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Multi-Objective Optimization of Short-Inverted Transport Scheduling Strategy Based on Road–Railway Intermodal Transport

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Abstract: This study focuses on the 'short-inverted transportation' scenario of intermodal transport. It proposes a vehicle unloading reservation mechanism to optimize the point-of-demand scheduling system for the inefficiency of transport due to the complexity and uncertainty of the scheduling strategy. This paper establishes a scheduling strategy optimization model to minimize the cost of short backhaul and obtain the shortest delivery time window and designs a hybrid NSGWO algorithm suitable for multi-objective optimization to solve the problem. The algorithm incorporates the Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm based on the Grey Wolf Optimizer (GWO) algorithm, compensating for a single algorithm's premature convergence. The experiment selects a logistics carrier's actual road–rail intermodal short-inverted data and compares and verifies the above data. The results show that the scheduling scheme obtained by this algorithm can save 41.01% of the transport cost and shorten the total delivery time by 46.94% compared with the original scheme, which can effectively protect the enterprise's economic benefits while achieving timely delivery. At the same time, the optimized scheduling plan resulted in a lower number of transport vehicles, which positively impacted the sustainability of green logistics.

Keywords: road–rail intermodal transport; short-inverted transport; scheduling strategy; multi-objective optimization

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1. Introduction

Currently, China's logistics hub is a new hotspot in the field of logistics and a new trend in the development of the logistics industry [1]. It is also an important place and carrier for gathering regional logistics service elements. The development of the supply chain industry and the surge in demand for product distribution have led to the continuous adjustment and optimization of China's transport structure, and road–rail intermodal transport has become an emerging mode of efficient and green logistics. At the same time, it has the advantages of low cost and the large capacity of railway transport, as well as the mobility and flexibility of road transport. The combination of the two can effectively alleviate the pressure of road transportation and fully use the surplus capacity of railroads [2]. It continues to be in the stage of innovation and development. With the in-depth promotion of the "Road-Railway-Road" transport mode, the proportion of the national railway freight volume has been increasing. Figure 1 shows the cargo turnover of China's railroads and highways in the past five years. It is easy to see that China's railroad and highway transportation market demand shows a rapid growth trend. However, compared with developed countries in Europe, the United States, and other places, it is still in the backward stage. In such a market background and building the trunk transportation channels between hubs, the essence lies in developing and improving the trunk and branch lines for the organic convergence of the problem. Moreover, road–railway intermodal transportation integrates the high timeliness of railroad transportation and the substantial convenience of road transportation, adjusting the transportation proportion of the two.

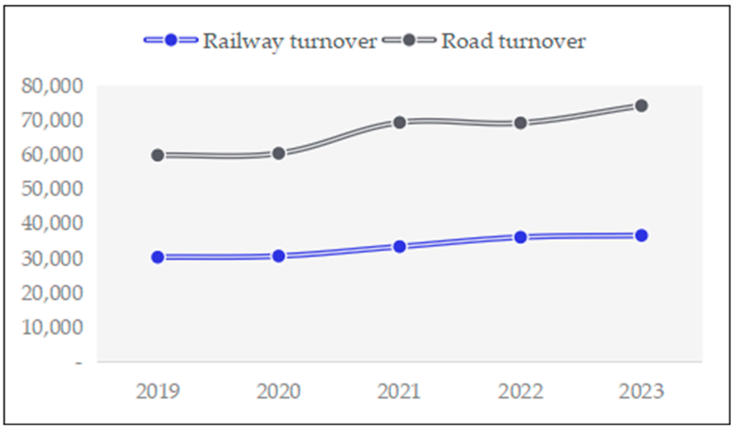

Figure 1. China's railway and road cargo turnover (billion tons kilometers) (2019–2023).

What is more, there are many carbon emission sources in logistics transportation. The balanced development of road–rail intermodal transportation can alleviate the traffic congestion problem of road transportation caused by complicated road conditions to a greater extent. Reducing the logistics industry's dependence on road freight transportation can effectively enhance the greening of logistics in the region. Giving full play to the railroad's green transportation advantages will drive the freight market's sustainable operation and break the resistance to the circulation of goods that restricts economic development. However, there still needs to be a significant gap in the infrastructure construction of road–railway intermodal transportation waiting to be improved. In some countries, including China, intermodal terminals and warehousing centers are geographically dispersed and difficult to integrate for unified organization and management [3]. Today, the transport industry is yet to address the pain point of the smooth and collaborative management of rail and road transport operations while meeting customers' growing service level needs.

Road–railway intermodal transportation usually covers the three processes of "collection", "evacuation", and "transportation" [4]. Although road transport is more expensive than rail transport, there are various constraints on constructing railway lines in the more remote areas of some countries, such as western China, and road transport has a clear advantage in the transshipment process. As a result, a business process that applies to transshipment—short-inverted transport—has emerged in the operational flow of road–rail transport. Short-inverted transport mainly involves the circulation of goods in the two sections of the journey from the place of origin to the train departure station and from the train departure station to the demand point, and it can realize the function of transporting goods in a short distance and at a high frequency. Typically, vehicles travel to and from the supply and demand end for replenishment, reversal, and recycling. At the same time, road transport's efficiency and effectiveness directly impact the system's economic functioning. Although the overall development trend of road freight transport has been good in recent years, from a macro point of view, it still stays in the low-efficiency stage. China's rail container freight volume is also far below the level of about 40% of freight volume in developed countries [5].

Road–railway intermodal transport is containerized chiefly, with a diverse range of cargo types, including front- and rear-end transport operations at this stage. In the case of coal, for example, the front-end transportation operations are mainly based on coal mines as suppliers. They load the output resources into containers secured to dump trucks by cranes and transport them to train terminals. The dispatching station uses the railroad as the transportation medium, assigns train shipments to each station, and provides regular cargo for the carriers. In turn, there are limits to the supplier's production capacity and available stock of each type of goods, alongside changes in customer demand. During transportation, objective factors such as the vehicle's condition and the road can also limit the total transportation time of the car. This back-end transportation operation is in the start-up phase when the carrier receives the shipment. The airline calculates the daily coal transportation volume based on the customer's pre-submitted cargo demand and station receipt volume. The exact shipment is delivered within the same time window requirement and transported by the same type of vehicle.

The scheduling efficiency of short-inverted transportation is affected by carriers' existing capacity resources and transportation capability [6]. Whether it is the front-end vehicle loading or the back-end vehicle unloading, it is necessary to operate according to the sequence of orders. At the same time, this consumes a certain amount of loading and unloading time. This time mainly includes the mechanical and manual operation time and waiting time for the operation to start. Regarding its practical application value, each short-pour transportation order usually has a fixed service time and quantity constraint. Suppose the front- and back-end operation time should be shorter. In that case, it will directly affect the total service time window of the carrier for the delivery of the order, reduce customer satisfaction, and, thus, affect the service quality and operating costs of the whole enterprise.

In particular, when short-distance vehicles are on the road, there is a specific route plan between the supply and demand points. The vehicle dispatch plan relies on the decision-maker's preferences for transportation costs, time, service levels, and subjective experience [7]. The customer has a daily capacity demand, which makes it challenging to coordinate the extension of the delivery window of the order, which puts forward higher requirements for the timeliness of the transport fulfillment. However, as analyzed in many conflicting objectives studies, it is often difficult to continue to achieve the saturation of customer satisfaction while prioritizing costs. Cost reduction at the expense of customer satisfaction does not bring the desired gain to the business. Therefore, decision-makers need to plan for scheduling drivers' transport options. Rational decision making on scheduling strategies reduces high costs and responds positively to the 'dual-carbon' goal proposed by the 75th session of the United Nations General Assembly in 2020 [8] and closes the loophole of energy overconsumption.

(1) In this paper, based on considering the delivery process of "rail to the road," we propose the problem of a scheduling strategy for the short-inverted transport of goods based on the existing point-of-demand scheduling system and adding the reservation mechanism for unloading vehicles. Foreseeing the quota of allowed operations in each time slot and sending requests in advance can effectively alleviate the common vehicle queuing and congestion problems at the demand point.
(2) We aimed to establish a scheduling strategy optimization model with total transport cost and delivery time window minimization as the objective function, improve the GWO algorithm, mix the NSGA-II algorithm based on the GWO algorithm, and carry out numerical experiments on multiple sets of data to validate the beneficial effects of the model to enhance the efficiency of the integrated logistics service of enterprises.

This paper is further organized as follows: Section 2 presents the literature review. Section 3 describes the short-inverted transport problem and explains the variables and parameters of the model. Section 4 designs the NSGWO algorithm for the model solution, and Section 5 analyzes an experimental case of the operation of an actual carrier enterprise. Section 6 discusses the vehicle scheduling plan and the conflicting relationship between the objectives obtained from the experiment. Finally, Section 7 summarizes the conclusions of this study.

2. Literature Review

Logistics scheduling focuses on the coordinated planning of relevant vehicles and human resources based on the requirements of the type of cargo, weights, specifications, and delivery speeds to achieve both efficiency and effectiveness. Most existing studies use traditional scheduling theory and mathematical methods to solve logistics scheduling problems. Standard objective functions of scheduling models include cost [9–13], time window [14–19], and energy consumption [20,21]. More specifically, establishing the objective function includes both single-objective and multi-objective aspects.

First, recent academic research and industry surveys have shown that cost reduction and efficiency improvement are essential research directions in logistics scheduling management [22–25]. Many scholars have conducted cost–benefit analyses of logistics transportation and scheduling in different scenarios. Wu et al. [26] considered the scheduling problem in delayed delivery, customer heterogeneity was taken as an influencing factor, and a vehicle rescheduling model was constructed with penalty cost as an objective. Chen et al. [27] introduced the strategy of the simultaneous loading and partial charging of electric vehicles. Their research results, combined with market electricity prices, reduced logistics and electricity costs.

In addition, the operation of vehicles is complicated and cumbersome, and many factors affect management costs. Rahman et al. [28] analyzed the interactions between distance, order quantity, delivery frequency, and transportation costs by combining logistics costs with full-truck (TL) and less-than-truckload (LTL) transportation modes. Ishii et al. [29] used a local case study in Japan to investigate the impact of collection, transportation, and storage factors on the logistics costs of renewable energy. The results show that the selling price is heavily dependent on production capacity. At the same time, scholars have also become interested in the logistics scheduling of drones under unique geographical constraints. Hosang et al. [30] considered the uncertainty of multimodal transport based on UAVs. They found that the operating cost decreased with the increased operating time of UAV delivery in the cost analysis. Arne [31] compared the flight costs of UAV transportation in urban and rural models.

Some studies have shifted their focus to time constraints, such as order immediacy and production planning timing. Bac et al. [32] integrated the characteristics of long charging times for electric vehicles, considering the charging scheduling problem of electric cars in multiple charging stations and heterogeneous fleet structures. Li et al. [33] proposed a logistics scheduling algorithm that minimizes the total downtime of the bottleneck process machine, improving the production capacity of the photovoltaic cell production workshop. Yu et al. [34] designed a scheduling strategy from a game perspective to minimize the completion time of steel coil storage and retrieval. Dai et al. [35] developed a personalized crowdsourcing delivery time prediction model to solve the O2O real-time logistics scheduling decision-making problem. Bac et al. integrated the characteristics of long charging times for electric vehicles, considering the charging scheduling of electric vehicles with multiple charging stations and heterogeneous fleet structures. Yu et al. [36] used the maximum completion time as the optimization goal to solve the distributed flexible job shop scheduling problem of the transportation time between machines.

As research results have continued to accumulate, scholars have no longer been satisfied with studying single-objective scheduling problems. They have considered more and more constraints and combined single-objective functions to study conflicting multi-objective scheduling models. Alireza et al. [37] modeled slot allocation and selective pick-up/delivery integration with time windows, significantly reducing the cost of pick-up/delivery vehicle usage. Zhang et al. [38] designed a function that considers time-varying road conditions and vehicle energy consumption while considering the time window requirement, which is used to dispatch fuel and electric vehicles. Zhang et al. [39] comprehensively considered the dual objectives of scheduling cost and vehicle loading rate in urban commercial logistics to build a heterogeneous vehicle logistics scheduling model. Wei et al. [40] shifted their research focus to inland container transportation systems and established a mixed-integer linear programming (MILP) model that can effectively reduce the cost of selecting transfer stations and container transportation costs. Xu et al. [41] established an order allocation decision model that includes three aspects: transportation mode selection, vehicle loading, and supplier selection, in the context of the intelligent scheduling of vehicle logistics. Liu et al. [42] used a joint-scheduling algorithm that can reduce the average response time and maximum completion time while ensuring the success rate of the scheduling.

Other scholars are working to reduce carbon emissions and study sustainable development trends in transportation and scheduling in green logistics. Lu et al. [43] comprehensively summarized the current status of research on energy transportation scheduling for green vehicles in the harbor area. Zhang et al. [44] designed a multi-autonomous guided vehicle with green indicators in energy-saving flexible workshop scheduling.

In addition, the emergence of big data, cloud computing, and artificial intelligence has gradually shifted the research focus of scheduling strategy optimization from traditional mathematical algorithms to high-quality optimization methods based on intelligent algorithms [45]. The research methods for solving scheduling models are generally swarm intelligence algorithms. For example, Guerrero Carlos et al. [46] proposed a resource elasticity management method based on a non-dominated sorting genetic algorithm (NSGA-II) in the cloud architecture of container allocation. Choi et al. [47] used an improved ant colony algorithm to optimize the operational routes of RMC transport vehicles, consider carbon emissions, and plan a vehicle delivery scheduling scheme. Hu et al. [48] investigated the joint vehicle scheduling and stockpile allocation problem in an automated container terminal, established a hybrid linear programming model, and developed a three-stage decomposition method based on greedy search to solve the problem. Hu et al. [49] analyzed the extensive container cluster loading and unloading operation scenarios, proposed a multi-objective mathematical model for multi-vessel container loading and unloading planning, and verified the model validity using a heuristic adaptive genetic algorithm. The differential evolution (DE) algorithm developed by Chen et al. [50] simplifies the empty container allocation model in the logistics supply chain of containers. Wang et al. [51] optimized the logistics scheduling and orderly charging collaborative management of existing automated guided vehicles (AGVs) in automated terminals using an improved particle swarm algorithm. Zhao et al. [52] incorporated the vehicle model into the main influencing factors to establish a cooperative scheduling optimization model for transport paths and solve it with an improved particle swarm algorithm. Zhou et al. [53], meanwhile, considered the particular cyclic pickup pattern in the supply chain center and constructed an adaptive artificial bee colony algorithm to solve the problem so that the total energy consumption and distribution time penalty of EVs is minimized.

In addition to the generally applicable intelligent algorithms, some scholars are also working on mining new algorithmic models. Islam et al. [54] used a meta-heuristic chemical reaction optimization algorithm (CRO) to solve the transportation scheduling problem in the third-party logistics supply chain. Zhuang et al. [55] developed a two-stage memetic algorithm (TSMA) to analyze the integration of production transportation and equipment operation in third-party logistics.

Compared with the existing literature, the innovations of our research are summarized as follows: This study considers a particular short-inverted transportation scenario in combined rail–road transportation, which considers the impact of the unloading process of vehicles in the park warehouse on the operation of third-party carriers under the back-end transportation of "rail to the road". Secondly, we introduce a new unloading appointment mechanism to solve the continuous impact relationship between more extended congestion queuing times, transportation costs, and delivery time windows. Finally, this study proposes a new intelligent method that can effectively solve the choice of scheduling strategy in the actual short-distance transfer of enterprises. In summary, the existing research on transport scheduling strategy optimization considering the short distance and the multi-trip situation in this article is relatively limited. Regarding road–rail intermodal transport as a scenario of theoretical support, there is still ample research space. Transport and traffic are closely linked, and short-inverted freight transport involves changes in the process handover of multiple modes of transport, which significantly impacts the order completion time and the total cost of the enterprise.

3. Problem Description and Modeling

3.1. Scenario Construction

Under road–rail intermodal transport, Figure 2 illustrates the specific execution process of loading vehicles involved in short-haul backhaul transport at the dispatching station.

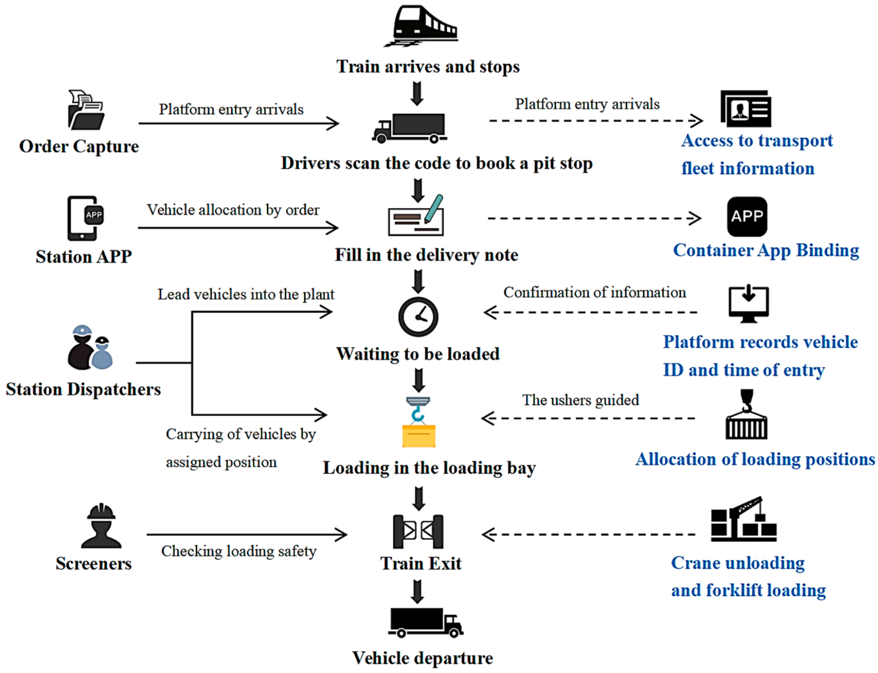

Figure 2. Vehicle inbound loading process.

According to the flowchart, inbound approvals are usually operated directly by an intelligent management system, which makes the process fast and easy.

In actual production operations, the unloading areas of the park warehouses at each demand point are geographically limited. Short-inverted vehicles generally contain containers and other large transportation equipment. Their volume is significant, and vehicle parking space is limited. This also leads to waiting for the unloading of vehicles in front of the warehouse or even the warehouse around the road queue, and ultimately following the order of entry into the factory to work. As a result, it reduces the turnover efficiency of short-term transportation and extends the deadline for the final delivery of each order. Vehicles in the queuing process are still out of work. The decision maker, to ensure that the customer-specified hard delivery time window is adhered to, will choose to send other vehicles to participate in the short-inverted transport. The increase in the number of transport vehicles will also lead to higher transportation costs.

At the same time, in actual short-inverted transport, each vehicle can only serve one demand point at a time and return to the site immediately after unloading at the demand point warehouse to replenish the goods so that the pickup and delivery of goods alternate many times in a cycle until the completion of the order of the specified amount of freight, and the vehicle arrives at the customer's specified unloading point of the unloading process, as shown in Figure 3. According to the flow chart, the queue after the driver arrives at the receiving point accounts for a significant proportion of the transport process.

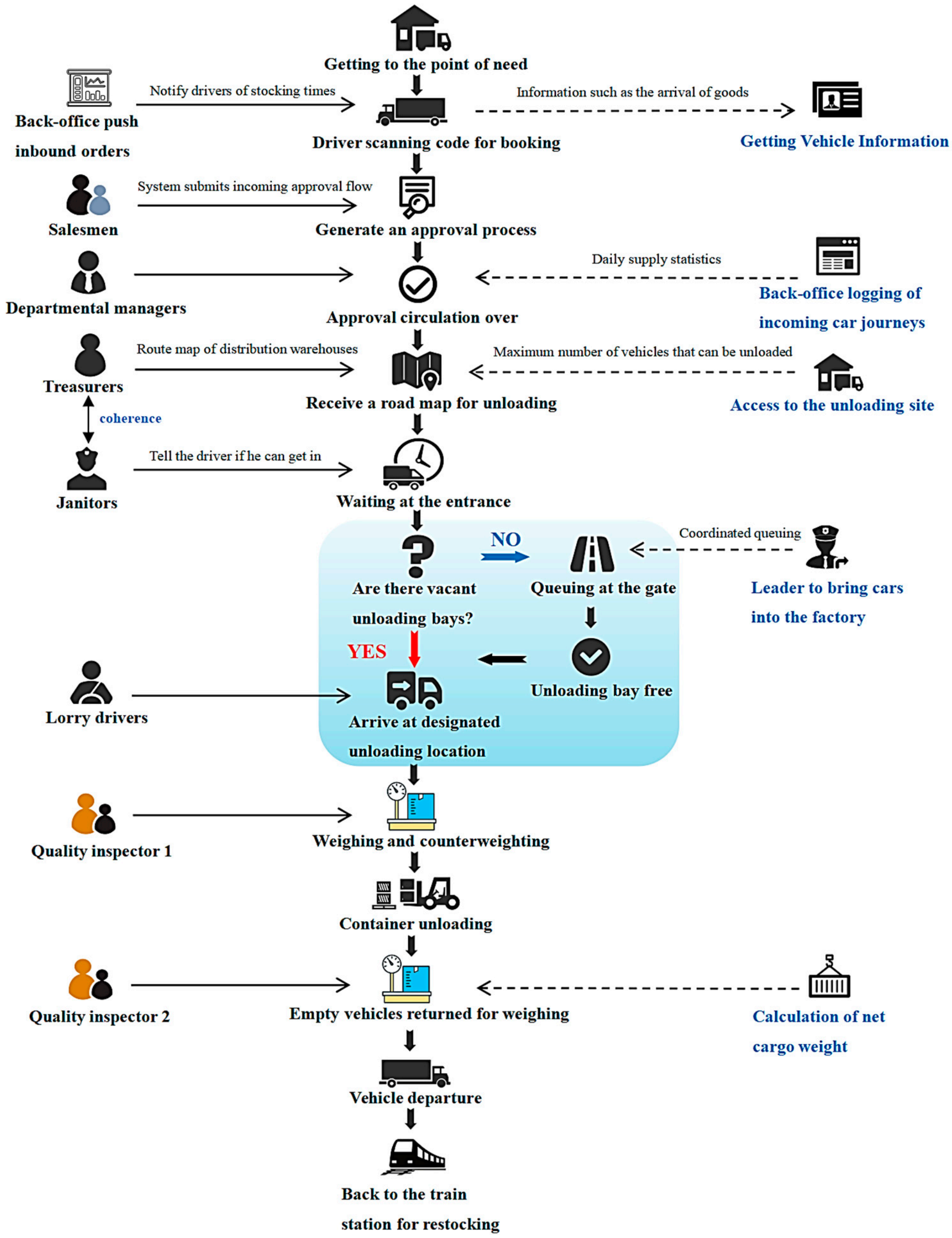

Figure 3. Vehicle arrival at demand point unloading process.

3.2. Description of the Problem

The problem of scheduling under a supply chain for short-inverted cargo transport consisting of freight terminals, carriers, and customers is studied. The network structure of short-distance logistics and transport is shown in Figure 4. In this supply chain, the airline is responsible for storing goods. In addition, since the airline has the decision-making power over the transport program, many uncertainties influence factors in the operation, such as the number of transfers and vehicle configuration. Constructing a short-inverted transportation scheduling model can help the decision-maker set each vehicle's short-inverted transportation time. Moreover, it also enables planning the quota for inbound unloading at each demand point. The model helps to screen out time-consuming and inefficient vehicles from the transportation program. Therefore, this study further considers the queuing problem of vehicle arrival for unloading by setting up a booking mechanism.

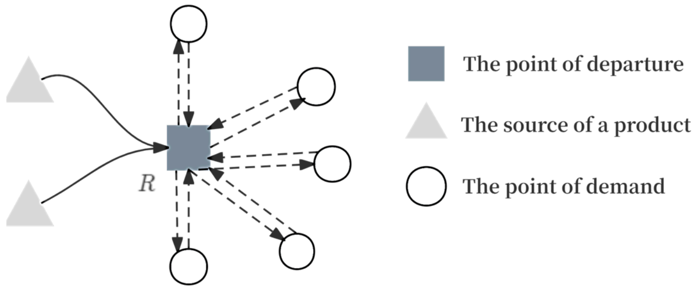

Figure 4. Structure of the short-inverted transport network.

At the same time, this study takes into account the characteristics of actual short-inverted transport scenarios and makes the following assumptions:

Assume that there is a single train depot in the supply chain network, that the customer locations are known, that there is a demand for short-inverted transport at each customer point, that the vehicle loads are standard cargo, that the capacity of a single vehicle is sufficient for single transport, and that each car travels at a constant speed. The vehicle arrives at the customer's warehouse, completes the unloading, and then returns to the shipping station for replenishment, allowing one vehicle to serve the same demand point multiple times. Specifically, the modeling also needs to satisfy the following constraints:

(1) The place of origin or the supplier shall be in a normal state during the supply period so that the total volume of supply from the dispatching station cannot be less than the total demand of the customer.
(2) Stopping platforms allow trains to leave the station only after the goods have arrived and have been fully unloaded, irrespective of empty or overrun orders.
(3) The customer's total demand for the day divided by the vehicle load capacity shall be no greater than the number of vehicles available to the carrier for daily transport.
(4) The carrier's logistics company has a sufficient number of vehicles available for short backhaul transport, i.e., the number of cars owned by the carrier is equal to the number of vehicles waiting or in transit at each time point.

3.3. Description of Parameters

Based on the above problem description and assumptions, Table 1 describes each variable and parameter used in the model to facilitate the optimization model building for short-inverted transport scheduling.

Table 1. Parameters and variables of the proposed model.

Notation	Instructions
Collection:	
J	The set of all demand points, J = {j | j = 1,2,3,. . ., n}
S	The set of all time windows s, S = {s | s = 1,2,3,. . ., 12}, s = 1 means the time window is between 0 and 2 h
H	The set of all transport vehicles h, H = {h | h = 1,2,3,. . ., n}
Related parameters:	
i	The originating station
d_{ij}	The transport distance from the point of dispatch i to the end of customer demand j, km
v	The average speed at which the vehicle is traveling, km/h
T_1	The time at which vehicle 1 completes loading at the point of dispatch, h
T_2	The time for vehicle 1 to complete unloading at the point of demand, h
T_{ijh}	The total time for vehicle h to complete the delivery of a short-pour transport order from originating station i to demand point j, h
at_j	The lower bound of the time at which demand point J requires goods to arrive, h
bt_j	The upper time limit for the arrival of goods requested by demand point j, h
t_{ijh}	The time taken by vehicle h to complete a transport order between dispatching station i and demand point j, h
a_j	The daily demand for goods at the demand point j, ton

Table 1. *Cont.*

Notation	Instructions
o_{js}	The number of vehicles allowed to book unloading appointments at demand point j in the time window s
o_{is}	The number of booking requests initiated by originating station i on the same day
c_{ij}	The total cost of short-inverted transport of a vehicle from originating station i to demand point j and back, RMB per trip
z_h	The load capacity of vehicle h
s_n	The size of the divided single appointment time window, h
T_{ih}	The maximum number of hours per day that vehicle h can work at dispatch station i, h
e_{hij}	The number of transports of vehicle h from originating station i to demand point j, trip
y_{js}	The number of bookings issued by the sending station to demand point j in time window s

3.4. Objective Function

This model has the objective of minimizing the total cost of short-inverted transport and minimizing the delivery time, and Equation (1) represents the multi-objective objective function scheduling model:

$$Z = \min[f_1, f_2] \tag{1}$$

$$f_1 = \min \sum_{h \in H} \sum_{j \in J} c_{ij} e_{hij} \tag{2}$$

$$f_2 = \min \sum_{j=1} \sum_{h=1} T_{ijh} \tag{3}$$

where Equation (2) represents the minimization of the total cost of short-inverted transportation, in this model, considering the characteristics of short-inverted transportation, the operation mode of a short-pour transportation business is primarily the demanding enterprise and the third-party logistics company cooperating. The total cost c_{ij} for a vehicle to complete a short backward transportation order from the dispatching station i to the demand point j includes the total freight and vehicle usage costs. The total freight cost equals the sum of the freight costs of all vehicles involved in the short backward transportation. The freight cost of each car is the product of the single-trip short backhaul freight cost and the actual number of transportation trips. The amount of freight for a single journey is set and paid by the enterprise according to the actual transportation distance.

Given that demand, companies use a logistics outsourcing model, and freight payments are usually set based on the number of trips transported. The cost mainly includes fuel, the driver's salary, and vehicle maintenance, where driver wages are constant and priced according to the distance traveled. Vehicle maintenance costs primarily involve the wear and tear of tires and other infrastructure, and the factors that influence these costs are the road conditions of the transportation section and the length of vehicle use. In this study, we calculate the maintenance cost by combining the loss of ordinary fuel vehicles. Fuel costs are more variable than vehicle maintenance and account for a more significant proportion of freight costs. Hence, reducing fuel costs plays a leading role in total cost optimization. Meanwhile, the rational planning of short-inverted vehicle transportation schemes can reduce the number of vehicles needed in the transfer process, thus reducing the cost to a certain extent. The cost of vehicle use, which includes the cost of acquisition of the means of transport, insurance, and user taxes over a 365-day operating period, is divided by the number of orders and the vehicle turnover rate, and the result is apportioned equally to the cost of each short-inverted trip.

Equation (3) represents the sum of the total time to deliver vehicles to complete a short-inverted order from dispatch station i to demand point j. It consists of the sum of the actual delivery times for each order.

Equations (4)–(10) are the constraint functions:

$$y_{js} \le o_{js}, \forall j \in J, \forall s \in S \tag{4}$$

Equation (4) expresses that the number of booking requests sent by the sending station to the demand point j during the S time window equals the maximum limit on the number of vehicles booked into the plant at the demand point j during this period.

$$bt_j \leq t_{ijh} + T_1 + T_2 \leq at_j \tag{5}$$

$$T_{ijh} = \sum_{j=1}^{J} \left(\frac{2 \times d_{ij}}{v} + T_1 + T_2 \right) \cdot e_{hij} \tag{6}$$

Equations (5) and (6) indicate that the maximum value of booking requests received at demand point j per day equals the demand divided by the vehicle's capacity, where d_{ij} and v are known quantities.

$$\sum_{s=1} O_{is} \geq \frac{\sum_{j=1} a_j}{z_h}, \forall s \in S, j \in J \tag{7}$$

Equation (7) indicates that the total number of transport booking trips initiated by originating station i per day shall not be less than the number of orders demanded by demand point j on that day, where the number of orders to be fulfilled by the originating station is equal to the order demand at each demand point divided by the vehicle's load capacity.

$$\sum_{j=1} t_{ijh} \leq s_n \leq \sum T_{ih}, \forall h \in H \tag{8}$$

Equation (8) indicates that the division of a single booking time window should be within the range of a vehicle's single transport hour and maximum daily working hours.

$$\sum_{h=1}^{i} f_{hs} = 1 \tag{9}$$

Equation (9) indicates whether vehicle h is operational within the s time window. If yes, $f_{hs} = 1$; otherwise, $f_{hs} = 0$.

$$\sum_{j=1}^{i} x_{ijh} = 1, \forall j \in J, h \in H \tag{10}$$

Equation (10) indicates whether the logistics company sends a vehicle h to deliver the goods from the shipping station i to the demand point j. When $x_{ijh} = 1$, it will send a vehicle; when $x_{ijh} = 0$, it will not.

4. NSGWO Algorithm

4.1. Algorithm Description and Flow

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is based on the theory of the NSGA algorithm [56,57] and introduces the concepts of a fast, non-dominated sorting strategy and elite retention strategy in response to its deficiencies. Meanwhile, Seyedali Mirjalili [58] and other scholars proposed the Grey Wolf Optimization algorithm (GWO) in 2014. It utilizes the predatory behavior and collaborative mechanism of wolf pack groups to achieve optimization based on preserving population diversity. It performs better in terms of both convergence speed and solution accuracy [59].

The short-inverted transport multi-objective scheduling strategy model is a multi-decision variable, multi-constraint, two-objective model. In a constrained multi-objective model, the constraints restrict the feasible domain, making searching and selecting the optimal solution more complex. The Grey Wolf algorithm (GWO) is more suitable for solving single-objective problems, while the Non-Dominated Sorting Multi-Objective Genetic algorithm (NSGA-II) is a representative algorithm for solving multi-objective problems. NSGA-II and GWO are meta-heuristic algorithms for finding globally optimal solutions based on population iteration. The former reflects the advantage of performing more robust global searches [60] but can significantly slow them down. Although the latter is prone to premature convergence [61], the structural framework of the algorithm is relatively simple and stable, has relatively few adjustment parameters, and is easy to implement while complementarily solving the problems of NSGA-II. Therefore, this paper proposes a hybrid algorithm based on the GWO algorithm plus the fusion of the NSGA-II algorithm, which retains the unique advantages of the two algorithms and compensates for the common deficiencies to achieve better overall optimization results. The selection of the initial population closely affects the convergence speed and optimization ability of the NSGA-II algorithm, and a good population is more capable of selecting the best individuals and transferring their excellent gene segments to other individuals in the crossover process or for genetic inheritance. In addition, in searching for the optimal solution, the exchange of adequate coding information can improve the algorithm's ability to find the optimal solution and accelerate the algorithm's computational speed as a whole. On the contrary, if the initialization of the population is poor, the crossover operator can hardly pass the promising gene segments when inheriting to the next generation, which will not only fail to achieve the ideal crossover effect but also increase the output time of the optimal solution.

The steps to implement the NSGWO hybrid algorithm are as follows (Figure 5).

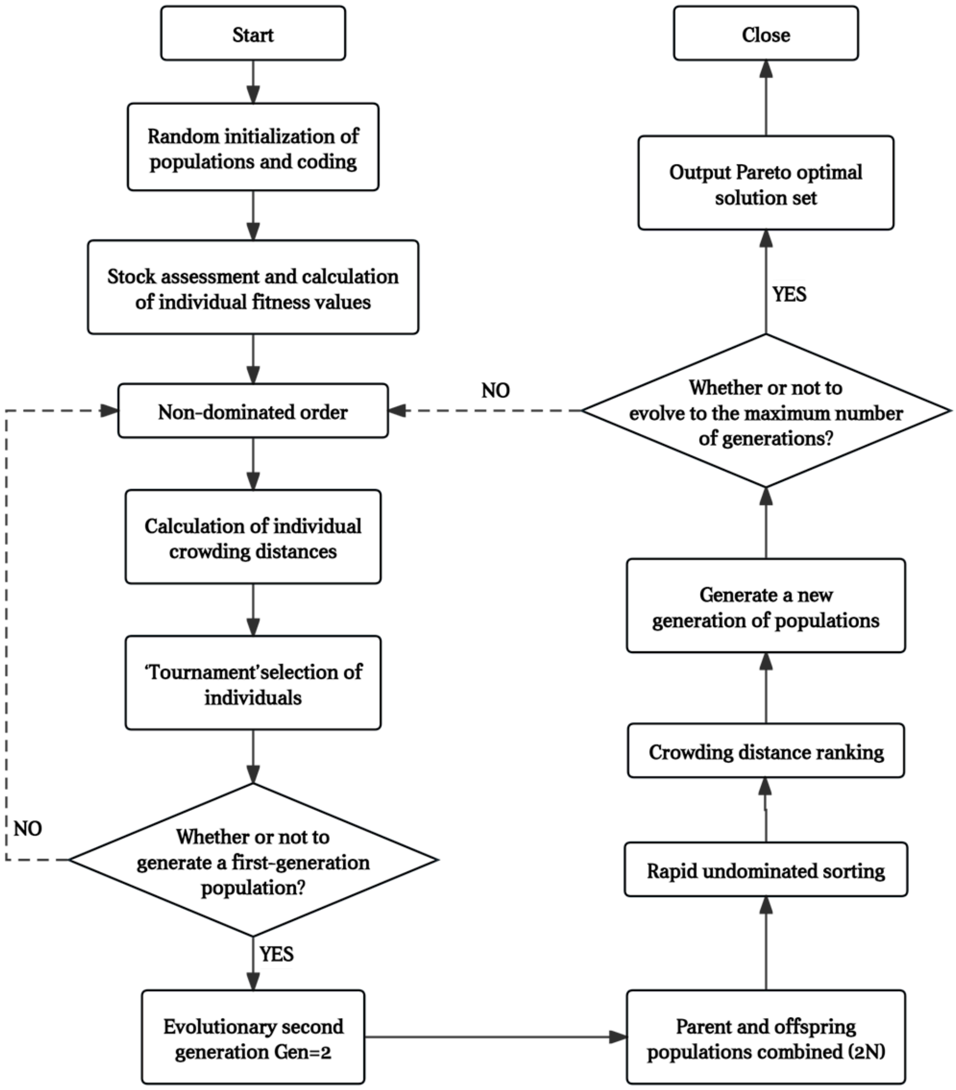

Figure 5. The processing flow of NSGWO algorithm.

Step 1: Population initialization. Randomly initialize the NSGWO algorithm population and code each grey wolf as a solution, evaluate the population, and calculate the fitness value of each individual according to the objective function.

Step 2: After the non-dominated sorting, the individuals in the population form different non-dominated frontiers (fronts). At the same time, it is essential to ensure that the other individuals in the frontier do not dominate the individuals in each non-dominated frontier and that the first frontier (frontier 1) is the updated set of optimal solutions. The solution generated above is the current searched Pareto optimal solution in the objective function space.

Step 3: Calculate crowding distances. Crowding distances are calculated for each individual in all non-dominated fronts to maintain diversity in the initial population. Individuals closer together in the objective function space will have smaller crowding distances.

Step 4: Operator selection. Through the tournament selection method, randomly screen some individuals in the parent generation, judge the non-dominated ordering and crowding distance, and preferentially select the individuals with the top non-dominated ordering and the more considerable crowding distance for genetic operation.

Step 5: Update alpha, beta, and delta wolf positions. Generate new positions based on the position update formula for alpha, beta, and delta wolves, and then combine the information of the three wolves to generate a new solution set of individuals to enrich the diversity of the population at this stage and also introduce randomness to explore the search space.

Step 6: Create the offspring population. Merge the parent and child populations to form a combined population of size 2N (N is the size of the population).

Step 7: Fast non-dominated sorting. Perform fast, non-dominated sorting on the individuals of the merged population and use the principle of non-domination to retain the N best individuals in the parent generation to form a new population again.

Step 8: Crowding distance sorting. If the best N individuals cannot be contained entirely within the last frontier when selecting the best N individuals, select which individuals in the previous frontier can enter the new population based on the crowding distance.

Step 9: Repeat the iteration. When performing the next iteration, use the new generation of populations just obtained. Determine whether the current iteration number G evolves to the maximum number of iterations; if so, jump out of the algorithm; otherwise, repeat Steps 2–8 until the stopping condition is satisfied by the output of the optimal solution.

4.2. Algorithm Convergence and Stability Test

To assess the convergence and stability of the NSGWO algorithm, the benchmark multi-objective test function ZDT [62] (ZDT1-ZDT4 and ZDT6), which is suitable for two optimization objectives, is chosen in this paper to comprehensively investigate the solving ability of the NSGWO algorithm in multi-objective optimization problems. The ZDT test function can support up to 30 inputs of decision variables. Table 2 demonstrates the two objectives optimized for each test set.

Table 2. Comparison of results of standard test functions for each algorithm.

Test Function	Define	Decision Variables	Best Case Scenario
ZDT1	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{x_1/g(x)}\right]$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n-1)$	$x_i \in [0,1]$ $i = 1,\ldots,n$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,\ldots,n$
ZDT2	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - (x_1/g(x))^2\right]$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n-1)$	$x_i \in [0,1]$ $i = 1,\ldots,n$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,\ldots,n$

Table 2. *Cont.*

Test Function	Define	Decision Variables	Best Case Scenario
ZDT3	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{\frac{x_1}{g(x)}} - \frac{x_1}{g(x)}\sin 10\pi x_1\right]$ $g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n-1)$	$x_i \in [0,1]$ $i = 1,\ldots,n$	$x_1 \in [0, 0.0830]$ $\cup[0.1822, 0.2577] \cup$ $[0.4093, 0.4538] \cup$ $[0.6183, 0.6525] \cup$ $[0.8233, 0.8518]$ $x_i = 0$ $i = 2,\ldots,n$
ZDT4	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{x_1/g(x)}\right]$ $g(x) = 1 + 10(n-1) + \sum_{i=2}^{n}[x_i^2 - 10\cos 4(\pi x_i)]$	$x_1 \in [0,1]$ $x_i \in [-5,5]$ $i = 2,\ldots,n$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,\ldots,n$
ZDT6	$f_1(x) = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$ $f_2(x) = g(x)\left[1 - (\frac{f_1(x)}{g(x)})^2\right]$ $g(x) = 1 + 9\left[(\sum_{i=2}^{n} x_i)/(n-1)\right]^{0.25}$	$x_i \in [0,1]$ $i = 1,\ldots,n$	$x_1 \in [0,1]$ $x_i = 0$ $i = 2,\ldots,n$

The shapes of the real Pareto optimal frontier solutions of the above test sets are known, the population sizes of the test functions are all set to 200, the maximum number of iterations is 200, and the size of the Pareto frontier solution set is 100. In addition, to quantify the respective algorithms' stability, the average values of the performance indexes of the above test functions are taken after running them independently 30 times. Table 3 shows the specific numerical results.

Table 3. Comparison of results of standard test functions for each algorithm.

Test Function	Performance Indicators	NSGA-II	NSPSO	NSGWO
ZDT1	HV	0.7040	0.7184	0.7193
	GD	0.00018	0.0002	8.675×10^{-5}
	IGD	0.0185	0.0052	0.0047
ZDT2	HV	0.4291	0.4417	0.4442
	GD	3.522×10^{-5}	4.948×10^{-5}	4.471×10^{-5}
	IGD	0.0197	0.0070	0.0049
ZDT3	HV	0.5803	0.5991	0.5996
	GD	7.570×10^{-5}	0.00018	0.00017
	IGD	0.0358	0.0057	0.0053
ZDT4	HV	-	-	0.7198
	GD	0.3810	5.2272	5.617×10^{-5}
	IGD	4.9253	11.1861	0.0044
ZDT6	HV	0.3593	0.3851	0.3882
	GD	2.363×10^{-5}	3.520×10^{-5}	3.104×10^{-5}
	IGD	0.0342	0.0086	0.0038

This paper uses three performance metrics to evaluate NSGWO and compare it with the NSGA-II and NSPSO algorithms, respectively. The three performance metrics are the generation distance (GD), inverse generation distance (IGD), and hypervolume metric (HV).

Among them, the generation distance (GD) and inverse generation distance (IGD) are the more representative convergence metrics [63], and Equation (11) is the expression for the generation distance (GD):

$$GD(N, PF^*) = \frac{\left(\sum_{i=1}^{|N|} d_{1i}^{p}\right)^{\frac{1}{p}}}{|N|} \tag{11}$$

N is the optimal solution set of the test algorithm; PF* is the optimal solution set of the natural Pareto frontier; p takes a value of 2; and d1i is the Euclidean distance between the i-th solution of the solution set N in the target space and the nearest reference point in the solution set PF*. GD mainly measures the Euclidean distance between the Pareto front formed by the optimal solution of the test algorithm and the actual Pareto front PFture and takes the mean of all Euclidean distances after summing them up. The smaller the value of the GD metric is, the better the algorithm converges. When the target result is 0, then N = PF*.

Equation (12) is the expression for the inverse generation distance (GD):

$$IGD(PF^*, N) = \frac{\left(\sum_{i=1}^{|PF^*|} d_{2i}^{p}\right)^{\frac{1}{p}}}{|PF^*|} \tag{12}$$

N is the optimal solution set of the test algorithm; PF* is the optimal solution set of the natural Pareto frontier; p takes a value of 2; and d2i is the Euclidean distance between the i-th solution in the solution set PF* and the nearest position of the reference points in the solution set N. The inverse generation distance (IGD) metric is the opposite of the generation distance (GD). It represents the average of the minimum Euclidean distance between all solutions in the natural Pareto frontier PFture and the optimal Pareto solution set obtained by the test algorithm. The smaller the value of the IGD metric, the better the algorithm converges and the more homogeneous the distribution of the solutions. The hypervolume metric (HV) is a stability metric used to measure the volume of the target space in the region enclosed by the non-dominated solution set N obtained by the algorithm and the reference points formed by the actual Pareto front.

Equation (13) is the expression for the hypervolume metric (HV):

$$HV(N, PF^*) = \lambda\left(\cup_{i=1}^{|N|} v_i\right) \tag{13}$$

N is the optimal solution set of the test algorithm, λ is the Lebesgue measure, and vi is the hypervolume formed by the theoretical reference point and the i-th solution in the solution set N in the target space. The most significant difference between HV, and GD and IGD is that there is no need to know the actual Pareto front of the theoretical optimum, which is a comprehensive and robust indicator, and the bigger the value of the HV indicator is, the better the Pareto front of the algorithm converges, and the more uniformly distributed the solutions are.

The analysis in Table 3 shows that the NSGWO algorithm proposed in this paper achieves good optimization results regarding the GD, IGD, and HV metrics. The result of running the test function 50 times and selecting the optimal solution set, Figure 6, demonstrates that with this result, this algorithm can obtain the non-dominated Pareto solution set with better quality and distribution. Through the comparative analysis of the data of the three indexes, combined with the analysis of the distribution map situation, the NSGWO algorithm proposed in this paper obtains a better quality and distribution of the non-dominated solutions, and the stability of the algorithm performs better, compared with the traditional NSGA-II algorithm and NSPSO algorithm.

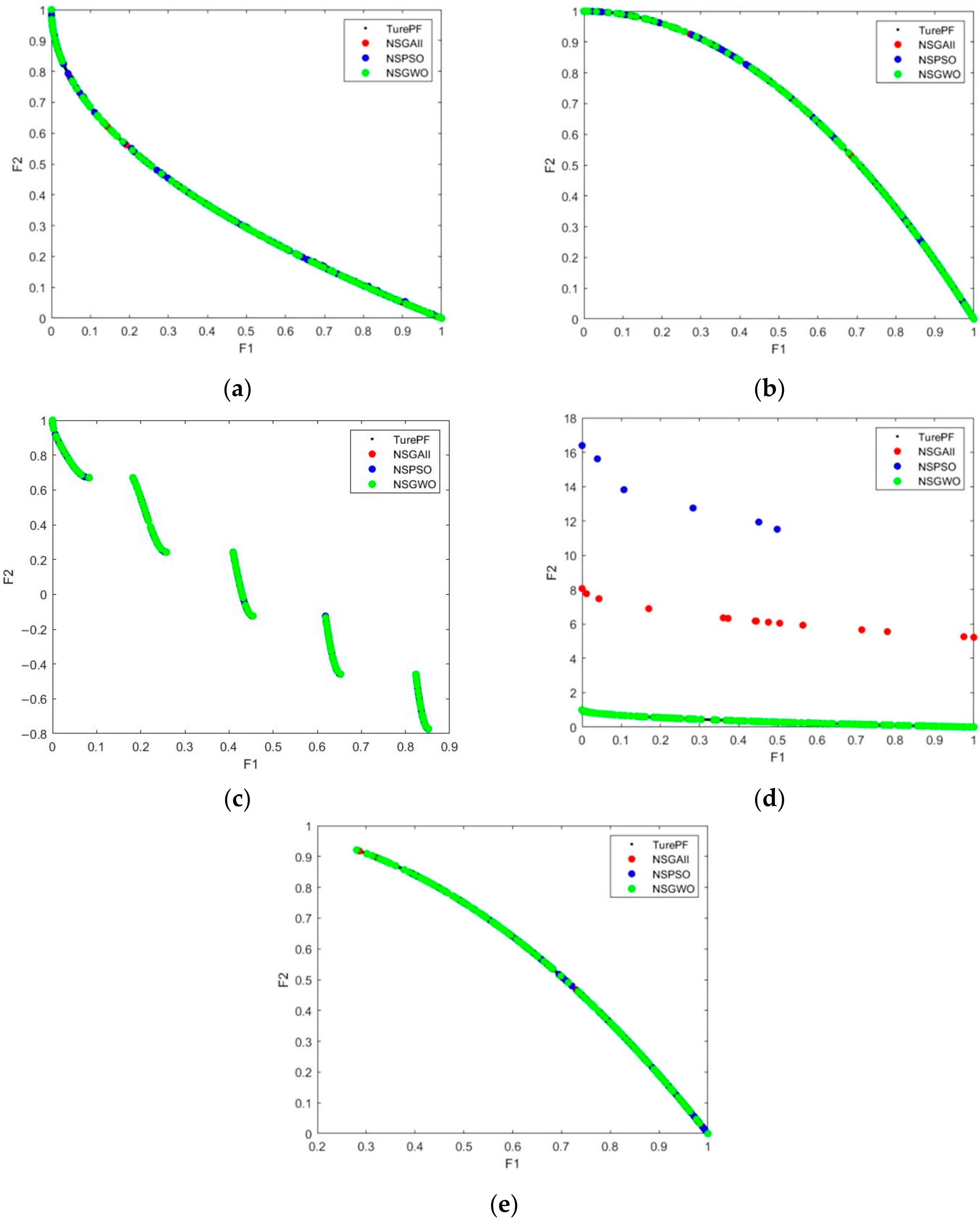

Figure 6. NSGWO algorithm standard test results. (**a**) ZDT1; (**b**) ZDT2; (**c**) ZDT3; (**d**) ZDT4; and (**e**) ZDT6.

5. Experimental Analysis

5.1. Scenario-Based Problem Analysis

In response to severe congestion and long queues in the unloading area at the point of demand, this study considers the development of a vehicle unloading booking mechanism in the carrier's existing intelligent platform system for short-inverted vehicle scheduling. Figure 7 shows the system topology of this platform. Among the relevant information management of the shipping station, this study reserves the operation management system for docking the existing business, mainly related to upstream and downstream customers, to achieve on-demand aggregation and real-time collection of business data, provide data support for the company's management decision making, and effectively improve customer stickiness.

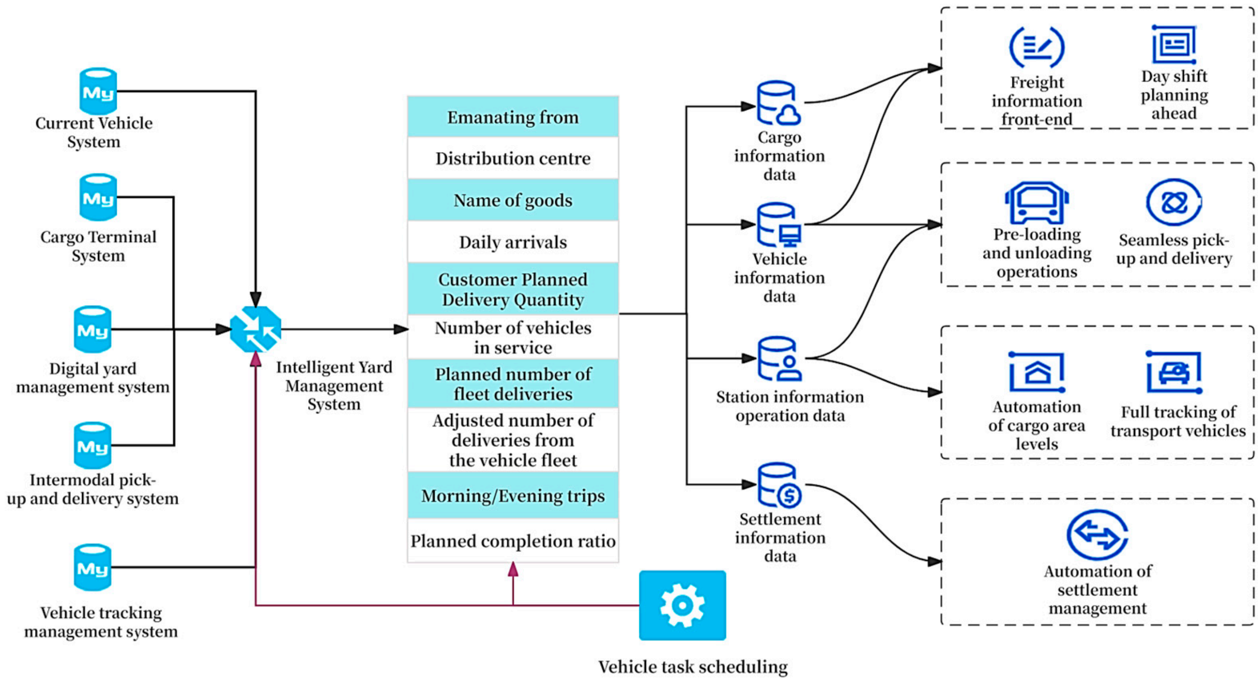

Figure 7. The system topology of a vehicle short-inverted scheduling platform based on intelligent station information.

Under the existing platform system, short-inverted vehicles must initiate applications in advance. At the same time, according to the number of appointments requested for unloading, based on the scheduling strategy optimization model, the maximum number of vehicles allowed to enter in each time slot can be obtained at the demand point. This reservation mechanism enables the carrier to know the real-time congestion conditions of the back-end of the transport in advance, and then staggered deployment, and reduces the excessive queuing time spent by truck drivers at the unloading point. This booking mechanism divides the range of bookable time windows according to a maximum time limit of 4 h for a single transport as a lower bound. At the unloading point specified by the customer, the business specialist can set the number of vehicles to be unloaded for each appointment or randomly select a specific time window for the appointment in the booking mechanism according to the individual needs and the availability of the dispatching station. The carrier should provide the customer with the transport vehicle ID and the day's delivery volume. In addition to this, when the reservation quota of vehicles allowed to unload at a demand point is zero, or the car has a reservation failure or is unable to make a reservation, the dispatcher can screen the system for other demand points that can receive a reservation within the current time window under this reservation mechanism and make a re-subscription for that vehicle until there is a demand point that can receive it. Figure 8 illustrates the flow of the vehicle offloading reservation mechanism.

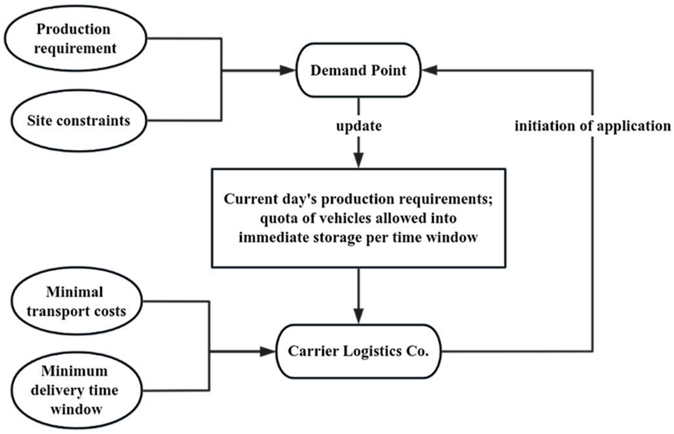

Figure 8. Flowchart of the reservation mechanism for unloading vehicles at the point of demand.

5.2. Optimal Scheduling Strategy Solution for Short-Inverted Vehicles

The experiment selects a capital city of a province in western China. As the departure station, it uses a railway station point, which is mainly responsible for the road–railway intermodal transportation business. It carries out short-inverted transportation to nine demand points around the station platform. Figure 9 shows the route program of short-inverted transport operations the leading carriers undertake.

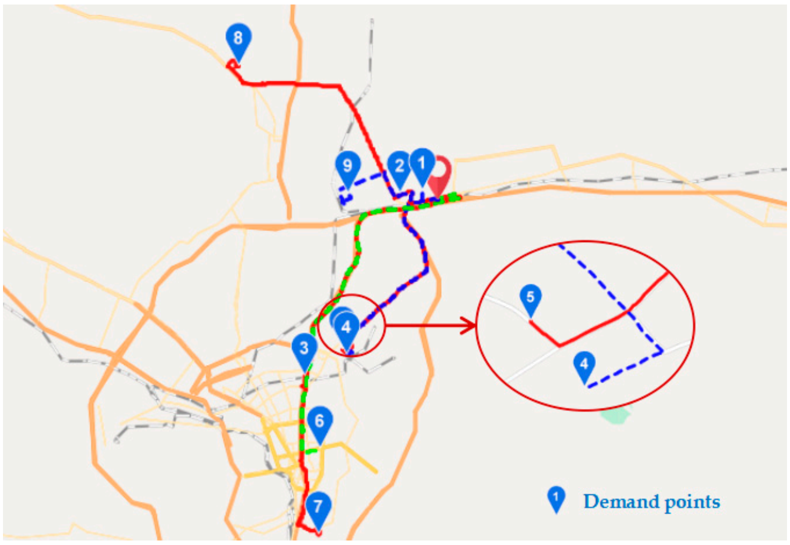

Figure 9. Operational route program for short-inverted haulage.

In this case, the number of train dispatching stations is one, and the short-inverted haulage occurs between this platform and the nine surrounding demand points. The relevant parameters of the carrier are set and the specific values are shown in Table 4. The capacity of a single vehicle is 32T of standard cargo, and it travels at a constant speed during the transport. This study specifies that the company's fleet of short-inverted haulage vehicles works 365 days per year. The average daily shipment is found based on the annual demand at each demand point.

Usually, the primary purpose of transport is to fulfill the requirements of the order placed by the customer, so the number of trips made by one vehicle per day is rounded upward. In addition, if a vehicle's single trip is less than the standard cargo of 32T, the carrier must dispatch a car to transport the remaining amount. The customer information in this study comes from third-party logistics enterprises that carry short-inverted transportation. Among them, the annual capacity of each demand point is relatively fixed. Therefore, the average value of the yearly demand for short-inverted cargo at each demand point for the past five years is selected. Furthermore, the enterprises price the freight rates. Table 5 shows the customer- and freight-specific information obtained.

Table 4. Basic parameters.

Name	Numerical Value	Unit
Number of shipping stations	1	-
Number of demand points	9	-
Maximum vehicle weight	32	ton
Average vehicle speed	55	km/h
Maximum number of vehicles available	500	-
Vehicle loading hours	0.25	h
Vehicle unloading hours	0.25	h
Maximum vehicle operating hours	10	h/day

Table 5. Customer information.

Demand Point	Annual Demand (T)	Distance (km)	Average Daily Departures (Vehicles)	Number of Trips per Vehicle (Trips)	Freight (RMB/Trip)
I	55	3	6	8	50
II	220	4	20	10	50
III	160	65	70	2	180
IV	60	35	20	3	130
V	100	35	30	3	130
VI	100	48	30	3	150
VII	200	65	35	2	60
VIII	80	8	9	8	60
IX	30	48	13	2	150

5.3. Analysis of Results

The NSGWO parameter sets the number of initial populations defined as 100 and the number of iterations as 200. Meanwhile, to ensure the algorithm's fluency, the short-inverted transport scheduling problem of road–railway intermodal transport is solved by simulation with the help of MATLAB 2022b. Table 6 shows the simulation results. The table reflects the reservation information of each demand point under the reservation mechanism for a random day during the working day.

Table 6. Status of bookings at each point of demand on a random day.

Demand Point	Number of Requests for Appointments Required (Times/Day)	Transport Time per Vehicle (Trips/h)	Maximum Bookable Quota (Vehicles/h)
I	48	0.51	7
II	189	0.55	27
III	137	2.77	137
IV	52	1.67	26
V	86	1.67	43
VI	86	2.15	86
VII	172	2.76	172
VIII	69	0.69	14
IX	26	2.15	26

The NSGWO algorithm was run 30 times for the short-inverted transport optimization experiments above. The optimal set of non-dominated frontier solutions was selected among the results obtained, as shown in Figure 10. According to the objective function values obtained, the NSGWO algorithm used in this study presents a good diversity. The distribution of the non-dominated frontier solutions derived by this algorithm is relatively uniform, which is of some relevance for the decision-maker's choice.

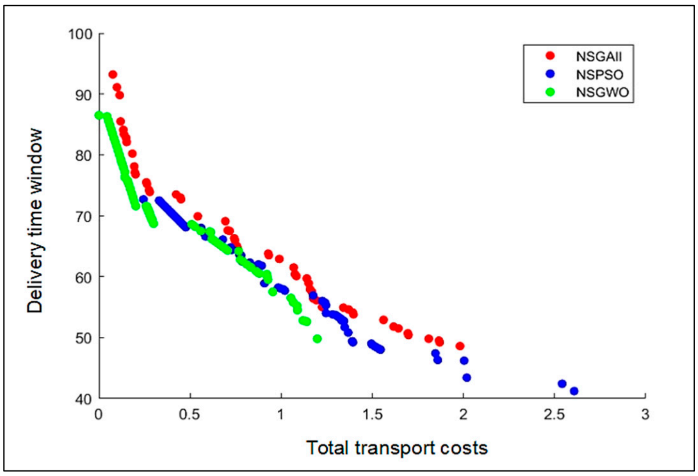

Figure 10. Non-dominated frontier solution for NSGWO algorithm.

As can be seen from Table 7, the use of swarm intelligence algorithms has a specific optimization effect on multi-vehicle short reversal scheduling for centralized loading and unloading operations in actual parks. Reducing the number of vehicles for short-inverted dispatching using the swarm intelligence algorithm is about one-third of the original scheme compared with the original scheme before optimization. The NSGWO algorithm is optimized to require the least number of vehicles involved in short-inverted dispatching, using 10 and 7 fewer cars than the NSGA-II and NSPSO algorithms, respectively. The results of this experiment reflect the mutual constraints of the queuing time in the unloading area and the vehicle replenishment trips. Reducing the waiting time for vehicles to unload in the park helps vehicles to be put on the next trip quickly. The reduction in vehicles reduces the fuel cost. It also directly affects the total cost of short-inverted transportation. Using the NSGWO algorithm under the same conditions saves 41.01 percent of the total transport cost. It reduces the total delivery time by 46.94 percent compared with the carrier's current logistics scheduling strategy, effectively improving the short-inverted scheduling and vehicle turnover efficiency. In addition, compared with the data obtained by the NSGA-II and NSPSO algorithms, the total transport cost is reduced by 2.3 percent and 2.25 percent, respectively, and the delivery time window is reduced by 12.4 percent and 10.4 percent, respectively, by using the NSGWO hybrid algorithm to solve the problem during the same shift.

Table 7. Comparison of results by algorithm.

Optimization Algorithm	Total Cost of Transport/RMB	Delivery Time Window/h	Number of Vehicles Transported	Spatial Indicators (Spacing)
None	203,200	93.86	300	—
NSGA-II	122,618	56	213	1121.37
NSPSO	122,565	55	210	1569.89
NSGWO	119,860	49.8	203	921.23

Secondly, Table 7 gives the values of the spatial metric (spacing) of the three algorithms, which measures the distributivity of the set of non-dominated solutions based on the shortest distance between the non-dominated solutions obtained by each algorithm. The NSGWO algorithm outperforms the other two algorithms in this metric to obtain the scheduling strategy with the minimum total transport cost and the shortest delivery time window. When the customer's acceptable time window allows an extensive range of adjustments or the order does not require high timeliness, the enterprise will generally give priority to the lowest cost as the primary goal; when the delivery time has a mandatory requirement, or the penalty cost triggered by overtime is too high, it will choose the solution with a lower delivery time window.

A set of non-dominated frontier solutions is selected from the above experimental results and the specific results of this experiment are described. Table 8 visualizes the specific vehicle reservation quotas for each time window in demand points I–IX. For example, demand point II provides bookable hours for eight time windows. The number of inbound vehicles allowed to be booked in a single time window is 11 for the first four time windows and increases to 16 for the last four time windows. According to this table, the decision-makers of the carrier companies and the drivers of short-inverted transport can know the real-time arrival working status of the vehicles at the demand points in advance before receiving the tasks and make a reasonable plan for the transfer tasks.

Table 8. Comparison of results by algorithm.

Time Window	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
I	7	7	7	7	0	0	0	0	0	0
II	11	11	11	11	16	16	16	16	0	0
III	0	0	0	0	137	137	137	137	0	0
IV	0	0	0	0	23	23	23	23	41	41
V	86	86	86	86	0	0	0	0	0	0
VI	86	86	86	86	0	0	0	0	0	0
VII	0	0	0	0	13	13	13	13	2	2
VIII	23	23	23	23	0	0	0	0	0	0
IX	10	10	10	10	18	18	18	18	0	0

The short-inverted scheduling plan obtained based on this intelligent hybrid algorithm in this study is more specific than the random scheduling plan given by the initial system. The present model retains the time interval for each vehicle to initiate two consecutive reservation requests, which further prevents the drawback of the insufficient time interval for initiating reservation requests and also reserves the necessary rest time for the drivers.

6. Discussion

According to the above experimental results, the newly set appointment mechanism shortens the time for short-inverted vehicles to unload at the demand point. In the complete intermodal supply chain formed by suppliers and customers, the working status of vehicles includes three main stages: front-end loading, in-transit transportation, and back-end unloading. The smoothness of the unloading process directly affects transportation costs. Moreover, this reservation mechanism uses an intelligent scheduling system based on the Internet of Things technology, which can effectively avoid additional hardware and software costs. At the same time, the NSGWO algorithm designed in Section 3.3 can obtain a non-dominated frontier with a more stable distribution than the other two algorithms, whether in terms of the test function or the actual data of the enterprise.

Another objective of this study is to discuss the problem of decision-maker selection under conflicting objectives. Intelligent scheduling can only partially meet customer satisfaction with most companies' plans. Human decision-making is still required. Combined with the actual business operations, it can be found that the total transport cost and the total delivery time window, as two optimization objectives in the short-inverted transport scheduling problem, are interrelated but conflicting in the distribution of the non-dominated frontier solutions. Realizing an equilibrium state in which both objectives are ideal is impossible. Multiple alternative scheduling solutions are obtained in each run when solved using an intelligent optimization algorithm. However, the conflict between the various objectives makes it difficult to obtain the optimal solution with both cost and time. The carrier can select the optimal solution by choosing the more important objective as the primary variable based on the demand of the order placed by the customer. Although the growth in demand in the market for time-sensitive freight transport indirectly raises the level of transport services demanded by customers [64], companies generally prioritize cost minimization as their primary objective when the customer's acceptable time window allows for a wide range of adjustments or when the order does not have a high timeliness requirement. When there are mandatory requirements for the delivery time or the cost of penalties arising from time overruns is too high, it will choose a solution with a lower delivery time window.

7. Conclusions

The railway is a vital strategic resource for urban development. However, the railway transport of bulk goods will become increasingly popular. China's freight transport still cannot be wholly divested of road transport. So far, the emergence and promotion of road–rail intermodal transport have also made the domestic logistics and trading channels gradually smoother, greatly enhancing the level of facilitation of traditional freight transport. This study considered the requirements of cargo transshipments under intermodal transportation and combined the characteristics of the high turnover rate of short-dump transportation. Aiming to address the vehicle congestion queuing problem caused by the limited location of the unloading area, this study adopted a new vehicle reservation mechanism, including the vehicle unloading time sequence and the park warehouse unloading space scheduling operation problems. The existing intelligent scheduling system at the demand point was optimized. In addition, this paper's study of short-inverted transportation essentially analyzed the scheduling problem of vehicles in a short-inverted, centralized handling scenario. To react more realistically to the transportation status quo between the train dispatching station and the demand point, this article visualized the articulation of various links in the vehicle loading and unloading processes.

This paper constructed a multi-objective optimization model of a short-inverted transport scheduling strategy based on road–rail intermodal transport, with the objectives defined as the lowest total cost of short-inverted transport and the shortest delivery time window. It solved the problem using the NSGWO hybrid algorithm, which cleans the inferior solution and retains the elite solution more in line with the Pareto frontier.

Taking a logistics enterprise in a western region of China as an example, the experimental results show that (i) the algorithm performs well in solving practical problems and significantly reduces the number of short-inverted transport vehicles. (ii) Compared with the same non-dominated sorting algorithm, the NSGWO algorithm used in this study can obtain solutions with lower costs and shorter delivery time windows.

In summary, the vehicle scheduling plan obtained from the experiment can effectively alleviate the congestion of vehicles at the transfer station and the inefficiency of short-inverted transportation, ensuring the efficiency and economic benefits of enterprise decision-making. In addition, from the perspective of transportation tools, the reservation mechanism proposed in this study can directly reduce the number of vehicles involved in short-inverted transportation scheduling. This also means that the optimized transportation scheduling plan reduces unnecessary fuel costs in detour transportation and achieves lower carbon emissions. On this basis, it promotes the spread of the emerging concept of green logistics. Reducing energy consumption further encourages the sustainable development of the logistics industry.

However, this paper also has certain limitations. The problem studied in this paper is suitable for the short-inverted transportation of bulk goods by rail–road combined transport and needs to distinguish between other types of goods. However, during the actual transfer process, there may be particular types of goods, such as dangerous goods with high transportation risks [65–70] or cold chain goods with freshness requirements [71–75]. This is also one of the hot topics of many scholars at the moment. The transportation of these goods also needs to consider factors such as the safety of the transfer process, the goods' storage environment, and the vehicle's speed. The research results show much room for optimization in scheduling short-inverted transportation of “rail to the road”. The multiple links of short-inverted transportation continue to affect each other. These include the capacity and service quality of the back-end transportation and the production planning and scheduling of the front-end supply. This paper focused only on the demand side of receiving goods. Moreover, in the future, we can consider the scheduling strategy of the supply side or transshipment side and add the impact of road impedance or multiple vehicle models on the scheduling efficiency to further improve the transport scheduling system with road–rail intermodal transport.

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