Computers & Industrial Engineering 194 (2024) 110338

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Two incentive policies for green shore power system considering multiple objectives

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ARTICLE INFO

Keywords:
Shore power equipment
Berth allocation
Multi-objective model
Two-stage algorithm

ABSTRACT

Shipping significantly contributes to air pollution and greenhouse gas emissions, accounting for more than 80% of global trade. Consequently, governments have been focused on air pollution reduction for many years. The adoption of shore power systems has increased, recognized for their effectiveness in reducing emissions. This study introduces multi-objective mixed-integer programming models to investigate the impacts of government-subsidy-based and berthing-priority-based incentive policies on various types of expense benefits from the perspectives of different stakeholders. This paper aims to optimize shore power equipment deployment, berth allocation, and ship scheduling while balancing environmental benefits, costs associated with shore power, and operational efficiency. We design an improved NSGA-II with a two-stage solution algorithm to solve the studied problem, which is more suitable for large-scale case calculations. Following the case study, we offer insights for stakeholders to navigate the complexities of sustainable port development and promote the adoption of shore power systems.

1. Introduction

Due to the rapid growth of economic globalization, shipping now accounts for more than 80% of all international trade (UNCTAD, 2022; Zhou & Kim, 2020a, 2020b). Additionally, shipping substantially contributes to air pollution, particularly in ports and coastal cities, and significantly adds to global warming through emissions (Gössling et al., 2021). Ports are a major source of pollution while being a crucial part of international maritime commerce, primarily because moored ships rely on auxiliary engines for various operations such as cooling, heating, lighting, and running pumps and fans (Qi et al., 2020). Carbon dioxide (CO_2), nitrous oxides (NO_x), sulfur oxides (SO_x), and particulate matter (PM) are the main pollutants released by marine diesel engines that have a significant negative impact on the environment and human health (Yu et al., 2019). The International Maritime Organization (2020) reported that the percentage of shipping emissions in worldwide anthropogenic emissions had climbed from 2.76% in 2012 to 2.89% in 2018. Merk (2014) anticipated that port-related shipping emissions will grow four times from their 2011 levels by 2050. Therefore, there is growing concern over vessel emissions from the academic and maritime industries at ports.

Methods such as utilizing liquefied natural gas (Burel et al., 2013), reducing shipping speeds, and implementing shore power systems (He et al., 2020; Ye et al., 2022; Yin et al., 2022; Zis et al., 2014) have been developed to minimize emissions from vessels that are moored at ports for loading and unloading cargo. Among these, the shore power system (SP), also known as alternative maritime power or cold ironing, has emerged as a crucial strategy for controlling emissions at ports (Chen et al., 2019; Tiwari et al., 2021). This system consists of the shore-side electricity supply infrastructure (SPI) and the equipment on ships (SPE) that facilitates connection to shore power. It enables ships to shut down their auxiliary engines and run on electricity in ports (Wu & Wang, 2020).

While shore power systems effectively reduce emissions (Ballini & Bozzo, 2015; Winkel et al., 2016; Zis, 2019), the adoption of shore power systems faces significant challenges due to barriers in technological application, economic cost, operation and management, and policy system (Chen et al., 2019; Dai et al., 2019; Jasmi & Fernando, 2018; Yigit & Acarkan, 2018). A typical "chicken and egg" paradox complicates the promotion of SP (Winkel et al., 2016; Zis, 2019). This paradox arises because a shipowner can only retrofit a ship profitably

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https://doi.org/10.1016/j.cie.2024.110338
Received 3 December 2023; Received in revised form 20 May 2024; Accepted 25 June 2024
Available online 4 July 2024
0360-8352/

if a sufficient number of visited ports provide shore-side facilities, and similarly, a port authority can only invest profitably in the SPI if a consistent number of ships utilize and pay for its services, largely due to economic considerations (Radwan et al., 2019; Tseng & Pilcher, 2015). Thus, the government generally provides subsidies (GSIP) to convince self-interested individuals such as shipowners and ports to construct SP equipment for environmental benefits (Li et al., 2020; Wang et al., 2021, 2022).

In practice, GSIP has proven less attractive than anticipated (Wang et al., 2021, 2022). This is partly because shipowners, who are sensitive to price fluctuations, may opt not to use SPI if the cost of electricity surpasses that of diesel (Wang et al., 2021). Furthermore, the high installation costs of SPE make the available government subsidies insufficient (Wang et al., 2022). Despite about 50% of China's coastal ports being equipped with SPI by the end of 2020, less than 1% of ships have installed SPE (Yin et al., 2020). This significant mismatch in the adoption rates between SPI and SPE has limited the use of SP. To increase the utilization of shore power systems, beyond optimizing the government subsidy structure (Wang et al., 2021, 2022; Wu & Wang, 2020), ports could implement measures such as offering priority berth of ships using the SP (BPIP) (Dai et al., 2019; Li et al., 2020; Yin et al., 2020), thereby incentivizing shipowners to retrofit ships.

GSIP and BPIP have been implemented globally. For example, in EU countries, government subsidies for SP include direct subsidies, tax advantages, and risk transfer to the government (International Transport Forum, 2019). In China, regulations such as China's Ministry of Transport's Administrative Measures for Port and Ship Shore Power encourage ports to grant priority service to ships utilizing SP. These policies affect stakeholders in the shore power system, who are engaged in a strategic interplay, while the government aims to maximize environmental benefits through investment, shipowners seek to minimize costs, and ports strive to maintain transportation efficiency. Considering the diverse interests of various stakeholders, this study assesses the impact of policies on different stakeholders. Moreover, based on the current situation of insufficient SPE on ships, we focus on the strategic decisions of shipowners regarding the installation of SPE. Our contributions are summarized as follows:

1. We conduct multi-objective mixed-integer programming models to balance environmental benefits, the costs associated with SP, and operational efficiency from the perspectives of different stakeholders. Our model optimizes decisions concerning SPE deployment, berth allocation, and ship scheduling.
2. To solve the proposed problem, we develop an improved multi-objective algorithm that combines a two-stage solution algorithm with the non-dominated sorting genetic algorithm (NSGA-II).
3. We examine the effects of GSIP and BPIP policies on multiple objectives and SPE installations, explore solutions that balance the benefits among multiple stakeholders and provide insightful management observations based on our findings.

The remainder of this paper is organized as follows: Section 2 introduces the literature review; Section 3 presents the mathematical formulation and proposed solution approaches to our problem; The experimental results are shown in Section 4; Finally, the conclusions are given in Section 5.

2. Literature review

This section presents a literature review covering two linked topics: (2.1) barriers and policies for the development of SP systems; (2.2) multi-objective problems in the context of SP systems. Table 1 presents a summary of all the literature relevant to our study.

2.1. Barriers and policies for the development of SP systems

In exploring the broader application constraints of SP systems, Qi et al. (2020) highlighted economic concerns and management flaws in their systematic literature review, reflecting the diverse perspectives of multiple stakeholders, including shipowners, ports, and governments. Arduino et al. (2011) identified three principal challenges in Europe related to establishing SP systems: the high costs involved, the absence of standardized equipment, and a lack of supportive legislation. Similarly, Radwan et al. (2019) and Tseng and Pilcher (2015) emphasized that significant financial outlays for electrical energy and the SP infrastructure investment constitute primary barriers to the SP adoption. Furthermore, Chen et al. (2019) discovered that inadequate policies, insufficient support systems, and rigid construction standards, along with rules and regulations, have obstructed SP adoption in China. In response to these challenges, Winkel et al. (2016) proposed that comprehensive policies integrating financial and fiscal incentives, alongside operational and technical considerations, are essential for enhancing SP systems in Europe. Yin et al. (2020) assessed the effectiveness of SP regulations in China and concluded that they were ineffective due to unattractive cost-benefit ratios and poorly targeted government subsidies. Dai et al. (2019) examined the economic viability of current investments in SP infrastructure at the Port of Shanghai, unveiling significant financial shortcomings. Based on these findings, Dai et al. (2019) recommended that subsidies should be redirected from the construction phase to the operational phase to improve financial sustainability and effectiveness.

Several studies have explored the impact of the government subsidy incentive policy (GSIP) (Peng et al., 2023; Song et al., 2017; Wang et al., 2022; Wu & Wang, 2020). Song et al. (2017) developed an SP economic model that adjusted electric pricing to maximize stakeholder benefits and analyzed the relationship between government subsidy rates and port benefits. Li et al. (2020) constructed a two-echelon maritime supply chain that included ports and ship companies, and employed game theory to optimize government subsidy intensity and the subsidy reduction point. Wu and Wang (2020) investigated SP deployment within container transport networks from a governmental perspective, aiming to devise a subsidy scheme that reduces emissions during mooring. Wang et al. (2021) addressed the issue of low SP utilization across several stakeholders, including government, ports, and shipowners, by developing and optimizing a framework to enhance the efficiency of government subsidies. Subsequently, Wang et al. (2022) further refined this subsidy structure using a Stackelberg game theory model. Similarly, Peng et al. (2023) compared two GSIPs within the Stackelberg game framework and found that subsidizing the price of SP is more cost-effective than subsidizing facility investment, particularly when the government budget is sufficient and the benefits from emission reduction are significant. Other recent studies have broadened the scope to assess the impact of various government policies, including GSIP, on SP adoption. Tan et al. (2023) evaluated environmental incentives (EI) and infrastructure subsidies, while Luo et al. (2024) contrasted subsidies, carbon taxes, and green awareness initiatives, and analyzed their effects through game-theoretical models in different adoption phases.

Limited previous studies have measured the impact of the berthing priority incentive policy (BPIP) on SP systems (Gong et al., 2024; Zhen et al., 2022). According to Yin et al. (2020), shipowners are particularly concerned about policies or regulations that could improve their operational efficiencies, such as those granting priority for entrance and berthing. Li et al. (2020) and Wang et al. (2021) also suggested that ports could offer service priority to SP users. Zhen et al. (2022) were the first to assess and address these two incentive policies, GSIP and BPIP, optimizing the deployment of SPE, ship scheduling and berth allocation to minimize overall system costs. Expanding on this, Gong et al. (2024) introduced three novel policies: a subsidy policy based on the number of SP uses (SNTP), an environment fee discount policy

Table 1
Summary of related studies in the context of SP systems.

Papers	Research aim						Research method					
	Adoption and barriers	Strategy and development	Resources optimization and allocation	Policy assessment			Case study and statistical analysis	Game model	Single-objective optimization model	Multi-objective optimization model		
				GSIP	BPIP	Others				SP costs	Environment benefits	Operational efficiency
Arduino et al. (2011)	√						√					
Tseng and Pilcher (2015)	√						√					
Winkel et al. (2016)	√						√					
Song et al. (2017)		√		√					√			
Chen et al. (2019)	√						√					
Dai et al. (2019)	√						√					
Peng et al. (2019)			√				√			√	√	
Radwan et al. (2019)	√						√					
Yu et al. (2019)		√		√			√			√	√	
Li et al. (2020)				√			√	√				
Wu and Wang (2020)		√		√					√			
Yin et al. (2020)	√			√			√					
Peng et al. (2021)			√							√	√	
Wang et al. (2021)				√			√					
Wang et al. (2022)		√		√				√				
Zhen et al. (2022)			√	√	√				√			
Peng et al. (2023)				√				√				
Tan et al. (2023)		√		√		√				√	√	
Gong et al. (2024)			√	√	√	√			√			
Luo et al. (2024)				√		√		√				
Wang et al. (2024)			√			√					√	√
This study			√	√	√					√	√	√

(EFDP), and a mixed policy that combines various incentives. However, neither Zhen et al. (2022) nor Gong et al. (2024) accounted for the game-theoretic interactions among different stakeholders concerning their various expenses. Building on this, our study further explores the balance among environmental benefits, SP costs, and operational efficiency from the perspectives of diverse stakeholders.

2.2. Multi-objective problems in the context of SP systems

In recent years, some studies have started to explore multi-objective problems within the context of SP systems (Peng et al., 2021, 2019; Wang et al., 2024; Yu et al., 2019). However, to our knowledge, this study is the first to assess policies, including GSIP and BPIP, from a multi-objective perspective in SP systems. Peng et al. (2019) proposed an SPI allocation scheme for ships with uncertain arrivals, aiming to balance SP expenses with carbon emissions. Extending this work, Peng et al. (2021) introduced a multi-objective collaborative optimization model to address the problems of SPI deployment and ship allocation, focusing on minimizing SP installation and application costs while maximizing environmental benefits. Additionally, Wang et al. (2024) integrated SPI assignment with berth and quay crane allocations, thereby optimizing operational, energy consumption, and carbon taxation costs. Notably, both Peng et al. (2019) and Peng et al. (2021) based their models on the unrealistic assumption that all incoming ships were equipped with the SPE while Wang et al. (2024) overlooked the costs of retrofitting ships. Given that SPE coverage is less than that of SPI and the associated installation costs are considerable, our study emphasizes optimizing SPE deployment. Yu et al. (2019) developed a strategic plan for shipowners to retrofit ships to maximize environmental benefits and minimize the dynamic payback period of retrofit investment. However, Yu et al. (2019) did not consider the critical aspects of berth allocation and ship scheduling, and assumed that SPI was universally available across all berths. Our research addresses these gaps by focusing on SPE deployment in ports with limited SPI, and incorporated decision variables such as SPE installation, berth allocation and ship scheduling.

To address the complex multi-objective problems associated with SP systems, various algorithms have been developed. Peng et al. (2019) utilized a simulation-based method, while Peng et al. (2021) applied a multi-objective swarm optimization algorithm. Wang et al. (2024) employed an adaptive immune clone selection algorithm, and Yu et al. (2019) adopted an improved multi-objective genetic algorithm (NSGA-II). In our study, we further combine a two-stage solution algorithm with a tailored NSGA-II to address our specific optimization challenges. The NSGA-II algorithm is particularly advantageous due to its three main features: it performs a swift non-dominated sorting process that reduces computational load, it employs a crowded distance over fitness sharing to maintain diversity within the solution pool, and it integrates an elite strategy that retains superior solutions in subsequent generations, thereby enhancing the evolutionary process.

3. Methodology

3.1. Problem description

This study focuses on a port consisting of several berths, denoted as B, a portion of which are equipped with SPI. In each scheduling cycle, shipowners whose ships lack SPE are faced with decisions regarding its installation, as presented in Fig. 1. Concurrently, the port's responsibility is to allocate berths and organize the sequence of services

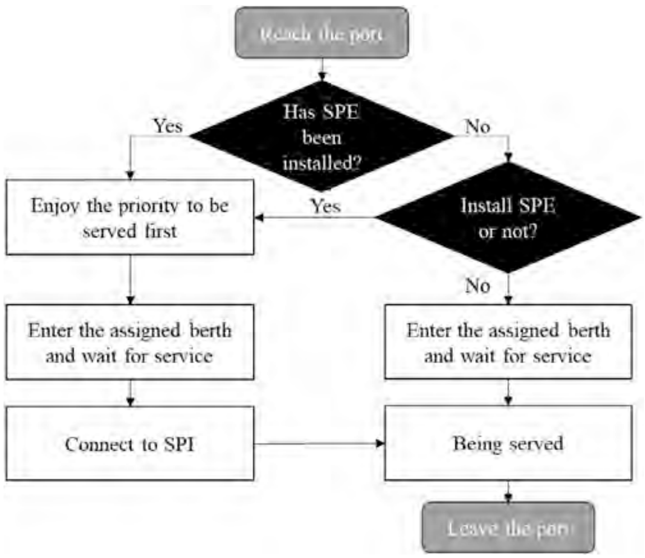

Fig. 1. Ship service flow.

for the ships, as exemplified in Fig. 2, where e^{arr} indicates the ship's arrival time, and h_i^{berth} and h_i^{test} represent the service time and the SP commissioning time, respectively. Generally, shipowners are not willing to bear the high costs associated with SPE installation c and usage p^{oper}, especially when the expense of fuel consumption p^{fuel} is cheaper. From the perspectives of the government and port authorities, there is an incentive to implement policies that influence shipowners' decisions to align with broader environmental and operational goals.

This study evaluates the effects of two significant policies: GSIP and BPIP. Based on BPIP, ships equipped with SPE or planning to install it are given priority treatment, as detailed in Fig. 1. Moreover, the port combines the BPIP with a strategy of immediately available berth allocation. For instance, presented in Fig. 2, Ship 4, arriving at 6:00, must wait for a berth to become available. When Berth 2 becomes available, Ship 5 is given precedence over Ship 6 due to BPIP, even though they arrive simultaneously. Under GSIP, the government provides subsidies for SPE installation and operational costs at rates x and y. We aim to assess the qualitative effects of these policies on SPE installation decisions and to balance multiple costs, including fuel consumption, time penalties, and SPE conversion and operating costs, while considering the diverse interest concerns of the government, ports, and shipowners.

Before establishing mathematical models to describe the proposed problem, we define the related notations and parameters in Table 2.

3.2. Model formulation

Zhen et al. (2022) developed a single-objective optimization model to minimize system costs and derive management insights pertaining to the application of GSIP and BPIP. However, this model consolidates the diverse interests of various stakeholders, including the government, ports, and shipowners, into a unified objective. Such an aggregation may obscure the distinct impacts of these policies. To address this limitation, our study extends this research by developing multi-objective models that separately assess the specific impacts of GSIP and BPIP on different cost components, including fuel consumption costs, time penalty costs, as well as SPE transformation, and operating costs.

Reducing fuel consumption costs and thereby improving environmental benefits is the principal goal in the promotion of SP systems, and it represents a critical concern for the government. Fuel consumption costs for ships occur both while waiting for service and during service operations, specifically, during the test time for ships using SPI and throughout the entire service period for ships not using SPI. These considerations form the basis of the objective formulated in equation (1):

$$F_{\mathrm{fuel}} = \sum_{i\in V} p^{\mathrm{fuel}}(\sigma_i - e_i^{\mathrm{arr}}) + \sum_{i\in V}\sum_{b\in B}[\phi_i a_b \beta_{i,b} p^{\mathrm{fuel}}(h_i^{\mathrm{test}} - h_i^{\mathrm{berth}}) + p^{\mathrm{fuel}} h_i^{\mathrm{berth}}], \tag{1}$$

where the first item represents the fuel consumption cost during the ships' waiting time before service, and the second item covers the fuel consumption cost during service time, accounting for whether or not the ships are using SPI.

Unlike the government, shipowners are more sensitive to additional costs. Here, additional costs refer to expenses incurred if shipowners decide to use SPI, which include the cost of ship transformation for the initial installation of SPE and the operational costs for each use of SPI. Note that GSIP mainly influences these costs, where x represents the subsidy rate for installing SPE and y is the subsidy rate for using SPI. Objective (2) is defined as follows:

$$F_{\mathrm{SP}} = \sum_{i\in V} \alpha_i c(1-x) + \sum_{i\in V}\sum_{b\in B} \phi_i a_b \beta_{i,b}(1-y) h_i^{\mathrm{berth}} p^{\mathrm{oper}}, \tag{2}$$

where the first item represents the transformation cost when shipowners decide to install SPE, and the second item covers the operational cost when ships use SPI.

Following government recommendations, most ports are willing to adopt BPIP to enhance the utilization of SP systems, thereby increasing the usage rate of berths equipped with SPI. During this process, ports pay more attention to operational efficiency, which is reflected in our model as penalties for ships' waiting and delays, as detailed in objective (3). Here, $(t)^+$ denotes taking the maximum value between t and 0:

$$F_{\mathrm{time}} = \sum_{i\in V} r^{\mathrm{w}}(\sigma_i - e_i^{\mathrm{arr}}) + \sum_{i\in V} r^{\mathrm{d}}(\theta_i - e_i^{\mathrm{dep}})^+, \tag{3}$$

where the first item represents penalties for ships' waiting times, and the second penalties for ships' delays.

Within the comprehensive SP operation system, the single-objective formulation provides a baseline by focusing on a combined set of goals without distinguishing between different stakeholder interests, as expressed by objective (4). When we primarily consider the government's interest in environmental benefits, which diverges from the economically driven concerns of other stakeholders such as shipowners and ports, we extend this model into a two-objective Eq. (5). Moreover, to encompass the comprehensive perspectives of all stakeholders, we develop a three-objective Eq. (6). This model differentiation allows us to tailor strategies according to specific stakeholder interests and to validate the robustness of our proposed algorithms through the inter-comparison of these models.

Single-Objective:

$$\min \quad F_{\mathrm{total}} = F_{\mathrm{fuel}} + F_{\mathrm{SP}} + F_{\mathrm{time}}. \tag{4}$$

Two-objective:

$$\min \quad \{F_{\mathrm{fuel}}, F_{\mathrm{SP}} + F_{\mathrm{time}}\}. \tag{5}$$

Three-objective:

$$\min \quad \{F_{\mathrm{fuel}}, F_{\mathrm{SP}}, F_{\mathrm{time}}\}. \tag{6}$$

All constraints applicable to each of these objectives are specified in constraints (7)–(20), adapted from Zhen et al. (2022). Constraints (7)–(14) regulate ships' access, waiting, and service in accordance with port regulations:

$$\sigma_i \geq e_i^{\mathrm{arr}} \quad \forall i \in V, \tag{7}$$

$$\sum_{b\in B} \beta_{i,b} = 1 \quad \forall i \in V, \tag{8}$$

$$\sum_{j\in V\cup\{I_b\}} \psi_{i,j,b} = \beta_{i,b} \quad \forall i \in V, \forall b \in B, \tag{9}$$

$$\sum_{j\in V\cup\{I_b\}} \psi_{o_b,j,b} = 1 \quad \forall b \in B, \tag{10}$$

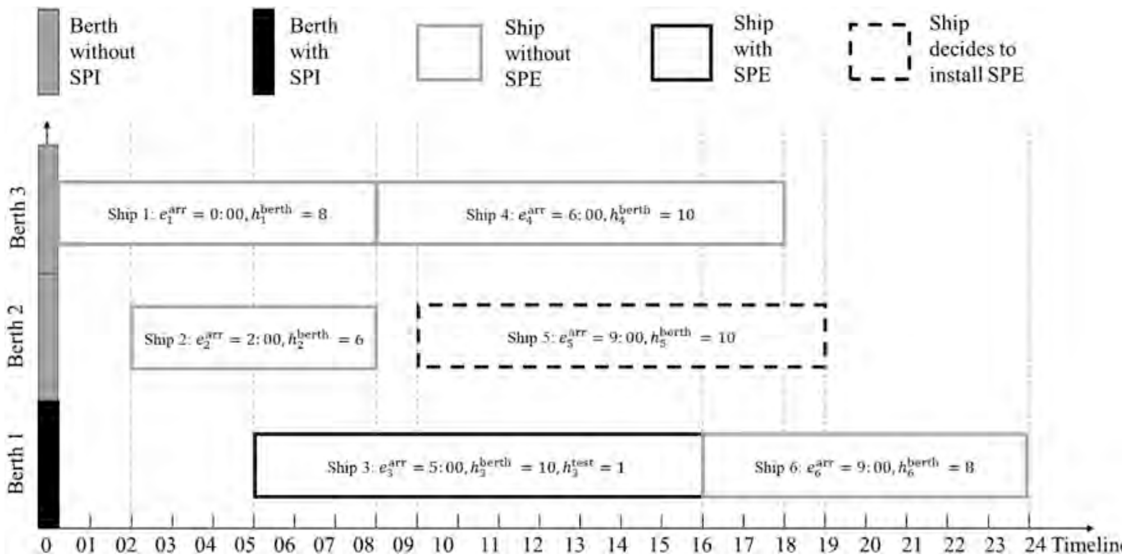

Fig. 2. Port berth assignment.

Table 2
Parameters and decision variables used in this paper.

Sets:	
V	Set of ships expected to arrive in a scheduling cycle;
S	Set of ships for the scheduling cycle, including 2 virtual ships;
B	Set of berths at the port;
Indices:	
i, j, k	Index for ships;
b	Index for berths;
o_b	Virtual ship, representing the head node at berth b;
l_b	Virtual ship, representing the tail node at berth b;
Parameters:	
c	Average installation cost of SPE for a ship (transformation cost);
p^{fuel}	Fuel consumption cost per hour without using SPI;
p^{oper}	Operational cost per hour when using SPI;
x	Subsidy rate for SPE installation provided by government;
y	Subsidy rate for using SPI provided by government;
h_i^{berth}	Service time for ship i;
h_i^{test}	Testing time for SPE connection to SPI for ship i;
e_i^{arr}	Arrival time of ship i;
e_i^{dep}	Leave time of ship i;
r^{w}	Awaiting penalty per hour for a ship;
r^{d}	Delay penalty per hour for a ship;
d_i	Equals 1, when ship i has installed SPE, otherwise 0;
a_b	Equals 1, when berth b has installed SPI, otherwise 0;
Decision Variables:	
α_i	Equals 1 if ship i decides to install SPE during this cycle, otherwise 0;
$\beta_{i,b}$	Equals 1 if ship i is assigned to berth b, otherwise 0;
ϕ_i	Equals 1 if ship i has SPE (either installed or decided to install), otherwise 0;
$\psi_{i,j,b}$	Equals 1 if ship j following ship i at berth b, otherwise 0;
σ_i	Handling start time for ship i;
θ_i	Handling end time for ship i.

$$\sum_{i\in V\cup\{o_b\}} \psi_{i,l_b,b} = 1 \quad \forall b \in B, \tag{11}$$

$$\sum_{j\in V\cup\{l_b\}} \psi_{i,j,b} = \sum_{j\in V\cup\{o_b\}} \psi_{j,i,b} \quad \forall i \in V, \forall b \in B, \tag{12}$$

$$\theta_i \le \sigma_j + (1-\psi_{i,j,b})M \quad \forall i,j \in V, i \ne j, \forall b \in B, \tag{13}$$

$$\theta_i = \sigma_i + \phi_i h_i^{test} + h_i^{berth} \quad \forall i \in V. \tag{14}$$

Constraints (15)–(16) define the conditions under which SP is utilized:

$$\phi_i = d_i + \alpha_i \quad \forall i \in V, \tag{15}$$

$$\alpha_i \le (1-d_i)M \quad \forall i \in V. \tag{16}$$

Constraint (17) ensures that priority service is provided to ships equipped with SPE:

$$-M(e_j^{arr}-\theta_i)^+ + (\phi_j-\phi_k)\psi_{i,k,b} \le (\phi_j-\phi_k)\psi_{i,j,b} + (e_k^{arr}-\theta_i)^+ M$$
$$\forall i,j,k \in V\cup\{o_b\}, i\ne j, i\ne k, j\ne k, \forall b\in B. \tag{17}$$

Constraints (18)–(20) define the domains of the decision variables:

$$\alpha_i, \beta_{i,b}, \phi_i \in \{0,1\} \quad \forall i \in V, \forall b \in B, \tag{18}$$

$$\psi_{i,j,b} \in \{0,1\} \quad \forall i,j \in V, \forall b \in B, \tag{19}$$

$$\sigma_i, \theta_i \ge 0 \quad \forall i \in V. \tag{20}$$

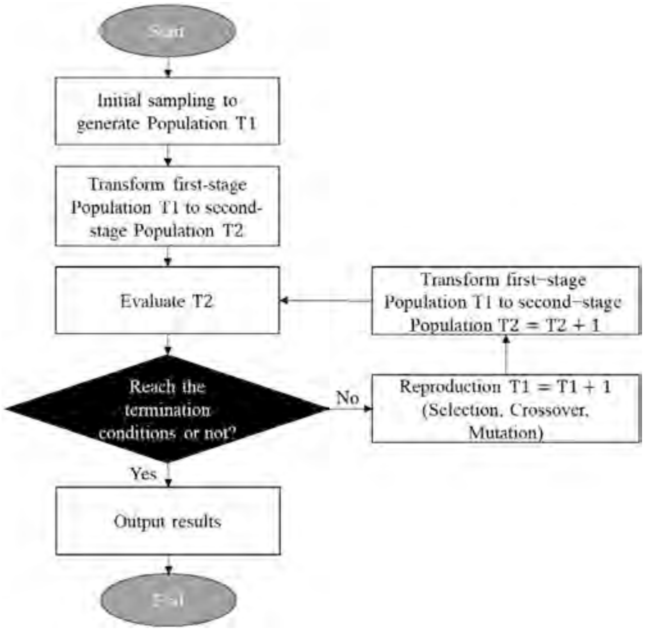

Fig. 3. Algorithm flow.

3.3. Modified cplex solver for the single-objective problem

We utilize the optimal objective value from the single-objective problem, solved using the Cplex solver, to control the quality of solutions generated by our heuristic algorithm for multi-objective problems. Specifically, we establish an acceptance interval, denoted as acc, based on the optimal value of the single-objective problem. For instance, we set the acceptance interval at 5% . If the minimum objective value achieved by the Cplex solver is 10,000, any solution from the heuristic algorithm with a cumulative objective value of 10,500 or less is considered satisfactory.

To improve the computational efficiency of the Cplex solver, we refine the linearization method originally proposed by Zhen et al. (2022), and focus on the non-negative taking formula applied to F_{time} and constraint (17). This formula, typically represented as $(t)^+$ or $z = max(t, 0)$, can be linearized using a binary variable δ and a large constant M, leading to the linear inequalities specified in (21)–(25):

$$z \leq t + (1 - \delta)M, \tag{21}$$

$$z \geq t + (1 - \delta)M, \tag{22}$$

$$z \leq \delta M, \tag{23}$$

$$t \leq \delta M, \tag{24}$$

$$z \geq 0. \tag{25}$$

These modifications significantly improve the solver's efficiency, and we document detailed performance comparisons in Section 4.3.

3.4. Two-stage solution algorithm for multi-objective problems

Considering the complexity of our multi-objective models, we cannot directly solve them due to potential constraint violations and excessive computation times. Therefore, this study proposes a novel, problem-oriented multi-objective algorithm that combines a two-stage solution process with the non-dominated sorting genetic algorithm (NSGA-II). We implement this approach using Python and the Pymoo library (Blank & Deb, 2020) to ensure efficient problem resolution. Fig. 3 illustrates the algorithm's flow, and presents how we address the problem's complexity.

In the first stage, we randomly generate a population $T1$ of first-stage solutions, using a basic greedy algorithm. Each solution is encoded as $Solution = \{b_1, b_2, \dots, b_i, \alpha_1, \alpha_2, \dots, \alpha_i\}$ for $i = 1, 2 \dots, |V|$, and spans a length of $2|V|$. Here, b_i represents that ship i is assigned to berth $b = b_i$, thus satisfying $\beta_{i,b_i} = 1$. In the second stage, we transform these initial solutions into a complete solution set, $T2$, based on detailed parameters such as ships' arrival times, service times, test times, and existing SPE installations. Fig. 4 illustrates an example with $|V| = 3$ and $|B| = 2$, with an initial solution set $Solution = \{1, 2, 1, 1, 0, 0\}$. In this scenario, the port assigns ships 1 and 3 to berth 1, and ship 2 to berth 2, and only the owner of ship 1 decides to install SPE. Algorithm 1 further details the two-stage solution generation.

Algorithm 1. Two-stage solution algorithm:

First stage

Input: Number of berths $|B|$ and ships $|V|$, ships' arrival times e_i^{arr}, and service times h_i^{berth}.
Output: A valid first-stage partial solution, $Solution$ of length $2|V|$.

Initialize arrays P_1, P_2 and $departure.times$; list $berth.order$ with a list of berth indices;
For i in $|V|$ **do**:
  If $i \leq |B|$ **then** $b \leftarrow berth.order[i]$;
  Else $b \leftarrow$ index of berth with the minimum departure time in $departure.times$;
  $b_i \leftarrow b$ and $P_1[i] \leftarrow b_i$; // Generate berth assignment b_i
  $departure.times[b_i] \leftarrow e_i^{\text{arr}} + h_i^{\text{berth}}$;
 $P_2 \leftarrow$ np.random.randint(0, 2, $|V|$); // Generate SPE installation decision α_i
 $Solution \leftarrow$ np.hstack(P_1,P_2);

Second stage

Input: First-stage $Solution$, number of berths $|B|$ and ships $|V|$, ship's arrival times e_i^{arr}, service times h_i^{berth}, test times h_i^{test}, and existing SPE installation d_i.
Output: A complete second-stage solution, $Complete.Solution$.

For i in $|V|$ **do**:
  $\beta_{i,b_i} \leftarrow 1$; // Generate berth assignment $\beta_{i,b}$
  $\phi_i \leftarrow \alpha_i + d_i$; // Generate SPE installation status ϕ_i
Set length(P) $\leftarrow$ number of berths $|B|$;
For b in $|B|$ **do**:
  $P(b) \leftarrow$ ships of berth in P_1 and sort $P(b)$ based on e_i^{arr};
  For each i in $P(b)$ **do**: // Generate ship scheduling $\psi_{i,j,b}$ and handling start time of ship σ_i
    If $index(i) = 0$ **then** $\psi_{|V|,i,b} \leftarrow 1$ and $\sigma_i \leftarrow e_i^{\text{arr}}$;
    Else if $index(i) = length(P(b)) - 1$ **then** $\psi_{i,|V|+1,b} \leftarrow 1$;
    Else $\psi_{pre.i,i,b} \leftarrow 1$, where $pre.i$ is the ship before i in $P(b)$
      If $\theta_{pre.i} > e_i^{\text{arr}}$ **then** $\sigma_i \leftarrow \theta_{pre.i}$;
      Else $\sigma_i \leftarrow e_i^{\text{arr}}$;
    $\theta_i \leftarrow \sigma_i + \phi_i h_i^{\text{test}} + h_i^{\text{berth}}$ // Generate handling end time of ship θ_i
$Complete.Solution \leftarrow$ np.hstack($\beta_{i,b}$,α_i,ϕ_i,$\psi_{i,j,b}$,σ_i,θ_i)

After completing the initial two steps of the algorithm, we evaluate the second-stage solution population, $T2$, and return multi-objective values using the functions defined in (5) or (6). Termination of the algorithm occurs when the average tolerance in the objective space is below tol. Additionally, the algorithm skips $n.skip$ iterations after reaching this tolerance level before terminating. Here, we regularly check every $period$ iterations

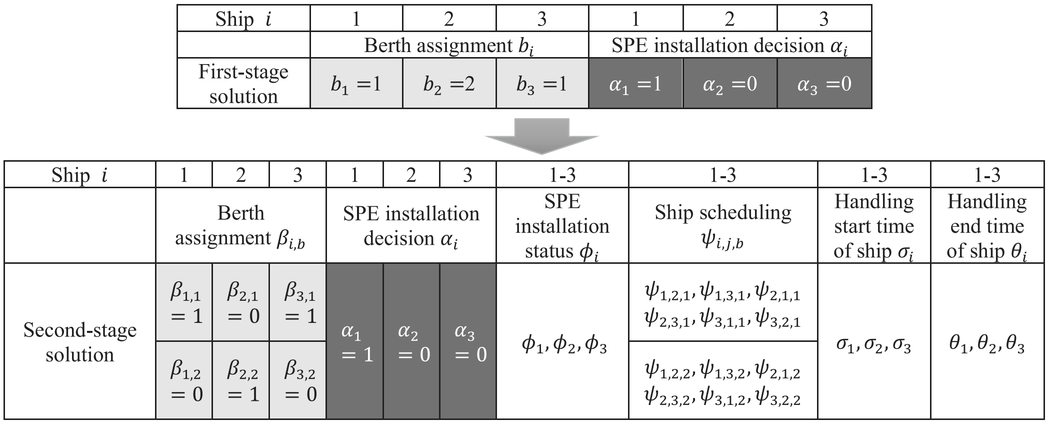

Fig. 4. Solution generation and transformation.

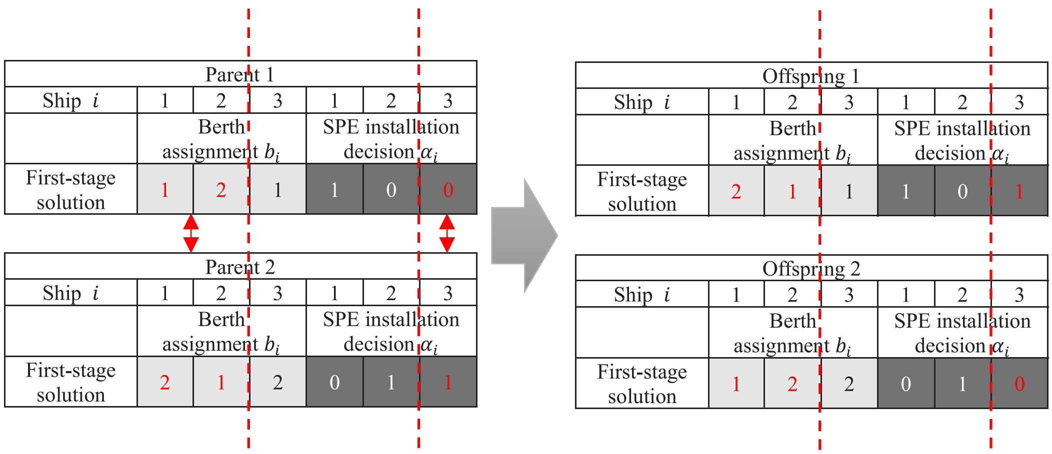

Fig. 5. A two-point crossover operation.

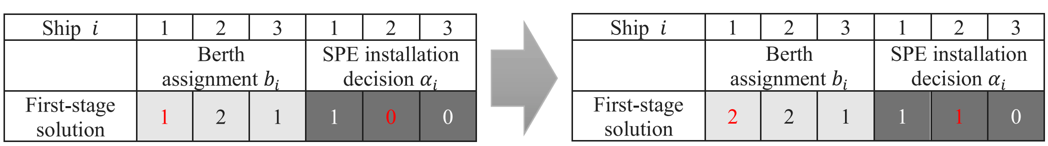

Fig. 6. A mutation operation.

to ensure compliance with the termination criteria. If the termination conditions are not met, we reproduce population $T1$ through selection, crossover and mutation, and then transform it into the two-stage population $T2$. We loop this process until the termination conditions are met, then output results.

Following the algorithm flow outlined in Fig. 3, we develop both basic and improved genetic operators for the first-stage population reproduction. The basic genetic operators include random selection, high-rate mutation, and uniform crossover. Specifically, we randomly select $p.size$ individuals from the mating pool to form a new parent population and apply uniform crossover, where the crossover probability is 0.5 for inheriting traits from either parent. For mutations, we set a relatively high probability, $pro.high$, and mutate each gene segment based on a random draw. If the random number is less than $pro.high$, the mutation occurs.

Compared with the basic genetic operators, the improved genetic operators for our problem are demonstrated to be more efficient, as detailed in Section 4.3. Initially, we apply a binary tournament selection method for parent selection in crossover. Specifically, we randomly select two individuals from the mating pool, which includes $p.size$ individuals from the parent population and $c.size$ individuals from the offspring population, then choose the individual with superior fitness. This process is repeated until the new parent population reaches $p.size$. For crossover, we utilize a two-point crossover method, which has proven to be efficient and error-free for solutions obtained from the first stage, as shown in Fig. 5. Furthermore, mutation of each gene segment occurs with a specific probability pro, based on its location. In the first-stage solution, b_i represents berth assignments, allowing for random mutations between berths with uniform probability. As for α_i, which is a binary variable, mutation involves toggling between 0 and 1. Fig. 6 presents mutations affecting the first and fifth gene segments below pro, while those of other segments meet or exceed this threshold.

4. Experiment study

In this section, we conduct experiments to demonstrate the effectiveness of the proposed problem and algorithm. All experiments are run on a computer with an Intel(R) Core(TM) i7-10750H CPU @2.60 GHz and 16 GB of RAM. Our algorithms are implemented using Cplex 12.10.0 and Python 3.7.1.

Table 3
Case settings.

Case ID	$\|S\|$	$\|V\|$	$\|B\|$	$\sum_{i\in V} d_i$	$\sum_{b\in B} a_b$	Equality constraints	Inequality constraints
Case 1	12	10	5	2	3	130	1670
Case 2	18	16	9	3	5	338	12 272
Case 3	22	20	11	4	6	502	29 300

* $|S|$: Number of ships, including dummy ships;
* $|V|$: Number of incoming ships;
* $|B|$: Number of berths at the port;
* $\sum_{i\in V} d_i$: Number of ships with SPE;
* $\sum_{b\in B} a_b$: Number of berths with SPI.

Table 4
Parameter settings.

Parameter	Range/value	Description
c	\$1000/day	Average transformation cost of a ship
p^{fuel}	\$233/h	Fuel consumption cost per hour for ship operation
p^{oper}	\$434/h	Operational cost per hour for using SP, including electricity and service charges
h_i^{berth}	{6,8,10} h	Handling time for ship i based on class (feeder, medium, jumbo)
e_i^{arr}	[0,24) h	Expected arrival time for ship i within a day
e_i^{dep}	$e_i^{\text{arr}} + h_i^{\text{berth}}$ h	Expected departure time for ship i
x	0.8	Government subsidy rate for SPE installation
y	0.6	Government subsidy rate for the operational cost of using SPI
h_i^{test}	1 h	Test time for ship i connecting to SPI
r^{w}	\$66/h	Waiting penalty per hour for ship i beyond its expected arrival time
r^{d}	\$66/h	Delay Penalty per hour for ship i departing later than its scheduled time

4.1. Case and parameter settings

We set up three cases, as shown in Table 3, with different numbers of berths ($|B|$) and ships ($|V|$) arriving within a 24-h period. Since the coverage of SPE is lower than that of SPI, we designated $\lceil 0.5|B|\rceil$ berths to have SPI and $\lfloor 0.2|V|\rfloor$ ships with SPE. Specifically, the berths equipped with SPI are 1 to 3 in case 1, 1 to 5 in case 2, and 1 to 6 in case 3. In different instances, we randomly assign ships equipped with SPE, according to the specified numbers.

We define input parameters for our numerical experiments based on existing literature. Handling times for different ship classes (feeder, medium and jumbo) range from 6 to 10 h, and the average transformation cost of a ship is set at \$1000/day, as referenced in Zhen et al. (2022). Fuel costs (p^{fuel}) and operational costs for SP (p^{oper}) are derived from the findings of Cheng and Li (2019). Specifically, we set p^{fuel} at \$233/h, accounting for an average power usage of 1880 kW, with fuel costs ranging from \$0.067/kWh to \$0.181/kWh. The operational costs of using SP, which include electricity and service charges, are set at \$434/h, calculated based on electricity and service costs at Shanghai Yangshan Port and an average electric load of 1900 kW. These parameters are consistently applied across all scenarios to ensure comparability in performance evaluations. We summarize detailed settings in Table 4.

4.2. Parameter impact analysis

To validate the parameter settings outlined in Table 4, we conduct a comprehensive parameter impact analysis. The control group settings are derived directly from Table 4, while experimental groups are tested with varied parameter settings to explore their impacts. This analysis specifically examines government subsidy rates (x and y), SP test time (h_i^{test}) and unit time penalties (r^{w} and r^{d}). We employ the modified Cplex solver to obtain a single optimal solution by minimizing the total costs, as specified in Eq. (4), which allows us to assess the effects of these parameters on the cost components: F_{fuel}, F_{time} and F_{SP}. The detailed outcomes are presented in Appendix A, which aggregates the mean results from both control and experimental groups across 10 instances for the three cases outlined in Table 3. The results also indicate percentage changes resulting from various experimental groups compared to the baseline results in the control group. We summarize our observations and conclusions as follows:

1. We set the subsidy rate for SPE installation at $x = 0.8$. At this level, compared to lower subsidy rates, there is a significant improvement in the incentive effect on SPE installation decisions, leading to a notable reduction in F_{fuel}, which is a primary concern of the government. However, raising the subsidy to $x = 0.9$, while increasing the incentive, also results in higher costs associated with F_{time} and F_{SP}. These increased costs could potentially affect the satisfaction levels of ports and shipowners. Similarly, we set the subsidy rate for SPI usage at $y = 0.6$ to effectively balance various cost concerns. Furthermore, the variations in costs with $x = 0.6$ and $x = 0.7$, or $y = 0.4$ and $y = 0.5$ are minimal, and we highlight the distinct values for these groups in the Table A.1 to underscore the efficiency of our chosen settings.
2. We set the SP test time at 1 h based on regular operational scenarios. Extended h_i^{test} times discourage shipowners from utilizing SP, as reflected by decreased F_{SP} and cases where $\alpha_i = 0$, which indicates no SP installation decisions. Concurrently, the increased waiting times in port lead to increased F_{fuel} and F_{time}. Our set aims at managing these costs effectively while ensuring sufficient incentives for SP installation.
3. We standardize the unit waiting and delay time penalties at $r^{\text{w}} = r^{\text{d}} = 66$. As demonstrated in Table A.1, these penalties distinctly influence associated costs such as F_{fuel}, F_{time} and F_{SP}. Specifically, increasing r^{d} generally raises F_{time}, however, in case 2, increasing r^{d} from 132 to 264 markedly reduces this cost. Conversely, higher r^{d} settings discourage SPE installation and usage, as evidenced by reductions in α_i and a decrease in F_{SP}, while simultaneously increasing F_{fuel}. Changes in r^{w} have no significant impact on F_{fuel} and F_{SP} but tend to increase F_{time}. By setting r^{w} and r^{d} at a moderate level of 66, we aim to promote adopting environmentally friendly SP practices while maintaining operational efficiency at ports.

4.3. Algorithm efficiency evaluation

As discussed in Section 3.3, we introduce an acceptance interval, acc, to ensure high solution quality for multi-objective problems. For this study, we set the acceptance interval at 5% for all cases. Additional details regarding the parameters used in the multi-objective problems' algorithm are outlined in Table 5. Initially, the single-objective problem is solved using a modified Cplex solver. Following this, our proposed algorithm is applied within a

Table 5
Multi-objective problems' algorithm parameter settings.

Parameter	Value	Description
acc	5%	Acceptance interval for the sum of multiple objective values, set based on the single-objective problem's optimal objective values
tol	0.005	Tolerance level for the difference between the best and worst multiple objective values on average
n.skip	5	Number of generations to skip before checking if the termination criterion is met
period	30	Number of generations after which the termination criterion is checked
p.size	20	Number of individuals in the parent population
c.size	10	Number of individuals in the offspring population
pro	0.5	Mutation rate determines the number of gene segments mutated in one generation
pro.high	0.7	High-level mutation rate determines the number of gene segment mutated in one generation

Table 6
Efficiency improvement of the Cplex solver.

Case ID	T_{MC} (s)	T_C (s)	$(T_C - T_{MC})/T_C$ (%)
Case 1	11.78	22.84	48.44
Case 2	38.12	731.32	94.79
Case 3	357.34	9233.47	96.13

* T_{MC}: Average running time with the modified Cplex solver;
* T_C: Average running time with the original Cplex solver proposed in Zhen et al. (2022).

Table 7
Algorithm performance comparison.

Performance of algorithms			Case 1			Case 2			Case 3		
Two-objective problem			F_{fuel}	$F_{time} + F_{SP}$		F_{fuel}	$F_{time} + F_{SP}$		F_{fuel}	$F_{time} + F_{SP}$	
	Baseline (Cplex)	Avg	78 871	7619		247 854	12416		393 071	7136	
	Basic operators	Avg	81 265	5919		252 886	10647		391 845	12668	
		Gap	−3.04%	22.31%		−2.03%	14.25%		0.31%	−77.52%	
		SD	2514	3239		3655	3190		4004	3836	
	Improved operators	Avg	82 181	4015		254 757	6216		392 459	9085	
		Gap	−4.20%	47.31%		−2.79%	49.93%		0.16%	−27.31%	
		SD	1928	1884		2795	2983		3142	3559	
Three-objective problem			F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}
	Baseline (Cplex)	Avg	79 570	374	6387	250 042	575	9488	391 347	647	8030
	Basic operators	Avg	82 229	663	4538	254 118	2014	8486	392 661	2455	10 221
		Gap	−3.34%	−77.35%	28.95%	−1.63%	−250.17%	10.55%	−0.34%	−279.52%	−27.28%
		SD	2263	462	2473	3842	803	3189	4481	976	3654
	Improved operators	Avg	81 899	277	4076	254 780	752	5632	393 081	1230	7385
		Gap	−2.93%	26.01%	36.18%	−1.89%	−30.70%	40.64%	−0.44%	−90.14%	8.03%
		SD	2369	194	2228	3154	775	2794	2696	581	2297
			F_{fuel}	$F_{time} + F_{SP}$		F_{fuel}	$F_{time} + F_{SP}$		F_{fuel}	$F_{time} + F_{SP}$	
	Improved operators	Avg*	81 899	4353		254 780	6384		393 081	8615	
		Gap*	0.34%	−8.43%		−0.01%	−2.69%		−0.16%	5.17%	

* Avg: Average objective values from Cplex solutions and heuristic algorithms run across 10 seeds;
* Gap: Percentage improvement of heuristic operators over Cplex, calculated as (Baseline Avg - Operator Avg)/Baseline Avg*100%;
* SD: Standard deviation across heuristic algorithm seed runs;
* Avg*: Average of ($F_{time} + F_{SP}$) for the three-objective model;
* Gap*: Percentage improvement of the three-objective model over the two-objective model with improved operators, calculated as (Two-objective Avg - Three-objective Avg)/Two-objective Avg*100%.

range determined by multiplying the single-objective problem's optimal objective value by $(1 + acc)$. Table 6 demonstrates the improved efficiency of the Cplex method, especially for larger case scenarios, compared to the method previously utilized in Zhen et al. (2022). Notably, the running times reported represent the average across 10 instances, which indicates the method's consistent performance across multiple trials.

4.3.1. Comparative analysis of heuristic algorithms performance

We conduct a comparative analysis with the traditional weighted sum method, commonly used in multi-objective optimization, to assess the efficiency of our heuristic algorithms, including both basic and improved genetic operators. This method consolidates multiple objectives into a single composite objective by applying distinct weights to each goal as expressed in Eq. (26):

$$\min \quad F_{total} = w_1 F_{fuel} + w_2 F_{SP} + w_3 F_{time}, \tag{26}$$

where w_1, w_2, and w_3 are weights assigned to fuel costs, SP costs, and time penalties, respectively.

To establish a comparison baseline, we utilize the modified Cplex solver to test various weight configurations of Eq. (26), with detailed results presented in Appendix B. For the two-objective model, we create 23 test instances where $w_1 \neq w_2 = w_3$, ranging from (1,1,1) to (1,20,20), including inversely proportional configurations such as (20,1,1), as detailed in Table B.1. For the more complex three-objective scenarios, we further examine 68 configurations that feature equal weights ($w_1 = w_2$ or $w_1 = w_3$) and varied weights (e.g., $w_1 = 1$, $w_2 = 2$, $w_3 = 3$), as shown in Table B.2. Despite extensive testing, the weighted sum method exhibits limitations in capturing all Pareto-optimal solutions within the solution space, and the Cplex solver struggles to resolve some instances within a three-hour limit, particularly in medium (Case 2) and large-sized cases (Case 3).

Quantitative comparisons in Table 7 assess the performance of our heuristic algorithms relative to the Cplex baseline. Across all cases, heuristic algorithms generally perform close to or surpass the Cplex baseline, with improved operators mostly outperforming the basic operators. Specifically, in two-objective scenarios, heuristic operators slightly under-perform compared to Cplex for F_{fuel} in small and medium cases, but they show

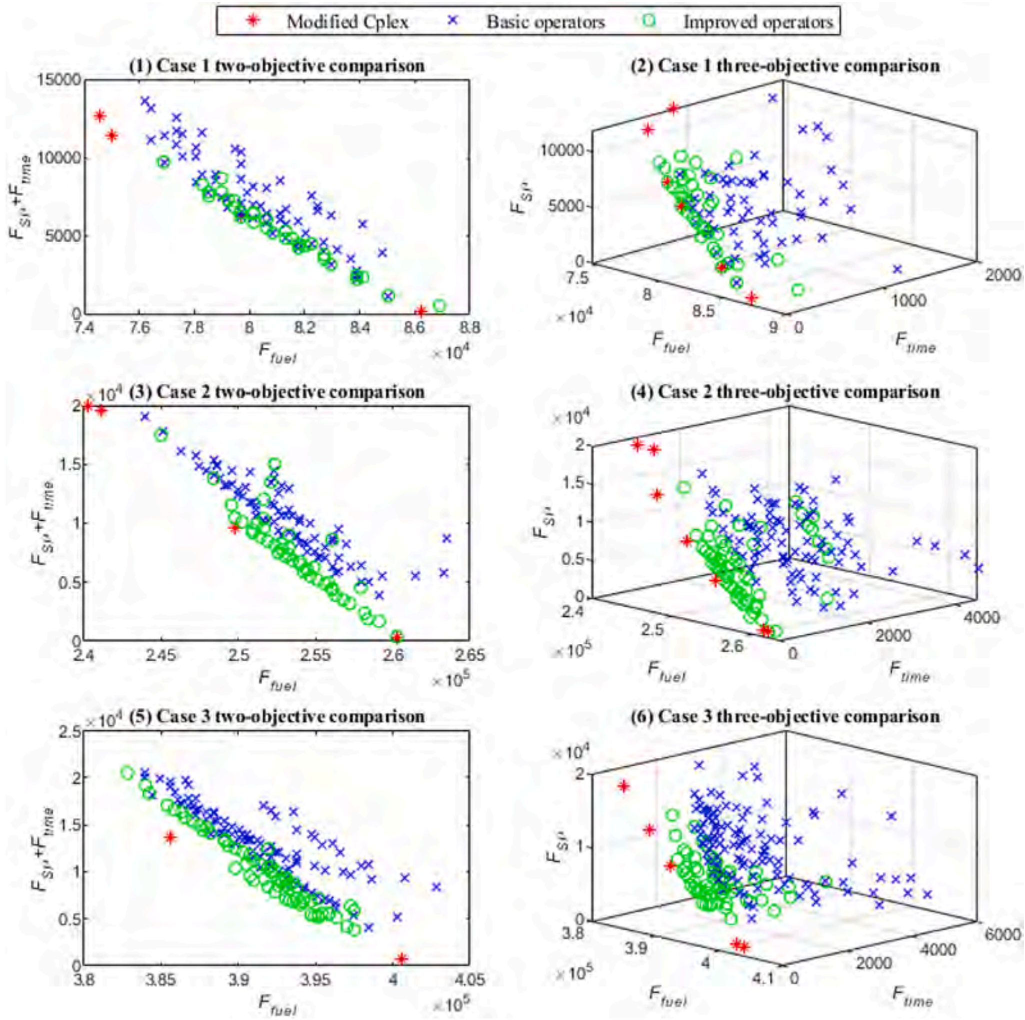

Fig. 7. Algorithm performance comparison..

advantages in larger cases. For $F_{\text{time}} + F_{\text{SP}}$, improved operators significantly outperform in both small and medium cases. In three-objective scenarios, heuristic solutions for F_{fuel} align closely with Cplex results. However, for F_{time} and F_{SP}, while improved operators generally outperform the basic ones, they do not consistently exceed the Cplex benchmarks, especially for F_{time} in medium and large cases. Additionally, we evaluate $F_{\text{time}} + F_{\text{SP}}$ within the three-objective model to facilitate the inter-comparisons across different multi-objective models using improved operators. As the case size increases, the optimization benefits for F_{fuel} become more pronounced in the two-objective model. Conversely, the three-objective model significantly enhances the exploration and optimization of F_{time} and F_{SP}. This distinction highlights the advantage of decomposing objectives, as it allows for more precise enhancements tailored to each specific goal, aligning with theoretical multi-objective optimization principles.

In Table 7, generally lower standard deviation (SD) values for the improved operators across 10 seed runs indicate their enhanced reliability and effectiveness compared to basic operators. The superior performance is visually supported by Fig. 7, which displays all solutions generated by Cplex from Appendix B alongside outcomes from both basic and improved heuristic operators under identical settings. Specifically, in two-objective scenarios (panels 1, 3, and 5), the improved operators achieve more efficient convergence towards optimal solutions. In three-objective scenarios (panels 2, 4, and 6), both heuristic approaches explore a broader solution space than the weighted sum method, with improved operators clustering more closely to the Pareto front. These results highlight the superior exploration capabilities and robust performance of the improved operators and emphasize the effectiveness of our proposed algorithms in tackling complex multi-objective optimization challenges.

4.3.2. Detailed performance metrics evaluation

Building on insights from Fig. 7, we further utilize five metrics summarized by Zhou and Lee (2020) to assess and compare the the performance of basic and improved genetic operators across 10 seed runs. These metrics are categorized into qualitative (items 1 to 3) and quantitative groups (items 4 and 5):

1. Number of Pareto solutions (NPS): Measures the count of non-dominated solutions, where a higher count indicates greater flexibility in decision-making.
2. Diversity (Div): Reflects the range of values across the Pareto front,with greater diversity suggesting a better spread of solutions. It is calculated using the following formulas for two- and three-objective models, respectively:

   • For the two-objective model:

$$Div = \sqrt{\left(\max_{i \le NPS} F^{i}_{\text{fuel}} - \min_{i \le NPS} F^{i}_{\text{fuel}}\right)^2 + \left(\max_{i \le NPS} (F_{\text{SP}} + F_{\text{time}})^i - \min_{i \le NPS} (F_{\text{SP}} + F_{\text{time}})^i\right)^2}. \tag{27}$$

   • For the three-objective model (see Box I):

3. Spacing ($Sp.var$): Assesses the evenness of the distribution of solutions along the Pareto front, where lower variance indicates a more

$$Div = \sqrt{\left(\max_{i \le NPS} F^i_{\text{fuel}} - \min_{i \le NPS} F^i_{\text{fuel}}\right)^2 + \left(\max_{i \le NPS} F^i_{\text{SP}} - \min_{i \le NPS} F^i_{\text{SP}}\right)^2 + \left(\max_{i \le NPS} F^i_{\text{time}} - \min_{i \le NPS} F^i_{\text{time}}\right)^2}. \quad (28)$$

Box I.

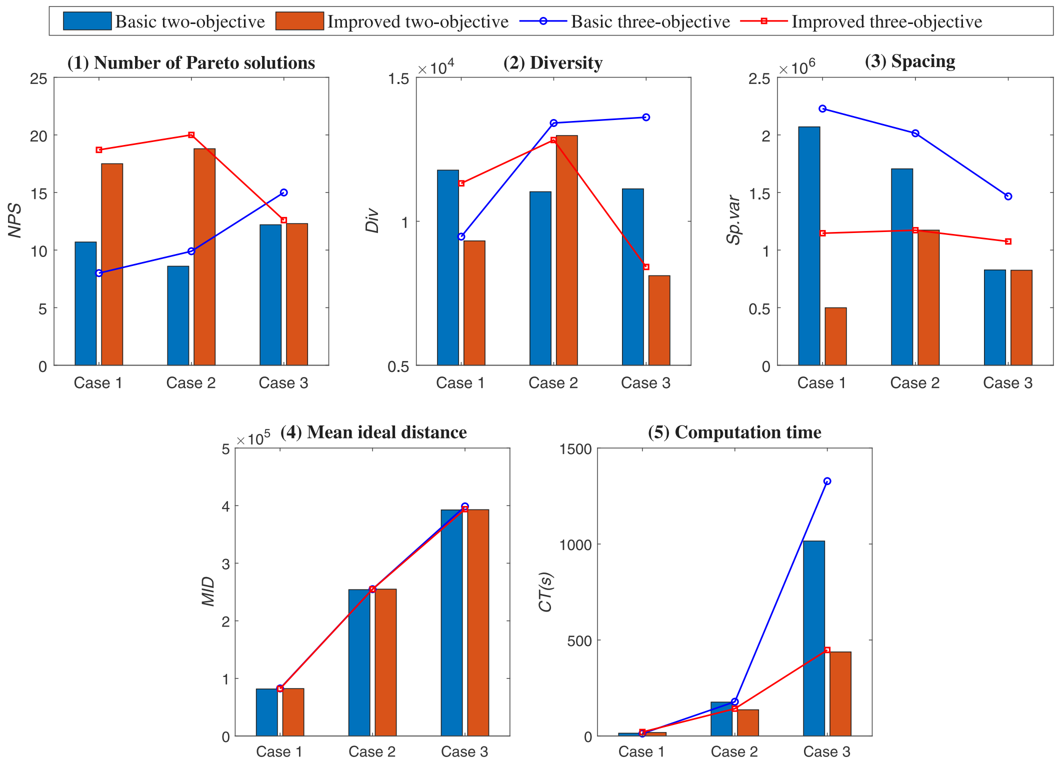

Fig. 8. Five performance metrics for basic and improved genetic operations..

uniform spread. Calculated as:

$$Sp.var = \frac{1}{NPS - 1} \sum_{i=1}^{NPS} \left(\bar{d} - d_i\right)^2, \quad (29)$$

where d_i is the nearest neighbor Manhattan distance for the ith solution, and $\bar{d}$ is the average of all d_i.

4. Mean ideal distance (MID): Averages the Euclidean distance from each solution to an ideal point, where lower values indicate closer proximity to this ideal. Calculated as:
   - For the two-objective model:

$$MID = \frac{\sum_{i=1}^{NPS} \sqrt{F_{\text{fuel}}^2 + (F_{\text{SP}} + F_{\text{time}})^2}}{NPS}. \quad (30)$$

   - For the three-objective model:

$$MID = \frac{\sum_{i=1}^{NPS} \sqrt{F_{\text{fuel}}^2 + F_{\text{SP}}^2 + F_{\text{time}}^2}}{NPS}. \quad (31)$$

5. Computation time (CT): Measures the time required to complete an algorithm run, with shorter times indicating higher efficiency.

We analyze five key metrics across each run and average the results, as depicted in Fig. 8. Improved operators demonstrate a consistent advantage in the spacing metric, especially within small cases of the two-object model. In terms of computation time, both improved and basic operators efficiently resolve small and medium cases across different objective models. As case complexity increases, the improved algorithm maintains average computation times of less than 450 s for large cases, significantly outperforming the basic operators. The mean ideal distance (MID) exhibits minimal differences between the two types of operators under the same settings, with only slight variations between the two-objective and three-objective models. And MID values tend to increase with the size of the case. For the number of Pareto solutions, improved operators outperform in small and medium cases. In large cases, the performance of improved operators in the two-objective model aligns more closely with the basic operators and slightly lags in the three-objective model. Diversity metrics vary between models and case sizes, with basic operators generally achieving greater diversity. However, despite their higher diversity, these solutions often fall into local optima, compromising solution quality. On the other hand, improved operators, though featuring lower diversity, generally deliver solutions that more effectively approach Pareto optimally. In summary, improved genetic operations generally show superior performance compared to basic ones, particularly in terms of efficiency and solution quality, by more effectively approaching Pareto optimally and maintaining stability across varying case complexities.

Fig. 9 presents the box plot of metrics results, where the median is marked by the middle line of each box and statistical outliers are presented by small circles. The box plots illustrate that improved operators consistently demonstrate advantages in the number of Pareto solutions in small and medium cases, and exhibit more efficient computation times in large cases, as indicated by their compact box ranges. In terms of spacing,

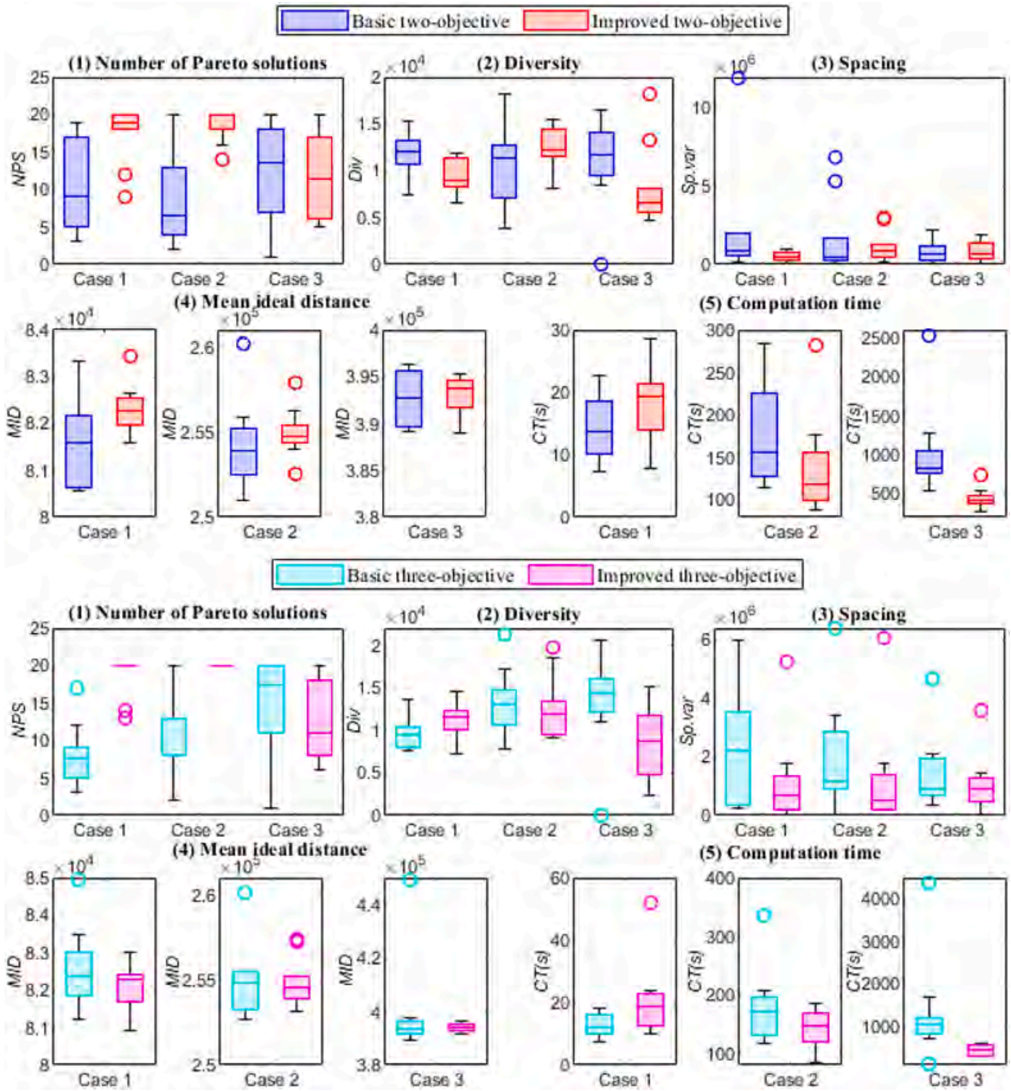

Fig. 9. Box plot of five performance metrics for basic and improved genetic operations..

improved operators maintain smaller and tighter distributions than basic operators, and basic operations occasionally result in large spacing values, notably in two-objective scenarios. Although the differences in the mean ideal distance are minimal, improved operators show relatively smaller box ranges, further underscoring their stability across various case complexities.

4.4. Policy impact analysis

Using the proposed heuristic algorithm, which incorporates improved genetic operators, we evaluate multi-objective outcomes and SPE installation decisions under four distinct scenarios: 1. Application of both the government subsidy incentive policy (GSIP) and the berthing priory incentive policy (BPIP), denoted as 'with policies'; 2. Application of only GSIP, denoted as 'with GSIP'; 3. Application of only BPIP, denoted as 'with BPIP'; 4. Non-application of either policy, denoted as 'without policies'. Our standard model formulation, outlined in Section 3.2, integrates both policies by default. If GSIP is not implemented, we set the subsidy rates x and y to zero. If BPIP is not applied, the associated constraint, denoted by (17), is removed.

4.4.1. Impact on multi-objective results

Fig. 10 provides a comprehensive analysis of the impact of policy interventions on objective values across two-objective and three-objective scenarios, illustrated through the Pareto fronts.

1. BPIP in small cases: In situations where port capacities sufficiently meet the demands of incoming ships, BPIP shows a minimal impact on operations. Particularly in the three-objective scenarios, the exclusive use of BPIP maintains SP and time costs within acceptable ranges. Thus, in small case scenarios where the fleet size matches the terminal capacity, it is recommended that ports implement BPIP directly, as it does not disrupt existing operations and may enhance long-term SP utilization and financial returns.
2. Effectiveness of GSIP: GSIP, whether implemented alone or alongside BPIP, consistently improves performance metrics closer to the ideal point than scenarios without GSIP. This is evidenced by lower fuel costs and combined SP and time costs in two-objective scenarios (panels 1, 3, and 5), as well as reduced F_{fuel} and F_{SP} in three-objective settings (panels 2, 4, and 6), albeit with some increase in time costs. GSIP effectively aligns the interests of both the government and shipowners, although it necessitates some compromises regarding time efficiency.

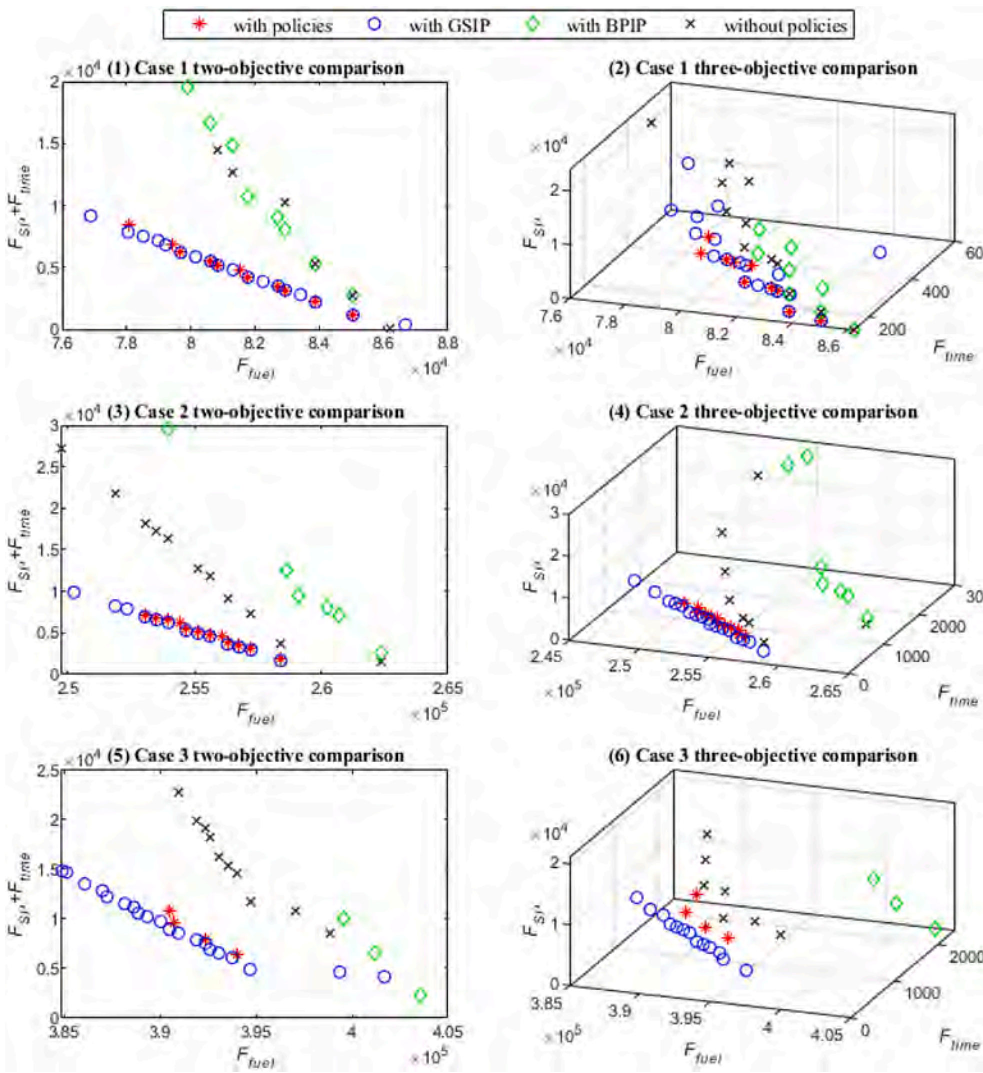

Fig. 10. Pareto fronts in two-objective and three-objective problems across four scenarios..

3. Policy impact in larger cases: As the case size increases, GSIP's focus on minimizing F_{fuel} becomes more pronounced and maintains its effectiveness even when combined with BPIP. However, utilizing BPIP alone in medium and large cases negatively impacts both F_{fuel} and F_{time}. Specifically, achieving lower F_{SP} necessitates higher F_{fuel}, and moderate F_{fuel} correlates with increased SP and time expenses. This indicates that without effective GSIP support, the sole application of BPIP fails to balance various costs adequately. We advise that ports should not implement BPIP without GSIP in larger scenarios as it diminishes operational efficiency.

In summary, for optimal environmental benefits, the government should lead with GSIP and set appropriate subsidy rates as tested in Section 4.2. The application of BPIP should be context-specific; it is typically effective when integrated with actively promoted GSIP. In contrast, BPIP alone in larger cases fails to align stakeholder interests adequately and negatively impacts operational efficiency, which is a significant concern for ports.

4.4.2. Impact on SPE installation decisions

We further analyze how policies influence decisions regarding SPE installations (α_i) across different scenarios. Table 8 presents the average number of SPE installations per scenario.

Interestingly, the combination of GSIP and BPIP does not consistently lead to the highest rates of SPE installation. This trend is particularly notable in large cases within the two-objective problem, where the combined policies result in fewer installations than in scenarios featuring GSIP alone. This outcome may be attributed to BPIP potentially increasing service times for ships utilizing SPI, along with longer waiting periods for other ships, which could diminish its incentive effect. Across all scenarios, GSIP consistently encourages more SPE installations than other conditions, which underscores the strong influence of financial incentives on promoting environmental investment decisions. In contrast, BPIP alone generally has a lower impact on SPE installations compared to GSIP.

Table 8
Average SPE installation decisions.

Case ID	with policies	with GSIP	with BPIP	without policies
		Two-objective problem		
Case 1	1.25	1.45	0.84	0.45
Case 2	2.80	2.25	2.07	1.50
Case 3	1.56	2.40	0.00	0.80
		Three-objective problem		
Case 1	1.00	1.68	0.65	0.95
Case 2	3.50	2.75	2.31	1.70
Case 3	1.75	1.58	0.00	0.36

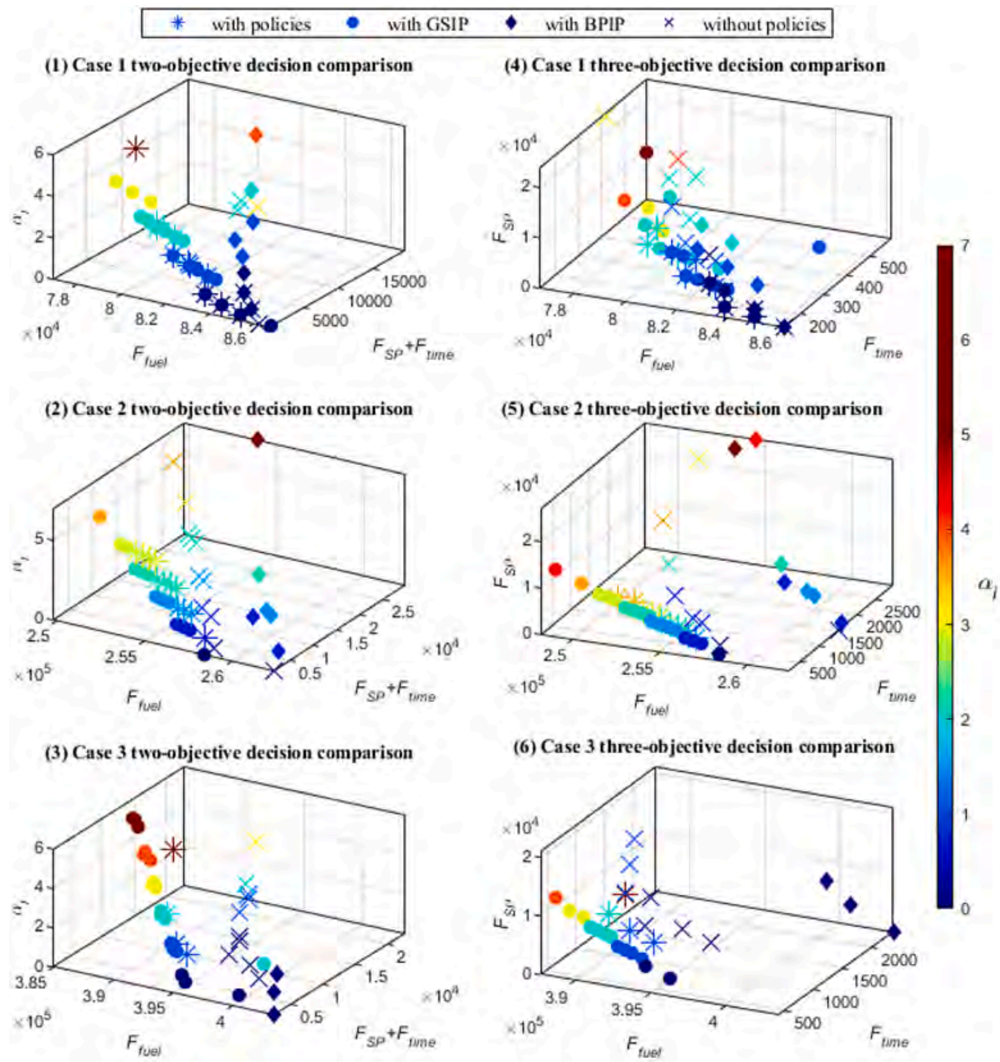

Fig. 11. SPE installation decisions in two-objective and three-objective problems across four scenarios..

Fig. 11 shows the detailed relationship between different objectives and SPE installation decisions under various policy frameworks. The results indicate that increased SPE installations can mitigate fuel consumption but lead to higher SP and time costs.

1. Effectiveness of dual policy implementation: Implementing both GSIP and BPIP sometimes reduces SP and time costs more effectively than using GSIP alone. This is particularly evident in medium-sized cases within two-objective scenarios, where the combination shows an advantage in reducing the combined objective function $F_{\text{SP}} + F_{\text{time}}$ at equivalent levels of SPE installation. In corresponding three-objective scenarios, this benefit primarily impacts F_{time}, while maintaining relatively acceptance values of F_{fuel} and F_{SP}.
2. Comparison of GSIP and BPIP: GSIP alone generally tends to result in higher SPE installations than BPIP alone. The integration of both policies shows that GSIP can amplify the effectiveness of BPIP. This synergy is especially pronounced in large cases, where the combined policies typically lead to the highest installation decision number of 5, which significantly improves outcomes observed with BPIP alone.

In summary, to improve the coverage of SPE installation, GSIP proves to be an effective policy. When combined with BPIP, this dual-policy approach can further satisfy both port authorities and shipowners, and occasionally more effectively encourage shipowners to install SPE. However, BPIP alone should not be used, especially in large cases, which can lead to higher costs for governments and ports, while achieving only lower levels of SPE installation decisions.

4.4.3. Carbon emission considerations in extended problems

Building on our comprehensive analysis of policy impacts on multi-objective outcomes and SPE installation decisions, we introduce a carbon emission factor, C_e, to transition from solely fuel-based costs (with the related parameter p^{fuel} set at \$233/h) to broader environmental concerns. Based on the emission coefficient of diesel at 3.021 kg of pollutant per kg of fuel according to Zis (2019), alongside data on the average power of ship auxiliary engines (1880 kW) and a fuel consumption rate of 0.235 kg/kWh from Cheng and Li (2019), we redefine the environmental cost parameter as $C_e = 1335$ kg/h. This adjustment allows us to replace the traditional fuel consumption cost (F_{fuel}) with a carbon emission cost, denoted as F_{carbon}, in all proposed multi-objective models, which aligns more closely with governmental environmental priorities. The new objective formulation is presented in Eq. (32):

$$F_{\text{carbon}} = \sum_{i\in V} C_e(\sigma_i - e_i^{\text{arr}}) + \sum_{i\in V}\sum_{b\in B}[\phi_i a_b \beta_{i,b} C_e(h_i^{\text{test}} - h_i^{\text{berth}}) + C_e h_i^{\text{berth}}]. \tag{32}$$

Fig. 12 displays the outcomes under the revised objective across different policy scenarios. The introduction of F_{carbon} significantly shifts the optimization focus, evident from the expanded range of $F_{\text{SP}} + F_{\text{time}}$ in two-objective scenarios and F_{SP} in three-objective scenarios. This enhanced environmental consideration leads to higher SPE installation decisions,

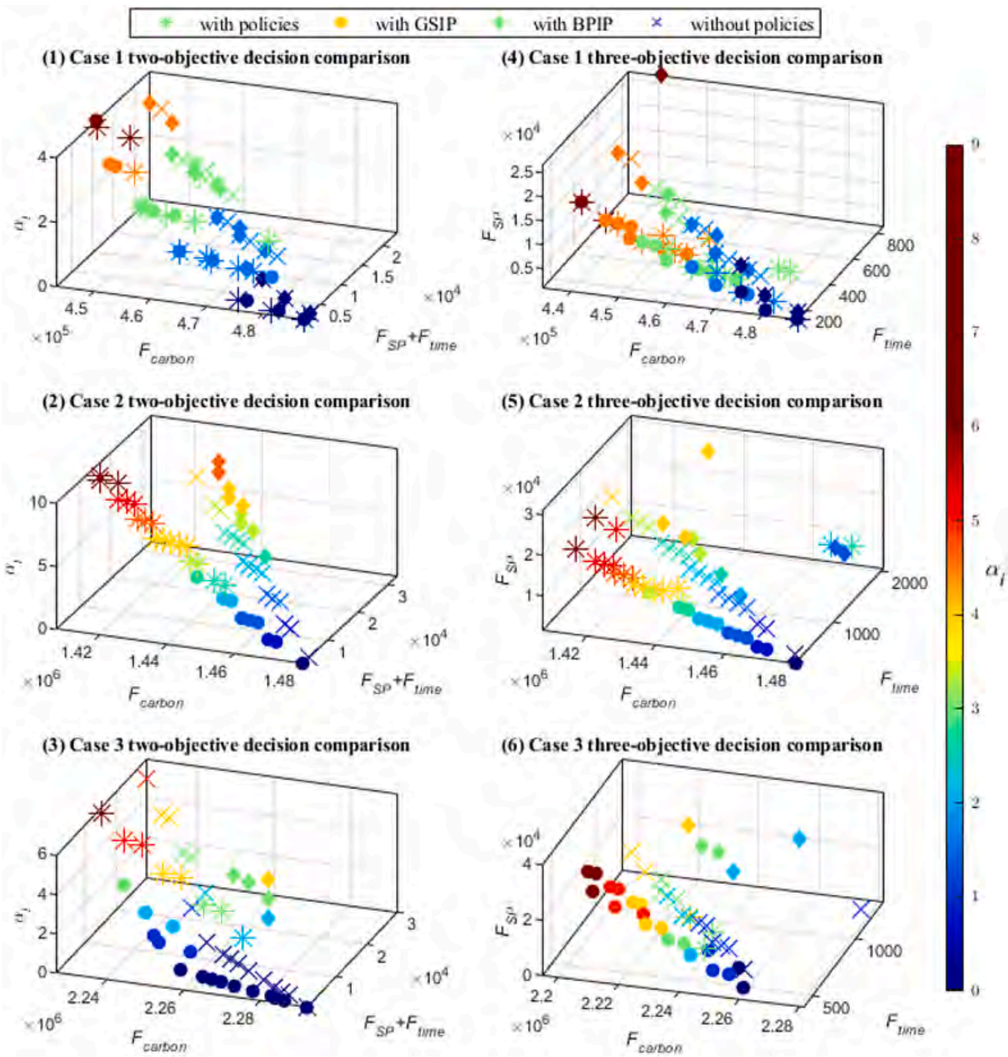

Fig. 12. Objectives and decisions in two-objective and three-objective problems considering carbon emission.

reaching up to 9, compared to a previous maximum of 7 in the results shown in Fig. 11.

Notably, the synergistic effects of combining GSIP and BPIP become more pronounced under the new multi-objective models considering carbon emissions, particularly in medium cases. Despite some trade-offs in F_{time} and F_{SP}, the dual-policy framework allows for more substantial reductions in carbon costs. Thus, to enhance environmental benefits, it is crucial for governments to implement reasonable GSIPs and encourage ports to adopt BPIP. This combination facilitates easier decisions for shipowners regarding SPE installations.

5. Conclusions

This study studies the effects of the government subsidy incentive policy (GSIP) and the berthing priority incentive policy (BPIP) on various objectives, including environmental benefits, operational efficiency, and cost management. We consider these impacts from the perspectives of governments, ports, and shipowners, highlighting the complex balance required for sustainable port development. Moreover, we focus on optimizing ship-side shore power (SPE) deployment, berth allocation, and ship scheduling through the application of multi-objective mixed-integer programming models. To address these complex challenges, we develop a specific algorithm that combines a two-stage solution process with the non-dominated sorting genetic algorithm (NSGA-II), enhanced by improved genetic operations. The proposed method consistently delivers superior performance in handling complex multi-objective problems by achieving better-aligned Pareto fronts. Through comprehensive experiments, we summarize insights for various stakeholders as follows:

1. Government perspective: Our research underscores the pivotal role of government in steering sustainable port initiatives. By leveraging our model, policymakers can seek appropriate subsidy rates to maximize their impact on shore power expansion while balancing stakeholders' satisfaction. In this paper, GSIP with subsidy rates set through parameter impact analysis is proven to be effective in experiment analysis. Furthermore, our analysis highlights the importance of GSIP in fostering the adoption of BPIP, while considering its operational scale implications.
2. Port perspective: For port authorities and operators, our research offers nuanced insights into the integration of sustainable practices within the operational framework. While BPIP presents opportunities for enhancing returns through shore-side electricity supply infrastructure (SPI) utilization, its applicability depends on the scale of operations and the efficiency of other policies in practice. Our study emphasizes the need for port operators to carefully assess the operational implications of BPIP implementation through our model to mitigate potential efficiency losses.
3. Shipowners perspective: Shipowners stand to benefit significantly from our research through decision-making regarding SPE installations. By utilizing our model, ship fleets can optimize SPE installation

rates to balance cost-effectiveness and operational efficiency, while aligning with regulatory policies and industry standards.

In summary, our study contributes a comprehensive framework for stakeholders to navigate the complexities of sustainable port development in the context of shore power systems. By integrating empirical evidence with robust modeling techniques, we provide a holistic approach to evaluating policy interventions and operational strategies, thus fostering resilience and efficiency within the maritime industry.

The future studies could be considered the following aspects. The reinforcement learning method is a powerful tool used for solving complex combinatorial optimization problems in recent years, which could be adopted for solving the studied problem.

CRediT authorship contribution statement

Ziyi Zhong: Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Huan Jin:** Writing – review & editing, Writing – original draft, Conceptualization. **Yuyao Sun:** Visualization, Software, Data curation. **Yanjie Zhou:** Writing – review & editing, Writing – original draft, Supervision, Project administration.

Data availability

Data will be made available on request.

Acknowledgments

This work was financially supported by the National Natural Science Foundation of China (No. 72201252). The authors want to thank Cong Jin, who verified and provided the source code of the mathematical model proposed by Zhen et al. (2022).

Appendix A. Results of parameter impact analysis

See Table A.1.

Table A.1
Control and experimental group results across settings.

Setting	Case ID	F_{fuel}	F_{time}	F_{SP}	α_i
		Control groups (baseline)			
$x = 0.8$; $y = 0.6$;	Case 1	85 884	686	6318	3
$h_i^{\text{test}} = 1$; $r^{\text{w}} = 66$;	Case 2	251 454	422	10 679	3
$r^{\text{d}} = 66$	Case 3	388 667	594	14 640	5
		Experimental groups (percentage changes)			
	Case 1	88004(+2.47%)	627(−8.65%)	**4662**(−26.21%)	2
$x = 0.6$	Case 2	258374(+2.75%)	205(−51.56%)	**4311**(−59.64%)	0
	Case 3	**398104**(+2.43%)	**297**(−50.00%)	**5988**(−59.10%)	0
	Case 1	88004(+2.47%)	627(−8.65%)	**4512**(−28.58%)	2
$x = 0.7$	Case 2	258374(+2.75%)	205(−51.56%)	**4301**(−59.73%)	0
	Case 3	**397894**(+2.37%)	**304**(−48.89%)	**6161**(−57.91%)	0
	Case 1	83624(−2.63%)	799(+16.35%)	8103(+28.25%)	4
$x = 0.9$	Case 2	247027(−1.76%)	607(+43.75%)	14369(+34.55%)	6
	Case 3	383495(−1.33%)	812(+36.67%)	18864(+28.86%)	8
	Case 1	**91709**(+6.78%)	640(−6.73%)	**1666**(−73.63%)	1
$y = 0.4$	Case 2	263383(+4.74%)	205(−51.56%)	20(−99.81%)	0
	Case 3	404977(+4.20%)	297(−50.00%)	60(−99.59%)	0
	Case 1	**91243**(+6.24%)	640(−6.73%)	**1866**(−70.47%)	1
$y = 0.5$	Case 2	263383(+4.74%)	205(−51.56%)	20(−99.81%)	0
	Case 3	404977(+4.20%)	297(−50.00%)	60(−99.59%)	0
	Case 1	81760(−4.80%)	957(+39.42%)	8157(+29.10%)	6
$y = 0.7$	Case 2	243415(−3.20%)	825(+95.31%)	14594(+36.65%)	9
	Case 3	369305(−4.98%)	990(+66.67%)	18345(+25.31%)	11
	Case 1	90031(+4.83%)	911(+32.69%)	3008(−52.39%)	2
$h_i^{\text{test}} = 2$	Case 2	260657(+3.66%)	422(0.00%)	2624(−75.43%)	0
	Case 3	400364(+3.01%)	594(0.00%)	4524(−69.10%)	0
	Case 1	91709(+6.78%)	1175(+71.15%)	1664(−73.67%)	1
$h_i^{\text{test}} = 3$	Case 2	263430(+4.76%)	620(+46.88%)	0(−100.00%)	0
	Case 3	405047(+4.21%)	865(+45.56%)	20(−99.86%)	0
	Case 1	85884(0.00%)	591(−13.49%)	6318(0.00%)	3
$r^{\text{w}} = 33$	Case 2	251454(0.00%)	422(0.00%)	10679(0.00%)	3
	Case 3	388667(0.00%)	591(−0.56%)	14640(0.00%)	5
	Case 1	85884(0.00%)	878(+27.88%)	6318(0.00%)	3
$r^{\text{w}} = 132$	Case 2	251454(0.00%)	422(0.00%)	10679(0.00%)	3
	Case 3	388667(0.00%)	601(+1.11%)	14640(0.00%)	5
	Case 1	85884(0.00%)	1261(+83.65%)	6318(0.00%)	3
$r^{\text{w}} = 264$	Case 2	251454(0.00%)	422(0.00%)	10679(0.00%)	3
	Case 3	388667(0.00%)	614(+3.33%)	14640(0.00%)	5
	Case 1	83973(−2.22%)	482(−29.81%)	8175(+29.39%)	4
$r^{\text{d}} = 33$	Case 2	248005(−1.37%)	284(−32.81%)	14036(+31.43%)	6
	Case 3	384403(−1.10%)	389(−34.44%)	18791(+28.35%)	8
	Case 1	85884(0.00%)	1181(+72.12%)	6318(0.00%)	3
$r^{\text{d}} = 132$	Case 2	251454(0.00%)	**845**(+100.00%)	10679(0.00%)	3
	Case 3	388877(+0.05%)	1168(+96.67%)	14446(−1.32%)	5
	Case 1	87981(+2.44%)	1907(+177.88%)	4382(−30.64%)	2
$r^{\text{d}} = 264$	Case 2	258374(+2.75%)	**818**(+93.75%)	4291(−59.82%)	0
	Case 3	398104(+2.43%)	1168(+96.67%)	5928(−59.51%)	0

Appendix B. Results of weighted sum method

See Tables B.1 and B.2.

Table B.1
Weighted sum results in two-objective problem.

$w1, w2, w3$	Case 1				Case 2				Case 3			
($w_1 \neq w_2 = w_3$)	F_{fuel}	F_{time}	F_{SP}	$F_{\text{time}} + F_{\text{SP}}$	F_{fuel}	F_{time}	F_{SP}	$F_{\text{time}} + F_{\text{SP}}$	F_{fuel}	F_{time}	F_{SP}	$F_{\text{time}} + F_{\text{SP}}$
1,1,1	79 686	264	5955	6219	249 776	396	9280	9676	385 615	660	12 952	13 612
1,2,2	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,3,3	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,4,4	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,5,5	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,6,6	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,7,7	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,8,8	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,9,9	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,10,10	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,15,15	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
1,20,20	86 210	132	0	132	260 261	330	0	330	400 527	660	0	660
2,1,1	75 026	528	10 922	11 450	241 155	1188	18 466	19 654	–	–	–	–
3,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
4,1,1	74 560	858	11 816	12 674	241 155	1188	18 466	19 654	–	–	–	–
5,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
6,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
7,1,1	74 560	858	11 816	12 674	240 223	990	19 013	20 003	–	–	–	–
8,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
9,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
10,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
15,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–
20,1,1	74 560	858	11 816	12 674	–	–	–	–	–	–	–	–

Table B.2
Supplementary results in three-objective problem.

$w1, w2, w3$	Case 1			Case 2			Case 3		
($w_1 \neq w_2 \neq w_3$)	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}
1,2,3	86 210	132	0	260 261	330	0	400 527	660	0
1,3,2	86 210	132	0	260 028	264	200	400 061	528	400
2,1,3	86 210	132	0	260 261	330	0	400 527	660	0
2,3,1	75 026	528	10 922	240 223	990	19 013	–	–	–
3,1,2	75 026	528	10 922	240 223	990	19 013	–	–	–
3,2,1	75 026	528	10 922	–	–	–	–	–	–
1,3,5	86 210	132	0	260 261	330	0	400 527	660	0
1,5,3	86 210	132	0	260 261	330	0	400 527	660	0
3,1,5	86 210	132	0	260 261	330	0	400 527	660	0
3,5,1	75 026	528	10 922	240 223	990	19 013	–	–	–
5,1,3	75 026	528	10 922	–	–	–	–	–	–
5,3,1	74 560	858	11 816	–	–	–	–	–	–
1,5,10	86 210	132	0	260 261	330	0	400 527	660	0
1,10,5	86 210	132	0	260 261	330	0	400 527	660	0
5,1,10	86 210	132	0	260 261	330	0	400 527	660	0
5,10,1	75 026	528	10 922	240 223	990	19 013	–	–	–
10,5,1	74 560	858	11 816	–	–	–	–	–	–
10,1,5	75 026	528	10 922	–	–	–	–	–	–
1,10,20	86 210	132	0	260 261	330	0	400 527	660	0
1,20,10	86 210	132	0	260 261	330	0	400 527	660	0
10,1,20	86 210	132	0	260 261	330	0	400 527	660	0
10,20,1	75 026	528	10 922	240 223	990	19 013	–	–	–
20,1,10	74 560	858	11 816	–	–	–	–	–	–
20,10,1	74 560	858	11 816	–	–	–	–	–	–
2,2,1	75 026	528	10 922	240 223	990	19 013	–	–	–
3,3,1	75 026	528	10 922	–	–	–	–	–	–
4,4,1	75 026	528	10 922	–	–	–	–	–	–
5,5,1	75 026	528	10 922	–	–	–	–	–	–
6,6,1	75 026	528	10 922	240 223	990	19 013	–	–	–
7,7,1	74 560	858	11 816	240 223	990	19 013	–	–	–
8,8,1	74 560	858	11 816	–	–	–	–	–	–
9,9,1	74 560	858	11 816	–	–	–	–	–	–
10,10,1	74 560	858	11 816	–	–	–	–	–	–
15,15,1	74 560	858	11 816	240 223	990	19 013	–	–	–
20,20,1	74 560	858	11 816	–	–	–	–	–	–
1,1,2	86 210	132	0	260 261	330	0	400 527	660	0
1,1,3	86 210	132	0	260 261	330	0	400 527	660	0
1,1,4	86 210	132	0	260 261	330	0	400 527	660	0

(continued on next page)

Table B.2 (*continued*).

$w1, w2, w3$ ($w_1 \neq w_2 \neq w_3$)	Case 1			Case 2			Case 3		
	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}
1,1,5	86 210	132	0	260 261	330	0	400 527	660	0
1,1,6	86 210	132	0	260 261	330	0	400 527	660	0
1,1,7	86 210	132	0	260 261	330	0	400 527	660	0
1,1,8	86 210	132	0	260 261	330	0	400 527	660	0
1,1,9	86 210	132	0	260 261	330	0	400 527	660	0
1,1,10	86 210	132	0	260 261	330	0	400 527	660	0
1,1,15	86 210	132	0	260 261	330	0	400 527	660	0
1,1,20	86 210	132	0	260 261	330	0	400 527	660	0
$w1, w2, w3$ ($w_1 = w_3 \neq w_2$)	Case 1			Case 2			Case 3		
	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}	F_{fuel}	F_{time}	F_{SP}
2,1,2	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
3,1,3	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
4,1,4	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
5,1,5	78 055	330	7544	244 883	594	14 046	–	–	–
6,1,6	78 055	330	7544	244 883	594	14 046	–	–	–
7,1,7	78 055	330	7544	244 883	594	14 046	–	–	–
8,1,8	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
9,1,9	78 055	330	7544	244 883	594	14 046	–	–	–
10,1,10	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
15,1,15	78 055	330	7544	244 883	594	14 046	380 722	858	17 718
20,1,20	78 055	330	7544	244 883	594	14 046	–	–	–
1,2,1	79 686	264	5955	249 776	396	9280	385 615	660	12 952
1,3,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,4,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,5,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,6,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,7,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,8,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,9,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,10,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,15,1	83 880	132	2083	253 970	264	5408	389 809	528	9080
1,20,1	83 880	132	2083	253 970	264	5408	389 809	528	9080

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