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A Novel Virtual Arrival Optimization Method for Traffic Organization Scenarios

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Abstract: The International Maritime Organization (IMO) has been progressively implementing stricter regulations on ship carbon emissions, leading to many vessels adopting the virtual arrival (VA) method to reduce their carbon footprint. However, the effectiveness of the traditional VA method often varies in busy ports with complex traffic organization scenarios. To address this, our study presents a novel, comprehensive model that integrates vessel scheduling with the VA approach. This model is designed to achieve a dual objective: reducing carbon emissions through virtual arrival while simultaneously minimizing vessel waiting times. In addition to these goals, it incorporates essential aspects of safety, efficiency, and fairness in port management, utilizing the NSGA-2 algorithm to find optimal solutions. This model has been tested and validated through a case study at Ningbo-Zhoushan port, employing its dataset. The results demonstrate that our innovative model and algorithm significantly outperform traditional scheduling methods, such as First-Come-First-Serve (FCFS) and Virtual-Arrival Last-Serve (VALS), particularly in terms of operational efficiency and reduction in vessel carbon emissions.

Keywords: virtual arrival; traffic organization; carbon emission reduction; waiting time; multi-objective optimization

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1. Introduction

Sea-going trade contributes approximately 2.9% of global CO_2 emissions. Mitigating greenhouse gas emissions (GHG) from the international shipping industry constitutes a prominent and multifaceted challenge within both business and policy domains. This critical issue stands as a focal point in contemporary research endeavors [1–3]. The International Maritime Organization (IMO) has set ambitious targets to reduce emissions from sea-going vessels by 50% in 2050 compared to 2008, with a gradual decline in emissions from 2030 onwards [4,5]. To achieve the emission reduction goals set by the IMO and mitigate environmental impacts, it is imperative to reduce vessel emissions. Current research [6–10] suggests that significant potential exists for emission reductions by improving navigational efficiency (traveling at the minimum speed necessary). Reducing carbon emissions from vessels and minimizing the waiting time at busy ports not only contributes to environmental amelioration but also yields manifold economic benefits. By embracing more environmentally friendly ship designs and clean energy sources, we can effectively curtail carbon emissions, address climate change, and enhance air quality. Furthermore, the reduction in port waiting times not only enhances the efficiency of maritime transportation, thereby reducing fuel and maintenance costs, but also facilitates trade circulation, thereby elevating the economic competitiveness of both ports and nations.

Generally, a ship's fuel consumption is linearly related to the third or fourth power of its speed. Currently, ships tend to travel to ports at a higher speed and have to wait at anchor, which increases fuel consumption and carbon emissions both when sailing in the sea near the port and during the waiting period of the ship. One promising approach is virtual arrival (VA), which is used in maritime operations to reduce carbon emissions and improve efficiency in shipping. VA allows vessels to adjust their speed during voyages to meet a required time of arrival at their destination, considering known delays at the port. VA can reduce average sailing speeds by utilizing the time spent waiting to berth as extra sailing time. Thus, speed optimization can lower fuel consumption and CO_2 emissions. It was estimated that around 15% of the total emissions of vessels are produced during port visits [11].

Central to this method is sophisticated communication and planned coordination, enabling ships to adjust their speed according to the latest port availability updates. In contrast to the traditional approach, where ships maintain their speed and subsequently wait at the port, VA dictates a reduction in speed during transit, synchronizing the ship's arrival with the availability of a berth. This strategy reduces the time ships spend idling and waiting, leading to operational cost savings, and substantially decreases fuel consumption, thereby contributing to a reduction in carbon emissions. However, the success of this method relies heavily on the precision of the information received and the effective coordination among various maritime stakeholders. This can present challenges, especially in scenarios with stringent schedules. Consequently, while the VA method has emerged as a critical strategy in the maritime industry for its potential to optimize operational efficiency and environmental sustainability, its implementation and effectiveness can vary depending on the specific logistical circumstances.

At some mega ports like Ningbo-Zhoushan, the effectiveness of the VA method is further shaped by a diverse set of factors, extending well beyond the simple availability of berths. These factors encompass pilotage requirements, the accessibility of deepwater channels, and the intricacies of port traffic organization. For example, deepwater channels, essential for larger vessels, are often constrained by both natural conditions and existing traffic, requiring detailed timing and coordination. To enhance the operational efficiency of such ports, traffic organization is usually adopted, designed to coordinate vessel movements through the Vessel Traffic Service (VTS). Such a multifaceted environment poses significant challenges to the VA method, as it introduces additional variables that may impact the optimal speed adjustments for incoming vessels. Given these intricate conditions, there is a pressing need for further research on the VA method in the context of traffic organization at busy ports, focusing on a specialized optimization method for vessel entry scheduling to ensure that the VA method remains effective in optimizing efficiency and reducing environmental impact under traffic organization scenarios.

Given the research gaps and challenges outlined, this paper aims to explore and propose an advanced VA optimization method in the traffic organization scenarios of the core port area of Ningbo-Zhoushan. To achieve this, we have developed a sophisticated mathematical model that considers a range of factors, such as channel navigation rules, tidal resources, and other important constraints. Non-dominated Sorting Genetic Algorithm II (NSGA-2) is employed to solve complex mathematical problems, resulting in the optimal vessel service order.

The rest of this paper is organized as follows: In Section 2, a review of the literature related to traffic organization optimization and VA is provided. Section 3 describes and analyzes the studied problem, along with an explanation of the relevant factors. In Section 4, a mathematical optimization model is constructed, considering complex navigation rules and channel constraints. Section 5 introduces a heuristic algorithm that has been proposed for solving the model. In Section 6, actual inbound data from the core port area of Ningbo-Zhoushan is utilized to build a specific model and conduct a case study. The model is then compared with other models, such as First-Come-First-Served (FSFC), to validate its effectiveness under different scenarios. Section 7 ends the study with a conclusion and future work.

2. Literature Review

2.1. Virtual Arrival

VA differs from scheduled voyages in that its purpose is not to reserve berthing time in advance but only to adjust speed in response to known delays to avoid ships waiting at anchor in advance. Firstly, as VA only minimizes the time spent at anchor before berthing by slowing down the sailing speed, transport capacity is not affected; secondly, because the total voyage time remains the same, cargo in-transit inventory costs will not increase as in the case of slow-steaming [12]. In addition, VA has lower investment costs and is easier to implement compared to other technologies aimed at reducing the carbon intensity of ship operations [13,14].The fuel-saving potential of VA has been analyzed in several studies. Alvarez et al. [15] used a simulation model where berth allocation, land-side equipment assignment, and speed optimization were considered; their results suggest that the VA can reduce fuel consumption by about 6% compared to the traditional FCFS policy. Johnson and Styhre et al. [16] conducted a case study in which they analyzed the effect of VA on two 5000 gross tonnage ships in short-sea shipping. They combined interviews with Statement of Facts data to quantify the total waiting time during port calls for the two ships. Through interviews, three "likely scenarios" were developed, estimating the potential reduction in port call duration hours achieved by adopting slower sailing speeds. The findings revealed a fuel reduction ranging from 2% to 8%, contingent on the chosen scenario. These estimates were derived from ship-specific operational and design specifications, enhancing the credibility of the results with empirical data from the case study. However, the methodology and sample size limit the generalizability of the results.

In a study by Jia et al. [8], 5066 worldwide reductions in fuel consumption and emissions were empirically assessed for a fleet of 483 VLCCs between 2013 and 2015 using Automatic Identification System (AIS) vessel position data, which was based on the potential reduction in fuel consumption and emissions from the implementation of a virtual arrival policy. The average sailing speed was reduced by using non-productive waiting time at the destination port, assuming that the vessel speed could be adjusted throughout the voyage. Their results show that fuel savings depend on how much unnecessary waiting time can be utilized while sailing, with 7.26% fuel savings if waiting time is reduced by 25% and 19% fuel savings if all waiting time is eliminated.

Andersson and Ivehammar et al. [17] conducted a study using AIS data from Baltic Sea countries to estimate the impact of the VA strategy and compare it with traditional methods that involve significant waiting times. In analyzing speed reduction scenarios, they assumed possible reductions of 5%, 10%, 25%, and 50%. Additionally, they considered situations where ships could reduce speed 1, 4, 12, and 24 h before their estimated arrival time. According to their research findings, if vessels reduce speed by 5% 12 h before arrival, it could lead to annual fuel savings of 4826 tons and 15,106 tons of carbon dioxide emissions.

Merkel et al. [12] estimated the actual time spent by the ship at anchor waiting to berth. Secondly, speed-related elasticities are applied to estimate the speed/fuel function at different speeds to assess the potential for fuel savings from VA measures compared to when waiting at anchor to sail. Using data from Swedish ports as an example, the potential for fuel reduction (savings as a share of total voyage consumption) is considered to be about 4.7–4.12% when speed is reduced 1–7 h prior to planned arrival.

Based on the research above, the abatement potential of a virtual arrival vessel depends primarily on:

- The extent to which vessels can reduce their speed.
- How far in advance of the estimated arrival time do vessels receive reliable information.

2.2. Vessel Traffic Optimization

Vessel traffic optimization refers to organizing a large number of vessels to enter and leave the canal in an orderly manner within a given period of time so that waiting time is shorter, thus reducing vessel delays and improving the efficiency of vessel traffic. The target of the traffic organization is all the ships of different types and sizes that pass through the canal every day, some of which enter the port via the canal from the outer sea or outer anchorage [18–21].

Lübbecke et al. [22] studied the vessel traffic control problem in the Kiel Canal, considering constraints such as channel environment and safety intervals to minimize the total vessel waiting time and navigation rules, and constructed a heuristic combination algorithm to solve the traffic problem in an optimization study of vessel traffic organization. Zhang et al. [23] developed a mixed integer linear programming (MILP) model to improve ship transport efficiency with the shortest total waiting time as the optimization objective while considering the constraints of navigation rules and safety intervals. A heuristic algorithm combined with a simulated annealing algorithm and a genetic algorithm is also used to solve the port-ship transportation scheduling model. Zhang and Zheng et al. [24] developed an optimization model for traffic organization considering tides, aiming to achieve the shortest total vessel waiting time. The model considers constraints such as tidal time windows and navigation rules, and the results show that the scheduling is more efficient than other strategies, including first-come, first-served (FCFS) and random scheduling. Liu et al. [25] proposed a MILP model for one-way channel vessel scheduling in ports. The model aims to reduce the weighted dwell time of all vessels, considering constraints such as berths, navigation rules, and tidal time windows. An adaptive large neighborhood search algorithm is constructed to solve the model.

Studies of vessel scheduling have primarily focused on improving the traffic efficiency of ships in waterways; the constraints of the studies are time slot allocation, tide [7,26,27], berth [28], vessel speed, traffic conflict, and capacity of sidings. However, there is a significant gap in the literature when it comes to integrating the ship emissions problem with ship scheduling optimization. Recent studies have shown that incorporating ship emissions reduction into the scheduling process can yield a comprehensive and effective ship emission reduction method. For instance, Jiang et al. [29] considered the complex problem of vessel scheduling in a restricted channel, the berth allocation problem, and a combined model that considers carbon emissions and proposed an adaptive, double-population, multi-objective genetic algorithm (NSGA-II-DP) to calculate the mathematical model. Xia et al. [30] propose a ship scheduling with speed reduction (SCR) model aimed at optimizing ship arrival sequences and reducing ship speeds to achieve the objectives of reducing the total scheduling time and carbon emissions of ships in port. Through a series of experiments based on accurate port data, they have validated the effectiveness of this novel ship emission reduction method, which can lead to a reduction in ship emissions of 8.0% to 11.9% and an improvement in traffic efficiency of 3.8% to 6.2%.

However, as mentioned in the previous section, the speed reduction of vessels may affect their voyage planning. It leads to an increase in the inventory cost of the ships compared to the VA. Therefore, this paper summarizes the emission reduction measures for VA and establishes a new method for reducing vessel emissions in ports by combining it with the traffic organization problem.

3. Problem Description

In studies on the optimization of the entry sequence, the FCFS criterion is usually applied, in which vessels entering the port area earlier are given priority to cross the channel reporting line over those entering later. However, in the process of vessel traffic organization, there is a virtual arrival of the vessel that has been expected to arrive but has not yet actually entered the port state of the vessel. A rudimentary example is used to illustrate the existence of the solution set under the optimization model. Traffic organization is actually the coordination of the timing and sequence of the passage of two types of ships approaching the port through the reporting line, as shown in Figure 1. Nonetheless, as the number of vessels increases, it can be inferred from the knowledge of permutations that the number of inbound orders will continue to grow. By considering factors such as reporting line time and speed, there are increased possibilities for effective vessel traffic organization.

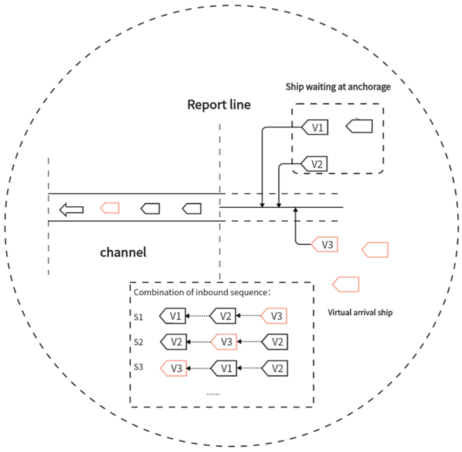


Figure 1. Diagram of inbound ship traffic organization through channel (V1, V2 represent ship waiting at anchorage; V3 represents virtual arrival ship; S1–S3 represent the inbound sequence).

The primary focus of this study is to ascertain how to determine the necessity for virtual arrival and the waiting time for two types of vessels in the anchorage area to enter the port. This includes optimizing the speed of the virtual arrival vessel in accordance with the entry time window.

The FCFS principle can lead to problems in certain scenarios as the depth of the channel varies over time. To ensure safe passage through tidal waterways, vessels with large draughts often rely on the tide. A precise calculation of time windows for each vessel is imperative to determining their safe passage. Safety is ensured by maintaining a certain distance between successive ships, which can be converted from space to time to create a safe time interval. Optimal traffic organization involves coordinating the sequence and start time of vessel entries to match the tidal time windows. Furthermore, this study assumes that the virtual arrival vessel is able to change its speed immediately after obtaining the order of traffic organization.

In summary, the following factors should be considered in our model:

- Vessel speed limit.
- Port navigation rules.
- Safe time intervals for ensuring navigation safety.
- The tidal time window of large vessels.

4. Methodology

4.1. Vessel Fuel Consumption Calculation

Fuel consumption is influenced by various factors, including engine type, ship design and size, sailing resistance, and navigation conditions [31]. The Admiralty formula is used to determine the specific fuel consumption per unit of time shown in Equation (1).

$$F_i = \left(\frac{v_i}{v_{d,i}}\right)^m \times \left(\frac{r_i}{r_{d,i}}\right)^n \times F_{d,i} \tag{1}$$

where F_i is the hourly propulsive fuel demand of the vessel i while sailing at the current speed v_i; $v_{d,i}$ is the design speed for the vessel i; r_i/r_d is the current to maximum draft ratio; $F_{d,i}$ is the fuel consumption under standard conditions. The parameter m is set to 3, and the parameter n is set to 2/3 [12,32].

4.2. Modeling Approach for Implementation of VA

A counterfactual 'pseudo' speed is constructed for VA vessels, representing the speed at which the vessel could have sailed to avoid waiting at anchor. The basic formulation of the pseudo-speed for vessel i is given in Equation (2):

$$v_i' = \max[D_i/(t_{0,i} + \Delta t_i), v_{\min,i}] \tag{2}$$

where v_i' represents the counterfactual pseudo speed for the vessel i; represents the sailing distance between the vessel's position when speed optimization can begin; the port of call, $t_{0,i}$ represents the original sailing time to port at the time when speed optimization can begin; Δt_i represents the time spent by the vessel at anchor; and $v_{\min,i}$ represents a lower bound with a minimum threshold beyond which speed reduction does not generate fuel savings. The expression thus shows the speed that would be required for a vessel to eliminate.

Based on the vessel's initial sailing speed in the traffic organization and the calculated virtual arrival speed, the difference in expected fuel consumption resulting from speed adjustments can be estimated. To achieve this estimation, the main engine fuel consumption is computed at both speeds during the period from speed adjustment to arrival, as shown in Equation (3).

$$\Delta F_i = B_i \times v_i^3 \times t_0 - B_i \times v_i'^3 \times \frac{D_i}{(t_{0,i} + \Delta t_i)} \tag{3}$$

where $v_i' <= v_i$; B_i is fixed parameters for fuel consumption of different vessels i.

To calculate the potential decrease in CO_2 emissions, we can utilize the fuel savings calculation while also taking into consideration the emission factor (EF). The EF is a representation of the amount of CO_2 released for each kilogram of fuel that is consumed. By factoring in the type of fuel utilized by the vessel, we can accurately determine the potential CO_2 reduction in Equation (4):

$$\Delta E_i = \Delta F_i \times EF \tag{4}$$

4.3. Model Assumptions

The organization of vessel traffic in waterways involves multiple departments and resources. At the same time, many factors affect the passage of ships through waterways. Based on a comprehensive analysis of the mechanisms of traffic organization in multiple waterways, critical common factors are extracted, and some other special factors are simplified. To facilitate this study, the proposed model has the following assumptions:

(1) Berths, anchorages, and loading and unloading equipment are not considered.
(2) The ship traffic organization studied in this article does not consider wind, visibility, and flow
(3) The virtual arrival ship meets a speed greater than the average speed of incoming ships by 10 knots, and the distance to the port is more than 100 nautical miles.
(4) The virtual arriving vessel starts to optimize the sailing speed immediately after learning the traffic organization scheme.

4.4. Mathematical Model

The model's primary goal is to optimize the efficiency of port operations for all vessels presently engaged, ensuring their tasks are completed swiftly and effectively. Simultaneously, it places a strong emphasis on minimizing carbon emissions to the lowest feasible level by reducing the speed of virtual arriving vessels. This objective is pursued while meticulously taking into account critical factors such as the strategic spacing between adjacent vessels, adherence to safe sailing speeds, and the consideration of each vessel's draft. We simplify the planning time by discretizing it into equal periods. The length of each period is determined as the maximum common unit time for the relevant operation duration. This approach allows us to represent various arrival times in a standardized manner, streamlining the planning process. Variable and parameter settings can be seen in the table below (Table 1).

Table 1. Notations and descriptions.

Notation	Description
n:	the number of incoming ships that need to be dispatched at the current stage;
I:	set of all inbound ships, we use the index $i \in I = \{1 : n\}$;
l_i:	the length of the vessel i;
r_i:	the draft depth of the vessel i;
T_{ai}:	the estimated arrival time of the vessel i;
$T_{safetyi}$:	the safety time interval between the vessel and the preceding vessel;
d:	the distance of the vessel from the anchorage to the waterway;
v_i:	the average speed of the vessel i;
D_i:	the distance between the vessel i and the port when adjusting its speed;
B_i:	the fixed parameters for fuel consumption of different vessel i;
$V_{adjusti}$:	the adjust speed of the VA vessel i;
CL:	the length of the waterway;
Cd:	the original depth of the waterway;
$TH_{(t)}$:	the tidal height considering time;
SWD_i:	the surplus water depth of the vessel;
Io_i :	if the vessel i is a virtual arrival vessel, it is 1. Otherwise, it is 0.
T_{starti}:	the start of vessel dispatch time (from the time of entering the port from the outer anchorage);
T_{starti}:	the start of vessel dispatch time (from the time of entering the port from the outer anchorage);
T_{ini}/T_{outi}:	the time when the vessel arrives at the beginning and end of the waterway;
$A_{ii'}$:	the entry and exit sequence of vessel i and vessel $i\prime$, where$A_{ii'} = 1$ indicates that ship i is scheduled before vessel $i\prime$, and $A_{ii'}$ = 0 indicates that vessel i is scheduled after vessel

The mathematical model of vessel optimal scheduling is as follows:

$$Max\ E = \sum_{i \in I} \Delta F_i \times EF \tag{5}$$

$$Min\ T = \sum_{i \in I} (T_{start,i} - T_{ai}) \tag{6}$$

$$\Delta F_i = Io_i \times (B_i \times (\frac{D_i}{T_{ai}})^3 \times T_{ai} - B_i \times (V_{adjusti})^3 \times (T_{starti})), \forall i \in n \tag{7}$$

$$V_{adjust,i} = Io_i \times \max(D_i/T_{starti}, V_{\min}), \forall i \in n \tag{8}$$

$$T_{starti} \geq T_{ai}, \forall i \in I \tag{9}$$

$$T_{safetyi} = 6 \times l_i/v_i, \forall i \in I \tag{10}$$

$$T_{ini} = T_{start,i} + d/v_i \tag{11}$$

$$T_{outi} = T_{ini} + CL/v_i \tag{12}$$

$$M \times (1 - A_{ii'}) + T_{ini'} - T_{ini} \geq T_{safetyi}, \forall i \in I \tag{13}$$

$$Cd + TH_{(t)} = CD_{(t)} \tag{14}$$

$$r_i + SWD_i \leq CD_{(T_{ini})} \tag{15}$$

$$r_i + SWD_i \leq CD_{(T_{outi})} \tag{16}$$

$$r_i + SWD_i \leq \min CD_{(T_{inii}, T_{outi})} \tag{17}$$

$$A_{ii'} + A_{i'i} = 1, \forall i, i' \in I \tag{18}$$

$$A_{ii'} \in \{0,1\}, \forall i \in I \tag{19}$$

Equation (5) represents the maximization of the total reduction of carbon emissions from vessels; Equation (6) represents the minimization of the total waiting time for all vessels; Equation (7) represents the reduction of carbon emissions from ships; Equation (8) represents the speed limit for virtual arrival to ensure safe navigation of ships in port; Equation (9) ensures that the vessel dispatch time is greater than the expected arrival time; Equation (10) represents the safe time interval between the two vessels entering the port; Equation (11) indicates the time when the ship enters the waterway (reporting line); Equation (12) indicates the time when the ship leaves the waterway; Equation (13) represents the actual water depth of the channel considering the T time of the tide, used to calculate whether the water depth of the channel meets the requirements for safe navigation of ships during navigation, avoiding grounding. Equation (14) denotes that the depth of the channel meets the requirements for vessel navigation, considering the safety margin when the vessel enters the channel; Equations (15) and (16) ensure that the depth of the channel meets the navigation requirements when the vessel leaves the channel; Equation (17) ensures that the depth of the vessel's navigation channel meets the requirements during navigation; due to the periodic changes in tides, it is not only necessary to ensure that the water depth meets the requirements when entering and leaving the channel, but also to ensure that the water depth that changes during the navigation of the ship must always meet the navigation requirements; and Equations (18) and (19) indicate the sequence in which vessels i and $i\prime$ entered the port.

5. Algorithm Design

Due to the inherent complexity of the port vessel scheduling problem, it involves a multitude of variables and constraints, contributing to substantial temporal intricacies. Consequently, the scheduling of vessels at ports is recognized as a challenging and uncertain polynomial (NP) problem, given its intricate nature and the multitude of factors influencing scheduling decisions [33,34]. The solution of the model for this problem mainly involves the sequence of ships entering and leaving the port, and the model is a multi-objective optimization. Considering the model constraints and the complexity of the multiple optimization objectives, it is not possible to use some exact solution software for the solution. Employing heuristic algorithms, including genetic algorithms, list search methods, and particle swarm optimization algorithms, facilitates the identification and comparison of a spectrum of feasible solutions. This enables the determination of a relatively optimal solution through a comparative analysis. Consequently, the quest for a more optimal ship scheduling algorithm necessitates the design of an enhanced and efficient approach.

Currently, multi-objective optimization algorithms are more commonly used in dealing with multiple-objective optimization problems. Deb [35] proposed the NSGA-II algorithm. It is widely used in many fields. The main feature of this algorithm is the fast, non-dominated sorting idea. The NSGA-II algorithm searches along the direction of Pareto's front and obtains an optimal solution set in line with the model optimization after many iterations. Hence, this study opts for the application of NSGA-II to address the proposed model. Beginning with a randomly generated initial population, the algorithm calculates the fitness value for each individual. It then selects those individuals for the next generation based on the principle of non-dominated sorting. Subsequently, a portion of the population undergoes crossover operations, guided by a predetermined crossover probability. Additionally, a selection of individuals is subjected to mutation operations in accordance with the set mutation probability. This process iterates progressively, generating new populations in each cycle until the pre-defined stopping conditions are met. Through several generations of evolution, the algorithm gradually converges, ultimately identifying the individual in the population with the optimal fitness. The specific steps are shown in Figure 2.

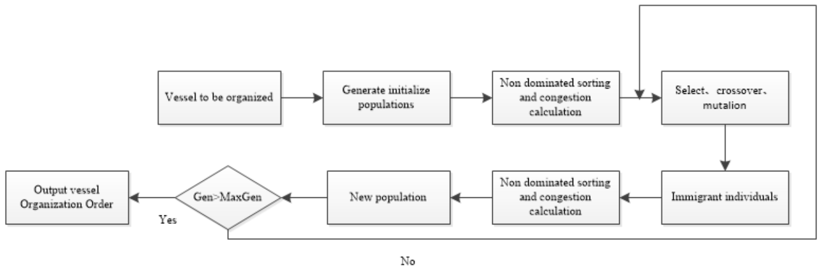


Figure 2. NSGA-II flowchart.

5.1. NSGA-II Algorithm

The process involves selection, crossover, and mutation following a fast, non-dominated sort. The resulting offspring are then amalgamated with the initial group, doubling the population size. The new group undergoes hierarchical organization through fast, non-dominated sorting and crowding distance calculation. This stratification categorizes the population based on the level of individual non-inferior solutions. The new groups are sequentially added according to their hierarchical levels during selection. Subsequently, the final output is then achieved after deriving the Pareto front iteratively, where the progress is depicted in Figure 3.

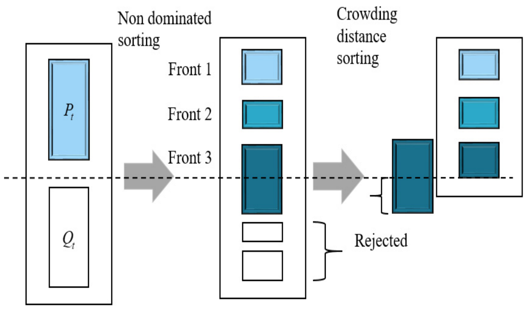


Figure 3. Group change in the NSGA-II algorithm.

5.2. Gene Coding and Population Initialization

Vessels are assigned numbers based on the quantity set I and the chronological order of their application to enter the port. In Figure 4, vessel numbers serve as gene codes. To create a chromosome, the number sequence is intentionally disrupted, generating a random permutation (with $I!$ possible combinations). The inbound times of vessels are then arranged according to this sequence, adhering to the constraint that the scheduling time of a vessel is influenced by the scheduling times of vessels preceding it. This process is iterated to generate the specified number of chromosomes, collectively forming the initial population.

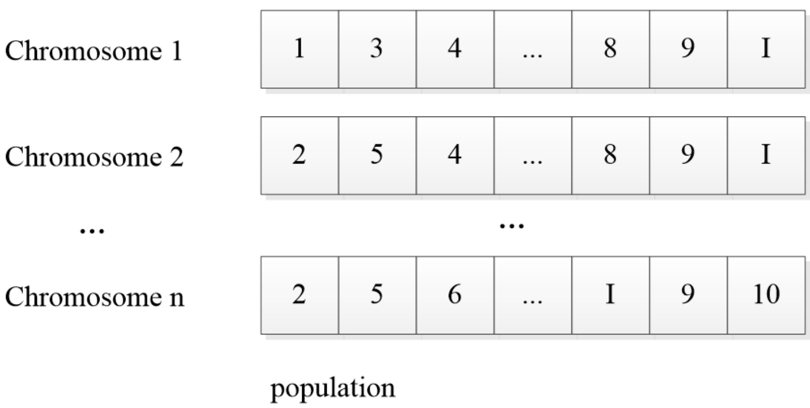


Figure 4. Chromosomes and population.

5.3. Non-Dominated Sorting and Congestion Calculation

A set of excellent non-dominated solutions can be obtained by non-dominated sorting, which outperforms multiple objective functions and is not dominated by other solutions.

The set of individuals of different Pareto ranks is obtained by fast, non-dominated sorting, but for the set of individuals of the same rank, it is necessary to introduce the calculation of crowding distance. In the calculation of the crowding distance for each rank, the maximum and minimum solutions of each objective function are assigned infinite values; the crowding distance of the intermediate part of the solutions is equal to the absolute difference between the function values of the two neighboring solutions after normalization.

$$i_d = \sum_{j=1}^{m} \left(\left| f_j^{i+1} - f_j^{i-1} \right| \right) i - 1 \quad (20)$$

5.4. Fitness, Selection, Crossover, and Mutation

Fitness: Equation (5) maximizes the carbon emission reduction value, and its fitness is the objective function itself; Equation (6) minimizes the total waiting time, and the fitness function is the reciprocal of the objective function.

Selection: The criterion used to select individuals for reproduction is Roulette Wheel Selection. Therefore, the higher the fitness value it has, the greater the probability of being selected.

Crossover: The two-point crossover is used in the GA. First, it randomly generates two integers as two crossover points, then the chromosome is divided into two segments; second, the middle genes are exchanged while the rest of the genes are retained and mapped, thus ensuring that the chromosome remains valid.

Mutation: First, two mutation points are generated randomly, and then the genes in the positions are exchanged.

6. Case Study

The actual port ship scheduling is relatively complex, and the proposed model cannot fully meet the actual situation. Therefore, this article uses simulation methods to validate the model and algorithm. Using the ship data information of a particular channel in Ningbo Port for one day, the calculation results of the model algorithm are compared with those based on the FCFS principle and the Virtual Arrival Last-Served (VALS) principle. In this case, the length of the channel is 20 nautical miles (nmail), the initial depth is 11.5 m, and the anchorage is 10 nmail from the port. The tidal equation is shown below.

$$TH_{(t)} = 2.65 \sin(42t + 0.75) + 1.99 \sin(30t + 2.3) \quad (21)$$

The basic information about the ship is obtained by processing AIS data, as shown in Table 2, including vessel number, average sailing speed, draft, estimated arrival time, etc. The virtual arrival vessel has a virtual vessel value of 1. The parameter of NSGA-II Algorithm settings are shown in Table 3.

Figure 5 presents the comparison of effectiveness between the particle swarm optimization algorithm (PSO) and NSGA-II. The left figure shows the relationship between the number of generations and the best total waiting time. It can be clearly seen that both algorithms can reduce the best total waiting time of ships within a limited number of generations (e.g., 350), and the optimization results of NSGA-II are significantly better than PSO, resulting in a greater reduction in the waiting time of ships. In terms of solving efficiency, PSO is more prone to getting stuck in local optima, as seen from the graph as a stepped green curve, while NSGA-II can stably approach the optimal solution until convergence. The right figure shows the relationship between the number of generations and the reduction in emissions. Similarly, as the number of generations increases, the emissions gradually decrease, and NSGA-II outperforms PSO. Specifically, for NSGA-II, the optimal solution was found in approximately 250 steps, resulting in a reduction of

98.5 tons in emissions, while PSO did not complete convergence. This comparison underscores the proficiency of the NSGA-II algorithm in adeptly optimizing the organization of maritime traffic for virtual arrivals, affirming its robustness in multi-objective optimization scenarios. Furthermore, Figure 6 illustrates the correlation between the total waiting time and the optimized speed of virtual arrival ships. As the total waiting time increases, the optimized speed tends to decrease towards the lower speed limit. However, it is worth noting that when the total waiting time reaches 9000 min, although the carbon emission reduction attains its maximum value, it may not be practical due to the prolonged waiting periods. Such extended waiting times could adversely impact the overall efficiency of port operations.

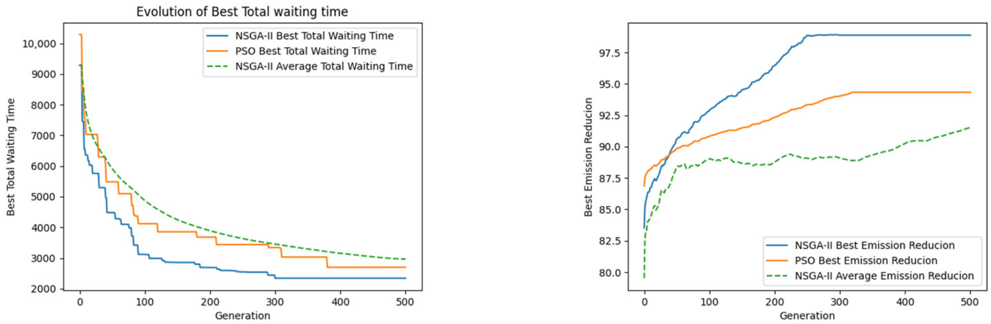
Table 2. Information on vessels entering the port at the current stage.

Id	Length	Aaverage_Speed	Estimated_Arrival_Time	Draft	Virtual Vessel
1	335	9	120	11	0
2	295	7.9	180	11.4	0
3	300	7.4	180	13.1	0
4	147	11	250	6.7	0
5	337	12	255	11.1	0
6	304	10	280	10.6	0
7	143	8	300	8	0
8	172	12.8	330	8.4	0
9	289	15	350	13	0
10	143	8	360	8	1
11	330	15	365	14	0
12	399	12	375	14.2	1
13	172	12.8	400	8.4	0
14	137	12.5	400	10	1
15	100	7.8	425	12.6	1
16	157	8.2	436	13.8	0
17	252	6.1	438	12.5	1
18	178	6.5	442	13.7	0
19	312	13	460	13.1	0
20	173	12	460	10.4	1
21	259	13.7	490	10.6	0
22	148	7.3	523	12	0
23	229	7.4	550	13.1	0
24	217	16	560	13.7	1
25	223	8	575	12.7	1
26	330	12	600	15	0
27	200	13.3	628	14	0
28	330	15	630	10	1
29	180	7.1	639	13.7	0
30	217	7	700	12.9	0
31	166	8	730	8.8	0
32	229	7	760	12	0

Table 3. The parameter settings of the algorithm.

Parameter	Values
Population size	50
Probability of crossing	0.8
Probability of variation	0.1
Number of iterations	500

Table 4 shows information about the Pareto optimal solution set obtained. Each Pareto optimal solution represents the entry order of the ship in sequence. The Pareto frontiers of the 11 optimal solutions are shown in Figure 7 (red cross represents the optimal solution, blue dot represents the general solution). It demonstrates a pattern observed in the NSGA-II results, where improving one objective leads to a weakening of the other objective: the lower the carbon emissions, the lower the fuel consumption, the slower the ship, the longer the voyage time will increase, and the longer the total waiting time will be.



(**a**) (**b**)

Figure 5. Convergence diagram:(**a**) Best Total Waiting Time (**b**) Best Emissions Reduction.

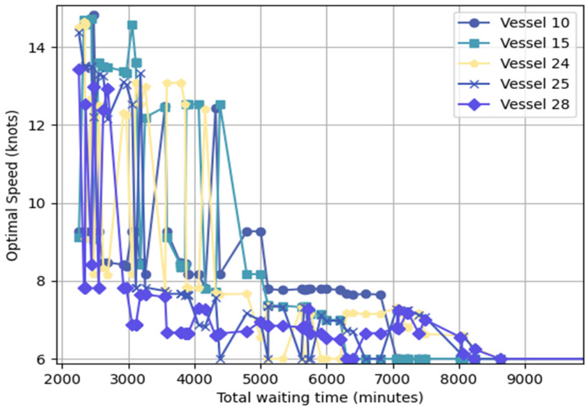


Figure 6. Optimal speed convergence curve.

Table 4. Pareto optimal set.

Serial Number	Vessel Order	Emission Reduction Value (Ton)	Total Waiting Time (Min)
1	[1, 4, 5, 7, 6, 2, 10, 8, 13, 21, 14, 20, 15, 3, 16, 18, 11, 17, 22, 25, 29, 26, 12, 19, 28, 9, 30, 27, 23, 24, 31, 32]	52.91	2367
2	[1, 4, 5, 7, 6, 2, 10, 8, 13, 21, 14, 20, 17, 15, 11, 18, 16, 3, 22, 12, 29, 26, 19, 30, 28, 9, 25, 27, 23, 24, 31, 32]	58.56	2429
3	[1, 4, 5, 7, 6, 2, 10, 8, 20, 21, 14, 16, 15, 13, 3, 18, 17, 11, 22, 12, 29, 25, 26, 30, 23, 9, 28, 19, 27, 24, 31, 32]	60.17	2526
4	[1, 4, 5, 7, 6, 2, 10, 8, 13, 21, 14, 16, 15, 3, 20, 18, 17, 11, 22, 9, 12, 25, 26, 19, 28, 29, 30, 27, 32, 24, 31, 23]	62.72	2590
5	[1, 4, 5, 7, 6, 2, 10, 8, 13, 21, 14, 16, 15, 3, 11, 22, 17, 20, 18, 12, 9, 25, 26, 19, 28, 29, 30, 27, 32, 24, 31, 23]	63.61	2665

Table 4. *Cont.*

Serial Number	Vessel Order	Emission Reduction Value (Ton)	Total Waiting Time (Min)
6	[1, 4, 5, 7, 6, 2, 10, 8, 13, 21, 14, 16, 15, 3, 20, 18, 17, 11, 22, 25, 19, 26, 12, 28, 9, 29, 30, 27, 32, 24, 31, 23]	65.95	2743
7	[1, 4, 5, 7, 6, 2, 10, 8, 20, 21, 14, 16, 13, 15, 17, 18, 11, 3, 22, 25, 12, 26, 29, 9, 28, 30, 19, 27, 32, 24, 31, 23]	70.08	2927
8	[1, 4, 5, 7, 6, 2, 10, 8, 14, 13, 21, 20, 16, 3, 19, 17, 11, 10, 26, 22, 12, 25, 9, 18, 27, 28, 29, 31, 32, 24, 27, 23]	77.23	3342
9	[1, 4, 5, 7, 6, 2, 10, 8, 17, 20, 14, 21, 16, 15, 3, 18, 13, 11, 22, 12, 29, 26, 28, 25, 9, 19, 30, 31, 32, 24, 27, 23]	79.46	3514
10	[1, 4, 5, 7, 6, 2, 10, 8, 17, 13, 14, 21, 15, 3, 19, 17, 16, 11, 22, 12, 29, 26, 28, 30, 25, 31, 9, 24, 32, 18, 27, 23]	82.39	3639
11	[1, 4, 5, 7, 6, 2, 10, 8, 13, 20, 14, 21, 15, 3, 19, 17, 16, 11, 22, 25, 29, 26, 28, 30, 12, 31, 32, 18, 9, 24, 27, 23]	84.49	3865

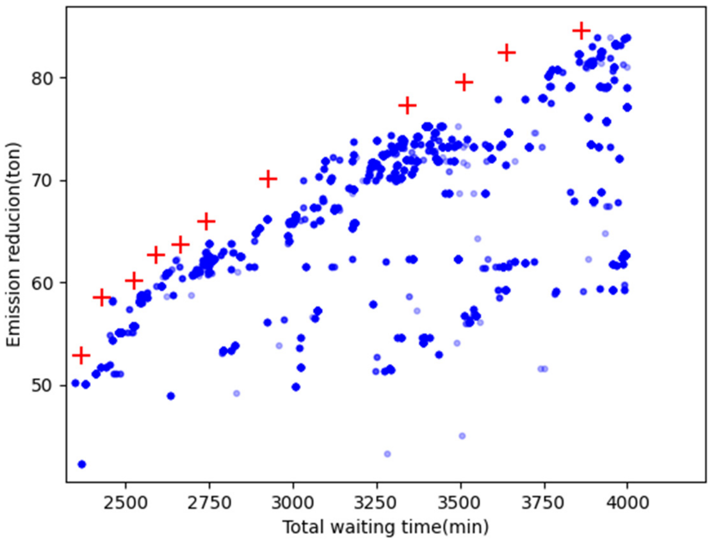


Figure 7. Pareto front.

The objective values under different traffic organization schemes can be seen in Figure 8. The detailed schedule for the first Pareto-optimal solution for ship scheduling can be found in Table 5. This table displays the scheduled times for each ship in the sequence, as well as a comparison to the results obtained through the FCFS and VALS approaches. By utilizing the Pareto-optimal solutions provided by the proposed model, the total waiting time can be reduced by up to 31.41% compared to FCFS and up to 65.37% compared to VALS. Additionally, all virtual arrival ships can reduce their CO_2 emissions by at least 23.29% compared to the original sailing conditions. Table 6 shows the results of vessel speed optimization.

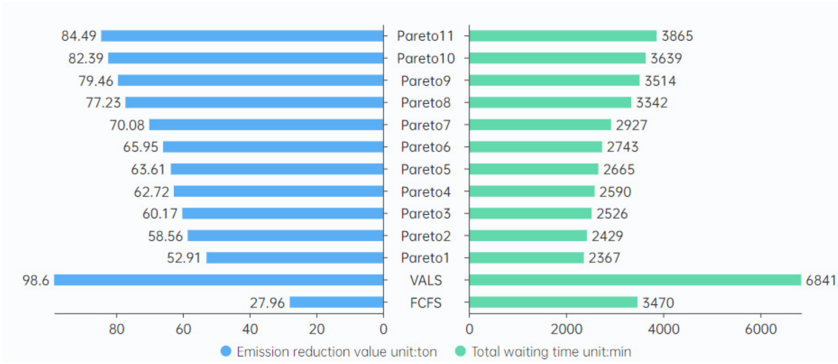


Figure 8. Two objectives in various strategies.

Table 5. Scheduling scheme of various strategies.

ID	Estimated_Arrival_Time (Min)	NSGA-II (Pareto1)	FCFS Actual_Start_Time	VALS
1	120	120	120	120
2	180	308	331	333
3	180	499	500	500
4	250	250	507	766
5	255	262	509	509
6	280	353	514	514
7	300	300	519	425
8	330	363	522	643
9	350	664	524	524
10	360	360	529	768
11	365	514	532	528
12	375	648	536	532
13	400	400	542	538
14	400	493	544	540
15	425	497	546	1230
16	436	506	548	542
17	438	518	551	438
18	442	509	559	442
19	460	654	564	558
20	460	495	570	570
21	490	490	572	563
22	523	526	575	566
23	550	708	578	659
24	560	710	581	1304
25	575	575	584	1306
26	600	643	600	600
27	628	706	628	628
28	630	660	631	1311
29	639	639	639	639
30	700	700	700	700
31	730	730	730	730
32	760	760	760	760
Total waiting time(min)		2367	3454	6841

Table 6. Virtual arrival vessel speed optimization of Pareto1.

ID	Initial Speed (Knots)	Optimal Speed (Knots)
9	17.14	9.03
19	13.04	9.17
23	16.45	13.54
24	15.89	13.48
27	14.33	12.74

7. Conclusions

This article proposes a new comprehensive model that combines vessel scheduling and virtual arrival methods to improve operational efficiency in complex traffic organization scenarios. Specifically, a model was constructed to minimize waiting time and carbon emissions while considering the optimization solution using the NSGA-2 algorithm. This model has been tested and validated through a case study at Ningbo-Zhoushan port. The results demonstrate that our innovative model and algorithm significantly outperform traditional scheduling methods.

- The total waiting time can be reduced by up to 31.41% when compared to FCFS and up to 65.37% when compared to VALS.
- Through the implementation of virtual arrival, all ships involved exhibit a notable reduction in CO_2 emissions, achieving a minimum decrease of 23.29% compared to their original sailing conditions.
- This model has robust scalability to other ports due to its design based on algorithms and strategies rather than relying on the special properties of specific ports.

Above all, it can increase port operational effectiveness and guarantee the delivery of more dependable services. In addition, due to the algorithmic and strategic design of this model, as opposed to relying on the characteristic properties of specific ports, it exhibits robust scalability to other ports. Other ports can adapt and apply this model according to their individual characteristics and datasets to optimize vessel scheduling and reduce carbon emissions. This adaptability is underpinned by the model's capacity to accommodate diverse port-specific features and data patterns. For instance, distinct ports may encounter varying traffic flow patterns, cargo demands, and geographical conditions. By fine-tuning the model parameters, a more precise alignment with these variations can be achieved, enhancing its efficacy within specific environmental contexts. Finally, through the exchange of best practices and data sharing, different ports can mutually benefit from each other's experiences, facilitating further refinement of the model to cater to localized demands. This collaborative effort contributes to establishing a global standard for port management, propelling the industry towards a more environmentally sustainable and efficient trajectory. In summary, the scalability of this model not only reinforces its applicability to specific ports but also provides a solid foundation for international collaboration and mutual development.

However, this study can be further improved in several directions. One future research direction can focus on the complex interaction relationship between entering and exiting ports instead of entering the port. In addition, by integrating IoT technology, ports can utilize real-time data from sensors and devices on ships to capture and reflect current ship information more accurately. The integration of real-time data helps provide more accurate information support, enabling virtual arrival optimization to be adjusted timelier, thereby improving the accuracy of decision-making and operational efficiency [36,37].

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