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Optimal subsidy design for shore power usage in ship berthing operations

Shuaian Wang^a, Jingwen Qi^{a,*}, Gilbert Laporte^{b,c}

^a*Department of Logistics & Maritime Studies, The Hong Kong Polytechnic University, Hung Hom, Hong Kong*

^b*Department of Decision Sciences, HEC Montréal, Montréal, Québec, Canada*

^c*School of Management, University of Bath, Bath, United Kingdom*

Abstract

Maritime transportation is the backbone of international trade but ships emit a large amount of air pollutants at ports. To encourage ships to use clean energy while berthing at port, subsidies are provided to ship operators that use clean energy and the subsidy amount is generally determined based on subjective judgment. We therefore examine the optimal subsidy design for government-operated ports, aiming at balancing the environmental benefits and subsidy expenses. Considering the uncertainty of energy requirements by ships, we build a stochastic optimization model. Taking advantage of the problem structure, we convert the model into a deterministic one by applying sample average approximation and a binomial distribution. The model is then linearized and solved by CPLEX. A series of numerical experiments with realistic parameters are conducted to validate the model and useful managerial insights are obtained.

Keywords: Maritime transportation; stochastic problem; chance constraint; sample average approximation; binomial distribution.

*Corresponding author. Email addresses: wangshuaian@gmail.com (S. Wang), jingwen.qi@connect.polyu.hk (J. Qi), gilbert.laporte@cirrelt.ca (G. Laporte).

1. Introduction

Shipping is the backbone of international trade. Due to the gradual increase in maritime cargo volume, exhaust fumes from the maritime industry have become a common societal concern (UNCTAD, 2019; Wang et al., 2021b; Xu et al., 2021b) and one of the major challenges faced by the industry (Bell and Meng, 2016). The Fourth International Maritime Organization Greenhouse Gas Study (Faber et al., 2020) indicates that the maritime industry is responsible for 15%, 13%, and 2.89% of the global anthropogenic emissions of nitrogen oxides (NO_x), sulfur dioxide (SO₂), and carbon dioxide (CO₂), respectively. As is well known, ships consume fuel oil and emit exhaust gases to obtain propulsion while sailing. During the berthing period, they also need electricity to power onboard machines. Traditionally they rely on their auxiliary engines to generate power for onboard machines, and large volumes of exhaust fumes are produced (Ballini and Bozzo, 2015). The emission volume keeps growing and ships in ports will generate approximately 70 million tons of CO₂, 1.3 million tons of NO_x and 0.16 million tons of SO₂ in the year 2050, according to Merk (2014). Because ports are typically close to densely populated coastal cities, emissions from berthing ships are very harmful and deserve particular concerns (Teye et al., 2018; Toscano and Murena, 2019).

Multiple technologies can be applied to reduce ship emissions at berth, among which shore power is one of the most promising options. Shore power, also known as “shore-side power,” “on-shore power supply,” “shore-to-ship power,” “alternative maritime power,” “cold-ironing,” and “high-voltage shore connections (HVSC),” is the technology that allows ships to shut down their auxiliary engines and use the electricity provided by the port to power on-board machines. This approach moves the power production from dirty onboard sources to greener and more efficient large-scale power stations, and can therefore decrease ship emissions and bring environmental

benefits. According to [New South Wales Environment Protection Authority of Australia \(2015\)](#), shore power can reduce ship emissions while berthing by up to 95%. In order to promote the use of shore power, governments of various countries and areas have approved regulations to support the installation of shore power facilities, including onboard facilities and onshore facilities. To be specific, some of the governments provide subsidies to ports and ships in order to cover part of the shore power system installation cost ([The Government of Canada, 2017](#); [Ministry of Transport of the People's Republic of China, 2017](#); [Shenzhen Transportation Commission, 2014](#); [European Executive Agency for Competitiveness and Innovation, 2009](#)).

In practice, the environmental benefits depend on the proportion of ship visits that use shore power ([Ballini and Bozzo, 2015](#); [Vaishnav et al., 2016](#)). However, for economic reasons, ships with an on-board shore power system are not always willing to use it. In areas with regulations aiming at reducing ship emissions at ports, for example the United Kingdom ([Department of Transport, 2019](#)) and California ([California Air Resources Board, 2020](#)), the utilization rate of shore power system is higher than that of areas without such regulations. In those areas, many ship operators refuse to use shore power because it is expensive, and as a result the emission reduction effect is not obvious. Economic subsidies are promising methods to promote the shore power usage, and they have been used by the government in other incentive programs under government policies. For example, [Zhuge et al. \(2019, 2020\)](#) presented nonlinear models for designing subsidy for ships that slow down within a certain distance from ports to reduce the air emissions near the port; [Yi et al. \(2021\)](#) proposed an innovative bi-level programming model to design an optimal subsidy for promoting intermodal transport of prefabricated construction products. Hence, the introduction of subsidies that can make shore power more economical and increase the usage rate of existing shore power facilities is a pressing need ([Ship Technology, 2017](#); [Chen et al., 2019](#); [Radwan et al.,](#)

2019). At present, such policies are implemented in various forms. The first form is the preferential shore power price. This method is straightforward: it reduces the price of shore power and hence makes it more economical than the traditional method of electricity generation during the berthing period. Another measure is to subsidize ship operators for each time they use shore power.

Three parties are involved in shore power operations: the government, the port, and ship operators. The government focuses on the environmental benefits of shore power and the subsidies that promote its use. The port considers the economic benefit of providing shore power, and ship operators aim to minimize their operating costs. As a heavily polluting and self-governing entity, a port must consider both its profits and the government's environmental regulations. A port's optimization target can be appropriately described as a mixed objective that is the weighted sum of these two factors, as discussed by [Hu et al. \(2021\)](#). However, as ports are an important element of maritime transportation, some ports are government-operated. In a government-operated port, the use of shore power involves two parties, the port authority (the government) and ship operators. In such cases, the port considers both the environmental and economic benefits when deciding on subsidies for ship operators. In a self-operated port, three parties are involved. The government considers the environmental benefits and expenditure when subsidizing the port. A self-operated port, which only considers its own economic profit, sets the shore power price and the subsidy amount for each ship that uses shore power. In both types of ports, ship operators make the most economical choice. In this paper, we focus on government-operated ports. Thus, we consider how environmental benefit, economic benefit, and subsidy expenditure affect specific shore power incentive policies, including the shore power price and subsidy amount. Numerical experiments with a self-operated port are conducted and discussed in [Section 4](#).

1.1. Emission control regulations

Due to the need for emissions reduction, a number of countries and regions have established emission control areas (ECAs), which are specific maritime spaces along the coastline in which ships should reduce their emissions according to corresponding regulations. At present, there are four main ECAs around the world: the Baltic Sea area, the North Sea area, the North American area and the United States Caribbean Sea area. In these ECAs ships have to burn fuel with 0.1% or less sulfur from 1 January 2015 ([International Maritime Organization, 2018](#)). Besides, ships are required to use fuel with no more than 0.1% sulfur in mass while berthing at ports within the European Union ([European Union, 2016](#)). As stipulated in the Adjustment Plan of Ship Emission Control Area, from 1 January 2020, fuel oil that contains 0.1% or less sulfur is required during the docking period for ships that visit coastal ports in China ([Ministry of Transport of the People's Republic of China, 2018](#)). The establishment of ECAs and strict emission regulations encourage the adoption of green shipping technology on board, including shore power ([Zhen et al., 2020](#)). Marine diesel oil (MDO) is a low-sulfur fuel frequently used to abide by the 0.1% sulfur content regulation, and the cost of using it can be regarded as a standard by which to measure the cost-effectiveness of shore power for ship operators.

1.2. Current shore power subsidy policies

In this subsection we provide instances of the application of two types of measures, namely preferential shore power price, and subsidies for ship visits that use shore power.

For ports, the cost to provide shore power usually covers two parts: the electricity cost charged by the power company and the equipment maintenance cost. As summarized in [Li \(2019\)](#), for ports along the coastline of China, shore power is provided at the rate of 1.2–1.4 CNY/kWh (approximately 0.17–0.2 USD/kWh), which is close to the cost of generating power by

consuming MDO, 1.24–1.84 CNY/kWh (approximately 0.17–0.26 USD/kWh). Nevertheless, the price is not very attractive, considering the extra manpower and time for the cable connection and disconnection for ships to adopt shore power (Li, 2019). Therefore, multiple local governments in China have established regulations to encourage the usage of shore power.

More specifically, ports in Shenzhen sell shore electricity to ships at the government guided price (Shenzhen Municipal Committee of Communication, 2019), which ensures that the cost of using shore power is a fraction of the cost of using MDO while berthing. In addition, for shipping companies that adopt shore power at more than 10% of their visits to ports in Shenzhen, a subsidy (800–2000 CNY, approximately 122–306 USD) will be granted for each visit that uses shore power. In Shanghai, ships from companies that have joined the Shanghai Port Green Convention and promised to use shore power can enjoy the shore power service at a favorable price while visiting international container terminals and cruise terminals. This favorable price is decided by the government and is positively related to the MDO marine fuel oil closing price at the end of the month in Singapore's Platts open market The Shanghai Government (2019).

In the European Union, one of the main barriers to the promotion of shore power is related to taxation policies. Ships berthing at ports in the European Union have to pay taxes applied to electricity for shore power, while the electricity generated by the auxiliary engines onboard is tax-exempt. This difference makes electricity generation on-board cheaper than the shore power (European Commission, 2019). To remove this obstacle, some member states of the European Union, including Sweden, Germany and Denmark, have decided to apply a reduced tax rate on shore power for ships (Offshore Energy, 2018). The reduction in tax rate lowers the cost of using shore power and increases its competitiveness.

1.3. Literature review

From the perspective of a port, it is an optimization problem to determine its shore power price, as well as the amount of subsidy to be provided. In order to obtain the optimal incentive measures, the port needs to maximize a function equal to the total benefits minus the costs, which can be calculated as environmental benefits plus shore power selling revenues, minus extra electricity cost and subsidies given to ship visits that use shore power. In existing studies focusing on the economic aspect of shore power (McArthur and Osland, 2013; Song, 2014; Wang et al., 2015; Winkel et al., 2015; Innes and Monios, 2018), ship visits' berthing time, emission volumes, electricity demands and other related information are assumed to be known. However, details of coming visits are uncertain until the ship leaves, which involve stochastic parameters such as berthing times and emission volumes. As for the value of these parameters of visits, academic studies and technical reports usually make two types of assumptions. One is to use the average value for all visits (Song, 2014; Song and Li, 2017; Wang et al., 2015), the other is to divide ships into several categories of homogeneous vessels (McArthur and Osland, 2013; Winkel et al., 2016; Innes and Monios, 2018; Starcrest Consulting Group, 2019) and use the same value for all vessels in the same category. However, in practice the parameters of future visits may differ substantially from those observed in the past. Therefore, the aforementioned assumptions about parameter values of visits are not sufficiently accurate to approximate reality.

In addition, the application of policies, including the shore power price, the subsidy amount, and the reduced tax rate, have not been covered by existing studies as an optimization problem from the standpoint of a single port. Most of the existing incentive policies are made by the government based on its experience. The subsidy expenditure that will be given and the environmental benefit that will be achieved have not been quantitatively analyzed. Since the decision of whether to

use shore power is made for each ship visit, the operation situations of berthing ships are critical to the policy decision. Meanwhile, each port has its own location and strategy, as a result the distributions of berthing time and the emission volume of ship visits vary significantly. Therefore, not all ports can maximize their benefits minus their costs by applying such experiential policies. Research on the optimization of shore power policies is indispensable to the further promotion of this technology.

This paper aims to fill this research gap and figure out how to make use of the information of historical ship visits of the port to approximate the possible situations of future visits and determine suitable shore power incentive policies. In some maritime studies, uncertainty in demand has been considered and integrated into models ([Meng and Wang, 2010](#); [Ng, 2015](#); [Ng and Lo, 2016](#)). In this paper, visiting ships are consumers of shore power, and we take the uncertainty of their operation situations into account. To handle uncertainty, we build a stochastic model to describe the problem, in which the occurrence of future visits is random. However, it is hard to solve the stochastic model directly, so we adopt the sample average approximation (SAA) method, which is one of the classic ways of handling stochastic problems ([Mak et al., 1999](#); [Kleywegt et al., 2001](#); [Pagnoncelli et al., 2019](#)), and has been widely used in the area of maritime transportation ([Meng and Wang, 2010](#); [Long et al., 2015](#)). For each future visit, we substitute stochastic parameters with possible values. At the same time, we make use of a binomial distribution to handle the chance constraint in the stochastic model. Considering the large number of visits in a year, there are a great number of different scenarios of all visits, and the problem becomes intractable. To make the problem tractable, we use knowledge of mathematical statistics to reduce the problem scale without loss of generality. After linearization, the model is converted into a mixed integer linear program.

This paper has several differences from other studies that examine subsidies of shore power applications. [Xu et al. \(2021a\)](#) investigate the influence of government subsidies on the promotion of shore power and the relationships between stakeholders' decisions. Focusing on strategy, [Xu et al. \(2021a\)](#) present a general discussion of the implementation of incentives at different stages in the development of shore power. This paper, however, focuses on a specific subsidy plan, and includes the port's characteristics in the estimates of expected ship visits and in optimizations of the subsidy amount. Therefore, the problem investigated in this paper is totally different from that in [Xu et al. \(2021a\)](#).

[Wang et al. \(2021c\)](#) optimize the structure of a government subsidy to a port, which is related to the problem we discuss, but this paper differs from [Wang et al. \(2021c\)](#) in three respects. First, [Wang et al. \(2021c\)](#) investigate the optimal government subsidy for the construction of a shore power system and for the operation of a shore power system. This paper studies the optimal subsidy to encourage ship operators to use shore power. Second, [Wang et al. \(2021c\)](#) assume that the number of ships visits that use shore power is linearly proportional to the gap between the cost of using shore power and the cost of using auxiliary engines while berthing. However, this paper considers the uncertainty of ship visits and uses historical data to make an approximation. Third, [Wang et al. \(2021c\)](#) aim to maximize the subsidy efficiency of at-berth emissions reduction per monetary unit, whereas this paper aims to maximize the overall benefits.

[Wang et al. \(2021a\)](#) explore the deployment of government-subsidized shore power facilities in maritime ports using a bilevel model that consists of the government and port levels. They focus on the government subsidy and shore power deployment, whereas this paper mainly considers the port's subsidy plan and ship operators' decisions to use shore power. Furthermore, in [Wang et al. \(2021a\)](#), ship visits are assumed to use shore power when it is available instead of when it is

economical, and it is assumed that the port is entirely profit-driven. However, both scenarios with government- and self-operated ports were discussed in this study.

Li et al. (2020) analyze a simple two-echelon maritime supply chain consisting of a port and a shipping line. The port is located in an emission control area, and the government subsidizes the shipping line's use of shore power. Different from this paper, Li et al. (2020) focus on the effect of the shore power subsidy on the service fee, shore power reliability, and the shipping line's freight rate. This paper considers all ship visits, whereas only one shipping line is considered in Li et al. (2020).

The remainder of the paper is organized as follows. Section 2 provides the formal problem description and the mathematical model. Section 3 describes how the stochastic model is converted into a small-scale mixed integer linear program. Numerical experiments and results are presented in Section 4. The paper closes with conclusions in Section 5.

2. Mathematical model

In this section, we first provide a general model for the problem. This is followed by a model based on historical data.

2.1. General model

In this paper we consider a port that has already installed shore power facilities and provides shore power service to ships. Some of the ships that visit the port are equipped with onboard shore power facilities, but not all of them use shore power at the port. To encourage these ships to use shore power as much as possible, the port has decided to provide shore power at an attractive price and a subsidy to ship operators for each visit that uses shore power. Therefore, the port focuses on determining the optimal shore power price and the subsidy amount. Because a ship

visits various ports on its route, the shore power price and subsidy at a single port have little effect on the decision of the ship operator on whether to install onboard shore power facilities or not. In other words, the shore power subsidy policy has little effect on ships currently without shore power facilities. Therefore, this paper only considers ships with shore power facilities. In the following, “ships” refers to ships that have onboard shore power facilities, and “ship visits” refers to visits made by ships with shore power facilities.

Considering that the trade volume and the port throughput are seasonal, we work with a one-year planning horizon. A port with a set \mathcal{V} of ship visits in a year has to determine the subsidy amount s and the shore power price p . In order to obtain an optimal decision, the port needs to balance the environmental benefits of emission reduction, the revenue of selling electricity to ships, the cost of electricity purchasing, and the subsidy for visits using shore power. The port obtains B USD of environmental benefits per ton of emissions reduction. At the same time, it costs the port C_E USD per kWh to purchase the electricity consumed by ship visits as shore power.

Because some details of a ship visit are uncertain before departure from the port, they are represented by a series of random parameters. The i^{th} visit consumes \tilde{E}_i kWh electricity, $i \in \mathcal{V}$. There are two options for the ship operator. One is to use auxiliary engines onboard to generate electricity, in which case \tilde{Q}_i^F tons of MDO will be used to generate one kWh of electricity, and $\tilde{Q}_i^F \times \tilde{E}_i$ tons of MDO will be consumed during the berthing period. As a result, the visit will emit \tilde{Q}_i tons of exhaust gases in total. The other option is to connect to the shore power system and use electricity provided by the port. The decision of the i^{th} visit whether to use shore power is denoted by a binary decision variable x_i . From the perspective of ship visits, besides the cost of shore power fee, there is also a disutility to use shore power due to the extra manpower and time needed for the cable connection and disconnection. Since the proficiency of crew members needed

related to shore power usage varies from one visit to the next, the i^{th} visit chooses to use shore power only when the benefits of doing so is at least equal to the disutility \tilde{D}_i . In this section, we develop a mathematical model [M1] to describe the stochastic problem. First we present the list of notations that will be used before giving the model.

Deterministic parameters

- \mathcal{V} the set of ship visits, $\mathcal{V} = \{1, \dots, |\mathcal{V}|\}$, in which i represents the i^{th} ship visit;
- B the average environmental benefit of emissions reduction (USD/ton), equal to the economic value of emissions' environmental pollution;
- P_F the price of MDO (USD/ton);
- C_E the cost of providing electricity to ships (USD/kWh), equal to the electricity generating cost;
- α, β confidence parameters in chance constraint, which are determined by the port and represent the port's requirement on the ratio of the ship visits that use shore power;
- M a large positive number.

Random parameters

- \tilde{Q}_i the emission volume of the i^{th} ship visit when MDO is used during berthing (ton);
- \tilde{E}_i the electricity demand of the i^{th} ship visit while berthing (kWh);
- \tilde{Q}_i^F the MDO volume that is consumed during the i^{th} ship visit to generate one kWh of electricity (ton/kWh);
- \tilde{D}_i the disutility brought by the shore power usage (USD) for the i^{th} ship visit.

Decision variables

- x_i binary variable, equal to 1 when the i^{th} ship visit uses shore power, 0 otherwise;
- s the subsidy for each ship visit that uses shore power (USD);
- p the price of shore power (USD/kWh).

In the following model [M1] we optimize the subsidy policy that consists of two parts: one is the subsidy awarded for each visit that uses shore power, and the other is the shore power price that is attractive to ship operators. Since the purpose is to stimulate ship operators to use their shore power facilities as much as possible, it is reasonable to set the price according to the cost incurred to generate power using MDO, like some existing policies do. However, the MDO volume required to generate one kWh of electricity varies from ship to ship. Meanwhile the shore power should be provided to all ship visits at the same price. Therefore, in [M1] the shore power price is a decision variable but there is no fixed ratio of the shore power usage cost to the MDO cost. As the shore power utilization will lead to some disutility, for example the extra connection and disconnection processes, it is assumed that ship operators will put their shore power facilities to use when the economic benefit exceeds the disutility. Here we present the stochastic model [M1]:

$$[\mathbf{M1}] \quad \text{maximize } Z = \mathbb{E} \left\{ \sum_{i \in \mathcal{V}} \left[\tilde{Q}_i B + \tilde{E}_i (p - C_E) - s \right] x_i \right\} \quad (1)$$

subject to

$$\Pr \left\{ \left(\sum_{i \in \mathcal{V}} x_i / |\mathcal{V}| \right) \geq 1 - \alpha \right\} \geq 1 - \beta \quad (2)$$

$$\tilde{E}_i (\tilde{Q}_i^F P_F - p) + s - \tilde{D}_i - M x_i \leq 0, \quad \forall i \in \mathcal{V} \quad (3)$$

$$\tilde{D}_i - \tilde{E}_i(\tilde{Q}_i^F P_F - p) - s - M(1 - x_i) \leq 0, \quad \forall i \in \mathcal{V} \quad (4)$$

$$x_i = 0, 1, \quad \forall i \in \mathcal{V} \quad (5)$$

$$s \geq 0 \quad (6)$$

$$p \geq 0. \quad (7)$$

The objective function (1) maximizes the expected value of the profit from all ship visits, which equals the revenue minus the cost. Constraint (2) is a chance constraint which means that with a probability at least equal to $1 - \beta$, no less than a proportion $1 - \alpha$ of visits will chose to use shore power. This constraint is introduced to indicate the port's requirement on the shore power utilization rate, which is set to ensure a certain level of emissions reduction. To measure the benefit from the subsidy more accurately, we consider the uncertainty of ship visits. Whether a ship will adopt shore power on each visit is also uncertain. A chance constraint is commonly used to handle uncertainty in shipping. Considering the stochasticity in sea condition and ship conditions, [PSA Marine \(2021\)](#), the largest container terminal operator in the world, sets its pilotage service level at 90%, indicating that 90% of pilotage tasks will be finished within 30 minutes of the predetermined service time. [The Port of Los Angeles \(2021\)](#) requires that a fleet with shore power facilities use them for at least 80% of its visits. Therefore, a chance constraint is used to integrate such requirements into the model. Robust optimization can be applied, but it is not as readily comprehensible to managers in industry as a chance constraint. Constraints (3) and (4) guarantee that ship visits only use shore power when the profit of using it exceeds the disutility. Constraints (5)–(7) define the domains of the variables.

One of the main challenges in solving [M1] is that, in practice, the exact distributions of the

parameters are unknown. Therefore, we use distributions summarized from existing ship visit data as surrogates for the actual unknown distribution of parameters.

2.2. Model based on historical data

To obtain empirical distributions of the random parameters, the port collects data from a set of existing visits denoted by \mathcal{V}' . The known parameters associated with ship visits in \mathcal{V}' , indexed by l , are listed below:

Notations for historical visits

- \mathcal{V}' the set of existing visits;
- Q'_l the emission volume when MDO is used during berthing (ton) of the l^{th} existing visit;
- E'_l the electricity demand while berthing (kWh/visit) of the l^{th} existing visit;
- Q'^F_l the MDO volume consumed to generate one kWh of electricity (ton/kWh) of the l^{th} existing visit.
- D'_l the disutility brought by the shore power usage (USD) for the l^{th} existing visit.

We apply the SAA method and consider each existing visit l as a set of possible values of random parameters in a future visit, which means that the random parameters in each future visit will be identical to one set of possible values, and all sets of values have the same probability. Then, the empirical distribution of the random parameters can be described as $\Pr\left(\left(\tilde{Q}_i, \tilde{E}_i, \tilde{Q}_i^F, \tilde{D}_i\right) = \left(Q'_l, E'_l, Q'^F_l, D'_l\right)\right) = 1/|\mathcal{V}'|, \forall l \in \mathcal{V}'$.

We further assume that for different ship visits $i, i \in \mathcal{V}$, the parameters $\left(\tilde{Q}_i, \tilde{E}_i, \tilde{Q}_i^F, \tilde{D}_i\right)$ have independent and identical distribution. As a result, there are $|\mathcal{V}'|^{|\mathcal{V}|}$ different scenarios for the parameters of all ship visits in the next year. We build [M2] to maximize the expected value of

the total port profit from future ship visits with constraints on the shore power usage ratio. Here we list new notations that will be used:

Parameters of scenarios

- Ω the set of possible scenarios of parameters of all ship visits in the next year,
 $\Omega = 1, \dots, |\mathcal{V}'|^{|\mathcal{V}|}$;
- \hat{Q}_{ij} the emission volume of the i^{th} ship visit when MDO is used during berthing in the j^{th} scenario (ton), $\forall i \in \mathcal{V}, \forall j \in \Omega$;
- \hat{E}_{ij} the electricity demand of the i^{th} ship visit while berthing in the j^{th} scenario (kWh), $\forall i \in \mathcal{V}, \forall j \in \Omega$;
- \hat{Q}_{ij}^F the MDO volume that is consumed to generate one kWh of electricity of the i^{th} ship visit in the j^{th} scenario (ton/kWh), $\forall i \in \mathcal{V}, \forall j \in \Omega$;
- \hat{D}_{ij} the disutility brought by the shore power usage (USD) for the the i^{th} ship visit in the j^{th} scenario, $\forall i \in \mathcal{V}, \forall j \in \Omega$.

Decision variables

- \hat{x}_{ij} binary variable, equal to 1 when the i^{th} ship visit adopts shore power in the j^{th} scenario, 0 otherwise, $\forall i \in \mathcal{V}, \forall j \in \Omega$;
- \hat{y}_j binary variable, equal to 1 when the proportion of ship visits that use shore power in the j^{th} scenario is no less than $1 - \alpha$, 0 otherwise, $\forall j \in \Omega$.

Adopting empirical distributions, we convert [M1] into the following model:

$$[\mathbf{M2}] \text{ maximize } Z = \frac{1}{|\Omega|} \sum_{j \in \Omega} \sum_{i \in \mathcal{V}} \left[\hat{Q}_{ij} B + \hat{E}_{ij} (p - C_E) - s \right] \hat{x}_{ij} \quad (8)$$

subject to

$$(6), (7)$$

$$\sum_{j \in \Omega} \hat{y}_j / |\Omega| \geq 1 - \beta \quad (9)$$

$$\sum_{i \in \mathcal{V}} \hat{x}_{ij} - |\mathcal{V}|(1 - \alpha) < M\hat{y}_j, \quad \forall j \in \Omega \quad (10)$$

$$|\mathcal{V}|(1 - \alpha) - \sum_{i \in \mathcal{V}} \hat{x}_{ij} \leq M(1 - \hat{y}_j), \quad \forall j \in \Omega \quad (11)$$

$$\hat{E}_{ij}(\hat{Q}_{ij}^F P_F - p) + s - \hat{D}_{ij} - M\hat{x}_{ij} \leq 0, \quad \forall i \in \mathcal{V}, \forall j \in \Omega \quad (12)$$

$$\hat{D}_{ij} - \hat{E}_{ij}(\hat{Q}_{ij}^F P_F - p) - s - M(1 - \hat{x}_{ij}) \leq 0, \quad \forall i \in \mathcal{V}, \forall j \in \Omega \quad (13)$$

$$\hat{x}_{ij} = 0, 1, \quad \forall i \in \mathcal{V}, \forall j \in \Omega \quad (14)$$

$$\hat{y}_j = 0, 1, \quad \forall j \in \Omega. \quad (15)$$

The objective function (8) maximizes the expected value of profit from all ship visits in the next year. Constraint (9) guarantees that in all scenarios, at least $(1 - \beta)|\Omega|$ scenarios have at least $(1 - \beta)|\mathcal{V}|$ visits using shore power. Constraints (10) and (11) state the relationship between the \hat{y}_i and \hat{x}_{ij} variables. Constraints (12) and (13) mean that in any scenario, a ship visit will adopt shore power only when the benefit of doing it exceeds the disutility. Constraints (14) and (15) define the domains of \hat{y}_i and \hat{x}_{ij} .

Because the random variables in [M1] are replaced by a series possible scenarios in [M2], there exist some differences between the constraints of the two models. For the constraints on the number of ship visits using shore power, in [M1] the lower limit of the probability that each ship visit adopts

shore power with probability at least equal to $1 - \alpha$ is defined by constraint (2). However, in [M2] constraints (9)–(11) set the ratio of scenarios under which no fewer than $|\mathcal{V}|(1 - \alpha)$ visits use shore power to be at least equal to $1 - \beta$. The other difference is the ship visits’ decision on shore power usage. In [M2], the decision of each ship visit under each scenario is described by constraints (14) and (15).

To solve [M2] exactly, we would have to enumerate all possible scenarios of the future visits. When $|\mathcal{V}| = 1000$ and $|\mathcal{V}'| = 100$ there are 100^{1000} scenarios in total, which is impossible to enumerate. Therefore, we need to devise another method to solve the problem.

3. Model reformulation

In this section, we develop a tailored solution method to address the intractable model [M2]. We first use a binomial distribution to handle the constraints on the expected number of ship visits that use shore power, thus converting the model into a mixed integer nonlinear program, which is then linearized to be a mixed integer linear program that can be solved by an off-the-shelf solver CPLEX.

3.1. Model conversion

The main difficulty in solving [M2] is the very large number of possible scenarios, which makes the problem computationally intractable. In order to make the problem tractable, we reduce the problem scale without loss of generality. As mentioned, the total number of future visits that use shore power depends on the existing data set. Specifically, given p and s , we denote the number of visits in \mathcal{V}' that use shore power as k , and the probability of a future visit to use shore power is calculated as $k/|\mathcal{V}'|$. We introduce an intermediate decision variable x'_i to denote the decision of visits with different sets of values to use shore power or not.

Intermediate decision variable

x'_l binary decision variable, equal to 1 when the visit with the l^{th} set of values adopts shore power, 0 otherwise.

Then we have

$$k = \sum_{l \in \mathcal{V}'} x'_l. \quad (16)$$

From constraint (16) we can see that k is closely related to the variables x'_l , which depend on the decision variables p and s . Therefore, k is a function of p and s . For all future visits, we denote the number of visits that use shore power as \tilde{K} . For each coming visit, it will adopt shore power with probability $k/|\mathcal{V}'|$ because k out of \mathcal{V}' value sets will lead the visit to use shore power. Hence, the random variable \tilde{K} , which equals the sum of $|V|$ identically and independently distributed binary random variables, is a binomial random variable: $\tilde{K} \sim B(|V|, k/|\mathcal{V}'|)$. Constraint (9) sets the lower limit of the proportion of scenarios in which more than $|\mathcal{V}|(1-\alpha)$ coming visits will use shore power. In constraints (10) and (11), the variable \hat{y}_j indicates whether the j^{th} scenario has enough visits using shore power or not. Introducing the intermediate decision variable x'_l , we can use \tilde{K} to represent the number of coming visits that will use shore power, and \hat{y}_j become unnecessary. Therefore, constraints (9) to (11) can be replaced by constraint (16) and

$$\sum_{u=\lceil(1-\alpha)|\mathcal{V}\rceil}^{|\mathcal{V}|} \binom{|\mathcal{V}|}{u} (k/|\mathcal{V}'|)^u [1 - (k/|\mathcal{V}'|)]^{(|\mathcal{V}|-u)} \geq 1 - \beta. \quad (17)$$

We use $\lceil(1-\alpha)|\mathcal{V}\rceil$ as the lower bound of the summation in constraint (17) because $(1-\alpha)|\mathcal{V}|$ could

be fractional. As shown in constraint (17), the left-hand side is strictly monotonically increasing in k . Therefore, we denote the minimal value of k that satisfies constraint (17) as k_{min} , which can be obtained by applying a dichotomous search method. Before presenting the logic of this method,

$$\text{we define } f(k) = \sum_{u=\lceil(1-\alpha)|\mathcal{V}'\rceil}^{|\mathcal{V}'|} \binom{|\mathcal{V}'|}{u} (k/|\mathcal{V}'|)^u [(1 - (k/|\mathcal{V}'|))^{\lceil|\mathcal{V}'\rceil - u} - (1 - \beta)].$$

Algorithm 1 Dichotomous method for k_{min}

Input: intermediate variable $k_L, k_R, k_M, term$. // k_L, k_R are the lower and upper limits of k_{min} , k_M is the arithmetic mean of k_L and k_R , $term$ is a binary variable that works as the termination condition of the algorithm.

Output: k_{min}

```

1: Initialization: initial variables  $k_L = 0, k_R = |\mathcal{V}'|, term = 0$ , initial solution  $k_{min} = 0$ .
2: while  $term = 0$  do
3:   if  $f(k_L)f(k_R) < 0$  then
4:      $k_M = \lceil(k_L + k_R) / 2\rceil$ 
5:     if  $k_R = k_M$  then
6:        $k_{min} = k_R$ 
7:        $term = 1$ 
8:     else
9:       if  $f(k_M) = 0$  then
10:         $k_{min} = k_M$ 
11:         $term = 1$ 
12:       else if  $f(k_M) > 0$  then
13:         $k_R = k_M$ 
14:       else if  $f(k_M) < 0$  then
15:         $k_L = k_M$ 
16:       end if
17:     end if

```

18: **end if**
19: **end while**
20: **return** k_{min}

In Algorithm (1), we have $f(0) < 0$ and $f(|\mathcal{V}'|) > 0$. Keeping $f(k_R) > 0$ and $f(k_L) < 0$, we can iteratively update the values of k_L and k_R by checking the value of $f(k_M)$ until the minimum value of k_R that makes $f(k_R) > 0$ is found. We will prove the following property.

Property 1. *All values of k that satisfy constraint (17) can be enumerated as: $k_{min}, k_{min} + 1, k_{min} + 2, \dots, |\mathcal{V}'| - 1, |\mathcal{V}'|$.*

Proof. *The smallest value of k that satisfies constraint (17) is k_{min} because for $k = 0, 1, \dots, k_{min} - 1$ we have $f(k) < 0$, and constraint (17) is not satisfied. Considering that the left-hand side of constraint (17) is strictly monotonically increasing in k , for $k = k_{min} + 1, k_{min} + 2, \dots, |\mathcal{V}'|$ we have $f(k) > f(k_{min}) \geq 0$, and constraint (17) is satisfied.*

Then constraint (17) can be replaced with

$$k \geq k_{min}. \tag{18}$$

In the objective function in [M2], the two sum calculations can be swapped:

$$\text{maximize } Z = \sum_{i \in \mathcal{V}} \sum_{j \in \Omega} \frac{1}{|\Omega|} \left[\hat{Q}_{ij} B + \hat{E}_{ij} (p - C_E) - s \right] \hat{x}_{ij}. \tag{19}$$

For each ship visit, there are $|\Omega|/|\mathcal{V}'|$ out of $|\Omega|$ scenarios in which the values of parameters are identical to the l^{th} value set, $l \in \mathcal{V}'$. Therefore, the profit expectation that the port

can get from the i^{th} coming visit, $\sum_{j \in \Omega} \frac{1}{|\Omega|} [\hat{Q}_{ij}B + \hat{E}_{ij}(p - C_E) - s] \hat{x}_{ij}$, can be rewritten as $\sum_{l \in \mathcal{V}'} \frac{|\Omega|}{|\mathcal{V}'|} \frac{1}{|\Omega|} [Q'_l B + E'_l(p - C_E) - s] x'_l$. Then the objective function (19) can be rewritten as

$$\text{maximize } Z = \sum_{i \in \mathcal{V}} \sum_{l \in \mathcal{V}'} \frac{1}{|\mathcal{V}'|} [Q'_l B + E'_l(p - C_E) - s] x'_l. \quad (20)$$

As shown in objective function (20), $[Q'_l B + E'_l(p - C_E) - s] x'_l$ is not related to i , namely $\sum_{l \in \mathcal{V}'} \frac{1}{|\mathcal{V}'|} [Q'_l B + E'_l(p - C_E) - s] x'_l$ equals the same value for different i . Therefore, objective function (20) can be rewritten as

$$\text{maximize } Z = \frac{|\mathcal{V}|}{|\mathcal{V}'|} \sum_{l \in \mathcal{V}'} [Q'_l B + E'_l(p - C_E) - s] x'_l. \quad (21)$$

In conclusion, the problem now becomes that of searching for a solution that maximizes the total profit of the port by providing shore power to ship visits with existing value sets, with the constraint that at least k_{min} visits with existing value sets choose to use shore power while berthing, as shown in [M3]:

$$\mathbf{[M3]} \quad \text{maximize } Z = \frac{|\mathcal{V}|}{|\mathcal{V}'|} \sum_{l \in \mathcal{V}'} [Q'_l B + E'_l(p - C_E) - s] x'_l \quad (22)$$

subject to

$$E'_l(Q'_l{}^F P_F - p) + s - D'_l - Mx'_l \leq 0, \quad \forall l \in \mathcal{V}' \quad (23)$$

$$D'_l - E'_l(Q'_l{}^F P_F - p) - s - M(1 - x'_l) \leq 0, \quad \forall l \in \mathcal{V}' \quad (24)$$

$$x'_l = 0, 1, \quad \forall l \in \mathcal{V}' \quad (25)$$

(6), (7), (16), (18).

The model [M3] is a mixed integer nonlinear program whose size is much smaller than that of [M2].

We denote by p^* and s^* the optimal solution of [M3]. We assume that at least one historical visit l satisfies $E'_l(Q'_l{}^F P_F - p^*) + s^* - D'_l > 0$ because otherwise no subsidy program is needed. We also assume that at least one of p^* and s^* is strictly greater than 0, because otherwise the problem becomes trivial as the port does not need to provide any incentives. After analyzing [M3], we establish the property following:

Property 2. *For any set of historical ship visits \mathcal{V}' , at least one visit l satisfies $E'_l(Q'_l{}^F P_F - p^*) + s^* - D'_l = 0$.*

See Appendix A for the proof to Property 2.

Based on Property 2, when the shore power price p (subsidy s) is predetermined as p_{Pre} (s_{Pre}), we can enumerate all possible optimal solutions $\{(p_{pre}, s_l) | E'_l(Q'_l{}^F P_F - p_{pre}) + s_l - D'_l = 0, \forall l \in \mathcal{V}'\}$ ($\{(p_l, s_{Pre}) | E'_l(Q'_l{}^F P_F - p_l) + s_{Pre} - D'_l = 0, \forall l \in \mathcal{V}'\}$) and the objective function value of each solution, denoted by Z_l^s (Z_l^p). After comparing $Z_l^s, \forall l \in \mathcal{V}'$ ($Z_l^p, \forall l \in \mathcal{V}'$), we can obtain the optimal objective function value and the corresponding optimal solution.

3.2. Model linearization

The objective function of [M3] contains the product of decision variables, namely $[Q'_l B + E'_l(p - C_E) - s]x'_l$. Therefore, we linearize [M3] by introducing a series of decision

variables before solving it.

Decision variable

z'_l the overall profit the port obtains from a ship visit with the values of the l^{th} set, equal to $Q'_l B + E'_l (p - C_E) - s$ when the visit uses shore power, 0 otherwise.

Then the objective function is converted to

$$[\mathbf{M3}] \text{ maximize } Z = \frac{|\mathcal{V}|}{|\mathcal{V}'|} \sum_{l \in \mathcal{V}'} z'_l \quad (26)$$

with two sets of constraints added:

$$z'_l - M(1 - x'_l) - [Q'_l B + E'_l (p - C_E) - s] \leq 0, \quad \forall l \in \mathcal{V}' \quad (27)$$

$$z'_l - Mx'_l \leq 0, \quad \forall l \in \mathcal{V}'. \quad (28)$$

The value of M in constraints (27) and (28) is a sufficiently large number. For any $z'_l, l \in \mathcal{V}'$, when $x'_l = 0$, namely the ship visit with the l^{th} set of values does not adopt shore power, constraint (27) for l is slack, and constraint (28) is equivalent to $z'_l \leq 0$. Because the objective function is to find the maximum value, we have $z'_l = 0$. Similarly, when $x'_l = 1$, namely the ship visit does adopt shore power in the l^{th} scenario, constraint (28) for l is slack, and constraint (27) is equal to $z'_l = Q'_l B + E'_l (p - C_E) - s$.

After the linearization, we obtain a mixed integer linear program, which can be solved by a generic solver such as CPLEX.

4. Numerical experiments

To validate the model, we conducted multiple numerical experiments with different values of crucial parameters, including α , β , B , C_E , and P_F . CPLEX 12.10 was used to solve the model. Sensitive analyses were carried out to show the influence of different parameters on the optimal objective value.

4.1. Parameter settings

The parameters were determined on the basis of existing studies and reports. It is assumed that the following numerical experiments have 10,000 future ship visits in the next year but only 100 different possible sets of values for random parameters. The collecting and preparing process of the parameters and data are shown in this subsection. Before the possible value sets of random variables, values of other parameters are determined as follows. First, for the average environmental benefit of emission reduction (B), we benefit from existing studies that have researched the social cost factor of emissions from shipping. According to Nunes et al. (2019) and Song (2014), the social cost factor of different emissions, namely NO_X , SO_2 , $\text{PM}_{2.5}$, and CO_2 , are 6,282 USD/ton, 11,123 USD/ton, 61,179 USD/ton, and 33 USD/ton, respectively. From multiple reports that investigate ship emissions (European Commission, 2002; Cooper and Gustafsson, 2004; International Maritime Organization, 2012; Ng et al., 2016; Smith et al., 2014), we know that exhaust gases from berthing ships contain approximately 2% of NO_X , 0.3% of SO_2 , 0.04% of $\text{PM}_{2.5}$, and 97.66% of CO_2 . Therefore, the overall average environmental benefit of emission reduction (B) equals 216 USD/ton. Referring to the market price, the price of MDO is set at 400 USD/ton ($P_F = 400$ USD/ton). According to Sascha (2017), it costs around 0.18 USD for the power station to generate one kWh of power ($C_E = 0.18$ USD/kWh), using hard coal as the fuel. The confidence parameters in chance

constraints are set at $\alpha = 0.05$ and $\beta = 0.1$.

To validate the model and the algorithm, we constructed two groups of possible value sets, one including 100 sets and the other including 1000 sets, under the same principle. The ships use their auxiliary engines to generate power by consuming MDO while berthing. We assume that 217 grams of MDO are required for one kWh of power (Cooper and Gustafsson, 2004). In other words, we have $Q'_l{}^F = 2.17 \times 10^{-4}$ ton/kWh ($\forall l \in \mathcal{V}'$). The emission volume (Q'_l) and electricity demand (E'_l) of the l^{th} historical visit are related to the vessel type, ship capacity and berthing time (Starcrest Consulting Group, 2019). Winkel et al. (2015) state that shore power is the most popular among cruise ships, container ships, tankers, reefers, and RORO ships (cargo ships and ferries). In this paper, we generate a set of historical ship visits on the basis of the ship visit record of the Port of Los Angeles in 2018 (Starcrest Consulting Group, 2019) because it is one of the ports with the most developed shore power system (more recent records are not available). In the report, the ship visit data are sorted by vessel type and capacity level, including the power requirement and the berthing time information (minimal, maximal and average values). In this paper, five different ship types are considered as potential shore power consumers, and we further assume that in each category the number of visits that are equipped with shore power system is proportional to the total number of visits. We generated two groups of possible values for random variables, one with 100 sets and the other with 1000 sets, the number of value sets with each vessel type and each capacity level is proportional to ship visit data from Starcrest Consulting Group (2019), and the electricity demands of visits in each capacity level in the report are also used. Within each capacity level, we generate a series of berthing times that satisfy the minimal, maximal and average values. Considering European Commission (2002); Cooper and Gustafsson (2004); International Maritime Organization (2012); Ng et al. (2016); Smith et al. (2014), we determined that the vessel emits

712.1 grams of exhaust gases to generate one kWh of electricity while berthing for all visits. Then through simple calculations, we obtain Q'_l and E'_l , $l \in \mathcal{V}'$. The disutility brought by the shore power usage is hard to quantify, and there are no existing papers that focus on this problem, so we generated D'_l randomly between 50 to 200 USD.

4.2. Results and sensitive analysis

Computational experiments were conducted on a LENOVO XiaoXinPro-13IML 2019 laptop with i7-10710U CPU, 1.10 GHz processing speed and 16 GB of memory. The model and the algorithm were implemented in C++ programming. The mixed integer linear model [M3] was solved by CPLEX 12.10, and all numerical experiments with 100 value sets were completed within a few seconds, and the numerical experiment with 1000 value sets was completed within 11.5 seconds. We conducted sensitive analysis with the group of possible values with 100 sets. To cover the situation that the port is a pure for-profit firm, we also conducted numerical experiments in which the port is self-operated and aims to maximize its own economic profit while the government provides a certain subsidy policy. The details are stated in the following.

4.2.1. Government-operated port

We conducted the numerical experiment $N1$ with the data collected and the result shows that the optimal solution is $s_1^* = 200.06$ USD, $p_1^* = 0.087$ USD/kWh, and the port will gain $Z_1^* = 39,398,700$ USD in a year for providing shore power service to ships. In this numerical experiment, k_{min}^1 in constraint (18) equals 96 and visits with all possible value sets will opt to use shore power with such shore power price and subsidy amount. We also conducted other numerical experiments with the same parameters, namely $N2$ that the port provides only the favorable shore power price ($s = 0$, $p \geq 0$), $N3$ that the port gives only subsidy to visits that use shore power

($s \geq 0, p = C_E$), and $N4$ that the port provides no incentive policies ($s = 0, p = C_E$). In addition, the constraint (18) on the number of historical visits that use shore power was also removed from $N2, N3$, and $N4$. The results of all four numerical experiments are listed in Table 1, in which we use the $g_q = (Z_q^* - Z_1^*) / Z_1^* \times 100\%$, $q = 2, 3, 4$ to represent the gap between the optimal solution value of $N2, N3, N4$ and the optimal solution value of $N1$.

From Table 1 we can see that the incentive policies have an obvious influence on the port side shore power facilities' usage ratio. With both the favorable shore power price and subsidy for visits that use shore power, visits with all possible value sets choose to use shore power and the port can earn 39,398,700 USD by providing shore power to ships. Meanwhile, the port can earn 35,902,000 USD, 982,141 USD, and 0 USD with only the favorable shore power price, only the subsidy, and no incentive policy applied, respectively. These numbers demonstrate the necessity of the incentive policies and the relevance of our problem.

In [M2], constraints (9)–(11) reflect the port's expectation of the percentage of ship visits that use shore power. To better understand how this expectation influences the optimal solution, we calculated the value of k_{min} with different values of α and β . And Table 2 shows that the value of k_{min} is closely related to the value of α . For a numerical experiment (N), we denote the optimal value of Z by Z^* ; for the numerical experiment with the same parameters but without constraints (9)–(11) (N'), which means that the port focus on the maximization of the total profit and does not care about the shore power usage rate, we denote the optimal value of Z and k as Z_0^* and k_0^* . When the value of k_{min} in $N1$ is higher than k_0^* , the optimal objective value Z^* is most likely to be lower than Z_0^* , and sometimes Z^* can be negative. For example, for a port with $B = 150$ USD, $C_E = 0.18$ USD/kWh and when the price of MDO $P_F = 350$ USD/ton, the

optimal solution value without constraints (9)–(11) is $Z^* = 655,922$ USD with $s^* = 62.25$ USD, $p^* = 0.075$ USD/kWh, and $k^* = 47$. When $\alpha \geq 0.6$ ($k_{min} \leq 41$), the optimal solution remains unchanged, and when $\alpha < 0.6$, namely $k > 50$, there will be a negative correlation between Z^* and α . With $\alpha = 0.2$, $0.1 \leq \beta \leq 0.4$ the port can still earn 295,924 USD, but the optimal profit becomes negative ($Z^* = -26,822.9$ USD) when $\alpha = 0.05$ and $0.1 \leq \beta \leq 0.4$. Therefore, ports should evaluate the environmental benefits B of emission reduction and the electricity purchasing price C_E to determine the expected proportion of ship visits that use shore power. An unrealistic high expected value may yield a negative profit, which is undesirable.

The environmental benefits B and the electricity cost C_E differ from port to port, and the MDO price P_F also fluctuates, so we conducted sensitive analysis to understand how these parameters affect the optimal solution. A series of numerical experiments with different parameters, as shown in Table 3, were conducted to demonstrate the influence of these parameters on the optimal profit (Z^*).

Specifically, 3,500 ($= 5 \times 5 \times 7 \times 20$) numerical experiments were conducted. Because it would be tedious to list results of all numerical experiments, we selected two groups of them to show the correlations between the parameters and the objective value. In group 1, denoted by [G1], the experiments are conducted with the base case values $B = 150$ USD, $C_E = 0.18$ USD/kWh, and $P_F = 350$ USD/ton. The optimal solution value of the basic numerical experiment without constraints (9)–(11) is $Z^* = 655,922$ USD with $s^* = 62.25$ USD, $p^* = 0.075$ USD/kWh, and $k^* = 47$. In group 2, denoted by [G2], the experiments are conducted with the base case values $B = 210$ USD, $C_E = 0.2$ USD/kWh, and $P_F = 250$ USD/ton. The optimal solution value of the

basic numerical experiment without constraints (9) to (11) is $Z^* = 1,153,180$ USD with $s^* = 61.52$ USD, $p^* = 0.053$ USD/kWh, and $k^* = 46$. For both basic numerical experiments, we changed one parameter at a time and observed the variation of the objective value. In Figure 1 (a) we only show the results for $k_{min} \geq 50$ because the value of k^* in two numerical experiments was 46 and 47. Figure 1 (a) shows that Z^* decreases with the value of k_{min} , which is understandable because a higher value of k_{min} means a stricter constraint on k . Figure 1 (b) shows that there is a positive correlation between Z^* and P_F . The reason is that for a higher P_F , ship visits will be willing to adopt shore power at a higher price p , which leads to a higher shore power selling revenue as well as a higher total profit Z^* . Meanwhile, Z^* decreases with C_E because the electricity cost of the port goes up with C_E . The correlation is shown in Figure 1 (c). Lastly, the port tends to earn more with a higher value of B , and this result is also intuitive because B has a positive influence on the environmental benefits for the port.

(a)(b)(c)(d)

Figure 1: Sensitivity analysis of the parameters

We also found that in some numerical experiments, such as the instance with $B = 150$ USD/ton, $C_E = 0.18$ USD/kWh, and $P_F = 250$ USD/ton, an optimal objective value $Z^* = 0$ was obtained without constraints (9)–(11). This means that the port cannot gain through the shore power project; also with an expectation of positive shore power usage rate the port will suffer a loss. One of the approaches to reducing emissions from berthing ships and avoiding loss is to lower the electricity price C_E . The port authority could request a government subsidy on the electricity price (Dai et al., 2019). When the electricity is reduced to 0.15 USD/kWh, as the numerical experiment shows, the port could earn 5,574,730 USD and 99% of the historical ship visits will choose to use

shore power and reduce ship emissions.

4.2.2. Self-operated port

In this subsection, we conduct numerical experiments in which the government provides certain subsidy policies, and a self-operated port only considers its profit, which equals the profit of selling shore power, minus the subsidy offered to the ship beyond the amount provided by the government. Therefore, we set $k_{min} = 0$ in this subsection because the port only considers its economic profit.

Based on numerical experiment $N1$, we conduct four additional numerical experiments with a self-operated port, namely N_{Self}^1 to N_{Self}^4 . In N_{Self}^1 , the government subsidy to the port is $Gs = 200.09$ USD for each ship visit that uses shore power and $Gp = 0.093 (= 0.18 - 0.087)$ USD per kWh of shore power used by those ships. In N_{Self}^2 , the government only gives the per ship visit subsidy; in N_{Self}^3 it only gives the per kWh subsidy; and in N_{Self}^4 the government gives no subsidy. [Table 4](#) shows the results of $N1$ and N_{Self}^1 to N_{Self}^4 .

In [Table 4](#), ZP_q^* represents the optimal value of the port's profit ZP , which can be calculated as follows:

$$ZP = \frac{|\mathcal{V}|}{|\mathcal{V}'|} \sum_{l \in \mathcal{V}'} [E'_l (p - C_E + Gp_q) - s + Gs_q] x'_l. \quad (29)$$

Meanwhile, ZG_q^* represents the optimal value of the government's profit ZG , which equals the environmental benefits, minus the government's subsidy expenditure and can be calculated as

follows:

$$ZG = \frac{|\mathcal{V}|}{|\mathcal{V}'|} \sum_{l \in \mathcal{V}'} [Q'_l B - E'_l G p_q - G s_q] x'_l. \quad (30)$$

The results in [Table 4](#) indicate that the environmental benefits are the main motive for the promotion of shore power. As shown in the N_{Self}^1 column, receiving the same subsidy as in $N1$, a port that focuses on its own economic profit puts in little effort to encourage the shore power usage. In that case, only two historical ship visits use shore power. In case N_{Self}^2 to N_{Self}^4 , the government gives only one or no subsidy to the port, and no ship visits use shore power. The results of the numerical experiments for a self-operated port show the influence of government subsidies on the optimal solution.

[Table 5](#) shows that ZG_q^* reaches its highest value, 31,237,500 USD, when $G p_q = 0.108$ USD/kWh and $G s_q = 0$ USD. The results also suggest that a higher subsidy does not necessarily lead to a higher ZG_q^* . With $G p_q \geq 0.162$ USD/kWh, ZG_q^* becomes negative. The results in [Table 6](#) reveal that ZP_p^* increases with $G p_q$ and $G s_q$, which is intuitive because higher government subsidies bring extra income to the port but no additional expenditures.

5. Conclusions

Shore power is a practical method for the reduction of ship emissions at berth. However, the existing shore power systems are not frequently used by ships because they are not economical in some scenarios. In order to encourage ships to use their shore power facilities onboard, governments

of various countries and regions have implemented incentive policies. (Note that in road transport, usually tolls instead of incentives are used; see e.g. [Eliasson \(2021\)](#).) In this paper, we have investigated the problem of shore power incentive policies design, including the shore power price and subsidy amount determination, which has not yet been studied as an optimization problem from the standpoint of a port. We focus on the situation that the port is operated by the government, and therefore integrate two parties, namely the government-operated port and ship operators into the model. Considering the characteristics of ports, such as the environmental benefits of emission reduction, the electricity price, and the historical data of ship visits, a stochastic model was built to describe the problem. The sample average algorithm was applied to the original model. We took the advantage of the existing data of ship visits to make an approximation of the visits in the coming year, which is a closer estimate than that of existing relevant studies ([Zheng, 2021](#)). At the same time, binomial distribution was adopted to handle the chance constraint. However, the great number of scenarios of ship visits in a year makes the model computationally intractable. Then, without the loss of generality, we reformulated the model and made the model tractable so that it could be solved by CPLEX.

A large number of numerical experiments with different parameters were conducted to validate the model. Using a comparison based on results obtained when both a favorable shore power price and subsidy are applied, only one of them, and no incentives at all, we have demonstrated that a favorable shore power price and subsidy for visits that use shore power are effective in encouraging ship visits to use shore power and hence reducing ship emissions while berthing. Sensitive analysis has shown that the total profit of the port increases with the environmental benefits of one tonnage of emission reduction and with MDO price; it decreases with the expected number of value sets with which visits would use shore power and with the electricity purchasing price. Our results also

suggest that an unreasonably high requirement on shore power usage rate can lead to a negative total profit, so the port should take this fact into consideration when setting the shore power usage ratio requirements. In addition, for ports that cannot benefit from shore power when there is no requirements on usage ratio, government subsidies on electricity price could help encourage shore power usage and reduce ship emissions at berth. Besides, numerical experiments with a self-operated port were also conducted and analyzed.

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