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Original Article

HYPER-HEURISTIC ALGORITHM FOR HUBPORT HINTERLAND DIVISION AND TRANSPORTATION NETWORK OPTIMIZATION WITH LOW-CARBON ORIENTATION

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Highlights:
- a multi-objective mixed integer linear programming model is constructed to design a port hinterland transportation network;
- a CF-based selection HH algorithm is developed, incorporating tabu-search-guided population initialization, multi-criteria optimization framework, and elite pool with intensified local search;
- the impacts of different carbon trading prices and carbon quotas on the optimization of port hinterland transportation networks are analysed.

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Abstract. To mitigate resource inefficiencies arising from the homogeneous competition among ports and advance a low-carbon transportation network of hubports, multimodal freight transportation systems with low-pollution and low-consumption have gained significant scholarly attention. In the port hinterland transportation network, a reasonable hinterland for the main hubport can effectively eliminate homogeneous competition, realize the optimal allocation of transport resources, and promote the integrated and coordinated development of the region. From the perspective of hinterland division and coordination of transportation organization methods, a multi-objective mixed integer programming model is established to minimize the total transportation cost, total transportation time, and carbon emission cost. A novel CF-based selection Hyper-Heuristic (HH) is developed that employs an initial population generation mechanism based on tabu-list and an elite solution pool to explore the solution space. A case study of the Yangtze River Delta in China is conducted to verify the validity of the model and algorithm. The results show that the hinterland of Shanghai Port and Ningbo-Zhoushan Port are basically equal in scope, the Shanghai Port is in the upper part of the Yangtze River Delta region, mainly in Jiangsu and parts of Anhui and the Ningbo-Zhoushan Port is in the lower part of the Yangtze River Delta region and Jiangxi. Additionally, the carbon emission reduction effect reaches 34.2%. Finally, this research contributes dual policy implications: network design guidelines for port authorities, and carbon trading mechanism refinements through regional spatialization.

Keywords: transportation network, multi-objective mixed integer programming, hyper-heuristic algorithm, carbon emission, hubport.

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Notations

Abbreviations:

AGA – adaptive genetic algorithms;
AGV – automated guided vehicle;
AHP – analytic hierarchy process;
AM – all move acceptance;
CF – choice function;
CF-AM-GD-HH – choice function – all move acceptance – generational distance based hyper-heuristic algorithm;
CF-AM-RNI-HH – choice function – all move acceptance – ratio of non-dominated individuals based hyper-heuristic algorithm;

CF-AM-UD-HH – choice function – all move acceptance – uniform distribution of a non-dominated population based hyper-heuristic algorithm;
CTF – closest task 1st;
ELECTRE – elimination and choice translating reality (in French: *Elimination Et Choix Traduisant la Réalité*);
ETS – emission trading system;
FTF – furthest task 1st;
GD – generational distance;
GDA – grate deluge acceptance;
HH – hyper-heuristic;
IGD – inverted GD;
LA – late acceptance;
SA – simplified assignment;
NSGA-II – non-dominated sorting genetic algorithm II;
SPEA2 – strength Pareto evolutionary algorithm 2;
TEU – 20-foot equivalent unit;
RNI – ratio of non-dominated individuals;
SSC – size of the space covered;
UD – uniform distribution of a non-dominated population.

Variables and functions:

A – set of all edges in the network, $A = A_{CR} \cup A_{RP} \cup A_{CP}$;
$AVGC_i$ – carbon emissions per unit transfer in the hub-station n_i, $n_i \in R \cup P$ [kg/TEU];
C – set of hinterland nodes;
C_g – carbon trading price [¥/kg];
CHC_{ij} – transfer cost per TEU time from n_i to n_j [¥/TEU-h];
CHT_{ij} – transfer time per TEU from n_i to n_j [h/TEU];
CTF – according to the distance matrix from the hinterland to the hub port, the distance between each hinterland and the nearest hub port is extracted, and after sorting in ascending order, the hinterland sorting sequence is obtained;
d_{ij} – road/rail distance from n_i to n_j, $(i, j) \in A$ [km];
DMM_i – demand quantity of containers in node n_i, $n_i \in C \cup P$ [TEU];
E_g – carbon allowances for transport enterprises [kg];
FTF – according to the distance matrix from the hinterland to the hub port, the distance between each hinterland and the nearest hub port is extracted, and after sorting in descending order, the hinterland sorting sequence is obtained;
GHC_{ij} – carbon emissions per TEU distance from n_i to n_j [kg/TEU-km];
HDC_i – carbon emissions per unit stored in the hub-station n_i, $n_i \in R \cup P$ [m^3/month];
K – set of transport mode, K = {1, 2} (k = 1 indicates road; k = 2 indicates rail);
M – a positive number of infinities;
N – set of all nodes in the transportation network, $N=C \cup R \cup P=\left\{n_i, n_j, ..., n_h\right\}$;
$Ncap_i$ – handling capacity of n_j, $n_i \in R \cup P$ [TEU/h];
P – set of hub port nodes;
R – set of dry port nodes;
SA – randomly select the hinterland number without repeating it to get the hinterland sorting sequence;
SPM_i – supply quantity of containers in node n_i, $n_i \in C \cup P$ [TEU};
STC_i – storage cost per TEU from n_i to n_j [¥ /TEU-h];
STT_{ij} – storage time per TEU from n_i to n_j [h/TEU];
tcq_{ij} – number of containers from n_i to n_j, $(i, j) \in$ [TEU];
TRC_{ij} – transportation cost per TEU distance from n_i to n_j [¥/TEU-km];
TRT_{ij} – transportation time from n_i to n_j [h];
x_{ij}^k – indicates whether n_i is connected to n_j ($x_{ij}^k = 1$ indicates that n_i is connected to n_j use transport mode k; $x_{ij}^k = 0$ indicates that n_i is not connected to n_j use transport mode k), $(i, j) \in A$;
Z^+ – positive integers.

1. Introduction

Amid accelerating trade globalization, modern ports function as strategic multimodal hubs within transnational supply chains, generating spatial economic effect through core-periphery interactions in regional development systems (Zhong *et al.* 2023). China's coastal ports have undergone significant expansion, with hinterland access emerging as a central strategic priority in port development, resulting in the homogenization of port competition and a waste of transportation resources. Dryports, serving as strategic mechanisms to extend hinterland (Qiu *et al.* 2015), could reasonably allocate transportation resources, mitigate road transportation congestion, and reduce carbon emissions. It gradually plays an increasingly important role in the transportation network of port hinterland. Therefore, the geospatial distribution of dryports and optimization of hinterland transport networks constitute essential strategies for maintaining port competitiveness, while simultaneously enabling hinterland segmentation and fostering benign inter-port competition (Bouchery, Fransoo 2015).

Concurrently, the intensifying global scrutiny of carbon neutrality imperatives has precipitated the formulation of multilateral decarbonization frameworks (Zheng *et al.* 2017, 2021, 2022, 2023). For example, China has put forward the target of "3060" of carbon peak neutrality (Liu *et al.* 2018), and introduced a carbon ETS policy, transforming the original unconstrained emission rights into limited resources to urge enterprises to reduce carbon emissions (Jiang 2014). Global transport sector emissions constitute 25% of anthropogenic CO_2 output, positioned as the 2nd-largest contributor following energy generation systems (electricity/heat: 38%, World Energy Outlook (IEA 2022)). Within this sector, road freight dominates emission profiles at 72.3% of modal share, contrasting sharply with rail

(1.9%) and inland waterways (2.1%) (Du *et al.* 2019). This emission hierarchy underscores the strategic imperative for China's decarbonization agenda to prioritize intermodal shift strategies. Consequently, the implementation of rail-water coordinated freight corridors within port-hinterland logistics networks has emerged as a critical pathway for achieving China's "3060" goal. Meanwhile, hubports have developed ambitious strategies to foster inland multimodal transport to expand their economic hinterland (Pourmohammad-Zia *et al.* 2023; Zhong *et al.* 2023). On the one hand, hinterland expansion can help strengthen port competitiveness. On the other hand, ports play important and socially responsible roles to mitigate carbon emissions via their hinterland multimodal network optimization. Therefore, the construction of a low-carbon multimodal transportation network and a sustainable comprehensive transportation system is an effective way to achieve energy conservation and emission reduction in the transportation industry (Yin *et al.* 2024).

Based on the research, this article constructs a multi-objective mixed integer linear programming model for the design of a port hinterland transportation network under consideration of transportation cost, transportation time, and carbon emission and proposes a novel HH algorithm to solve the model (Maashi *et al.* 2015; Burke, Bykov 2017; Simões *et al.* 2023). The Yangtze River Delta is taken as a case for verification. This study's main contributions are as follows:

- a multi-objective mixed integer linear programming model is constructed to design a port hinterland transportation network considering cost, time, and carbon emission generated during transportation, storage, and transfer of cargo;
- a novel HH algorithm is proposed, which contains an initial population generation mechanism based on tabu-list, the CF, the low-level heuristic of (AGA, NSGA-II, SPEA2), the performance evaluation criteria of (RNI, GD, IGD, UD, SSC), and the elite population pool;
- the impacts of different carbon trading prices and carbon quotas on the optimization of port hinterland transportation networks are analysed with a case study in the Yangtze River Delta, so as to provide decision-making recommendations for the government and port strategic departments to effectively allocate transportation resources, promote low-carbon and sustainable port hinterland transportation networks, and provide relevant support for the formulation of emission control and emission reduction policies in the transportation industry.

The remainder of this article is organized as follows. Current Section 1 – introduction. Section 2 is the literature review covering the topics of port hinterland transportation, carbon emissions, and HH algorithms. The optimization of port hinterland transportation network problems is defined and modelled in Section 3. Section 4 describes the framework of the proposed HH algorithm. Section 5 contains the result analysis. Section 6 – discusion section. Section 7 concludes the study by highlighting its novelty and limitations.

2. Literature review

2.1. Transportation carbon emissions

With the increasing global concern on carbon emissions, reduction strategies and measures for the optimization of low-carbon transportation networks have been studied in recent years. This study mainly considers 3 categories: objective function, solution method, and application domain. The contributions are similarly focused on limiting total carbon emissions, introducing carbon tax mechanisms (Xie *et al.* 2022; Zhong *et al.* 2023), and carbon trading mechanism (Rosič, Jammernegg 2013; Yin *et al.* 2025), to further achieve carbon emission control in the transportation industry. Roso *et al.* (2009) constructed the constraints or objective functions of the model with carbon emissions to reduce carbon emissions. In addition, carbon emissions can be directly converted into carbon emissions costs with carbon tax policies (Xie *et al.* 2022). Qiu *et al.* (2021) suggested that using barge transport in container cargo transportation between port and hinterland can effectively alleviate traffic congestion and reduce carbon emissions. Guo *et al.* (2022) realized that transportation structure and energy choice are 2 key factors that affect carbon reduction in transportation networks and can provide a basis for carbon reduction strategies. Pourmohammad-Zia *et al.* (2023) proposed that applying AGV platoons in port hinterland corridors offers significant cost and time savings and provides a low-carbon emission transportation mode. Guo *et al.* (2025) suggested that speed, capacity, and tranship condition are key factors when considering carbon emissions in a multimodal transportation networks. These studies show that the use of policy mechanisms and means can effectively control transportation carbon emissions and then achieve the sustainable development goal in the transportation industry.

2.2. Port hinterland transportation network optimization

The research on port hinterland transportation network optimization mainly focuses on the node location and the network design (Witte *et al.* 2019).

In terms of the node location of the port hinterland transportation network, the literature mainly focuses on dryport location. Roso *et al.* (2009) extended the dryport concept to 3 dryport categories: distant, midrange, and close. Ka (2011) combined Fuzzy AHP and ELECTRE to propose a method for decision makers to select optimal dryport location. Nguyen & Notteboom (2016) proposed a conceptual framework for the inclusion of multiple criteria in the evaluation of dryport locations in developing countries from a multiple stakeholder perspective.

In terms of the design of the port hinterland transportation network, Qiu & Lam (2018) studied the shared transportation services in the dryport system, which consist of a dryport and a number of shippers, developed a bi-level model, and enumeration algorithm was proposed to solve the model. The result showed that sharing transportation services could bring significant profit improvement to the dryport and cost savings to shippers in most circumstances. Wei & Dong (2019) designed a new cross-border logistics network that connects the maritime logistics network with the inland cross-border logistics network through dryports and studied the organizational optimization problem of inland import and export cargos in different network scenarios. Yin *et al.* (2021a) proposed a multi-objective mixed integer linear programming model for the design of a port hinterland transportation network. The result could provide decision-making recommendations for the government and port strategic departments to adjust the transportation system and raise the level of multimodal transportation. Yin *et al.* (2023) established a hubport multimodal freight transportation network optimization model considering space-time constraints to further promote regional integration development. These studies show that the rational allocation of transportation resources and the coordinated development of the regional economy can be further promoted by optimizing the transportation network of port hinterland.

2.3. HH algorithm

The HH algorithm, developed gradually in recent years, is simply understood as a heuristic to find heuristics (Zheng *et al.* 2015; Yıldırım *et al.* 2021). It can be defined as a high-level control methodology that consists of selection strategies and move acceptances that explore a search space of low-level heuristics or heuristic components to solve computational optimization problems. The HH algorithm can be categorized into 2 main classes: generation HHs (Branke *et al.* 2016) and selection HHs (Ahmed *et al.* 2019), a generation HH algorithm applies a high-level control methodology to explore constructed low-level heuristics to generate a newly created solution at each step of a search, while a selection HH algorithm applies a selected low-level heuristic to "perturb" the current solution at each step of a search, then decides whether to accept or reject the newly created solution. If the search stagnates, a locally optimal solution is found (Drake *et al.* 2020; Li *et al.* 2023).

HyFlex is a basic framework of a HH algorithm that has been widely used by researchers (Ochoa *et al.* 2012). McClymont *et al.* (2013) proposed a HH algorithm based on Markov chain and reinforcement learning as the high-level control strategy and NSGA-II and SPEA2 as the low-level heuristic strategy to solve the water resource allocation network planning problem. Leng *et al.* (2019) proposed a novel HH algorithm based on a quantum-based approach as a high-level selection strategy to solve the location-routing problem. Zhao *et al.* (2025) proposed a Q-learning-based HH algorithm with fuzzy policy decision technology to solve multi-objective real-world problems. Zhong *et al.* (2025) proposed a novel large language model assisted HH optimization algorithm. The above research shows that the HH algorithm has good portability and generality, which allows researchers to focus solely on a variety of computational optimization problems, especially multi-objective optimization problems.

This article aims to address the issue of carbon emission reduction in the port hinterlands transportation network by applying HH algorithms. At present, the optimization problems of the port hinterland transportation network are usually solved by the traditional heuristic algorithms or its improvement, but the HH algorithm is rarely used. In addition, HH algorithms have gradually emerged and been applied in the research field in recent years. Therefore, the innovation point of this article is to consider the carbon trading mechanism and apply a novel HH algorithm to solve the optimization problem of the port hinterland transportation network, so as to provide decision-making recommendations for the government and port strategic departments to effectively divide hinterland and allocate transport network resources. Such an analysis extends previous studies to investigate a potentially more effective and comprehensive policy package.

3. Modelling methodology

3.1. Problem description

The article assumes that the transportation network consists of hinterland nodes, dryport nodes, and hubport nodes. Freight transportation between the hubports and the hinterlands can select 2 transportation schemes: road–rail multimodal transportation and direct road transportation. Road–rail multimodal transportation requires transfer at the dryport, and the cargo flow from hinterlands to dryports is transported by road, and the cargo flow from dryport to hubport is transported by rail. Direct road transportation does not require transfers to dryports. The schematic diagram of the transportation network could be shown in Figure 1.

Concerning the optimization of port hinterland transportation networks, governmental and port strategic authorities have traditionally prioritized transportation cost efficiency and transportation time reduction as primary performance indicators. However, under China's dual carbon strategy (carbon peaking by 2030 and carbon neutrality by 2060), these stakeholders are increasingly integrating carbon emission metrics into their evaluation frameworks.

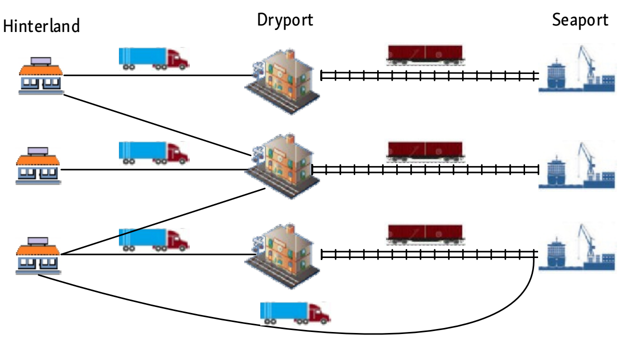

Figure 1. Schematic diagram of port hinterland transportation network

Therefore, in this study, transport enterprises need to simultaneously consider the minimum transportation cost, transportation time, and carbon emission cost. In addition, with the influence of the carbon trading mechanism, transport enterprises will be allocated a certain amount of carbon emission credits, but if they exceed the amount of carbon allowances, they need to purchase additional carbon emission permits through the carbon trading market, resulting in carbon trading costs, which are determined by the amount of carbon allowances purchased and the carbon trading price.

3.2. Model

The model assumptions are given below:

- considering that cargo is generally transported in containers during transportation, the cargo flow is indivisible during transportation, and the mode of transport can only be changed at a node;
- to facilitate the model solving and ensure the flow balance between the nodes in the network, the study assumes that there are no multiple transfers between nodes of the same level in the transportation network, so as to avoid the excessive transportation volume of a node that exceeds the processing capacity of a node.

The multi-objective mixed-integer linear programming model constructed in this article with the objectives of minimizing transportation cost, minimizing transportation time, and minimizing carbon trading cost is as follows.

The total transportation cost including transportation cost, transfer cost, and storage cost of cargos. The transportation cost is related to the volume of cargos passing through this route, the distance along the route, and the transportation mode. The transfer cost and storage cost are related to the cargos volume, the cargos processing cost per unit, and the cargos processing time per unit during the storage and transfer of cargos at the hub-station.

$$\min F_{\cos t} = \sum_{(i,\, j) \in A} TRC_{ij} \cdot tcq_{ij} \cdot d_{ij} \cdot x_{ij}^{k} + \sum_{(i,\, j) \in A,\, n_i \notin C} CHC_{ij} \cdot CHT_{ij} \cdot tcq_{ij} \cdot x_{ij}^{k} + \sum_{(i,\, j) \in A,\, n_i \notin C} STC_{ij} \cdot STT_{ij} \cdot tcq_{ij} \cdot x_{ij}^{k}. \quad (1)$$

The total transportation time, including transportation time, transfer time, and storage time of cargos. The transportation time is related to the route and transportation mode. The transfer time and storage time are related to the cargos volume and the cargos processing time per unit during the storage and transfer of cargos at the hub-station.

$$\min F_{time} = \sum_{(i,\, j) \in A} TRT_{ij} \cdot x_{ij}^{k} + \sum_{(i,\, j) \in A,\, n_i \notin C} CHT_{ij} \cdot tcq_{ij} \cdot x_{ij}^{k} + \sum_{(i,\, j) \in A,\, n_i \notin C} STT_{ij} \cdot tcq_{ij} \cdot x_{ij}^{k}. \quad (2)$$

The total carbon emissions cost, which is determined by the carbon trading price and the carbon emissions excess between the carbon quota amount of the transportation enterprise and the carbon emissions from the transportation of cargos. The carbon emissions are composed of the carbon emissions generated per unit distance during the transportation of cargos and the carbon emissions per unit during the storage and transfer of cargos at the hub-station.

$$\min F_{carbon} = \left(\sum_{(i,\, j) \in A} GHC_{ij} \cdot tcq_{ij} \cdot d_{ij} \cdot x_{ij}^{k} + \sum_{n_j \notin C} AVGC_{j} \cdot tcq_{ij} \cdot x_{ij}^{k} + \sum_{n_j \notin C} HDC_{j} \cdot x_{ij}^{k} - E_g \right) \cdot C_g \quad (3)$$

subject to:

$$\sum_{(k,\, i) \in A} tcq_{ki} = \sum_{(i,\, j) \in A} tcq_{ij},\ n_i \in R \cup P; \quad (4)$$

$$\sum_{(i,\, j) \in A} tcq_{ij} = SPM_{i},\ n_i \in C; \quad (5)$$

$$\sum_{(i,j) \in A} tcq_{ij} = DMM_{j},\ n_j \in C; \quad (6)$$

$$\sum_{(i,\, j) \in A} tcq_{ij} \le Ncap_{j},\ n_j \in R \cup P; \quad (7)$$

$$tcq_{ij} \le M \cdot x_{ij}^{k},\ (i, j) \in A,\ k \in K; \quad (8)$$

$$\sum_{k \in K} x_{ij}^{k} \le 1,\ (i, j) \in A; \quad (9)$$

$$tcq_{ij} \in Z^{+},\ (i, j) \in A; \quad (10)$$

$$x_{ij}^{k} \in \{0, 1\},\ (i, j) \in A,\ k \in K. \quad (11)$$

The Objective Function (1) minimizes the total transportation cost, including transportation cost, transfer cost, and storage cost of cargos. The Objective Function (2) minimizes the total transportation time, including transportation time, transfer time, and storage time of cargos. The Objective Function (3) minimizes the total carbon emissions cost, which is determined by the carbon trading price and the carbon emissions excess between the carbon quota amount of the transportation enterprise and the carbon emissions from the transportation of cargos. Constraint (4) indicates the cargo flow balance for intermediate nodes. Constraints (5) and (6) indicate that both the supply and the demand of containers can be satisfied. Constraint (7) ensures that the cargo flow through a dryport or seaport does not exceed the handling capacity. Constraint (8) indicates the relationship between decision variables. Constraint (9) indicates that the transport route from n_i to n_j can only select one transport mode. Constraints (10) and (11) specify the types of decision variables.

4. A CF-based HH algorithm

The solution of the multi-objective optimization model is generally integrated into a single objective function by setting the weight coefficient (Maashi *et al.* 2015; Pour *et al.* 2018), and then a heuristic algorithm is used to solve the problem. However, multiple objective evaluation criteria for multi-objective problems are related to the weight coefficients, which are difficult to determine, and the traditional heuristic algorithm is easy to fall into the "trap" of local optimal. To overcome this drawback, a novel HH algorithm based on CFs is proposed to solve this model (Maashi *et al.* 2015; Leng *et al.* 2019; Simões *et al.* 2023). The algorithm design is described as follows below.

4.1. Generating the initial population

To improve the quality of the solution and speed up the convergence of the algorithm, we present a constructive mechanism for initial population generation based on 3 different ordering strategies in order to assign hinterlands to dryports and hubports. Firstly, matrix coding is used in chromosome design. Then, in the generation of population individuals, each hinterland is allocated to a dryport and a hubport, depending on the ordering strategy being used. 3 ordering strategies are defined to decide the order in which hinterlands are allocated: FTF, CTF, and SA based on the distance between hinterlands and dryports and hubports. To ensure that hinterlands are distributed fairly among all dryports and hubports, a tabu-list is used to keep balance between nodes in the transportation network (Pour *et al.* 2018). Finally, according to the population size, the initial population is generated by giving different proportions to the 3 individual generation mechanisms.

Chromosome code design. This article adopts matrix encoding mode and consists of 5 layers: hinterland number, dryport number, hubport number, freight volume, and departure time from the hinterland. Each column represents a transportation route, as shown in Table 1.

Table 1. Chromosome code design

Hinterland No	1	2	3	4	5	...	*N*
Dryport No	2	1	8	4	1	...	5
Seaport No	5	8	1	3	4	...	5
Freight volume	40	290	160	400	80	...	200
Departure time	6	2	2	4	5	...	2

Generation of population individuals. According to the ordering sequence of hinterland nodes generated by different sorting strategies, considering the balance of cargo flow in the transportation network and preventing the excessive flow of nodes in a certain network, a tabu-list is used to maintain balance between nodes in the transportation network (Pour *et al.* 2018). In this way, the number of hinterlands assigned to each dryport and hubport is balanced while constructing the solution. *Algorithm 1* presents the pseudocode for the constructive mechanism of initial population individual generation.

Algorithm 1: Ordering mechanism employed to generate population individual

```
Order list according to ordering strategy (FTF or CTF or SA)
Initialize seaport tabu-list and dryport tabu-list as empty
Set seaport tabu-list size to number of seaport size – 1
Set dryport tabu-list size to number of dryport size – 1
for each element l in oList do
If Size of dryport tabu-list equals to maximum size of dryport tabu-list then
empty the dryport tabu-list
Allocate l to closest non-tabu dryport member c
Add c to dryport tabu-list
If Size of seaport tabu-list equals to maximum size of seaport tabu-list then
empty the seaport tabu-list
Allocate l to closest non-tabu seaport member d
Add d to seaport tabu-list
end for
```

The initial population generation. According to the population size, the initial population is generated by giving different proportions to the 3 population individual generation mechanisms. *Algorithm 2* presents the pseudocode for the constructive mechanism of initial population generation.

Algorithm 2: Generating initial solutions based on ordering mechanism

```
Get proportions of SA, FTF, CTF based on the problem setting
Calculate quantity of SA, FTF, CTF by population size
Initial count, SA-count, FTA-count, CTA-count equal 0
While count less than population size do
Randomly select choice from SA, FTF, CTF
Switch choice
Case SA:
If SA-count less than the number of SA then
Generate SA based initial solution and add it to solutions
SA-count +=1: count += 1
Case FTF
If FTF-count less than the number of FTF then
Generate FTF based initial solution and add it to solutions
FTF-count +=1: count += 1
Case CTF:
If CTF-count less than the number of CTF then
Generate CTF based initial solution and add it to solutions
CTF-count +=1: count += 1
```

4.2. High-level heuristics

4.2.1. Selection strategy

This article adopts the CF (Pour *et al.* 2018) as a high-level heuristic. By selection strategy, at each decision point, the low-level heuristic with the highest score, calculated using the CF, is selected and applied to the current solution. The complete formulation is as follows:

$$CF\left(h\right)=a\cdot f_1\left(h\right)+b\cdot f_2\left(h\right), \quad (12)$$

where: $f_1(h)$ represents the performance of the low-level heuristic h, which is usually reflected by multi-objective optimization evaluation criteria; $f_2(h)$ represents the running time when the low-level heuristic h is used [s]; a, b denote the parameter value (normally, a takes a much larger value than b).

4.2.2. Move acceptance

This article adopts AM, GDA (Dueck 1993; Tsao, Linh 2018), and LA (Burke, Bykov 2017) as the move acceptance of the proposed HH algorithm. The framework of 3 move acceptances could be shown in Figures 2–4.

4.3. Low-level heuristics and elite solution pool

We introduce 3 low-level heuristics that the HHs select from: AGA (Wei, Dong 2019), NSGA-II (Yin *et al.* 2023), and SPEA2 (Zitzler *et al.* 2001). The framework of 3 low-level heuristics could be shown in Figures 5–7.

At each iteration of the HH algorithm, in order to avoid the elimination of the optimal solution that is unaccepted by the acceptance criteria, the elite solution pool is designed into the algorithm framework, and the capacity of the elite population pool is set to ensure the solution quality in the elite solution pool.

4.4. Framework of the proposed HH algorithm

Algorithm 3 presents the pseudocode for the proposed CF-based selection HH framework. Firstly, generate an initial population based on the ordering mechanism. Then the algorithm enters the main loop to find the optimal solution. At each iteration, select and calculate each low-level heuristic from the low-level heuristics pool and sort the results based on the evaluation criteria. The CF value is then computed for each low-level heuristic; the low-level heuristic with the highest score is selected and applied to the iterative solution. Then, call the acceptance procedure

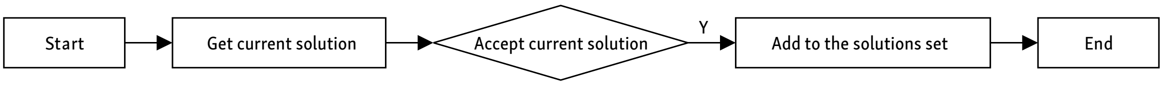

Figure 2. AM framework

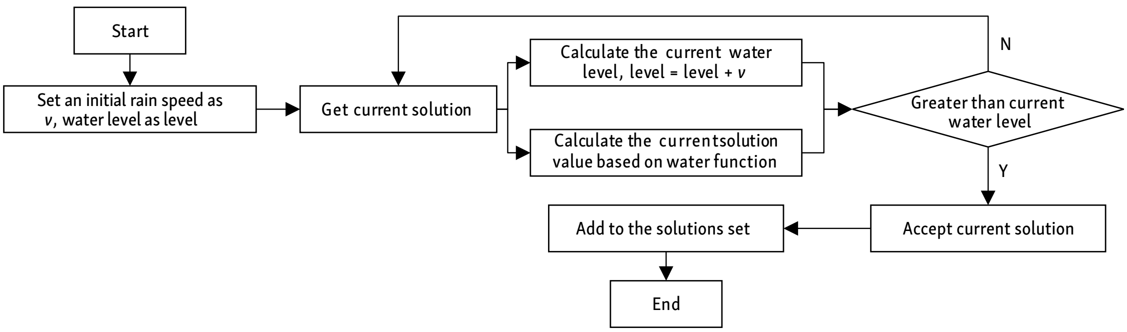

Figure 3. GDA framework

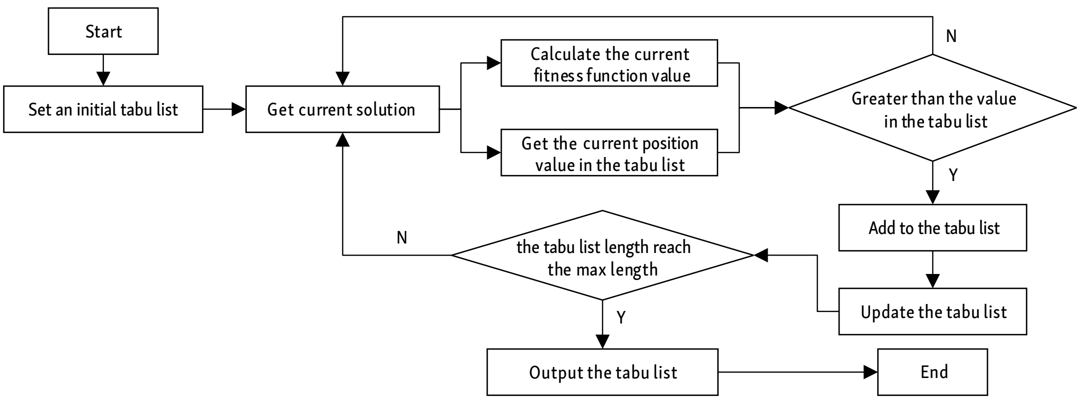

Figure 4. LA framework

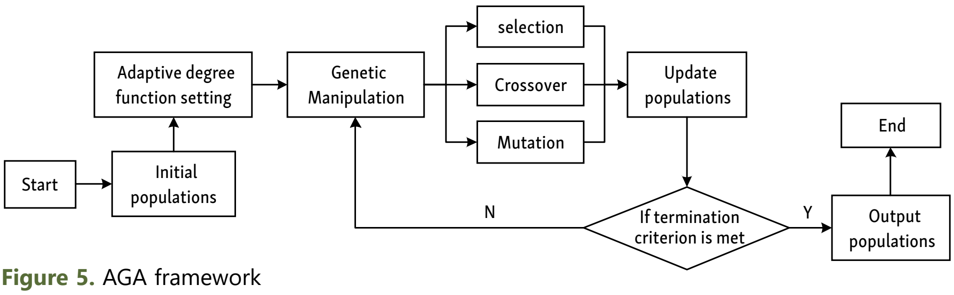

Figure 5. AGA framework

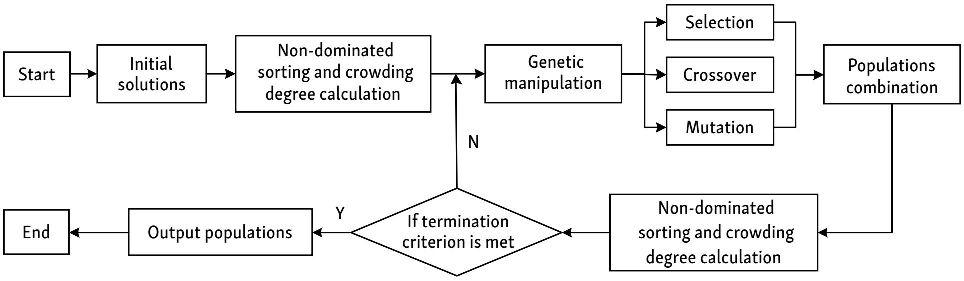

Figure 6. NSGA-II framework

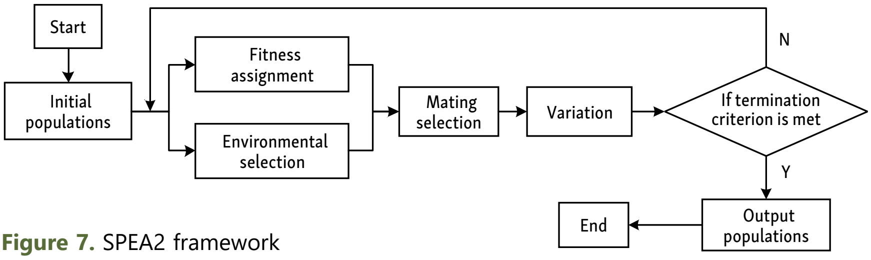

Figure 7. SPEA2 framework

to determine whether to accept the iterative solution into the next algorithm iteration. At the same time, the solution eliminated by the accepted criteria is compared with the solution of the elite population pool to avoid the elimination of the optimal solution. Then update the iterative solution and elite population pool until termination criteria are met. Finally, output the solution and corresponding indexes. The framework of the proposed CF-based selection HH could be shown in Figure 8.

Algorithm 3: Pseudocode of the CF-based selection HH framework

Produce an initial solution S using initial solution generation algorithm, the elite solution pool using an initial solution S
Initialize heuristic set $H = \{h1, h2, h3\}$, H is a set of the low-level heuristics
Repeat
Update the rank of h, $h \in H$ based on the ranking scheme
Update $CF(h)$, $h \in H$
Select h with the largest $CF(h)$, $h \in H$
Call the acceptance procedure (AM, GDA, LA)
Update solution S, the elite solution pool
until (termination criteria)
return solution

5. Case study

The Yangtze River Delta region is one of the regions with the most active economic development, the highest degree of openness, and the strongest innovation capacity in China. It is also one of the regions with the most complete industrial system and the highest level of regional integration. Therefore, this study selects 20 hinterlands, 5 dryports, and 2 hubports in the Yangtze River Delta region, with Shanghai Port and Ningbo-Zhoushan Port as the hubports, as shown in Figure 9. In addition, the traditional heuristic algorithm NSGA-II is used to compare with the proposed HH algorithm to verify its effectiveness. The basic data of the case is shown in Appendix. The initial carbon quota is set at 4000 kg, and the carbon trading price is 0.05 ¥/kg. All experiments were coded in MATALB (*https://se.mathworks.com/products/matlab.html*) and were run using an *Intel*(*R*)*Core*(*TM*) i7-8550U CPU@1.99GHz, with 8.00GB RAM.

5.1. Parameter setting and performance evaluation criteria

The parameter settings of the algorithm are shown in Table 2.

In general, the results of multi-objective optimization are difficult to compare directly, and performance evaluation criteria is generally used to evaluate the results quantitatively.

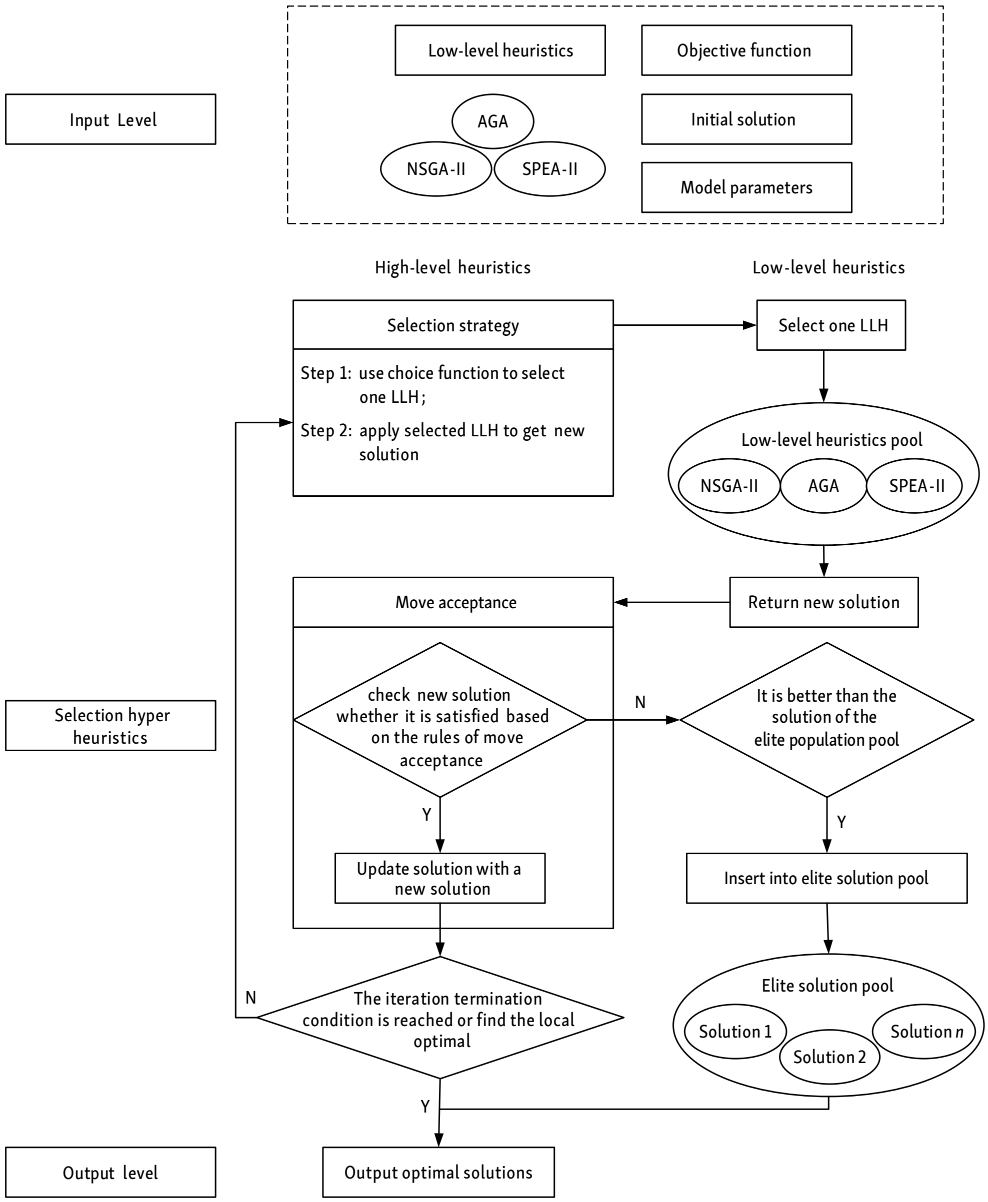

Figure 8. Proposed CF-based HH framework

Table 2. Parameter settings

Parameter	Value
Iteration number of low-level heuristics	50
Iteration number of HH algorithm	20
Individual number of the population	50
Crossover probability	0.7
Mutation probability	0.05
Elite solution pool	10
[FTA, CTA, SA]	[0.3, 0.3, 0.4]
[*a*, *b*]	[100, 1]
Average road speed	60 km/h
Average railway speed	80 km/h

The performance evaluation criteria are designed based on certain aspects of the results, such as the time effectiveness and degree of dispersion of the solution. In this article, RNI (Tao, Wu 2021), UD (Maashi *et al.* 2015), GD (Srinivas, Deb 1994), IGD (Tao, Wu 2021), and SSC (Bringmann, Friedrich 2013) are adopted as multi-objective optimization performance evaluation criteria.

5.2. Comparison between the HH algorithm and NSGA-II

The basic data is input into MATLAB for calculation, and 3 kinds of HH algorithms, CF-AM-RNI-HH, CF-AM-GD-HH, and CF-AM-UD-HH, are proposed to solve a multi-objective optimization problem aiming to minimize both total transportation cost and total transportation time, and the traditional heuristic algorithm NSGA-II is used as the control group to verify the effectiveness. The algorithm's computation time is shown in Table 3. The number of calls from the low-level heuristics is shown in Figure 10. The comparison of the Pareto solution of the algorithm is shown in Figure 11.

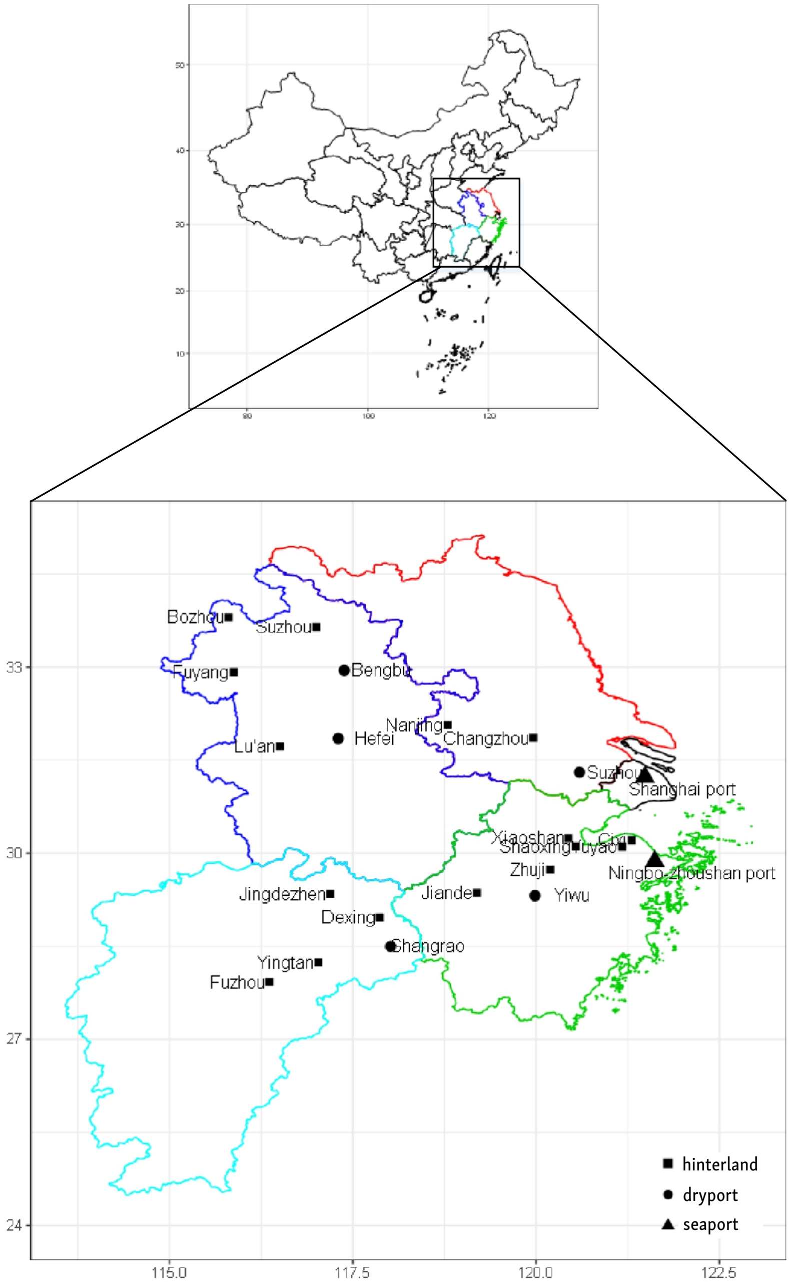

Figure 9. Schematic diagram of case study transportation network

Table 3. Comparison of the computation time

Algorithm	HH			NSGA-II
	CF-AM-RNI-HH	CF-AM-GD-HH	CF-AM-UD-HH	
Time [s]	23.1718	22.9415	24.7529	14.7669

From Table 3, it can be concluded that the computation time between the HH algorithms does not differ much when 3 kinds of performance evaluation criteria are used. However, the computation times are all longer than NSGA-II. This is because in the iteration of the HH algorithm, it is necessary to continuously select through the high-level control strategy and accept the result of the low-level heuristic, while NSGA-II does not have the option to select and accept the result but directly solves it. Therefore, in terms of computation time, the HH algorithm has no advantage over the traditional heuristic algorithm NSGA-II. In the future, there are some methods, such as parallel processing, dynamic performance metrics, and Q-learning mechanism to accelerate the process of guide the high-level heuristic selection.

From Figure10, it can be concluded that NSGA-II is called more often in the CF-AM-RNI-HH, SPEA2 is called more often in the CF-AM-GD-HH, and AGA is called more

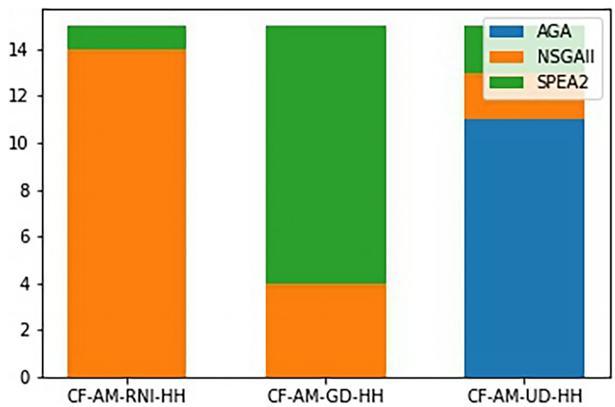

Figure 10. Number of calls from the low-level heuristics

often in the CF-AM-UD-HH. In general, NSGA-II is selected most often (44%), and AGA is selected least often (25%). Therefore, it is reasonable to select NSGA-II as the comparison of the HH algorithms.

It can also be concluded that the HH algorithm suffers from some randomness and uncertainty in the invocation of the low-level heuristics; moreover, different evaluation criteria have certain preferences for the invocation of the low-level heuristics. For example, the number of calls of NSGA-II is selected more than the other 2 under RNI, while the number of calls of SPEA2 is selected more under GD.

Figure 11a shows that the Pareto solution obtained by CF-AM-GD-HH is uniformly distributed throughout the solution space and tends to be stable, which has a clear advantage over the Pareto solution obtained by NSGA-II. Figure 11b shows that the Pareto solution obtained by CF-AM-UD-HH is uniformly distributed throughout the solution space; however, there are still some perturbations. Overall, the solution fitting effect is not as good as CF-AM-GD-HH, but it still has an advantage over NSGA-II. In Figure 11c, the Pareto solution derived from CF-AM-RNI-HH is uniformly distributed throughout the solution space and has a significant advantage over the solution obtained from NSGA-II. In Figure 11d, the Pareto solutions obtained by the HH algorithm that combines the 3 criteria are compared with those obtained by NSGA-II, and it is obvious that the Pareto solution calculated by the HH algorithm is better than NSGA-II, CF-AM-GD-HH performs best among them.

In summary, the HH algorithm does not have an advantage in terms of time consumption. However, despite the HH algorithm having some randomness, the overall Pareto solution is better than that of NSGA-II. Moreover, it can be seen from the comparison of the results that the CF-AM-GD-HH calculation is the best.

5.3. Results analysis

In Section 5.2, compared with the traditional heuristic algorithm NSGA-II, the proposed HH algorithm has proven its effectiveness in the multi-objective optimization problem, aiming to minimize both total transportation cost and total transportation time. Then the above HH algorithm is used to solve the multi-objective optimization problem with the total transportation cost, total transportation time, and carbon emission cost as targets. The algorithm's computation time of HH algorithms is shown in Table 4.

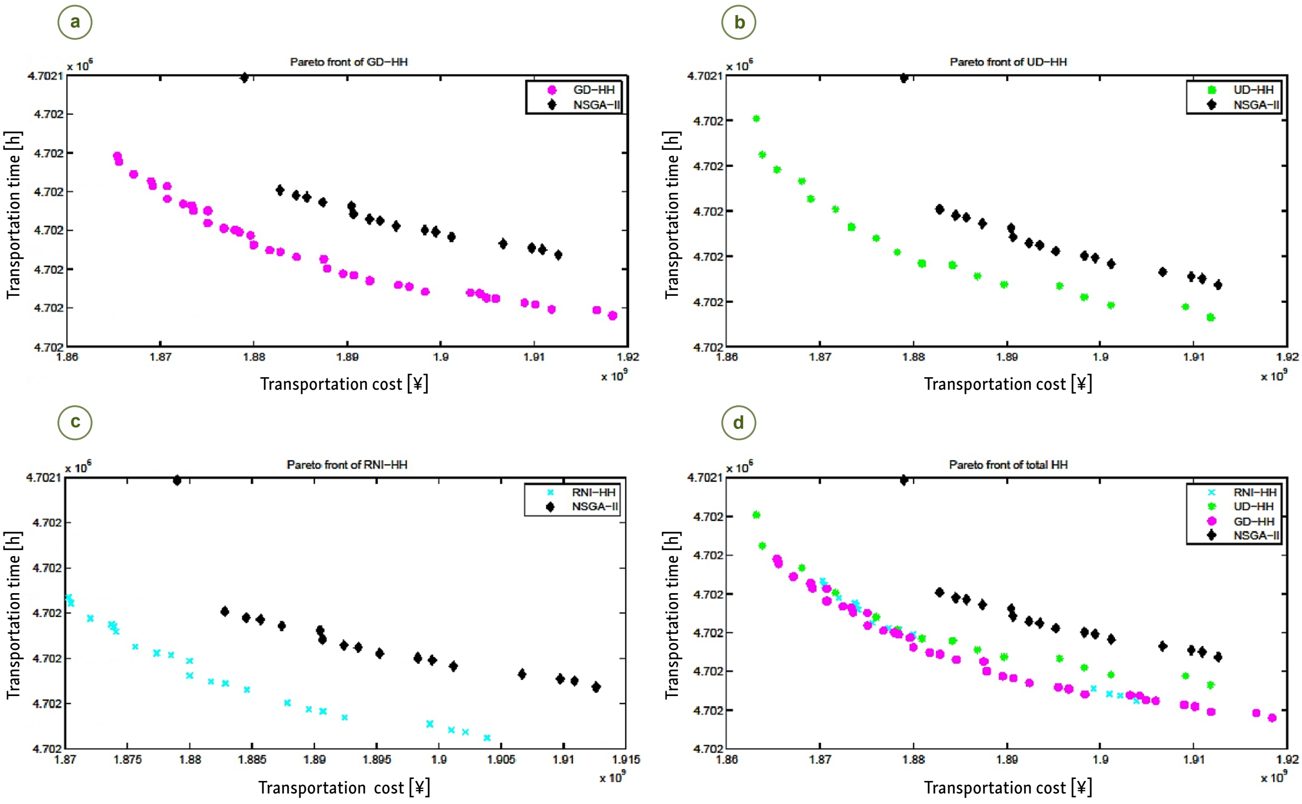

Figure 11. Comparison of Pareto solution of HH and NSGA-II algorithm

Table 4. Comparison of the computation time of HH algorithms

HH	CF-AM-RNI-HH	CF-AM-GD-HH	CF-AM-UD-HH	CF-AM-IGD-HH	CF-AM-SSC-HH
Time [s]	12.7980	184.6670	14.8830	123.2050	13.8970
HH	CF-LA-RNI-HH	CF-LA-GD-HH	CF-LA-UD-HH	CF-LA-IGD-HH	CF-LA-SSC-HH
Time [s]	12.8550	129.1960	15.0620	105.6800	16.3010
HH	CF-GDA-RNI-HH	CF-GDA-GD-HH	CF-GDA-UD-HH	CF-GDA-IGD-HH	CF-GDA-SSC-HH
Time [s]	12.8480	104.1960	14.6620	129.7270	16.2450
Average time [s]	12.8336	139.3530	14.8690	119.5373	15.4810

The number of calls from the low-level heuristics is shown in Figure 12. The comparison of the Pareto solution of HH algorithms is shown in Figure 13 (the results are obtained by running the HH algorithm 10 times).

From Table 4, it can be concluded that there is some difference in average computation time between 5 kinds of HH algorithms based on performance evaluation criteria. It can also be seen that RNI-HH, UD-HH, and SSC-HH are significantly superior to GD-HH and IGD-HH in algorithm computation time. For example, CF-AM-RNI-HH takes the shortest time (12.7980 s), but CF-AM-GD-HH takes the longest time, reaching 184.6670 s, which is nearly 15 times higher than that of CF-AM-RNI-HH. This is caused by the mechanism of performance evaluation criteria. The evaluation criteria of GD and IGD need to calculate Euclidean distance between populations in each iteration, which means that the calculation process of GD and IGD needs to reach each individual in the population, which takes a long time, while RNI only needs to compare the proportion of non-dominant individuals in the population during each iteration. Therefore, it can be concluded that RNI-HH algorithm takes the shortest time.

From Figure 12, it can be concluded that in general, NSGA-II is selected most often (50%), AGA accounts for 28%, and SPEA2 is selected least often (25%). In addition, GD-HH has better richness in the invocation of the low-level heuristic and can make full use of the advantages of the HH algorithm. The number of calls from the low-level heuristics is all NSGA-II in SSC-HH, so it can be concluded that SSC-HH has a strong preference for NSGA-II in the calls of the low-level heuristics.

From Figure 13, it shows the comparison of the Pareto solution to HH algorithms. RNI-HH, as shown in Figure 13a, performs well and basically forms a Pareto surface between transportation cost, transportation time, and carbon emission cost. It also can be seen that CF-AM-RNI-HH performs better than the other 2, and the Pareto solutions are evenly distributed in the whole solution space, basically presenting a relatively smooth Pareto surface. Moreover, its algorithm also takes the shortest time in the combination of the other HH algorithms and has a large advantage in computing time. GD-HH, as shown in Figure 13b, performs not as well as RNI-HH, and the algorithm's computing time is longer, so there is no advantage in computing time. Although the number of calls from the low-level heuristics is relatively rich, which could make full use of the advantage of HH algorithms, the result calculated by CF-GDA-GD-HH does not present a smooth Pareto surface in 3-dimensional space. At the same time, it can be seen that adding the goal of carbon emission cost into the model will limit the uniformity of the solution results in the solution space and also lay the foundation for the sensitivity analysis of carbon emissions in the next Section. In general, CF-LA-GD-HH and CF-AM-GD-HH basically form Pareto surfaces, but the solution results are limited to the local region of the solution space. Compared with CF-AM-RNI-HH, the smoothness and uniformity of the surfaces are poor. Moreover, because the mechanisms of GD-HH and IGD-HH are consistent, it can be seen that GD-HH and IGD-HH prefer to use AM and LA as acceptance criteria, and their algorithm effect is better than GDA. UD-HH, as shown in Figure 13d, CF-LA-UD-HH, CF-GDA-UD-HH, and CF-AM-UD-HH do not form smooth Pareto surfaces in the solution space, which means that UD-HH performs poorly. SSC-HH, as shown in Figure 13e, performs well, and basically forms a Pareto surface, and is evenly distributed in the whole solution space. In addition, it can be seen that CF-GDA-SSC-HH performs better than the other 2.

Therefore, when the performance of 15 HH algorithms is compared in terms of the algorithm's computing time, the number of calls from the low-level heuristics, and the performance of the algorithm solution, the following conclusions can be drawn:

- RNI-HH has the shortest algorithm time and CF-AM-RNI-HH performs best in the area of algorithm computing time;
- SSC-HH has a strong tendency to choose NAGA-II in the number of calls from the low-level heuristics;
- compared with GD-HH, IGD-HH, and UD-HH, RNI-HH and SSC-HH have better uniformity and consistency of solution results. Therefore, the solution calculated by RNI-HH is selected as the final solution.

From the solution calculated by RNI-HH, we extract 2 transportation solutions, as shown in Table 5. Solution I is to pursue the goal of minimizing transportation time, and Solution II is to pursue the goal of minimizing transporta-

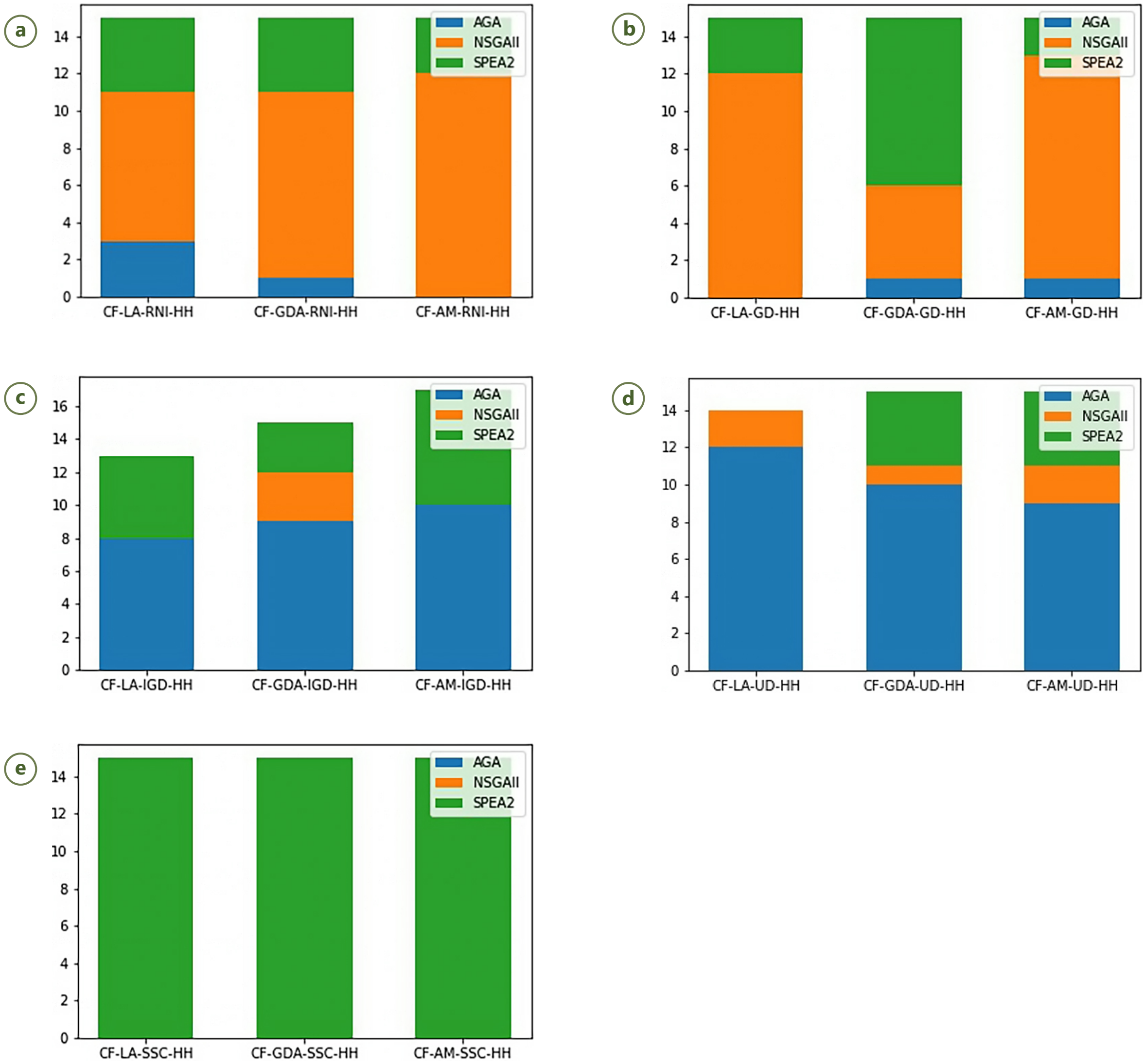

Figure 12. Number of calls from the low-level heuristics:
a – RNI-HH; b – GD-HH; c – IGD-HH; d – UD-HH; e – SSC-HH

Table 5. Comparison of the transportation solutions

Objective value	Minimize transportation cost	Minimize transportation time	Ratio
The total transportation cost [¥]	$1.049900 \cdot 10^{10}$	$1.053400 \cdot 10^{10}$	0.33%
The total transportation time [h]	$3.448115 \cdot 10^{6}$	$3.448079 \cdot 10^{6}$	–26 h
Carbon emission cost [¥]	$6.926000 \cdot 10^{5}$	$4.556900 \cdot 10^{5}$	–34%

tion cost. Therefore, if the focus of transportation enterprises is on the timeliness of transportation, the solution of minimizing transportation time is considered. The schematic diagram of Solution I transportation network is shown in Figure 14. If the focus of transportation enterprises is on the lowest transportation cost, then the solution of minimize transportation cost is considered. The schematic diagram of Solution II transportation network is shown in Figure 15. Combining Figure 14 and Figure 15, it can be concluded that the hinterland of Shanghai Port and Ningbo-Zhoushan Port are basically equal in scope. More specifically, the hinterland of Shanghai Port is in the upper part of the Yangtze River Delta region, mainly in Jiangsu and parts of Anhui. The hinterland of Ningbo-Zhoushan Port is in the lower part of the Yangtze River Delta region and Jiangxi. At the same time, we found that reasonable allocation of dryports and strengthening the cooperative relationship between dryports and hubports can effectively achieve healthy competition between ports, which plays a positive role in optimizing resource allocation.

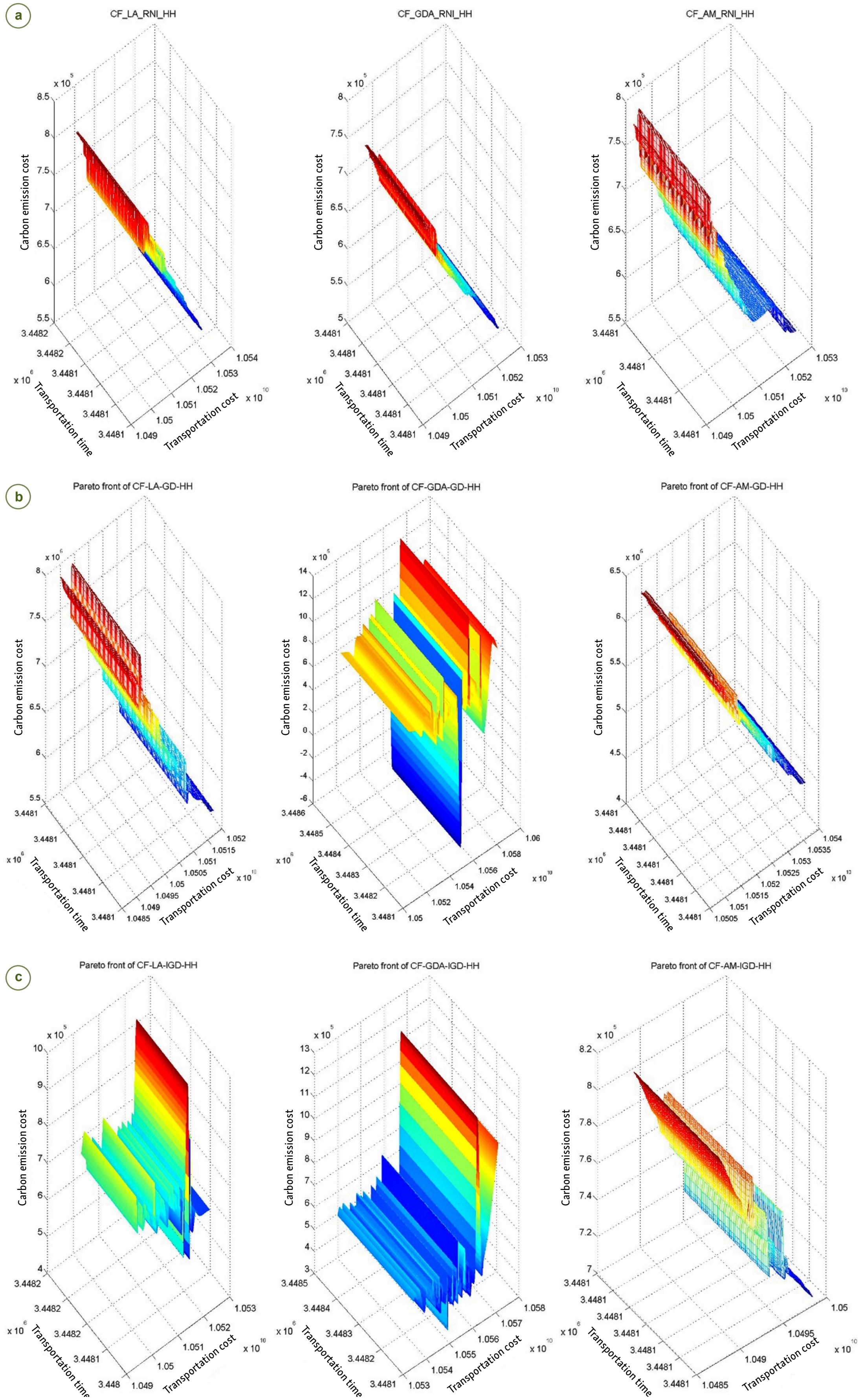

Figure 13. *Continued on the next page*

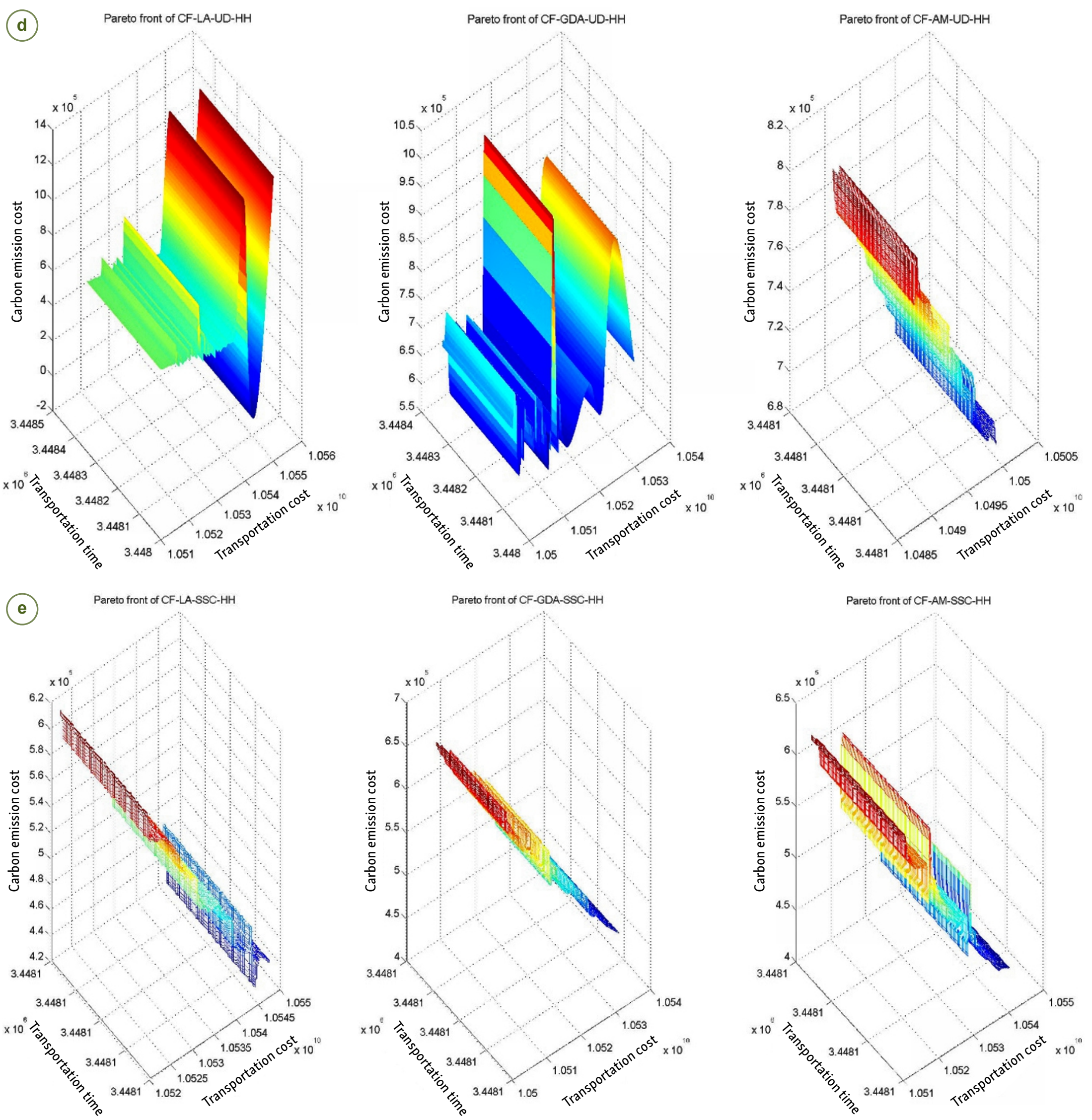

Figure 13. Comparison of Pareto solution of HH algorithms: (a) – RNI-HH; (b) – GD-HH; (c) – IGD-HH; (d) – UD-HH; (e) – SSC-HH

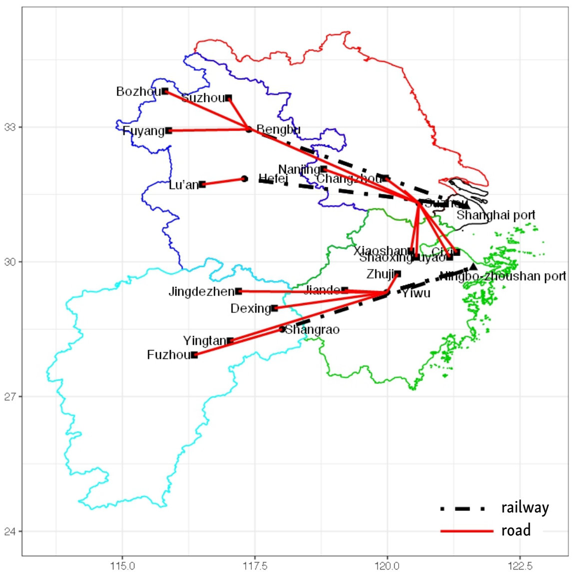

Figure 14. Solution I transportation network

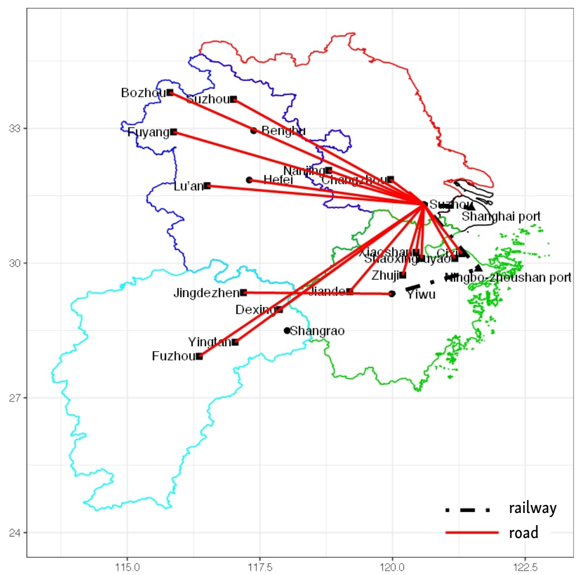

Figure 15. Solution II transportation network

5.4. Sensitivity analysis

From the result analysis in Section 5.3, after adding the carbon emission cost target into the model, the uniformity and richness of the solution result are reduced, which further affects the choice of transportation mode and transportation route. Therefore, in this Section, we do the sensitivity analysis of carbon quota and carbon trading price to evaluate the effects of the choice of transportation mode and transportation route, and CF-AM-RNI-HH, CF-LA-RNI-HH, and CF-GDA-RNI-HH are selected as the solution algorithms for sensitivity analysis based on the excellent performance of RNI-HH. Section 5.4.1 is the sensitivity analysis of carbon quota, and Section 5.4.2 is the sensitivity analysis of carbon trading price.

5.4.1. The sensitivity analysis of carbon quota

Within other parameters and data that remain unchanged, the average value of the Pareto optimal solution under different carbon quotas is calculated by changing the carbon quota amount to 0…18000 kg, as shown in Figure 16.

From Figure 16, it can be seen that with the increase in carbon quota, transportation time is basically consistent with the change trend of carbon emission cost, contrary to the change trend of transportation cost, which is consistent with the actual operation process, and the increase in carbon emission cost will increase the cost "burden" of government policy departments and transport enterprises, so as to encourage them to choose the road–rail multimodal transport mode with dryport as the main mode to achieve the purpose of reducing carbon emissions. In addition, the average value of the calculated Pareto optimal solution does not show a monotonous linear change with the gradual increase of carbon quota, which verifies from the side that the proposed HH algorithm still has a certain randomness, but at the same time gives the algorithm more space to dive into the solution space and explore the Pareto optimal solution. When the range of carbon quota is [0,18000] and the selected carbon quota is 10000 kg, the carbon emission cost reaches the lowest point, and the transportation time also reaches the lowest point, and the transportation cost only increases by 0.22%.

5.4.2. The sensitivity analysis of carbon trading price

The carbon price in China's carbon trading market has obvious differences and volatility between and within regions. According to the findings of ICF International Consulting company's (Slater *et al.* 2023), the actual price level of the national carbon market in 2022 is still very uncertain, but since last year's survey, the expected range for the same year has narrowed. Therefore, it is necessary to analyse the sensitivity of carbon trading prices (Tao, Wu 2021). Within other parameters and data that remain unchanged, the average value of the Pareto optimal solution under different carbon trading prices is calculated by changing the carbon trading price to 0…0.20 ¥/kg, as shown in Figure 17.

From Figure 17, it can be seen that the model is highly sensitive to the change in the carbon trading price. While other data remain unchanged, the carbon emission cost increases with the increase in carbon trading prices, forcing government policy departments and enterprises to consider the cost of carbon emissions in the whole transportation process and thus be more inclined to choose the road–rail multimodal transport mode. This is similar to the conclusions obtained by Lättilä *et al.* (2013) and Rosič

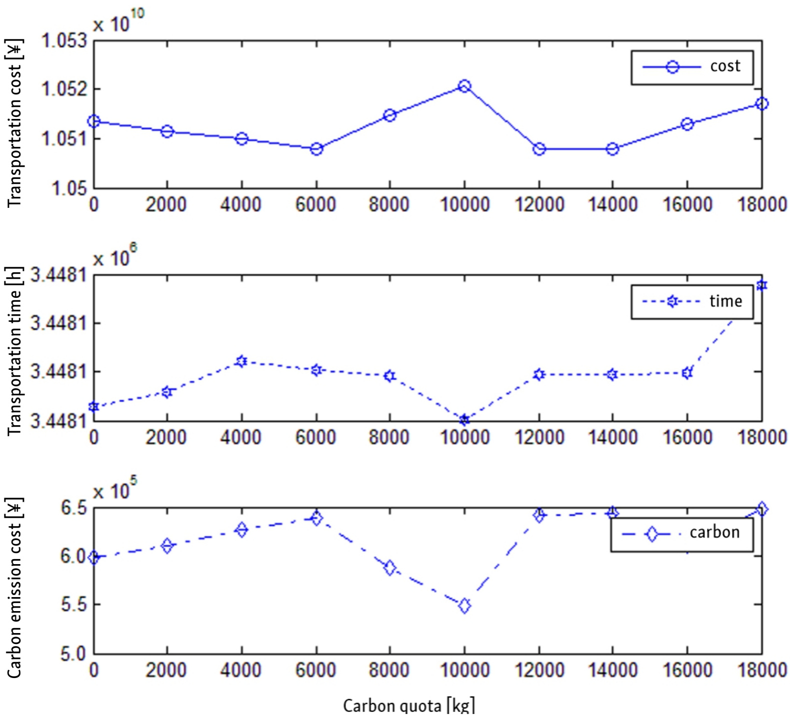

Figure 16. Sensitivity analysis of carbon quota

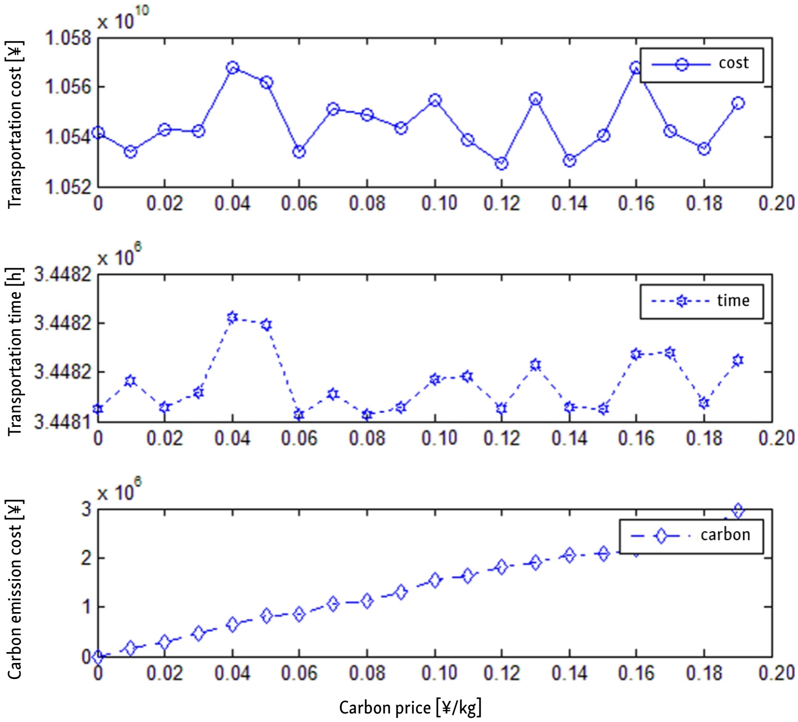

Figure 17. Sensitivity analysis of carbon trading price

& Jammernegg (2013). Additionally, it can also be seen that the change in transportation cost is only 0.38%, and the change in transportation time is not significant, only 0.002%. Therefore, we can speculate that the Pareto optimal solution has not changed, and adopting multimodal transportation can effectively reduce carbon emission costs and promote the low-carbon and sustainable development of port hinterland transportation networks.

6. Discussion

6.1. Discussions

By studying the optimization of the port hinterland transportation networks, it could be concluded that the port hinterland transportation mode helps optimize the transport structure and promotes the sustainable development of multimodal transport. At the same time, it's crucial to effectively achieve healthy competition between ports through the division of port hinterland transportation networks. The findings match those observed in earlier studies (Yin *et al.* 2021b; Guo *et al.* 2025).

In the proposed optimization model, 3 factors are considered: transportation cost, transportation time, and carbon emissions. The port hinterland transportation scheme that incorporates the impact of carbon emissions demonstrates significant improvements compared to other schemes. Specifically, the carbon emission cost from the minimize transportation time scheme was reduced by 34.2% compared to other transportation schemes. This reduction indicates that ports in the Yangtze Delta are actively transforming under China's "dual carbon" goals, with shore power facilities greening, multimodal transportation reloading facilities upgrading, and intelligent management being performed in an orderly manner. At the same time, China's "dual carbon" goals would encourage ports to prefer rail-based multimodal transportation for cargo transport. These efforts help reduce the carbon emission pressure of port hinterland transportation.

Based on the simulation results and sensitivity analysis results, adopting multimodal transportation can effectively reduce carbon emission costs and promote the low-carbon and sustainable development of port hinterland transportation network. At the same time, with the increase in carbon quota, transportation time is basically consistent with the change trend of carbon emission cost, contrary to the change trend of transportation cost, which is consistent with the actual operation process, and the increase in carbon emission cost will increase the cost "burden" of government policy departments and transport enterprises, so as to encourage them to choose the road–rail multimodal transport mode with dryport as the main mode to achieve the purpose of reducing carbon emissions.

6.2. Policy implications

Currently, the key to the improvement of transportation efficiency port hinterland transportation network of the Yangtze Delta is the connection of multimodal transport facilities, especially the entry rate of special port railway lines into the ports, which is lower than developed countries. For example, only the Nanjing, Suzhou, Nantong, and Zhenjiang ports in the Jiangsu Province are directly connected via railways to the main national transportation network. Simultaneously, the "last kilometre" issue of railway special lines entering ports is particularly prominent, with many problems needing urgent solutions due to land, environmental protection, and capital constraints (Yin *et al.* 2024). For example, Shanghai Yangshan Port still needs to trucks for short barge road transport from rail station to port. Additionally, the government should systematically plan the layout of port railway collection and distribution facilities to promote seamless integration of railroad lines and terminals, and realizing the integration of modern comprehensive transportation.

With the global climate change, more and more countries and regions begin to pay attention to carbon emissions. The transportation sector is one of the main sources of global carbon emissions, and green low-carbon transformation has become the top priority of its development. The carbon quota and carbon price measures mentioned in China's "dual carbon" policy can effectively promote the reduction of carbon emission and efficiency of the transportation industry. However, with the increase of carbon price, the carbon emission cost is gradually transferred to the port and transportation enterprises, which will undoubtedly increase the operating cost of enterprises. Therefore, the government decision-making departments could attract more transport enterprises to choose multimodal transport by formulating freight rate subsidy policies, so as to reduce carbon emissions in the field of transportation, optimize the transport structure and improve transport efficiency. For example, Yin *et al.* (2024) proposed the rail freight subsidy significantly contributes to the design of the low-carbon transportation network, and suggested the government has introduced railway freight subsidy policies to guide the transformation of transport structures towards low-carbon alternatives.

Finally, the model and HH algorithm are universal and applicable to different regions. The Yangtze River Delta region is one of the regions with the most active economic development, the highest degree of openness, and the strongest innovation capacity in China, and has great transportation location conditions. So, when other regions better apply this model and HH algorithm, fully consider the regional transportation infrastructure, economic development level and production innovation capacity.

7. Conclusions and future research

7.1. Conclusions

This study aimed to efficiently divide the hubport hinterland, optimize the transportation network, and promote benign competition among hubports. We constructed a multi-objective mixed integer linear programming model for the design of a port hinterland transportation network, considering cost, time, and carbon emissions. A novel HH algorithm is proposed to solve the model. The conclusions are as follows:

The dryport, as one of the tools to extend the scale of hinterland (Qiu *et al.* 2015), could reasonably allocate transportation resources and reduce carbon emissions. The model proposed in this study is universal and can provide decision-making recommendations for the government and port strategic departments to divide the hinterland areas among hubports, optimize the allocation of transportation resources, and promote the low-carbon and sustainable development of regional transportation systems (Yin *et al.* 2025).

A novel HH algorithm is proposed and compared with the traditional heuristic algorithm NSGA-II. The HH algorithm does not have an advantage in terms of time consumption. However, despite the HH algorithm having some randomness, the overall Pareto solution is better than that of NSGA-II. Meanwhile, we found that there are different degrees of preference among the high-level move acceptances, performance evaluation criteria, and the low-level heuristics of the HH algorithm. For example, SSC-HH has a strong preference for NSGA-II in the calls of the low-level heuristics. The performance of 15 HH algorithms is compared in terms of the algorithm's computing time, the number of calls from the low-level heuristics, and the performance of the algorithm solution, the solution calculated by RNI-HH is selected as the final solution. In addition, HH algorithms have good portability and generality, which allows researchers to focus solely on a variety of computational optimization problems, especially multi-objective optimization problems.

It can be concluded that the result can effectively achieve healthy competition between ports. In addition, the solution obtained by pursuing the shortest transportation time can effectively reduce the carbon emissions of the entire transport network compared with the solution obtained by pursuing the minimum transportation cost, and the carbon emission reduction effect reaches 34.2%, and the increase in transportation cost is not significant. It provides a novel idea for the government and port strategic departments to carry out the optimization design of the port hinterland transport network in the future.

This study also highlights the impact of carbon quota and carbon trading price on hinterland division and transportation network optimization of hubport hinterland. With the increase in carbon quota, transportation time is basically consistent with the change in carbon emission cost, contrary to the change in transportation cost. When the range of the carbon quota is [0,18000] and the selected carbon quota is 10,000 kg, the carbon emission cost and transportation time simultaneously reach their lowest point. When the range of the carbon trading price is 0...0.20 ¥/kg, the carbon emission cost increases with the increase of the carbon trading price. Therefore, the carbon trading price has a significant impact on the optimization of the port hinterland transport network. In the future, we can set the basic carbon quota and focus on the carbon trading price to promote the low-carbon and sustainable development of the port hinterland transportation network.

7.2. Limitations and future research

Regardless of these implications, several limitations should also be noted:

- the model constructed in this article only considers direct road transportation and road–rail multimodal transportation, several multimodal transport schemes such as road-water, water-rail, and air transport between the hubport hinterland can be considered to further explore feasibility of transportation;
- in the future, we can collect more freight volume data from hubports, dryports, and hinterland cities, expand the scope of the research area, and radiate more hinterlands through the location of dryports;
- as the carbon trading mechanism in China is still in the early stages of development, the regulatory landscape can vary significantly across different regions, and there is a lack of a unified management system, resulting in limited access to carbon emission data, which inevitably leads to a certain gap between the research results and the actual situation;
- the proposed model still has some limitations, stochastic or robust optimization techniques could be added the model to strengthen its universality and stability, such as ellipsoidal uncertainty can be added to simulate the uncertain conditions;
- the proposed HH algorithm still has some improvement; such as reinforcement learning mechanism or the activation function of the neural network can be added to the high-level selection strategy, such as sigmoid function.

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Author contributions

Daofeng Zhong: methodology, software, visualization.

Chuanzhong Yin: conceptualization, methodology, writing (original draft), funding acquisition.

Ying-En Ge: conceptualization, writing (review and editing).

Zi-Ang Zhang: conceptualization, writing (original draft).

Shiyuan Zheng: conceptualization, supervision.

Disclosure statement

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Declaration on the use of Artificial Intelligence (AI)

During the preparation of this work, the authors confirm that no Artificial Intelligence (AI) tools or Large Language Models (LLMs) were used in any aspect of this work, including but not limited to study design, data collection and analysis, result interpretation, manuscript writing, figure generation, or coding.

All content is the original work of the authors, and we take full responsibility for the integrity and accuracy of the presented data.

Appendix. Basic data

The city node data are shown in Table A1. The inter-nodal distances and freight rates are shown in Tables A2–A5. The storage and transfer prices at the dryports are shown in A6. The carbon emission data of dryports and seaports is shown in Table A7. The carbon emission data of transportation are shown in Table 8 and the carbon quota and carbon trading price is shown in Table A9.

Random data are used for the freight volume in the hinterland. Carbon emission data are gathered from different literatures (Qiu, Lam 2018; Tsao, Linh 2018; Tao, Wu 2021), and the results of carbon emissions per unit freight turnover and carbon emissions per unit transfer of different transport modes are shown in Table A8.

At present, the carbon trading market of various provinces and cities in China lacks objective data to determine the carbon quota of multimodal transport enterprises (Zhang *et al*. 2025, 2026b). Since railway transportation has significant advantages such as low energy consumption and less pollution, it is the leading direction of future transportation structure optimization (Zhang *et al*. 2026a). Therefore, the carbon emission data of 20 ft container railway transport are now used as the basis for carbon quota allocation, and the carbon quota is set at 4000 kg.

According to the findings by ICF International Consulting company (Slater *et al*. 2023), the average carbon price in the national carbon market is expected to be 59 ¥/t in 2022, and will rise to 87 ¥/t in 2025 and 130 ¥/t before 2030 (Zhang *et al*. 2026c). While there remains considerable uncertainty about the actual price level, the range of expectations for the same year has narrowed since last year's survey. Prices in the 20…80th percentile range increased from 49…60 ¥/t in 2022 to 58…180 ¥/t in 2030. Therefore, based on the forecast results of the above carbon trading price, the carbon trading price is set at 50 ¥/t or 0.05 ¥/kg.

In summary, the data of carbon quota and carbon trading price are shown in Table A9.

Table A1. City data

Type	City
Hinterlands	Nanjing, Suzhou (Jiangsu), Wuxi, Changzhou, Hefei, Lu'an, Fuyang, Bozhou, Suzhou (Anhui), Xiaoshan, Cixi, Zhuji, Shaoxing, Yuyao, Jiande, Yiwu, Fuzhou, Yingtan, Dexing, Jingdezhen
Dryports	Shangrao, Hefei, Suzhou (Jiangsu), Bengbu, Yiwu
Hubports	Ningbo-Zhoushan Port, Shanghai Port

Table A2. Road transport cost from hinterlands to dryports and hubports [¥/t]

City	Dryports					Hubports	
	Shangrao	Hefei	Suzhou (Jiangsu)	Bengbu	Yiwu	Ningbo-Zhoushan Port	Shanghai Port
Nanjing	338	120	186	132	222	229	176
Suzhou (Jiangsu)	284	214	233	219	167	174	93
Wuxi	303	198	219	203	182	189	100
Changzhou	293	180	216	185	191	198	122
Hefei	263	0	229	113	274	280	145
Lu'an	288	70	218	146	299	305	167
Fuyang	335	188	223	121	348	354	199
Bozhou	368	209	137	147	361	370	215
Suzhou (Anhui)	272	155	131	80	329	328	175
Xiaoshan	190	238	316	248	89	104	128
Cixi	235	272	292	279	138	55	166
Zhuji	171	253	333	274	89	132	149
Shaoxing	209	248	299	274	89	89	135
Yuyao	231	266	322	282	125	52	159
Jiande	131	281	336	290	91	169	203
Yiwu	153	274	323	291	0	124	169
Fuzhou	129	269	374	318	228	310	322
Yingtan	84	286	354	297	193	281	294
Dexing	79	226	337	278	169	245	260
Jingdezhen	159	238	378	262	194	262	282

Source: *https://www.deppon.com/price?source=&menu=PRICE* (in Chinese), set 1 TEU = 20 t.

Table A3. Road transport distance from hinterlands to dryports and hubports [km]

City	Dryports					Hubports	
	Shangrao	Hefei	Suzhou (Jiangsu)	Bengbu	Yiwu	Ningbo-Zhoushan Port	Shanghai Port
Nanjing	543.4	172.5	214.1	205.9	410.8	480.8	369.8
Suzhou (Jiangsu)	492.0	381.9	0.0	401.8	268.2	274.2	164.6
Wuxi	535.4	353.4	42.3	373.3	311.6	317.7	203.1
Changzhou	542.2	312.8	91.6	315.2	345.7	359.6	247.3
Hefei	524.3	0.0	381.3	151.8	533.4	632.3	536.6
Lu'an	547.9	74.9	465	194.9	617.2	716.0	620.4
Fuyang	684.5	217.5	541.8	193.9	748.8	809.8	697.9
Bozhou	789.7	322.7	613.5	236.3	820.7	881.5	769.3
Suzhou (Anhui)	760.0	237.6	484.2	107.1	691.4	752.3	639.9
Xiaoshan	333.9	425.5	167.4	488.4	118.2	196.5	205.6
Cixi	436.1	537.4	179.8	574.1	201.2	110.2	176.6
Zhuji	294.4	484.7	220.2	576.8	55.2	212.4	249.3
Shaoxing	354.5	467.8	180.2	531.5	120.5	166.6	203.5
Yuyao	415.1	518.5	196.8	582.3	180.2	103.9	220.0
Jiande	200.7	498.1	293.3	605.1	135.8	336.4	345.5
Yiwu	255.1	532.5	268.0	608.0	0.0	235.8	307.5
Fuzhou	208.2	537.4	693.3	682	453	681.9	744.6
Yingtan	103.7	471.8	588.8	616.4	348.4	577.4	640.1
Dexing	104.6	466.6	499	611.2	287.8	516.7	542.0
Jingdezhen	206.8	337.8	525.6	482.4	335.1	564.1	578.6

Source: *https://map.baidu.com* (in Chinese).

Table A4. Railway transport cost between dryport and hubport [¥/TEU]

City	Shangrao	Hefei	Suzhou (Jiangsu)	Bengbu	Yiwu
Ningbo-Zhoushan Port	2337.0	2836.2	2219.5	3540.7	1662.6
Shanghai Port	2703.8	2875.5	1086.1	2534.6	1826.9

Source: *http://www.95306.cn* (in Chinese).

Table A5. Railway transport distance between dryport and hubport [km]

City	Shangrao	Hefei	Suzhou (Jiangsu)	Bengbu	Yiwu
Ningbo-Zhoushan Port	555	616	398	586	264
Shanghai Port	557	468	84	485	312

Source: *http://www.95306.cn* (in Chinese).

Table A6. Dryport storage and transfer prices (Wei, Dong 2019) [¥/TEU]

Storage price	Transfer price
2600	3500

Table A7. Storage of carbon emission data in dry and seaports (Tsao, Linh 2018) [m^3/month]

Dryport	Seaport
10000	1000

Table A8. Carbon emission data for transport and transfer [kg]

Transportation mode	Carbon emissions per unit of freight turnover [kg·(TEU·km)$^{-1}$]	Transfer mode	Carbon emissions per unit transfer operation [kg·TEU^{-1}]
Rail	0.109	rail–road	2.819
Road	0.631	rail–water	2.685
Water	0.260	road–water	2.685

Table A9. Data of carbon quota and carbon trading price

Carbon quota	Carbon trading
4000 kg price	0.05 ¥/kg

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