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Simulation Study on Intelligent Construction Path of Green Port for Carbon Peak and Carbon Neutrality

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Abstract Global environmental pollution and climate warming are becoming more and more serious, and ports, as important hubs of transportation and key nodes of logistics system, have high carbon emissions. In this paper, based on the carbon peak carbon neutral goal, a green port intelligent platform is constructed, a green and low-carbon oriented berth-shore-bridge allocation optimization model is designed, and a nested-loop solving algorithm is proposed. In terms of methodology, firstly, a green port intelligence platform with cloud architecture containing facility layer, data layer, service layer and application layer is constructed; then a berth-shore and bridge allocation coupling model is established with ship operation time as the coupling variable, and ship fuel consumption and carbon emission are embedded in the optimization objective; finally, a nested loop solving algorithm combining greedy algorithm and distributed hybrid genetic algorithm is designed. The simulation results show that the proposed nested loop algorithm has better convergence performance than NSGA-II and MNSGA-II, and the average running time is 22.1% lower than that of NSGA-II when solving the 24-ship scale problem; The multi-objective optimization model achieves a reduction of 31 kiloliters of carbon emissions by sacrificing 2.576 minutes of operation time; the 5G technology-enabled intelligent platform improves traffic density by 125 times, connection density by 20 times, and energy efficiency by 120 times compared with the traditional 4G platform. The study shows that the intelligent construction of green ports can effectively reduce carbon emissions, optimize resource allocation, improve port operation efficiency, and provide technical support and solutions for ports to achieve carbon peak carbon neutrality.

Index Terms Green port, Intelligent platform, Berth-shore bridge allocation, Carbon emission, Nested loop algorithm, 5G technology

Introduction

As global climate change becomes increasingly severe, countries have increased their emphasis on green development. In this context, China has put forward the “double carbon” goal, emphasizing the realization of “carbon peak” and “carbon neutral” to cope with the environmental crisis and promote high-quality economic development [1]. As an important node of international trade, with the rapid construction and increasing volume of cargo trade, the environmental impacts of ports on the sea and land are becoming more and more prominent, such as water quality, air quality, noise and solid waste pollution [2]-[4]. Promoting the development of green ports is not only a necessary measure to realize the goal of “double carbon”, but also a necessary path to enhance the competitiveness of ports [5], [6].

The core concept of green port construction is to realize the low-carbon, high-efficiency and environmental protection of port logistics activities through comprehensive environmental protection measures and the application of emerging technologies under the premise of meeting customer needs [7]. In the context of the new era, intelligent technology can be utilized to empower port operation and management methods, thus providing technical support and guarantee for green port construction. For example, based on the Internet of Things (IoT) technology, the location and status of goods and ships can be monitored and tracked in real time to optimize ship scheduling and freight paths, thus reducing carbon emissions [8]. With the help of blockchain technology, a port logistics information sharing platform can be established to ensure the traceability and transparency of the data in each link, and to strengthen supply chain cooperation and trust building [9]. The application of artificial intelligence technology can realize intelligent ship scheduling and facility management, and improve energy utilization efficiency [10]. The use of cloud computing technologies enables data storage and sharing to support transportation planning and decision-making processes [11]. Based on these emerging technologies and measures, improving the informatization level of port construction and optimizing the layout of the port logistics network will inject new vitality into the development of the port industry and promote the industry to develop in a greener and more intelligent direction [12]-[14].

Against the background of global climate change and the intensification of energy crisis, the development of low-carbon economy has become the consensus of all countries. As an important hub and node of international trade and transportation, ports not only carry a huge amount of cargo throughput, but also produce a large amount of carbon emissions. According to the International Maritime Organization (IMO) statistics, greenhouse gases emitted by ports and the shipping industry account for about 2.5% of the global total, and is on the rise. Among them, carbon emissions from port shore-based operations, ship berthing, loading and unloading, and logistics within the port area are particularly prominent, and have become a bottleneck restricting the sustainable development of ports. Major developed countries in the world have formulated port carbon emission reduction strategies, such as the European Union “Green Port Action Plan” proposed to reduce port carbon emissions by 55% by 2030 compared with 2019. The U.S. Environmental Protection Agency has also launched the “Clean Ports Program” to encourage the use of innovative technologies to reduce the environmental impact of ports. Under the background of the “dual carbon” strategy, China has vigorously promoted the green, low-carbon and intelligent development of ports, and the National Coastal Port Layout Plan has clearly proposed to strengthen the construction of intelligent and green ports. However, the traditional port management mode is characterized by information fragmentation, equipment aging, energy waste, and inefficient scheduling, which seriously restricts the realization of port carbon emission reduction goals. The rapid development of modern information technology, especially the Internet of Things, big data, cloud computing, artificial intelligence and other technologies, provides an important opportunity for the intelligent transformation of ports. How to use these advanced technologies to build an intelligent platform for green ports, optimize port scheduling decisions, improve energy use efficiency, and reduce carbon emissions has become a hot issue in current theoretical research and practical exploration.

Based on the above background, this study constructs the intelligent construction path of green port for carbon peak and carbon neutral from two dimensions of intelligent construction and green and low carbon. Firstly, a green port intelligentization platform based on cloud architecture is designed, and the platform architecture is completely constructed from four levels, namely, facility layer, data layer, service layer and application layer, and 5G technology is used to realize port business networking. Secondly, for the core operation link of the port, a green and low-carbon berth-bridge allocation optimization model is established, which incorporates ship fuel consumption and carbon emission into the optimization target, and takes ship operation time as the coupling variable to realize the synergistic optimization of berth allocation and bridge allocation. Again, a nested loop solving algorithm combining greedy algorithm and distributed hybrid genetic algorithm is designed to effectively solve the optimization problem of the coupled berth-bridge allocation model. Finally, the effectiveness of the proposed platform architecture and optimization model is verified through various simulation experiments. This study provides the theoretical basis and technical support for the port industry to realize the goal of carbon peak carbon neutral, and is of great significance in promoting the development of ports in the direction of green, low-carbon and intelligent development.

I. Intelligent building architecture for green ports

Ports are the gateway and hub for opening up to the outside world. In the booming development of information technology such as Internet of Things, big data, cloud computing, artificial intelligence, etc., the development of China's port and shipping industry has ushered in unprecedented opportunities, but also faces new challenges, and the construction of smart ports is an important way for China to build a “world-class strong port”. Under the dual-carbon background of carbon neutrality and carbon compliance, we integrate intelligence with green and low-carbon, and establish an intelligent platform for green ports, so as to realize the intelligent construction of green ports.

I. A. Intelligent development of green ports

I. A. 1)Green Port Technology Architecture

The port is an important hub of transportation and an important node of modern logistics system, with a vast operating area and complex topography, containing both land and water areas. Many modes of transportation coexist in the port, and the traffic organization is challenging, not only cargo ships, passenger ships, but also railroads, steamships, etc., as well as mobile machinery, corridors, pipelines, belt conveyors, etc., within the port area [15]. Under the goal of “double carbon”, it is a hot research topic how to effectively establish an intelligent platform for green ports and lay the foundation for the intelligent construction of ports. Based on this, this paper proposes a green port intelligent platform based on cloud architecture, and its specific architecture is shown in Figure 1. It is mainly composed of four parts: facility layer, data layer, service layer, and application layer, and its purpose is to further optimize the degree of green port intelligence and reduce carbon emissions during port dispatching, so as to better achieve carbon neutrality and carbon compliance.

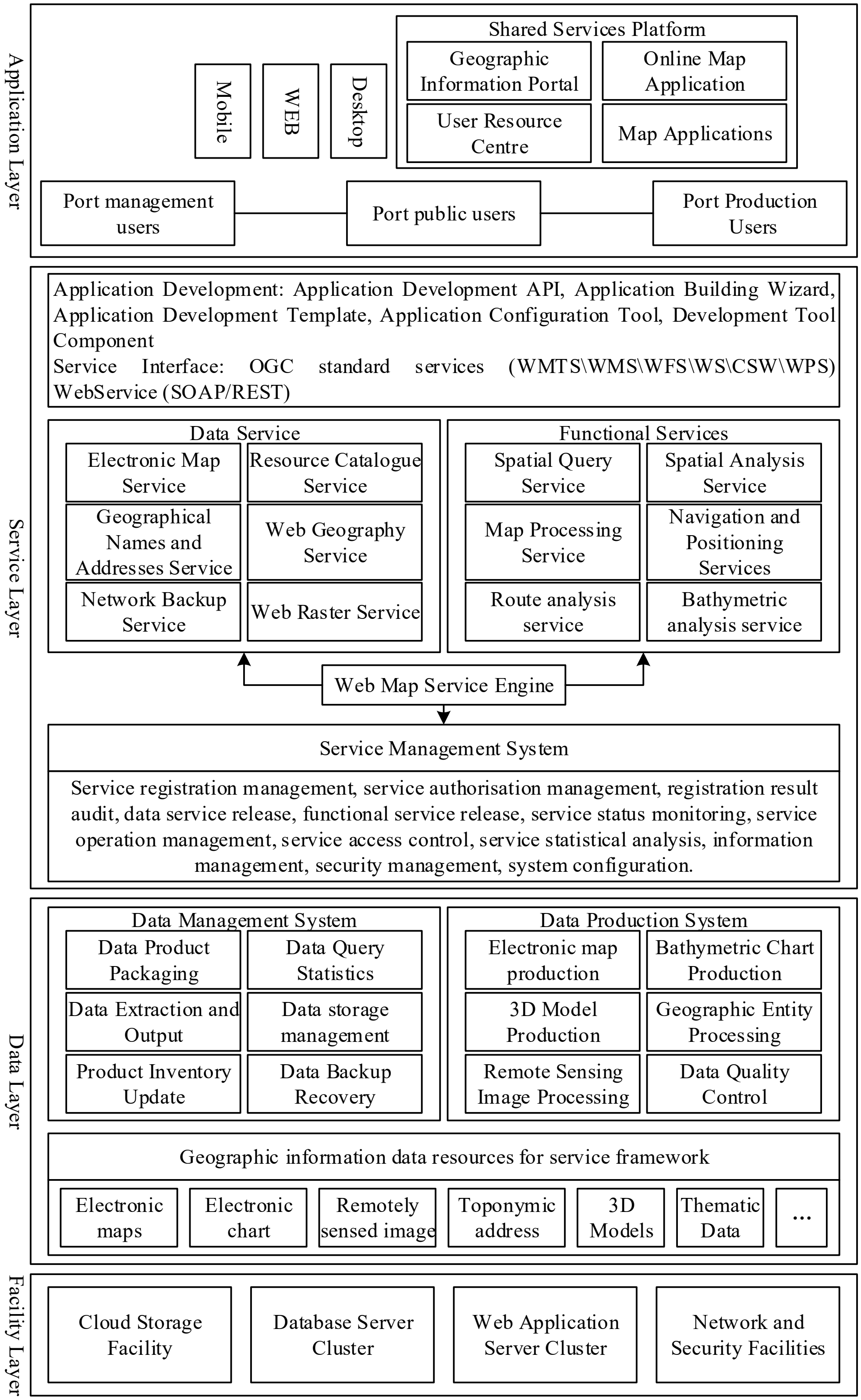


Figure 1: Green port technology architecture

(1) The facility layer mainly includes cloud storage facilities, database server clusters, Web application server clusters and network security facilities, etc., which are the external support conditions for the operation of the whole platform.

(2) The data layer includes the port element information such as electronic map, electronic chart, remote sensing image, three-dimensional model, basic data, thematic data, etc. in the intelligent construction of green port, and is equipped with data production system and data management system to realize the functions of production, processing, and storage of spatio-temporal geographic information.

(3) Service layer is the core link to support various business applications of green port intelligentization platform. Based on the network map service engine, it develops and builds the function service system, data service system and service management system to realize the management of all kinds of spatio-temporal information services. It also develops supporting service interfaces and service applications to support the realization of the functions of the green port intelligent platform.

(4) The application layer is mainly for the functional display of various types of port users, supporting various types of shared service functions for mobile, computer and network, including green port geographic information service, online map application, user resource center, map application cases and so on.

I. A. 2)Characteristics of green port development

Green port intelligence is not a simple stack of concepts such as automated ports and digital ports, but a more advanced stage evolved from information-based ports and digital ports. With the help of modern technology, the construction of green port should start from the perspective of global port supply chain, focus on top-down port planning and implementation, pay attention to the synergy of business units inside and outside the port, such as terminals, ships, railroads, and external management, consider the integration of the development of the port, industry and city, and pay attention to the integration of the port environment and the network environment. With the assistance of modern technology network, the green, efficient, safe and intelligent development of the port is realized.

The intelligent construction of green ports should achieve integrated planning and step-by-step advancement, and the overall planning and implementation of project construction should be characterized by a top-down approach. First of all, we should do a good job of top-level design, strengthen the strategic leadership, can be the intersection of intelligent technology and green port as a breakthrough, from the strategy, tactics, practice and protection of multiple levels of overall planning. Secondly, the middle-level construction program should be planned, and the middle-level planning should eliminate the barriers of data interconnection between the upper and lower levels, so as to achieve the effect of carrying on the upper and lower levels. Governments and port authorities at all levels will take the lead in promoting the results of exemplary green port projects around the world, promoting the desensitization of data of various stakeholders, and introducing supporting policies and documents in conjunction with the resource endowments and specific economic conditions of various places to promote the intelligent construction of first-class green ports. Finally, the port enterprises will implement the bottom specific arrangements, and under the regulation of the top-level design, implement the specific construction programs for the terminals, yards, gates, 5G network deployment and other aspects of each port. Encourage ports to learn from foreign green port practice experience and summarize green port intelligent construction results in a timely manner. Aiming at the problem of generalization of the current green port concept, it is necessary to establish and improve the green port evaluation index system and key technology implementation standards in a timely manner, so as to ensure the consistency between the top-level design and the final deliverables.

I. B. Green Port Intelligence Framework

I. B. 1)Green Port Construction Structure

The main business scenarios of traditional ports range from ship berthing management, cargo transportation management to vehicle scheduling management, port area management, etc., and the whole operation process involves very complex and diverse application scenarios. The green port intelligent construction architecture designed based on cloud architecture in this paper is shown in Fig. 2. Intelligent equipments (AGV/IGV, tire cranes, tugboats, cameras, etc.) in the port area are connected to the industry's virtual private network through terminals such as CPE, 5G modules, and so on.

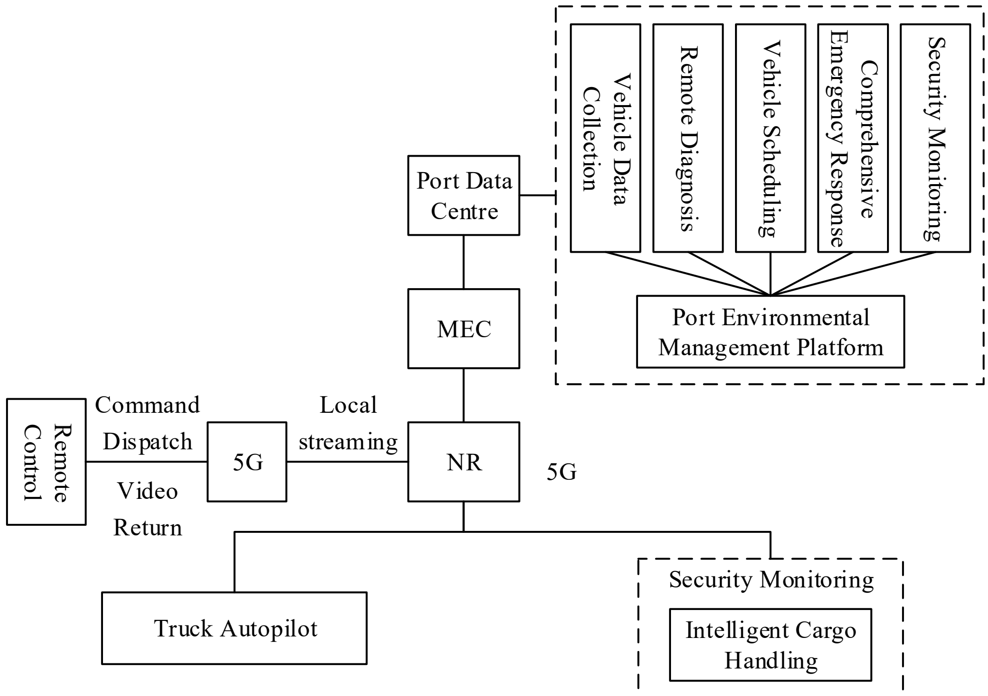


Figure 2: The intelligent construction framework of the port

MEC can be deployed flexibly, vertically and horizontally, behind the base station nodes or in other reasonable locations. Port MEC not only provides business processing and computing capabilities, but also streams data in and out of the port, which further improves the security of port data in addition to ensuring efficient processing capabilities and low-latency response. The port business server provides a unified port integrated business platform to support various businesses in the port, and the MEC platform provides data and services to various business systems in the port (including the port engine system, intelligent cargo handling system, container truck transportation system, and operation security system, etc.) through standardized northbound interfaces. The location of each specific business application in the port can be deployed flexibly according to the demand, and can be placed directly on the MEC close to the user or in the centralized data center room of the port to ensure that the data does not leave the park.

I. B. 2)Green Port Operations Networking

The 3GPP protocol defines three main scenarios for network applications, one is enhanced mobile broadband (eMBB) service, which requires high data rate and forwarding plane bandwidth of the network, and typical services such as ultra-high-definition video and other high-traffic mobile broadband services. The second is low-latency and high-reliability (uRLLC) service, which requires high end-to-end delay, security and reliability of the network, usually requiring end-to-end delay of less than 6ms and reliability of more than 99.99%. The third is the large connection low-power (mMTC) service, which meets the network requirements of low power consumption and massive connection.

Green port intelligent platform based on eMBB can carry out video monitoring, customs enforcement services, based on mMTC can carry out temperature and humidity monitoring, static electricity monitoring, logistics goods tracking and other services, based on eMBB and uRLLC can carry out automatic driving, remote control of the shore bridge and other services. 5G network according to the QoS, delay, security and other needs of the scenario, the allocation of network resources allocation end-to-end The 5G network allocates network resources to allocate end-to-end slices according to the QoS, delay, security and other requirements of the scenario, and combines the slices according to the actual requirements based on the network capacity, so that multiple logical subnets with different characteristics can be virtualized based on 5G network.

The deployment of green port services can be reasonably carried out in combination with the deployment of 5G system and actual business needs. At the initial stage of deployment, it is recommended to focus on NB-IoT IoT data collection, customs law enforcement services, and video monitoring in the port area. There are a large number of semi-trailers (collector trucks) transporting containers inside and outside the port, and in the middle stage of deployment, remote control of self-driving collector trucks and remote control of shore bridges can be carried out gradually. In the mature stage of development, vehicle networking can be deployed on a large scale to carry out self-driving collector trucks with network synergy and other innovative businesses in the port area.

II. Green and low-carbon oriented berth-bridge allocation optimization model

With the increasingly serious problems of environmental pollution and global warming, the concept of green development continues to penetrate into the transportation industry, and container terminals, as an important part of the transportation industry, are the key to promoting the construction of green ports. Container terminals, as an important part of the transportation industry, are the key to promoting the construction of green ports, and it is especially important to carry out the research on green and low-carbon operation scheduling. Green operation scheduling refers to the fact that when coordinating and scheduling the operation links, emission reduction or reduction of energy consumption will be taken into consideration as scheduling factors, so as to realize the low-carbon and energy-saving operation scheduling.

II. A. Coupled Berth-Shorebridge Allocation Modeling

II. A. 1) Sub-model for berth allocation under green low carbon

In the traditional Berth Allocation (BAP) model, ships continue to arrive at the port over time, and the port planner assigns shoreline berths and berthing times to each ship so that the ship can leave the terminal as soon as possible. Under the dual-carbon objective, this paper includes ship arrival time as a decision variable, which will offer the possibility to optimize ship fuel consumption and reduce carbon emissions. This new berth allocation strategy can be called VAT strategy. In the VAT strategy, the fuel consumption and carbon emissions of ships are integrated into the objective function of the BAP model for optimization [16].

In general, for ship i, the shipping company can control its arrival time at the port by adjusting its speed, i.e., a_i is used as a decision variable and is no longer regarded as a constant parameter. The value of a_i should lie between $[\underline{a}_i, \overline{a}_i]$, with $\underline{a}_i$ and $\overline{a}_i$ being determined by the ship's maximum and minimum speeds, respectively.

It is assumed that the berth allocation plan starts from moment zero, when ship i is at a distance of $m_i\left(nmile\right)$ from the port. According to international shipping management, the functional relationship between the fuel consumption f_i per sailing day of ship i and the adopted speed v_i can be expressed as:

$$f_i = c_i^1 + c_i^0 \cdot v_i^3 \tag{1}$$

where c_i^0 is the functional coefficient of ship i and c_i^1 is the auxiliary diesel fuel consumption of ship i per sailing day.

The fuel consumption F_i of ship i during traveling from the distance from the port $m_i\ nmile$ to the port can be expressed as:

$$F_i = \frac{1}{24} \cdot \left[c_i^1 + c_i^0 \cdot \left(\frac{m_i}{a_i} \right)^3 \right] \cdot a_i = \frac{1}{24} \cdot (c_i^1 \cdot a_i + c_i^0 \cdot m_i^3 \cdot a_i^{-2}) \tag{2}$$

Since the ship's arrival time a_i becomes a decision variable and is no longer a constant parameter, the original objective function value can be minimized by adjusting the values of a_i and y_i. However, a problem that must be considered is that a ship's arrival time is controlled by changing its sailing speed when approaching the port, which can minimize its waiting time and operation time in the port, but it will affect its departure time, and then affect the ship's schedule. In order to prevent all ships from approaching the port with the lowest speed to reduce fuel consumption and carbon emission, and at the same time to shorten the in-port operation time, the original objective function needs to be improved, i.e., the objective function of minimizing the average in-port operation time of the ship is modified to minimize the average delay time of the ship leaving the port.

The original objective function is modified to minimize the average ship departure delay time by using d_i to denote the expected ship departure time:

$$\min f = \frac{1}{n} \sum_{i \in V} (y_i + h_i - d_i)^+ \tag{3}$$

This results in the following BAP model for a low carbon economy:

$$\min f_1 = \frac{1}{24}\sum_{i\in V}(c_i^1 \cdot a_i + c_i^0 \cdot m_i^3 \cdot a_i^{-2}) \tag{4}$$

$$\min f_2 = \frac{1}{n}\sum_{i\in V}(y_i + h_i - d_i)^+ \tag{5}$$

$$s.t.\ x_i + l_i \le L, i \in V \tag{6}$$

$$x_i + l_i \le x_j + M(1-\sigma_{ij}), i, j \in V, i \ne j \tag{7}$$

$$y_i + h_i \le y_j + M(1-\delta_{ij}), i, j \in V, i \ne j \tag{8}$$

$$1 \le \sigma_{ij} + \sigma_{ji} + \delta_{ij} + \delta_{ji} \le 2, i, j \in V, i < j \tag{9}$$

$$a_i \le y_i, i \in V \tag{10}$$

$$\underline{a}_i \le a_i \le \overline{a}_i, i \in V \tag{11}$$

$$x_i \ge 0, \sigma_{ij}, \delta_{ij} \in \{0,1\}, i, j \in V, i \ne j \tag{12}$$

The objective function Eq. (4) is to minimize the fuel consumption of the ship during its approach to the port. Since ship CO_2 emissions are proportional to fuel usage, this objective is consistent with minimizing carbon emissions during ship voyages. The scaling factor between CO_2 emissions from ships and the amount of oil used varies slightly across the literature, and in this paper we use the Intergovernmental Panel on Climate Change (IPCC) ratio of 3.16 tons of CO_2 from the combustion of one ton of marine oil. The objective function Eq. (5) is to minimize the average ship departure delay time, which can also be used as a measure of the intelligent service level of green ports.

II. A. 2) Shore and bridge allocation sub-model

A berth allocation plan identifies the time windows for each vessel, i.e., the expected berthing time and the expected departure time. The shorebridge allocation problem refers to how to determine the operational shorebridge for each ship so that the loading and unloading operations of each ship can be completed within the specified time window. In this paper, a shorebridge allocation submodel is developed based on the simultaneous consideration of time window constraints and performance indicators of the shorebridge allocation plan [17].

Let S be the set of arriving ships, T be the set of time periods, $|T| = t$, C be the set of available shore bridges, $|C| = c$, E_i be the amount of containers loaded and unloaded by ship i, etb_i be the expected berthing time of ship i, etu_i be the estimated departure time of ship i, and $C\min_i$ be ship i's minimum number of assignable shore bridges, as determined by the agreement between the shipping company and the terminal company. $C\max_i$ is the maximum number of shore bridges that can be assigned to ship i, determined by the length of the ship and the safety distance of the shore bridges, v_0 is the efficiency of a single shore bridge operation (TEU/h), and the decision variable nc_i is the number of operational shore bridges assigned to ship i. The dependent variable th_i is the operation start time of vessel i, which in this paper is assumed to start only when all the required shore bridges are ready, and the dependent variable tf_i is the operation completion time of vessel i. The dependent variable $\theta_{ijk} = 1$ if the shorebridge k serves ship i in time period j, otherwise $\theta_{ijk} = 0$. The dependent variable $m_{ijk} = 1$ if the shorebridge k moves to ship i in time period j, otherwise $m_{ijk} = 0$. The shorebridge allocation submodel is as follows:

$$\min f_2 = \frac{1}{s}\sum_{i\in S}\sum_{j\in T}\sum_{k\in C} m_{ijk} \tag{13}$$

$$s.t. C\min_i \le nc_i \le C\max_i, \forall i \in S \tag{14}$$

$$tf_i = th_i + nc_i \times E_i / v_0, \forall i \in S \tag{15}$$

$$tf_i \le etu_i, \forall i \in S \tag{16}$$

$$\sum_{k \in C} \theta_{ijk} = nc_i, \forall i \in S, j = th_i, \cdots, tf_i \tag{17}$$

$$\sum_{k \in C} \sum_{j=1}^{ab_i - 1} \theta_{ijk} = 0, \forall i \in S \tag{18}$$

$$\sum_{k \in C} \sum_{j=au_i+1}^{t} \theta_{ijk} = 0, \forall i \in S \tag{19}$$

$$\sum_{i \in S} \theta_{ijk} \leq 1, \forall j \in T, k \in C \tag{20}$$

$$\sum_{k \in C} \sum_{i \in S} \theta_{ijk} \leq c, \forall j \in T \tag{21}$$

$$\theta_{ijk}, m_{ijk} \in \{0,1\}, \forall i \in S, j \in T, k \in C \tag{22}$$

The objective function (13) indicates that the average number of bridge movements required for a ship waiting operation is minimized, the constraint (14) indicates the range of values for the number of bridges assigned to each ship, and the constraint (15) indicates that the ship's operation time is directly proportional to the amount of containers loaded and unloaded by the ship and is inversely proportional to the number of bridges assigned to the ship. Constraint (16) ensures that all loading and unloading operations must be completed within the specified time window, and constraint (17) indicates that the number of bridges remains constant during ship operations. Constraints (18) and (19) indicate that no bridge operates on a ship outside the specified time window, and constraint (20) indicates that a bridge can serve at most one ship in each time period. Constraint (21) ensures that the number of all operating shore bridges cannot exceed the total number of shore bridges in each time window, and constraint (22) defines the dependent variables.

II. A. 3) Coupled Berth-Shorebridge Allocation Modeling

According to the previously designed berth allocation submodel and shore and bridge allocation submodel under green low-carbon, the berth-shore and bridge allocation coupling model is established with the ship operation time as the coupling variable as shown in Fig. 3. Firstly, the berth allocation scheme is obtained by setting the initial ship operation time and combining with the berth allocation optimization, and then the shore and bridge allocation scheme is obtained based on the obtained scheme, and then the berth allocation scheme is adjusted until the two models are both better.

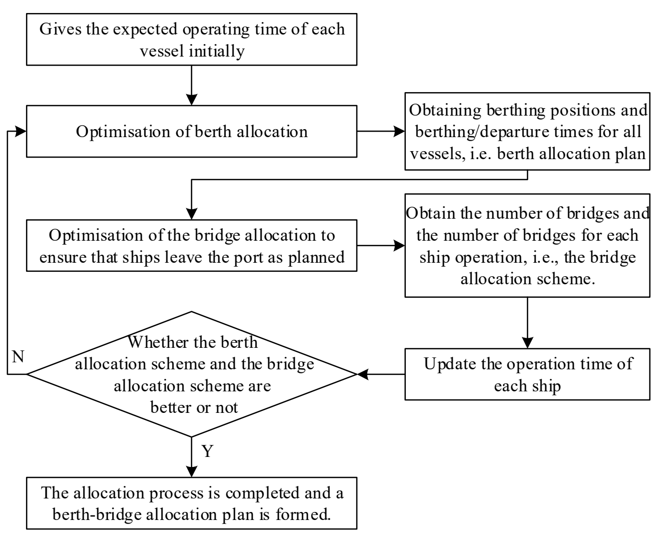


Figure 3: Berth - quay crane allocation coupling model

II. B.Algorithm for Solving the Berth-Shorebridge Allocation Model

The coupled berth-shore and bridge allocation model under tolerance constraints mainly consists of two subproblems, i.e., the berth allocation and the shore and bridge allocation subproblems under green low carbon. In order to solve the coupled berth-shore and bridge allocation model, an evolutionary algorithm based on nested loops is designed in this paper, with the inner loop as a greedy algorithm that generates the corresponding berth scheduling plan. The outer loop is a distributed hybrid genetic algorithm, which generates the corresponding shore and bridge scheduling plan based on the results of the inner loop.

II. B. 1) Inner loops: greedy algorithms

Two sets are created for ships arriving in port one after another, named Set A and Set B. Set A represents the set of ships arriving in port one after another, and Set B represents the set of ships that have been assigned berths after arriving in port. Each arriving ship has an actual arrival time a_i and a desired departure time d_i (where $0 \le B_i < f_i < \infty$) as well as an array set $M[i]$ to store the tolerance of ship i.

Firstly, the ships arriving in port one after another are added to the Set A set, and then the ships in Set A are selected according to the greedy strategy to add it to Set B. The greedy strategy in this paper means that it makes the choices that seem to be the best at that time at each step, and it always makes the locally optimal choices in the hope that such choices lead to the globally optimal solution. The solution steps of the greedy algorithm are as follows:

Step1 Initialize each set. Set A, which holds the set of ships arriving at the port to be processed, and its initialized size is the total number of ships arriving at the port, and set B is initialized to be empty, turn to Step2.

Step2 Judge whether Set A collection is empty, if it is empty, the program ends, otherwise turn to Step3.

Step3 Obtain the current status of berth occupancy, and the preferred berth, tolerance and other parameters of the ships in Set A, turn to Step4.

Step4 Use greedy strategy to select a ship from Set A, so that the value of the objective function of the ship after docking is minimized, turn to Step5.

Step5 Remove the docked ship from Set A and add it to Set B, turn to Step2.

II. B. 2) Outer loops: distributed hybrid genetic algorithms

In this paper, a distributed parallel hybrid genetic algorithm is introduced to solve the shore and bridge allocation sub-model in the following steps:

Step1 Coding form. In this paper, real number coding is adopted, that is, the original variables are directly used to constitute the individual, and the value composed of 1 odd-bit gene and 1 even-bit gene in each neighbor represents the number of the quay wall line where the ship berths, and the position of the gene represents the number of the ship.

Step2 Randomly generate each 1st generation sub-population. Set the subpopulation group size as n, and use the global random sampling mechanism to generate the initial population of each subpopulation.

Step3 Judge whether individuals are feasible or not. Retain the feasible individuals and mutate the infeasible individuals to change them into feasible individuals.

Step4 Adaptation evaluation. Each subpopulation calculates its individual fitness value independently and ranks them to determine the best and the worst individuals. The scale transformation calculation of the fitness value adopts the linear scale method, and for the minimization function, the smaller the individual fitness value means the higher the fitness of the individual. In the latter part of the genetic run, the adaptation scale transformation is a linear scale transformation, then the adaptation value of the kth parent individual can be expressed as:

$$F(k) = af(k) + b \tag{23}$$

where $f_{in} \ge \frac{c_{ave} - f_{\max}}{c - 1.0}$ when $a = \frac{f_{ave}}{f_{ave} - f_{min}}$, $b = \frac{-f_{in} \cdot f_{ave}}{f_{ave} - f_{min}}$. Otherwise $a = \frac{f_{ave}}{f_{ave} - f_{min}}$, $b = \frac{-f_{min} \cdot f_{ave}}{f_{ave} - f_{min}}$, $f_{\max}$, f_{ave} , and f_{min} denote the maximum, average, and minimum of the current adaptation value, respectively. Then:

$$f(k) = \sum_{i=1}^{n} \left| x_i - y_i \right| \tag{24}$$

Step5 Seed selection. The betting wheel algorithm is used to select the individuals of the l th parent generation that enter the mating pool. The optimal individuals of each sub-population are retained and enter the mating pool directly, and the other $(N-1)$ individuals are randomly selected using the gambler's wheel algorithm to form the l th generation of the mating pool population by executing the following steps:

a. Sum the adaptation values of all individuals n in the subpopulation, $sum=\sum_{i=1}^{n}F(x^i)$, and n is the subpopulation size.

b.Generate 1 random number RM between 0 and sum.

c.Starting with the 1st individual in the subpopulation, add its adaptation value to the adaptation values of the succeeding individuals until the cumulative sum is equal to or greater than RM, then the individual corresponding to the adaptation value of the last accession is enrolled. The probability of inclusion $P(x^j)=\frac{F(x^j)}{\sum_{i=1}^{n}F(x^i)}$, $j=1,2,\cdots,n$.

Step6 Each subpopulation is independently subjected to selection, crossover and mutation operations using STEADY-STATE genetic algorithm. The crossover operation adopts single point crossover and the mutation operation adopts Gaussian mutation. The 1 individual of Gaussian mutation population is from $X=\{x_0,x_1,\cdots,x_k,\cdots,x_s\}$ to $X=\{x_0,x_1,\cdots,x_{k'},\cdots,x_s\}$ is subjected to a Gaussian mutation operation, the component x_k is selected for mutation with a defined interval $[a_k,b_k]$, and the new gene value is denoted as:

$$x_k'=\frac{a_k+b_k}{2}+\frac{b_k-a_k}{6}\left(\sum_{i=1}^{n}r_i-6\right) \tag{25}$$

where r_i is the number of random numbers between $[0,1]$ and n is the number of random numbers uniformly distributed in the range $[0,1]$. How many overlapping individuals there are is determined by specifying the percentage that is replaced in each generation, introducing the parameter prep1 and taking the replacement percentage to be 20%. The obtained offspring individuals are used as the new parent subpopulation.

Step7 Immigration operation. This is performed according to the specified number of immigrants, the frequency of immigrants and the communication topology relationship between subpopulations. The exchange frequency is taken to be 4, i.e., the subpopulations transmit chromosomes to each other when the number of hereditary times is a multiple of 4. The number of immigrants is 6, i.e., each immigrant immigrates the 6 best individuals of the subpopulation to the neighboring subpopulation according to the determined method and receives 6 individuals from the neighboring subpopulation. The communication topology between subpopulations is in a ring structure, and if an immigration operation is performed, the immigrants reconstitute a new generation of subpopulation individuals. As the next generation of the parent group, each sub-population again evolves separately and independently, and goes to Step3, otherwise it goes to Step3 directly until the termination criterion is satisfied, ending the whole algorithm and outputting the optimal solution.

III. Simulation analysis of intelligent construction of green ports

With the rapid development of the global economy, the cargo throughput of most ports in general has maintained a sustained growth trend under a high base, but the ports are still facing multiple challenges in production management, such as obsolete port infrastructure and insufficient level of port informationization management. And in the context of carbon neutrality and carbon peaking, the importance of green port construction has been emphasized even more. Based on this, this paper constructs an intelligent platform for green ports and designs a green and low-carbon oriented optimization model for port berth-shore bridge allocation, aiming to further reduce the carbon emissions of green ports and thus promote ports to green and low-carbon development.

III. A. Optimization Simulation of Berth-Shore Bridge Allocation

III. A. 1) Comparative analysis of different algorithms

In order to better test the effectiveness of the nested loop solution algorithm designed in this paper, the comparison algorithms use the NSGA-II algorithm and the MNSGA-II algorithm as the comparison object. The number of ships to be docked in the harbor is selected as 12, 18, and 24 respectively, and the three algorithms are used to simulate the three cases, and run five times for each case to generate the Pareto solution set respectively.

The C(X,Y) metric is chosen to evaluate the advantages and disadvantages of the Pareto solution sets obtained by the algorithms, where X and Y denote the Pareto solution sets obtained by the two algorithms, respectively. If C(X,Y)=2 means that for any non-dominated solution in Y, there always exists a solution in X that dominates it, and

C(X,Y)=1 means that for any solution in Y, there is no solution in X that dominates it. Tables 1 and 2 show the comparison results of the C(X,Y) metrics and the number of nondominated solutions, where a, b, and c denote NSGA-II, MNSGA-II, and the algorithm of this paper, respectively.

From the analysis of C(X,Y) metrics, the simulation results of the nested loop algorithm proposed in this paper are better than NSGA-II and MNSGA-II algorithms, and all the non-dominated solutions obtained can dominate the non-dominated solutions obtained by NSGA-II and MNSGA-II algorithms. From the comparison analysis of the number of non-dominated solutions, the number of non-dominated solutions obtained by this paper's algorithm is significantly more than that of NSGA-II and MNSGA-II algorithms, and as the scale of the arithmetic case increases, the more obvious the advantage of the number of non-dominated solutions obtained by this paper's algorithm.

Table 1: Comparison of experiment result on three algorithms C(X,Y) index

Quantity of ships	Algorithm	Means	SD	Optimal value	Worst value
12	C (c, a)	2.00	0.02	2.00	2.00
	C (c, b)	2.00	0.01	2.00	2.00
	C (a, c)	1.00	0.01	1.00	1.00
	C (b, c)	1.00	0.02	1.00	1.00
18	C (c, a)	2.00	0.00	2.00	2.00
	C (c, b)	2.00	0.01	2.00	2.00
	C (a, c)	1.00	0.01	1.00	1.00
	C (b, c)	1.00	0.00	1.00	1.00
24	C (c, a)	2.00	0.02	2.00	2.00
	C (c, b)	2.00	0.01	2.00	2.00
	C (a, c)	1.00	0.00	1.00	1.00
	C (b, c)	1.00	0.01	1.00	1.00

Table 2: Comparison of experiment result on three algorithms Pareto fronts

Quantity of ships	Algorithm	Means	SD	Optimal value	Worst value
12	NSGA-II	15.28	1.235	12.25	17.53
	MNSGA-II	15.01	1.514	12.06	17.21
	Ours	14.37	1.827	10.78	15.38
18	NSGA-II	20.16	1.835	16.29	22.25
	MNSGA-II	19.89	2.061	15.83	22.67
	Ours	18.02	1.803	15.04	21.34
24	NSGA-II	25.03	2.414	19.52	27.93
	MNSGA-II	24.71	2.635	18.43	27.48
	Ours	22.15	3.127	17.56	25.57

In addition, this paper also compares the solution results of the three algorithms through the linear weighting method, and it can be clarified that the nondominated solutions obtained by this paper's algorithm are better than NSGA-II and MNSGA-II algorithms both in terms of the number and the distributivity, and the solution times of this paper's algorithm are better than those of NSGA-II and MNSGA-II algorithms. Based on this, it can show the effectiveness of this paper's nested loop algorithm combining greedy algorithm and distributed hybrid genetic algorithm in solving the coupled model of berth-shore and bridge allocation, and it also provides data references for the intelligent scheduling of berth allocation and shore and bridge allocation in the green port.

III. A. 2) Convergence effect of different algorithms

In order to clearly understand the convergence ability of the algorithms in this paper for solving the coupled berth-shorebridge allocation model, this paper designs 10 arithmetic examples (SL1~SL10) containing different berthing schedule periods and number of ships, and selects the greedy algorithm, genetic algorithm, and NSGA-II algorithm as comparisons, to explore the average running time of their solutions for the 10 different arithmetic examples. Then a representative example was selected from the 10 arithmetic cases, and the evolutionary convergence curves of different algorithms were obtained as shown in Fig. 4. Table 3 shows the average running time of different algorithms for solving SL1 to SL10.

Fig. 4 shows the convergence ability of different algorithms better, from which we can learn that the fastest converging algorithm is the nested loop algorithm counted in this paper, which is able to quickly converge to a relatively optimal solution after fewer iterations. It is followed by the NSGA-II algorithm and the genetic algorithm, and the difference between them is small. However, the algorithm in this paper is the best of the four algorithms in terms of both convergence persistence and convergence accuracy, and although the algorithm in this paper is able to converge more quickly, this ability to converge is also more likely to cause the algorithm to fall into a local optimum. In addition to the convergence of the algorithm, the computational complexity is also a key indicator of the effectiveness of the algorithm, which reflects the computational resources required in the algorithm solution process, and is an important core content of the algorithm performance analysis. For practical problems, the average running time index can directly reflect the feasibility and effectiveness of the algorithm application practice. In this paper, we collect the average running time indexes of algorithm solving related cases. As can be seen from Table 3, NSGA-II is more difficult to solve the berth-shorebridge allocation model among the four algorithms, followed by the greedy algorithm, and finally the GA algorithm. In addition, the relationship between the algorithm running time and ship size is not a simple linear relationship, but a kind of exponential relationship. Overall, the nested-loop algorithm proposed in this paper, which combines the greedy algorithm and the distributed hybrid genetic algorithm, has a better convergence ability when solving the coupled berth-shorebridge allocation model, and its average running time can meet the demand for solving accuracy relatively speaking.

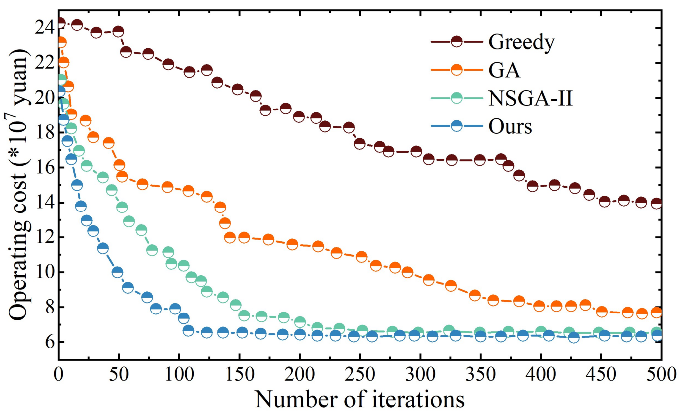


Figure 4: Evolution convergence curve of different algorithms

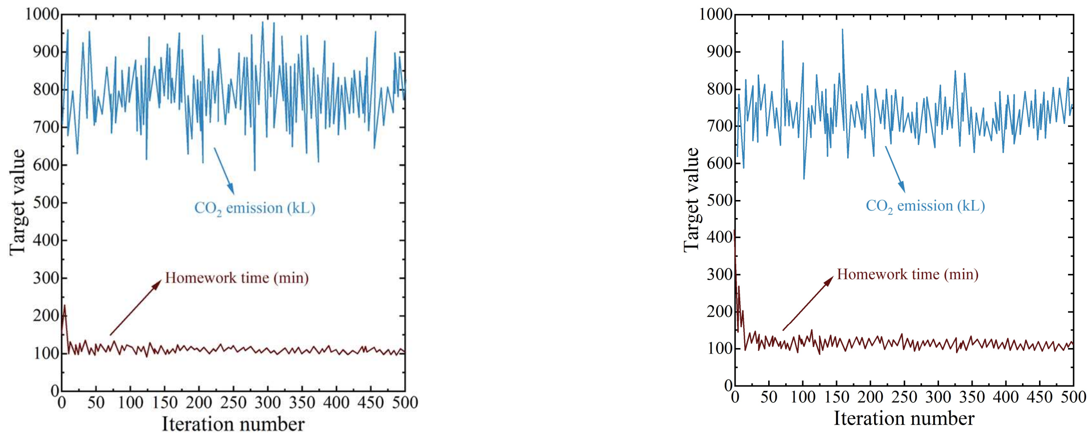
Table 3: Average running time of algorithms from SL1 to SL10 (s)

Example	Greedy	GA	NSGA-II	Ours
SL1	64.51	101.48	183.81	162.15
SL2	86.75	232.59	346.47	286.45
SL3	231.42	593.78	862.63	791.82
SL4	718.59	1763.61	2451.38	2013.74
SL5	46.72	149.47	232.74	165.72
SL6	135.34	355.58	532.76	425.86
SL7	336.27	816.42	1161.43	913.48
SL8	1463.51	2663.56	3951.28	3211.84
SL9	132.67	258.74	394.98	298.37
SL10	368.62	596.34	913.69	716.53

III. A. 3) Carbon emission optimization example

Based on the green low-carbon oriented berth-shore bridge allocation coupling model in the previous paper, the corresponding simulation parameters are set in MATLAB software. Using the nested-loop algorithm established in this paper to calculate the single-objective optimization (only optimize the operation time) and the multi-objective optimization model (taking into account the operation time and CO_2 emissions) respectively, the optimal convergence results after 500 iterations are shown in Table 4. The iterations in solving are shown in Fig. 5, where Fig. 5(a)~(b) shows the single-objective and multi-objective iterations, respectively.

According to the optimization results, it can be seen that under the multi-objective optimization model that takes into account the operating time and CO_2 emissions, it obtains a reduction of more than 31 kiloliters of CO_2 emissions by sacrificing the operating efficiency of 2.576 minutes in the previous embodiment. This fully demonstrates that the model in this paper can effectively help to achieve the goal of reducing carbon emissions under the circumstance of taking into account the operating time. In addition, the nested-loop algorithm designed in this paper only requires fewer iteration steps to make the objective function reach convergence, and the multi-objective optimization has better performance.



(a) Single objective (b) Multi-objective

Figure 5: The iterative situation during the solution

Table 4: Example of carbon emission optimization

Target value	Single objective	Multi-objective
CO_2 emission (kL)	753.219	721.897
Homework time (min)	104.138	106.714

In summary, it can be seen from the numerical examples that the multi-objective optimization computational results obtained by combining the greedy algorithm and the distributed hybrid genetic algorithm with the nested loop algorithm solution have a more balanced performance. From the numerical results, it can be seen that although the multi-objective optimization model cannot achieve the maximization of a single objective, it can maximize the overall performance of the two objectives with less sacrifice of one objective, and therefore it has a wider application value in solving the actual problems of terminal operations under green ports.

III. B. Performance of green and smart ports

In this paper, the cloud architecture and 5G interconnection technology are mainly adopted in the establishment of the green port intelligent platform, and in order to illustrate the performance of the green port intelligent platform supported by this method, this paper selects the port intelligent platform supported by traditional 4G technology as a comparison. Table 5 shows the comparison results of key performance indicators of green port.

The purpose of using cloud architecture and 5G technology in the green port intelligent platform is to further enhance the intelligent level of the green port. 5G technology integrates key technologies such as large-scale antennas, ultra-dense networking, flexible duplex, full duplex, spectrum sharing, advanced modulation coding, terminal passthrough technology, full-spectrum access, new type of multiple access, and new type of multicarrier. In addition, 5G technology uses a new architectural solution (network slicing) that allows for the creation of logically independent networks on top of a common physical information infrastructure, which can be tailored to the business needs of specific industries. Based on the comparative data in the table, it can be seen that the intelligent platform for green ports established in this paper has obvious performance improvement compared with the traditional 4G technology, which helps to better realize the green and low-carbon goals of ports and provides a reliable platform support for achieving carbon peak and carbon neutrality.

Table 5: Comparison of key performance indicators

Technical indicators	Ours	Traditional	Improve efficiency
Flow density	15 Mbit/(s·m^2)	0.12 Mbit/(s·m^2)	125 times
Connection density	2*10^6/km^2	10^5/km^2	20 times
Delay	1.2 ms	15 ms	12.5 times
Mobility	600 km/h	360 km/h	1.67 times
Energy efficiency	120 times	1 time	120 times
User experience rate	0.2~5 Gbit/s	15 Mbit/s	13~33 times
Peak rate	12 ~25 Gbit/s	1.2 Gbit/s	10~21 times
Spectral efficiency	3.5~6.5 times	1.2 times	2.92~5.42 times

IV. Conclusion

Intelligent construction of green port is an important way to realize carbon peak carbon neutral. In this paper, a green port intelligentization platform based on cloud architecture is constructed, a green low-carbon oriented berth-shore bridge allocation optimization model is designed, and a nested-loop solving algorithm is developed. Simulation analysis shows that the proposed nested loop algorithm has superior performance in solving multi-objective optimization problems, and has obvious advantages in the quantity and quality of non-dominated solutions obtained compared with NSGA-II and MNSGA-II algorithms. In the large-scale example with 24 ships, the average running time of this algorithm is 22.1% lower than that of NSGA-II, which effectively improves the real-time port scheduling decisions. Through the multi-objective optimization model that takes into account the operation time and CO_2 emission, the CO_2 emission can be reduced by 31 kiloliters by sacrificing only 2.576 minutes of operation efficiency, which reflects a significant environmental benefit. The 5G technology-based intelligent platform for green ports offers significant improvements over traditional 4G technology platforms in a number of performance metrics, including a 125-fold increase in traffic density, a 20-fold increase in connection density, a 12.5-fold reduction in average latency, and a 120-fold increase in energy efficiency. These performance improvements provide strong technical support for ports to realize intelligent scheduling, precise control and green operation. Future research will further consider the comprehensive energy management of ports, the optimization of the use of shore power on ships, and the coordinated scheduling of multiple modes of transportation, so as to promote the development of ports in the direction of more intelligent and low-carbonization.

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