participating enterprise obtains revenue at least equal to that of independent operation; constraint (13) excludes transportation routes directly between yards; and constraint (14) ensures that the number of trailers stored at each customer point does not exceed its capacity.

## IV. ALGORITHM DESIGN

Due to the high-dimensional solution space, uncertain time window constraints, and complex vehicle routing involved in the drop-and-hook transportation scheduling problem under a multi-depot alliance, traditional exact algorithms often suffer from limitations in computational efficiency and convergence speed. Therefore, heuristic algorithms are required for solving such problems. A multi-objective genetic algorithm is selected as the solution tool for its strong global search capability, making it well-suited for handling complex optimization problems. To further enhance the search efficiency and solution quality, simulated annealing and variable neighborhood search mechanisms are integrated into the algorithm. The algorithm design process is as follows:

(1) Chromosome Encoding

To effectively represent the task scheduling routes of drop-and-hook transport vehicles under a multi-depot alliance, this study adopts a real-number encoding method based on a natural number sequence and designs a task-driven chromosome structure. This encoding approach accounts for route segmentation, task uniqueness, and scheduling feasibility constraints. It is compatible with crossover and mutation operations in the genetic algorithm and facilitates solution reconstruction and local optimization during the simulated annealing and neighborhood search phases. In the encoding scheme, the digit 0 represents the empty container yard, 1 denotes the loaded container yard, 2 to 6 represent the five depots, and digits from 7 onward correspond to customer points. Each chromosome encodes a complete scheduling solution as a one-dimensional array $G = [s_1, n_1, n_2, ..., s_2, ..., n_k, s_k]$, where customer points are denoted by elements $n_i$, and depot identifiers, denoted as $s_j \in H$, act as both the starting and ending markers of vehicle routes, enabling the division of task subsequences among different vehicles.

Decoding Rules:

Step 1: Initialize VPaths. Create an empty list VPaths to store the decoded paths. Each path represents the task execution sequence of a single tractor.

Step 2: Initialize an index variable i to begin traversing the chromosome sequence from the start.

Step 3: while i < len(G). Begin iterating through the chromosome sequence G. As long as the index i has not reached the end, continue processing. Initialize a temporary list path to record the current tractor's task points.

Step 4: while G[i] not in H. This inner loop continues to read customer points until a depot identifier is encountered.

Step 5: path.append(G[i]). Add the current task identifier to the path.

Step 6: i += 1. Move the index forward to process the next gene.

Step 7: VPaths.append(path). Add the complete tractor path to the final result list VPaths.

Step 8: i += 1. Move the index forward again to prepare for reading the next path segment.

This process is repeated until the desired population size is reached, thereby generating the initial population.

(2) Fitness Function

Due to the differences in scale and units between alliance profit and customer satisfaction, normalization is required to unify their measurement. This study applies min-max normalization and transforms both objectives into a "the smaller, the better" format.

Alliance profit is normalized and converted to a negative value:

$$Z' = \frac{Z_{\max} - Z}{Z_{\max} - Z_{\min}} \tag{15}$$

Customer satisfaction is also normalized and converted to a negative value:

$$f' = \frac{f_{\max} - f}{f_{\max} - f_{\min}} \tag{16}$$

To ensure solution feasibility, the model incorporates the following penalty terms: the time window violation penalty is denoted as $P_i^{time}$, the tractor overtime penalty is denoted as $P_i^{work}$, and the enterprise fairness constraint penalty is denoted as $P_i^{fair}$. These penalties are integrated into a combined penalty term, formulated as:

$$Pi = \lambda_1 \cdot P_i^{time} + \lambda_2 \cdot P_i^{work} + \lambda_3 \cdot P_i^{fair} \tag{17}$$

where $\lambda_k$ is weight coefficients that adjust the influence of each type of constraint.

The final fitness function is defined as:

$$F_i = \alpha \cdot Z' + (1-\alpha) \cdot f' + \lambda \cdot P_i \tag{18}$$

where $F_i$ is the fitness value of individual $i$, $\alpha \in [0,1]$ is the preference coefficient balancing alliance profit and customer satisfaction, and $\lambda$ is the penalty adjustment coefficient. A smaller $F_i$ indicates a better solution. This fitness function is used both for non-dominated sorting and selection in the genetic algorithm and for acceptance criteria in the simulated annealing process.

(3) Selection Operator

This study adopts the binary tournament selection method. In each selection round, two individuals are randomly chosen from the population. By comparing their non-dominated ranks and crowding distances, the better individual is selected. This process is repeated until the number of selected individuals reaches the predefined size of the offspring population.

(4) Crossover Operator

Considering sequence constraints, time windows, and uniqueness of transportation tasks, the partially mapped crossover operator is used. Two parent chromosomes (A and B) are randomly selected. Two crossover points are identified, and the gene segments within these points are exchanged between the parents, generating offspring A and B. A mapping relationship between the exchanged gene segments is established to resolve conflicts. Duplicated genes outside the crossover segments in offspring chromosomes are replaced based on this mapping, ensuring the resulting offspring contain no duplicates. The variation process is illustrated in Fig. 1.

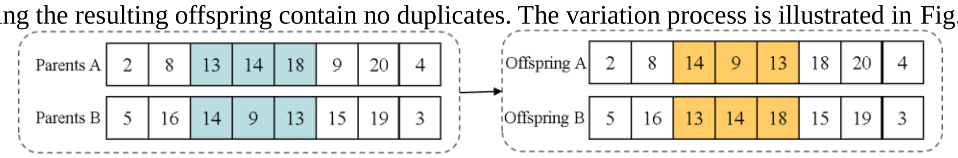


**Fig. 1. Selection of crossover points and exchange of gene segments**

(4) Mutation Operator

To enhance local search capability and population diversity, three variable neighborhood search perturbation strategies are introduced. One or a combination of these perturbations is randomly selected during mutation:

①1-0 Insertion Perturbation

A task is removed from one tractor's route and inserted into another tractor's route to facilitate task reallocation within the alliance. A task $r$ is randomly removed from tractor A's route, and feasible insertion positions in tractor B's route are explored. If insertion improves fitness and satisfies time-window constraints, the perturbation is accepted; otherwise, it is reverted or another task-vehicle pair is explored. The perturbation process is illustrated in Fig. 2.

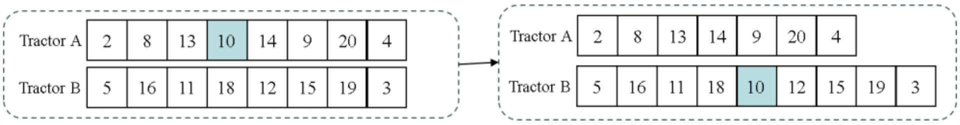


**Fig. 2. Chromosomal gene insertion diagram**

② 1-1 Task Exchange Perturbation

A one-to-one task exchange is performed between two tractors to balance workloads and improve timing. Tasks $T_1$ and $T_2$ are randomly selected from tractor routes A and B, respectively. Tasks are swapped if feasibility constraints are met and fitness improves; otherwise, the exchange is rejected. The perturbation process is illustrated in Fig. 3.

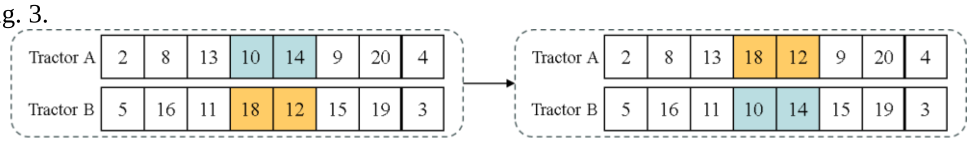


**Fig. 3. Schematic diagram of chromosomal gene exchange**

③ Route Subsequence Reversal Perturbation

A continuous subsequence of tasks within a tractor's route is selected and reversed to optimize time-window matching or profitability. A subsequence in tractor A's route is reversed, and feasibility regarding task order and timing is assessed. The perturbation is accepted if it leads to improved fitness. The perturbation process is illustrated in Fig. 4.

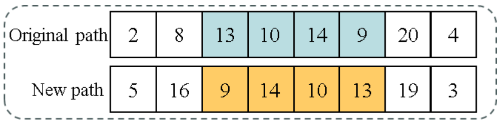


**Fig. 4. Schematic diagram of chromosomal gene inversion.**

(5) Simulated Annealing Operation

A simulated annealing step is incorporated using the Metropolis acceptance criterion. Given the current temperature $T_r$, a new solution $x_j$ is randomly chosen from the neighborhood $N(x_i)$ of the current solution $x_i$. The fitness difference $\Delta f = f(x_i) - f(x_j)$ is computed. If $\Delta f \le 0$, set $x_i = x_j$; if $\Delta f > 0$, compute $P = \exp(-\frac{\Delta f}{T_r})$ and the new solution is accepted immediately; The formula is as follows:

$$P = \begin{cases} \exp(-\frac{\Delta f}{T_r}), & \Delta f \le 0 \\ 1 & , \Delta f > 0 \end{cases} \tag{19}$$

The cooling operation is performed according to the temperature decay rate ω set by the simulated annealing algorithm. The updated temperature $T_{r+1}$ is calculated using the cooling function $g(T_r)$ as $T_{r+1} = g(Tr)$, with $r = r + 1$, where $r$ represents the iteration count and the cooling function is denoted as $g(T_r) = T_r * \omega$.

(6) Termination Criterion

The algorithm terminates when the number of iterations reaches a predefined maximum or when no significant improvement in the non-dominated solution set (Pareto front) is observed for $g$ consecutive generations, indicating convergence.

## V. CASE STUDY ANALYSIS

### 5.1 Data Description

Suppose there are five transportation enterprises, each having its own vehicle yard. These five enterprises form a transportation alliance. Coordinates for vehicle yards, the empty container depot, the loaded container depot, and customer points were randomly generated using numerical experiments. After multiple trials, data with suitable outcomes were selected for validation experiments. The positions are shown in Fig. 5.

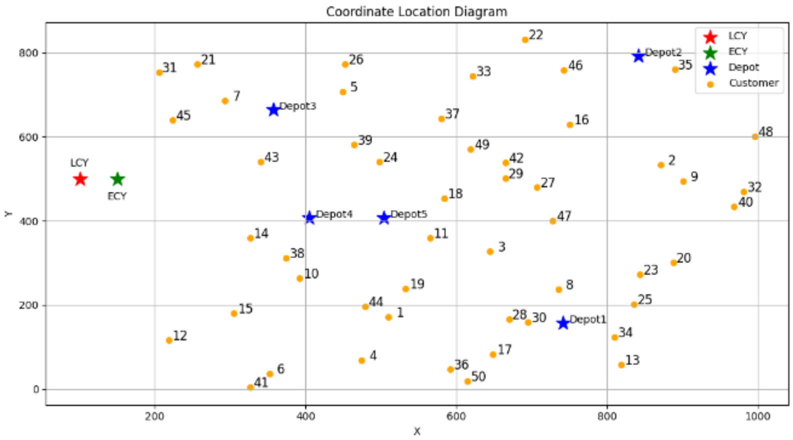


**Fig. 5. Coordinate Location Diagram**

All transportation enterprises use standardized container models for cargo loading, specifically 40-foot containers. A total of 70 transportation tasks are distributed among the five depots, which collaboratively complete all assigned tasks. A subset of the transportation tasks is shown in Table 2, with the full list provided in the appendix.

**Table 2 Transportation Task Information**

| Task No. | Task Type | Task Point | Trailers stored | Destination | Service Time Window |
|---|---|---|---|---|---|
| 1 | 1 | Point 13 | 1 | Point 25 | [17:05,17:25] |
| 2 | 2 | Point 17 | 2 | Empty depot | [10:33,10:53] |
| 3 | 2 | Point 19 | 3 | Point 23 | [14:23,15:13] |
| 4 | 1 | Point 28 | 1 | Loaded depot | [17:49,18:09] |
| 5 | 2 | Point 25 | 2 | Point 30 | [18:10,18:30] |
| … | … | … | … | … | … |
| 67 | 2 | Point 41 | 1 | Point 50 | [11:33,12:03] |
| 68 | 2 | Point 4 | 2 | Empty depot | [18:57,19:47] |
| 69 | 1 | Point 15 | 1 | Point 29 | [14:25,14:45] |
| 70 | 2 | Point 39 | 2 | Empty depot | [11:16,11:56] |

In order to facilitate the study, the settings of each parameter are shown in Table 3.

**Table 3 Numerical description**

| Numerical description | Parameter value |
|---|---|
| The daily working time window of the tractor | [8:00，22:00] |
| The annual fixed cost of a tractor | 170,000 CNY |
| Daily fixed cost | 472 CNY per vehicle per day |
| Price of domestic No. 0 diesel | 7.14 CNY per liter |
| Fuel consumption per 100 km when the tractor runs alone | 20 liters |
| Fuel consumption per 100 km when the tractor tows an empty trailer | 26 liters |
| Fuel consumption per 100 km when the tractor tows an empty container with trailer | 37 liters |
| Fuel consumption per 100 km when the tractor tows a loaded container with trailer | 45 liters |
| Penalty cost for violating the time window constraint | 700 CNY per hour |
| Revenue per unit distance when the tractor tows a loaded container with trailer | 0.5 CNY per ton per kilometer |
| Revenue per unit distance when the tractor tows an empty container with trailer | 5 CNY per kilometer |
| Revenue per unit distance when the tractor calls and tows an empty trailer | 2.8 CNY per kilometer |
| Revenue obtained from dispatching one empty container | 380 CNY per unit |
| Population size | 80 |
| Maximum number of iterations | 500 |
| Crossover probability | 0.9 |
| Mutation probability | 0.1 |
| Initial temperature of simulated annealing | 100 |
| Cooling rate | 0.95 |
| Maximum iterations of the outer loop | 500 |
| Maximum iterations of the inner loop | 200 |

### 5.2 Results and Comparative Analysis

This study employs an improved multi-objective genetic algorithm. To ensure the validity of the experimental results without considering other external factors, the proposed model is executed 10 times. Among these 10 simulation runs, the two optimal scenarios—one with the maximum total alliance revenue and the other with the highest customer satisfaction—are selected for comparative analysis.

(1) The scheduling scheme based on maximizing alliance total revenue is presented in Table 4.

**Table 4 Alliance Revenue-Maximized Scheduling Scheme**

| ID | Routing Path | $CO_2$ Cost | Total Revenue | Total Cost | Actual Profit |
|---|---|---|---|---|---|
| 1 | D-15-U-10-38-1-E-38-D | 104.70 | 3676.24 | 1926.19 | 1750.05 |
| 2 | B-2-9-49-E-28-U-C | 109.06 | 4233.76 | 2148.37 | 2085.39 |
| 3 | D-38-E-10-24-26-31-C | 108.86 | 4226.08 | 2146.68 | 2079.4 |
| 4 | C-29-41-42-44-42-1-F | 90.63 | 4318.16 | 1866.36 | 2451.8 |
| 5 | D-44-E-39-E-22-U-C | 96.21 | 4034.80 | 2250.66 | 1784.14 |
| 6 | B-40-E-30-E-F | 93.47 | 3628.48 | 1908.37 | 1720.11 |
| 7 | A-23-28-21-26-5-E-F | 116.35 | 4516.64 | 2257.49 | 2259.15 |
| 8 | F-4-U-8-36-A | 106.57 | 4136.88 | 2108.56 | 2028.32 |
| 9 | C-18-24-27-32-37-E-F | 106.10 | 4118.96 | 2102.25 | 2016.71 |
| 10 | C-45-U-1-10-4-E-F | 102.98 | 3997.52 | 2054.05 | 1943.47 |
| 11 | D-38-U-27-E-11-E-F | 115.52 | 2931.84 | 1633.14 | 1298.70 |
| 12 | B-16-E-16-22-44-U-C | 106.78 | 4145.20 | 2110.68 | 2034.52 |
| 13 | F-47-50-13-25-A | 106.69 | 4141.84 | 2110.54 | 2031.30 |
| 14 | D-15-29-47-U-13-34-A | 90.79 | 3524.40 | 1868.79 | 1655.61 |
| 15 | A-34-E-25-30-31-E-F | 107.74 | 4582.56 | 2124.64 | 2457.92 |
| 16 | F-39-46-1-U-C | 83.29 | 3233.28 | 1752.86 | 1480.42 |
| 17 | F-E-35-B | 47.46 | 4646.64 | 2308.01 | 2338.63 |
| 18 | A-50-E-48-B | 94.87 | 4207.52 | 2094.99 | 2112.53 |
| 19 | A-17-E-7-E-12-D | 112.90 | 3683.04 | 1930.22 | 1752.82 |
| 20 | A-25-U-E-43-C | 105.81 | 4382.72 | 2206.69 | 2176.03 |
| 21 | B-32-9-43-U-C | 94.51 | 3668.88 | 1924.26 | 1744.62 |
| 22 | F-E-21-41-50-A | 108.46 | 4210.32 | 2138.36 | 2071.96 |
| 23 | D-6-8-40-U-C | 101.34 | 3934.08 | 2029.94 | 1904.14 |
| 24 | B-33-37-36-E-42-F | 103.58 | 4020.88 | 2060.76 | 1960.12 |
| 25 | F-24-U-E-20-F | 116.85 | 4536.08 | 2264.33 | 2271.75 |
| 26 | C-7-U-19-23-A | 119.70 | 3003.28 | 1659.82 | 1343.46 |
| 27 | F-E-11-3-E-F | 77.36 | 3842.48 | 1920.01 | 1922.47 |

Based on the scheduling plan with maximum alliance revenue, the total tractor mileage is 17047.82 kilometers, actual total revenue obtained is 52675.54 yuan, average customer satisfaction reaches 74.53%, and total carbon emission costs are 2728.58 yuan. The alliance used 27 tractors in total: yard 1 dispatched 5 tractors, yard 2 dispatched 5 tractors, yard 3 dispatched 4 tractors, yard 4 dispatched 6 tractors, and yard 5 dispatched 7 tractors. Most tractors did not return to their original yards after completing tasks. It is evident from the tractor paths that yards 3, 4, and 5, located near the empty and loaded container depots, effectively minimized empty travel distances and times.

(2) The customer satisfaction-maximized scheduling scheme is presented in Table 5.

**Table 5 Customer Satisfaction-Optimized Scheduling Scheme.**

| ID | Routing Path | $CO_2$ Cost | Total Revenue | Total Cost | Actual Profit |
|---|---|---|---|---|---|
| 1 | A-23-28-19-23-A | 95.42 | 3525.52 | 2013.29 | 1512.23 |
| 2 | F-29-41-44-U-31-E-C | 119.65 | 4425.60 | 2344.27 | 2081.33 |
| 3 | A-34-E-12-26-31-C | 122.50 | 4531.68 | 2381.70 | 2149.98 |
| 4 | D-39-E-10-24-F | 76.80 | 2833.44 | 1755.37 | 1078.07 |
| 5 | A-2-9-27-32-15-29-F | 115.52 | 4272.40 | 2286.97 | 1985.43 |
| 6 | D-39-46-6-8-13-34-A | 106.92 | 3952.88 | 2171.37 | 1781.51 |
| 7 | F-18-24-1-10-47-U-D | 96.84 | 3578.32 | 2032.50 | 1545.82 |
| 8 | F-10-38-32-9-11-E-C | 98.07 | 3623.92 | 2049.37 | 1574.55 |
| 9 | C-7-U-E-38-42-1-A | 106.27 | 3928.64 | 2162.14 | 1766.5 |
| 10 | D-38-E-20-13-25-A | 105.73 | 3908.4 | 2151.91 | 1756.49 |
| 11 | D-38-U-27-E-F | 78.75 | 2934.32 | 1843.22 | 1091.1 |
| 12 | F-49-E-7-E-25-30-A | 121.79 | 4505.36 | 2370.94 | 2134.42 |
| 13 | F-44-E-25-U-D | 89.08 | 3290.00 | 1922.20 | 1367.80 |
| 14 | A-50-E-11-D | 82.31 | 3038.40 | 1832.38 | 1206.02 |
| 15 | B-22-E-3-E-C | 72.01 | 2784.08 | 1650.79 | 1133.29 |
| 16 | C-45-U-E-35-B | 91.62 | 3384.32 | 1957.19 | 1427.13 |
| 17 | D-E-21-41-50-22-U-D | 122.94 | 4548.00 | 2386.73 | 2161.27 |
| 18 | B-40-E-37-E-C | 76.66 | 3056.80 | 1914.59 | 1142.21 |
| 19 | A-15-U-42-44-E-42-D | 102.67 | 3794.96 | 2110.34 | 1684.62 |
| 20 | B-4-U-4-E-C | 95.68 | 3535.2 | 2015.57 | 1519.63 |
| 21 | C-21-26-8-36-1-U-C | 100.86 | 3727.44 | 2088.14 | 1639.3 |
| 22 | F-47-50-33-E-D | 95.80 | 3539.44 | 2017.83 | 1521.61 |
| 23 | D-E-43-E-48-B | 95.88 | 3542.48 | 2018.59 | 1523.89 |
| 24 | B-16-E-16-22-B | 95.30 | 3520.96 | 2007.66 | 1513.30 |
| 25 | B-33-37-43-U-C | 79.14 | 2920.56 | 1788.49 | 1132.07 |
| 26 | F-1-E-40-U-D | 74.28 | 2739.84 | 1722.55 | 1017.29 |
| 27 | D-12-E-17-E-C | 86.76 | 3203.68 | 1891.99 | 1311.69 |
| 28 | C-5-E-28-U-D | 77.13 | 3074.32 | 1824.02 | 1250.30 |
| 29 | F-24-U-36-E-F | 82.35 | 3226.20 | 1732.41 | 1493.79 |

Under the scenario prioritizing maximum customer satisfaction, total mileage increases to 18149.94 kilometers, total revenue obtained decreases to 44502.64 yuan, average customer satisfaction increases to 88.53%, and carbon emission costs increase slightly to 2764.73 yuan. The alliance used 29 tractors, distributed as follows: yards 1 and 2 dispatched 5 tractors each, yard 3 dispatched 4 tractors, yard 4 dispatched 7 tractors, and yard 5 dispatched 8 tractors.

(3) The comparative analysis of the two optimal dispatching schemes reveals the following characteristics: ① In the 10 experimental runs, when the total alliance revenue is maximized, the level of customer satisfaction is lower than that in the scenario with the highest customer satisfaction. Conversely, when customer satisfaction is maximized, the total revenue of the alliance is not optimal. This demonstrates that alliance revenue and customer satisfaction cannot be optimized simultaneously, which is consistent with the nature of multi-objective genetic algorithms. ② The comparison between the optimal schemes under maximum alliance revenue and highest customer satisfaction indicates that, although the total cost increases slightly when customer satisfaction is considered, the average customer satisfaction improves by 18.7%. This suggests that the proposed model can provide valuable support for enterprise decision-makers, enabling them to make more appropriate choices based on the current state of enterprise management.

## VI. CONCLUSION

Through systematic modeling and solution analysis of the drop-and-hook vehicle scheduling problem under time window constraints, this study arrives at the following main conclusions: First, under the context of multi-enterprise alliance operations, incorporating dual optimization objectives of customer satisfaction and alliance profit helps to balance economic efficiency and service quality, providing a more scientific basis for collaborative scheduling decisions among enterprises. Second, by reasonably accounting for practical factors such as trailer storage, tractor working hours, time window penalties, and carbon emission costs, the model more accurately reflects the complexity and dynamic nature of drop-and-hook transportation scheduling, thereby enhancing its applicability and practical value. Third, the integrated optimization algorithm, which combines a multi-objective genetic algorithm with simulated annealing and variable neighborhood search, significantly improves computational efficiency and solution diversity, demonstrating strong stability and flexibility in large-scale task allocation and vehicle routing problems. Lastly, experimental comparisons between strategies focused on maximizing alliance profit and those focused on maximizing customer satisfaction reveal that the former helps reduce costs and resource input, while the latter enhances service value by improving customer satisfaction. This indicates that the proposed model can support alliance enterprises in flexibly formulating scheduling strategies based on their operational objectives.

Despite the contributions of this study, there remains room for further exploration. Future research may focus on the following areas: (1) incorporating dynamic demand variations, real-time traffic conditions, and unexpected events into the scheduling process; (2) investigating fair profit-sharing mechanisms within alliances in greater depth; and (3) exploring scheduling optimization in more complex network structures under multimodal transportation environments to better align with real-world transportation demands.

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## APPENDIX

**Appendix Table 1 Transportation Task Information**

| Task No. | Task Type | Task Point | Trailers stored | Destination | Service Time Window | Task No. | Task Type | Task Point | Trailers stored | Destination | Service Time Window |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Point 13 | 1 | Point 25 | [17:05,17:25] | 36 | 1 | Point 38 | 2 | Loaded depot | [08:18,08:38] |
| 2 | 2 | Point 17 | 2 | Empty depot | [10:33,10:53] | 37 | 1 | Point 42 | 1 | Point 44 | [16:45,17:15] |
| 3 | 2 | Point 19 | 3 | Point 23 | [14:23,15:13] | 38 | 2 | Point 49 | 0 | Empty depot | [09:08,09:48] |
| 4 | 1 | Point 28 | 1 | Loaded depot | [17:49,18:09] | 39 | 2 | Empty depot | 0 | Point 38 | [13:29,13:59] |
| 5 | 2 | Point 25 | 2 | Point 30 | [18:10,18:30] | 40 | 1 | Point 44 | 0 | Loaded depot | [18:11,18:51] |
| 6 | 2 | Point 34 | 0 | Empty depot | [11:36,12:16] | 41 | 1 | 客户点 10 | 1 | Point 24 | [13:44,14:34] |
| 7 | 1 | Point 23 | 1 | Point 28 | [09:53,10:13] | 42 | 2 | Point 1 | 2 | Empty depot | [11:18,12:18] |
| 8 | 2 | Point 30 | 2 | Empty depot | [11:48,12:48] | 43 | 2 | Empty depot | 0 | Point 42 | [18:27,19:17] |
| 9 | 2 | Point 13 | 0 | Point 34 | [18:32,18:52] | 44 | 1 | Point 24 | 2 | Loaded depot | [09:30,10:00] |
| 10 | 1 | Point 25 | 2 | Loaded depot | [11:58,12:38] | 45 | 1 | Point 42 | 0 | Point 1 | [18:19,18:59] |
| 11 | 1 | Point 2 | 1 | Point 9 | [08:09,08:29] | 46 | 2 | Point 44 | 3 | Empty depot | [09:15,09:45] |
| 12 | 2 | Point 16 | 2 | Empty depot | [13:02,13:22] | 47 | 2 | Empty depot | 0 | Point 11 | [13:24,13:44] |
| 13 | 1 | Point 22 | 3 | Loaded depot | [13:59,14:29] | 48 | 2 | Point 38 | 2 | Empty depot | [10:46,11:06] |
| 14 | 2 | Point 27 | 1 | Point 32 | [12:15,12:45] | 49 | 2 | Point 10 | 1 | Point 38 | [09:52,10:12] |
| 15 | 2 | Point 40 | 1 | Empty depot | [08:23,08:43] | 50 | 1 | Point 1 | 0 | Loaded depot | [19:37,20:07] |
| 16 | 2 | Empty depot | 0 | Point 20 | [12:03,12:53] | 51 | 2 | Point 3 | 1 | Empty depot | [16:27,17:17] |
| 17 | 2 | Point 22 | 1 | Empty depot | [08:02,09:02] | 52 | 1 | Point 4 | 2 | Loaded depot | [11:28,12:08] |
| 18 | 1 | Point 32 | 2 | Point 9 | [12:58,13:18] | 53 | 1 | Point 6 | 1 | Point 8 | [10:51,11:11] |
| 19 | 1 | Point 40 | 1 | Loaded depot | [18:08,18:38] | 54 | 2 | Point 12 | 0 | Empty depot | [08:58,09:38] |
| 20 | 2 | Point 16 | 1 | Point 22 | [16:53,17:33] | 55 | 2 | Empty depot | 0 | Point 35 | [17:33,18:33] |
| 21 | 2 | Point 27 | 2 | Empty depot | [13:32,14:32] | 56 | 1 | Point 39 | 2 | Point 46 | [08:07,08:47] |
| 22 | 2 | Empty depot | 0 | Point 48 | [19:39,19:59] | 57 | 1 | Point 47 | 0 | Point 50 | [09:58,10:58] |
| 23 | 2 | Point 5 | 1 | Empty depot | [13:20,14:20] | 58 | 2 | Point 36 | 1 | Empty depot | [14:20,15:10] |
| 24 | 2 | Point 7 | 0 | Empty depot | [13:00,13:20] | 59 | 2 | Empty depot | 0 | Point 43 | [17:35,17:55] |
| 25 | 1 | Point 21 | 2 | Point 26 | [11:50,12:10] | 60 | 1 | Point 15 | 1 | Loaded depot | [08:35,09:25] |
| 26 | 2 | Point 31 | 1 | Empty depot | [19:03,19:33] | 61 | 1 | Point 29 | 1 | Point 41 | [14:22,15:12] |
| 27 | 2 | Point 33 | 0 | Point 37 | [13:04,13:24] | 62 | 2 | Point 50 | 0 | Empty depot | [08:21,09:21] |
| 28 | 1 | Point 45 | 2 | Loaded depot | [08:40,09:00] | 63 | 2 | Empty depot | 0 | Point 12 | [16:52,17:12] |
| 29 | 1 | Point 26 | 0 | Point 31 | [18:29,18:49] | 64 | 1 | Point 47 | 2 | Loaded depot | [15:40,16:10] |
| 30 | 2 | Point 37 | 1 | Empty depot | [16:28,17:28] | 65 | 1 | Point 8 | 0 | Point 36 | [17:28,18:18] |
| 31 | 2 | Empty | 0 | Point 21 | [09:21,09:51] | 66 | 1 | Point | 1 | Loaded | [16:51,17:51] |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | depot | | | | | | 43 | | depot | |
| 32 | 1 | Point 7 | 2 | Loaded depot | [09:07,09:57] | 67 | 2 | Point 41 | 1 | Point 50 | [11:33,12:03] |
| 33 | 1 | Point 1 | 1 | Point 10 | [12:15,13:05] | 68 | 2 | Point 4 | 2 | Empty depot | [18:57,19:47] |
| 34 | 2 | Point 11 | 0 | Empty depot | [18:31,19:31] | 69 | 1 | Point 15 | 1 | Point 29 | [14:25,14:45] |
| 35 | 2 | Point 18 | 3 | Point 24 | [09:54,10:14] | 70 | 2 | Point 39 | 2 | Empty depot | [11:16,11:56] |