Journal of
Marine Science and Engineering

MDPI

Article

Overall Scheduling Model for Vessels Scheduling and Berth Allocation for Ports with Restricted Channels That Considers Carbon Emissions

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Abstract: As maritime transportation develops, the pressure of port traffic increases. To improve the management of ports and the efficiency of their operations, vessel scheduling must be optimized. The vessel scheduling problem can be divided into channel scheduling and berth allocation. We considered the complex problem of vessel scheduling in a restricted channel and the berth allocation problem, and a combined model that considers carbon emissions was developed. This model should reduce vessel waiting times, improve the quality of the berth loading and unloading service, meet the requirements of "green" shipping, and improve the overall scheduling efficiency and safety of ports. An adaptive, double-population, multi-objective genetic algorithm NSGA-II-DP is proposed to calculate the mathematical model. In the case study, the rationality verification and sensitivity analysis of the model and algorithm are conducted, and the NSGA-II-DP and NSGA-II were compared. Results demonstrate that the overall convergence of the NSGA-II-DP algorithm is better than that of NSGA-II, demonstrating that the NSGA-II-DP algorithm is a useful development of NSGA-II. In terms of port scheduling, the results of our model and algorithm, compared with the decisions provided by the traditional First Come First Service (FCFS) strategy, are more in line with the requirements for efficiency and cost in the actual port management, and more dominant in the port management can provide better decision support for the decision-makers.

Keywords: vessel scheduling; restricted channel; berth allocation; carbon emissions; NSGA-II-DP

Citation: Jiang, X.; Zhong, M.; Shi, J.; Li, W.; Sui, Y.; Dou, Y. Overall Scheduling Model for Vessels Scheduling and Berth Allocation for Ports with Restricted Channels That Considers Carbon Emissions. *J. Mar. Sci. Eng.* **2022**, *10*, 1757. https://doi.org/10.3390/jmse10111757

Academic Editor: Md Jahir Rizvi

Received: 12 October 2022
Accepted: 11 November 2022
Published: 15 November 2022

1. Introduction

Ocean transportation has always been the primary transportation mode used for global trade, accounting for 75% of global transportation. According to the report of the United Nations Conference on Trade and Development (UNCTAD), global marine trade in 2021 increased by 4.3%; the average growth rate of seaborne trade in the past two decades has been 2.9%, and the commercial shipping fleet will increase by 3% in 2020 [1]. In addition to the vigorous development of maritime trade, the cargo volume and fleet as well as the number of vessels visiting ports has increased owing to which the traffic pressure is increasing daily. However, in the short term, it is difficult for ports to employ expensive and tedious methods to relieve traffic pressure and increase their operating capacity such as expanding the port, improving their infrastructure, or widening channels. Therefore, the best approach to effectively solve traffic conflicts and improve the efficiency of port management and operations is to optimize the scheduling of vessels [2].

For ports with restricted channels, a vessel first enters the restricted channel from its anchorage. At this time, the vessel is constrained by the complex navigation rules of the restricted channel. After entering the harbor basin via the restricted channel, the vessel enters its allocated berth for both loading and unloading. The berth must meet the requirements of the vessel length and draft, and its service cargo type must be consistent with the type of cargo transported by the vessel. The loading and unloading times will be affected by the working efficiency of the berth. When the vessel has finished loading and unloading, it leaves the berth and then the port, again via the restricted channel.

To date, in most studies, the channel scheduling problem and the berth allocation problem have been separately considered. However, because of the complexity of the navigation rules for restricted channels, for example, allowing two-way navigation in one section but only one-way navigation in another section because of the narrow channel; or because of the insufficient depth of the channel, vessels with deep draft require to consider entering and leaving the port as per the tide [3]. Therefore, when a vessel enters the restricted channel, it is difficult to predict its impact on other vessels. Moreover, an unreasonable scheduling sequence in the channel may lead to multiple vessels being delayed. If a vessel fails to enter the port on schedule, it will affect the berth allocation plan. The working efficiency of the berth that has been allocated as per the berth allocation plan affects the berthing time of the vessel, thus affecting the departure time of the vessel and indirectly affecting the scheduling plan for the restricted channel. Therefore, an optimal scheduling plan obtained from a separate consideration of the channel scheduling and berth allocation problems may, in fact, be suboptimal; it is necessary to consider both problems together to conduct an overall scheduling study. Furthermore, to promote "green" shipping, terminal operators, shipping companies, and relevant environmental protection departments are extremely concerned about carbon emissions and pollution during navigation. Therefore, as part of the overall scheduling, it is necessary to consider the carbon emissions of vessels and to make reasonable speed arrangements for different types of vessels within the speed limit of the port. It is thus extremely important to comprehensively consider multiple factors such that reasonable vessel scheduling and berth allocation sequences can be devised. However, it is difficult to achieve fast and effective scheduling using the fixed vessel scheduling sequences produced by the traditional FCFS strategy used by ports.

Based on the abovementioned considerations, the optimization of channel scheduling and berth allocation in ports was considered from the overall perspective of the management of the port operations in this study.

In this paper, we will consider the complex vessel scheduling problem for a restricted channel along with the berth allocation problem, a comprehensive model for vessel scheduling in a restricted channel and berth allocation that considers carbon emissions is developed.

Tide times, traffic conflicts, port scheduling resources, and other factors will be considered in the overall scheduling model to make the model more realistic. Furthermore, the degree of matching between the berth and vessel is based on the type of cargo served by the berth and the distance from the yard, thus improving the safety of the cargo handling and reducing the amount of cargo damage and transportation costs during cargo handling. The carbon emissions during navigation will be considered in the model, which brings the research more in line with the real requirements of port management and the general trend toward sustainable shipping.

To address the defects of the traditional multi-objective genetic algorithm, an adaptive two-population multi-objective genetic method will be proposed and applied to the model.

The rest of this study is organized as follows. In Section 2, we summarize the relevant literature on vessel scheduling. In Section 3, we describe and analyze the problems that were studied and explain the factors to be considered in the proposed model. In Section 4, the proposed mathematical model for the optimization of vessel scheduling and berth allocation is described. In Section 5, the adaptive double-population multi-objective genetic algorithm on which the model is based is described. In Section 6, the rationale for using the proposed algorithm and model is discussed along with a consideration of their effectiveness and their superiority to other methods in different cases. In Section 7, the content of the article is summarized and the prospects for future research are discussed.

2. Related Literature

A brief introduction to the relevant literature on vessel scheduling in ports is provided in this section. The purpose of port scheduling operations is to improve the operational efficiency of the port and to ensure the safety of its operations. Based on considerations of different optimization methods and research directions, the scheduling problem can be divided into a channel scheduling problem and a berth allocation problem. The relevant literature will be summarized from these two perspectives and a detailed comparative analysis of the relevant literature is provided in Table 1.

Table 1. Details of earlier studies on related topics.

Authors	Research Topic			Channel	Constraint														Objective Function	Algorithm
	CSP	BAP	CSP + BAP		1	2	3	4	5	6	7	8	9	10	11	12	13	14		
Zhang et al.	√			one-way	√			√			√								1 + 2	GA
Zhang et al.	√			one-way	√	√													1	SA + GA
Kasm et al.	√			one-way	√				√	√									3	CHA
Hill et al.	√			two-way	√	√		√											1	CS
Zhang et al.	√			two-way	√	√													1	GA
Lalla-Ruiz et al.	√			compound	√														1	SA + TSP
Zhang et al.	√			compound	√						√								1	GA
Li et al.	√			restricted	√	√	√	√			√								1 + 2	GA
Abbas et al.		√		-	√					√	√	√	√						4	CS
Correcher et al.		√		-						√	√	√	√						5	CHA
Maxim et al.		√		-						√	√	√							6	AIEA
Eduardo et al.		√		-	√					√	√	√	√						7	GA + CHA
Liu et al.		√		-						√	√	√	√						8	SWA + CHA
Sami et al.		√		-						√	√	√							7	O-MaSE
Hu et al.		√		-						√	√	√			√				9 + 10	ε
Guo et al.		√		-						√	√	√					√		11 + 12	PSO
Wu et al.		√		-						√	√	√				√			13	CHA
Guo et al.		√		-						√	√	√	√					√	14	GA
Zhang et al.			√	one-way	√					√	√	√	√						1	SA + GA
Liu et al.			√	one-way	√	√			√	√	√	√	√						15	CHA
Liu et al.			√	two-way	√	√			√	√	√	√	√						16	CG
Present study			√	restricted	√	√	√	√	√	√	√	√	√	√	√			√	1 + 10 + 17	GA

Constraints: 1: safety interval (distance/time); 2: tidal time window; 3: speed; 4: traffic conflict; 5: dispatch resources (tugs, etc.); 6: number of berths; 7: berthing time and location; 8: berth allocation; 9: berth physical environment; 10: berth matching degree; 11: carbon emissions; 12: time buffer; 13: weather conditions; 14: distance between berth and storage space in yard. Research topics: CSP: channel scheduling problem; BAP: berth allocation problem. Objective functions: 1: minimization of the total waiting time; 2: minimization of the total dispatch time; 3: minimization of the maximum waiting time; 4: minimization of the vessel flow time; 5: minimization of the waiting and delay costs; 6: minimization of the total weighted service cost; 7: minimization of the total service time; 8: minimization of the basic planning cost and the expected recovery cost in all possible cases; 9: minimization of the delay length; 10: minimization of the carbon emissions from navigation and berthing; 11: minimization of delay penalties; 12: minimization of the crane service costs; 13: minimization of the total outbound vessel delay; 14: minimization of the total distance traveled by trucks; 15: minimization of the total weighted vessel dwell time; 16: minimization of the weighted sum of the completion time of the shift operations for inbound and outbound vessels; 17: maximization of the berth matching. Algorithms: SA: simulated annealing algorithm; GA: genetic algorithm; SWA: sliding-window method; CHA: self-built heuristic algorithm; CS: commercial software; AIEA: adaptive island evolutionary algorithm; O-MaSE: multi-agent systems engineering; ε: ε-constraint method; PSO: particle swarm optimization; CG: column vector generation.

In their research into the channel scheduling problem, Zhang et al. [4] considered the constraints related to berths, safety intervals, and one-way channel navigation rules. Although the berth factor was considered, the berth was assumed to have been allocated in advance in this study, and the only consideration was whether the vessel was in conflict when berthing. A mixed-integer linear program (MILP) model that had the minimum total scheduling time and vessel waiting time as its aim was constructed, and the non-dominated sorting genetic algorithm (NSGA) was used to calculate and verify the reliability of the model. Zhang et al. [5] established a mathematical model that was based on a comprehensive consideration of constraints such as the tide and the navigation rules for a one-way channel and that had the shortest total waiting time for vessels as its goal. In the study by Abou Kasm [6], the aim was to minimize the maximum delay of vessels, considering the one-way channel navigation rules and the constraints of port resources. An MIP model was then built, and a combination of a heuristic algorithm and a relaxation strategy was used to solve the model. Hill [7] considered the constraints caused by the channel, the tidal time window, and two-way channel navigation rules and developed a linear integer model with the aim of minimizing the total vessel waiting time to solve the vessel scheduling problem for channels at ports. With the aim of reducing the total vessel waiting time, Zhang et al. [8] developed a vessel scheduling model for a two-way channel that considers tides, safety intervals, and other constraints and uses a genetic algorithm to solve the model. Lalla-Ruiz et al. [9] considered multiple constraints and developed a vessel scheduling model for composite channels. To reduce the vessel waiting times, this model assigned different channels to different vessels during scheduling and combined greedy and simulated annealing algorithms to calculate the model. Based on the actual layout of Tianjin port, Zhang et al. [10] considered the minimum total waiting time of vessels as the objective function and developed a mathematical model for vessel scheduling in a composite channel; this model was based on a genetic algorithm. Li et al. [3] based their model on the physical layout of Huanghua port and considered the minimum total scheduling time and the minimum total waiting time of vessels as the objectives. A vessel adjustment model for a restricted channel that was based on the NSGA-II algorithm was then developed.

In a study of berth allocation, al Refaie [11] comprehensively considered constraints such as the physical environment of the berth, the vessel safety interval, and the satisfaction of the service provider while aiming to avoid vessel berthing conflicts. INLP models for berth allocation were then developed for normal conditions and for the case of an emergency arrival and solved with commercial software. Correcher et al. [12] aimed to minimize the addition of the cost of waiting before berthing and the cost of delays for each vessel; this work was based on an irregular berth layout after considering constraints such as the physical environment of the berth and the aim of avoiding vessel berthing conflicts. An MILP model for the berth allocation was developed, and an iterative local search heuristic algorithm was built to solve it. To solve the berth allocation problem, Dulebenets [13] proposed a new adaptive island evolutionary algorithm. The aim of this study was to minimize the total weighted service cost for vessels; the vessel berthing time and location were considered constraints in the model. Bacalhau et al. [14] established a berth allocation model with the aim of minimizing the total vessel service time. This model included a comprehensive consideration of constraints such as the vessel safety interval, the physical environment of the berth, and vessel berthing conflicts. A genetic algorithm and a domain search algorithm built by the authors were used to solve the model. Liu [15] examined the berth allocation problem for uncertain conditions. With the aim of minimizing the basic planning cost and the expected recovery cost under all possible circumstances, constraints such as vessel berthing conflicts and the physical environment of the berth were considered. An MILP model was constructed, and the model was solved using commercial software and the sliding-window method. Mnasri [16] established a single-objective berth allocation LP model with the aim of minimizing the service time, including the waiting time, for all vessels. Furthermore, the aim was to avoid vessel berthing conflicts, and multi-agent systems engineering was used to identify the solution. Hu [17] established a multi-objective berth allocation model with the aim of minimizing the delay time and the carbon emissions from navigation and berthing. This model considered possible berthing conflicts and vessel carbon emissions ε-constraint method. To examine the berth allocation problem where the loading and unloading times are uncertain because of the weather, Guo [18] first built a model for vessel loading and unloading times under different weather conditions that consider the weather, the number of cranes, the vessel capacity, and other factors. The relationship between the weather and the loading and unloading times was then investigated using machine learning; constraints such as avoiding vessel berthing conflicts, minimizing the cost of using cranes, and penalties for delays to vessels were considered, and a berth allocation model for situations where the vessel loading and unloading times are uncertain was developed for different weather conditions. The model was solved using a particle swarm optimization algorithm. Wu [19] established a mixed-integer program (MIP) model for berth allocation with the aim of minimizing the total vessel departure delay. In this case, the constraints that were considered included berthing conflicts and the continuity of berth service; a time buffer was included in the berth allocation plan to ensure that the overall berth allocation plan would not be affected in the event of a short delay to the arrival of a vessel. A self-built search algorithm was used to solve this model. To examine the joint allocation of berths and yards, Guo [20] considered such constraints as the vessel loading workload, physical environment of berths, number of allocated yards, number of containers in the yards, and vessels' berthing times and locations. An IP model was then built to minimize the total distance traveled by trucks; a genetic algorithm was used for the calculations.

In a study of the overall problem of channel scheduling and berth allocation, Zhang [21] set the minimum total waiting time as the aim and built an MILP model for one-way channel scheduling and berth allocation. This model considered constraints such as the safe time interval, the physical environment of the berths, and the vessel berthing time, in addition to the avoidance of berthing conflicts; a simulated annealing algorithm and a genetic algorithm were used to identify the solution. Liu [22] comprehensively considered constraints such as navigation safety intervals, navigation rules, tides, the physical environment of berths, and vessel berthing conflicts and considered the minimization of the weighted total dwell time for all vessels as the aim. An MILP model for overall one-way channel scheduling was constructed, which was solved by a self-built adaptive large neighborhood search algorithm. On the basis of the 2020 study, the following year, Liu [23] considered two-way channel constraints and built an MILP model for the overall scheduling of vessels in a two-way channel. In this study, the aim was to minimize the weighted sum of the completion time of the shift operations for inbound and outbound vessels; a column generation algorithm was used to solve the problem.

From the abovementioned analysis and the information presented in Table 1, a number of researchers have considered the problems of channel scheduling and berth allocation separately in their research to date. However, few studies have considered the channel vessel scheduling problem and the berth allocation problem in combination.

There have been certain preliminary studies on the overall scheduling problem that have combined considerations of channel vessel scheduling and berth allocation. However, in these studies, one- and two-way channels with relatively simple constraints have generally been considered, and there is a lack of research on restricted channels with complex navigation environments and rules. There has been little consideration of the factors that actually affect scheduling such as tide times, traffic conflicts, and port scheduling resources. During the process of berth allocation, only the physical environment of berths and vessels' berthing times and locations have been considered, without considering the degree of matching between berths and berthing vessels. Currently, in order to promote environmentally sustainable shipping, terminal operators, shipping companies, and environmental protection departments are very concerned about reducing carbon emissions and pollution from shipping. However, the carbon emissions related to the overall scheduling of vessels is rarely considered. In order to address these issues, in this study, we improve on the existing research by proposing a model for vessel scheduling in restricted channels as well as berth allocation that takes carbon emissions into account. Compared with previous studies, we consider the channel and berth scheduling problem at the same time, avoiding the sub-optimal results of separate optimization, and add constraints more in line with the actual situation of port scheduling in the model for the above problems, so that the model is more practical, and the results are more effective. The specific improvements are as follows.

By combining the complex restricted channel vessel scheduling problem with the berth allocation problem, this paper constructs the overall scheduling model of vessel scheduling in the restricted channel and berth allocation considering carbon emission, expands the model of this research direction, and provides basic theoretical support for further expanding this research direction.

Tide time, traffic conflict, port scheduling resources, and other factors are considered in the overall scheduling model to make the model more realistic. At the same time, the matching degree between the berth and the vessel is constructed according to the type of cargo served by the berth and the distance from the stockyard space in the yard and is considered in the model, so as to improve the safety of cargo handling in the scheduling and reduce the cargo damage and transportation cost during cargo handling. In addition, the carbon emission during navigation is considered in the model, which makes the research more in line with the actual management needs and the general trend of green shipping.

3. Problem Description

Based on an analysis of the layout of the coal port at the port of Huanghua, we constructed a port layout that included restricted channels and harbor basin berths, as illustrated in Figures 1 and 2. Our analysis and description of the vessel channel scheduling and berth allocation problems were based on this layout.

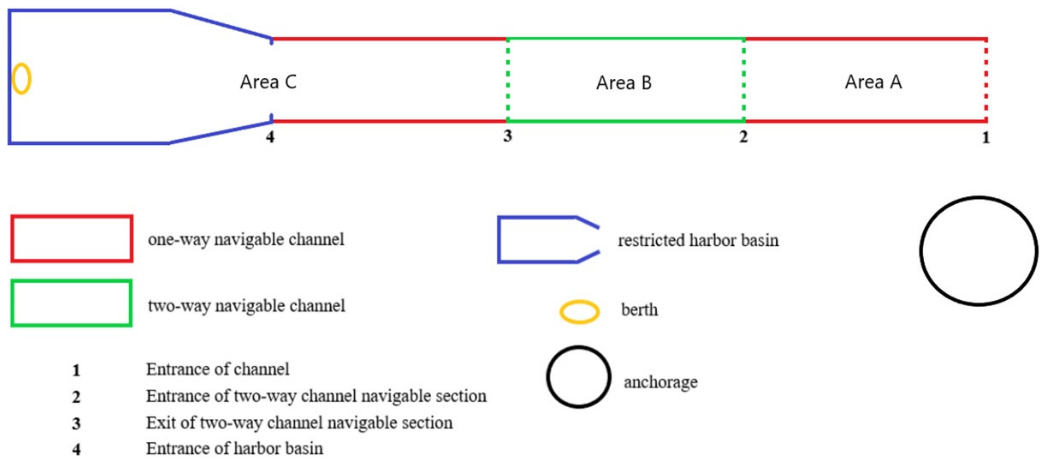

Figure 1. The constructed port layout, including an anchorage, restricted channel, and harbor basin.

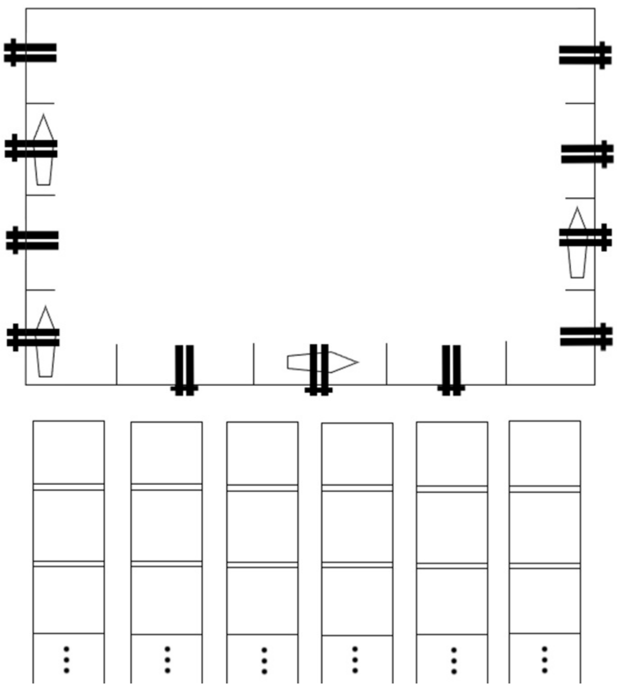

Figure 2. Layout of the berths and yard.

In terms of vessel scheduling, in the above layout, the restricted channel can be considered to be composed of a two-way navigable channel and two one-way navigable channels. The harbor basin is connected to the outlet of the restricted channel. After being allowed to enter the port, an incoming vessel that has been waiting at the anchorage arrives at the entrance of the restricted channel then proceeds into the channel from the entrance and enters the harbor basin. In particular, as the vessel enters the port, the pilot vessel first carries a pilot on board, and then the pilot assists the vessel to enter the port. Once the vessel enters the restricted channel, it begins to use the channel resources. Then, when the vessel enters the harbor basin, a tug is used to assist the pilot to bring the vessel into the berth. Finally, the vessel is moored in its berth. During the departure operation, the vessel is first unberthed, the pilot vessel embarks, and a tug assists the vessel to reach the outlet of the harbor basin. The vessel then leaves the port via the restricted channel. During these operations, to ensure the safety of navigation, it is prohibited to overtake in the same direction during the internal navigation of the restricted channel and harbor basin. The length of time that each resource is used depends on the speed of the vessel; the speed limits that apply to the vessel in the harbor basin and within the channel will be different. Moreover, because a vessel's carbon emissions are related to its fuel consumption and because the speed directly affects the fuel consumption and indirectly affects the carbon emission cost, it is necessary to set reasonable speeds for the different types of vessels entering and leaving the port, within the speed limits specified by the port. Generally, pilots are assigned by the pilot terminal after the vessel scheduling plan has been formulated and submitted to the pilot station. Therefore, pilot resources were not considered in this study. During vessel scheduling, it is necessary to comply with the navigation rules of the restricted channel. At the same time, due to the impact of environmental factors related to the restricted channel, it is necessary to consider the safe distance between vessels and the tide-riding factors of large vessels.

As shown in Figure 2, the berths in the layout that was constructed were discrete, and the physical conditions such as the draft and length of the berths were fixed. Additionally, according to the type of service provided, berths can be divided into universal berths and appropriated berths. Different types of berths are equipped with different types of specialized equipment and facilities for dealing with different types of cargo. The use of specialized equipment and facilities can reduce the difficulty of operations, improve safety during loading and unloading, and reduce the loss of cargo during loading and unloading [24]. Therefore, when allocating berths, in addition to considering whether the physical conditions of the vessel and the berth match, it is also necessary to consider the degree of matching between the type of cargo to be loaded or unloaded and the type of cargo served by the berth. After the cargo has been unloaded at the berth, it will be transported from the berth to the yard for storage. The horizontal distance between the berth and the stockyard spaces in the yard is also an important factor affecting the overall operational efficiency and running costs of the port. Therefore, the horizontal transportation distance between the berth and the vessel's allocated space in the stockyard should also be considered during the allocation of berths, so as to reduce costs [25] (also see [20,26,27]). As shown in the two-dimensional Gantt chart of the berth allocation (Figure 3), in the case of vessels served by the same berth, later vessels can enter the berth only after the servicing of the previous vessel is complete: the berth service times of two vessels cannot overlap.

To sum up, in this study, the joint problems of vessel scheduling and berth allocation in a restricted channel were considered while taking carbon emissions into account. The following factors were considered when constructing a model of the problem.

1. The resources required for inbound and outbound operations: channels, tugs, and berths
2. The requirement for a reasonable vessel service sequence
3. The port's navigation rules
4. The safe time intervals needed to ensure the safety of navigation
5. The tidal time windows for large vessels
6. The physical factors and service types of the berth

7. The distance between berths and the stockyard space in the yard
8. The service times of different vessels using the same berth
9. The carbon emissions of vessels (in relation to reasonable speed arrangements)

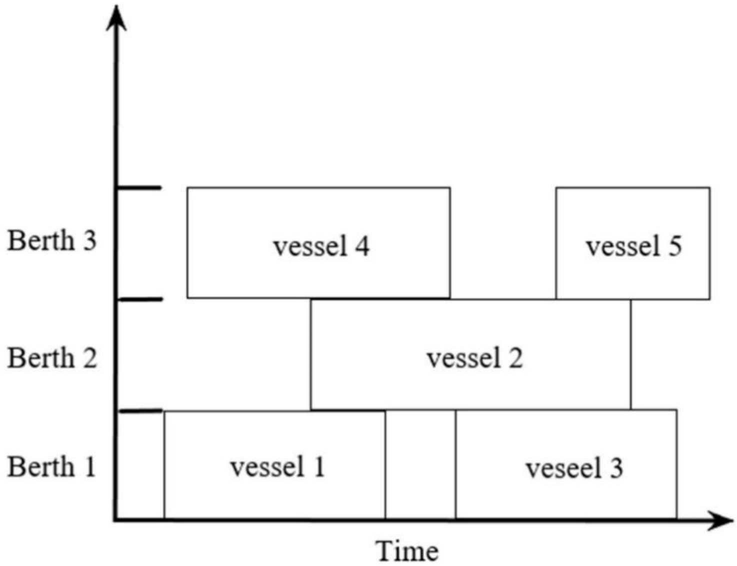

Figure 3. Two-dimensional Gantt chart of berth allocation.

4. Mathematical Model and Formulas

4.1. Model Assumptions

Based on the considerations described in Section 3, in this section, the construction of the vessel scheduling and berth allocation model will be described.

In order to facilitate the construction of the model, the following assumptions were made.

1. It is assumed that the time for all tugs to arrive at the inbound and outbound vessels is the same, and the distance from all berths to the entrance of the harbor basin is the same. This is based on the reasonable assumption that the distances within the harbor basin are small and have little impact on the overall scheduling.
2. In order to highlight the research focus, the yard and reclaimer allocation and scheduling are not considered at this stage. Therefore, it is assumed that there will be sufficient yard and reclaimer resources in the port to meet the needs of loading and unloading. As shown in Figure 2, the stockyard spaces in the yard are discrete. Each vessel is allocated stockyard spaces before entering the port to avoid any conflict.
3. It is assumed that there are sufficient pilots at the pilot station and sufficient resources for wharf loading and unloading. The weather and visibility are assumed to be good and the pilot and captain to be experienced. It is also assumed that no accidents occur during navigation.

4.2. Mathematical Model

The overall planning cycle is discrete, and the start and end times of all operations are represented by discrete time.

Sets:

I: the set of all vessels; vessels are indexed using i.

I_{cj}: the set of vessels that need to enter the port by tide.

I_{cc}: the set of vessels that need to leave the port by tide.

I_1: the set of inbound vessels that can conduct two-way navigation according to the navigation rules.

I_2: the set of outbound vessels that can conduct two-way navigation according to the navigation rules.

I_{1t}: the set of inbound vessels that need one-way navigation according to the navigation rules.

I_{2t}: the set of outbound vessels that need one-way navigation according to the navigation rules.

T: the length of the planning cycle, indexed using t.

K: the set of inbound and outbound vessel types.

D_s: the set of distances between the stockyard space, s, in the yard and all of the berths in the port, indexed by parameter d_{sb}.

B: the set of all berths, indexed by b.

S_i: the set of stockyard spaces in the yard allocated to vessel i.

Parameters:

a_{i1}: time of vessel i applying for inbound operations.

a_{i2}: time of vessel i applying for outbound operations.

t_{si}: the time that the nearest tidal window for vessel i starts.

t_{ei}: the time that the nearest tidal window for vessel i ends.

t_{1i}: the time that inbound vessel enters the channel from the anchorage.

t_{2i}: the length of time for inbound and outbound vessels to pass through area A (see Figure 1).

t_{3i}: the length of time for inbound and outbound vessels to pass through area B (see Figure 1).

t_{4i}: the length of time for inbound and outbound vessels to pass through area C (see Figure 1).

t_{5i}: within area C, the time required for the inbound vessel i to reach its berth from the entrance of the harbor basin, or the time required for the outbound vessel i to reach the entrance of the harbor basin from its berth.

t_{6i}: within area C, the time that the inbound vessel i reaches the entrance of the harbor basin from the exit of the two-way navigable channel, or the time that the outbound vessel i reaches the exit of the two-way navigable channel from the entrance of the harbor basin.

t_{safe}: the safe time interval.

t_{wi}: the berthing time of the inbound vessel i or the unberthing time of the outbound vessel i.

D_1: the distance from the anchorage to the channel entrance.

D_2: the distance from the channel entrance to the entrance of the two-way navigable channel.

D_3: the distance from the entrance to the exit of the two-way navigable channel.

D_6: the distance from the exit of the two-way navigable channel to the entrance of the harbor basin.

D_5: the distance from the entrance of the harbor basin to the berth.

v_{1i}: the speed of vessel i before it enters the entrance of the harbor basin.

v_{2i}: the speed of vessel i after it enters the entrance of the harbor basin.

v_t: the tug speed.

$v_{1\max}$: the maximum speed of the vessel before entering the harbor basin, as stipulated by the navigation rules.

$v_{1\min}$: the minimum speed of the vessel before entering the harbor basin, as stipulated by the navigation rules.

W: the total number of tugs.

W_i: the number of tugs required for vessel i.

T_{i1}: the total time required for vessel i to complete the inbound operation.

T_{i2}: the total time required for vessel i to complete the outbound operation.

S_{sb}: the degree of matching between berth b and stockyard space s (as a percentage).

d_{sb}: the horizontal distance between stockyard space s and berth b.

R_b: the matching degree of the service type provided at berth b.

R_{sb}: the degree of matching between berth b and stockyard space s.

g_i: the fuel consumption rate of the main engine of vessel i.

d_i: the distance sailed by vessel i.
D_i: the drainage volume of vessel i during navigation.
C: the admiralty coefficient.
L_i: the length of vessel i.
L_b: the berth length.
dp_i: the vessel draft.
dp_b: the depth of water in the berth.
W_{ih}: the weight of cargo loaded and unloaded by vessel i.
v_b: the loading and unloading speed at berth b.
K_i: the vessel type for vessel i.
NS_i: the number of stockyard spaces in set S_i.
Decision variables:
t_{i1}: the actual inbound time of vessel i.
t_{i2}: the actual outbound time of vessel i.
T_s: the total scheduling time.
v_k: the inbound or outbound speed of a vessel of type k.
Q_i: the fuel consumption of vessel i when entering or leaving the port.
R_{bi}: the degree of matching between berth b and vessel i.
IO_{ijb}: has a value of 1 if vessel j is assigned to enter berth b after vessel i; otherwise, 0.
IO_{ib}: has a value of 1 if berth b is allocated to vessel i; otherwise, 0.
IO_{ihb}: has a value of 1 if berth b can service cargo h of vessel i; otherwise, 0.
IO_{it}: has a value of 1 if vessel i starts its inbound or outbound operations at time t; otherwise, 0.

In this model, the main objective is to minimize the total scheduling time, which is the sum of the differences between the time a vessel applies for the inbound operations and the time when it completes the outbound operations:

$$\min T_s = \sum_{i \in I} (T_{i2} - a_{i1}) \tag{1}$$

In addition, in order to improve the overall operational efficiency of the port and reduce the cost of operations, and in line with the general trend toward reducing carbon emissions related to the global shipping industry, in this study, the degree of matching between berths and vessels and the carbon emissions of inbound and outbound vessels were considered and taken as secondary targets in the model.

Bulk cargo ports are different from container ports. As cargo vessels carry a wide range of cargo, bulk cargo ports are equipped with both universal berths and cargo-appropriate berths. Cargo-appropriate berths are equipped with different types of specialized equipment and facilities for servicing different types of cargo. Although a cargo vessel can berth at a special berth for cargo, it can also berth at a universal berth. However, it is certain that the match degree is higher if a vessel is serviced at a special berth for cargo; this will reduce the difficulty of the loading and unloading operations and the loss of cargo during these processes. The distance that cargo is transported between the berth and the stockyard space is another important factor that affects the overall operational efficiency of a port and the cost of its operations. Therefore, we assigned a rank to the berths according to these two factors to reflect the degree to which a particular berth matched the cargo. For convenience, cargo-special berths were assigned a rank, denoted by R_b, of 3, universal berths that can service two different types of cargo were assigned a rank of 2, and universal berths that can service three different types of cargo were assigned a rank of 1. As well as this, the Manhattan distance between the central point of the stockyard space and the center of the berth was used to define the horizontal distance over which the cargo was transported between each stockyard space and the berth. This was then used to calculate the degree of matching, S_{sb}, between berth b and stockyard space s:

$$S_{sb} = \frac{\max(D_s) - d_{sb}}{\max(D_s) - \min(D_s)}, \forall d_{sb} \in D_s \tag{2}$$

The value of S_{sb} is expressed as a percentage. When S_{sb} is greater than 0.8, the degree of matching, R_{sb}, between berth b and stockyard space s is 5. When S_{sb} is less than 0.8 and greater than 0.6, R_{sb} is 4, and so on, until R_{sb} is 1. The overall degree of matching, R_{bi}, between berth b and vessel i is given by

$$R_{bi} = R_b + \frac{\sum\limits_{s \in S_i} R_{sb}}{NS_i}, \forall i \in I, b \in B \tag{3}$$

As a result of recent developments in the shipping industry, more attention is being paid to reducing the carbon emissions of vessels by the international community [28]. Vessels emit a large amount of carbon dioxide (CO_2) when entering and leaving port. The amount of CO_2 emitted is generally calculated using the formula: carbon emitted = carbon emission factor × vessel fuel consumption. The carbon emission factor is a fixed parameter, so reducing the carbon emissions of vessels entering and leaving port requires reducing their fuel consumption. The amount of fuel consumed by a ship i as the ship enters and leaves the port, Q_i, is given by the formula

$$Q_i = 0.7355 \times \frac{g_i \times d_i \times {D_i}^{2/3} \times {v_i}^2}{C} \times 10^{-6} \tag{4}$$

where v_i is the speed at which the vessel is sailing. It can be seen from this equation that when the distance traveled by the vessel and the vessel's draft are fixed, the vessel's fuel consumption is related to the vessel's speed, which means that the vessel's carbon emissions are also related to its inbound and outbound speed. Therefore, in order to reduce the carbon emissions of vessels, reasonable speed arrangements need to be made for different types of vessels within the port's speed limit.

Given the above, the two secondary objectives of the model were

$$\max \sum_{i \in I} R_{bi} \tag{5}$$

and

$$\min \sum_{i \in I} Q_i \tag{6}$$

The complete mathematical model for the optimization of vessel scheduling is described below.

Main objective: (1).

Secondary objectives: (5), (6).

St: (2)–(4).

$$R_{sb} = \begin{cases} 5, \ S_{sb} \geq 0.8 \\ 4, \ 0.6 \leq S_{sb} < 0.8 \\ 3, \ 0.4 \leq S_{sb} < 0.6 \\ 2, \ 0.2 \leq S_{sb} < 0.4 \\ 1, \ 0 \leq S_{sb} < 0.2 \end{cases} \tag{7}$$

$$g(x) = max\{x, 0\} \tag{8}$$

Time window constraint:

$$a_{i1} \leq t_{i1} \ \forall i \in I_1 \cup I_{1t} \tag{9}$$

$$a_{i2} \leq t_{i2} \ \forall i \in I_2 \cup I_{2t} \tag{10}$$

Tidal time window constraint:

$$\begin{cases} n = \{0, 1, 2 \cdots, n-1, n\} \\ t_{si} + n \cdot 720 \leq t_{i1} & \forall i \in I_{cj} \\ t_{si} + n \cdot 720 \leq t_{i2} & \forall i \in I_{cc} \\ t_{ei} + n \cdot 720 \geq t_{i1} + t_{1i} + t_{2i} + t_{3i} + t_{4i} + t_{wi} & \forall i \in I_{cj} \\ t_{ei} + n \cdot 720 \geq t_{i2} + t_{wi} + t_{4i} + t_{3i} + t_{2i} & \forall i \in I_{cc} \end{cases} \tag{11}$$

Safe time interval constraint:
Same direction:

$$\begin{cases} \sum\limits_{j \in I_1 \cup I_{1t}, j=1, j \neq i}^{|I_1 + I_{1t}|} \sum\limits_{t=g(t_{i1}+t_{1i}-t_{1j})}^{g(t_{i1}+t_{1i}+t_{safe}-t_{\min}-t_{1j})} IO_{jt} \leq 0 & \forall i \in I_1 \cup I_{1t} \\ \sum\limits_{j \in I_1 \cup I_{1t}, j=1, j \neq i}^{|I_1 + I_{1t}|} \sum\limits_{t=g((t_{i1}+t_{1i}+t_{2i}+t_{3i}+t_{4i}+t_{wi})-(t_{1j}+t_{2j}+t_{3j}+t_{4j}+t_{wj}))}^{g((t_{i1}+t_{1i}+t_{2i}+t_{3i}+t_{4i}+t_{wi})-(t_{1j}+t_{2j}+t_{3j}+t_{4j}+t_{wj})+t_{safe}-t_{\min})} IO_{jt} \leq 0 & \forall i \in I_1 \cup I_{1t} \\ \begin{cases} T_{i1} > T_{j1},\ t_{i1} + t_{1i} > t_{j1} + t_{1j} \\ T_{i1} < T_{j1},\ t_{i1} + t_{1i} < t_{j1} + t_{1j} \end{cases} & \forall i, j \in I_1 \cup I_{1t}, j \neq i \end{cases} \tag{12}$$

$$\begin{cases} \sum\limits_{j \in I_2 \cup I_{2t}, j=1, j \neq i}^{|I_2 + I_{2t}|} \sum\limits_{t=g(t_{i2})}^{g(t_{i2}+t_{safe}-t_{\min})} IO_{jt} \leq 0 & \forall i \in I_2 \cup I_{2t} \\ \sum\limits_{j \in I_2 \cup I_{2t}, j=1, j \neq i}^{|I_2 + I_{2t}|} \sum\limits_{t=g((t_{i2}+t_{wi}+t_{2i}+t_{3i}+t_{4i})-(t_{wj}+t_{2j}+t_{3j}+t_{4j}))}^{g((t_{i2}+t_{wi}+t_{2i}+t_{3i}+t_{4i})-(t_{wj}+t_{2j}+t_{3j}+t_{4j})+t_{safe}-t_{\min})} IO_{jt} \leq 0 & \forall i \in I_2 \cup I_{2t} \\ \begin{cases} T_{i2} > T_{j2},\ t_{i2} > t_{j2} \\ T_{i2} < T_{j2}, t_{i2} < t_{j2} \end{cases} & \forall i, j \in I_2 \cup I_{2t}, j \neq i \end{cases} \tag{13}$$

Different direction:

$$\sum_{j \in I_1 \cup I_{1t}, j=1}^{|I_1 + I_{1t}|} \sum_{t=g(t_{i2}+t_{wi}+t_{2i}+t_{3i}+t_{4i}-t_{1j})}^{g(t_{i2}+t_{wi}+t_{2i}+t_{3i}+t_{4i}+t_{\text{safe}}-t_{\min}-t_{1j})} IO_{jt} \leq 0 \ \forall i \in I_2 \cup I_{2t} \tag{14}$$

$$\sum_{j \in I_2 \cup I_{2t}, j=1}^{|I_2 + I_{2t}|} \sum_{t=g(t_{i1}+t_{1i}+t_{2i}+t_{3i}+t_{4i})}^{g(t_{i1}+t_{1i}+t_{2i}+t_{3i}+t_{4i}+t_{wi}-t_{\min})} IO_{jt} \leq 0 \ \forall i \in I_1 \cup I_{1t} \tag{15}$$

Channel constraint:

$$\sum_{i \in I_1, i=1}^{|I_1|} \sum_{t'=g(t-t_{2i}-t_{1i}+t_{\min})}^{g(t-t_{1i})} IO_{it'} \cdot \sum_{j \in I_2, j=1}^{|I_2|} \sum_{t'=g(t-t_{2j}-t_{3j}-t_{4j}-t_{wj})}^{g(t-t_{3j}-t_{4j}-t_{wj})} IO_{jt'} \leq 0 \ \forall t \in T \tag{16}$$

$$\sum_{i \in I_1, i=1}^{|I_1|} \sum_{t'=g(t-t_{4i}-t_{3i}-t_{2i}-t_{1i}-t_{wi}+t_{\min})}^{g(t-t_{3i}-t_{2i}-t_{1i})} IO_{it'} \cdot \sum_{j \in I_2, j=1}^{|I_2|} \sum_{t'=g(t-t_{4j}-t_{wj}+t_{\min})}^{g(t)} IO_{jt'} \leq 0 \ \forall t \in T \tag{17}$$

$$\sum_{i \in I_{1t}, i=1}^{|I_{1t}|} \sum_{t'=g(t-t_{4i}-t_{3i}-t_{2i}-t_{1i}-t_{wi}+t_{\min})}^{g(t-t_{1i})} IO_{it'} \cdot \sum_{j \in I_2 \cup I_{2t}, j=1}^{|I_2 + I_{2t}|} \sum_{t'=g(t-t_{wj}-t_{4j}-t_{3j}-t_{2j})}^{g(t)} IO_{jt'} \leq 0 \ \forall t \in T \tag{18}$$

$$\sum_{i \in I_1 \cup I_{1t}, i=1}^{|I_1 + I_{1t}|} \sum_{t'=g(t-t_{4i}-t_{3i}-t_{2i}-t_{1i}-t_{wi}+t_{\min})}^{g(t-t_{1i})} IO_{it'} \cdot \sum_{j \in I_{2t}, j=1}^{|I_{2t}|} \sum_{t'=g(t-t_{wj}-t_{4j}-t_{3j}-t_{2j})}^{g(t)} IO_{jt'} \leq 0 \ \forall t \in T \tag{19}$$

Tug constraint:

$$\sum_{i \in I_1 \cup I_{1t}, i=1}^{|I_1+I_{1t}|} \sum_{t'=g(t-t_{4i}-t_{3i}-t_{2i}-t_{1i}-t_{wi}+t_{\min})}^{g(t-t_{6i}-t_{3i}-t_{2i}-t_{1i}+t_t)} IO_{it'} \cdot W_i + \sum_{j \in I_2 \cup I_{2t}, j=1}^{|I_2+I_{2t}|} \sum_{t'=g(t-t_{wj}-t_{5i}+t_{\min})}^{g(t+t_t)} IO_{jt'} \cdot W_j \leq W \ \ \forall t \in T \tag{20}$$

Berth constraints:

$$L_i < L_b, \forall i \in I, b \in B, IO_{ib} = 1 \tag{21}$$

$$dp_i < dp_b, \forall i \in I, b \in B, IO_{ib} = 1 \tag{22}$$

$$T_{j1} < t_{i2}, \forall i \in I, j \in I, IO_{ijb} = 1 \tag{23}$$

$$\sum_{b \in B} IO_{ib} * IO_{ihb} = 1, \forall i \in I \tag{24}$$

Time calculation:

$$T_{i1} = t_{i1} + t_{1i} + t_{2i} + t_{3i} + t_{4i} + t_{wi} \ \forall i \in I_{1t} \cup I_1 \tag{25}$$

$$T_{i2} = t_{i2} + t_{2i} + t_{3i} + t_{4i} + t_{wi} \ \forall i \in I_{2t} \cup I_2 \tag{26}$$

$$a_{i2} = T_{i1} + \frac{W_{ih}}{v_b} \ \forall i \in I \tag{27}$$

$$t_{4i} = t_{5i} + t_{6i} \ \forall i \in I \tag{28}$$

$$t_{1i} = D_1 \div v_{1i} \ \forall i \in I_{1t} \cup I_1 \tag{29}$$

$$t_{2i} = D_2 \div v_{1i} \ \forall i \in I \tag{30}$$

$$t_{3i} = D_3 \div v_{1i} \ \forall i \in I \tag{31}$$

$$t_{6i} = D_6 \div v_{1i} \ \forall i \in I \tag{32}$$

$$t_{5i} = D_5 \div v_{2i} \ \forall i \in I \tag{33}$$

Speed constraint:

$$v_{1i} = v_k, \forall i \in I, k \in K, K_i = k \tag{34}$$

$$v_{1i} = \begin{cases} v_{1\min},\ v_{1\min} > v_{1i} \\ v_{1i},\ v_{1\min} < v_{1i} < v_{1\max} \\ v_{1\max},\ v_{1\max} < v_{1i} \end{cases} \ \forall i \in I \tag{35}$$

$$v_{2i} = v_t \ \forall i \in I \tag{36}$$

Binary requirements for variables:

$$IO_{it} = \begin{cases} 1, t_{i1} = t \parallel t_{i2} = t \\ 0, \quad otherwise \end{cases} \quad \forall i \in I, t \in T \tag{37}$$

Objective Function (1) is used to minimize the total scheduling time. Objective Function (5) is used to maximize the degree of matching between the berth, the vessel, and the cargo. Objective Function (6) is used to minimize the fuel consumption of vessels entering and leaving the port; that is, to minimize carbon emissions. Constraints (2), (3), (4), and (7) are used to calculate the decision variables. Constraint (8) ensures that the calculated time result does not have a negative value. Constraints (9) and (10) ensure that the actual start time of a vessel's inbound and outbound operations is later than the start time applied for. Constraint (11) ensures that the actual start and end times of the inbound and outbound operations of large vessels that need to sail according to the tide are within the appropriate tidal time windows. During the inbound and outbound operations, constraints (12) and (13) ensure that there is always an appropriate safe time interval between two consecutive inbound vessels or two consecutive outbound vessels after they enter the channel; these constraints also ensure that the vessels will not overtake one another. Constraint (14) ensures that there is an appropriate safe time interval between the time that an outbound vessel leaves the channel and the time that an inbound vessel enters the channel, so as to prevent conflict. Constraint (15) ensures that after an inbound vessel arrives at the berth, no vessel will carry out its outbound operations before the inbound vessel has completed mooring. Constraints (16) and (17) ensure that there will be no two-way navigation of vessels in the one-way section of the restricted channel (see Figure 1). Constraints (18) and (19) ensure that inbound and outbound vessels that can only conduct one-way navigation according to the navigation rules will adopt one-way navigation throughout their voyage. Constraint (20) ensures that the number of tugs used does not exceed the total number of tugs available at the port. Constraints (21) and (22) ensure that a vessel meets the physical constraints of the berth allocated to it. Constraint (23) ensures that the servicing times of vessels allocated to the same berth do not conflict. Constraint (24) ensures that each vessel is served by at least one berth and that the cargo carried by each vessel conforms to the type of cargo that can be serviced by the berth. Constraints (25)–(33) are used to calculate time and ensure time continuity. Constraints (34)–(36) ensure that the speed arrangements for each vessel meet the speed constraints of the port. Constraint (37) is the requirement of zero one variable of the model.

5. Algorithm Design

It can be seen from the above description that the vessel scheduling and berth allocation model is complex and includes many constraints. When the number of vessels and the feasible solution set are both large, it is difficult to obtain the optimal solution by using traditional methods that give exact solutions [8]. However, heuristic algorithms, such as the simulated annealing algorithm, genetic algorithm, and particle swarm optimization algorithm, can search within the range of feasible solutions to compare optimal solutions and thus obtain relatively optimal solutions. The proposed model is a multi-objective optimization model. At present, the mainstream solution methods that can be applied to such models can be divided into multiple criteria decision-making approaches in which multiple objectives are combined into one objective using weighting [29], and multi-objective evolutionary algorithms (MOEAs) based on Pareto optimization [30]. Using the former type of method, human factors have a great influence on the results, which are cruder. Therefore, the nondominated sorting genetic algorithm (NSGA-II), which is a widely used MOEA, was selected as the solution method in this study. The NSGA algorithm was proposed by Deb in 1995 [31]. In 2000, the same author optimized the algorithm complexity and added the elite retention strategy to the original algorithm to produce the NSGA-II algorithm. In contrast to traditional multi-objective algorithms, the NSGA-II algorithm does not need to consider the target weight. Other features of the algorithm include a low complexity of the process, high computational efficiency, and a well-distributed Pareto solution set. The algorithm also uses its own elite strategy and has high convergence efficiency; it can better approach the Pareto front and has many advantages in terms of solving multi-objective problems. NSGA-II algorithm has the disadvantage that individuals in the population tend to the same state and stop evolving, which then leads to the decline of population diversity, and the solution falls into the local optimum. In order to deal with this defect, in this study, we combined the NSGA-II algorithm with the double-population strategy. By referring to the relevant literature on adaptive probability, we then developed an adaptive algorithm that we named NSGA-II-DP. The proposed algorithm is described in detail below.

5.1. Gene Coding and Population Initialization

In the proposed model, the set of all vessels is labeled I, and 1-I represents each incoming and outgoing vessel. Vessel types, which constitute the set K, are numbered 1 ... K. Set B is the set of berths, which are numbered 1 ... B. As shown in Figure 4, the chromosome is coded using multiple coding information, which is used to encode information in the inbound and outbound stages of the vessel. The chromosome is divided into three layers. The first 1-I codes in the first layer correspond to 1-I inbound vessels. These 1-I codes are copied from coding positions I + 1 to I + I to represent the outbound stage of the same vessels. The codes from I + I + 1 to I + I + K are fixed vessel-type numbers. The first 1-2I codes in the second layer correspond to the overall service sequence of all vessels entering and leaving the port (entry and exit are considered together), and the codes 2I + 1 to 2I + K correspond to the speeds arranged for vessels of different types. The first 1-I codes in the third layer correspond to the numbers of the berths where vessels stop after entering the port. These 1-I codes are copied to the coding positions I + 1 to I + I to represent the berth numbers where vessels are located before they leave the port. Codes I + I + 1 to I + I + K have no meaning and are set to 0. The above steps are repeated in a similar fashion to generate a specified number of populated chromosomes to form the initial population (the first line of the NSGA-II-DP algorithm).

	Inbound stage						Outbound stage								
Vessel number and vessel type number	1	2	···	···	I-1	I	1	2	···	···	I-1	I	1	···	K
Overall service sequence of inbound and outbound vessels and speed of different types of vessels	1	2	···	···	I-1	I	I+1	I+2	···	···	2I-1	2I	8.1	···	9.1
Berth allocated to vessel	3	6	···	···	10	8	3	6	···	···	10	8	0	0	0

Figure 4. Genes and chromosomes.

5.2. Fitness, Selection, Crossover, and Mutation

The fitness value is determined by the value of the model's objective function. Because the objective is to find the maximum value of the berth matching degree, its negative value is taken when calculating the fitness, which will calculate the minimum value like the other two fitness values. The chromosomes are decoded, and the value of the objective function is calculated to determine the fitness value (lines 7 and 18 in the NSGA-II-DP algorithm). In decoding, the chromosomes may correspond to an unreasonable service order. In the chromosome code, the sequence number of the service sequence of the same vessel at the outbound stage must be greater than at the inbound stage, and the positions in this sequence of different vessels at the same berth must also meet the priority relationship to ensure that the outbound time of the previous vessel has already been arranged when the next vessel arranges its inbound time. Therefore, the chromosome needs to be modified to ensure that it is reasonable (lines 6 and 17 in the algorithm).

The tournament selection method was used for the chromosome selection (line 14 in the algorithm). Two chromosomes were selected each time, and the dominant one was selected as the parent. If the two chromosomes were the same, one of them was randomly selected to be the parent for subsequent reproduction. If neither chromosome was dominant and the chromosomes were not the same, the selection operation was performed again.

As shown in Figure 5, because the coding logic is different for the service sequence, berths, and vessel speeds, different methods are used for the cross-operation in each case (line 15 in the algorithm). Take out the service sequence code, berth code, and speed code of the two parent generations, respectively, for the cross-operation. For the coding of the service sequence, the sequence crossing method is used.

1. After the crossover operation has been determined based on the crossover probability, two numbers between 0 and 2I are randomly generated as the crossover points, and the genes between the service sequence encoding crossover points of two parents are taken as the selected genes.
2. Child 1 is generated with the same gene and location as the selected gene of parent 1.
3. The position of the selected gene of parent 1 in parent 2 is found; the remaining genes of parent 2 are added to child 1 in order.
4. Similarly, the selected gene of parent 2 is used to generate child 2.

This step avoids the generation of unfeasible service sequence codes and reduces the number of correction operations.

The two-point crossing method is used for the berth coding, as follows.

1. After the crossover operation has been determined by the crossover probability, two numbers between 0 and I are randomly generated, and the genes between the berth coding intersections of the two parents are selected as the selected genes.
2. The selected genes of the berth codes of the two parents are exchanged.
3. The 1-I genes of child 1 are copied to gene positions I + 1 to I + I; the same operation is then performed on child 2 to generate two new berth codes for the offspring.

The two-point crossing method is also used for the speed coding as follows.

1. After the crossover operation has been determined by the crossover probability, two numbers between 0 and K are randomly generated as the intersection points, and the genes between the intersection points of the speed codes of the two parents are selected as the genes.
2. The selected genes of the speed codes of the two parents are exchanged to generate two new speed codes for the offspring.

Two new child chromosomes are then generated by integrating the progeny codes generated by the three crossover operations described above.

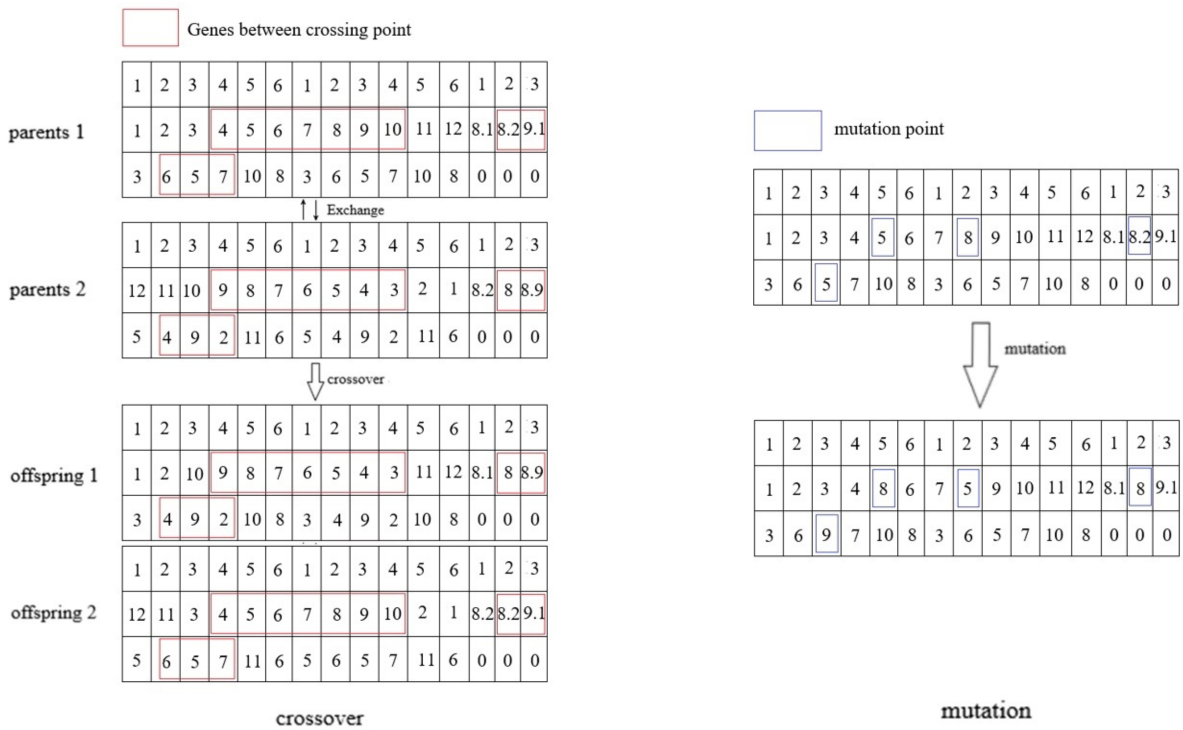

Figure 5. Illustration of the crossover and mutation operations.

After determining the mutation operation to be performed based on the mutation probability, for the service sequence encoding, two numbers between 0 and 2I are randomly generated as the mutation points, and the genes of the two mutation points are exchanged in the chromosome. For the berth encoding, a number between 0 and I is randomly generated as the mutation point, and a berth is randomly selected from the assignable berths based on the vessel's position; the number of this berth is then used to replace the mutation point gene. For the speed encoding, a number between 0 and K is randomly generated as the mutation point; the speed is then randomly generated within the specified speed range and used to replace the mutation point gene. After the mutation operation has been performed on all of the chromosomes (line 16 in the algorithm), the correction operation (line 17) is carried out to generate the offspring population.

5.3. Elite Retention Policy

The NSGA-II algorithm has its own elite retention policy. First, the parent population and the offspring population are merged to give a new joint population. Using fast nondominated sorting, the nondominated set Li is obtained. The smaller the i, the better an individual in the nondominated set. First, the individuals of set L1 are added to the new population; the nondominated sets L2, L3, . . . Li are then also added to the new population in order. When putting set Li into the new population, if the new population exceeds the upper population limit, the degree of crowding for each individual in Li is calculated and these are compared. The individuals in set Li are then arranged in descending order of the degree of crowding, and the individuals that meet the upper limit of the size of the new population are selected from the set in the same descending order and added to the new population (lines 23 and 24 of the algorithm). This ensures that the outstanding individuals from each generation will enter the next generation.

5.4. Adaptive Probability and Double-Population Strategy

The NSGA-II algorithm generally selects a fixed crossover probability and mutation probability within a given probability interval; however, a small probability will lead to the algorithm falling into the local optimum, whereas a large probability will destroy the heredity of the algorithm and affect the convergence. Therefore, after referring to the relevant literature, we chose to use the following crossover and mutation probabilities, which can be adjusted adaptively according to the population algebra [24]:

$$\begin{cases} P_c = P_{c\min} + (P_{c\max} - P_{c\min}) * \frac{iter}{numiter} \\ P_m = P_{m\min} + (P_{m\max} - P_{m\min}) * \frac{iter}{numiter} \end{cases} \tag{38}$$

Here, P_c and P_m are, respectively, the crossover and mutation probabilities of each generation in the iteration; $P_{c\max}$ and $P_{c\min}$ are the maximum and minimum values of the crossover probability, respectively; $P_{m\max}$ and $P_{m\min}$ are the maximum and minimum values of the mutation probability, respectively; *iter* is the number of current iterations; and *numiter* is the upper limit on the number of iterations. When the number of iterations is small, large crossover and mutation probabilities are obtained, which means that the algorithm can search over a large range to prevent it falling into a local optimum. When the number of iterations is large, the probability of crossover and mutation becomes smaller; this causes the algorithm to search close to the current optimal solution so that the loss of the optimal solution due to the destruction of heredity can be avoided.

As previously mentioned, when applying the NSGA-II algorithm, there is the problem of population individuals tending toward the same state and ceasing to evolve; the population diversity then decreases, and the algorithm falls into the local optimum. To address this problem, we adopted a double-population strategy and integrated this into the NSGA-II algorithm. The details of this strategy are as follows.

First, two initial populations are generated according to the population parameters and are selected, crossed, and mutated, and the elite individuals are retained. Next, the two populations will form their own nondominated set L1, and both replace the worst individuals in their populations with each other's nondominated set L1, thereby forming two new populations for the next iteration. If the number of the worst individuals in both populations, m, is less than the number of individuals from LI in the nondominated set of the other population, denoted n, then m individuals from LI that have a higher crowding degree will be used to replace the worst individuals so as to prevent the number of individuals in the new population from exceeding the upper limit (line 25 in Algorithm 1 NSGA-II-DP). Using this strategy, not only do the two populations evolve separately, which enhances the search ability of the algorithm, but each generation also introduces the optimal individuals of both sides into the other population. This prevents individuals from reaching the same state and ceasing to evolve, ensures the diversity of the population of each generation, reduces the possibility of the solution falling into local optimum, increases the heredity of the optimal individuals, and improves the convergence of the algorithm.

According to the above strategy, the NSGA-II-DP algorithm, which was intended to address the shortcomings of the NSGA-II algorithm, was constructed. This new algorithm was then used for the model calculations.

Algorithm 1: NSGA-II-DP

Algorithm parameters: chromosome (p), chromosome number (popsize), current algebra generation, upper limit on number of iterations (maxgeneration), maximum crossover probability (pcmax), minimum crossover probability (pcmin), maximum mutation probability (pmmax), minimum mutation probability (pmmin), best set of nondominated solutions of each generation (L_1), objective function of Pareto solution (bestD), Pareto optimal solution set (bestpop)

1: initial population [pop1, pop2] = {p_1, p_2, $p_{popsize-1}$, $p_{popsize}$}
2: globalD←Inf
3: generation←1
4: **while** (generation < maxgeneration) **do**
5: if (generation = 1) **then**
6: [pop1, pop2]←correction(pop1, pop2)
7: [D1, D2]←calculate fitness(pop1, pop2)
8: go to line 14
9: **else**
10: [pop1, pop2]←[nnewpop1, nnewpop2]
11: [D1, D2]←[newD1, newD2]
12: go to line 14
13: **end if**
14: [pop_{s1}, pop_{s2}]←selection(pop1, pop2)
15: [pop_{c1}, pop_{c2}]←crossover(pop_{s1}, pop_{s2}, pcmax, pcmin)
16: [pop_{m1}, pop_{m2}]←mutation(pop_{c1}, pop_{c2}, pmmax, pmmin)
17: [pop_{o1}, pop_{o2}]←correction(pop_{m1}, pop_{m2})
18: [D_{o1}, D_{o2}]←calculate fitness(pop_{o1}, pop_{o2})
19: combinepop1←{pop1, pop_{o1}}
20: combineD1←{D1, D_{o1}}
21: combinepop2←{pop2, pop_{o2}}
22: combineD2←{D2, D_{o2}}
23: [newpop1, L11]←elite retention(combineD1, combinepop1)
24: [newpop2, L12]←elite retention(combineD2, combinepop2)
25: [nnewpop1, nnewpop2]←Dual Population(newpop1, L11, newpop2, L12)
26: [newD1, newD2]←calculate fitness(nnewpop1, nnewpop2)
27: combinepop←{nnewpop1, nnewpop2}
28: combineD ←{newD1, newD2}
29: L1←elite retention(combineD, combinepop)
30: bestpop←L1
31: bestD←calculate fitness(L1)
32: generation←generation + 1
33: **end while**
34: **output**: bestpop, bestD

6. Case Study

6.1. Case Study

In this section, a simulation that was performed using the model described in Section 4 will be discussed. This simulation involved the dispatch of 15 vessels and was based on the port layout described in Section 3. Details of the types of vessels and the berths used in the simulation are given in Tables 2 and 3, respectively. Due to the limitations of the channel width, 75000 DWT bulk carriers required one-way navigation throughout the simulation. Due to the limitations of the water depth in the channel, if fully loaded, the same class of carriers needed to enter and leave the port by the tide. The port has semi-diurnal tides, and the first tidal time window is at time [120, 480]. The distance data for the simulation are given in Table 4. The berthing time, t_{wi}, of inbound vessels was generally 40 min, and the unberthing time, t_{wi}, of outbound vessels was 15 min. The safe time interval, t_{safe}, was set as 15 min, the unit time of discretization time was 1 min, the number of tugs in the port was 10, and the speed of the tugs was 5 knots. The speed limit range in the port channel was [8, 10] knots, and the speed of the vessels in the harbor basin had to match the speed of the tugs. Specific data for the 15 vessels used in the simulation are listed in Table 5; these include details of the tonnage, type of operation (loading or unloading), cargo type, serial number of the stockyard space allocated to the vessel, coordinates of the center of this space, time of the vessel applying for inbound operations, and number of tugs required.

Table 2. Specifications of the different types of vessels used in the simulation.

Type of Vessel	35000 DWT Bulk Carrier	35000 DWT Bulk Carrier	35000 DWT Bulk Carrier
Dead weight (t)	16,000	13,000	12,000
Net load weight (t)	35,000	50,000	75,000
Vessel length (m)	190	200	225
Vessel draft (m)	10	12	14
Fuel consumption rate (g/kWh)	167	130	127

Table 3. Berth details.

Berth Number	Water Depth (m)	Length (m)	Types of Cargo Serviced	Center Point Coordinates	Loading and Unloading Speed (t/h)
Berth 1	230	15	ore, steel, coal	(20, 2212)	4200
Berth 2	210	13	coal	(20, 1942)	4600
Berth 3	210	13	coal, ore	(20, 1682)	4900
Berth 4	195	11	ore	(20, 1429.5)	5200
Berth 5	210	13	steel	(205, 1282)	4600
Berth 6	210	13	coal, grain, ore	(465, 1282)	4300
Berth 7	210	13	steel, coal	(725, 1282)	5300
Berth 8	195	11	steel, ore	(910, 1429.5)	3900
Berth 9	195	11	grain, coal	(910, 1674.5)	5400
Berth 10	210	13	grain	(910, 1927)	4600
Berth 11	230	15	grain, ore	(910, 2197)	3600

Table 4. Distance data.

Parameter	Distance $_{\text{(nautical miles)}}$
D_1	4.4
D_2	4.1
D_3	4.2
D_5	1.25
D_6	1.85

We used a computer with a 2.59 GHz CPU and 16 GB RAM, together with MATLAB2017b software to run the NSGA-II-DP algorithm and solve the model. For the NSGA-II-DP algorithm, the parameter is set to: the population size was 300, and the upper limit on the number of iterations was 300. For the genetic algorithm, the crossover probability is generally between 0.5 and 1.0 and the mutation probability is usually between 0.001 and 0.5 [32]. Therefore, we set the maximum value of the crossover probability as 1.0 and the minimum value as 0.5; the maximum value of the mutation probability was set to 0.5 and the minimum value to 0.001.

The final results of applying the NSGA-II-DP algorithm to our model consisted of Pareto solution sets containing optimization solutions for different target weights. These results could be used by port decision-makers according to the specific demands of the management of their own ports. The target values for each Pareto solution are listed in Table 6, and the Pareto frontier diagram is illustrated in Figure 6. The convergence curve and average value curve for each generation of the optimal values—F1, F2, and

F3—of the three targets of the total scheduling time, berth matching degree, and fuel consumption are shown in Figures 7–9, respectively. As explained in Section 4, fuel consumption can be used to represent carbon emissions: the lower the fuel consumption, the lower the carbon emissions, and the greater the fuel consumption, the greater the carbon emissions. From Table 6 and Figure 6, it can be seen that the values of the two secondary targets (berth matching degree and fuel consumption) will affect the values of the primary target (total scheduling time). For a given berth matching degree, the smaller the fuel consumption—that is, the lower the carbon emissions—the longer the total scheduling time because the smaller the fuel consumption, the slower the speed of the ship, which will increase the sailing time. For a given fuel consumption—that is a given amount of carbon emissions—the greater the berth matching degree, the greater the total scheduling time. If vessels of the same type carrying the same cargo choose the same berth because it has a high matching degree, this will increase the waiting time of vessels in the queue. If an idle berth with a low matching degree is selected under these circumstances, the waiting time will be reduced but the matching will be too. The optimal solution for the total scheduling time from the Pareto solution set was then selected for verification of the model. The results of this are shown in Table 7.

Table 5. Details of the 15 vessels used in the simulation.

Vessel Number	Loading or Unloading	Tonnage (t)	Types of Cargo	Serial Number of Stockyard Space Allocated to the Vessel	Coordinates of Central Point of Stockyard Space	Time of Vessel Applying for Inbound Operation (min)	Number of Tugs Required
1	Unloading	50,000	Ore	14, 49, 8	(240, 939), (90, 177), (240, 1066)	0	2
2	Loading	50,000	Ore	44, 34, 37	(240, 304), (540, 558), (90, 431)	11	2
3	Unloading	75,000	Steel	30, 20, 42, 59	(840, 685), (240, 812), (840, 431), (690, 50)	35	2
4	Unloading	35,000	Coal	5, 45	(690, 1193), (390, 304)	120	2
5	Loading	35,000	Coal	41, 4	(690, 431), (540, 1193)	126	2
6	Unloading	35,000	Steel	1, 2	(90, 1193), (240, 1193)	145	2
7	Unloading	50,000	Grain	12, 26, 54	(840, 1066), (240, 685), (840, 177)	170	2
8	Loading	50,000	Grain	7, 22, 23	(90, 1066), (540, 812), (690, 812)	179	2
9	Loading	35,000	Ore	58, 53	(540, 50), (690, 177)	240	2
10	Unloading	50,000	Coal	36, 28, 33	(840, 558), (540, 685), (390, 558)	300	2
11	Loading	75,000	Ore	60, 52, 6, 29	(840, 50), (540, 177), (840, 1193), (690, 685)	332	2
12	Loading	50,000	Grain	10, 19, 40	(540, 1066), (90, 812), (540, 413)	476	2
13	Unloading	50,000	Steel	35, 17, 25	(690, 558), (690, 939), (90, 685)	540	2
14	Loading	50,000	Steel	11, 39, 43	(690, 1066), (390, 431), (90, 304)	641	2
15	Unloading	75,000	Coal	46, 18, 47, 31	(540, 304), (840, 939) (690, 304), (90, 558)	645	2

Table 6. Target values of solutions in the Pareto solution set.

Total Scheduling Time (min)	Berth Matching Degree	Fuel Consumption (t)
12,542	82.33	10.05
12,544	82.33	9.52
12,567	82.33	9.13
12,922	82.67	9.40
12,987	83.83	9.37
12,994	85.33	9.13

Table 6. *Cont.*

	Total Scheduling Time (min)	Berth Matching Degree	Fuel Consumption (t)
	13,365	86	9.13
	13,476	86.33	9.13
	13,911	87	9.22
	13,913	87	9.13
	13,959	87.33	9.13
	14,040	88.33	9.13
	14,897	89	9.13
Optimal value	F1	F2	F3
	12,542	89	9.13

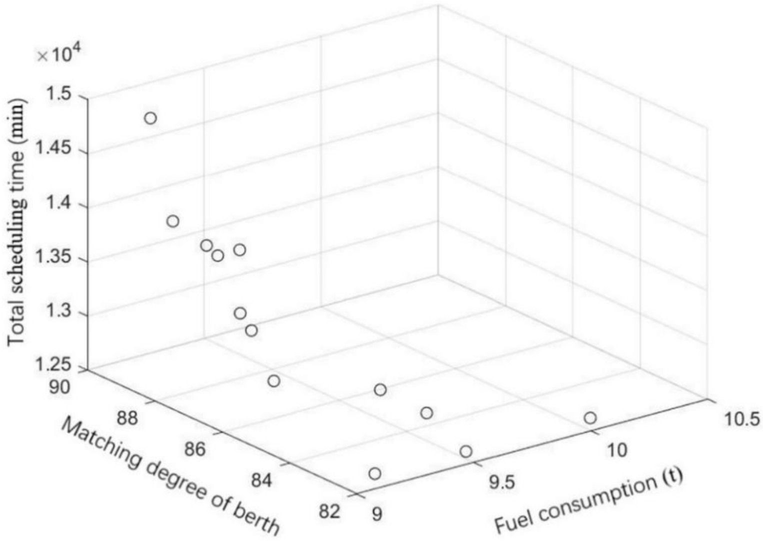

Figure 6. Pareto frontier diagram.

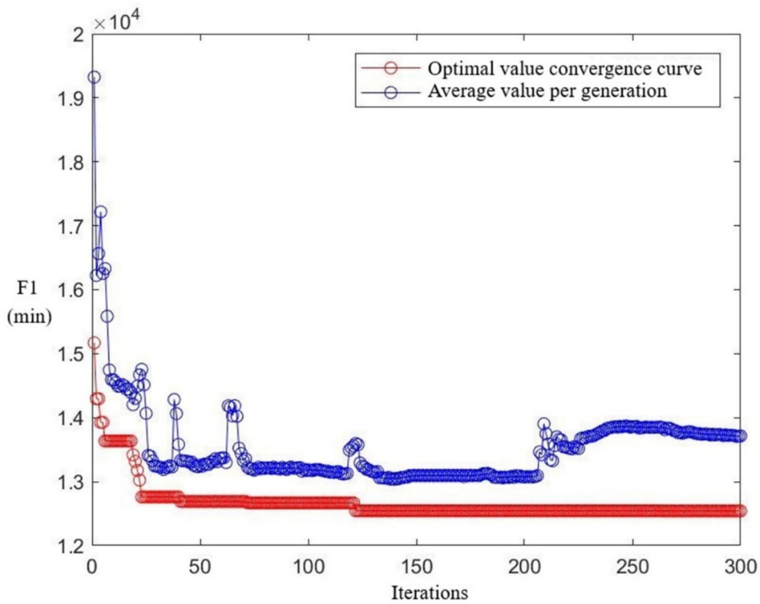

Figure 7. Optimal value convergence curve of total scheduling time and average value curve of each generation.

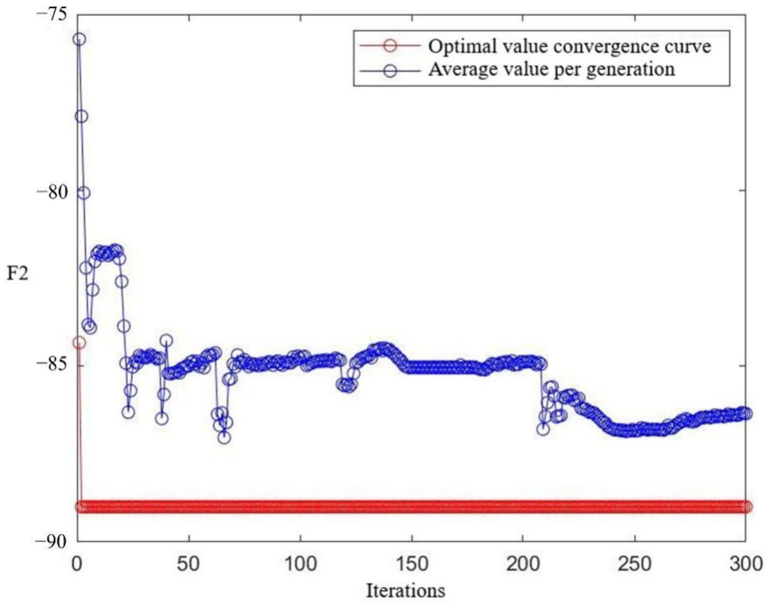

Figure 8. Optimal value convergence curve of the matching degree of the berth and average value curve of each generation.

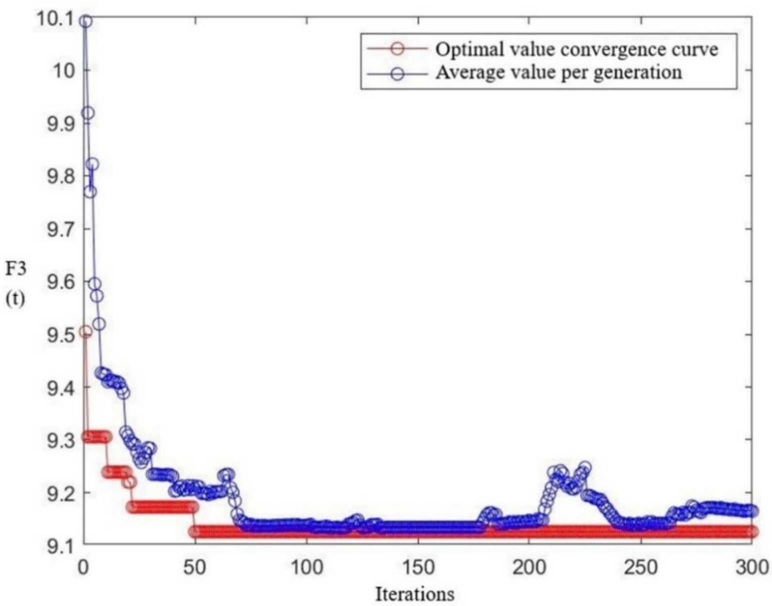

Figure 9. Optimal value convergence curve of fuel consumption and average value curve of each generation.

6.2. Rationality Verification

This section will test the rationality of the model according to the optimal solution with the optimal total scheduling time in the Pareto solution set given in Table 7 and the requirements of navigation rules and port resource constraints.

As shown in Table 7, the actual start times of the individual vessels are not earlier than the start times that were applied for the inbound time. Additionally, the start and end times of vessels 3 and 15, which need to enter the port by the tide and of vessel 11, which needs to leave the port by the tide, are within the relevant tide time windows. The times that each vessel enters and leaves areas A, B, and C (see Figure 1) are listed in Table 8. A Gantt chart for the channel and berths is shown in Figure 10.

Table 7. Optimal solutions with the optimal total scheduling time in the Pareto solution set.

Vessel Number	Start Time of Inbound Operations That Was Applied for (min)	Actual Start Time of Inbound Journey (min)	Start Time of Outbound Operations That Was Applied for (min)	Actual Start Time of Outbound Operations (min)	Allocated Berth	Vessel Speed (Knots)	
						Channel	Harbor Basin
1	0	0	613	629	3	8	5
2	11	15	713	806	6	8	5
3	35	152	1224	1230	1	8.9	5
4	120	120	509	509	9	8.7	5
5	126	135	532	532	7	8.7	5
6	145	193	650	650	5	8.7	5
7	170	170	823	823	10	8	5
8	179	771	1424	1424	10	8	5
9	240	240	644	665	4	8.7	5
10	300	300	953	953	2	8	5
11	332	332	1582	1582	11	8.9	5
12	476	786	1484	1484	6	8	5
13	540	615	1268	1268	5	8	5
14	641	641	1208	1208	7	8	5
15	645	1667	2739	2739	1	8.9	5
Total vessel scheduling time (min)					Berth matching degree	Fuel consumption (t)	
12,542					82.33	10.05	

Table 8. Time data for vessels entering and leaving areas A, B, and C.

Vessel Number	Time of Entry to Area A (min)		Time Leaving Area A (min)		Time of Entry to Area B (min)		Time Leaving Area B (min)		Time of Entry to Area C (min)		Time Leaving Area C (min)	
	Inbound	Outbound	Inbound	Outbound	Inbound	Outbound	Inbound	Outbound	Inbound	Outbound	Inbound	Outbound
1	33	705	64	736	64	673	96	705	96	629	165	673
2	48	882	79	913	79	850	111	882	111	806	180	850
3	182	1302	210	1330	210	1273	239	1302	239	1230	327	1273
4	151	581	180	610	180	552	209	581	209	509	277	552
5	166	604	195	633	195	575	224	604	224	532	292	575
6	224	722	253	751	253	693	282	722	282	650	350	693
7	203	899	234	930	234	867	266	899	266	823	335	867
8	804	1500	835	1531	835	1468	867	1500	867	1424	936	1468
9	271	737	300	766	300	708	329	737	329	665	397	708
10	333	1029	364	1060	364	997	396	1029	396	953	465	997
11	362	1654	390	1682	390	1625	419	1654	419	1582	487	1625
12	819	1560	850	1591	850	1528	882	1560	882	1484	951	1528
13	648	1344	679	1375	679	1312	711	1344	711	1268	780	1312
14	674	1284	705	1315	705	1252	737	1284	737	1208	806	1252
15	1697	2811	1725	2839	1725	2782	1754	2811	1754	2739	1822	2782

According to the information in Table 8 and Figure 10, within the one-way navigation area, there is no time overlap between the inbound and outbound vessels. It can also be seen from Figure 10 that the inbound and outbound vessels that are not allowed to undertake two-way navigation (vessels 3, 11, and 15) remain in one-way navigation mode throughout the process of entering and leaving the port. In addition, according to these results, an appropriate safe time interval is maintained between successive inbound and outbound vessels. Therefore, it can be concluded that the results obtained by using the

NSGA-II-DP algorithm to solve the proposed model conform to the navigation rules, which indicates that, in terms of time and navigation rules, the model constraints are reasonable.

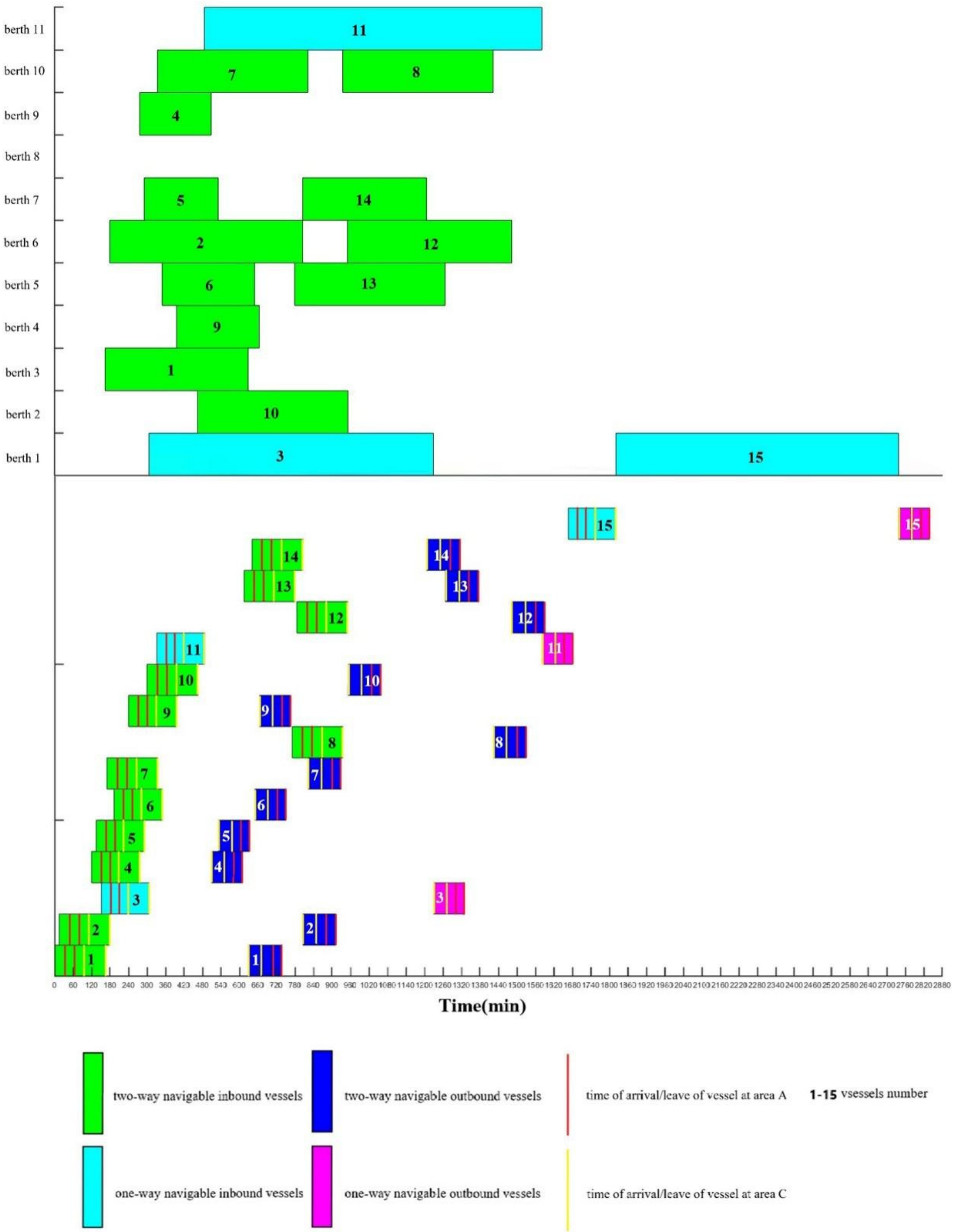

Figure 10. Gantt chart of the navigation channel and berths.

As for the berth constraints, it can be seen from the Gantt chart in Figure 10 that there is no conflict between the berthing time and the berth space when the vessels are berthing and no time conflict between the vessels continuously berthing at the same berth. Therefore, again, the berth constraints in the model can be said to be reasonable.

The number of use of tugs scheduled for use at different times throughout the planning period is shown in Figure 11. It can be seen that the maximum number of tugs in use at the same time does not exceed the number of tugs in the port. This shows that the resource constraints in the model are also reasonable.

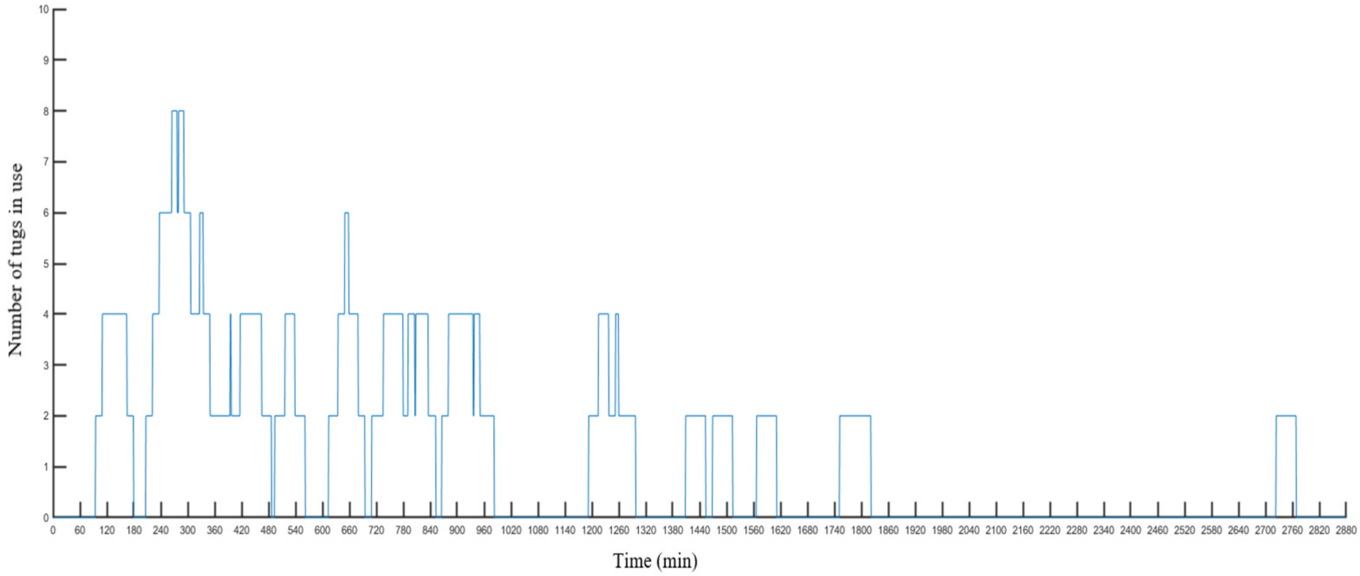

Figure 11. Number of tugs scheduled to operate at different times.

The speed allocated by the model to each vessel type in the case study conforms to the speed constraints of the port, indicating that the model effectively accounts for the speed constraints.

It can be concluded that, based on the results presented in Table 8 and Figure 10, the model produces reasonable results.

6.3. Sensitivity Analysis

In the previous two sections, the proposed model was verified by analyzing the results of the case study involving 15 vessels. In this section, the results for cases with different numbers of tugs and different numbers of vessels will be analyzed. The results obtained using our model and the NSGA-II-DP algorithm will then be compared with the results obtained using the traditional FCFS strategy used by ports. This will allow the reliability of the model and the robustness of the algorithm, as well as their advantages, compared to the traditional FCFS strategy, to be tested.

Cases involving small, medium, and large vessels were generated. For these different cases, the results of applying the NSGA-II-DP algorithm and traditional FCFS strategy will be compared in this section. Because the traditional FCFS strategy arranges vessels according to the order of the time of vessel applying for inbound and outbound operations, the order for servicing vessels is fixed. However, there are no detailed regulations on berth allocation. Therefore, for this analysis, we followed the principle of the FCFS strategy to allocate the berths as follows. The vessels that arrived earliest were allocated berths in order of the berth matching degrees (from high to low). For berths with the same matching degree, one of these berths was randomly selected. If all berths suitable for vessels have been allocated at this time, the berth with the earliest service end time was allocated to the vessel. If multiple berths were idle at the same time during the subsequent allocation, the berth with the highest matching degree was preferred for allocation. If several berths had the same matching degree, the random selection of berths could produce several different berth allocation plans, which could affect the results. Since the goal of using the FCFS strategy is to reasonably arrange the total vessel scheduling time, we selected the optimal result for the total scheduling time for comparison with the optimal solution with the optimal total scheduling time in the Pareto solution set obtained using the NSGA-II-DP algorithm. Table 9 shows the optimal values, F1, F2, and F3, for different targets calculated by the NSGA-II-DP algorithm for different numbers of vessels (5, 10, 15, 20, 25, and 30). It can be seen from the table that, for different numbers of vessels, Pareto solution sets containing optimized solutions with different objective weights can still be obtained using our model and the NSGA-II-DP algorithm. This illustrates the reliability of the model and the robustness of the NSGA-II-DP algorithm.

Table 9. Results of applying the NSGA-II-DP algorithm to cases with different numbers of vessels.

Number of Vessels	NSGA-II-DP		
	Optimal Value of Total Scheduling Time in Pareto Solution Set, F1 (min)	**Optimal Value of Berth Matching Degree in Pareto Solution Set, F2**	**Optimal Value of Fuel Consumption in Pareto Solution Set, F3 (t)**
5	3285	28.25	3.1202
10	6316	61.25	6.1631
15	13,146	89	9.126
20	20,696	120	12.1289
25	30,649	148.25	15.1318
30	40,213	173.25	18.252

Table 10 and Figure 12 show a comparison under different numbers of vessels between the results for the optimal vessel scheduling time that were obtained using the traditional FCFS strategy and optimal solution with the optimal total scheduling time in the Pareto solution set obtained using the NSGA-II-DP algorithm; here, F1 is the optimal scheduling time and F2 is the berth matching degree. Since vessel speeds cannot be set using the FCFS strategy, the speed from the NSGA-II-DP solution was used in this case. As a result, the fuel consumption and carbon emissions for the two sets of results were the same and no comparison between these was made. According to the analysis in Section 6.1, if different vessels of the same type carrying the same cargo choose the same berth with a high matching degree, the overall matching degree of the solution will increase; however, this will also increase the total scheduling time. If instead, one of these vessels chooses an idle berth with a low matching degree, the vessel's waiting time will be reduced; however, the overall matching degree will also be lower. In the cases with 5 and 10 vessels described above, based on the settings of the vessel and berth parameters, the number of berths in the port can meet the requirements of all vessels even if they enter the port at the same time. Therefore, according to the previous analysis, the optimal solution for the total vessel scheduling time selected from the Pareto solution set is a solution obtained by optimizing the total vessel dispatch time and the berth matching degree at the same time under the conditions that the same berth is not reused and the total scheduling time accounts for a large target weight. According to the above analysis, under the condition that berths are not reused, the berth allocation of the FCFS strategy is equivalent to taking the optimization of the berth matching degree as the goal, and because it does not need to consider the optimization of the total scheduling time, the FCFS strategy will obtain a better matching degree of berths similar to the former. Because in the case of 5 and 10 vessels, we set only one one-way navigable vessel, which is in the front of the fixed vessel service sequence of FCFS strategy, and it also needs priority scheduling in the optimization results given by our model and algorithm, and their service sequence has little impact on the scheduling time. Therefore, the fixed vessel service sequence used by the FCFS strategy is similar to the optimized vessel service sequence given by our model and algorithm and can produce good results in terms of the total scheduling time. Therefore, in these two special cases related to the parameter settings, the FCFS strategy will produce a solution similar to the optimal solution for optimal total scheduling time obtained using our model and the NSGA-II-DP algorithm. In the 5- and 10-vessel cases, the solutions obtained using the two methods each have their own advantages, but there is not much difference between them. However, as the total number of vessels increases, the number of one-way vessels increases; the fixed vessel service sequence of the FCFS then has difficulty in obtaining a better total scheduling time. In addition, the advantages related to berth resources become fewer, and the complexity of the berth allocation increases. It is difficult to provide a berth allocation scheme with a good berth matching degree based on the principle of first come first serve. Compared with the FCFS strategy, the use of our model together with the NSGA-II-DP algorithm can produce better solutions that meet the needs of multi-objective optimization. In this comparison, we choose the solution with the best total scheduling time in the Pareto solution set; compared with other solutions in the set, the berth matching degree for the optimal solution was relatively low. In contrast, the berth allocation method we used for the FCFS strategy tends to give priority to berths with a high matching degree. Therefore, compared with the results obtained using the FCFS strategy, the ability of the proposed method to optimize the total scheduling time is more obvious; the berth matching degree is also improved, and these advantages become greater as the number of vessels increases. In addition, the use of the proposed model with the NSGA-II-DP algorithm produces Pareto solution sets containing optimized solutions with different objective weights. The solution sets also contain other solutions in which the results for all objectives are better than the results obtained using the FCFS strategy when the number of vessels is small (this does not include the solution with the optimal total scheduling time in the solution set). Decision makers can be chosen by themselves according to management needs. Therefore, our model and NSGA-II-DP algorithm have more advantages in assisting port decision management.

Table 10. Results of applying the traditional FCFS strategy and the NSGA-II-DP algorithm to different numbers of vessels.

Number of Vessels	FCFS		NSGA-II-DP		Gap (%)	
	F1 (min)	F2	F1 (min)	F2		
5	3293	26.75	3285	26.75	−0.24	0
10	6334	54.42	6292	53.92	−0.66	−0.92
15	14,231	80.83	12,542	82.33	−11.87	1.86
20	23,549	108.17	18,651	109.83	−20.80	1.53
25	38,058	130.08	26,910	138.92	−29.88	6.80
30	62,134	156.42	36,154	161.75	−41.81	3.41

A case study in which the number of tugs was varied was also performed, with the case of 15 vessels in Section 6.1 as the basic case, and the number of tugs was changed to generate different cases. Table 11 and Figure 13 show a comparison between the results obtained using our model together with the NSGA-II-DP algorithm and those obtained using the traditional FCFS strategy. As before, since the vessel speed could not be set using the FCFS strategy, the speed from the NSGA-II-DP solution was used, which again meant that the fuel consumption and carbon emissions for the two sets of results were the same and no comparison was made. From the results, it can be seen that, for both sets of results, changing the number of tugs has little effect on the berth matching degree. In terms of the total vessel scheduling time, there is little change for the total scheduling time obtained through our model and the NSGA-II-DP algorithm when the upper limit on the number of tugs is 4, 6, 8, or 10; when the upper limit on this number is changed to two, the total vessel scheduling time obtained through our method increases slightly, whereas, for the FCFS strategy, the total vessel scheduling time increases significantly once the upper limit on the number of tugs falls below six. Because the FCFS strategy provides a fixed vessel service sequence, it cannot produce a better scheduling result if the number of tugs is changed, so the number of tugs has a great impact on the total scheduling time. However, our model and the NSGA-II-DP algorithm can always give an optimized vessel service sequence through optimization in cases of different upper limits of the number of tugs. This leads to better vessel scheduling results and reduces the impact of the change in the number of tugs on the results, which proves the reliability of our model and the robustness of the NSGA-II-DP algorithm. Overall, if the number of tugs is changed, the use of our model and the NSGA-II-DP algorithm always gives a better solution in terms of the multiple objectives of port scheduling than the FCFS strategy. In cases with different numbers of tugs, the results of our model and NSGA-II-DP algorithm are always better than the traditional FCFS strategy, and have obvious advantages in total scheduling time, which is in line with the previous analysis.

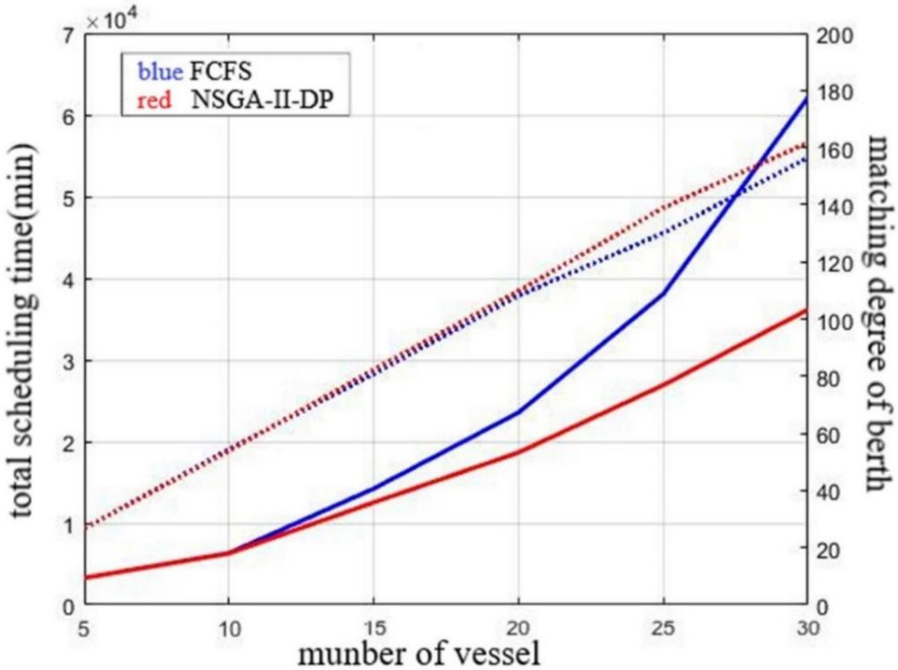

Figure 12. Comparison between the results of the NSGA-II-DP and FCFS strategies for different numbers of vessels.

Table 11. Comparison between the results of the total vessel scheduling time obtained using the traditional FCFS strategy and those obtained using the NSGA-II-DP algorithm for different numbers of tugs.

Number of Tugs	FCFS		NSGA-II-DP		Gap (%)	
	F1 (min)	F2	F1 (min)	F2		
2	19,572	79.25	13,532	83.33	−30.86	5.15
4	15,169	81.5	12,561	82.33	−17.20	1.01
6	14,857	81.5	12,543	83.17	−11.87	2.04
8	14,208	80.83	12,539	82.83	−11.74	2.49
10	14,231	80.83	12,542	82.33	−11.87	1.86

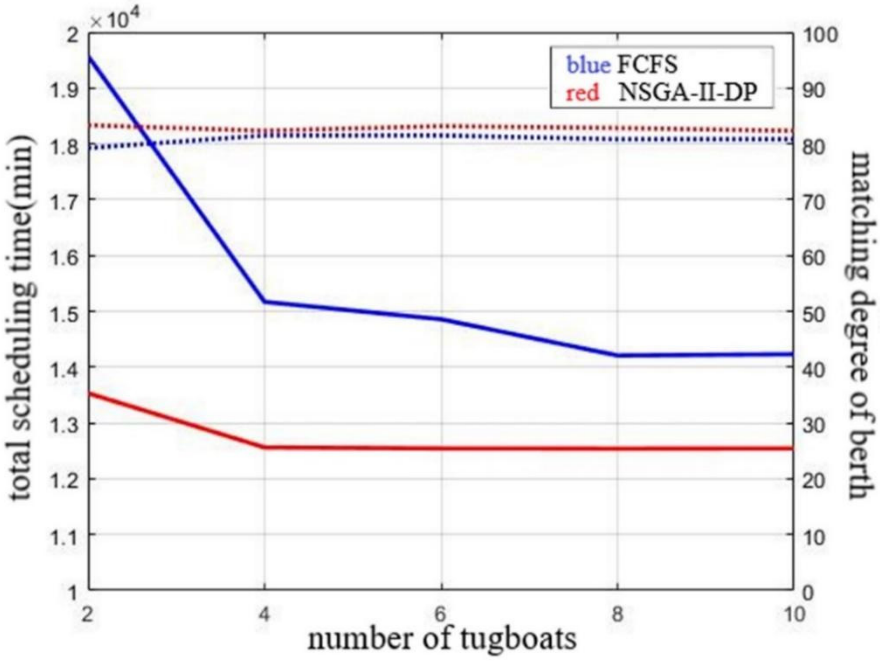

Figure 13. Comparison between the results of the total vessel scheduling time and the berth matching degree obtained using the traditional FCFS strategy and those obtained using the NSGA-II-DP algorithm for different numbers of tugs.

In this section, the reliability of the proposed optimization model and the robustness of the NSGA-II-DP algorithm were verified, as was the superiority of the proposed model and NSGA-II-DP algorithm over the traditional FCFS strategy used by ports in terms of meeting the multiple objectives of vessel scheduling. In port management, it is necessary to consider not only the total vessel scheduling time, but also other objectives. The FCFS strategy cannot be used to optimize the fuel consumption of vessels, and, as the number of vessels increases, the results for the total scheduling time and berth matching degree become poorer. However, by applying the proposed model and the NSGA-II-DP algorithm, better solutions for the multiple objectives can be obtained, and the advantages of the proposed method become clearer as the number of vessels increases. Using the traditional FCFS strategy, changing the number of tugs does not lead to better scheduling results because of the fixed vessel service sequence used. Additionally, as the number of tugs is reduced, the total scheduling time increases significantly. Using the proposed model together with the NSGA-II-DP algorithm, the vessel service sequence can always be optimized. This leads to better results for vessel scheduling and reduces the impact of changing the number of tugs on the results. The results obtained using our model and the NSGA-II-DP algorithm are better than those obtained using the traditional FCFS strategy for any number of tugs. In addition, using the proposed model with the NSGA-II-DP algorithm produces a Pareto solution set, which can be used by decision-makers to select the solutions appropriate to their requirements and preferences. The results obtained using this model and NSGA-II-DP algorithm thus conform better to port management needs and can provide better assistance for decision-makers.

6.4. Sensitivity Analysis

In this section, a comparison between the results of applying the NSGA-II algorithm and NSGA-II-DP algorithm to different numbers of vessels will be used to demonstrate the superiority of the NSGA-II-DP algorithm. In order to ensure a fair comparison, the algorithms were both run 10 times in each case. Each calculation produces a Pareto solution set and optimal values for three objectives (total dispatch time, berth matching degree, and fuel consumption). The worst, best, and average values of the optimal values of each target in 10 calculations are shown in Table 12. The average values of these optimal values for different numbers of vessels over the 10 calculations are shown in Figures 14–16.

Table 12. The optimal values of the three targets calculated for different numbers of vessels. The results are based on running the algorithms 10 times in each case.

Number of Vessels			5	10	15	20	25	30
F1: optimal value of total scheduling time (min)	NSGA-II	Worst value in 10 calculations	3285	6358	12,962	19,896	29,506	40,393
		Best value in 10 calculations	3285	6305	12,564	18,468	27,341	36,450
		Average of 10 calculations	3285	6331.6	12,807.1	19,211.6	28,298.1	38,475.3
	NSGA-II-DP	Worst value in 10 calculations	3285	6353	12,913	19,566	28,211	38,913
		Best value in 10 calculations	3285	6292	12,542	18,651	26,910	36,154
		Average value of 10 calculations	3285	6315.8	12,723.8	19,188.4	27,665.3	37,188.9
F2: optimal value of berth matching degree	NSGA-II	Worst value in 10 calculations	28.25	61.25	87.67	116.5	146.42	170.08
		Best value in 10 calculations	28.25	61.25	89	120	149.58	175.75
		Average value of 10 calculations	28.25	61.25	88.47	118.6	148.13	172.85
	NSGA-II-DP	Worst value in 10 calculations	28.25	61.25	87.67	120	147.92	175.08
		Best value in 10 calculations	28.25	61.25	89	120	150.92	178.92
		Average value of 10 calculations	28.25	61.25	88.87	120	150.42	177.60
F3: optimal value of fuel consumption (t)	NSGA-II	Worst value in 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25
		Best value in 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25
		Average value of 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25
	NSGA-II-DP	Worst value in 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25
		Best value in 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25
		Average value of 10 calculations	3.12	6.16	9.13	12.13	15.13	18.25

From Table 12 and Figures 14–16, it can be seen that because the range of speeds is small, the feasible solution range for the fuel consumption is also small. Therefore, the NSGA-II and NSGA-II-DP algorithms give the same optimal value as each other for fuel consumption in cases of different numbers of vessels. For the total scheduling time and berth allocation, when the number of vessels is small (five vessels in the case of the total scheduling time and five or ten vessels in the case of the berth allocation), the feasible solution range is again small and the two algorithms converge to the same optimal values. However, as the number of vessels increases, the range of feasible solutions increases.

Although in the case of 20 vessels, the best value of the optimal value of total scheduling time obtained using the NSGA-II algorithm over 10 calculations is slightly better than that obtained using the NSGA-II-DP algorithm, the overall results and average values of the 10 calculations show that the NSGA-II-DP algorithm performs better than the NSGA-II algorithm. This shows that the NSGA-II-DP algorithm converges more strongly than the NSGA-II algorithm and can effectively avoid falling into the trap of local optimization and premature convergence. The proposed NSGA-II-DP algorithm is an effective improvement on the original NSGA-II algorithm.

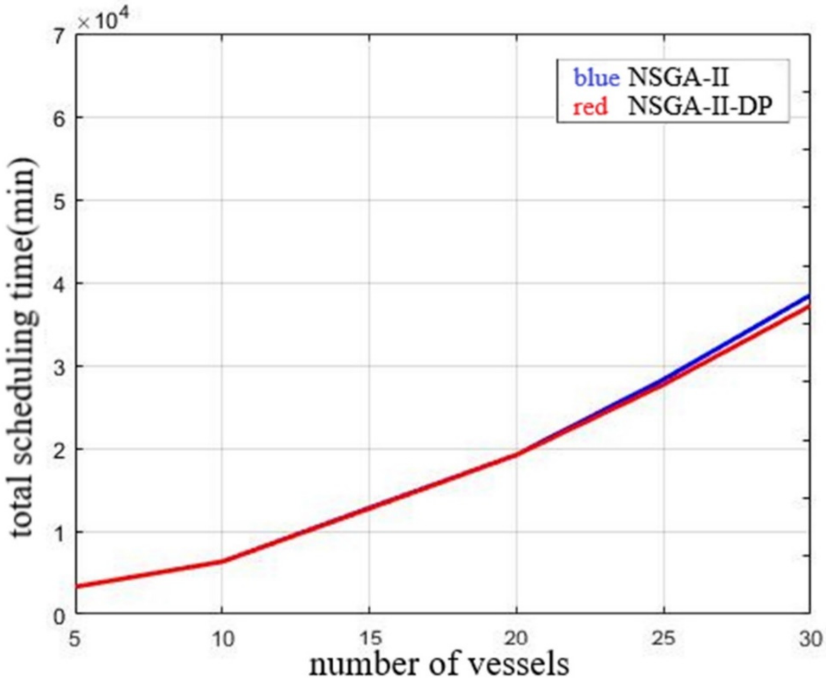

Figure 14. The average value of the optimal value of the total scheduling time over 10 calculations.

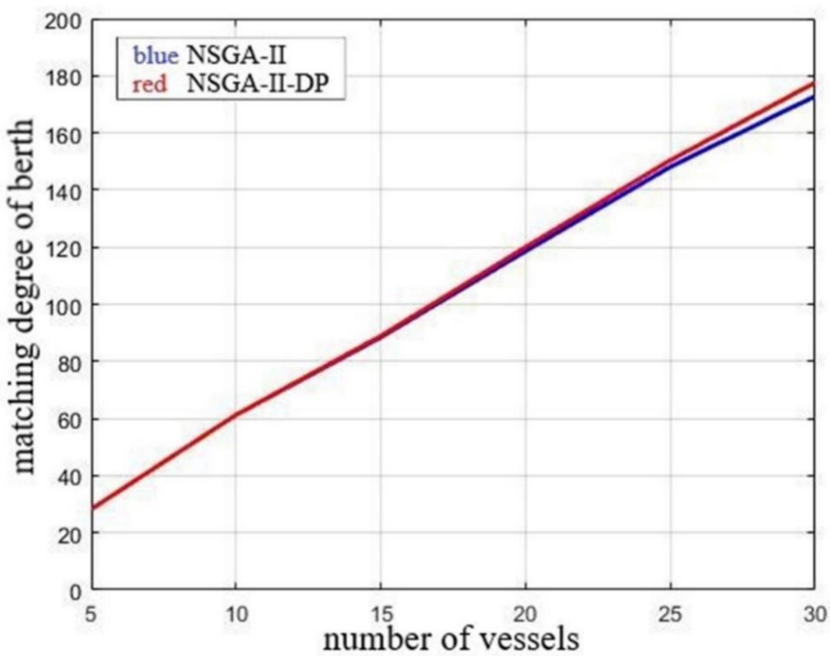

Figure 15. The average value of the optimal value of the berth matching degree over 10 calculations.

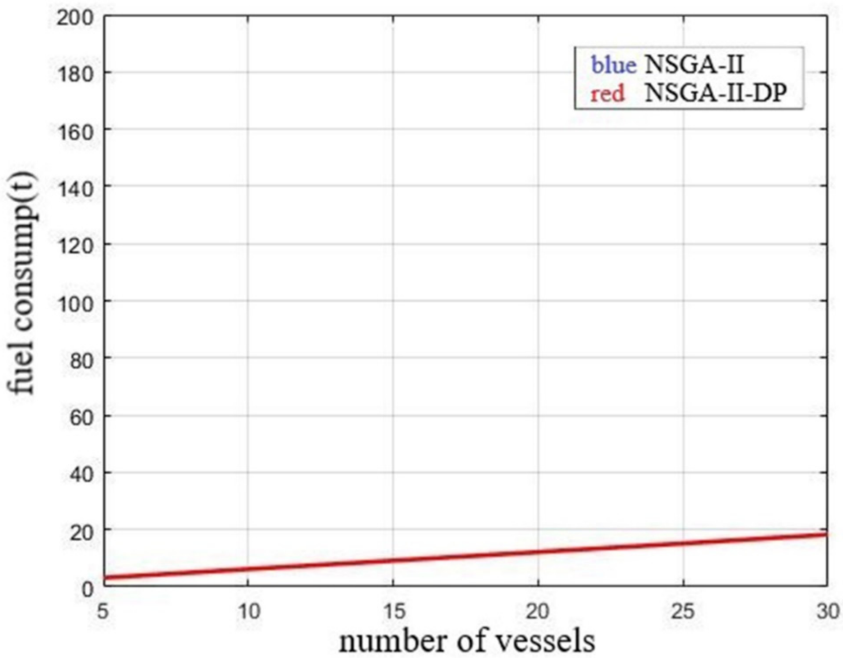

Figure 16. The average value of the optimal value of the fuel consumption over 10 calculations.

7. Conclusions

Based on a port layout that included a restricted channel and harbor basin berths, in this paper, the problem of the scheduling of vessels in a restricted channel in conjunction with berth allocation was analyzed and described. The factors and target requirements to be considered were analyzed, and a multi-objective overall scheduling model for the vessel scheduling and berth allocation that took carbon emissions into account was then constructed. A newly developed algorithm, the NSGA-II-DP algorithm, was used for the calculations. The main contributions are as follows:

(1) By considering both the complex vessel scheduling problem for a restricted channel along with the berth allocation problem, a comprehensive model for vessel scheduling in a restricted channel and berth allocation that considers carbon emissions is developed. avoiding the sub-optimal results of separate optimization.
(2) Tide times, traffic conflicts, port scheduling resources, and other factors are considered in the overall scheduling model to make the model more realistic. Furthermore, the model also considers the matching degree between the berth and the ship and the carbon emissions during navigation, which brings the research more in line with the real requirements of port management and the general trend toward sustainable shipping. Through the experimental results, we explained the relationship between the three objectives, verified the rationality of the model results, and proved the superiority of our model and algorithm compared with the traditional FCFS strategy of port dispatching in different situations.
(3) In order to solve the problem that the population diversity of the NSGA-II algorithm decreases and the solution falls into the local optimum, we have constructed the algorithm NSGA-II-DP. We compared the results of applying the original NSGA-II algorithm and the NSGA-II-DP algorithm to cases with different numbers of vessels. The results showed that the overall convergence of the NSGA-II-DP algorithm is better than that of the NSGA-II algorithm and thus that the proposed NSGA-II-DP algorithm is a successful improvement on the NSGA-II algorithm.

In this study, the problem of vessel scheduling in a restricted channel was considered together with berth allocation while considering carbon emissions. The research included the further development of an existing model and algorithm and provides basic theoretical support for the further development of this research direction. The results have practical significance as they can be used to support the decisions of port managers who can select solutions appropriate to their requirements. The proposed mathematical model is universally applicable and can be modified according to the actual needs of individual ports. However, there are still some additional problems that remain to be considered such as vessel delays, inner anchorages, pilot scheduling, and yard allocation. We will expand our research to include considerations of these problems in future studies.

Author Contributions: Conceptualization, X.J.; Data curation, X.J.; Formal analysis, X.J.; Funding acquisition, M.Z.; Project administration, M.Z. and W.L.; Software, X.J.; Supervision, M.Z.; Writing—original draft, X.J.; Writing—review & editing, X.J., M.Z., J.S., W.L., Y.S. and Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by [National Science Foundation of China] grant number [52101399] and [National Social Science Fund of China] grant number [22BGJ034] And the APC was funded by [National Social Science Fund of China, grant number 22BGJ034].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. UNCTAD. Review of Maritime Transport 2021. United Nations Conference on Trade and Development. Available online: https://unctad.org/webflyer/review-maritime-transport-2021 (accessed on 1 October 2022).
2. Jia, S.; Li, C.-L.; Xu, Z. Managing navigation channel traffic and anchorage area utilization of a container port. *Transp. Sci.* **2019**, *53*, 728–745.
3. Li, J.; Zhang, X.; Yang, B.; Wang, N. Vessel traffic scheduling optimization for restricted channel in ports. *Comput. Ind. Eng.* **2021**, *152*, 107014.
4. Zhang, X.; Chen, X.; Ji, M.; Yao, S. Vessel scheduling model of a one-way port channel. *J. Waterway Port Coast. Ocean. Eng.* **2017**, *143*, 04017009.
5. Zhang, B.; Zheng, Z. Model and algorithm for vessel scheduling through a one-way tidal channel. *J. Waterw. Port Coast. Ocean. Eng.* **2020**, *146*, 04019032. [CrossRef]
6. Abou Kasm, O.; Diabat, A.; Bierlaire, M. Vessel scheduling with pilotage and tugging considerations. *Transp. Res. E.* **2021**, *148*, 102231. [CrossRef]
7. Hill, A.; Lalla-Ruiz, E.; Voß, S.; Goycoolea, M. A multi-mode resource-constrained project scheduling reformulation for the waterway ship scheduling problem. *J. Sched.* **2019**, *22*, 173–182.
8. Zhang, B.; Zheng, Z.; Wang, D. A model and algorithm for vessel scheduling through a two-way tidal channel. Marit. *Policy Manag.* **2020**, *47*, 188–202. [CrossRef]
9. Lalla-Ruiz, E.; Shi, X.; Voß, S. The waterway ship scheduling problem. *Transp. Res. D.* **2018**, *60*, 191–209. [CrossRef]
10. Zhang, X.; Li, R.; Lin, J.; Xu, C. Optimisation modeling of vessel traffic scheduling for Y shaped bifurcated compound waterway. *J. Dalian Marit. Univ.* **2018**, *44*, 1–14.
11. Al-Refaie, A.; Abedalqader, H. Optimal berth allocation under regular and emergent vessel arrivals. *Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ.* **2021**, *235*, 642–656. [CrossRef]
12. Correcher, J.F.; Van den Bossche, T.; Alvarez-Valdes, R.; Vanden Berghe, G. The berth allocation problem in terminals with irregular layouts. *Eur. J. Oper. Res.* **2019**, *272*, 1096–1108.
13. Dulebenets, M.A. An Adaptive Island Evolutionary Algorithm for the berth scheduling problem. *Memetic Comput.* **2020**, *12*, 51–72.
14. Bacalhau, E.T.; Casacio, L.; Tavares de Azevedo, A. New hybrid genetic algorithms to solve dynamic berth allocation problem. *Expert Syst. Appl.* **2021**, *167*, 114198. [CrossRef]
15. Liu, C.; Xiang, X.; Zheng, L. A two-stage robust optimization approach for the berth allocation problem under uncertainty. *Flexible Serv. Manuf. J.* **2020**, *32*, 425–452.
16. Mnasri, S.; Alrashidi, M. A comprehensive modeling of the discrete and dynamic problem of berth allocation in maritime terminals. *Electronics* **2021**, *10*, 2684.
17. Hu, Z.H. Low-emission berth allocation by optimizing sailing speed and mooring time. *Transport* **2020**, *35*, 486–499.
18. Guo, L.; Wang, J.; Zheng, J. Berth allocation problem with uncertain vessel handling times considering weather conditions. *Comput. Ind. Eng.* **2021**, *158*, 107417. [CrossRef]
19. Wu, Y.; Miao, L. An efficient procedure for inserting buffers to generate robust berth plans in container terminals. *Discret. Dyn. Nat. Soc.* **2021**, *2021*, 6619538. [CrossRef]

20. Guo, W.; Ji, M.; Zhu, H. Multi-period coordinated optimization on berth allocation and yard assignment in container terminals based on truck route. *IEEE Access* **2021**, *9*, 83124–83136.
21. Zhang, X.; Lin, J.; Guo, Z.; Liu, T. Vessel transportation scheduling optimization based on channel–berth coordination. *Ocean Eng.* **2016**, *112*, 145–152. [CrossRef]
22. Liu, B.; Li, Z.C.; Sheng, D.; Wang, Y. Short-term berth planning and ship scheduling for a busy seaport with channel restrictions. *Transp. Res. E* **2021**, *154*, 102467.
23. Liu, B.; Li, Z.C.; Sheng, D.; Wang, Y. Integrated planning of berth allocation and vessel sequencing in a seaport with one-way navigation channel. *Transp. Res. B Methodol.* **2021**, *143*, 23–47.
24. Wang, B. Research on Bulk Cargo Port Ship Scheduling System Based on Multi-Objective and Genetic Algorithm. Master's Thesis, Beijing Jiaotong University, Beijing, China, 2021. (In Chinese).
25. Al-Hammadi, J.; Diabat, A. An integrated berth allocation and yard assignment problem for bulk ports: Formulation and case study. *RAIRO-Oper. Res.* **2017**, *51*, 267–284.
26. Iris, C.; Lam, J.; Siu, L. Recoverable robustness in weekly berth and quay crane planning. *Transp. Res. Part B Methodol.* **2019**, *122*, 365–389.
27. Iris, C.; Pacino, D.; Ropke, S.; Larsen, A. Integrated berth allocation and quay crane assignment problem: Set partitioning models and computational results. *Transp. Res. Part E Logist. Transp. Rev.* **2015**, *81*, 75–97.
28. Venturini, G.; Iris, C.; Kontovas, C.A.; Larsen, A. The multi-port berth allocation problem with speed optimization and emission considerations. *Transp. Res. Part D Transp. Environ.* **2017**, *54*, 142–159.
29. Coello, C.A.C. An updated survey of GA-based multiobjective optimization techniques. *ACM Comput. Surv.* **2000**, *32*, 109–143.
30. Fonseca, C.M.; Fleming, P.J. Genetic algorithms for multiobjective optimization—Formulation, discussion and generalization. In Proceedings of the Annual Meeting for the 5th International Conference on Genetic Algorithms, University Illinois Urbana Champaign. Urbana, IL, USA, 17–21 July 1993.
31. Srinivas, N.; Deb, K. Multiobjective function optimization using nondominated sorting genetic algorithms. *Evlutionary Comput.* **1995**, *2*, 221–248.
32. Yu, J.; Yin, Y. Assembly line balancing based on an adaptive genetic algorithm. *Int. J. Adv. Manuf. Technol.* **2010**, *48*, 347–354. [CrossRef]