Stimulating Sustainable Energy at Maritime Ports by Hybrid Economic Incentives: A Bilevel Optimization Approach

Anahita Molavi[a], Gino J. Lim[a], Jian Shi[b,*]

[a] *Department of Industrial Engineering, University of Houston*
[b] *Department of Engineering Technology, University of Houston*

Abstract

Over the past few decades, maritime ports have faced ever-increasing critiques regarding their significant production of air emissions resulting from their energy activities. To promote sustainability at ports, regulatory authorities have introduced the concept of regulations and economic incentives. In this paper, we analyze the process in which a regulatory authority defines regulations, incentives, and tax policies to motivate one or more ports in the region to initiate energy sustainability and emission-reduction efforts. We model the behaviors of both the regulatory authority and the participating ports in the form of a multi-objective mixed-integer nonlinear bilevel optimization problem to capture the hierarchy of the policy-making process and the existing competitions among the ports. The proposed model finds the optimal incentive and tax policies for the policy-maker in the upper-level and provides the ports in the region with the optimal choice of sustainable energy solutions and service prices in the lower-level. Simulation results show that the proposed approach can effectively reduce the region-wide emission from the port activities while ensuring port entities' welfare, competitiveness, and sustainable growth as regional energy hubs.

Keywords: Port Energy Systems, Sustainability, Economic Incentives, Policy Analysis, Bilevel Programming

---

1. Introduction

Maritime transportation accounts for 90% of cross-border world trade, as measured by volume. Ports are considered to be the backbone of this network by connecting value chains and markets in different parts of the world [1]. In 2018, U.S. ports contributed $5.4 trillion to the economy of the country, which accounts for nearly 26% of the nation's $20.5 trillion economic output [2]. As dependence on these ports grows, so does the severity of challenges against them. The main operation of ports is to load and unload vessels and transport the cargo to warehouses and other destinations, which has made maritime ports to be major *energy hubs*. The increasing energy demand for port operations has brought forward urgent issues related to the port industry's substantial impacts on the environment and public health [3]. To satisfy their energy demands, port entities produce a significant amount of environmental pollution through land and sea transportation, waste disposal, and expansion activities [4]. According to the air emission inventory organized by the Port of Los Angeles (POLA) in 2015, the principal sources of airborne emissions at ports are directly linked to the activities of major consumers in the port energy system, such as ocean-going vessels (OGVs), cargo handling equipment (CHE), heavy-duty vehicles (HDVs), harbor crafts, and locomotives [5]. It is reported that approximately 230 million people are directly exposed to emissions originating from the top 100 global container ports. The existence of air pollutants produced by ports is estimated to quadruple by 2050; this equates to approximately 70 million tons of CO_2 and 1.3 million tons of NO_x [6]. Air emissions directly impact the health conditions of residents living in the communities surrounding ports and cause diseases such as asthma, lung cancer, cardiovascular diseases, and premature mortality [7]. Meanwhile, greenhouse gases (GHGs) are considered to be the primary contributing factor to climate change and global warming [8]. To address these pressing issues, many port entities and authorities are exploring new decarbonization and emission mitigation solutions to the traditional port energy management paradigm in port energy systems. These proposed solutions will allow for the movement towards a port industry that promotes and facilitates renewable energy, sustainable development, steady economic growth, and better quality of life and social welfare for citizens living in the port neighborhood [4, 9].

Existing port sustainable energy solutions embrace technical, operational, and economic dimensions. The abatement measures for OGVs are classified into four categories: alternative fuels or power sources (e.g., liquefied natural gases (LNG), biofuels, solar and wind energy, and nuclear energy), operational measures (e.g., hull conditioning, propeller conditioning, trim and draft optimization), technical measures (e.g., the machinery of main and auxiliary engines, underwater measures for propeller and hull), and structural changes (e.g., port efficiency, vessel speed reduction, and cold ironing) [10, 11, 12]. Zero-emission electric transport vehicles and cranes are readily deployable to reduce CHE emission [10, 13, 14]. Moreover, alternative fuels, speed optimization, idling reduction, and truck

---

[*] Corresponding author

Email addresses: `amolavi@uh.edu` (Anahita Molavi), `ginolim@central.uh.edu` (Gino J. Lim), `jshi14@uh.edu` (Jian Shi)

Nomenclature

Indices

d	Iteration number in solution algorithm
i	Ports, $i = 1, \dots, N$
j	Emission source at the port, $j = 1, \dots, M$
k	Emission abatement solution, $k = 1, \dots, U$
l	Index for weights in the regulator objective function, $l = 1, \dots, L$
LO	Superscript for lower bound of variables
UP	Superscript for upper bound of variables

Parameters

β_i	Emission cap upper bound for port i
ϵ	A very small value
ω_l	Weight associated with term l in the regulator objective function
τ_i	Total tax paid by port i
$\tilde{\tau}$	Tax rate (per unit of excess emission)
$\tilde{s}$	Incentive rate (per unit of reduced emission)
a	Constant term in the port energy demand function
B	Regulator budget dedicated to emission reduction at ports in the region
b	Coefficient term in the port energy demand function
$e^{c,LO}$	Initial lower bound for e^c
$e^{c,UP}$	Initial upper bound for e^c
FC_{jk}	Fixed cost of jk^{th} solution implementation
L_{jk}	Service capacity of a unit of jk^{th} solution (#TEUs per unit of solution)
M	A very large number
Q	Maximum energy demand for a port
r	Scaling coefficient, $r \in (0, 1]$
R_{jk}	Emission reduction rate of jk^{th} solution per TEU
s_i	Total incentive received by port i
VC_{jk}	Variable cost of jk^{th} solution implementation (per unit)
π_i^*	Maximum profit that port i can potentially receive
p_i^*	Service price for port i that results in π_i^*
q_i^*	Service demand for port i that results in π_i^*
s_i^*	Incentive for port i that results in π_i^*

Variables

λ_i^s	Paying incentive status for port i
λ_i^τ	Paying tax status for port i
π_i	Port i profit
σ	Auxiliary variable for handling multi-objective lower-level model
e_i^0	Emission level at port i before abatement procedure
e_i^c	Emission cap assigned to port i
e_i^t	Emission level at port i after abatement procedure
p_i	Port i service price
q	Energy demand for a port
x_{ijk}	Number of components installed from jk^{th} solution at port i
y_{ijk}	Implementation status of jk^{th} solution at port i
z_{LBD}	Objective function value of the lower-bounding problem
z_{UBD}	Objective function value of the upper-bounding problem
e_T	Total emission level from ports' activities in the region

Abbreviations

AB	Emission abatement cost
LBD	Lower-bounding model
OPS	Onshore power supply
TEUs	Twenty-foot equivalent units
UBD	Upper-bounding model

platooning can be adopted for HDVs emission reduction [15, 16, 17]. Alternative fuels, hybrid, and all-electric harbor craft and locomotives are also available to mitigate emissions [18, 19]. Optimizing practices and operational measures at ports in order to mitigate emission has been the topic of various studies in the literature. Vessel speed optimization, berth allocation, crane scheduling, and shipping routing and scheduling are major subjects of these works ([20], [21], [22]).

Despite the existence of the aforementioned sustainable energy technologies and suggested practices, ports and shipping liners are reluctant to initiate them due to the barriers of implementation cost and time. As profit-driven organizations, port entities are constantly challenged by their stakeholders to justify the pursuit of emission-reduction efforts and the investment of sustainable energy solutions in terms of payback, return on investment, and revenue enhancement. To address this issue, the concept of regulations and economic incentives has emerged to promote emission reductions in the ports' energy activities [23]. According to the United States Environmental Protection Agency, three types of instruments are available for policymakers: i) *mandatory regulations* (command-and-control), ii) *market-based policies*, and iii) *hybrid approaches* (a combination of command-and-control and market-based policies) [24]. Mandatory regulations refer to the traditional mandates and standards which oblige specific limits, technologies, or processes that polluters must adopt to reduce their emission. Market-based policies, used as performance-based standards, rely on market forces to motivate emission reduction by economic means such as incentives and taxes [25]. Regulatory approaches provide certainty in mitigating emission, while market-based policies provide flexibility and willingness to polluters [26] to meet the emission standard. Hybrid approaches combine the certainty and flexibility of these two and hence, are becoming more appealing to policy-makers. However, the design of such policies is not straightforward. Attributes such as operational costs, continuity of operations, regulation compliance, port competitiveness, and regulation attractiveness have to be taken into consideration collectively to form an overall "sensible" solution [27].

The necessity of economic regulations for emission reductions at ports has been discussed in the literature [28, 29]. In particular, the need for pollution taxes was highlighted and revealed through a survey with port operators and government officials in [30]. The results of the survey emphasized the importance of a practical policy-making approach that motivates ports to reduce their emission. The impacts of different environmental policies on air emission mitigation are analyzed in [31]. An important regional characteristic that should be incorporated in the design of an effective economic policy is whether there are multiple ports or one port in the region. A market-based approach for pollution control in a region with multiple ports is studied in [32]. In regard to environmental regulations, the effectiveness of a unilateral maritime emission regulation versus a uniform maritime emission regulation in the presence of multiple ports has been investigated in [33]. The results of this investigation indicated that a unilateral regulation may lead to increased emissions, whereas a uniform regulation always reduces the total emission. The literature has also noted the adoption of bilevel optimization models used to design tax and incentive policies that promote clean energy. In this context, a bilevel optimization model has been developed in [34] to study the renewable incentive design for generation capacity expansion. Moreover, a situation where the government aims to minimize the total CO_2 emissions by using carbon tax and subsidies, and the consumers want to minimize their costs by choosing the optimal combination of energy was considered in [35]. As another instance, authors in [23] designed a carbon tax scheme based on the production emission factor via bilevel programming. However, the hybrid economic approach remains largely unexplored in the literature for port energy system design and emission mitigation.

In this paper, we propose a novel hybrid economic approach to aid both the regulatory entities (e.g., government agencies, policy-makers) and the polluting entities (e.g., ports entities, shipping liners) to holistically improve the sustainability of a region consisting of multiple ports. The proposed approach allows the regulatory authority to minimize the emission caused by port energy activities through carbon taxes and subsidies in a way that the port customers' (i.e., energy consumers) welfare and competitiveness are not noticeably impaired. More specifically, we propose to formulate the problem as a multi-objective bilevel programming model in which the upper-level provides the optimal set of tax and incentive policies for the regulatory entity as well as emission goal, and the lower-level offers the optimal investment decisions regarding the choice of green and sustainable energy solutions and the setting of port service prices for the port entities. Simulation results verify that the proposed approach is capable of simultaneously satisfying the demands of the regulator, ports, and port customers while providing the first two with optimal policies.

The contributions of this paper are highlighted as follows:

- This paper develops a novel hybrid economic approach to stimulate sustainable energy activities at maritime ports. The proposed approach is one of the pioneering research efforts that aim to combine the certainty of command-and-control and the flexibility of market-based economic incentives in the unique context of maritime transportation.

- This paper presents a novel multi-objective bilevel programming model to enable the co-operation of two key stakeholders of the port energy system, the regulatory authority and the competing port entities, based on their points of interest as well as the hierarchy and competition among them.

- This paper presents case studies based on actual port data. The simulation results offer practical insights into the effectiveness of taxes, incentives, and the combination of the two on mitigating emissions with the consideration of the satisfaction of port energy demand.

The remainder of this paper is organized as follows. The methodology section presents the proposed model and its associated solution methodology. Section III illustrates our approach through numerical examples and performance analysis. Finally, Section IV concludes the paper by highlighting the contributions and results of our study as well as insights for future research.

2. Methodology

As set forth above, our problem setting involves two groups of decision-makers: a regulatory authority and competing ports in the associated region. The regulatory authority aims to promote sustainable growth that lowers the combined emission from polluting ports in the region, all while maintaining service availability for the ever-growing energy demand. This is achieved through the establishment of a target emission limit, i.e., an emission cap for each port, to motivate the implementation of sustainable and green energy solutions. The port receives incentives if its emission level is below the cap. Otherwise, the port is penalized by an emission tax. Our approach is hybrid in the sense that it incorporates the certainty of command-and-control by establishing the emission caps while offering economic stimulation to encourage port entities to adopt sustainable energy technologies and meet the assigned emission caps through profitable approaches. The regulatory authority also considers the welfare of the port customers, modeled by the amount of fulfillment of port energy demand. It is noted that in this work, this demand is measured by the total volume of containers handled by the port facility.

The second group of decision-makers is comprised of competing ports in the region that seek to maximize their profits from providing services to port customers (i.e., vessels and ship liners). This profit is impacted by the choice of sustainable energy technologies, the emission tax, and the potential incentive. Note that in this paper, we consider a fixed cost and a variable cost associated with the implementation of sustainable energy solutions. The fixed cost represents the initial investment that has to be made to support the adoption of the technology, while the variable cost is determined by the unit price of the equipment and the number of units to be purchased. Each solution lowers the emission from the associated energy consumption source by a constant rate (L_{jk}) for a given period.

To consider the hierarchical nature of the decision-making process in this problem and the existing competition among the ports, we propose a bilevel programming model. In this model, the regulator acts first as the leader and attempts to make optimal decisions, and then the ports, as the followers, react to the regulator's decisions in a way that is individually optimal. Due to the consideration of policy transparency, which indicates that both the leader and the followers have access to each other's objectives and green technology [36], perfect information is assumed in this paper.

The port energy demand is modeled as a linear function of the port service price for handling each container (Equation (1)) [37]. If there are more than one port in the region (i.e., N ports), we can obtain each port demand by Equation (2) [38].

$$q = \frac{a-p}{b} \tag{1}$$

$$q_i = \begin{cases} 0 & p_i > a \ or \ p_i > p_j, \ i \neq j \\ \dfrac{a-p_i}{Nb} & p_i = p_j, \ i \neq j \\ \dfrac{a-p_i}{b} & p_i \leq min(a, p_j), \ i \neq j \end{cases} \tag{2}$$

The emission level after implementing green solutions at port i equals the initial emission level at the port (i.e., e_i^0) minus the mitigated emission (Equation (3)). Tax and incentive for each port are assumed to be linearly dependent on the gap between the associated emission cap and emission level (Equations (4) and (5)).

$$e_i^t = e_i^0 - (\sum_j \sum_k R_{jk} L_{jk} x_{ijk}) q_i \tag{3}$$

$$\tau_i = \tilde{\tau}(e_i^t - e_i^c) \tag{4}$$

$$s_i = \tilde{s}(e_i^c - e_i^t) \tag{5}$$

We denote the profit of port i by π_i, which is calculated by subtracting the emission tax and the emission abatement costs, if any, from the total port revenue and incentive (Equation (6)).

$$\pi_i = p_i q_i + s_i - \tau_i - \Big[(\sum_j \sum_k FC_{jk} y_{ijk}) + (\sum_j \sum_k VC_{jk} x_{ijk}) \Big] \tag{6}$$

Then, the bilevel model for $i = 1, \ldots, N$, $j = 1, \ldots, M$, and $k = 1, \ldots, U$ can be formulated as follows:

$$\min_{e_i^c} \omega_1 \sum_i \frac{e_i^t}{e_i^0} + \omega_2 \sum_i \frac{(e_i^c - e_i^0)^2}{(e_i^0)^2} + \omega_3 (\frac{Q - \sum_i q_i}{Q}) + \omega_4 \sum_i \frac{e_i^c}{e_i^0} \tag{7}$$

$$s.t. \sum_i s_i \leq B \tag{8}$$

$$0 \leq e_i^c \leq \beta_i \tag{9}$$

$$\sum_i q_i \leq Q \tag{10}$$

$$\min \ \sigma \tag{11}$$

$$s.t. \frac{\pi_i^* - \pi_i}{\pi_i^*} \leq \sigma \tag{12}$$

$$x_{ijk} \leq M y_{ijk} \tag{13}$$

$$-M\lambda_i^s \leq e_i^t - e_i^c \leq M\lambda_i^\tau \tag{14}$$

$$\lambda_i^s + \lambda_i^\tau = 1 \tag{15}$$

$$0 \leq e_{ij}^t \tag{16}$$

$$x_{ijk} \in Z^+, y_{ijk}, \lambda_i^s, \lambda_i^t \in \{0, 1\}, 0 \leq p_i \tag{17}$$

Equations (7)–(10) define the upper-level model, and Equations (11)–(17) define the lower-level model. Given the regulatory role of the policy-makers, the regulator objective function (i.e., the objective function of the upper-level model) is a convex combination of four normalized terms: 1) the emission level from port activities, 2) the gap between the assigned emission cap and the initial emission level of each port, 3) the gap between the satisfied port service demand and the total demand, and 4) the emission cap assigned to each port (Equation (7)). Note that the second term is included to model a fair regulator which assigns emission caps based on the port's initial emission level.

The total incentive that the ports can receive is subject to the budget constraint of the regulator (Equation (8)). The assigned emission caps are subject to their respective upper bounds (Equation (9)), and should always be positive. The satisfied demand for port service should be less than or equal to the total market demand (Equation (10)).

In the lower-level model, the goal is to maximize the profit of the ports (Equation(18)).

$$\max_{x_{ijk}, y_{ijk}, p_i} (\pi_1, \pi_2, \ldots, \pi_N) \tag{18}$$

To handle the multi-objective lower-level problem, we reformulate Equation (18) into Equation (11) and add Equation (12) to the lower-level model. In Equation (12), π^* is a parameter referring to the maximum profit that each port could potentially receive. Parameter π^* is calculated by Equation (19).

$$\pi_i^* = p_i^* q_i^* + s_i^* \tag{19}$$

Equation (13) ensures that the fixed cost of implementing solutions will be considered along with the variable cost. Equation (14) decides whether the port entity pays emission tax or

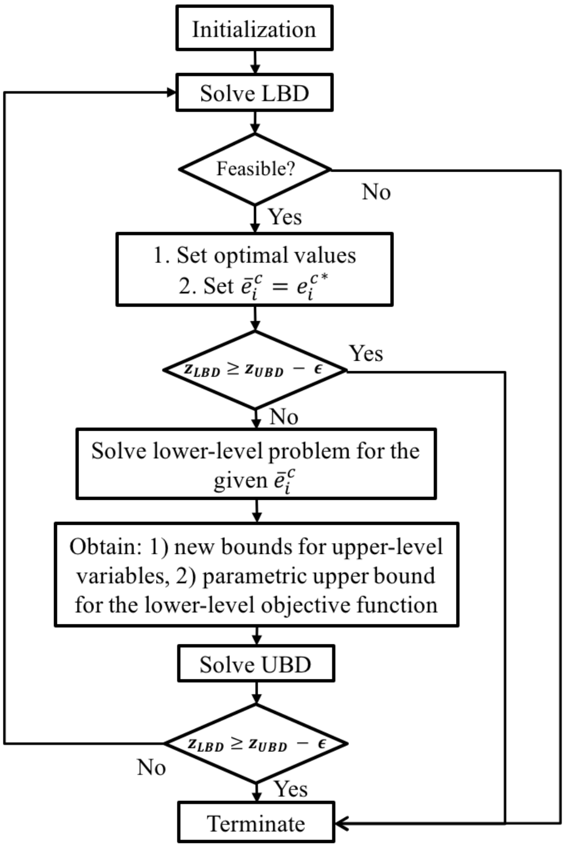


Fig. 1. Algorithm implemented for solving the bilevel model presented in Equations (7)–(17)

receives incentives according to its emission level and the emission cap assigned to it, respectively. Equation (15) ensures that each port either pays taxes or receives incentives. The emission level associated with each polluting source in the port facility cannot be negative (Equation (16)). Finally, Equation (17) enforces the range of the variables.

While several solution methodologies exist for linear bilevel programming models (e.g., vertex enumeration, Kuhn-Tucker conditions, and penalty approaches) [36, 39], they are not well studied for a mixed-integer nonlinear bilevel model with a nonconvex lower-level problem, as formulated in the previous discussion. In this paper, we adopt and extend the general algorithm proposed in [40] to formulate a problem-specific solution methodology. As indicated in [40], three assumptions have to be met to ensure the convergence of the algorithm. We illustrate them in the context of this paper as follows:

Assumption 1: Explicit bounds are known for all variables.

Comments: All variables in our problem formulation have box-constrained host sets; hence, the first assumption is met.

Assumption 2: All functions are assumed to be continuous on continuous variables for the given integer variables.

Comments: All of the functions in the developed bilevel model (Equations (7)–(17)) are either linear or quadratic on continuous variables; therefore, the second assumption is met.

Assumption 3: Consider $f^l(z^u, z^l)$ as the lower-level objective function as a function of upper-level variables (i.e., z^u) and lower-level variables (i.e., z^l). If some upper-level variables are continuous, there exists some $\bar{\epsilon}^u > 0$ such that for each feasible upper-level variable, i.e., $\bar{z}^u$, at least one of the following two conditions hold:

- For any $\bar{\epsilon}^l > 0$, there exists a feasible vector of lower-level variables, i.e., $\tilde{z}^l$, such that
$$f^l(\bar{z}^u, \tilde{z}^l) \le f^{l,*}(\bar{z}^u) + \bar{\epsilon}^l \tag{20}$$
- The upper-level objective function value is worse than its optimal value by $\bar{\epsilon}^u$.

Comments: The second condition of the third assumption is met in this paper because of the contradictory objectives of the upper-level and the lower-level, such as the emission level in the first term of the upper-level objective function, i.e., e_i^t.

As shown in Figure 1, for the initialization of the algorithm, the upper bound (i.e., z_{UBD}) and the lower bound (i.e., z_{LBD}) for the regulator objective function are set to + inf and − inf, respectively. At each iteration, the lower-bounding problem (LBD) is solved and if feasible, an optimal solution is obtained, and we set $\bar{e}_i^c = e_i^{c*}$. Then, if the convergence condition is not met, the lower-level model is solved using fixed values for the emission caps (i.e., $\bar{e}_i^c$). Thus, the parametric upper bound for the lower-level objective function, as well as the new bounds of the emission caps, can be obtained. The last step is solving an upper-bounding problem (UBD) and updating the optimal solution. If the convergence is not met, new constraints will be added to the LBD to direct the algorithm toward the optimal solution. The details for each step are discussed further below.

The lower bound is obtained by solving the LBD, a mixed-integer nonlinear program containing the upper-level objective function, constraints of the lower-level model, and constraints of the upper-level model. The convergence of the LBD is achieved by including a parametric upper bound to the optimal objective function of the lower-level program. This parametric upper bound is enforced by adding a logical constraint (Equation (22)). Note that D is the set of iterations, d is the iteration number, and E_i^d is the host set obtained at iteration d for the upper-level variable e_i^c.

$$\min_{e^c,x,y,p,\lambda} z_{LBD} = \omega_1 \sum_i \frac{e_i^t}{e_i^0} + \omega_2 \sum_i \frac{(e_i^c - e_i^0)^2}{(e_i^0)^2} + \omega_3\left(\frac{Q - \sum_i q_i}{Q}\right) + \omega_4 \sum_i \frac{e_i^c}{e_i^0} \tag{21}$$

$$s.t.\ (8)-(10),(12)-(17)$$

$$e_i^c \in E_i^d \implies \sigma \le \sigma^d, \forall d \in D \tag{22}$$

In the first iteration of the algorithm, Equation (22) considers the initial host set for e^c and σ^d = inf. However, in the following iterations, this set of equations will force a new upper-bound on the lower-level objective function for the associated ranges of e^c. The parametric upper bound of the lower-level objective function at iteration d is obtained by solving the lower-level model and obtaining the optimal objective function value (i.e., σ^d equals σ^* at iteration d). This lower-level parametric upper bound is based on the optimal solution of the lower-level model for a given e^c and the subsets of the host set of e^c, for which this solution remains lower-level feasible. Assuming $r \in (0,1]$ as a scaling coefficient for updating the bounds of e_i^c, the new bounds (i.e., E_i^d) for e_i^c can be obtained from Algorithm 1. This algorithm obtains successively tighter bounds for the upper-level variables (i.e., e_i^c) until all of the potential values for e_i^c within the bounds are feasible for the current lower-level optimal decisions.

Algorithm 1 Finding new bounds for e_i^c

```
for $i = 1, \ldots, N$ do
    Set r = 1.
    repeat
        if $\bar{e}_i^c - 0.5r(e_i^{c,UP} - e_i^{c,LO}) < e_i^{c,LO}$ then
            Set $e_i^{c,d,LO} = e_i^{c,LO}$.
            Set $e_i^{c,d,UP} = e_i^{c,LO} + r(e_i^{c,UP} - e_i^{c,LO})$.
        else if $\bar{e} + 0.5r(e_i^{c,UP} - e_i^{c,LO}) > e_i^{c,UP}$ then
            Set $e_i^{c,d,LO} = e_i^{c,UP} - r(e_i^{c,UP} - e_i^{c,LO})$.
            Set $e_i^{c,d,UP} = e_i^{c,UP}$.
        else
            Set $e_i^{c,d,LO} = \bar{e}_i^c - 0.5r(e_i^{c,UP} - e_i^{c,LO})$.
            Set $e_i^{c,d,UP} = \bar{e}_i^c + 0.5r(e_i^{c,UP} - e_i^{c,LO})$.
        Check if the lower-level optimal decisions for all of the realizations of $e_i^c$ within the bounds remain valid.
        if The range is valid then Terminate the loop else Set $r = 0.5r$.
    until True;
end
```

The optional upper bound to the optimal solution of the bilevel program is obtained by solving an augmented upper-level problem for fixed upper-level variables. To obtain the upper bound of the optimal objective function, we consider an upper-bounding model for a given $\bar{e}_i^c$ as follows:

$$\min_{x,y,p,\lambda} z_{UBD} = \omega_1 \sum_i \frac{e_i^t}{e_i^0} + \omega_2 \sum_i \frac{(\bar{e}_i^c - e_i^0)^2}{(e_i^0)^2} + \omega_3 (\frac{Q - \sum_i q_i}{Q}) + \omega_4 \sum_i \frac{\bar{e}_i^c}{e_i^0} \tag{23}$$

$$s.t. \ (8), (10), (12), (13), (15), (16), (17)$$

$$0 \leq \bar{e}_i^c \leq \beta_i \tag{24}$$

$$\sigma \leq \sigma^d + \epsilon_f^l \tag{25}$$

$$-M\lambda_i^s \leq e_i^t - \bar{e}_i^c \leq M\lambda_i^\tau \tag{26}$$

As shown in Figure 1, after solving the UBD, the convergence condition is checked. If it is not met, a new logical constraint (Equation 22) based on σ^d and the new bounds of e^c will be added to the LBD to begin the next iteration.

Note that bilevel models may not possess a solution even when the functions are continuous, the constraint region of the problem is nonempty and compact, and the follower has some room to respond for all decisions taken by the leader [36]. This happens when the set of all solutions to the follower problem for a fixed leader decision consists of some nontrivial subset of a hyperplane. This means that the follower is indifferent to any point on that hyperplane while the leader might not feel the same indifference with respect to its objective function. However, the leader has no way to induce the follower to change its decisions. The points on this hyperplane are called indifference points which lead to the nonexistence of solutions. A simple way to see whether a solution, $(e_i^{c*}, x_{ijk}^*, y_{ijk}^*, p_i^*, \lambda_i^{\tau*} \lambda_i^{s*})$, to the model presented in Equations (7)–(17) is unique is to solve the following problem in which S is the constraint region of the bilevel problem and σ is the lower-level objective function:

$$\begin{aligned}
&\min\{\sigma : (e_i^c, x_{ijk}, y_{ijk}, p_i, \lambda_i^\tau, \lambda_i^s) \in S, \\
&\omega_1 \sum_i \frac{e_i^t}{e_i^0} + \omega_2 \sum_i \frac{(e_i^c - e_i^0)^2}{(e_i^0)^2} \\
&+\omega_3 (\frac{Q - \sum_i q_i}{Q}) + \omega_4 \sum_i \frac{e_i^c}{e_i^0} \\
&= \omega_1 \sum_i \frac{e_i^{t*}}{e_i^0} + \omega_2 \sum_i \frac{(e_i^{c*} - e_i^0)^2}{(e_i^0)^2} \\
&+\omega_3 (\frac{Q - \sum_i q_i^*}{Q}) + \omega_4 \sum_i \frac{e_i^{c*}}{e_i^0}\}
\end{aligned} \tag{27}$$

If the corresponding solution produces an objective function value that is less than the objective function value associated with $(e_i^{c*}, x_{ijk}^*, y_{ijk}^*, p_i^*, \lambda^{\tau*} \lambda_i^{s*})$, then the uniqueness condition does not hold.

3. Case Study

In this section, we will demonstrate and evaluate the performance of the proposed approach in reducing emission and designing efficient tax and incentives through two simulation-based case studies: 1) a region with one port, and 2) a region with two ports. For both cases, we consider the following sustainable energy solutions: onshore power supply (OPS) for cold-ironing vessels, LNG-fueled trucks, LNG-fueled yard tractors, hybrid-electric tugboats, and LNG-fueled locomotives. Onshore power supply provides power to vessels at the berth through shore-to-ship power cables in which auxiliary engines on-board can be turned off, which leads to a significant reduction of emissions from diesel fuels. Currently, many industrial ports around the globe, including Port of Antwerp, Port of Gothenburg, POLA, and Port of Seattle, are testing and moving toward integrating OPS [41, 42] technologies into their terminal electricity distribution systems. Alternative fuels such as LNG provide another sustainable and cost-effective way for mitigating GHG emissions and other polluting substances, such as NO_x and PM from traditional, diesel-fueled trucks and tractors [43]. The hybrid-electric tugboat is a recently presented solution recommended by POLA and Port of Long Beach (POLB). The preliminary

Table 1
Information pertaining to sustainable energy solutions for port entities

	Fixed cost ($thousands)	Variable cost ($thousands)	Emission reduction rate (% of current emission rate)	Service capacity (annual #TEUs per unit of solution)
Onshore power supply	2,000	800	98%	52,344
LNG-fueled trucks	2,000	211	50%	653
LNG-fueled yard tractors	1,800	120	43%	7,022
Hybrid-electric tugboat	0	2,000	44%	72,300
LNG-fueled locomotives	7,296	5,000	92%	81,338

evaluation results indicated that hybrid-electric tugboats can significantly decrease NO_x, CO_2, and PM [44]. Finally, LNG-fueled locomotives can also reduce air emissions and are sustainable alternatives to current diesel-fueled locomotives, as suggested by a study conducted by the Port of Tarragona [45]. The specific costs, emission reduction rates, and service capacity associated with these sustainability solutions are provided in Table 1 ([43], [45], [41]).

The effectiveness of both the economic policies and green solutions is studied for a one-year period. Model (7)–(17) and the solution algorithm have been implemented in GAMS [46]. The Branch-And-Reduce Optimization Navigator (BARON) [47] in GAMS is used for solving the MINLP models at each step of the algorithm [48]. The algorithm has been carried out on a Linux server with 384 GB of RAM and 40 Intel Xeon E5-2690 processors (10 cores per socket) at 3.00 GHz. The time for the algorithm to converge to an optimal solution varies between 1.43 seconds for the single-port case study to 8 hours and 12 minutes for the two-port case study. This convergence time significantly depends on the input parameters such as weights in the government objective function as well as tax and incentive rates.

3.1. Case 1: Single-Port Region

As an example of a large container port in a region, we consider the Port of Houston, which is the largest U.S. export port. Using the port operating revenue and the energy demand information between 2003 and 2013 ([49], [50]), we performed a linear regression analysis that considers the inflation rates in order to obtain the y-intercept and the coefficient terms in Equation (1). Specifically, a and b in Equation (1) are set to \$123.89 and $\$3.06\times10^{-6}$, respectively. As an example of a harmful polluting substance that has not been sufficiently mitigated, we focus on the emission of NO_x. However, the proposed model, solution approach, and policies are applicable to other air pollutants, as well. The emission production rates for each polluting source at each respective port is given in Table 2. According to this table, ocean-going vessels are accredited as the most polluting sector of the Port of Houston, as they produce a significant amount of NO_x. The initial NO_x level from OGVs, HDVs, CHEs, harbor crafts, and locomotives amount to 8,113 (tons). In the regulator objective function (Equation (7)), we set the following weight parameters: $\omega_1 = 0.1, \omega_2 = 0.25, \omega_3 = 0.25$, and $\omega_4 = 0.4$. The selection of these parameters prioritizes the regulator's role to promote emission reduction through economic incentives. We test the following four combinations of tax and incentive policies:

- Case 1.1) $\tilde{\tau} = 0$ and $\tilde{s} = 0$ (\$thousands/tons of NO_x)
- Case 1.2) $\tilde{\tau} = 0$ and $\tilde{s} = 10$ (\$thousands/tons of NO_x)
- Case 1.3) $\tilde{\tau} = 10$ and $\tilde{s} = 0$ (\$thousands/tons of NO_x)
- Case 1.4) $\tilde{\tau} = 10$ and $\tilde{s} = 10$ (\$thousands/tons of NO_x)

Table 3 shows the results for these four test cases. Case 1.1 serves as the performance benchmark where both tax and incentive rates are set to 0. We can observe that despite the assignment of an emission cap (1623 tons), due to the lack of the economic stimulation, the port chooses not to invest in green solutions (AB = \$0) and its emission level remains unchanged from the initial value, i.e., $e^t = e^0 = 8113$ tons. The port's profit comes from the revenue of handling all of the 1,952,122 containers (Equation (6)). Case 1.2 analyzes the port behavior in the presence of incentive and no tax. We observe that the same results are obtained in this case as Case 1.1. The results suggest that for this particular problem setting when there is no emission tax and the incentive rate is not as competitive, the port will not be motivated to mitigate its emission level to meet the emission cap. Cases 1.3 and 1.4 show that the reduction in emission level can be achieved when the emission tax is enforced, both in the presence and absence of an incentive. In both cases, the port has to invest \$32.4 million to provide OPS for 38 container vessels for emission abatement and pay \$18.14 million in emission tax for an emission level e^t of 3,436 tons. This investment causes a decline in port profit from \$230.2 million to \$179.66 million. The optimal port service price per container is obtained to be

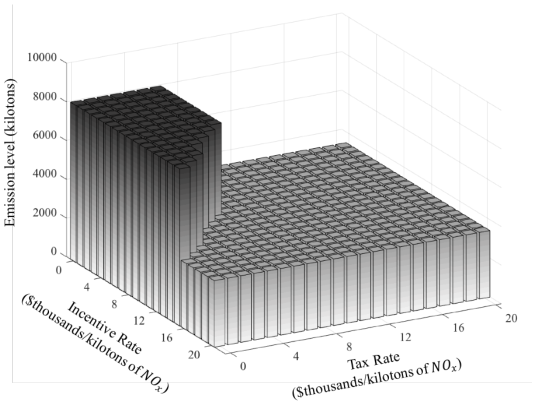
Table 2
NO_x emission rates from different sources at the Port of Houston (2013)

Inventory Component	NO_x (tons/TEUs)
OGV	0.002399
HDV	0.000600
CHE	0.000674
HC	0.000184
Locomotive	0.000299

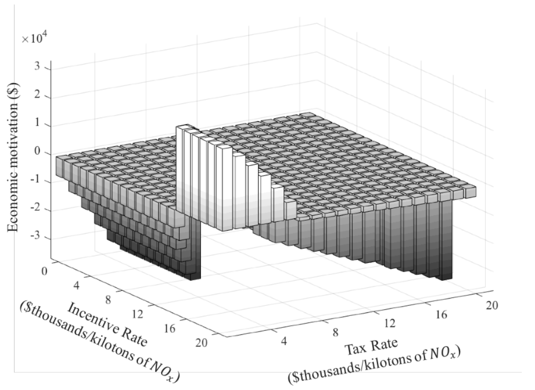
Table 3
Results for the single-port region

Case No.	e^t (tons)	e^c (tons)	p ($thousands)	q (# of containers)	π ($thousands)	AB ($thousands)	τ ($thousands)	s ($thousands)
1.1	8113	1622.80	0.12	1,952,122	230,199	0	0	0
1.2	8113	1622.80	0.12	1,952,122	230,199	0	0	0
1.3	3436	1622.80	0.12	1,952,122	179,661	32,400	18,139	0
1.4	3436	1622.80	0.12	1,952,122	179,661	32,400	18,139	0

$120, and the total port demand is satisfied in all of the four instances.



(a) Port emission level for different tax and incentive rates



(b) Economic motivation for different tax and incentive rates

Fig. 2. Analysis of the influence of different economic policies

Table 4
NO_x emission rates from different sources at POLA and POLB (2017)

Inventory Component	LA: NO_x (tons/TEUs)	LB: NO_x (tons/TEUs)
OGV	0.00033	0.00056
HDV	0.00016	0.00015
CHE	0.00005	0.00005
HC	0.00007	0.00008
Locomotive	0.00009	0.00008

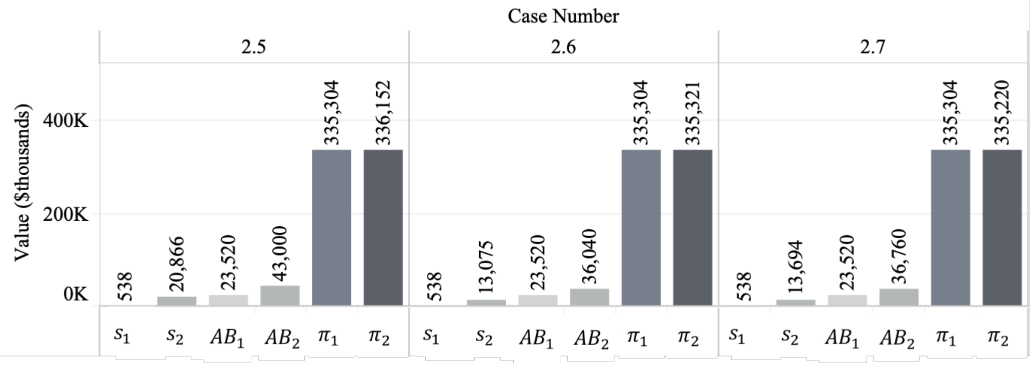
Additional results are obtained and depicted in Figures (2a) and (2b) to further analyze the influence of different combinations of tax and incentive rates ranging from 0 to 20 thousand dollars per tons of NO_x emission. Figure (2a) illustrates the variations of port emission with regards to different tax and incentive rates. We observe that the lowest emission level achieved in this case study is 3,436 tons. It is also noticeable that when the tax rate is low, high incentive rates should be considered to motivate the port (e.g., $\tilde{\tau} = 0$ and $\tilde{s} = \$15000$). Meanwhile, the combination of high tax rates and low incentive rates would also stimulate emission reductions (e.g., $\tilde{\tau} = \$7000$ and $\tilde{s} = \$9000$). Figure (2b) presents the payment flow between the port and the regulatory authority for different tax and incentive rates. It can be observed that incentives can only be obtained in a few instances when the tax rates are low, and the incentive rates are high. This indicates that in those few instances, tax by itself cannot sufficiently motivate the port to mitigate its emission. Comparing Figures (2a) and (2b), we notice that for lower tax and incentive rates, the port is reluctant to initiate emission abatement and is willing to pay the tax instead. However, with the increasing tax or incentive rates, the port becomes more willing to proactively decrease its emission level to avoid emission taxes and to seek the opportunity of meeting the emission cap to receive incentives.

3.2. Case 2: Two-Port Region

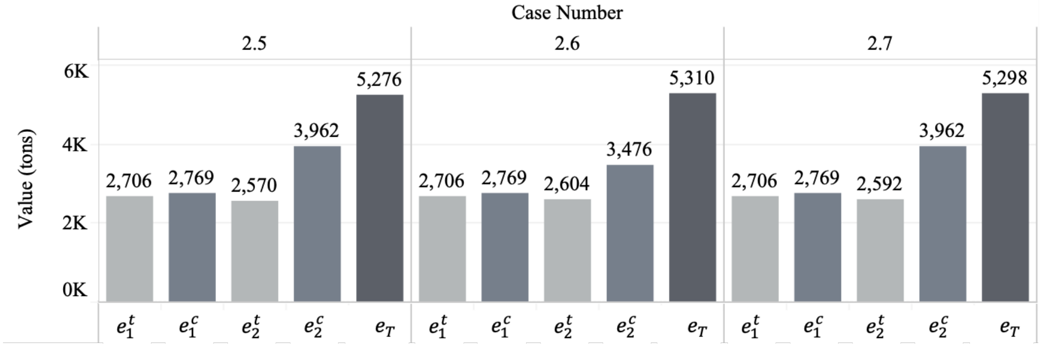
For the second case study, we consider an instance involving two container ports in the same region: POLA and POLB. These two ports are located side-by-side in San Pedro Bay but are two separate entities and compete with each other for business [51]. According to data for year 2017 ([5],[52],[53]), the number of total containers handled at POLA and POLB, respectively, were 9,343,192 and 7,544,507, while the operating revenue at each respective port amounted to $475 million and $381 million. Hence, in the ports' demand function (Equation (2)), a is set to $90.84, and b is set to $\$2.87 \times 10^{-6}$. Details of each ports' emission inventories are provided in Table 4. Without loss of generality, the weight parameters in the regulator objective function are set for this particular example as follows: $\omega_1 = 0.25$, $\omega_2 = 0.25$, $\omega_3 = 0.25$, and $\omega_4 = 0.25$. Four combinations of tax and incentive rate are considered: Case 2.1: $\tilde{\tau} = 0$ and $\tilde{s} = 0$ ($thousands/tons of NO_x), Case 2.2: $\tilde{\tau} = 0$ and $\tilde{s} = 10$ ($thousands/tons of NO_x), Case 2.3: $\tilde{\tau} = 10$ and $\tilde{s} = 0$ ($thousands/tons of NO_x), and Case 2.4: $\tilde{\tau} = 10$ and $\tilde{s} = 10$ ($thousands/tons of NO_x).

Table 5
Results for the two-port region: Port of Los Angeles and Port of Long Beach - Equal tax and incentive rates

Case No.	$\mathbf{e_T}$ (tons)	$(e_1^t; e_2^t)$ (tons)	$(e_1^c; e_2^c)$ (tons)	$(p_1; p_2)$ (\$thousands)	$(q_1; q_2)$ (# of containers)	$(\pi_1; \pi_2)$ (\$thousands)	$(AB_1; AB_2)$ (\$thousands)	$(\tau_1; \tau_2)$ (\$thousands)	$(s_1; s_2)$ (\$thousands)
2.1	**11,307**	(4,886;6,421)	(4,886;3,475)	(0.05;0.05)	(7,691,361;7,691,361)	(354,721;354,658)	(0;0)	(0;0)	(0;0)
2.2	**7,170**	(4,515;2,655)	(3,126;6,389)	(0.05;0.05)	(6,979,576;6,979,576)	(354,404;354,404)	(4,400;41,800)	(0;0)	(0;37,337)
2.3	**5,419**	(2,691;2,728)	(3,268;3,484)	(0.05;0.05)	(7,471,608;7,471,608)	(330,687;329,287)	(27,800;29,200)	(0;0)	(0;0)
2.4	**5,298**	(2,706;2,592)	(2,760;3,962)	(0.05;0.05)	(7,513,368;7,513,368)	(335,303;335,220)	(23,520;36,760)	(0;0)	(538;13,694)



(a) Economic performance of POLA and POLB under unilateral tax and incentive rates



(b) Environmental performance of POLA and POLB under unilateral tax and incentive rates

Fig. 3. Analysis of the influence of unequal tax and incentives

Table 5 shows the results obtained for this case study. Case 2.1 serves as the performance benchmark and reflects the ports' optimal decisions when there is no tax nor incentive. The total emission level in the region, denoted by e_T, is 11,307 tons of NO_x, which is affected only by the number of handled containers in this case. The abatement costs are zero for both ports, and the maximum port profit is achieved by setting $p_i = \$50$. The number of total handled containers in the region is 13,959,152. We observe that in all of the instances, both ports have decided to set similar service prices (i.e., $p_1 = p_2$) and satisfy an equal amount of demand (i.e., $q_1 = q_2 = \dfrac{a - p_i}{2b}$). This is in accordance with Equation (2), as its Pareto optimal solution can be achieved when the ports set similar service prices.

In Case 2.2, POLA invests \$4.4 million and equips 3 vessels with OPS while POLB invests \$41.8 million in providing OPS for 35 vessels, purchasing 50 LNG-fueled yard tractors, and investing in 2 hybrid-electric tugboats. By lowering its emission level to 2,655 tons, POLB gains an incentive of \$37.34 million. The overall regional emission is reduced by 32%.

In Case 2.3, the positive tax rate results in a significant reduction of emission levels from both ports. More specifically, POLA mitigates its NO_x level by investing \$27.8 million in 50 LNG-fueled tractors, one hybrid-electric tugboat, and providing OPS for 20 vessels. POLB spends \$29.2 million to provide OPS to 34 vessels. The overall regional emission is further reduced to 5,416 tons, which is about 52% of the initial emission level.

The minimum emission level of 5,298 tons is achieved in Case 2.4. With positive tax and incentive rates, both ports lower their emission levels below the emission cap to receive incentives. POLA provides OPS for 34 vessels and purchases 31 LNG-fueled yard tractors through the investment of \$23.5 million in emission abatement. On the other hand, POLB invests \$36.8 million in obtaining OPS for 34 vessels and purchasing 48 LNG-yard tractors. This allows both ports to collect incentives.

In Case 2.1-Case 2.4, we have analyzed the optimal decisions in the presence of uniform (i.e., equal) tax and incentive rates for the competing ports. However, in practice, governments and regulators might impose unilateral (i.e.,unequal) emission policies for port entities such as emission control areas and region-specific carbon taxes. In the following discussion, we will investigate the overall optimal operational (i.e., economic and environmental) strategies for POLA and POLB under unilateral emission policies as profit-maximizing decision makers. In this way, the effects of uniform and unilateral emission regulations on the profits, cargo volumes and emissions can be compared in a competitive environment. More specifically, Case 2.5-2.7 are presented in the following discussion to study how port entities would respond to unilateral emission policies when one port has a higher incentive rate, a higher tax rate, and higher incentive and tax rates simultaneously. The results for these cases are shown in Figures 3a and 3b.

- Case 2.5) $\tilde{\tau}_1 = 10$, $\tilde{\tau}_2 = 15$, $\tilde{s}_1 = 10$ and $\tilde{s}_2 = 15$ ($thousands/tons of NO_x)
- Case 2.6) $\tilde{\tau}_1 = 10$, $\tilde{\tau}_2 = 10$, $\tilde{s}_1 = 10$ and $\tilde{s}_2 = 15$ ($thousands/tons of NO_x)
- Case 2.7) $\tilde{\tau}_1 = 10$, $\tilde{\tau}_2 = 15$, $\tilde{s}_1 = 10$ and $\tilde{s}_2 = 10$ ($thousands/tons of NO_x)

It can be observed that in all three cases, the regulatory policies have facilitated the adoption of sustainable energy solutions for both POLA and POLB to reduce their emission levels below their associated emission caps to avoid the emission tax, i.e., τ_1 and τ_2 are both 0. Furthermore, in case 2.5, due to the elevated tax and incentive rates for POLB, the overall emission of the region e_T can be reduced to 5276 tons, which is the lowest emission level compared with the other policies for the two-port region. As POLB invests more in emission reduction, it receives more incentive, which results in a increased profit of $336,152,000 in this case. Moreover, ports set similar service prices and demand (i.e., $p = \$50$, $q = 7,471,609$ TEUs) which is in accordance with our previous discussion.

It can be also observed that under the proposed model, increasing the tax or incentive rate for one port does not significantly impact the overall performance of the other port. This observation is consistent with the port's revenue model represented in Equation (2). After the optimal service price and energy demand are determined, each port authority attempts to seek its maximum profit (Equation (19)) by acting in its own best interest. In this process, a port entity does not have to take into account the rate of tax or incentive allocated to the other port entities or their responses in mitigating emissions. This observation verifies the model presented in Equations (7)-(17). It also provides the regulatory authority with the flexibility and the option to assign uniform and unilateral tax and incentive rates to different ports, knowing that the required emission level, tax rate, and incentive rate for one port does not significantly impact the other ports in the region.

The results from the single-port region and the two-port region cases indicate that emission tax is capable of reducing emission level on its own; however, the combination of tax and incentive would promote further emission reduction without impairment for the ports. In all of the instances, the most effective choice among green solutions is the onshore power supply. This is due to the fact that the emission mitigation capacity of OPS outweighs its overall investment cost, making it the most appealing green technology choice for port entities to adopt. Contrarily, LNG-fueled locomotives were not chosen in any of these cases despite its high service capacity and high reduction rate. This is in accordance with the fact that vessels are commonly more substantial contributors to NO_x emissions compared to other polluting sources at ports.

4. Conclusion

This paper develops a novel hybrid economic approach to assist both the regulatory authority and the stakeholders of port entities to strike a balance between energy sustainability and fair competition in the competitive environment of a region consisting of multiple ports. Simulation results obtained in Section IV indicate that the proposed approach is capable of effectively promoting green energy and reducing emissions while ensuring port customers' welfare and sustainable growth. By looking into different combinations of tax and incentive policies in both case studies, we can conclude that emission tax is a more effective approach for emission mitigation than incentive. In fact, higher rates of incentive are required to push the adoption of sustainable energy solutions when there is no tax, while even low tax rates can provide sufficient stimulation for the ports. Furthermore, the combination of tax and incentive can perform better and further motivate emission reduction. In terms of the selection of green solutions, our results indicate that the port tends to invest in solutions that strike the right balance between emission mitigation and overall cost. For instance, ports in our case studies have invested more in implementing onshore power supply due to its significant effectiveness in mitigating emissions with a relatively low investment cost.

There are some limitations in this work that can be addressed as future research. To propose a computationally tractable optimization model for stimulating sustainable energy at maritime ports, this paper assumed a linear relationship (1) between the port service price and the service demand and (2) between the emission level and economic incentives. However, one can investigate further on various factors ports consider in developing sustainable energy solutions and more accurate functions capturing the relationships among them. Furthermore, the proposed model did not consider parameter uncertainty in the model. Hence, one can extend this work to propose an optimization model considering uncertainties on energy demand, service price, and sustainable energy solution cost within the framework of robust optimization or stochastic optimization. Because such models can be difficult to solve, there is a need for a computationally efficient solution algorithm for solving large scale sustainable energy optimization models involving parameter uncertainty.

We envision that our research effort presented in this paper will facilitate the transformation of traditional industrialized ports into an integral contributing component of a sustainable eco-system. The proposed research creates the necessary structural and functional framework not only to strengthen the particular application of maritime ports, as demonstrated in this paper, but also to provide critical insights into revitalizing other large energy-intensive facilities that exhibit significant impacts on the prosperity and well-being of local communities and are also subject to the ever-changing regulatory environment.

References

[1] American Association of Port Authorities (AAPA), 2018 National Economic Impact of the U.S. Coastal Port System (2018).
URL `https://www.ttnews.com/articles/ports-shipping-industry-responsible-26-us-gdp-study-says`

[2] American Association of Port Authorities, National Economic Impact of the U.S. Coastal Port System (2019).
URL `https://www.ttnews.com/articles/ports-shipping-industry-responsible-26-us-gdp-study-says`

[3] D. Gibbs, P. Rigot-Muller, J. Mangan, C. Lalwani, The Role of Sea Ports in End-to-End Maritime Transport Chain Emissions, Energy Policy 64 (2014) 337–348.

[4] A. Molavi, G. J. Lim, and B. Race, A Framework for Building a Smart Port and Smart Port Index, International Journal of Sustainable Transportation-DOI: 10.1080/15568318.2019.1610919.

[5] Port of Los Angeles, Inventory of Air Emission (2015).
URL `https://www.portoflosangeles.org/pdf/2015_Air_Emissions_Inventory.pdf`

[6] T. Smith, J. Jalkanen, B. Anderson, J. Corbett, J. Faber, S. Hanayama, E. O'keeffe, S. Parker, L. Johanasson, L. Aldous, et al., Third IMO GHG Study.

[7] J. J. Corbett, J. J. Winebrake, E. H. Green, P. Kasibhatla, V. Eyring, A. Lauer, Mortality from Ship Emissions: A Global Assessment, Environmental science & technology 41 (24) (2007) 8512–8518.

[8] J. S. L. Lam, T. Notteboom, The greening of ports: A comparison of port management tools used by leading ports in asia and europe, Transport Reviews 34 (2) (2014) 169–189.

[9] A. Molavi, J. Shi, Y. Wu, G. J. Lim, Enabling smart ports through the integration of microgrids: A two-stage stochastic programming approach, Applied Energy 258 (2020) 114022.

[10] H. Davarzani, B. Fahimnia, M. Bell, J. Sarkis, Greening ports and maritime logistics: A review, Transportation Research Part D: Transport and Environment 48 (2016) 473–487.

[11] E. K. Norlund, I. Gribkovskaia, Reducing emissions through speed optimization in supply vessel operations, Transportation Research Part D: Transport and Environment 23 (2013) 105–113.

[12] F. Zhao, W. Yang, W. W. Tan, W. Yu, J. Yang, S. K. Chou, Power management of vessel propulsion system for thrust efficiency and emissions mitigation, Applied energy 161 (2016) 124–132.

[13] D. Steenken, S. Voß, R. Stahlbock, Container terminal operation and operations research - a classification and literature review, OR Spectrum 26 (1) (2004) 3–49.

[14] S. S. Fazeli, S. Venkatachalam, R. B. Chinnam, A. Murat, Two-stage stochastic choice modeling approach for electric vehicle charging station network design in urban communities, IEEE Transactions on Intelligent Transportation Systems (2020) 1–16.

[15] D. Singh, K. Subramanian, S. Singal, Emissions and fuel consumption characteristics of a heavy duty diesel engine fueled with hydroprocessed renewable diesel and biodiesel, Applied Energy 155 (2015) 440–446.

[16] A. Windecker, A. Ruder, Fuel economy, cost, and greenhouse gas results for alternative fuel vehicles in 2011, Transportation Research Part D: Transport and Environment 23 (2013) 34 – 40. `doi:https://doi.org/10.1016/j.trd.2013.04.002`.

[17] G. Zamboni, M. André, A. Roveda, M. Capobianco, Experimental evaluation of heavy duty vehicle speed patterns in urban and port areas and estimation of their fuel consumption and exhaust emissions, Transportation Research Part D: Transport and Environment 35 (2015) 1 – 10. `doi:https://doi.org/10.1016/j.trd.2014.11.024`.

[18] M. Meinert, M. Melzer, C. Kamburow, R. Palacin, M. Leska, H. Aschemann, Benefits of hybridisation of diesel driven rail vehicles: Energy management strategies and life-cycle costs appraisal, Applied energy 157 (2015) 897–904.

[19] Z. Bi, T. Kan, C. C. Mi, Y. Zhang, Z. Zhao, G. A. Keoleian, A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility, Applied Energy 179 (2016) 413–425.

[20] T. E. Notteboom, B. Vernimmen, The effect of high fuel costs on liner service configuration in container shipping, Journal of Transport Geography 17 (5) (2009) 325 – 337. `doi:https://doi.org/10.1016/j.jtrangeo.2008.05.003`.

[21] C.-H. Liao, P.-H. Tseng, C.-S. Lu, Comparing carbon dioxide emissions of trucking and intermodal container transport in taiwan, Transportation Research Part D: Transport and Environment 14 (7) (2009) 493 – 496. `doi:https://doi.org/10.1016/j.trd.2009.05.002`.

[22] C. Beckx, L. I. Panis, J. Vankerkom, D. Janssens, G. Wets, T. Arentze, An integrated activity-based modelling framework to assess vehicle emissions: Approach and application, Environment and Planning B: Planning and Design 36 (6) (2009) 1086–1102.

[23] H. Almutairi, S. Elhedhli, Carbon tax based on the emission factor: a bilevel programming approach, Journal of Global Optimization 58 (4) (2014) 795–815.

[24] United States Environmental Protection Agency, Economic incentives (2017).
URL `https://www.epa.gov/environmental-economics/economic-incentives`

[25] C. D. Kolstad, Empirical properties of economic incentives and command-and-control regulations for air pollution control, Land Economics 62 (3) (1986) 250–268.

[26] R. N. Stavins, Market-based environmental policies, in: Public policies for environmental protection, Routledge, 2010, pp. 41–86.

[27] D. F. Drake, P. R. Kleindorfer, L. N. Van Wassenhove, Technology choice and capacity portfolios under emissions regulation, Production and Operations Management 25 (6) (2016) 1006–1025. `doi:10.1111/poms.12523`.

[28] P. Kageson, Economic instruments for reducing emissions from sea transport, European Federation for Transport and Environment, 1999.

[29] C.-h. Han, Strategies to reduce air pollution in shipping industry, The Asian Journal of Shipping and Logistics 26 (1) (2010) 7–29.

[30] Tseng, P. H., Pilcher, N., Exploring the viability of an emission tax policy for ships at berth in Taiwanese ports, International Journal of Shipping and Transport Logistics 6 (2016) 705–722.

[31] D. La Torre, D. Liuzzi, S. Marsiglio, Pollution control under uncertainty and sustainability concern, Environmental and Resource Economics 67 (4) (2017) 885–903.

[32] W. Homsombat, T. L. Yip, H. Yang, X. Fu, Regional cooperation and management of port pollution, Maritime Policy & Management 40 (5) (2013) 451–466. `doi:10.1080/03088839.2013.797118`.

[33] D. Sheng, Z.-C. Li, X. Fu, D. Gillen, Modeling the effects of unilateral and uniform emission regulations under shipping company and port competition, Transportation Research Part E: Logistics and Transportation Review 101 (2017) 99 – 114. `doi:https://doi.org/10.1016/j.tre.2017.03.004`.

[34] Y. Zhou, L. Wang, J. D. McCalley, Designing effective and efficient incentive policies for renewable energy in generation expansion planning, Applied Energy 88 (6) (2011) 2201 – 2209. `doi:https://doi.org/10.1016/j.apenergy.2010.12.022`.

[35] M. Kainuma, Y. Matsuoka, T. Morita, G. Hibino, Development of an end-use model for analyzing policy options to reduce greenhouse gas emissions, IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 29 (3) (1999) 317–324.

[36] J. F. Bard, Practical bilevel optimization: algorithms and applications, Vol. 30, Springer Science & Business Media, 2013.

[37] G. Alperovich, I. Weksler, A class of utility functions yielding linear demand functions, The American Economist 40 (1) (1996) 20–23.

[38] J. Tirole, The theory of industrial organization, MIT press, 1988.

[39] M. Amini, F. Yousefian, An iterative regularized mirror descent method for ill-posed nondifferetiable stochastic optimization, arXiv preprint arXiv:1901.09506.

[40] A. Mitsos, Global solution of nonlinear mixed-integer bilevel programs, Journal of Global Optimization 47 (4) (2010) 557–582. `doi:10.1007/s10898-009-9479-y`.
URL `https://doi.org/10.1007/s10898-009-9479-y`

[41] World Ports Climate Initiative, What is OPS? (2019).
URL `http://wpci.iaphworldports.org/onshore-`

`power-supply/what-is-ops/`

[42] J. E. Gutierrez-Romero, J. Esteve-Pérez, B. Zamora, Implementing onshore power supply from renewable energy sources for requirements of ships at berth, Applied Energy 255 (2019) 113883.

[43] R. D. Cameron, Roadmap for Moving Forward with Zero Emission Technologies at the Ports of Long Beach and Los Angeles (2011).
URL `http://www.cleanairactionplan.org/documents/zero-emissions-roadmap-technical-report.pdf/`

[44] V. Jayaram, M. Yusuf Khan, J. W. Miller, W. A. Welch, K. Johnson, and D. R. Cocker, Evaluating Emission Benefits of a Hybrid Tug Boat (2010).
URL `http://www.cleanairactionplan.org/documents/foss-hybrid-tug-development-project-2-evaluating-emissions-benefits-of-a-hybrid-tug-boat-october-2010.pdf/`

[45] C. Mrazik, M. Baron, and A. Stabbert, A Cost Benefit Analysis of Diesel and Liquid Natural Gas for Locomotive Engines (2015).
URL `http://sites.psu.edu/clm5947/wp-content/uploads/sites/33075/2015/09/Project_02_Final_Draft-2.pdf`

[46] R. E. Rosenthal, GAMS: A Users Guide, gAMS Development Corporation, Washington, DC, USA (2016).

[47] Nick Sahinidis, “BARON user manual v. 2019.7.13”, the Optimization Firm, LLC (2019).

[48] H. S. Ryoo, N. V. Sahinidis, Global optimization of nonconvex nlps and minlps with applications in process design, Computers & Chemical Engineering 19 (5) (1995) 551–566.

[49] Eastern Research Group, 2013 Goods Movement Air Emissions Inventory (2017).
URL `http://porthouston.wpengine.com/wp-content/uploads/2016/11/PHA-2013-GMEI-Executive-Summary-Report.pdf`

[50] Port of Houston, Annual Report 2017 - year in Review (2017).
URL `https://porthouston.com/wp-content/uploads/82004_POHAR_FINAL-1.pdf`

[51] W. Jacobs, Port competition between los angeles and long beach: an institutional analysis, Tijdschrift voor economische en sociale geografie 98 (3) (2007) 360–372.

[52] Port of Long Beach, Port of Long Beach: The Green Port.
URL `http://www.polb.com/`

[53] Muni-Fed Antea Group Energy Partners and The Port of Long Beach, Microgrid Technology White Paper (2016).
URL `http://www.polb.com/civica/filebank/blobdload.asp?BlobID=13595`