A Hierarchical Pricing Strategy for Shore-to-Ship Power Services Considering Ship Behaviors

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***Abstract*—Shore-to-ship power (SSP) technology is an effective way for developing sustainable maritime transportation systems. Its implementation requires attractive pricing and incentive policies. This paper proposes a time-of-use (TOU)-based pricing strategy for SSP services considering the ship behaviors. A hierarchical pricing framework is first proposed to characterize the interactions among government regulators (GR), seaport authorities (SA) and ships, which is formulated as a tri-level two-loop Stackelberg game model. On the ship-side, each ship is treated as an independent stakeholder and the queuing process caused by limited number of berths is considered. Correspondingly, a coupled voyaging-berthing-queuing (CVBQ) model is established for each individual ship to accurately formulate their voyage scheduling, berth selection, queuing behaviors and power dispatch. The optimal CVBQ decision of each ship depends on its queuing time, which cannot be known before all ships make their decisions. To this end, a first-come-first-serve (FCFS)-based ship queuing algorithm is developed to chronologically derive the optimal decisions of all ships. The proposed hierarchical pricing model is solved iteratively by combining heuristics and commercial solvers. Case studies demonstrate the effectiveness of the proposed method.**

***Index Terms*—Shore-to-ship power, pricing strategy, tri-level optimization, maritime transportation electrification.**

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NOMENCLATURE

A. Abbreviations

GR	government regulator
SA	seaport authority
CVBQ	coupled voyaging-berthing-queuing
SSP	shore-to-ship power
SSPB	shore-to-ship power berth
TB	traditional berth
DG	diesel generator
ESS	energy storage system
FCFS	first-come-first-serve
MIQP	mixed integer quadratic programming

B. Indices and Sets

k, m, i, g, t	index of ship, emission, DG, seaport generator, time period
K, M, I, G, T	set of ship, emission, DG, seaport generator, time period

C. Parameters

$B^{e/o}$	number of SSPB/TB
c^{fuel}	fuel oil price
D_k^{con}, D_k^{dis}	time taken for the SSP device connection and disconnection process of ship k
$a_{2,k,i}, a_{1,k,i}, a_{0,k,i}$	fuel oil consumption coefficients of the ith DG on ship k
$t_k^{arr,min}$	earliest arrival time of ship k
$\tau_k^{min}, \tau_k^{max}$	minimum and maximum voyage duration of ship k
$v_k^{(\cdot),min}, v_k^{(\cdot),max}$	minimum and maximum voyage speed of ship k at the corresponding voyage stage
d_k	required voyage distance of ship k
P_k^{SE}	service load of ship k
D_k^{berth}	berthing duration of ship k

$h_{2,g}$, $h_{1,g}$	cost coefficients of seaport generator g
p_t^{grid}	electricity price of the main grid at time t
$p_t^{\text{SSP,min/max}}$	lower/upper bound on SSP service price
$p^{\text{SSP,ave}}$	average SSP service price
$\lambda^{\text{sub,min/max}}$	lower/upper bound on GR subsidy
E_m, B_m	DG emission factor and unit emission reduction benefit of emission m

D. Variables

$P_{k,i,\tau}^{\text{DG,v}}$	power output of the ith DG on ship k at time τ
$P_{k,i,t}^{\text{DG,e/o}}$	power output of the ith DG on ship k at time t when the ship selects SSPB/TB
$P_{k,\tau}^{\text{ch/dis,v}}$	charging/discharging power of ESS on ship k at time τ
$P_{k,t}^{\text{ch/dis,e/o}}$	charging/discharging power of ESS on ship k at time t when the ship selects SSPB/TB
$E_{k,\tau}^{\text{ESS,v}}$	stored energy of ESS on ship k at time τ
$E_{k,t}^{\text{ESS,b}}$	stored energy of ESS on ship k at time t
$I_{k,\tau}^{(\cdot)}$	binary indicator, =1 if ship k is at the corresponding voyage stage at time τ
$\tau_k^{(\cdot),\text{start/end}}$	start/end time of the corresponding voyage stage
τ_k^{adj}	voyage duration adjustment of ship k
$v_{k,\tau}^{(\cdot)}$, $v_{k,\tau}$	voyage speed of ship k at time τ
$t_k^{\text{arr/berth/dep}}$	arrival/berthing start/departure time of ship k
$X_{k,t}^{\text{SSP}}$	ship status indicator, =1 if ship k is powered by SSP at time t
$Y_{k,t}^{\text{e/o}}$	ship status indicator, =1 if ship k is at seaports at time t and selects SSPB/TB
$I_k^{\text{e/o}}$	binary indicator, =1 if ship k chooses SSPB/TB
P_t^{grid}, $P_{g,t}$	power of the main grid and seaport generator g at time t
$P_{k,t}^{\text{SSP}}$	SSP demand of ship k at time t
p_t^{SSP}	SSP service price at time t
λ^{sub}	GR subsidy for SSP services

I. INTRODUCTION

A. Background and Motivation

SEAPORTS play a pivotal role in global trade and economy. Nevertheless, significant increase in the volume of oversea trade over the past few decades has made seaports a major source of shipping-related pollutions [1]. To address timely and urgent environmental issues and achieve sustainable development of maritime systems, several green techniques have been introduced into the seaport energy systems, e.g., renewable energy [2]–[4], energy storage [5]–[7], multiple energies [8]–[10], and so on. In addition, shore-to-ship power (SSP) [11], also known as cold-ironing, has recently emerged as another effective solution for the electrification and green-oriented transition of seaports. The SSP technology enables berthed ships to be supported by onshore electricity while completely switching off diesel generators (DGs). Numerous studies have demonstrated the advantages of SSP technology in environment protection and pollution elimination [12]. However, the actual environmental benefits heavily depend on the utilization of SSP services [13]. Ships may lack incentives to use SSP services due to the expensive service prices, resulting in poor emission reduction [14]. Thus, attractive prices and incentive policies are significant to facilitate SSP service usage.

B. Literature Review

The existing literatures related to SSP services mainly focused on the deployment of SSP infrastructure. We first provide a broad overview on SSP facility deployment. Then we discuss the difference between SSP facility deployment and SSP service pricing, and point out research gaps in SSP service pricing, which are relevant to our contributions.

In the studies on SSP facility deployment, three participants are generally involved: government regulators (GR), seaport authorities (SA), and ship companies. Based on the objects under attention, current literatures can be divided into three categories: 1) government subsidy designs; 2) seaport SSP facility deployment; 3) hybrid approaches. In category 1), the GR subsidy design is formulated as a single-level optimization problem, where the interests of SA and ship companies are simplified. Reference [15] built a stochastic optimization model considering uncertain energy requirements of ships to obtain the optimal subsidy. Reference [16] jointly optimized the subsidies for the construction and operation of SSP services to maximize unit subsidy efficiency. Reference [17] revealed the positive relationship between the emission reduction welfares and the development of SSP facilities. Reference [18] quantified the economic and environmental potential for SSP deployment in Europe and provided several insight recommendations on government policy design to accelerate the implementation of SSP in European harbors. Reference [19] developed a government subsidy program for the SSP deployment problems in a container shipping network, in order to achieve the optimal reduction of at-berth emissions in the network.

In category 2), the SA aims to determine the optimal investment strategy for SSP facilities to maximize its profits. The GR subsidy is fixed and the energy demands of ships are evaluated based on historical data. Reference [20] established a profit calculation model to analyze the trade-off between SSP facility construction costs and economic benefits. Reference [21] developed a multi-period dual objective optimization model to obtain optimal SSP facility deployment decisions under different subsidy strategies. Reference [22] examined the potential of installing SSP facility in a medium sized port with several small berths, by using the case of Aberdeen. The results show that it is feasible to install SSP technology in a medium sized port for vessels. Reference [23] investigated the feasibility of introducing SSP to electrically power ships using the example of Kaohsiung Port, where the cost of SSP adoption and potential emission reduction effect are compared. The above two lines of work emphasized on the profits of single entity, while simplifying the interests of other parties.

In category 3), each participant acts as a stakeholder to maximize its profit and affect the decisions-making process of other parts. Reference [24] proposed a bi-level model for the SSP facility deployment, where the GR in the upper level determines the optimal incentive policy to minimize at-berth emissions, while the SA in the lower level makes the optimal SSP facility investment decision to minimize emission control costs. Reference [25] developed a bilevel optimization model considering the mixed incentives of GR and the competitions among multiple SA. Reference [26] and [27] studied the mechanism of interaction among the strategic choices of GR, SA and ship companies based on evolutionary game theory. Reference [28] proposed to use the economic optimum principle to analyze the cost-effectiveness of SSP facility deployment for power grid companies, ports, ships and the government. In reference [29], a quantitative framework is constructed to evaluate the economics on SSP facility investment for the stakeholders of ports and ship operators. Reference [30] established a Stackelberg game framework between government and ports to determine the optimal subsidy policy for shore power promotion.

The above studies have made remarkable progress in SSP facility deployment, and some of them involved the SSP service price, e.g., [15], [16]. However, the pricing strategy for SSP services has not been specially and thoroughly investigated in the existing literatures. From a broad perspective, SSP can be regard as a special transaction energy applied in seaports. The pricing strategy of transaction energy has been widely studied in the electricity market [31]–[34]. In these works, the consumer behaviors are explicitly incorporated to increase the profits of operators, e.g., price and time sensitivity of data center users [31], EV driver's preference [32], [33], differentiated services in EV charging stations [34]. Similarly, rigorous modeling for ship behaviors is also essential for the SSP service pricing since ships are indispensable participants in SSP transactions. However, very few publications have focused on this issue in spite of the real-world significance.

For most of existing studies on SSP facility deployment, the SSP demands of ships are formulated as the function of GR and SA strategies, e.g., [16], [25]–[27], or evaluated based on historical data, e.g., [15], [21], [24]. These works generally adopt a nonatomic setting for ships, i.e., the heterogeneous power demands, berthing choices and queuing behaviors of individual ship are completely ignored. Such simplification is mild for SSP facility deployment since the action of a single ship has little impact on the deployment decisions from a long-term perspective. However, the daily distribution of SSP demands highly depends on the visiting decision of each ship. The ship behaviors will significantly influence on the decision-making process of GR and SA. Ignoring ship self-interested behaviors might cause the misestimate of SSP demands and total benefits. Thus, the SSP service price should be determined based on realistic ship visiting on each operational day, which necessitates an accurate formulation on ship behaviors. Besides, the current industry practice has indicated that different ships are primarily operated by respective companies. The interests of different ship companies may be compromised if ships are assumed to be operated by a single entity. In this sense, the scheduling of each ship should not be arbitrary. Conversely, each ship should be regarded as an independent stakeholder. Their self-interested behaviors and the mutual impacts among ships should be fully examined.

C. Research Gap and Contribution

In summary, the above literature review indicates two major research gaps in the existing works: 1) most of studies focused on the SSP facility deployment, while few works thoroughly investigated the pricing strategy for SSP services; 2) The SSP demands of ships are roughly estimated in most studies, while few works rigorously modeling the ship self-interested behaviors. Given these limitations, this paper conducts a study on the pricing strategy for SSP services with rigorous modeling on ship behaviors. The main contributions of this paper are summarized as follows:

1) A hierarchical pricing framework is proposed for SSP services by comprehensively considering GR incentives, SA pricing, and ship scheduling. In particular, each ship strategically participates in SSP service pricing as an independent stakeholder instead of part of a fleet. The proposed model accurately incorporates ship behaviors into SSP service pricing problems to better model real situation, thereby promoting the decision-making process of GR and SA, and forming a proper pricing strategy.

2) A coupled voyaging-berthing-queuing (CVBQ) model is proposed for individual ship, where joint voyage scheduling, berth selection, queuing process and power dispatch are explicitly formulated. To solve the model, the exact waiting time in the queue for each ship is needed, but it cannot be known before all ships make their decisions, leading to temporal logic contradiction. To this end, a ship queuing algorithm is designed to chronologically derive the optimal decisions of all ships. To our best knowledge, this is the first study to rigorously model ship self-interested behaviors for the SSP service pricing issues.

3) The proposed hierarchical pricing strategy is formulated as a tri-level two-loop Stackelberg game model. An iteration method combining heuristics and mixed integer quadratic programming (MIQP) is developed to solve the layered optimization model.

In a word, the proposed method fills the research gap in the field of SSP service pricing problems. By considering the interests of multiple stakeholders and incorporating detailed modeling on ship behaviors, the proposed TOU-based pricing strategy can effectively approach the real-world operations and thereby contribute to the decision-making process of GR and SA and determine a proper service price.

D. Organization

The rest of the paper is organized as follows. Section II presents the proposed pricing model. Section III introduces the developed ship queuing algorithm and solution method. Section IV gives numerical results. Section V concludes this paper.

II. Problem Description and Formulation

A. Proposed Hierarchical Pricing Framework

The proposed hierarchical pricing strategy for SSP services involves a GR, a SA and multiple ships as three major participants. The interaction among the three parts is formulated as a tri-level two-loop Stackelberg game as Fig. 1 shows. The tri-level means that there are three stakeholders participating in the game, where the GR is at upper-level, the SA is at middle-level and ships are at lower-level. The two-loop contains an outer loop and an inner loop. The outer loop is established between the GR and the entirety of SA and ships, where the GA receives the aggregated CBVQ decision of all ships and makes the optimal SSP service subsidy. The inner loop is achieved between the SA and ships, where the SA determines the optimal SSP service price based on the aggregated CVBQ decisions of all ships, while each ship makes their own optimal CVBQ decision considering the SSP service price released by the SA.

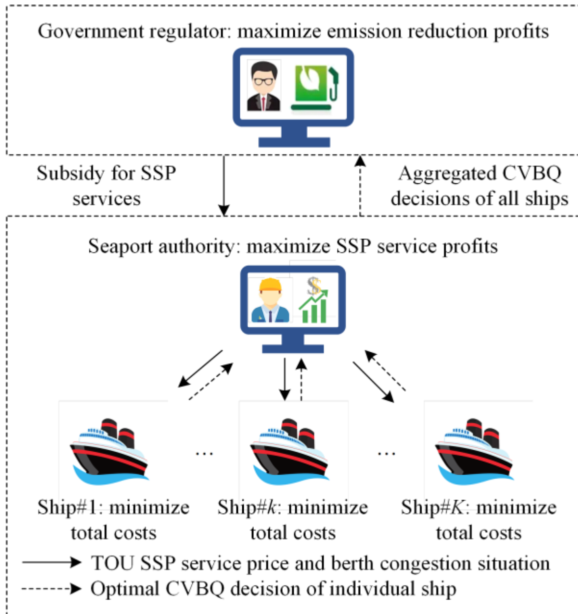

Fig. 1. Proposed hierarchical pricing framework for SSP services.

The three stakeholders participating in the Stackelberg game have different goals. The GR, as the leader of outer loop, subsidizes the SA with an optimal subsidy to achieve a satisfactory trade-off between emission reduction benefits and subsidy costs, i.e., maximize the profits of emission reduction. The SA acts as the leader of inner loop to accept the GR subsidy and determine an optimal TOU SSP service price for its profit maximization. The SA releases the SSP service price and berth congestion information to all ships. Each ship is an independent stakeholder and makes the optimal CVBQ decision to minimize its total costs associated to voyage, berthing, and waiting. The optimal CVBQ decision of each ship will be returned to the SA for the next round of decision-making in the inner loop.

The above two loops follow such principle when iterating: at each iteration of the outer loop, the inner loop between the SA and ships should reach the equilibrium firstly. Then, the aggregated CVBQ decisions of all ships are sent to the GR for the next round of decision-making in the outer loop. The details of two-loop iteration will be shown in Algorithm 2.

B. Ship: Coupled Voyaging-berthing-queuing Decision

In most of existing literatures on voyage and power scheduling of ships, e.g., [35], [36], only the offshore scheduling of a single ship is concerned. The voyage duration is generally fixed. The interaction between ships and seaports and the mutual impact among ships are not considered.

In this paper, not only offshore scheduling, but also onshore power dispatch, berth selection and queuing process are accurately formulated. Specifically, two types of berths are considered, i.e., shore-to-ship power berth (SSPB) and traditional berth (TB). Ships are free to choose one type of berths instead of being forced to use SSP. Since the TOU SSP service price at each time slot is different, ships can adjust voyage duration and arrival time by accelerating/decelerating to response to low service price if SSPB is chosen. Alternatively, TB can be chosen if it is more economical. Besides, due to multiple ships but limited number of berths, ships might need to wait in queue when berths are congested. The waiting time can be also reduced by voyage adjustment. Moreover, the power dispatch of ships presents throughout whether ships are voyaging or at seaports. Overall, the CVBQ decision means that the behaviors of voyage, berthing and queue are coupled together, and one of these behaviors will affect the decision of the other behavior. Thus, the optimal decisions of voyage, berthing and queue, i.e., CVBQ decision, should be determined collaboratively to minimize the total costs related to voyage, berthing and waiting.

To explicitly model ship behaviors, two types of time axis τ and t are introduced. As Fig. 2 shows, each ship has a time axis τ related to voyage. Due to upper and lower bounds on voyage speed, the voyage duration is limited within range $[\tau_k^{\min}, \tau_k^{\max}]$. The ship can adjust its voyage speed to change actual voyage duration $\tau_k^{\min}+\tau_k^{\mathrm{adj}}$ and arrival time t_k^{arr}. After arriving the seaport, all ships determine their berth type and berthing duration under the time axis t. The GR and SA also make their decisions under time axis t. Thus, the time axis τ is a virtual timeline to obtain τ_k^{adj} each ship, and the time axis t is a practical timeline for SSP service pricing problems. With Fig. 2, each ship can make its decision under its own time axis, which facilitates us to formulate the behavior of each individual ship. Meanwhile, we use equation (3c) to connect the time axis τ to time axis t. Due to that, the GR, SA and all ships can be co-optimized under the unified time axis t. In summary, the main purpose of Fig. 2 is making it easy to model each ship while facilitating the collaborative optimization of GR, SA and ships.

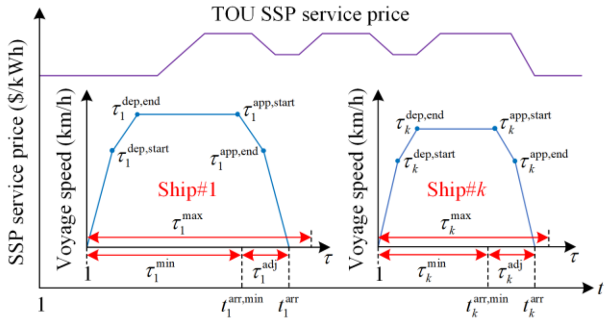

Fig. 2. Illustration of the two types of time axis.

For ship k, the objective is to minimize its total costs related to voyage, berthing and waiting, which is formulated as follows:

$$\min\left\{C_k^{\mathrm{v}}+C_k^{\mathrm{b}}+C_k^{\mathrm{w}}\right\} \tag{1a}$$

where

$$C_k^{\mathrm{v}}=c^{\mathrm{fuel}}\sum_{\tau=1}^{\tau_k^{\max}}\sum_{i\in\mathcal{I}}F_{k,i,\tau}^{\mathrm{DG,v}} \tag{1b}$$

$$C_k^{\mathrm{b}}=\sum_{t=t_k^{\mathrm{berth}}}^{t_k^{\mathrm{dep}}-1}\left(p_t^{\mathrm{SSP}}P_{k,t}^{\mathrm{SSP}}+c^{\mathrm{fuel}}\sum_{i\in\mathcal{I}}F_{k,i,t}^{\mathrm{DG,e}}+c^{\mathrm{fuel}}\sum_{i\in\mathcal{I}}F_{k,i,t}^{\mathrm{DG,o}}\right) \tag{1c}$$

$$C_k^{\mathrm{w}}=\sum_{t=t_k^{\mathrm{arr}}}^{t_k^{\mathrm{berth}}-1}\left(c^{\mathrm{fuel}}\sum_{i\in\mathcal{I}}F_{k,i,t}^{\mathrm{DG,e}}+c^{\mathrm{fuel}}\sum_{i\in\mathcal{I}}F_{k,i,t}^{\mathrm{DG,o}}\right) \tag{1d}$$

$$\begin{cases}F_{k,i,\tau}^{\mathrm{DG,v}}=a_{2,k,i}(P_{k,i,\tau}^{\mathrm{DG,v}})^2+a_{1,k,i}P_{k,i,\tau}^{\mathrm{DG,v}}+a_{0,k,i}\\ F_{k,i,t}^{\mathrm{DG,e/o}}=a_{2,k,i}(P_{k,i,t}^{\mathrm{DG,e/o}})^2+a_{1,k,i}P_{k,i,t}^{\mathrm{DG,e/o}}+a_{0,k,i}\end{cases} \tag{1e}$$

The voyaging cost C_k^{v} in (1b) is the fuel oil cost of DGs during voyage. The berthing cost C_k^{b} in (1c) depends on the selected berth. For SSPB, it takes time to connect and disconnect from SSP devices. Before the connection process is completed and after the disconnection process begins, ship k is powered by DGs. Thus, the first two terms of C_k^{w} are the SSP service cost and the DG fuel oil cost during SSP device connection/disconnection process. For TB, only the fuel oil cost of DGs is considered in the third term of C_k^{b}. When berths are congested, ships need to wait in the queue. The waiting cost C_k^{w} in (1d) is the fuel oil cost of DGs during waiting. Equation (1e) is the fuel oil consumption of the ith DG when ship k is voyaging and at the seaport, which is formulated by the second order polynomial of the power produced by DG [41].

The operational constraints are formulated as follows.

1) Voyage

As Fig. 2 shows, voyage is divided into three stages: depart from the origin $[\tau_k^{\mathrm{dep,start}}, \tau_k^{\mathrm{dep,end}})$, cruise $[\tau_k^{\mathrm{dep,end}}, \tau_k^{\mathrm{app,start}}]$, and approach to the seaport

$(\tau_k^{\text{app,start}}, \tau_k^{\text{app,end}}]$. The three stages are represented by three binary variables $I_{k,\tau}^{\text{dep}}$, $I_{k,\tau}^{\text{cru}}$, and $I_{k,\tau}^{\text{app}}$ respectively, which are defined in a similar way as follows (take $I_{k,\tau}^{\text{dep}}$ as an example):

$$I_{k,\tau}^{\text{dep}} = \begin{cases} 1, & \text{if } \tau \in [\tau_k^{\text{dep,start}}, \tau_k^{\text{dep,end}}) \\ 0, & \text{otherwise} \end{cases} \tag{2a}$$

Constraint (2a) is linearized as (2b) by the big-M method:

$$\begin{cases} \tau I_{k,\tau}^{\text{dep}} + M(1 - I_{k,\tau}^{\text{dep}}) \geqslant \tau_k^{\text{dep,start}}, \forall \tau \\ \tau I_{k,\tau}^{\text{dep}} \leqslant \tau_k^{\text{dep,end}} - 1, \ \forall \tau \\ \sum_{\tau=1}^{\tau_k^{\max}} I_{k,\tau}^{\text{dep}} = \tau_k^{\text{dep,end}} - \tau_k^{\text{dep,start}} \end{cases} \tag{2b}$$

The voyaging constraints are formulated as follows:

$$\begin{cases} \tau_k^{\text{dep,start}} = 2, \tau_k^{\text{dep,end}} \geqslant \tau_k^{\text{dep,start}} + 1, \tau_k^{\text{app,start}} \geqslant \tau_k^{\text{dep,end}} + 1, \\ \tau_k^{\text{app,end}} \geqslant \tau_k^{\text{app,start}} + 1, \tau_k^{\min} + \tau_k^{\text{adj}} \geqslant \tau_k^{\text{app,end}} + 1 \end{cases} \tag{2c}$$

$$I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}} \leqslant 1 \tag{2d}$$

$$I_{k,\tau}^{(\cdot)} v_k^{(\cdot),\min} \leqslant v_{k,\tau}^{(\cdot)} \leqslant I_{k,\tau}^{(\cdot)} v_k^{(\cdot),\max} \tag{2e}$$

$$v_{k,\tau} = v_{k,\tau}^{\text{dep}} + v_{k,\tau}^{\text{cru}} + v_{k,\tau}^{\text{app}} \tag{2f}$$

$$\sum_{\tau=1}^{\tau_k^{\max}} v_{k,\tau} \Delta \tau \geqslant d_k \tag{2g}$$

$$\sum_{i \in \mathcal{I}} P_{k,i,\tau}^{\text{DG,v}} + P_{k,\tau}^{\text{dis,v}} - P_{k,\tau}^{\text{ch,v}} = c_1 (v_{k,\tau})^{c_2} + (I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}}) P_k^{\text{SE}} \tag{2h}$$

$$(I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}}) P_{k,i}^{\text{DG,min}} \leqslant P_{k,i,\tau}^{\text{DG,v}} \leqslant (I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}}) P_{k,i}^{\text{DG,max}} \tag{2i}$$

$$(I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}}) P_k^{\text{ch/dis,min}} \leqslant P_{k,\tau}^{\text{ch/dis,v}} \leqslant (I_{k,\tau}^{\text{dep}} + I_{k,\tau}^{\text{cru}} + I_{k,\tau}^{\text{app}}) P_k^{\text{ch/dis,max}} \tag{2j}$$

$$\begin{cases} E_{k,\tau+1}^{\text{ESS,v}} = E_{k,\tau}^{\text{ESS,v}} + P_{k,\tau}^{\text{ch,v}} \Delta \tau \eta^{\text{ch}} - P_{k,\tau}^{\text{dis,v}} \Delta \tau / \eta^{\text{dis}} \\ E_k^{\text{ESS,min}} \leqslant E_{k,\tau}^{\text{ESS,v}} \leqslant E_k^{\text{ESS,max}} \end{cases} \tag{2k}$$

Constraint (2c) presents the relationship between start and end time of the three stages. Constraint (2d) ensures that ships can only be at one of the three stages at any time. Constraint (2e) imposes upper and lower bounds on the voyage speed of each stage. Constraint (2f) and (2g) present voyage speed and required voyage distance. Constraint (2h) states the power balance when ships are voyaging, where the first and second terms on the right side of the equation represent the propulsion load and service load [42]. Constraint (2i) limits the power output of DGs. Constraint (2j) and (2k) are operational constraints of energy storage system (ESS) when ships are voyaging.

2) Berthing and Queuing

After arriving the seaport, ships select one type of berths and determine their berthing duration, i.e., berthing start and departure time. Three binary variables $X_{k,t}^{\text{SSP}}$, $Y_{k,t}^{\text{e}}$ and $Y_{k,t}^{\text{o}}$ are introduced to represent ship status:

$$X_{k,t}^{\text{SSP}} = \begin{cases} 1, & \text{if } t \in [t_k^{\text{berth}} + D_k^{\text{con}}, t_k^{\text{dep}} - D_k^{\text{dis}}) \ \& \ I_k^{\text{e}} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3a}$$

$$Y_{k,t}^{\text{e/o}} = \begin{cases} 1, & \text{if } t \in [t_k^{\text{arr}}, t_k^{\text{dep}}) \ \& \ I_k^{\text{e/o}} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3b}$$

where $X_{k,t}^{\text{SSP}}$ represents SSP linking status of ships. considering the time taken for the connection/disconnection of SSP devices, $X_{k,t}^{\text{SSP}}$ is equal to 1 only when ship k is powered by SSP; and $Y_{k,t}^{\text{e/o}}$ is equal to 1 when ship k is at the seaport and selects SSPB/TB.

The transform of (3a) and (3b) can be referred to (2b) with modified constraints in the third line, i.e., $\sum_t X_{k,t}^{\text{SSP}} = I_k^{\text{e}}(t_k^{\text{dep}} - D_k^{\text{dis}} - t_k^{\text{berth}} - D_k^{\text{con}})$ and $\sum_t Y_{k,t}^{\text{e/o}} = I_k^{\text{e/o}}(t_k^{\text{dep}} - t_k^{\text{arr}})$.

The berthing and queuing constraints are listed as follows:

$$\begin{cases} t_k^{\text{arr}} = t_k^{\text{arr,min}} + \tau_k^{\text{adj}} \\ t_k^{\text{berth}} \geqslant \max(t_k^{\text{arr}}, I_k^{\text{e}} t_k^{\text{w,e}} + I_k^{\text{o}} t_k^{\text{w,o}}) \\ t_k^{\text{dep}} = t_k^{\text{berth}} + D_k^{\text{berth}} \end{cases} \tag{3c}$$

$$I_k^{\text{e}} + I_k^{\text{o}} = 1 \tag{3d}$$

In (3c), the first line links voyage and berthing. The second line indicates that arrival ships can start berthing only when berths are available, where the waiting time $t_k^{\text{w,e}}$ and $t_k^{\text{w,o}}$ are obtained according to the berth congestion information released by the SA. The third line defines departure time. Constraint (3d) ensures that only one type of berth can be selected by each ship.

For ships at SSPB, (3e) is satisfied. The first line is power balance constraint. Since DGs are switched off when ships are powered by SSP, the second line restricts that DGs work only when ships are waiting in the queue and during SSP device connection/disconnection process. The third line indicates that SSP replaces DGs as the main power source when ships are linking with SSP devices. The fourth line limits the charging and discharging power of ESS when ships select SSPB.

$$\begin{cases} \sum_{i \in \mathcal{I}} P_{k,i,t}^{\text{DG,e}} + P_{k,t}^{\text{SSP}} + P_{k,t}^{\text{dis,e}} - P_{k,t}^{\text{ch,e}} = Y_{k,t}^{\text{e}} P_k^{\text{SE}} \\ (Y_{k,t}^{\text{e}} - X_{k,t}^{\text{SSP}}) P_{k,i}^{\text{DG,max}} \leqslant P_{k,i,t}^{\text{DG,e}} \leqslant (Y_{k,t}^{\text{e}} - X_{k,t}^{\text{SSP}}) P_{k,i}^{\text{DG,max}} \\ X_{k,t}^{\text{SSP}} P_k^{\text{SSP,min}} \leqslant P_{k,t}^{\text{SSP}} \leqslant X_{k,t}^{\text{SSP}} P_k^{\text{SSP,max}} \\ Y_{k,t}^{\text{e}} P_k^{\text{ch/dis,max}} \leqslant P_{k,t}^{\text{ch/dis,e}} \leqslant Y_{k,t}^{\text{e}} P_k^{\text{ch/dis,max}} \end{cases} \tag{3e}$$

Similarly, ships at TB are limited by (3f).

$$\begin{cases} \sum_{i \in \mathcal{I}} P_{k,i,t}^{\text{DG,o}} + P_{k,t}^{\text{dis,o}} - P_{k,t}^{\text{ch,o}} = Y_{k,t}^{\text{o}} P_k^{\text{SE}} \\ Y_{k,t}^{\text{o}} P_{k,i}^{\text{DG,max}} \leqslant P_{k,i,t}^{\text{DG,o}} \leqslant Y_{k,t}^{\text{o}} P_{k,i}^{\text{DG,max}} \\ Y_{k,t}^{\text{o}} P_k^{\text{ch/dis,max}} \leqslant P_{k,t}^{\text{ch/dis,o}} \leqslant Y_{k,t}^{\text{o}} P_k^{\text{ch/dis,max}} \end{cases} \tag{3f}$$

The operational constraints of ESS when ships are at the seaport are listed in (3g). In the first line, one of $P_{k,t}^{\text{ch/dis,e}}$ and $P_{k,t}^{\text{ch/dis,o}}$ is equal to 0 due to (3d). The third line links the stored energy of ESS at the end of voyage and the start of arrival. The fourth line indicates that when ships leave the seaport, the stored energy of ESS should reach the target value to support the next voyage.

$$\begin{cases} E_{k,t+1}^{\text{ESS,b}} = E_{k,t}^{\text{ESS,b}} + (P_{k,t}^{\text{ch,e}} + P_{k,t}^{\text{ch,o}})\Delta\tau\eta^{\text{ch}} - \\ \quad (P_{k,\tau}^{\text{dis,e}} + P_{k,\tau}^{\text{dis,o}})\Delta\tau/\eta^{\text{dis}} \\ E_k^{\text{ESS,min}} \leqslant E_{k,t}^{\text{ESS,b}} \leqslant E_k^{\text{ESS,max}} \\ E_{k,\tau_k^{\min}+\tau_k^{\text{adj}}}^{\text{ESS,v}} = E_{k,t^{\text{arr}}}^{\text{ESS,b}} \\ E_{k,t^{\text{dep}}}^{\text{ESS,b}} \geqslant E_k^{\text{ESS,goal}} \end{cases} \tag{3g}$$

C. Seaport Authority: Sets TOU SSP Service Price

The SA sets an optimal TOU SSP service price considering the GR subsidy λ^{sub} and the reaction of all ships. The objective is to maximize the profits of SSP service as follows:

$$\max \sum_{t\in\mathcal{T}} \begin{bmatrix} (p_t^{\text{SSP}} + \lambda^{\text{sub}}) \sum_{k\in\mathcal{K}} P_{k,t}^{\text{SSP}} - p_t^{\text{grid}} P_t^{\text{grid}} - \\ \sum_{g\in\mathcal{G}} (h_{2,g}(P_{g,t})^2 + h_{1,g}P_{g,t}) \end{bmatrix} \tag{4a}$$

where the first term represents SSP service revenues, which includes the payment of all ships and the subsidy from the GR. The second and third terms are the costs of electricity purchase from the main grid and power generation of seaport generators.

The pricing constraints are listed as follows:

$$\begin{cases} p_t^{\text{SSP,min}} \leqslant p_t^{\text{SSP}} + \lambda^{\text{sub}} \leqslant p_t^{\text{SSP,max}} \\ \dfrac{\sum_{t\in\mathcal{T}} (p_t^{\text{SSP}} + \lambda^{\text{sub}})}{T} \leqslant p^{\text{SSP,ave}} \end{cases} \tag{4b}$$

where the first line imposes upper and lower bounds on SSP service price based on the GR subsidy. The GR can change the pricing range of SSP services by adjusting the subsidy. The second line limits the average price of SSP services to avoid that p_t^{SSP} is always equal to $p_t^{\text{SSP,max}} - \lambda^{\text{sub}}$ [37].

The operational constraints in seaport SSP supply systems are presented as follows:

$$\begin{cases} P_t^{\text{grid}} + \sum_{g\in\mathcal{G}} P_{g,t} = P_t^{\text{L}} + \sum_{k\in\mathcal{K}} P_{k,t}^{\text{SSP}} \\ \left|P_{g,t} - P_{g,t-1}\right| \leqslant P_g^{\text{ramp}} \\ P_g^{\min} \leqslant P_{g,t} \leqslant P_g^{\max} \end{cases} \tag{4c}$$

The first line states the power balance constraint, where P_t^{L} conventional power loads. The second and third lines are the ramping and power output limits of seaport generators.

D. Government Regulator: Decides Subsidy for SSP Services

The GR decides an optimal subsidy λ^{sub} for SSP services to maximize the profits of emission reduction. Since more subsidy corresponds to better utilization of SSP service and emission reduction benefits, but results in more subsidy costs, a satisfactory trade-off between emission reduction benefits and subsidy costs can be achieved. The objective is formulated as:

$$\max \left\{ C^{\text{em}} \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} F_{k,i,t}^{\text{DG,eq}} - \lambda^{\text{sub}} \sum_{k\in\mathcal{K}} \sum_{t\in\mathcal{T}} P_{k,t}^{\text{SSP}} \right\} \tag{5a}$$

The first term represents emission reduction benefits, where C^{em} is emission reduction benefit coefficient of all emissions (5b); $F_{k,i,t}^{\text{DG,eq}}$ is DG fuel oil consumption equivalent to SSP usage (5c), i.e., avoided fuel oil consumption due to the use of SSP services. The second term denotes the subsidy costs.

$$C^{\text{em}} = \sum_{m\in\mathcal{M}} E_m B_m \tag{5b}$$

$$\begin{cases} \sum_{i\in\mathcal{I}} P_{k,i,t}^{\text{DG,eq}} = P_{k,t}^{\text{SSP}} \\ F_{k,i,\tau}^{\text{DG,eq}} = a_{2,k,i}(P_{k,i,\tau}^{\text{DG,eq}})^2 + a_{1,k,i}P_{k,i,\tau}^{\text{DG,eq}} + a_{0,k,i} \end{cases} \tag{5c}$$

The lower and upper bounds on subsidy are set as follows:

$$\lambda^{\text{sub,min}} \leqslant \lambda^{\text{sub}} \leqslant \lambda^{\text{sub,max}} \tag{5d}$$

III. Proposed Solution Method

A. Ship Queuing Algorithm

In (3c), the exact waiting time $t_k^{\text{w,e}}$ and $t_k^{\text{w,o}}$ are required for each ship to make the optimal CVBQ decision. However, since berth congestion situation depends on the decisions of all ships, $t_k^{\text{w,e}}$ and $t_k^{\text{w,o}}$ cannot be known before all ships make their decisions. Thus, a ship queuing algorithm is developed to chronologically derive the optimal CVBQ decisions of all ships.

Note that in practical seaport operations, all ships arrive and start berthing sequentially based on the principle of first-come-first-serve (FCFS). This means that the ship arriving first has the priority in selecting a berth and being served by the seaport, while the ship arriving later must wait for the previous ship to start docking before they can choose a berth. The waiting time of the first arrival ship can be easily obtained based on the current berth congestion situation. After the ship starts berthing, the berth congestion situation can be updated and released to the subsequent arrival ships. Thus, the optimal CVBQ decision of each ship can be obtained chronologically by the following way.

Without loss of generality, the waiting time of the first arrival ship is assumed to be 0. Since it is difficult to determine in advance which ship will arrive first, the waiting time of all ships are set as 0 (i.e., $t_k^{\text{w,e}} = t_k^{\text{w,o}} = 0$) to obtain the initial CVBQ decisions of all ships. With the initial decisions, we determine which ships can and cannot start berthing based on their arrival order and berth congestion situation. For ships that cannot start berthing, their decisions will be remade based on the updated waiting time. After these ships update their decisions, new arrival order and berth congestion situation are obtained for the next round of calculation. Repeat above steps until no ships needs to remake their decisions.

Example: Figure 3 shows an example of ship queuing process. Considering only one type of berth, we assume there are two SSPBs and three ships, i.e., $B^{\text{e}} = 2$, $N^{\text{e}} = 3$. Given $t_k^{\text{w,e}} = 0$, the three ships make their initial decisions. Based on the FCFS principle, ship#3 cannot implement its initial decision due to berth congestion. Then, the waiting time $t_k^{\text{w,e}}$ of ship#3 is updated according to berth congestion situation (i.e., $t_k^{\text{w,e}}$ and $t_k^{\text{c,e}}$), and ship#3 redetermines its initial decision based on new waiting time $t_k^{\text{w,e}}$.

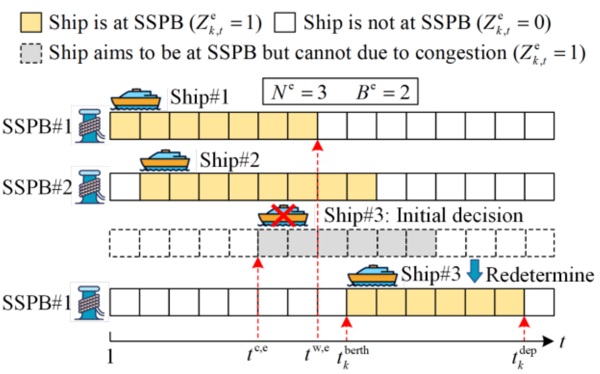

Fig. 3. Illustration of FCFS-based ship queuing process.

For the proposed method, three critical steps involve: 1) obtain required parameters; 2) find ships that need to remake their decisions; 3) determine the waiting time of these ships.

We first introduce how to obtain required parameters. A clear illustration of parameters used in the ship queuing algorithm is shown in Fig. 3. In (3a), $t_k^{\text{w,e}}$ and $t_k^{\text{w,o}}$ denote the waiting time of ship k. Here, $t_k^{\text{w,e/o}}$ and $t_k^{\text{c,e/o}}$ denote the waiting time and congestion time for SSPB/TB respectively. Binary variables $Z_{k,t}^{\text{e/o}}$ are introduced to represent ship berthing status at SSPB/TB, which are defined as follows:

$$Z_{k,t}^{\text{e/o}} = \begin{cases} 1, & \text{if } t \in [t_k^{\text{berth}}, t_k^{\text{dep}}) \;\&\; I_k^{\text{e/o}} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Since $t_k^{\text{w,e}}$ is calculated in the same way as $t_k^{\text{w,o}}$, we use index e/o to represent either of the two types of berths. Based on (6), the number of ships at SSPB/TB at time t is denoted as $\sum_{k\in\mathcal{K}} Z_{k,t}^{\text{e/o}}$. Then, the waiting time $t_k^{\text{w,e/o}}$ can be calculated according to the following situations:

1) $\sum_{k\in\mathcal{K}} Z_{k,t}^{\text{e/o}} < B^{\text{e/o}}, \forall t$: SSPB/TB are available at any time, thus $t_k^{\text{w,e/o}} = 0$.

2) $\sum_{k\in\mathcal{K}} Z_{k,t}^{\text{e/o}} = B^{\text{e/o}}, \exists t$ and $\sum_{k\in\mathcal{K}} Z_{k,t}^{\text{e/o}} \leqslant B^{\text{e/o}}, \forall t$: SSPB/TB are full but not congested. Thus $t_k^{\text{w,e/o}}$ is the time when berths change from full to available.

3) $\sum_{k\in\mathcal{K}} Z_{k,t}^{\text{e/o}} > B^{\text{e/o}}, \exists t$: SSPB/TB are congested. Let $N^{\text{e/o}}$ be the number of ships aiming to start berthing at SSPB/TB. First, sort all the ships that select the same type of berths based on their berthing order, i.e., compare their berthing start time t_k^{berth}. Then, find the last $N^{\text{e/o}} - B^{\text{e/o}}$ ships and let their berthing status $Z_{k,t}^{\text{e/o}}$ be 0 (i.e., these ships cannot actually start berthing due to congestion). After removing these ships, berths change from congested to full. Then, $t_k^{\text{w,e/o}}$ can be obtained by the method in the previous situation (i.e., SSPB/TB are full but not congested).

Similarly, $t_k^{\text{c,e/o}}$ is defined as the time when berths change from available or full to congested. $t_k^{\text{c,e/o}}$ is 0 only when berths are available or full at any time.

After obtaining $t_k^{\text{w,e/o}}$ and $t_k^{\text{c,e/o}}$, the next step is to find which ships need to remake their decisions and determine their waiting time $t_k^{\text{w,e/o}}$. Since two types of berths are considered, the following situations are discussed.

1) SSPB and TB are both congested (i.e., $t_k^{\text{c,e}} > 0$ and $t_k^{\text{c,o}} > 0$).

i) $t_k^{\text{c,e}} > t_k^{\text{c,o}}$: ships that aim to start berthing after $t^{\text{c,o}}$ need to remake their decisions: a) if SSPB are full at time $t^{\text{c,o}}$, the waiting time of ship k is $t_k^{\text{w,e}} = t^{\text{w,e}}$, $t_k^{\text{w,o}} = t^{\text{w,o}}$; b) if SSPB are available at time $t^{\text{c,o}}$, the waiting time of ship k is $t_k^{\text{w,e}} = 0$, $t_k^{\text{w,o}} = t^{\text{w,o}}$.

ii) $t_k^{\text{c,e}} = t_k^{\text{c,o}}$: ships that aim to start berthing after $t^{\text{c,e/o}}$ need to remake their decisions: $t_k^{\text{w,e}} = t^{\text{w,e}}$, $t_k^{\text{w,o}} = t^{\text{w,o}}$.

iii) $t_k^{\text{c,e}} < t_k^{\text{c,o}}$: This case can be analogized to the case of $t_k^{\text{c,e}} > t_k^{\text{c,o}}$. Ships that aim to start berthing after $t^{\text{c,e}}$ need remake their decisions.

2) SSPB are congested but TB are available or full (i.e., $t^{\text{c,e}} > 0$ and $t^{\text{c,o}} = 0$). Ships that aim to select SSPB and start berthing after $t^{\text{c,e}}$ need to remake their

decisions:

i) TB are available at any time: $t_k^{\mathrm{w,e}} = t^{\mathrm{w,e}}$, $t_k^{\mathrm{w,o}} = 0$.

ii) TB are available at time $t^{\mathrm{c,e}}$ but become full after $t^{\mathrm{c,e}}: t_k^{\mathrm{w,e}} = t^{\mathrm{w,e}}, t_k^{\mathrm{w,o}} = 0$.

iii) TB are full at time $t^{\mathrm{c,e}}: t_k^{\mathrm{w,e}} = t^{\mathrm{w,e}}, t_k^{\mathrm{w,o}} = t^{\mathrm{w,o}}$.

3) TB are congested but SSPB are available or full (i.e., $t^{\mathrm{c,e}} = 0$ and $t^{\mathrm{c,o}} > 0$). This situation can be analogized to situation (2).

The detail of ship queuing algorithm is shown in Algorithm 1.

Algorithm 1 Ship queuing algorithm

Input: TOU SSP service price, basic parameters of all ships, the number of SSPB/TB $B^{\mathrm{e/o}}$

Initialize $t_k^{\mathrm{w,e/o}} = 0$

Obtain the initial CVBQ decision of each ship by solving model (1)-(3), then calculate $Z_{k,t}^{\mathrm{e/o}}$, $t^{\mathrm{w,e/o}}$, $t^{\mathrm{c,e/o}}$

repeat

Find ships that need to remake their decisions and calculate their waiting time $t_k^{\mathrm{w,e/o}}$. Then reobtain their new CVBQ decisions based on $t_k^{\mathrm{w,e/o}}$

Update $Z_{k,t}^{\mathrm{e/o}}$, $t^{\mathrm{w,e/o}}$, $t^{\mathrm{c,e/o}}$ according to the new CVBQ decisions of ships

until berths are not congested, i.e., $t^{\mathrm{c,e}} = t^{\mathrm{c,o}} = 0$

Output: The optimal CVBQ decision of each ship

B. Iterative Solution Method for Tri-level Optimization Model

In literatures, a common way to solve layered optimization problems is to replace the convex lower-level model by Karush-Kuhn-Tucker (KKT) conditions and strong duality theory. In this study, the optimization problem of ship-level is not only a MIQP problem, but also involves Algorithm 1, which makes the KKT optimality conditions cannot be used.

To solve the proposed layered optimization model shown in Fig. 1, an iterative solution method combining heuristic and MIQP is developed in Algorithm 2. In the outer loop, Genetic Algorithm (GA) is adopted due to its strong global search ability to find the optimal GR subsidy [22]. In the inner loop, for each generated subsidy individual, the SA determines an optimal TOU SSP service price. The inner iteration converges until the SA finds the optimal service price that are accepted by all ships. After that, the GR calculates the profit of each subsidy individual and continues the iteration of outer loop until the optimal subsidy is obtained.

Note that it is difficult to derive a theoretical conclusion about the equilibrium existence and convergence condition of inner game due to MIQP and Algorithm 1 [32]. Some existing studies also encounter the same difficulty, e.g., [32], [39]. Considering that the SA is the leader of inner game, when it fails to converge, among all possible price options in the inner loop, the one that achieves the largest SA profits can be selected as the optimal SSP service price.

Algorithm 2 Iteration method for the layered optimization model

Input: Basic parameters of GR, SA and ships, stopping criterion $\varepsilon_{\mathrm{err}}$, maximal number of iterations $N_{\max}^{l}$ and $N_{\max}^{n}$

Initialize $l = 0$, $n = 0$, convergence flag $f_{\mathrm{con}} = 1$, subsidy population, TOU SSP service price $p_t^{\mathrm{SSP},(l)}$

repeat (out loop)

Send each subsidy individual to the SA

repeat for each subsidy individual (inner loop)

Ships accept the TOU SSP service price $p_t^{\mathrm{SSP},(l)}$ and return their optimal CVBQ decisions obtained by Algorithm 1 to the SA

The SA determines an optimal TOU SSP service price $p_t^{\mathrm{SSP},(l+1)}$ by model (4) based on GR subsidy and SSP demands $\sum_{k\in K} p_{k,t}^{\mathrm{SSP},(l)}$, and delivers the optimal service price to ships

$l \leftarrow l+1$. $\Delta p_{\mathrm{shore}} = \sum_t \left| p_t^{\mathrm{SSP},(l)} - p_t^{\mathrm{SSP},(l-1)} \right|$

if $l \geqslant N_{\max}^{l}$ then

Set $f_{\mathrm{con}} = 0$

break

end if

until $\Delta p_{\mathrm{shore}} \leqslant \varepsilon_{\mathrm{err}}$

if $f_{\mathrm{con}} = 1$ then

return the optimal service price $p_t^{\mathrm{SSP},*} = p_t^{\mathrm{SSP},(l)}$

else

Among all possible price options, $p_t^{\mathrm{SSP},*}$ is the one achieving largest SA profits

end if

The GR calculates its profits by (5a), i.e., fitness function, and generates new subsidy population for the SA

$n \leftarrow n+1$

until convergence or $n \geqslant N_{\max}^{n}$

return the optimal subsidy $\lambda^{\mathrm{sub},*}$

Output: optimal subsidy $\lambda^{\mathrm{sub},*}$ and TOU SSP service price $p_t^{\mathrm{SSP},*}$

IV. CASE STUDY

All simulations are implemented using Gourbi 10.0 and Python 3.9 on a laptop with an 8-core Intel Core i7 processor and 32 GB memory.

A. Test Case Setting

The proposed method is validated based on the modified data of Rizhao Port in China. The lower and upper bounds on GR subsidy are set as 0 and 0.13 \$/kWh. The SA owns 3 SSPBs and 3 TBs, and a generator rated at 5 MW. The electricity price of the main grid during valley (01:00–07:00, 24:00), normal (08:00–10:00, 16:00–18:00, 22:00–23:00) and peak (11:00–15:00, 19:00–21:00) hours are 0.0665, 0.116, and 0.187 \$/kWh respectively. Ten ships are considered. The parameters of ships and DGs can be referred to Table I and [40]. The fuel oil price c^{fuel} is set to be 0.629 \$/kg. The emissions emitted by DGs on ships include CO_2, NO_x, SO_2, $PM_{2.5}$. The DG emission factor E_m and unit emission reduction benefits B_m of each emission are shown in Table II. The model time resolution is 1 hour and the dispatch period is 48 hours.

TABLE I
PARAMETERS OF TEN SHIPS

Parameter	Value
$\tau_k^{\min}$ (hour)	6, 5, 7, 5, 6, 9, 7, 5, 5, 8
$\tau_k^{\max}$ (hour)	10, 6, 12, 7, 9, 20, 13, 8, 7, 15
d_k (km)	80, 40, 100, 50, 70, 150, 110, 70, 50, 130
$t_k^{\text{arr,min}}$ (hour)	3, 7, 10, 13, 16, 18, 21, 25, 29, 32
D_k^{berth} (hour)	12, 15, 10, 14, 13, 11, 9, 10, 9, 8
P_k^{SE} (MW)	3, 1, 2, 3, 2, 4, 2, 1, 2, 2
$v_k^{\text{dep,min}}, v_k^{\text{app,min}}$ (km/h)	10, 10, 10, 10, 10, 10, 10, 10, 10, 10
$v_k^{\text{dep,max}}, v_k^{\text{cru,min}}, v_k^{\text{app,max}}$ (km/h)	18, 18, 18, 18, 18, 18, 18, 18, 18, 18
$v_k^{\text{cru,max}}$ (km/h)	30, 30, 30, 30, 30, 30, 30, 30, 30, 30
$D_k^{\text{con}}, D_k^{\text{dis}}$ (hour)	1, 1, 1, 1, 1, 1, 1, 1, 1, 1
Capacity of ESS (MWh)	4.5, 1.5, 3.0, 4.5, 3.0, 6.0, 3.0, 1.5, 3.0, 3.0

TABLE II
PARAMETERS OF EMISSIONS

Emissions	DG emission factor E_m (kg /kg) [24]	Unit emission reduction benefits B_m (\$/kg) [6]
$PM_{2.5}$	0.0094	61.179
CO_2	3.2	0.033
NO_x	0.07	6.282
SO_2	0.0054	11.123

B. Optimization Results of Basic Case

Through the iterations of outer and inner loop, the optimal subsidy is obtained as 0.0603 \$/kWh. Under the optimal subsidy, the optimal TOU SSP service price and aggregated SSP demands of all ships are shown in Fig. 4.

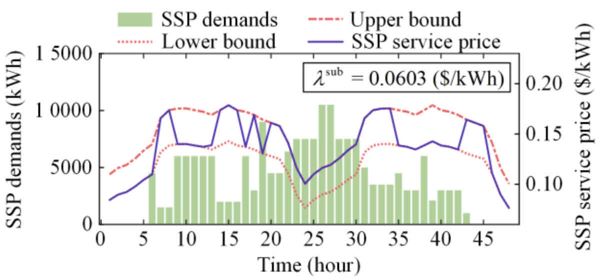

Fig. 4. Optimal SSP service price and SSP demands under optimal subsidy.

As Fig. 4 shows, since each ship makes an optimal decision to minimize its costs, i.e., the self-interested response to the SSP service price, the SSP demands mainly distribute at the periods when the price is low. During 5 to 20 hours and during 31 to 43 hours, the price reaches its lower bound when the SSP demands are high. During 21 to 30 hours, although the SSP service price reaches its upper bound, the SSP demands are still high due to the particularly low price. Thus, the results indicate that an equilibrium is reached between the SA and ships.

Figure 5 shows the queuing process of ships and how some ships remake their decisions based on berth congestion situation and SSP service price. As Fig. 5(a) shows, given $t_k^{\text{w,e/o}} = 0$, all ships initially choose SSPB because of the cheap service price. However, due to berth congestion, some ships cannot start berthing and need to remake their decisions. After queuing process, ship#5 and ship#7 choose TB because the total costs at TB are lower than the costs at SSPB. Ship#3 and ship#8 delay their berthing start time and still choose SSPB. This is because the SSP service price during 21 to 30 hours is particularly low, SSPB is a more economical choice for ship#3 and ship#8 despite of several hours of waiting.

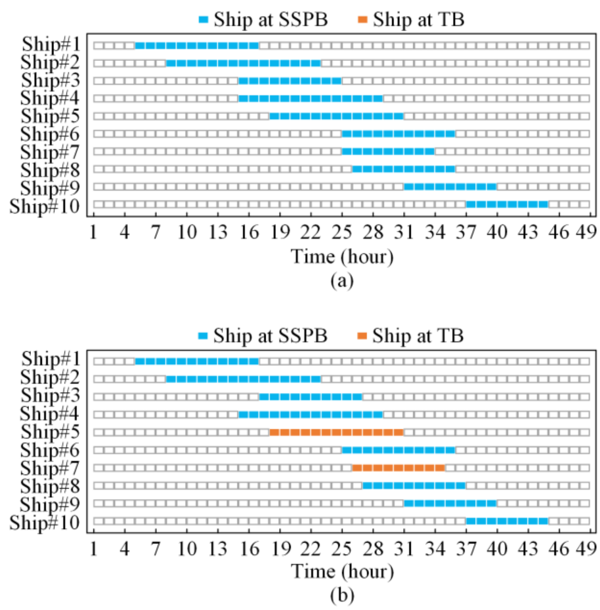

Fig. 5. Decisions of all ships under the optimal SSP service price. (a) Initial decisions. (b) Final decisions after queuing.

Moreover, the allowable range of arrival time for each ship is $[t_k^{\text{arr,min}}, t_k^{\text{arr,min}} + \tau_k^{\max} - \tau_k^{\min}]$, which can be obtained from Table I. Compare Table I with Fig. 5, it can be found that ships will adjust their voyage duration to chase or wait for the cheap service price, which illustrates that the optimal decisions of ships are made by comprehensively considering all the costs related to voyage, berthing and waiting, instead of one of them.

Last, as Fig. 5 shows, the optimal subsidy cannot achieve 100% utilization rate of SSP services, i.e., incentive all ships to choose SSPB. Despite that SSP service is cheaper than fuel oil during certain periods, some ships still choose TB due to high waiting costs at SSPB, e.g., ship#5. Only when the service price is very low, ships are willing to wait for SSPB. However, lower service price means higher subsidy and significant increase in GR subsidy costs. Although the emission reduction benefits will also increase, the costs will increase faster than the revenues, thereby reducing the GR profits. From this perspective, it can be seen that the ship self-interested behaviors have a significant impact on SSP service usage. The GR should incorporate ship behaviors into its decision-making process to maximize the emission reduction profits.

C. Convergence Process of Tri-level Two-loop Game

Figure 6 illustrates the convergence performance of the Algorithm 2. The outer loop converges after 28 iterations. At the beginning of iteration, the GR subsidy is a low initial value, corresponding to unsatisfactory SSP service utilization rate and GR profits. As the iteration proceeds, the GR increases the subsidy to obtain better SSP service usage rate and emission reduction benefits, thereby obtaining more profits. For the SA, because it can benefit from both the GR and ships, its profits are less volatile during iteration.

Figure 6 (b) shows the iteration process of inner loop under the optimal subsidy. The total costs of all ships reach its minimum at the second iteration. Since the SA is the leader of inner game and its profits are not globally optimal, the iteration continues. The iteration ends at the sixth iteration, where the SA profits are maximized and the inner loop reaches the equilibrium.

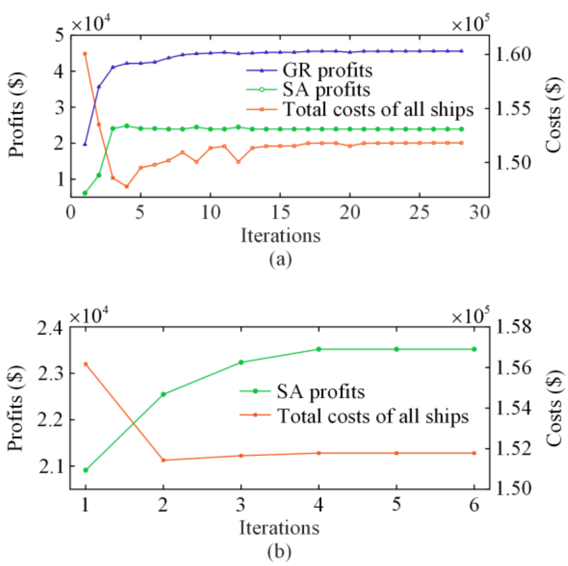

Fig. 6. Convergence process. (a) Outer loop. (b) Inner loop under the optimal subsidy.

D. Comparison of Different Pricing Methods

In this subsection, the proposed method is compared with other pricing methods which are set as follows:

Case 1: Proposed hierarchical pricing model with TOU SSP service price.

Case 2: Hierarchical pricing model with flat SSP service price (i.e., $p_t^{\mathrm{SSP}} = p^{\mathrm{SSP,ave}} - \lambda^{\mathrm{sud}}, \forall_t$), where the GR subsidy is same as that of Case 1.

Case 3: Hierarchical pricing model with TOU SSP service price, where the GR subsidy is same as that of Case 1. All ships are scheduled as a fleet instead of various independent stakeholders. The objective of ship-level is to achieve a collective optimality for the total costs of all ships, instead of an individual optimality for each single ship.

Case 4: Two-level pricing model with TOU SSP service price, where the GR and SA maximizes their profits via iterations. The berth selection of ships is totally determined in the SA pricing problem by only comparing SSP service and fuel oil prices. The ship self-interested CVBQ behaviors are completely ignored [24].

To be noted that the GR subsidy has a significant impact on the reactions of SA and ships. To compare the decisions of SA and ships in Cases 1, 2 and 3, the GR subsidies in the three cases are set as same eliminate the impact of GR subsidy on optimization results.

TABLE III
OPTIMIZATION RESULTS IN THE FOUR CASES

Terms		Case 1	Case 2	Case 3	Case 4
GR	Subsidy ($/kWh)	0.0603	0.0603	0.0603	0.0494
	Emission reduction revenue ($)	57 006	56 909	56 098	70 255
	Subsidy costs ($)	11 271	11 182	10 182	13 462
	Profits ($)	45 735	45 727	45 916	56 793
SA	SSP service revenues ($)	36 886	36 499	36 910	49 934
	Electricity supply costs ($)	13 367	15 268	13 581	17 999
	Profits ($)	23 519	21 231	23 329	31 935
Ships	Voyaging costs ($)	114 321	114 287	114 576	115 650
	Berthing costs ($)	37 029	36 497	35 378	45 230
	Waiting costs ($)	431	158	0	13 225
	Total costs ($)	151 781	150 942	149 954	174 105

Compared Case 1 with Case 2, the proposed pricing method increases the SA profits while keeping the GR profits and the costs of ship almost unchanged. Since the SA can shift the SSP demands to the periods when the electricity price of the main grid is low by setting TOU service price, and shave the peak demands by high service prices at some periods, Case 1 has lower electricity purchase and power generation costs. In contrast, the flat service price in Case 2 cannot flexibly adjust SSP demands. Thus, due to the TOU electricity price of the main grid and the quadratic characteristics of generation cost of seaport generators, Case 2 has higher electricity supply costs.

In Case 3, ships are scheduled as a fleet instead of various independent stakeholders. Since the objective is to maximizing collective interests of all ships, the total costs of all ships are lower than that of Case 1. However, the interests of some ships are compromised, which might reduce the motivation of these ships to execute the collective scheduling schemes in practical operations. Figure 7 compares the total costs of each individual ship in Case 1 and Case 3. The costs of ship#3, ship#6 and ship#8 in Case 3 are higher than that in Case 1. The interests of these ships are sacrificed to minimize the total costs of the ship fleet. Correspondingly, the costs of ship#1, ship#5 and ship#9 reduce in Case 3 by benefiting from collective scheduling. Considering that ship#3, ship#6 and ship#8 are actually operated by different individual ship companies, they might lack of motivation to be collectively scheduled since their interests are compromised. Thus, although the scheduling scheme in Case 3 appears to have a better economic performance, it might be difficult to be implemented in practical operations since it roughly treats all ships as a whole while ignoring the interests of individuals. In contrast, the proposed method respects the willingness of each individual ship, which is more feasible in practical operations.

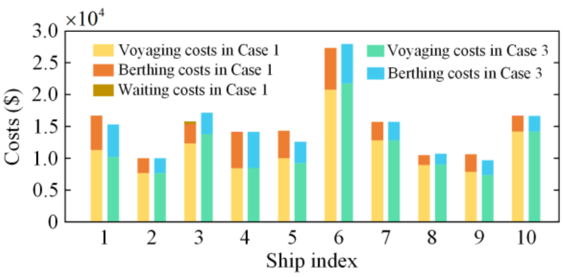

Fig. 7. The total costs of individual ship in Case 1 and 3.

Case 4 shows a two-level structure presented in many existing literatures, where the berth selection of ships is totally evaluated by the SA, and ship self-interested CVBQ behaviors are completely ignored. The GR subsidy and SSP service price are calculated under the most ideal situation of ship behaviors. Thus, the expected values of GR and SA profits are much higher than that of Case 1. However, the total costs of ships in Case 4 also increase greatly. Since ships are self-interested, they may lack of motivation to perform as expected due to high costs. As a result, the actual profits of GR and SA might decrease and deviate from the expected values due to the reluctance of ships.

It can be concluded from Case 3 and Case 4 that the self-interested behaviors of ships are crucial for SSP service pricing. When ship interests are compromised, they may lack of motivation to perform as what the upper-level leaders expect. In this case, the actual SSP demands might mismatch with the SSP service price. The optimality of the pricing strategy decreases, thereby reducing the profits of GR and SA.

E. Sensitivity Analysis

Sensitivity analysis is developed in this section to investigate the impact of exogenous parameters on optimization results.

Figure 8 shows the impact of fuel oil price on results. With the fuel oil price increasing, being supported by DGs become more expensive than SSP. Less subsidy is needed to guarantee the cheapness of SSP service, leading to the increase in the GR profits. Although the subsidy becomes less, the SA profits change little since it can get more profits from ships by setting higher SSP service prices. Correspondingly, the costs of ships increase due to higher prices of both fuel oil and SSP service.

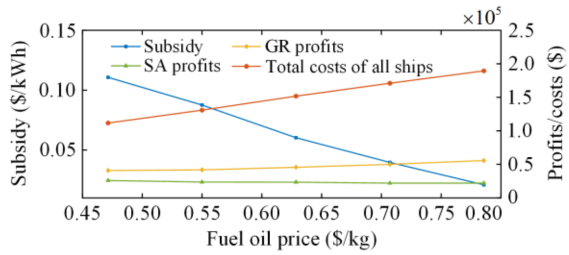

Fig. 8. Sensitivity analysis on fuel oil price.

In Fig. 9, the number of SSPB increases from 1 to 5 while keeping the total number of berths unchanged. When the number of SSPB is low, most ships tend to TB because of high waiting costs at SSPB. Although the subsidy is relatively high, the profits of GR and SA are not considerable. With the increase in number of SSPB, more ships choose SSPB and less subsidy is needed. The GR and SA profits increase due to more usage of SSP services. Besides, since ships are self-interested and can make the optimal decisions, their total costs change little.

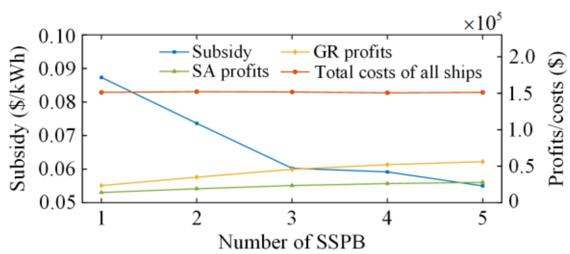

Fig. 9. Sensitivity analysis on the number of SSPB.

Last, the impacts of unit emission reduction benefits B_m on optimization results are shown in Fig. 10. With the increase of B_m, the unit emission reduction corresponds to more emission reduction revenues. In this case, the emission reduction revenues increase faster than the subsidy costs when more subsidy is implemented. To obtain more profits, the GR is willing to implement higher subsidy for SSP services.

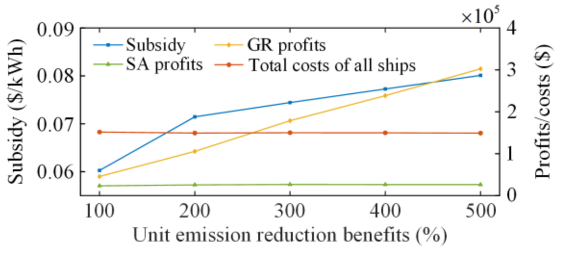

Fig. 10. Sensitivity analysis on unit emission reduction benefits.

V. CONCLUSION

This paper proposes a hierarchical pricing strategy for SSP services with rigorous formulation on ship behaviors. The proposed framework comprehensively considers the subsidy setting of GR, the SSP service pricing of SA and the scheduling of ships, which is formulated as a tri-level two-loop Stackelberg game model. On the ship-side, each ship acts as an independent stakeholder and makes optimal CVBQ decision to minimize its total costs. Considering the queuing process caused by a limited number of berth, a ship queuing algorithm is designed to chronologically derive the optimal CVBQ decisions of all ships. The proposed layered optimization model is solved by an iterative method combing heuristic and commercial solvers.

Case studies demonstrate that the explicit formulation on the self-interested behaviors of ships can help the GR and SA set more proper subsidy and SSP service price to increase their profits. On the contrary, the actual scheduling schemes of each ship might deviate from expectations when their interests are ignored and compromised, thereby reducing benefits of SSP services. This paper can help GR and SA to understand the significant impacts of ship self-interested behaviors on their decision-making process, which provides fresh insights into the operations of SSP services.

Since the electricity purchase price in seaports is determined the power grid company and this work assumes it as constant, the future work may consider the power grid company as another stakeholder and add it into the hierarchical pricing framework.

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AUTHORS' CONTRIBUTIONS

Yiwen Huang: conceptualization, methodology, software, writing-original draft. Wentao Huang: conceptualization, resources, supervision. Yan Xu: conceptualization, resources, supervision. Nengling Tai: conceptualization, validation, investigation, resources, supervision. Ran Li: methodology, resources, investigation.

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AVAILABILITY OF DATA AND MATERIALS

Please contact the corresponding author for data material request.

DECLARATIONS

Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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