INTERNATIONAL JOURNAL OF MARITIME TECHNOLOGY

IJMT Vol.10/No. 18/autumn and winter 2023 (25-48)

Available online at: www. ijmt.ir

A new multi-objective model for berth allocation and quay crane assignment problem with speed optimization and air emission considerations (A case study of Rajaee Port in Iran)

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ARTICLE INFO

Article History:
Received: 26 Apr 2022
Accepted: 09 Jan 2023

Keywords:
Container Terminals,
Berth Allocation Problem,
Quay Crane Assignment,
Mathematical Modeling,
Green Ports

ABSTRACT

Over the past two decades, maritime transportation and container traffic worldwide has experienced rapid and continuous growth. With the increase in maritime transportation volume, the issue of greenhouse gas (GHG) emission has become one of the new concerns for port managers. Port managers and government agencies for sustainable development of maritime transportation considered "green ports" to balance between environmental impacts and economic interests. Therefore, this study aims to integrate the Berth Allocation and Quay Crane Assignment Problem (BACAP) with speed optimization and vessels emission considerations. Rajaee port, the most important port in Iran, was selected as the case study. A mathematical model is developed based on the main characteristics of this port and is solved by GAMS IDE/CPLEX software. Given the NP-hard complexity of the BACAP, exact solution approaches need huge time, even for small and medium problems. Hence, an adapted Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) and a Multi-Objective Simulated Annealing (MOSA) algorithm are adopted to deal with the complexity of the proposed model. Sensitivity analysis is used to assess the applicability of the proposed model and evaluate the efficiency of the solution algorithms.

1. Introduction

Historically, humans have always strived to make good decisions and plan future actions to achieve the best results. This is an individual effort and a social endeavor [1]. During the first half of the twentieth century, commerce between regions in different continents experienced an upsurge with the development of diesel-driven cargo vessels, which increased maritime trade by improving freight transport efficiency. Moreover, the standardization of containers led to the construction of specialized vessels and ad hoc facilities at ports. Consequently, these infrastructures posed new operational planning

Please cite this article as: M. Mohammadizadeh, B. Pourabbas, K. Foroutani, M. Fallahian, Conductive polythiophene nanoparticles deposition on transparent PET substrates: effect of modification with hybrid organic-inorganic coating, International Journal of Engineering (IJE), TRANSACTIONS C: Aspects Vol. 28, No. 3, (March 2015) 321-329

problems, which began to be analyzed by management science. Maritime trade continues to grow in the twenty-first century, and the operations research (OR) community is increasingly interested in the mathematical analysis and formulation of the problems that container terminals encounter [2], [3]. Many of these problems consider the optimization of planning decisions so that scarce resources can be used efficiently. Thus, researchers attempt to tackle these problems by developing models and computational methods.

Nowadays, maritime transportation is the most widely used, the safest, and the cheapest mode of international freight transportation, which handles over 90% of world trade by volume for developing countries [4]. With the increasing demand for maritime trade, container shipping has become the core of modern logistics, and container terminals have become key nodes of international trading. One of the most important problems at the quayside of container terminals is the efficient allocation of quay space to the vessels berthing at the terminal over time, also known as the berth allocation problem (BAP). When ships berth at a quay, the quay cranes must be so assigned that vessel handling times are minimized. This leads to the quay crane assignment problem (QCAP). The BAP and QCAP are hard to be solved, even for medium and small-sized problems [5]. Therefore, artificial intelligence methods are employed to attain good solutions in reasonable computational times. In particular, this article addresses the integrated berth allocation and quay crane assignment problem (BACAP). This problem considers the assignment of berthing time and position (and QCs) to each vessel that is scheduled to arrive at anchorage at a certain time. Minimization of service time of vessels is the objective of the developed model. In formulating this problem, new and existing constraints arising in real-world cases, which give rise to interesting new variants, are taken into consideration.

With the rapid growth of the global economy, maritime transportation has become the most important mode of international trade. Meanwhile, emissions from maritime transportation have increased significantly. Some studies indicate that shipping emissions have increased ambient concentrations of air pollutants over vast areas of land and sea, and they are responsible for increases in premature deaths related to cardiopulmonary diseases and lung cancer in these areas [6]. This is related to the fact that ships operate much closer to where people live and work more than previously recognized. Typically, about 70% of emissions from international shipping occur within 400 km of the coastline [7]. One of the major environmental effects of seaports is air pollution that ways of tackling this issue and reducing greenhouse gas (GHG) emissions of ships, heavy trucks, inland transportation equipment, etc., are among the issues that many seaports are considering. On the other hand, port managers usually cannot focus solely on environmental issues, and often, constructive interaction between economic and environmental goals has to be considered, which will lead to a multi-objective decision making (MODM) problem. From the perspective of planning and optimization, the environmental sustainability of operations at ports requires appropriate models and approaches to consider and evaluate the environmental impacts of decision-making through various criteria. In particular, this research presents a multi-objective mathematical model and implements the augmented epsilon constraint (AEC), multi-objective simulated annealing (MOSA), and non-dominated sorting genetic algorithm-II (NSGA-II) methods to achieve Pareto solutions for the BACAP with speed optimization and air emission considerations.

Compared to pioneering studies, this study contributes to literature in the following ways. First, the fuel consumption and emissions of vessels are considered in an integral model of BACAP. Therefore, a multi-objective model is constructed for a tradeoff analysis between costs and environmental issues. Second, because the handling time of vessels at port markedly impact sailing times and speeds, the effects of quay-crane assignment are incorporated into the proposed model. This inclusion increases the flexibility when adjusting the schedules of vessels. Third, to the best of our knowledge, emissions from vessels during mooring periods are first quantified in literature for BAPs. Thus, emissions from vessels are examined for while moored and sailing. Fourth, arrival times of vessels at ports are formulated as decision variables, such that sailing speeds and quay-crane utilization can be balanced by adjusting the berthing times of vessels.

To optimize utilization of port resources and reduce a vessel's fuel consumption and emissions, this work attempts to optimize operational schedule at ports and vessels' shipping schedule. Moreover, service quality provided by port operators to vessels must not be reduced. This study applies a novel strategy for the hybrid berth and quay-crane allocation problem (BACAP), in which arrival times of vessels are formulated as decision variables of a nonlinear multi-objective mixed-integer programming model. The nonlinear objective is transformed into a second-order cone programming (SOCP) model. Further, vessel emissions while moored are calculated based on two parameters: wait time and emission factors. Finally, resource utilization at a port, impact of the number of quay cranes on port operational cost, and a vessel’s fuel consumption and emissions are analyzed.

The rest of the paper is organized as follows. Section 2 provides a concise literature review on previous studies related to BACAP. Section 3 defines the problem and special assumptions of the BACAP. Besides, a multi-objective mathematical model and the relationships between fuel consumption and GHG emissions are presented in this section. The applied solution methods are investigated in Section 4. Section 5 demonstrates and analyzes numerical experiments using real data of Rajaee Port. Finally, Section 7 concludes the research and presents recommendations for future studies.

2. Literature Review

As noted, Maritime logistics as the primary type of transportation has become the heart of worldwide trade. The industrialization of the world has increased the importance of sea transport. The standard of living has been improved by sea transportation of all kinds of products to people. Nowadays, the maritime industry has gained more importance than ever because the livelihoods of many people depend on it [8]. The main resource in seaports is the quay space (berths), which must be used efficiently by the port operators to provide a high-quality service to calling vessels. In container terminals, QCs also have to be assigned efficiently to moored vessels as they determine vessels' handling time and thus affect their schedules. Various versions of the BAP can be found in the literature depending upon the assumptions made on the spatial attribute, temporal attribute, handling time attribute, and performance measure. In particular, the alternatives for each attribute are as follows:

- **Spatial attribute.** This concerns the characteristics of the quay layout, which can be:
- Discrete (Disc). The quay is divided into several sections, called berths. In each berth, only a single vessel can be processed at a time. This partitioning may result from the actual layout of the quay or organizational criteria.
- Continuous (Cont). The quay is treated as a continuous segment along which vessels can be moored. The planning, in this case, is more complex than in the discrete case, but it allows better utilization of the space.
- Hybrid (Hyb). This is a discrete layout in which each berth may admit more than one vessel or vessels may occupy more than one berth under certain conditions. Here, there is also a special case of indented berths, in which two berths are opposite to each other.
- **Temporal attribute.** This attribute concerns restrictions on berthing and departure times, which can be:
- Static (Stat). No arrival times are given for the vessels or there are soft constraints. In the first case, it is considered that vessels are already waiting at the port, so they can berth at any time. In the second case, a vessel can berth before its expected arrival time at the expense of the cost of speeding up its arrival at the terminal.
- Dynamic (Dyn). A fixed arrival time is given for each vessel, so it cannot be moored before that time.
- Stochastic (Stoc). Arrival times are obtained from random distributions or may correspond to random scenarios.
- Cyclic (Cyc). Vessels call at the terminal periodically in fixed time intervals.
- **Handling time attribute.** The handling times of vessels can be:
- Fixed. They are given in advance as input to the problem and cannot be changed. For each vessel, the handling time may derive from a prior estimate made by both the terminal and the vessel operators.
- Position-dependent. The handling time of a vessel depends upon its berthing position.
- QCAP-dependent. They are obtained by solving the QCAP jointly with the BAP. Thus, the handling time of a vessel depends on how many cranes have been assigned to it.
- QCSP-dependent. They are obtained by solving the quay crane scheduling problem (QCSP) jointly with the BAP. Thus, the

handling time of a vessel depends on the work schedules of the assigned cranes.

- Stochastic. They are determined from random distributions.

- **Performance measure.** This concerns the factors taken into account in the objective function that is to be optimized. In most cases, the objective is to minimize a function comprising, for each vessel, such elements as waiting time before berthing, handling time, completion time, delay, speed-up cost, deviation from the desired position on the quay, or usage of equipment and manpower. Different weights are commonly used to set priorities between the elements considered and the vessels. In general, the time spent by each vessel at the terminal is usually considered in one way or another since it is a crucial factor in terminal competitiveness.

Many studies in the past have focused on the BAP and QCAP, among which optimization models have been widely used to analyze and plan the operations and events of container terminals. For a detailed review of research on the BAP and QCAP, see [9], [10], [11], and [12]. A brief classification of the previous berth allocation optimization models is presented in Table 1. With respect to the objective function, waiting and handling times are taken into account in most studies, and penalties related to delays and deviations from preferred positions are also common. Around 75% of the solution methods proposed are metaheuristics, whereas the remaining are exact approaches, based generally on integer linear models implemented on solvers. Exact methods are able to solve instances with a few vessels to optimality, while metaheuristics usually obtain good solutions in both small and large instances in very short computation times. These studies did not consider the impact of quay-crane allocation on fuel consumption and emissions. Moreover, emissions while moored are not considered in current formulations. To overcome these limitations, this work formulates a novel BACAP model that considers fuel consumption and emissions by vessels, and analyzes the impact of number of allocated quay cranes on port operational cost, and fuel consumption and emissions by vessels. In addition to integration of the BAP and the QCAP, using both exact and metaheuristic solution methods and considering environmental issues (fuel consumption and emissions) in the objective function of the presented model, as well as new realworld aspects (including time window service deadlines), are among the distinguishing features of this paper compared to previous studies.

In the standard BAP, handling times are usually assumed to be fixed and known in advance. However, in the seaside of container terminals, QCs are also a scarce resource that may affect the service time of vessels. The number of cranes simultaneously serving a vessel is often restricted between a minimum and a maximum number, for either technical or contractual reasons, and several vessels may be concurrently handled at the quay, so an efficient assignment of the cranes is also required to reduce the delays and the costs incurred by the terminal. Given that the handling time of a vessel depends on how many QCs have been assigned to it, and the handling time is taken into account in the BAP to berth ships, reaearchers are developing models by simultaneously considering these two problems. In the combined BACAP, in addition to time and berthing position, some cranes have to be assigned to each vessel. Moreover, two versions of the BACAP, i.e., a time-invariant version and a variable-in-time version, have been considered in the literature. In the time-invariant version, the number of cranes assigned to each vessel is fixed throughout its handling, while in the variable-in-time version, this number may change in each period. At any rate, the present study addresses the time-invariant BACAP. For more information, interested readers can see [13], [14], [15], [16] and [5].

3. Problem Definition and Formulation

Managers in many container terminals attempt to reduce costs by efficiently utilizing resources, including human resources, berths, container yards, container cranes, and various yard equipment [17]. Among all resources, berths are the most important resource whose good schedules will improve customers' satisfaction and increase port throughput, leading to higher revenues of the port. Port managers usually schedule the usage of berths by an intuitive trial-and-error method supported by a schedule board or a graphic user interface in a computer system [9]. This article attempts to satisfy various constraints for berthing container vessels by using a mixed-integer second-order conic programming (MISOCP) model.

The BACAP is the optimization problem of assigning berth position, cranes, and berthing time to calling vessels and minimizing the total assignment cost. As well, in the BAP, vessels are called to the available terminals over time and terminal planners assign a berthing position along the pier and a berthing time on the planning horizon for each vessel. The main reason is that the vessels can leave as soon as possible and the next vessels can be deployed to the dock.

Table 1. Summary of related articles

Articles	Type of Problem	Type of Formulation	Objective (s) (Minimization)	Solution Approach (s) (Algorithms)	Case Study or Real Data
[18]	BQCSP Cont, Stat	Integer Programming (IP)	The weighted summation of handling cost of containers, the penalty cost incurred by berthing earlier or later than the expected time of arrival, and the penalty cost of departure time	Lagrangean relaxation and the subgradient optimization procedure, the dynamic programming technique	--
[19]	BCAP Disc, Dyn	MIP	Total service time (including wait and handling times)	GA and maximum flow problem-based algorithm	--
[20]	BCSP Disc, Stat	MIP	The sum of the handling time, the waiting time, and the delay time for every vessel	GA	--
[21]	BSP Disc, Dyn	MIP	The total service time,the delayed departures, the total emissions, and the fuel consumption.	GA	--
[22]	BACAP Disc, Dyn	MILP & MIQP	The housekeeping costs generated by transshipment flows between vessels	CPLEX, Tabu search	✓ Port of Gioia Tauro, Italy
[23]	BAP Disc, Dyn	MIP	Operational expenditures, fuel cost, demurrage and cancellation penalties, dispatch credits	Hybrid simulation-optimization approach, C++ programming language	✓
[24]	BACAP Cont	MILP	The total handling time of vessels, the deviation from the preferred berthing location, the change in the number of cranes assigned to a vessel during its service	Rolling horizon framework	✓
[25]	BAP Hyb	MIP	Earliness/ Tardiness	Meta heuristics, VNS	--
[26]	BAP Disc	MIP	Minimizing the weighted sum of turnaround times of vessels	CPLEX	--
[27]	BACAP Disc	MIP	The trade-off between time-saving and energy-saving	MA (integrated simulation and optimization method)	--
[28]	BAP, QCAP Cont, Dyn	MIP	Total handling cost and average handling time per vessel	GAMS, CPLEX	--
[29]	BAP Disc, Dyn	Constraint Programming (CP)	Makespan, departure delay	Hybrid CP/IP (integer programming) algorithmic procedures	--
[30]	---	MIP	The weighted turnaround times	Rolling horizon & structural decomposition	--

[31]	Disc & Cont	MIP	The waiting time of vessels and the delay of vessels' departure	Column generation solution approach	--
[32]	Cont	MIP	The overall costs (including speeding, tardiness cost, and costs related to the QCs)	ALNS algorithm	--
[33]	BAP, QCSP Cont	MIP	The service completion time	RHH & branch and cut approach	--
[34]	BACAP Disc	MIP	The recovery cost	Reactive, RHOA	--
[35]	---	MINLP	Time, Cost, Demand	CPLEX, GAMS (novel collaborative agreement)	--
[36]	BAP Disc, Dyn	MIP	Cost, Time	Metaheuristic algorithms & competitive heuristic	--
[37]	BAP, QCSP Hyb, Dyn	MIP, MINLP	Makespan of handling all vessels	SA based simulation optimization	--
[38]	---	MIP	Optimize sailing routes and speeds within and outside the emission control areas (ECAs) while minimizing the total fuel cost and SO_2 emissions	Combining the two-stage iterative algorithm and fuzzy logic method based on the epsilon-constraint method	--
[39]	BAP Disc	MIP	The total cost of speed, delay, the penalty of vessels, and operational cost	Iterative heuristic	--
[40]	---	MINLP	Fuel, Emissions	Meta-heuristic algorithms	--
[41]	BAP Dyn	MIP	Total service time and quay occupation	Genetic algorithm and a dynamic programming method	✓ Port Administration of Paranaguá and Antonina (APPA), Brazilian coast
[42]	BSP and QCSP (BQCSP), Stoc	MIP	The deviations from target berthing locations and times as well as departure delays of all vessels.	Robust optimization, exact solution approach based on the EC method, SA and MOSA based metaheuristics and a pareto simulated annealing (PSA) approach	--
[43]	BAP, Stoc	MIP	The worst-case of the expected sum of delays with respect to a set of possible probability distributions of the handling times	Exact decomposition algorithm	--
[44]	Berth assignment and allocation problem (BAAP)	MILP, MINLP	Aims to assign proper number of berths for serving vessels of various liner clusters	CPLEX, Genetic algorithm	--
[45]	BAP, Stoc	Fully fuzzy multi-objective linear programming (FFMOLP)	The total waiting time of vessels and the makespan of the wharf operation	Lexicographic methods, Fuzzy epsilon-constraint method	--

[46]	BAP	Integer Programming (IP)	The baseline schedule cost in the deterministic situation and the recovery cost in the disruption scenarios	Multi-stage heuristic algorithm, CPLEX solver	--
This article	BACAP Hyb, Dyn	MILP, MISOCP	Port's operational costs, Vessel's fuel consumption, GHG emissions	AEC, MOSA, NSGA-II	✓ Rajaee port, Iran

The traditional aim of the BAP is to serve all vessels so that their handling times are minimized as much as possible and berthing constraints are satisfied too. In fact, in the BAP, planning of how to use the berth by arriving vessels at a specified time is decided. At different ports, the operators of each terminal are faced with this problem and according to the above definition, the terminal operator must determine the time and location of each vessel's berthing under the existing physical and time constraints [47]. This article aims to minimize operating costs at terminals and for shipping companies. On the other hand, the reduction of total fuel consumption and consequently, the reduction of the emissions at the port, which is produced by vessels, has also been considered in this formulation. Based on the scheme provided by [48], this problem can be classified as $\text{Hyb/Dyn/BAP} + \text{QCAP} / \sum \text{Operational Costs (wait. tard and tariff)} + \text{Fuel Consumption} + \text{Emissions}$.

In the problem addressed here, the pier has been considered a set of quay sections, each one admitting a limited number of vessels under special conditions (hybrid variant), and the number of quay cranes that serve a vessel is not changed after they are once assigned to the vessel during its handling. Furthermore, the maximum and the minimum number of cranes that it can admit and an estimate of its handling time for each number of cranes are known in advance. Vessels can be moored along the quay within a given time horizon, while QCs can move along the quay to serve the vessels provided that they do not cross each other. A berth plan can be rendered as a space-time diagram in which the vertical axis represents the position along the wharf and the horizontal one represents the time axis. Also, each vessel is shown with a rectangle. The handling (loading or unloading) time of the corresponding vessel is displayed with the length of a rectangle whereas the vessel length is represented by the height of a rectangle, as in the case of the BAP, now considering the number of cranes assigned to each vessel, too (Figure 1). The number of cranes for $v_1 = 3$, $v_2 = 2$, $v_3 = 2$, and $v_4 = 3$. As shown in Figure 1, each vessel has an optimal coordinate point for the mooring. The y-axis and the x-axis of the lower-left corner of a rectangle represent the berthing position and time of the corresponding vessel, respectively. The main purpose is to determine this place and time so that the existing conditions and restrictions are not violated.

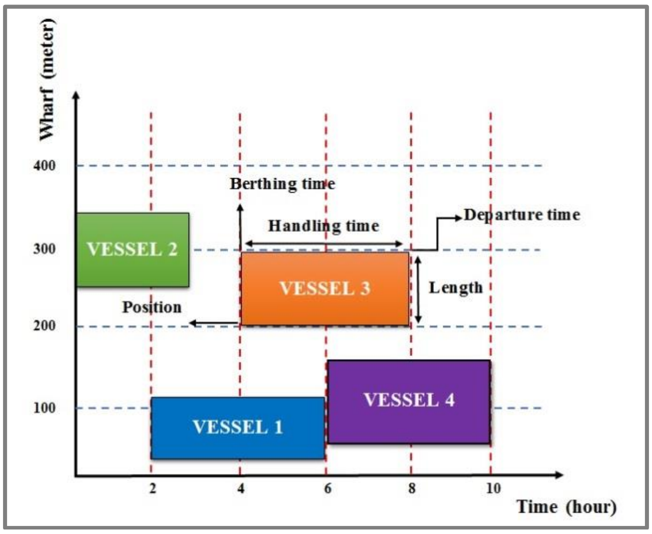

Figure 1. An example of a space-time diagram for the BACAP solution with 4 vessels and a quay 400m long

3.1. Assumptions

In general, the expected arrival time of a vessel is earlier than its berthing time. When a vessel is at the port, its auxiliary machinery will still operate, which will increase the fuel consumption of the vessel at the port. Generally, vessels' arrival times are optimized to achieve two objectives: (a) minimizing total fuel consumption and emissions hourly produced by all vessels during sailing and mooring periods, and (b) minimizing delayed departures of vessels. The main assumptions of this study are the following:

- Time:

- The planning horizon whose time unit is one hour is divided into multiple equal time segments.

- Containerships are to be moored within the planning horizon.
- Time windows can be of two types including an entering and a leaving window. At the entering windows, vessels can only pass through the channel one-way from the outer sea (or anchorage) to the inner terminals and one-way from the inner terminals to the outer sea during leaving windows. In other words, vessels are only allowed to arrive at the berth during entering windows and leave the berth during leaving windows.
- The minimum length of a time window is larger than the maximum time taken for a vessel to pass through the channel.

- Quay:

- Each position on the quay can accommodate one vessel at a time.
- There are some physical or technical restrictions such as container vessel and berth length, container ship draft, and water depth.

- Vessels:

- When a vessel is moored, the berthing position is kept unchanged in its entire handling process.
- Once the handling of a vessel has started, it cannot be interrupted (to avoid additional costs).
- The handling time of each vessel is considered to be independent of its berthing position. This assumption is reasonable if the quay has enough machinery and workers for container transportation between the yard and the quay at any moment. Hence, the cranes serving each vessel do not need to wait for vehicles. The increased transportation cost produced if the position of the vessel deviates from its desired position is included in the objective function.
- The handling time of each vessel is a function of cranes assigned to it. No specific relation is assumed between them, so it can be either linear or non-linear.
- The time for docking and undocking maneuvers is considered to be included in the vessel handling time.
- Vessels may have different relative importance. Therefore, cost coefficients are specific to each vessel. It means vessel priorities may be reflected by setting coefficients in the objective function for the waiting and delay costs.
- The inter-ship clearance is included in the vessel length. In general, for vessels longer than 130m, this clearance corresponds to 10% of its length. For small vessels, the minimum clearance is 10m.

- Cranes:

- The total number of QCs available at the quay (container terminal) is fixed, and all the cranes have the same characteristics.
- All QCs can move along the whole length of the quay, but they cannot cross each other.
- Each quay crane can be assigned to one vessel at most, in each time period.
- The number of quay cranes that have been assigned to a vessel does not change during its berthing time.
- The number of cranes that can be assigned to a vessel has a certain minimum and maximum.
- The emissions and working energy consumption of each QC per move have been ignored. In other words, the impact of quay crane allocation on fuel consumption and emissions is not considered in this article.

3.2. Relationship between Fuel Consumption and Sailing Speed

There is a nonlinear relationship between vessel speed (sailing speed) and fuel consumption [49]. Since there is a direct relationship between fuel emissions and fuel burnt, it is relevant to optimize sailing speed from the carrier and environmental perspective. The International Maritime Organization (IMO) has had a lot of considerations on measures of speed optimization, speed reduction, or slow steaming in recent years [50]. So, the aspects and effects of different measures have been subject of several studies. When designing a berth plan, the terminal planner considers the fuel consumption of vessels sailing to the ports during the berth planning period (e.g., a week). It is assumed that the berth planning time starts at time zero, and the distance from vessel i to terminal k is m_{ki} . The fuel consumption of vessel i, therefore, can be calculated by Equation (1) [51]:

$$F_{ki} = c_i^0 \times a_{ki} + c_i^1 \times m_{ki}^{\mu_i} \times a_{ki}^{1-\mu_i} \qquad (1)$$

where c_i^0, $c_i^1 > 0$ are the regression coefficients and $\mu_i \in$ [52]. It is assumed that $\mu_i = 3.5$ for feeder containerships (V_F), $\mu_i = 4$ for medium-sized containerships (V_M), and $\mu_i = 4.5$ for jumbo containerships (V_J) in this article. Meanwhile, Equation 1 is non-linear ($a_{ki}^{1-\mu_i}$), which significantly challenges the branchandbound solvers during computation. The compromise methods such as linear regression provided by [53] and speed discretization by [23] and [54] may result in calculation inaccuracy. Not avoiding this nonlinearity, it will be demonstrated that F_{ki} can be equivalently transformed to a linear objective subject to some second-order cone programming (SOCP) constraints, which makes it easy to solve the model to optimality in a reasonable time [55].

This work attempts to cast the non-linear fuel consumption equation F_{ki} as a linear objective subject to a group of SOCP constraints by substituting the term $a_{ki}^{1-\mu_i}$ with an auxiliary variable Q'_{ki} as presented in Equations 2-4 and obtain a computationally tractable MISOCP model where $\|\bullet\|_2$ denotes the Euclidean norm, u_{ki1}, u_{ki2}, u_{ki3}, $u_{ki4} \geq 0$, and a_{ki}, $Q'_{ki} > 0$.

$$\left.\begin{aligned}
&u_{ki1}^2 \leq a_{ki}.1 \Rightarrow \|(2u_{ki1}, a_{ki} - 1)\|_2 \leq a_{ki} + 1\\
&u_{ki2}^2 \leq u_{ki1}.Q'_{ki} \Rightarrow \|(2u_{ki2}, u_{ki1} - Q'_{ki})\|_2 \leq u_{ki1} + Q'_{ki}\\
&u_{ki3}^2 \leq u_{ki2}.a_{ki} \Rightarrow \|(2u_{ki3}, u_{ki2} - a_{ki})\|_2 \leq u_{ki2} + a_{ki}\\
&u_{ki4}^2 \leq u_{ki1}.1 \Rightarrow \|(2u_{ki4}, u_{ki1} - 1)\|_2 \leq u_{ki1} + 1\\
&1 \leq u_{ki3}.u_{ki4} \Rightarrow \|(2, u_{ki3} - u_{ki4})\|_2 \leq u_{ki3} + u_{ki4}
\end{aligned}\right\} \begin{matrix} i \in V_J \\ or \\ \mu_i = 4.5 \end{matrix} \qquad (2)$$

$$\left.\begin{aligned}
&u_{ki1}^2 \leq a_{ki}.Q'_{ki} \Rightarrow \|(2u_{ki1}, a_{ki} - Q'_{ki})\|_2 \leq a_{ki} - Q'_{ki}\\
&1 \leq a_{ki}.u_{ki1} \Rightarrow \|(2, a_{ki} - u_{ki1})\|_2 \leq a_{ki} + u_{ki1}
\end{aligned}\right\} \begin{matrix} i \in V_M \\ or \\ \mu_i = 4 \end{matrix} \qquad (3)$$

$$\left.\begin{aligned}
&u_{ki1}^2 \leq a_{ki}.1 \Rightarrow \|(2u_{ki1}, a_{ki} - 1)\|_2 \leq a_{ki} + 1\\
&u_{ki2}^2 \leq u_{ki1}.Q'_{ki} \Rightarrow \|(2u_{ki2}, u_{ki1} - Q'_{ki})\|_2 \leq u_{ki1} + Q'_{ki}\\
&1 \leq a_{ki}.u_{ki2} \Rightarrow \|(2, a_{ki} - u_{ki2})\|_2 \leq a_{ki} + u_{ki2}
\end{aligned}\right\} \begin{matrix} i \in V_F \\ or \\ \mu_i = 3.5 \end{matrix} \qquad (4)$$

3.3. Mathematical Formulation

This study establishes two novel models for the BACAP with variable and constant arrival time: i.e. a model with variable arrival time (VAT) and a model with constant arrival time (CAT). It is worth noting that with this BACAP formulation, terminal planners allocate the berthing positions and times to the vessels based on their expected arrival times. That is to say; the terminal operator regards the arrival time of each vessel as a constant known a priori. Similar to [56], this berth allocation strategy is referred as a CAT strategy. However, considering the arrival time of a vessel as a decision variable will provide the convenience of optimizing fuel consumption and emissions. This new berth allocation strategy is referred to as a VAT strategy. The numerical experiments, which are presented later in this study, reveal that the VAT strategy significantly outperforms the CAT strategy when taking fuel consumption and vessel emissions into account. The notations used in the mathematical model are listed below.

Sets:	
$V = \{1.2. \ldots . i\}$	The set of container ships under consideration in the berth plan
$Q = \{1.2. \ldots . k\}$	The set of container terminals under consideration in the berth plan
$N = \{1.2. \ldots . n\}$	The set of pollutants (CO_2, NO_x, and SO_x)
$T = \{1.2. \ldots . t\}$	The set of time periods in the planning horizon
$C = \{1.2. \ldots . c\}$	The set of quay cranes under consideration in the planning horizon
Parameters:	
R_{ki}	The requested departure time of vessel *i* at terminal *k*
P_{cki}	Specific handling time (estimated time of unloading and loading) of vessel *i* if crane *c* is assigned to it at terminal *k*
l_i	The length of vessel *i* (including the safe distance between adjacent vessels for mooring)
L	The total length of the container terminal
D_k	The water depth of terminal *k*
L_k	The length of terminal *k* (terminal endpoint

coordinates)

$d_i^{''}$ The draft of vessel *i*

m_{ki} The distance from vessel *i* to terminal *k*

sp_i The sailing speed of vessel *i*

LF The load ratio of average power used during normal operations to maximum rated power

PO_i The rated power of the engine of vessel *i*

AC_{ki} The average activity time of each engine of vessel *i* at terminal *k*

EF_{in} The emission factor of the *n*th pollutant for vessel *i* (in sailing periods)

EF'_{in} The emission factor of the *n*th pollutant for vessel *i* (in mooring periods)

FCF_n The fuel correction factor of the *n*th emission factor to reflect changes in fuel properties over time

EN_i The number of engines of vessel *i*

CAP_i The capacity of vessel *i* (quantity of vessels' cargo)

DEM Maximum warehouse capacity at terminal *k* (maximum freight required for delivery/discharge at terminal *k*)

DEN_l Minimum warehouse capacity at terminal *k* (minimum freight required for delivery/discharge at terminal *k*)

UT_k The upper bound of the time windows at terminal *k*

LT_k The lower bound of the time windows at terminal *k*

fc_{ki} The tariffs of terminal *k* for vessel *i*

Max_i The maximum number of quay cranes that can be assigned to vessel *i*

Min_i The minimum number of quay cranes that can be assigned to vessel *i*

w_i The weight of vessel *i* (the "weights" reflect the unit waiting costs of vessels)

IC_{ki} The idleness cost of vessel *i* at terminal *k*

M Big-M, a sufficiently large constant

Decision variables:

a_{ki} Arrival time of vessel *i* at terminal *k*

s_{ki} Time at which vessel *i* berths at terminal *k* on the space-time diagram (berthing start time)

f_{ki} The berthing position of vessel *i* at terminal *k* on the space-time diagram (berthing position)

r_{ki} Time at which vessel *i* leaves terminal *k* (departure time of vessel *i* at terminal *k*)

ε_{tki} Positive integer variable; total number of quay cranes assigned at time period *t* to vessel *i* at terminal *k*

II_{kij} Binary variable; $II_{kij} = 1$ indicates that vessel *i* is positioned below vessel *j* at terminal *k*, $II_{kij} = 0$, otherwise. Or when vessel *i* is positioned earlier than vessel *j* in the space-time diagram, $II_{kij} = 1$; otherwise, $II_{kij} = 0$. $i.j \in V.i \neq j$

III_{kij} Binary variable; $III_{kij} = 1$ indicates that vessel *i* is positioned left of vessel *j* along the wharf at terminal *k*, $III_{kij} = 0$, otherwise. $i.j \in V.i \neq j$

x_{ki} Binary variable; $x_{ki} = 1$ if vessel *i* berths at terminal *k*, $x_{ki} = 0$, otherwise.

∂_{tci} Binary variable; $\partial_{ci} = 1$ if quay crane *c* at time period *t* assigned to vessel *i*, $\partial_{ci} = 0$, otherwise.

The final model that is presented in the study is as follows:

$$Min\ f_1\ \sum_{k\in Q}\sum_{i\in V} w_i \times (s_{ki} + \sum_{t\in T}\sum_{c\in C}(\partial_{tci}\,.\,p_{cki}) - R_{ki}) + \sum_{k\in Q}\sum_{i\in V} IC_{ki} \times (s_{ki} - a_{ki}) + \sum_{k\in Q}\sum_{i\in V} fc_{ki} \times x_{ki} \quad (5)$$

$$Min\ f_2\ \sum_{k\in Q}\sum_{i\in V} c_i^0 \times a_{ki} + c_i^1 \times m_{ki}^{\mu_i} \times Q'_{ki} \quad (6)$$

$$Min\ f_3\ \sum_{k\in Q}\sum_{i\in V}\sum_{n\in\{CO_2,NO_x,SO_x\}} F_{ki} \times EF_{in} + \sum_{k\in Q}\sum_{i\in V}\sum_{n\in\{CO_2,NO_x,SO_x\}} x_{ki} \times (PO_i \times AC_{ki} \times LF \times FCF_{in} \times EN_i) \times EF'_{in} \quad (7)$$

Subject to: SOCP constraints (2)-(4) and:

$$s_{ki} + \sum_{t\in T}\sum_{c\in C}(\partial_{tci}\,.\,p_{cki}) \leq s_{kj} + M(1 - II_{kij}) \qquad \forall\, i.j \in V\ \&\ i \neq j\ \&\ k \in Q \quad (8)$$

$$f_{ki} + l_i \leq f_{kj} + M(1 - III_{kij}) \qquad \forall\, i.j \in V\ \&\ i \neq j\ \&\ k \in Q \quad (9)$$

$$II_{kij} + II_{kji} + III_{kij} + III_{kji} \geq 2 \times (x_{ki} + x_{kj} - 1) \qquad \forall\, i.j \in V\ \&\ i < j\ \&\ k \in Q \quad (10)$$

$$II_{kij} + II_{kji} + III_{kij} + III_{kji} \leq x_{ki} + x_{kj} \qquad \forall\, i.j \in V\ \&\ i < j\ \&\ k \in Q \quad (11)$$

$$\sum_{k\in Q} x_{ki} = 1 \qquad \forall\, i \in V \quad (12)$$

$$\underline{a}_{ki} \leq a_{ki} \leq \bar{a}_{ki} \qquad \forall\, i \in V\ \&\ k \in Q \quad (13)$$

$$s_{ki} \geq a_{ki} \qquad \forall\, i \in V\ \&\ k \in Q \quad (14)$$

$$s_{ki} = \sum_{t\in T}\sum_{c\in C}\partial_{tci} \times t \leq 1 \qquad \forall\, i \in V\ \&\ k \in Q \quad (15)$$

$$s_{ki} + \sum_{t\in T}\sum_{c\in C}(\partial_{tci}\,.\,p_{cki}) \leq r_{ki} \qquad \forall\, i \in V\ \&\ k \in Q \quad (16)$$

$$r_{ki} \leq s_{kj} + M(1 - II_{kij}) \qquad \forall\, i.j \in V\ \&\ i \neq j\ \&\ k \in Q \quad (17)$$

$$f_{ki} \geq x_{ki} \times L_{k-1} \qquad \forall\, i \in V\ \&\ k \in Q\ \&\ k > 0 \quad (18)$$

$$f_{ki} + l_i \leq \sum_{k\in Q} x_{ki} \times L_k \qquad \forall\, i \in V\ \&\ k \in Q \quad (19)$$

$$(d_i'' - D_k) \times x_{ki} \leq 0 \quad \forall\, i \in V \,\&\, k \in Q \quad (20)$$

$$DEN_k \leq \sum_{i \in V} CAP_i \times x_{ki} \leq DEM_k \quad \forall\, k \in Q \quad (21)$$

$$s_{ki} - M(1 - x_{ki}) \leq UT_k \quad \forall\, i \in V \,\&\, k \in Q \quad (22)$$

$$s_{ki} + M(1 - x_{ki}) \geq LT_k \quad \forall\, i \in V \,\&\, k \in Q \quad (23)$$

$$\sum_{c \in C} \sum_{i \in V} \varepsilon_{tki} \leq C \quad \forall\, t \in T \quad (24)$$

$$\sum_{t \in T} \sum_{c \in C} \partial_{tci} \leq 1 \quad \forall\, i \in V \quad (25)$$

$$Min_i \leq \sum_{t \in T} \sum_{c \in C} \partial_{tci} = \varepsilon_{tki} \leq Max_i \quad \forall\, i \in V \,\&\, k \in Q \quad (26)$$

$$II_{kij}, III_{kij}, x_{ki}, \partial_{ci} \in \{0,1\} \quad \forall\, i.j \in V \,\&\, i \neq j \,\&\, k \in Q \,\&\, c \in C \quad (27)$$

$$s_{ki}, f_{ki}, a_{ki}, r_i, Q'_{ki} \geq 0 \quad \forall\, i \in V \,\&\, k \in Q \quad (28)$$

In this formulation, port operational cost is defined as the objective function (5), which includes three components. The first statement is to minimize the total departure delay of all vessels, which is a typical measure of the service level of container terminals and popularly adopted by terminal planners. The second statement minimizes the cost of idleness time, and the third statement minimizes port and maritime service tariffs. The objective function (6) minimizes vessel fuel consumption. The first statement of the objective function (7) minimizes the volume of total GHG emissions when sailing to terminals, and the second term minimizes the volume of emissions during mooring. The set of constraints (8) to (11) enforce the non-overlapping conditions among vessels in the space-time planning diagram. Constraint (12) ensures that each vessel is berthed at only one terminal. Constraints (13) and (14) are related to the arrival time of vessels and mean that a vessel cannot be berthed before its arrival time. Constraints (15) link the berthing time of a vessel to variable ∂_{tci} to prevent inconsistencies. Constraints (16) and (17) are related to the calculation of the completion time of each vessel and state that vessels are not allowed to berth earlier than the time of departure of previous vessels at a terminal. Constraints (18) and (19) ensure that all vessels are berthed within the boundaries of the wharf; in other words, if the stern of vessel i is in terminal k, the bow of vessel i must also be in terminal k. Constraint (20) ensures that the draft of vessels is less than or equal to the water depths of terminals. Constraint (21) indicates the cargo capacity of the vessels, as well as the minimum and maximum cargo required by the terminals. Constraints (22) and (23) indicate the time windows of the terminals for the berthing of vessels. As such, they represent the upper and lower boundaries of these time windows, respectively. The set of constraints (24) to (26) are related to the assignment of quay cranes to vessels. Thus, constraint (24) indicates the limitation of the maximum number of available quay cranes. Moreover, the number of cranes assigned to vessels in each time period cannot be greater than the total number of cranes available at the quay due to constraints (24). Constraint (25) indicates the necessity or non-necessity of assigning a quay crane to a vessel (the handling of each vessel starts only once and with a fixed number of cranes) and constraint (26) indicates the minimum and the maximum number of quay cranes required to be assigned to a vessel. Finally, constraints (27) and (28) specify the domains and type (nature) of the variables used.

4. Solution Method

The presented mathematical model is solved by the solver of GAMS IDE. Meanwhile, due to the complexity of the formulated mathematical model, an adapted NSGA-II and a MOSA algorithm are employed. Given that all the local search procedures, rely on the constructive algorithm to obtain feasible solutions, valid solutions for the BACAP can also be obtained from other machine learning methods such as Artificial Neural Networks (ANNs) and Support Vector Regression (SVR). To understand the capabilities of the methods of machine learning, refer to [57] and [58]. First of all, the concept of multi-objective optimization that is necessary for this work is discussed.

4.1. Multi-objective Optimization

A single-objective optimization problem has only one objective function. But in a multi-objective mathematical programming (MOMP) problem, the number of objective functions that are optimized simultaneously is more than one. Assume M uncorrelated objectives to be minimized. Equation 29 represents the mathematical definition of a multi-objective optimization problem:

$$\min z = \big(f_1(x).f_2(x).\dots.f_m(x)\big) \quad \text{subject to } x \in X \quad (29)$$

where X is the set of feasible solution space, x is a feasible solution, and $f_1(x)$ is the first objective function value of solution x. Objective functions are often in contradiction so that the improvement of one leads to the deterioration of the other. Thus, a binary relationship of dominance acts as a comparative function between feasible solutions. It means that if the solution x_1 is better than the solution x_2 for all objectives, it is said that x_1 dominates x_2 and it is written as $x_1 \prec x_2$. But, in optimization problems, it is aimed to find a non-dominant solution (or solutions) that cannot be dominated by other feasible solutions. A set of non-dominated solutions is called Pareto set (or Pareto front) [59, 60]. In these cases, the decision-makers seek the "most preferred" solution versus the optimal solution. In MOMP, the concept of optimality is substituted with that of Pareto optimality or efficiency. The Pareto optimal (or efficient, non-dominated, non-inferior) solutions refer to the solutions that are impossible be improved in one objective function unless their performance in at least one of the rest is deteriorated [61].

4.2. AEC Method

A well-organized technique for solving MOMP problems, in which the main objective function is identified among all other objective functions, is known as the epsilon constraint (EC) method, which has several important advantages over the traditional weighting method. Despite its advantages over the weighted method, the EC method has two limitations that need attention. At first, the scope of the objective functions is not optimized more than the efficient set, and to solve this problem, the lexicographic optimization technique is presented. Secondly, the optimal Pareto solutions produced using the EC method may be dominant or ineffective. To overcome this defect, the augmented epsilon constraint (AEC) is presented, which is a new version of the EC method and prevents the production of weak Pareto optimal solutions. As a result, by preventing redundancies, the whole process is accelerated. In general, the AEC method leads to the most optimal Pareto optimal solution [62]. Interested readers are referred to [63] and [64] to learn more about the AEC method.

4.3. MOSA

Simulated annealing (SA) is a meta-heuristic algorithm that in an optimization problem, provides solutions using a probabilistic method. The algorithm starts from a desired solution in the problem space and then selects another solution in the neighborhood of the current solution. The algorithm then decides on the basis of a probability-based method whether to stay in the current solution or move to the neighboring solution. The algorithm, in order to escape from the local minimum and reach to the global minimum, investigates the problem space by imitating the metal annealing process and reducing the temperature to a low temperature [65]. Applications of SA can be seen in the parallel machine scheduling problem [66] or the problem of task scheduling in heterogeneous distributed computing systems [67].

The pseudo-code of SA is shown in Figure 2. In this pseudo-code, s_0 contains the solution, and minimization is assumed. This algorithm generates local solutions in the neighborhood of the current solution and accepts a new solution based on a function depending on the current temperature "t". The number of iterations to apply the algorithm (ITER) and the cooling schedule (CS) are considered as two main parameters of SA that have a significant effect on the performance of the algorithm. [52].

The use of SA in multi-objective (called "Multi-Objective Simulated Annealing", or MOSA in short) optimization was initially proposed by [68]. The work proposes to use a target-vector approach to solve a bi-objective optimization problem (several possible transition rules are proposed). A solution x' is generated in the neighbourhood of the current solution x. If $f(x')$ is non-dominated with respect to $f(x)$, it is accepted as the current state, and a set of non-dominated solutions is also updated. This is the basic approach used with local search procedures. The set or archive of non-dominated solutions constitutes the memory of the approach and allows the generation of several elements of the Pareto optimal set in a single run. Notice, however, that in this case, only local non-dominance is used to fill up the archive of solutions, and a further filtering procedure is required to reduce the number of non-dominated solutions presented to the decision-maker.

1. Select an initial (feasible) solution s_0
2. Select an initial temperature $t_0 > 0$
3. Select a cooling schedule CS
4. Repeat
    Repeat
        Randomly select $s \in N(s_0)$ // $N =$ neighborhood structure
        $\delta = f(s) - f(s_0)$ // $f =$ objective function
        If $\delta < 0$ then
            $s_0 \leftarrow s$
        Else

Generate random x // uniform distribution in the range (0,1)
If $x < \exp(-\delta/t)$ then
$s_0 \leftarrow s$
Until $max.num$ of iterations $ITER$ reached
$t \leftarrow CS(t)$
5. Until stopping condition is met

Figure 2. Simulated annealing pseudo code [69].

4.4. NSGA-II

NSGA-II is a generic non-explicit building-block multi-objective evolutionary algorithm (BB-MOEA) applied to multi-objective problems (MOPs) based on the original design of NSGA. As shown in Figure 3, it builds a population of competing individuals, ranks and sorts each individual according to non-domination level, applies evolutionary operations (EVOPs) to create a new pool of offspring, and then combines the parents and offspring before partitioning the new combined pool into fronts. NSGA-II then conducts niching by adding a crowding distance to each member. It uses this crowding distance in its selection operator to keep a diverse front by making sure each member stays a crowding distance apart. This keeps the population diverse and helps the algorithm to explore the fitness landscape [70], [71]. This MOEA is currently used in most MOEA comparisons. It has also been used as a foundation for other algorithm designs.

5. Numerical Experiments

In order to evaluate the performance of the proposed model, numerical experiments are executed. Because most articles in the literature use data generated randomly in their experiments, making comparisons between researches difficult, the data set for model validation in this article are generated by using the benchmark instances presented in [51]. All calculations are performed in GAMS software version 25.1.2 and on a PC with a 64-bit operating system, 4 GB RAM, 2.20 GHz CPU, and Intel (R) Core (TM) i3-2330M.

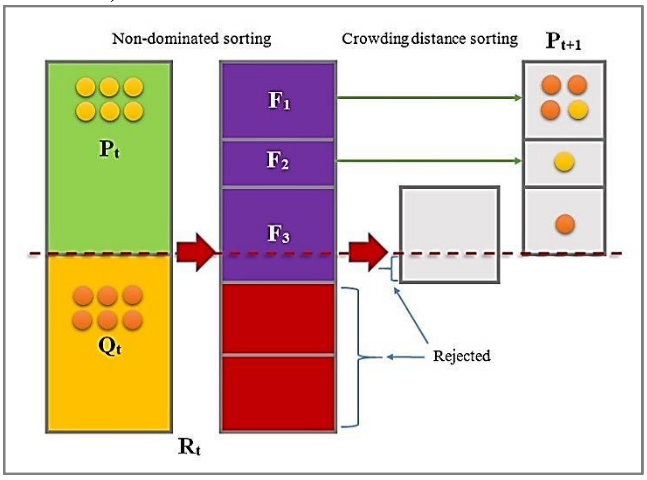

Figure 3. Flow diagram that shows how the NSGA-II works. Pt is the parents' population and Qt is the offspring population at generation t. F1 are the best solutions from the combined populations (parents and offspring). F2 are the second-best solutions and so on

5.1. Validation

To validate the proposed model, a set of 10 different vessels, 3 terminals, and 22 quay cranes are assumed. Each terminal can serve at least two containerships together and allocate a maximum of 4 to 6 and a minimum of 1 to 3 quay cranes per vessel. The total length of the wharf (L) is 1200 meters, and the planning horizon is one week (168 hours). The idleness coefficient or the cost of one hour of idleness at the terminal (IC_{ki}) is $200. The speed of vessels in terms of engine power and the amount of their cargo is calculated by uniform distribution between 8 and 28 knots (unit of speed in knots equal to 6076.12 feet per hour) and also the earliest and latest arrival times of vessels, the requested departure time of vessels, the distance between vessels and terminals (in nautical miles, 1 nautical mile is equal to 1852 meters), the cost of tariffs for each terminal to serve each of the incoming vessels, and the average activity time of each engine of vessels are as follows (time parameters are in hours):

$AC_{ki} = Uniform\,[10,30]$ $\quad\quad$ $\bar{a}_{ki} = Uniform\,[51,240]$

$R_{ki} = a_{ki} + p_{ki} \times Uniform\,[1,2]$ $\quad\quad$ $m_{ki} = a_{ki} \times \frac{sp_i}{2}$

$fc_{ki} = Uniform\,[100,200]$ $\quad\quad$ $\underline{a}_{ki} = Uniform\,[0,50]$

The constant regression coefficients c^0 and c^1 for all vessels are 699 and 0.004238, respectively. The load ratio (LF) is 0.5, and the number of engines per vessel (EN_i) is 4 since most sea-going vessels have 4-stroke auxiliary engines. The fuel correction factors of CO_2,

NO_x, and SO_x are 1, 0.948, and 0.04, respectively. Other relevant parameters are presented in Tables 2-4. The AEC method has been coded in GAMS, a widely used modeling language [72]. To apply the AEC method, this study considers the first objective function (minimizing total operational cost f_1) as the main goal and the second objective (minimizing fuel consumption f_2) as the minor goal. Besides, it limits the third objective (minimizing environmental effects f_3) to different amounts of epsilon. The implementation results of the proposed model (VAT and CAT) are summarized in Figure 4 and Table 5.

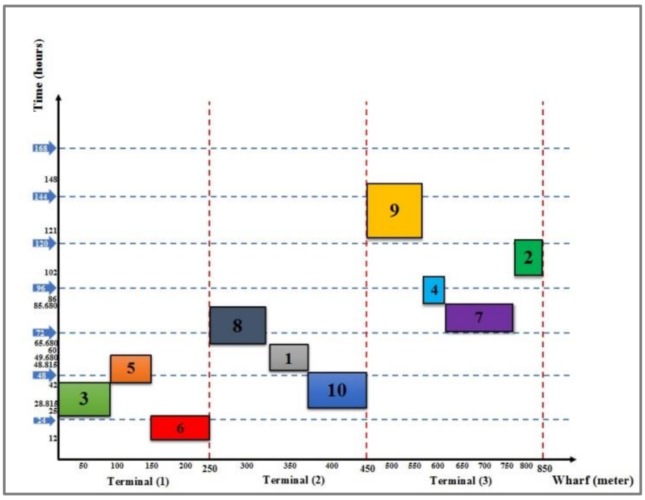

Figure 4. A feasible solution to the problem using the AEC method

Since the BACAP is NP-hard in general, it could be solved to optimality only for small instances, and many metaheuristics were used for large-scale instances. For more information, refer to [73]. In this section, large-scale instances are solved using metaheuristic algorithms of MOSA and NSGA-II, which are briefly explained below. All numerical experiments are formulated in MATLAB (ver. R2019b) environment using the computer system described above.

As was previously mentioned, the scale and nature of the research model at large terminals often makes it impossible (NP-hard) for the decisions made to be optimal. The exact solution of the AEC method is used in GAMS software for small and medium-size instances. Figure 5 shows a comparison of the model solution presented in this article using the three solution methods presented (in small scales). As can be seen, metaheuristic algorithms (MOSA and NSGA-II) have provided solutions close to the exact solution (AEC). Therefore, the outputs of these algorithms can be trusted to solve large BACAP problems with time budget and other limitations.

5.2. Case Study

Rajaee Port is located on the north shores of the Hormuz Strait and 23 kilometers west of Bandar Abbas, the capital of Hormozgan Province, in southern Iran. It is around 1500 kilometers (933 miles) southeast of Tehran, the capital of Iran. With 12 wharves, Rajaee Port is Iran's biggest multipurpose port, so over half of Iran's commercial trading is carried out at Rajaee. The port complex also accounts for over 90% of all container throughput in Iran. The Rajaee Port Complex has seen a spectacular jump in private sector investment, which has been unprecedented in the last 20 years. The stated port is interacting with more than 80 other ports in the world and has the highest rate of cargo transit throughout Iran. A large volume of cargo being shipped towards Central Asia passes through this port. The development plan for the port is composed of three phases to add berths capable of berthing largest modern vessels. Detailed descriptions of the Rajaee container terminal and its different modes of operation are provided by [74] and [75]. The general schematic of Rajaee Port is depicted in Figure 6.

5.3. Input Data

This subsection presents the data format collected from Rajaee Port (Table 6) and compares the performance of each of the applied algorithms. Unemployment costs at all berths are fixed (200$ per hour). There is also a penalty of 300$ per hour of delay (suspension) at the berths for vessels with a tonnage of less than 1000 TEU and 400$ for other vessels. fc_{ki} ($/hours) for problems (1) to (6), (7) to (12) and (13) to (20) using uniform distribution are equal to [100, 200), [200, 250) and [250, 400), respectively. Furthermore, the constant regression coefficient c^0 are [477.4, 719.9], [580.7, 718.6] and [491.7, 709.2] and the constant regression coefficient c^1 are [0.0151, 0.0245], [0.003709, 0.004299] and [0.000864, 0.000972] for feeder, medium, and jumbo vessels, respectively.

5.4. Parameter Tuning

The performance and quality (best response, solution time, etc.) of any meta-heuristic algorithm for optimizing a problem is strongly influenced by its parameter configuration. This study uses the Taguchi method for the configuration parameters [76]. The following effective parameters were configured for the MOSA and NSGA-II, respectively: temperature

(T), temperature reduction or damping rate (R), repository size or archive size (MaxA), population size (nPop), maximum number of iterations (MaxIt), maximum number of inner iterations, or number of the implementation of the neighborhood structure on each solution of the population (nMove), percentage of crossover (PC), percentage of mutation (PM), and mutation rate (MU). The final configurations of parameters for the two algorithms are summarized in Table 7.

Table 2. Specifications of berths

No. of berths	L_k *(meter)*	D_k *(meter)*	DEN_k *(TEU)*	DEM_k *(TEU)*	LT_k *(hours)*	UT_k *(hours)*
Berth 1	250	18	20	1300	12	168
Berth 2	450	14	20	950	24	168
Berth 3	850	24	20	1150	72	168

Table 3. Specifications of vessels

No. of vessels	*Type*	μ	CAP_i *(TEU)*	PO_i *(horsepower)*	W_i *($)*	l_i *(meter)*	d_i *(meter)*	P_{ki} *(hours)*
Vessel 1	Feeder	3.5	60	60	4	40	11	16
Vessel 2	Jumbo	4.5	140	400	1	80	23	19
Vessel 3	Medium	4	120	125	4	90	18	17
Vessel 4	Feeder	3.5	105	90	4	50	22	16
Vessel 5	Jumbo	4.5	135	320	8	60	18	18
Vessel 6	Medium	4	105	200	2	100	10	13
Vessel 7	Jumbo	4.5	145	350	4	150	12	14
Vessel 8	Medium	4	95	230	1	75	13	20
Vessel 9	Jumbo	4.5	70	270	3	120	19	27
Vessel 10	Medium	4	95	230	1	75	13	20

Table 4. Reference values of emission factors

Emission factors	*Unit*	SO_X	NO_X	CO_2
Emissions while sailing (EF_{in})	$\frac{g}{kg-fuel}$	60	87	3110
Emissions while mooring (EF'_{in})	$\frac{g}{kw-h}$	12.3	13	683

Table 5. The results of the AEC method with two strategies of VAT and CAT

	Type	**Solver**	**Parameters**	**Fitness obj 1**	**Fitness obj 2**	**Fitness obj 3**
1	MISOCP	CPLEX	VAT	439284.410	158207.361	5.826427×10^{8}
2	MIP	CPLEX	CAT	561470.207	2175022.739	7.131858×10^{9}

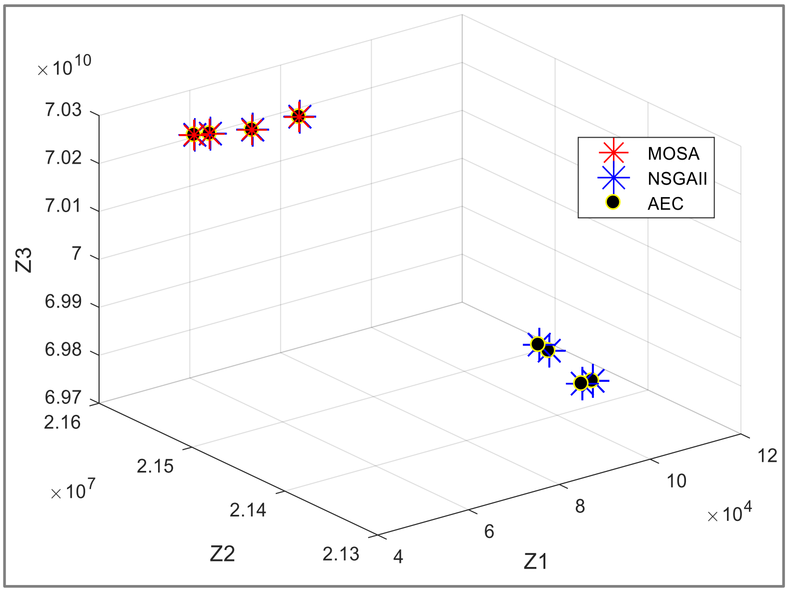

Figure 5. Validation of research algorithms

Figure 6. A general schematic of the Rajaee Port Complex

In general, the quality of the approximated sets has to be measured with a quantitative metric. There are several quantitative measurement approaches to compare different sets of Pareto solutions in the multi-objective literature. This article used four indices (performance criteria) proposed by [77] as follows: diversity or diversification matrix, the closeness between Pareto solution and ideal point (0,0) or mean ideal distance (MID), the spread of non-dominance solution (SNS), and the rate of achievement to three objectives simultaneously (RAS). The values obtained are shown in Table 8.

According to the results in Table 8, the NSGA-II algorithm has given better results than the MOSA in both MID and RAS evaluation metrics, and the MOSA algorithm is better in terms of Diversity and SNS criteria. Also, they are equal in terms of examining the average of the algorithms, and each of the two indices is superior to the other algorithm. To validate this superiority, it is necessary to use analysis of variance (ANOVA), which is discussed below. Also, Minitab software was used to check the normality of the data ($P-VALUE \geq 0.01$) (Figures 7 and 8).

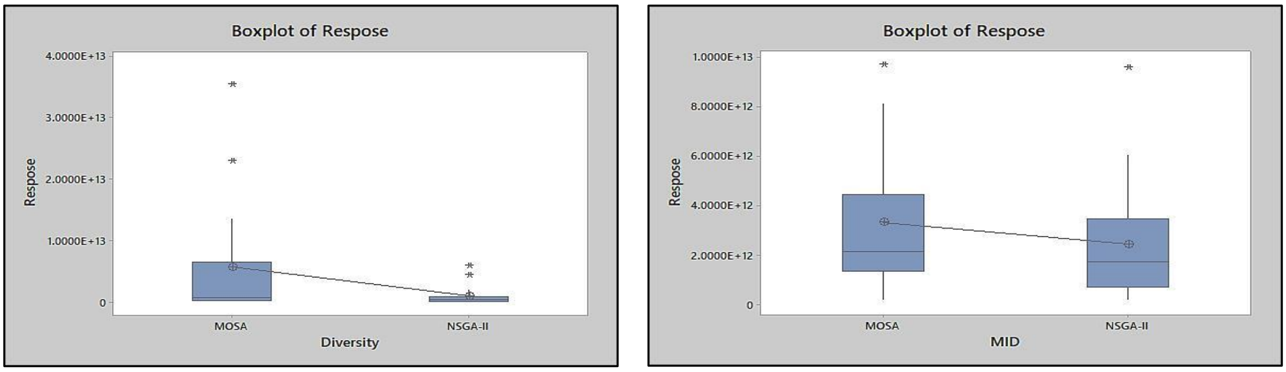

Figure 7. Graphical representation of the differences between the two algorithms (Diversity & MID)

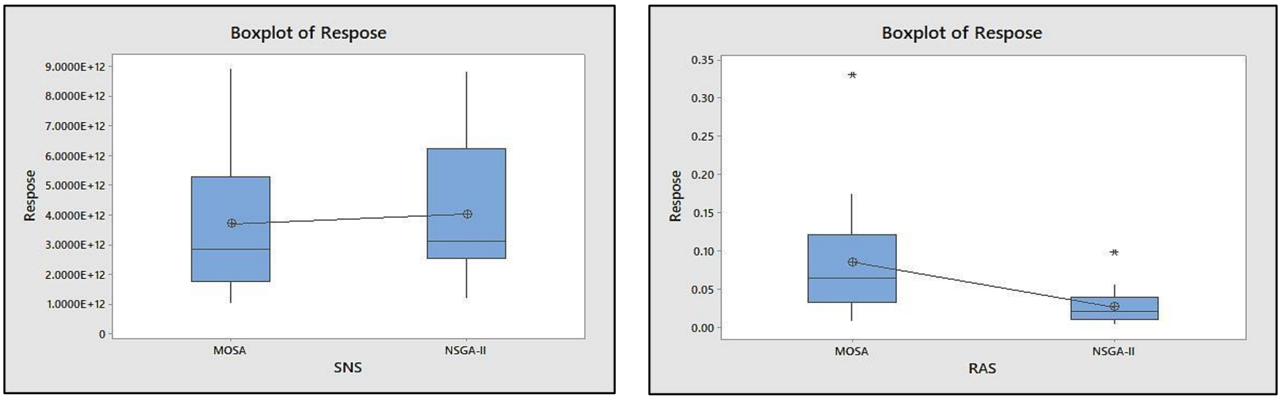

Figure 8. Graphical representation of the differences between the two algorithms (SNS & RAS)

In addition to the above metrics, to further investigate the algorithms, the solution time metric can also be included to conclude which algorithm performs better.

Table 6. Input data (mostly based on the data collected from Rajaee Port).

Size of vessels	***No of experiments***	***Vessels * Berths***	l_i ***(meter)***	d_i'' ***(meter)***	CAP_i ***(TEU)***	sp_i ***(Knots)***	PO_i ***(horsepower)***	P_{ki} ***(hours)***	AC_{ki} **(hours)**
Feeder	**(1)**	2 × 10	[45,100)	[5,8)	[50,200)	[10,24]	[50,100)	[6,30]	[6,12)
	(2)	3×10	[45,100)	[5,8)	[50,200)	[10,24]	[50,100)	[6,30]	[6,12)
	(3)	4×10	[45,100)	[5,8)	[50,200)	[10,24]	[50,100)	[6,30]	[6,12)
	(4)	3×15	[45,100)	[5,8)	[200,500)	[10,24]	[50,100)	[6,30]	[6,12)
	(5)	4×15	[45,100)	[5,8)	[200,500)	[10,24]	[50,100)	[6,30]	[6,12)
	(6)	5×15	[45,100)	[5,8)	[200,500)	[10,24]	[50,100)	[6,30]	[6,12)
e di	**(7)**	6×20	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)

	(8)	7×20	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)
	(9)	7×25	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)
	(10)	8×25	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)
	(11)	8×30	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)
	(12)	9×30	[100,170)	[8,12)	[500,800)	[12,28]	[100,250)	[10,54]	[12,20)
Jumbo	**(13)**	10×35	[170,230)	[12,15)	[800,1000)	[14,30]	[250,425)	[20,38]	[20,30)
	(14)	11×35	[170,230)	[12,15)	[800,1000)	[14,30]	[250,425)	[20,38]	[20,30)
	(15)	12×35	[170,230)	[12,15)	[800,1000)	[14,30]	[250,425)	[20,38]	[20,30)
	(16)	10×40	[230,300)	[12,15)	[1000,1500)	[14,30]	[250,425)	[20,38]	[20,30)
	(17)	12×40	[230,300)	[12,15)	[1000,1500)	[14,30]	[250,425)	[20,38]	[20,30)
	(18)	13×40	[230,300)	[12,15)	[1000,1500)	[14,30]	[250,425)	[20,38]	[20,30)
	(19)	14×45	[300, ∞)	[12,15)	[1500, ∞)	[14,30]	[250,425)	[20,38]	[30, ∞)
	(20)	15×50	[300, ∞)	[12,15)	[1500, ∞)	[14,30]	[250,425)	[20,38]	[30, ∞)

Table 7. Tuned values of the parameters by the Taguchi method

MOSA		***NSGA-II***	
Parameters	***Values***	***Parameters***	***Values***
T	100	*MaxIt*	150
R	0.99	*nPop*	60
MaxA	50	*PC*	0.7
NPop	80	*PM*	0.25
MaxIt	150	*MU*	0.02
nMove	8	--	--

Table 8. A comparison of evaluation metrics (Diversity, MID, SNS, and RAS)

Problems	**Criteria**							
	Diversity		**MID**		**SNS**		**RAS**	
	MOSA $\times 10^{11}$	**NSGA-II** $\times 10^{11}$	**MOSA** $\times 10^{11}$	**NSGA-II** $\times 10^{11}$	**MOSA** $\times 10^{12}$	**NSGA-II** $\times 10^{12}$	**MOSA** $\times 10^{-2}$	**NSGA-II** $\times 10^{-2}$
1	60.1	60.1	24.1	25.8	2.95	2.98	0.721	0.429
2	20.7	20.2	12.5	12.5	5.56	5.14	1.7154	0.7456
3	6.22	8.59	11.1	11.0	2.02	2.61	1.9923	0.685
4	3.54	9.51	53.6	50.6	1.10	3.49	2.6113	0.3777
5	2.78	2.13	36.8	34.7	8.95	6.72	3.1839	0.9543
6	4.33	6.51	20.3	60.7	8.79	1.80	3.665	2.1955
7	3.50	4.35	20.8	20.5	1.00	8.83	3.3867	1.6503
8	63.0	44.1	78.0	38.2	1.99	1.19	7.8306	4.3481
9	1.60	9.46	17.3	34.3	4.90	2.49	17.5578	9.8297
10	5.12	0.616	45.0	21.6	1.42	1.77	8.2249	2.6933
11	1.02	0.250	81.3	1.67	2.76	7.89	32.9588	5.5774
12	0.849	0.103	16.3	15.1	2.36	2.95	8.0849	1.9675
13	8.94	4.54	1.60	8.19	2.96	1.38	16.0245	4.5169

14	39.7	1.34	96.9	95.8	1.69	3.45	3.9118	1.1907
15	355	1.68	43.1	6.45	1.14	5.05	12.5912	2.7473
16	66.0	1.02	10.7	5.14	2.35	2.85	15.5374	2.3323
17	135	3.17	17.3	16.1	4.13	6.90	6.0602	2.4078
18	231	7.70	41.3	18.4	8.64	3.06	6.7014	4.5965
19	136	2.86	12.7	4.93	3.78	6.60	5.814	1.919
20	1.56	1.75	21.9	4.05	5.40	3.18	10.5791	1.4732
Average	57.3	9.5	33.1	24.3	3.69	4.02	8.4576	2.6319

According to Figure 9, it can be inferred that NSGA-II (average time solution = 15.3 min) performed better and achieved the optimal solution in less time than MOSA (average time solution=18.8 min).

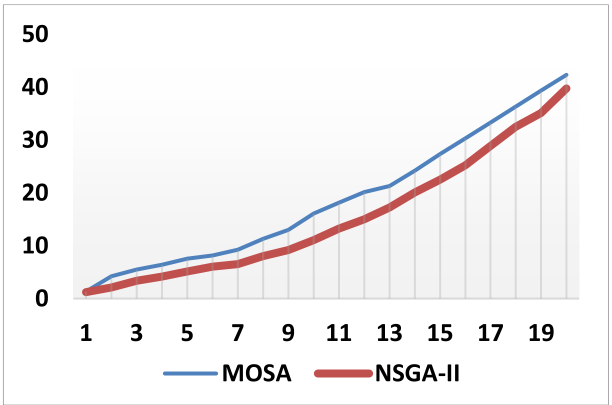

Figure 9. The solution time of each of the algorithms

5.5. Sensitivity Analysis

In this subsection, the parameters affecting the proposed mathematical model are changed to allow observing and examining the behavior of each in changing the output results. For this purpose, the critical parameters that are selected for sensitivity analysis (in which all other parameters, except for the parameter under consideration, are considered constant) are the speed of each containership, the type of port arrival time parameter, the cost of each time period waiting for mooring after entering the harbor, and the number of quay cranes.

5.5.1. The Effect of Speed on Fuel Consumption

As can be deduced from Figure 10, the optimum speed of movement for container vessels considered in this study is approximately 16 knots. Therefore, vessels with a current speed of more than 16 knots (less than 16 knots) must reduce (increase) their speed to save fuel.

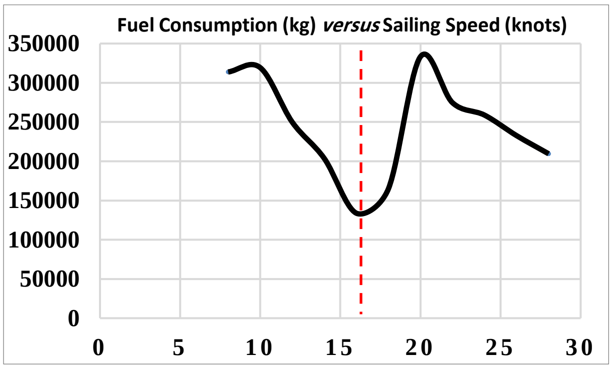

Figure 10. The relationship between fuel consumption and speed

5.5.2. Comparison Between VAT and CAT Strategies

This subsection evaluates the effects (performance) of the VAT and CAT strategies on the presented model. The focus is first placed on investigating the economic benefits for fuel consumption and the environmental benefits for vessel emissions. Then, some experiments are conducted on the number of QCs to further assess the berth utilization.

5.5.2.1. Operational Costs and Fuel Consumption

According to Table 9, as the number of container vessels increases over the planning horizon (one week), it is obvious that the port operating cost and the fuel consumption of the vessels will also increase. It can also be inferred from Table 9 that the values of operating costs and fuel consumption (kgallons) in the VAT mode have significantly decreased compared to the CAT mode. So, the VAT strategy has provided a better output in terms of reduction in the first and second objective functions. In addition, these analytical results show that there is comprehensive cooperation between port operators and shipping companies by setting the arrival time of vessels as a critical decision variable. In other words, port operators can suggest the arrival time of a vessel to the relevant shipping company. Having ample opportunity to improve the productivity of berths and quay cranes, and conversely, to adjust the speed of their vessels (sailing) by shipping companies according to the arrival time announced by port operators will lead to more currency and fuel savings.

5.5.2.2. GHG Emissions of Vessels During Sailing and Mooring

As shown in Table 10, the VAT strategy results in a more dramatic reduction in GHG emissions during sailing and mooring than the CAT strategy, so the environment of ports will be healthier in this mode.

5.5.2.3. Relationships of Operational Costs, Fuel Consumption, and the Number of Quay Cranes

A negative correlation exists between port operating costs and fuel consumption. In other words, as f_1 increases, f_2 decreases, and vice versa. Hence, the two parties involved (the port operator and the shipping company) seek to reach a balance point to reduce their costs through comprehensive cooperation. The number of quay cranes mainly affects the loading and unloading time, the departure time of a vessel, and berth utilization. Table 11 shows the impact of the number of quay cranes on port operational cost and fuel consumption when the number of incoming vessels in the planning horizon is 15. As shown in Table 11, the optimal number of cranes to service 15 containerships during the one-week planning horizon (considered in this study) is 22. If this number is less than 22, some vessels will not be serviced by the cranes available in a short time (increasing waiting time for mooring and increasing operating costs). Moreover, numerical experiments show that the port operational cost increase returned by solving CAT is greater than that of VAT when the number of available QCs decreases. These analytical results indicate that cooperation between port operators and shipping companies is beneficial. A vessel's arrival time is regarded as a decision variable to provide a concrete method for cooperation between port operators and shipping companies. Port operators can suggest the arrival time for a vessel to its shipping company to maximize berth and quay-crane utilization. Conversely, a shipping company can adjust the vessel's sailing speed according to the suggested arrival time.

5.5.3. Time Window Sensitivity Analysis

To investigate the effect of sailing time on the speed optimization results, the fuel consumption and the operational costs of vessels with the increase or decrease in speed are calculated under different time windows. Figures 11-13 show the fuel consumption, the vessel operating costs, and the emissions under the influence of the time window, respectively. As is shown in Figures 11-13, the fuel consumption, operating costs, and emissions gradually decrease with an increase in the time window. In the case of deceleration, the fuel consumption decreased from 12.7409×107 kgallons at 96 h to 6.3200×107 kgallons at 480 h. Increasing the time by 384 h resulted in a fuel consumption approximate reduction of 200% and a reduction in vessel operating cost by 431,450 $/hour.

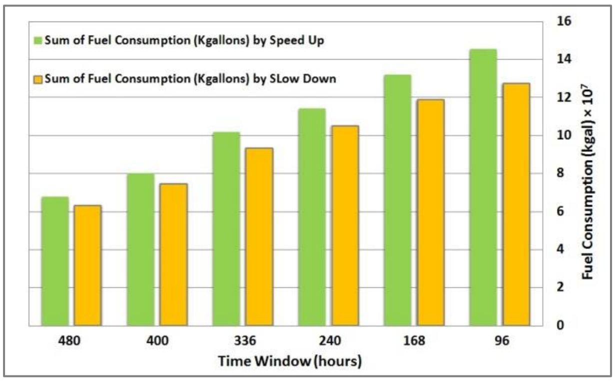

Figure 11. The effect of the time window on the main engine fuel consumption

As the time window increases, the differences in all three parameters of fuel consumption, operating costs, and emissions between the two cases (acceleration and deceleration) gradually decrease. The difference in fuel consumption decreased from 1.8092×107 kgallons at 96 h to 0.4630×107 kgallons at 480 h, the operating cost decreased from 1.2281×105 $/hour to 0.5056 $/hour and the emissions decreased from 0.6918×107 g to 0.2112×107 g. If the time window continues to increase, the difference in fuel consumption, the difference in operating costs, and the difference in emissions between the two cases will gradually disappear because the sailing speed of the two cases gradually becomes equal. Accordingly, the sailing speed optimization delicately varies with the time window, so speed can potentially be reduced and vessel energy efficiency can be enhanced with a larger time window constraint.

Table 9. A comparison of operating costs and fuel consumption according to the type of vessels' arrival time

No of vessels	VAT		CAT		Numerical difference	
	f_1 $\times10^5$	f_2 $\times10^7$	f'_1 $\times10^5$	f'_2 $\times10^7$	$f'_1 - f_1$ $\times10^5$	$f'_2 - f_2$ $\times10^7$
10	1.7362	2.9557	4.5674	3.2437	2.8312	0.2880
15	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050
20	3.3975	6.6739	5.9714	7.1400	2.5739	0.4661
25	5.6322	8.2947	7.8643	8.8702	2.2321	0.5755
30	7.4451	9.3370	10.5689	10.1200	3.1238	0.7830
35	9.0928	11.1812	12.4800	12.2090	3.3872	1.0278
40	11.8259	13.6971	15.1209	14.5560	3.2950	0.8589
45	13.0171	15.0413	18.4108	15.7035	5.3937	0.6622
50	15.2494	17.2035	19.3210	18.1030	4.0716	0.8995

Table 10. A comparison of GHG emissions between the VAT and CAT strategies

No of vessels	VAT			CAT			Numerical difference
	f_3 sailing + Mooring	Total waiting time for berthing (hours)	Average emission reduction for a vessel (g)	f'_3 sailing + Mooring	Total waiting time for berthing (hours)	Average emission reduction for a vessel (g)	$f'_3 - f_3$
10	0.0493×10^4	0	49.3	0.1164×10^4	0	116.4	0.0671×10^4
15	0.6770×10^5	3	4513	0.9680×10^5	5	6453	0.2910×10^5
20	2.6028×10^6	0	130140	5.1379×10^6	14	256895	2.5351×10^6
25	1.7853×10^7	1	714120	2.7927×10^7	22	1117080	1.0074×10^7
30	2.3291×10^7	8	776366	0.6931×10^9	24	23103000	6.69809×10^8
35	1.5253×10^8	4	4358000	0.1026×10^{10}	44	29314285	8.7347×10^8
40	2.8910×10^8	9	7227500	0.9503×10^{10}	56	237575000	9.2139×10^9
45	1.9424×10^9	1	43164000	0.2694×10^{11}	72	598666000	2.49976×10^{10}
50	2.2844×10^9	4	45688000	0.3496×10^{11}	86	699200000	3.26756×10^{10}

Table 11. Impact of number of QCs on f1 and f2

No of cranes	VAT		CAT		Numerical difference	
	f_1 $\times10^5$	f_2 $\times10^7$	f'_1 $\times10^5$	f'_2 $\times10^7$	$f'_1 - f_1$ $\times10^5$	$f'_2 - f_2$ $\times10^7$
10	5.3860	7.1500	7.2200	4.9450	1.8340	-2.2050
12	5.0034	6.7820	6.4670	4.9450	1.4636	-1.8370
14	4.8270	6.4110	5.6534	4.9450	0.8264	-1.4660
16	4.3512	5.9540	4.9900	4.9450	0.6388	-1.0090
18	3.7912	5.2130	4.4200	4.9450	0.6288	-0.2680
20	3.4440	4.7130	4.0100	4.9450	0.5660	0.2320
22	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050

24	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050
26	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050
28	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050
30	2.7889	4.5400	3.2407	4.9450	0.4518	0.4050

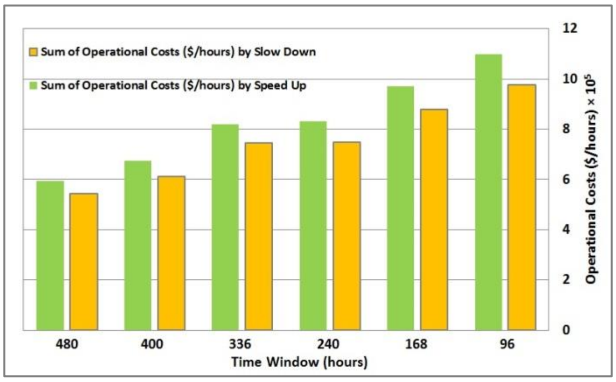

Figure 12. The effect of the time window on the ship's operational costs

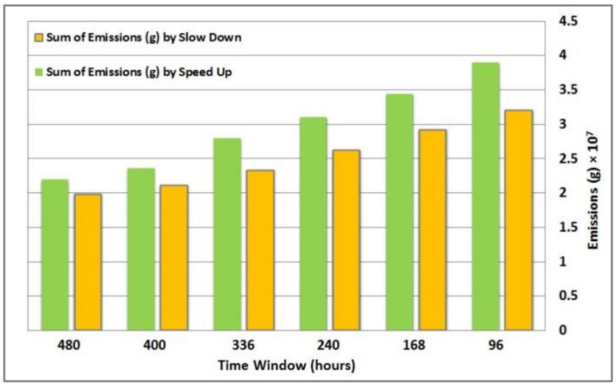

Figure 13. The effect of the time window on the emissions

6. Conclusion

Maritime transportation plays a crucial role in international trade and has experienced significant growth in recent years. Although near-port communities profit from this development, there are serious concerns regarding GHG emissions, which affect human health and climate change. In this article, the berth allocation problem and the quay crane assignment problem were simultaneously formulated into an integrated mathematical model by considering GHG emissions. The mathematical model was implemented in GAMS, which could only solve small-sized problems due to the high complexity of the mathematical model. An NSGA-II and a MOSA algorithm were proposed to solve large-size real-world problems. The effectiveness of the evolutionary algorithms was tested at Rajaee Port as a real case. The results demonstrated the effectiveness of the developed mathematical model and the proposed algorithms in finding a near-optimal solution within a reasonable time.

The study focused on GHGs of vessels as the main source of emission. There are other sources too, e.g. quay cranes, yard cranes, and yard trucks that could be considered sources of emission. Therefore, an integrated mathematical model can be developed in future studies by considering the GHG emissions of vessels, quay cranes, yard cranes, and yard trucks. In addition, it will be interesting to introduce stochastic factors to improve the robustness of the solutions when faced with uncertainty and unexpected contingencies, such as crane breakdowns or adverse weather conditions.

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