CHAPTER 6

PRESCRIPTIVE ANALYSIS

Our prescriptive analysis aims to develop and apply a mathematical model that evaluates and optimizes emissions from seaside port operations, thereby enhancing both operational efficiency and sustainability. This model not only aims to reduce environmental impact but also seeks to improve overall operational efficiency.

➢ **Sub Objectives**

- To develop and apply a mathematical model that evaluates and optimizes the emissions from seaside port operations, thereby enhancing both operational efficiency and sustainability.

6.1 Problem Description

The study includes static discrete berth allocation problem, containing multiple sets of berths with specific length and depth. The goal is to optimally allocate arriving vessels to berths while considering vessel service times, berth capacities, and operational constraints. Additionally, quay cranes are vital for cargo handling. However, the distinctive feature of this problem formulation is the incorporation of GHG Emission Cost. The fundamental principle of the GHG Emission Cost under consideration is to levy additional costs on GHG emissions originating from both the quay cranes (QCs) and vessels engaged in the operational processes (Song, 2024; Kenan et al., 2022). Within the framework of the proposed model, the primary objective revolves around minimizing the total incurred costs, which encompass the GHG Emission cost. Emission costs play a pivotal role in this optimization problem. When vessels are waiting at anchorage or idle at the berth, they emit pollutants. Similarly, quay cranes contribute to emissions while in motion or during cargo operations. These emissions have environmental and economic implications. Therefore, minimizing the emission costs becomes an integral objective. To address the discrete berth allocation and quay crane assignment problem while considering emission cost optimization, a mathematical non-linear programming model is proposed. The solution approach takes into account the available berth capacities, vessel arrival schedules, quay crane availability, and the intricate emission cost components.

In the given context, we address a scenario where a set of vessels, denoted as V, are waiting at anchorage. Vessels are already have given an expected arrival time at anchorage they should reach their before or exactly at their expected arrival time. If they arrive before their expected arrival time then vessels will be paid by an anchorage waiting cost. The operational expenses related to the quay cranes comprise operating cost per unit time, denoted as c_{oper} . The power consumption of a quay crane is activity-dependent, with p_{ql} during container loading/discharging, p_{qm} during lateral movement. Power consumption expenses are captured as c^e, and the corresponding GHG emission factor is represented by β^E.

Moreover, the power consumption and GHG emissions from vessels, indexed by i, vary based on various factors such as activity, vessel size, the number and size of engines, and type of fuel used. However, in this specific scenario, the focus is exclusively on the periods when vessels are berthed, implying that only auxiliary engines are operational. It is crucial to emphasize that the auxiliary engines of all berthed vessels are assumed to run on liquefied natural gas (LNG). Vessel-specific power consumption is quantified as p_{bi}, and the corresponding GHG emission factor for LNG is β^{LNG}. The additional GHG emission cost is termed as u_t, imposed for every unit of emitted GHG. Given this context, the overarching objective for the seaside operations is to efficiently complete operations associated with the approaching vessels, while minimizing the incurred costs inclusive of the emission cost.

The subsequent assumptions are considered in our problem (Alsoufi et al., 2018; Kenan et al., 2022; Pratap et al., 2017):

- The research centers around the discrete berth allocation problem.
- At any given time, each quay crane is dedicated to serving only one vessel.
- Wharf service commencement occurs subsequent to the ship's arrival.
- The total number of quay cranes concurrently serving berthed ships is limited and cannot surpass the count of available quay cranes.

- Quay cranes must complete an ongoing task before initiating another, ensuring task completion integrity.
- Vessels utilize liquefied natural gas (LNG) as their primary energy source.
- A uniform carbon tax rate is presumed, where the same tax rate applies for each unit of emitted carbon.

6.2 Model Formulation

Sets

V	Set of vessels to be scheduled, V = {1, 2, 3,….,i, j}
B	Set of available berths, B = {1, 2, 3,….,m}
Q	Set of quay cranes, Q = {1, 2, 3,…..,q}
T	Discrete set of time periods, T = {1, 2,3,……,t} (hr)

Parameters

l_i	Length of the vessel i, including safety distance, $i \in V$
l_m	Length of berth $m \in B$
d_m	Depth of berth $m \in B$
q_{maxi}	Maximum number of quay cranes that can be configured for vessel $i \in V$
q_{mini}	Minimum number of quay cranes that can be configured for vessel $i \in V$
d_i	Depth of immersion of vessel $i \in V$
t_{ai}	Expected arrival time of ship $i \in V$
bt_i	Buffer time required after vessel i berths and before quay crane starts their operation (in time periods)
β^E	Carbon emission factor for electricity (kg/kwh)
β^{LNG}	Carbon emission factor for LNG (kg/kwh)
u_t	Unitary tax rate for carbon emissions ($/kg)
c^e	Unit cost of electricity ($/kwh)
c_i	Total number of containers in a ship i
t_{qc}	Time required to handle a single container for a quay crane (in min)
c_{oper_q}	Operating cost per unit time of a quay crane
p_{ql}	Power consumption per unit time of a QC while loading/discharging (kw)

p_{qm}	Power consumption per unit time of a QC while moving (kw)
p_{bi}	Power consumed by vessel i per unit time (KW)
p_{max}	Maximum allowable power consumption at the port (kw)
e_{max}	Maximum allowable emission at the port (kg CO_2 equivalent)
$t_{\max\_si}$	Maximum time taken by allotted quay cranes to serve a vessel i
t_{qij}	Time taken by a crane q moving from vessel i to j
t_{qij}	$= d_{ij}$ (distance between vessel i and j) / $Speed_q$ (crane speed)
d_{ij}	Distance between vessel i and j
$Speed_q$	Typical speed of a quay crane at a berth

Decision variables

T_{bi}	Actual berthing time of vessel i, i ∈ V
T_{di}	Actual departure time of ship i, i ∈ V
T_{qsi}	Quay crane starts operating on ship i, i ∈ V
δ_{it}^{q}	If quay crane q is assigned to ship *I* at time t, the value is 1, otherwise it is 0
θ_{i}^{q}	If quay crane q is assigned to ship *I*, the value is 1, otherwise it is 0
μ_{qij}	Binary variable=1, if crane q works on vessel i before j, otherwise it is 0
X_{imt}	{0, 1}; when ship I is served on berth m at time t, the value is 1; otherwise, it is zero
C_{bfa}	Penalty cost per unit time if vessel i arrives prior to expected arrival time
E_{total}	Total emission (kgCO_2)
P_{total}	Total power consumption (kw)

Auxiliary Decision variables

SQ_{i}^{t}	Number of quay crane serving vessel I at time t, i∈V t
T_{hi}	Handling time of each vessel

6.2.1 Objective function

$$Min\ Z = \sum_{i\in V} C_{bfa}(T_{bi} - t_{ai}) + \sum_{i\in V} c_{oper\_q} SQ_i{}^t (T_{di} - T_{bi}) + (\beta_E u_t + c^e)\left[(p_{ql}\sum_{i\epsilon V} SQ_i{}^t (T_{di} - T_{bi})) + (p_{qm}\sum_{i\epsilon V}\sum_{j\epsilon V}\sum_{q\epsilon Q} t_{qij}\mu_{qij})\right] + \beta_{LNG} u_t \left[\sum_{i\in V} p_{bi} Max\big((T_{bi} - t_{ai}), 0\big) + \sum_{i\in V} p_{bi}(T_{di} - T_{bi})\right] + \sum_{i\epsilon V} \lambda_E E_{total} \quad 6\text{–}1$$

subject to:

$$\sum_{m\in B}\sum_{t\in T} X_{imt} = 1 \qquad \forall i \in V \qquad 6\text{–}2$$

$$\sum_{i\epsilon V} X_{imt} \le 1 \qquad \forall m \in B \ \ \forall t \in T \qquad 6\text{–}3$$

$$\sum_{t\epsilon T} X_{imt} \le 1 \qquad \forall m \in B \ \ \forall i \in V \qquad 6\text{–}4$$

$$t_{ai} \le T_{bi} \qquad \forall i \in V \qquad 6\text{–}5$$

$$\textstyle\sum_m \sum_t X_{imt} \times d_m \ge d_i \qquad \forall i \in V \qquad 6\text{–}6$$

$$\textstyle\sum_m \sum_t X_{imt} \times l_m \ge l_i \qquad \forall i \in V \qquad 6\text{–}7$$

$$q \le SQ^t{}_i \le q_{maxi} \qquad \forall i \in V, t \in T \qquad 6\text{–}8$$

$$\sum_{t\in T} SQ^t{}_i * X_{imt} \le Q \qquad \forall t \in T, \forall b \in m \qquad 6\text{–}9$$

$$T_{bj} + \big(1 - \mu_{qij}\big)M \ge T_{di} \qquad i,j \in V; q \in Q \qquad 6\text{–}10$$

$$\mu_{qij} + \mu_{qji} \le 1 \qquad i,j \in V; q \in Q \qquad 6\text{–}11$$

$$\mu_{qij} + \mu_{qji} \le \theta_i^q \qquad i,j \in V; q \in Q \qquad 6\text{–}12$$

$$\mu_{qij} + \mu_{qji} \le \theta_j^q \qquad i,j \in V; q \in Q \qquad 6\text{–}13$$

$$T_{hi} = \frac{c_i \times t_{qc}}{SQ^t{}_i * 60} + bt_i \qquad \forall i \in V \qquad 6\text{–}14$$

$$T_{bi} + T_{hi} \leq T_{di} \qquad \forall i \in V \qquad 6\text{–}15$$

$$T_{hi} \leq T_{max\_si} \qquad 6\text{–}16$$

$$\sum_{i \in V} \delta_{it}^q \leq 1 \qquad \forall q \in Q, \quad \forall t \in T \qquad 6\text{–}17$$

$$P_{total} = \sum_{i \epsilon V} \sum_{q \epsilon Q} \left[p_{ql} SQ\,{}_i^t (T_{di} - T_{bi}) + p_{qm} \sum_{j \epsilon V} t_{qij} \mu_{qij} \right] + \sum_{i \epsilon V} p_{bi} (T_{di} - T_{bi}) \qquad 6\text{–}18$$

$$P_{total} \leq p_{max} \qquad 6\text{–}19$$

$$E_{total} = \beta_E \sum_{i \epsilon V} \left[p_{ql} SQ\,{}_i^t (T_{di} - T_{bi}) + p_{qm} \sum_{j \epsilon V} t_{qij} \mu_{qij} \right] + \beta_{LNG} \sum_{i \epsilon V} p_{bi} (T_{di} - T_{bi}) \qquad 6\text{–}20$$

$$E_{total} \leq e_{max} \qquad 6\text{–}21$$

$$T_{bi} + bt_i \leq T_{qsi} \qquad \forall i \in V \qquad 6\text{–}22$$

$$T_{bi}\ ,\ T_{di},\ T_{hi}\ \geq 0 \qquad \forall i \in V \qquad 6\text{–}23$$

$$SQ\,{}_i^t \geq 0 \qquad \forall i \in V, \quad \forall t \in T \qquad 6\text{–}24$$

$$\delta_{it}^q \in \{0, 1\}, \qquad \forall i \in V, \quad \forall q \in Q, \quad \forall t \in T \qquad 6\text{–}25$$

$$\theta_i^q \in \{0, 1\}, \qquad \forall i \in V, \quad \forall q \in Q \qquad 6\text{–}26$$

$$\mu_{qij} \in \{0, 1\}, \qquad \forall i, j \in V, \quad \forall q \in Q \qquad 6\text{–}27$$

$$X_{imt} \in \{0, 1\}, \qquad \forall i \in V, \quad \forall m \in B, \quad \forall t \in T \qquad 6\text{–}28$$

The objective function, as articulated by equation 6–1, encompasses the cumulative expenditure attributed to both the allocation of berthing facilities and the assignment of quay cranes. This function is comprised of six distinct terms. The initial term pertains to the expenses incurred due to the period of idleness experienced by vessels while situated at anchorage prior to their anticipated arrival times. The second term denotes the operational expenditure attributed to each individual vessel, indexed as "i," throughout its duration of occupancy at the berth. The third term encapsulates a conglomeration of expenses linked to emissions. These costs encompass the emissions-associated expenditures incurred during quay crane relocation and loading/unloading activities. The fourth term addresses costs related to emissions stemming from vessels. These costs encompass both categories of emission-related expenditures incurred when a vessel is in a state of waiting at anchorage or while berthed. And, fifth term stands for total emission from each vessel. Equation 6–2 ensures that each vessel i is assigned to exactly one berth m at exactly one time period t. This is followed by Equation 6–3 guarantees that a berth can hold only one vessel at a time. Equation 6–4, prevents a vessel from being assigned to multiple berths simultaneously. Moving on to Equation 6–5, this mandates that a vessel cannot start berthing before it is scheduled to arrive. In compliance with maritime standards, Equation 6–6 ensures that the vessel's draft is accommodated by the water depth at the assigned berth, preventing grounding or operational issues due to insufficient depth. Equation 6–7 further guarantees that the berth assigned to the vessel is long enough to accommodate the entire length of the vessel. Addressing quay-crane allocation, Equation 6–8 enforces that the number of quay cranes designated for a ship must lie within acceptable bounds - neither surpassing the maximum threshold nor falling below the minimum threshold. Equation 6–9 maintains that the total number of operational quay cranes at any given time should not surpass the overall quantity of available quay cranes, a measure to prevent resource overutilization. Equations 6–10 - 6–13 collectively impose the limitation that each quay crane can only serve a single vessel at any given moment, a constraint designed to streamline crane utilization. Equation 6–14 calculates the handling time required for vessel i at a particular time t based on the number of quay cranes working on the vessel and its container quantity. Equation 6–15 ensures that the departure time of the vessel is not earlier than the handling time required for its operations. Equation 6–16 assures that the calculated handling time for vessel i at time t is less than or equal to the maximum service time, which helps in managing the operations within a predefined time limit. Equation 6–17 ensures that a quay crane can serve at most one vessel at a time t. Constraint 6–18 ensures that total power consumption doesn't exceed the power consumption limit on quay crane and vessels. Equation 6–19 ensures the total power consumption across all the vessels and quay cranes doesn't exceed the max. allowable threshold. Similarly, Constraint 6–20 determines the total emission based on power consumption of quay cranes and vessels. Equation 6–21 ensures the total emission remain within allowable environmental level. The constraint 6–22 ensures that the ship's berthing time and the required buffer time must be less than or equal to the start time of the quay crane's operations, preventing overlap and ensuring proper sequencing of activities. Equations 6–23 and 6–24 depicts the non-negative variables. Equations *6–25* to *6–28* introduce binary variables.

6.3 Solution approach

The discussed model is characterized as a non-linear model, notably incorporating a constraint (Constraint 14) that involves the multiplication of two decision variables, resulting in a binary expression. Being within Gurobi's capabilities, this particular form of non-linearity has been effectively addressed and solved by Gurobi (GAMS, 2023). Evidently, when confronted with extensive real-world datasets, it becomes evident that meta-heuristic techniques outperform the Gurobi solver, as substantiated by the findings presented by (Goerigk & Schöbel, 2013; Rahimian et al., 2017) in their study. Consequently, the current work addressed the Mixed-Integer Non-Linear Programming (MINLP) model using two comprehensive methodologies: the Gurobi solver and meta-heuristic approaches such as Elite Genetic Algorithms (GAs).

6.3.1 Experimental Setting

The experimental environment and device specifications used in this study encompass the following components: the operating system employed was Windows 10, the processor utilized was an Intel Core (TM) i5-7300HQ CPU operating at 2.50 GHz, and the programming language employed was Python 3.

6.3.2 Data of experiment

Research was conducted at a container port situated on the eastern coast of India, focusing on gathering data regarding ship arrivals, departures, and the availability of quay cranes. The anticipated arrival times of vessels were predetermined and communicated to the relevant authorities. The primary objective of this investigation is to efficiently assign berths to incoming vessels and allocate an appropriate number of cranes. Additionally, the aim is to minimize emissions stemming from both the vessels and quay cranes.

For the designated port in the east, this paper conducts a numerical study including three types of vessels Suezmax (S) and 24 Feedermax (F) and 15 are Panamax (P). The maximum and minimum numbers of quay cranes assigned to particular vessel are set from 1-9. The costs per unit is set to the value; C_{oper}=178, and C_{bfa}=200 for all vessels with a M= 100000.

6.3.3 Algorithm Parameters Design

The parameters were fine-tuned through an iterative testing approach using convergence graphs for multiple instances (1st, 4th, 7th, and 10th). Population size (P = 120) was selected after testing 50, 100, 120, and 150, balancing convergence speed and computational cost. Maximum generations (260) were chosen based on convergence trends, as most instances stabilized within 240-260 generations. Crossover probability (0.7) was optimal, ensuring fast convergence without excessive randomness, while mutation probability (0.05) provided gradual improvement, avoiding stagnation (at lower values) and instability (at higher values). These selections ensured efficient convergence and solution quality for Elite GA.

6.4 Results and Discussion

To validate the established mathematical model, the instances are solved with GUROBI Solver as the benchmark comparison. Problem instances were categorised in to three sizes namely; Small (S), medium (M), and Large (L). As the problem instances become more complex with larger numbers of vessels, berths, quay cranes, and time periods, the number of variables and constraints increases significantly. This reflects the growing complexity of real-world scenarios. The presented Table 6:1 summarizes key findings from a series of problem instances involving berth allocation, and quay crane optimization.

In the context of different problem instances, it is evident that GUROBI and Elite Genetic Algorithms (GA) exhibit varying performance characteristics. For smaller instances, GUROBI consumes more time, ranging from 19.24 to 98.65 seconds, to deliver solutions with objective values between 2.225×10^7 and 12.169×10^7. In contrast, Elite GA accomplishes the same tasks in a significantly shorter timeframe, taking only 8.79 to 17.55 seconds and providing near-optimal objective values from 2.387×10^7 to 12.608×10^7. As the size of the problem instance increases, GUROBI's computation time escalates to 154.12 - 1576.02 seconds, yielding objective values ranging from 19.641×10^7 to 27.254×10^7. Meanwhile, Elite GA maintains its efficiency, processing medium-sized instances in 38.08 - 84.87 seconds and producing near-optimal objective values of 20.037×10^7 to 27.598×10^7. GUROBI performs acceptably for larger instances, ranging from 33.626 to 47.388 seconds and providing objective values from 2322.61×10^7 to 2565.53×10^7. However, GUROBI fails to deliver results for the next larger instance. On the contrary, Elite GA operates efficiently for larger problem scales, taking 110.58 - 236.81 seconds and achieving near-optimal values within 34.114×10^7 – 54.185×10^7 range. Therefore, based on these results, it is apparent that Elite GA is a preferable approach for addressing real-world problems when expedited solutions with near-optimal values are sought. In contrast, GUROBI is better suited for scenarios where exact optimality is required, even if it entails longer computation times.

Notably, these results suggest that for complex real-world allocation and assignment challenges, Elite Genetic Algorithms strike a practical balance between solution quality and computational expediency, making them a valuable choice for decision-makers, contingent on specific problem requirements and available computational resources. To visually demonstrate the metaheuristics' outcomes, some convergence graphs for Elite GA has been included Figure 6:1. This graph illustrates the changes in the objective value concerning the number of generations. The graph distinctly reveals that Elite GA exhibits early convergence for smaller problem instances. However, for the medium-sized instance, it converges slightly later. As the problem size increases, the time required for convergence gradually extends.

Table 6:1 Computational results of 10 instances

Instance No		1	2	3	4	5	6	7	8	9	10
Instance' size		S			M			L			
Problem Instance (vessels, berths, quay cranes, time periods)		(7,4,12,36)	(10,6,18,36)	(14,7,21,36)	(20,8,24,36)	(23,10,30,36)	(27,12,36,36)	(33,15,45,36)	(38,18,54,36)	(44,20,60,36)	(50,24,72,36)
Number of variables	**Binary**	4480	10620	18522	63200	49680	73872	121770	178524	245520	356400
	Integer	252	380	532	1700	874	1026	1254	1444	1672	1900
	Continuous	21	30	42	60	69	81	99	114	132	150
	Total	4753	11030	19096	64960	50623	74979	123123	180082	247324	358450
Number of Constraints		2595	5694	10892	27876	35549	56727	102744	160938	237532	365106
Exact Solution Approach	**Objective function (USD) in**10^7	2.225	7.201	12.169	19.641	24.324	27.254	33.626	39.033	47.388	-
	Computation time (Seconds)	19.24	27.82	98.65	154.12	231.52	1576.02	2322.61	2485.53	2565.53	-
Elite Genetic Algorithms	**Objective function (USD) in**10^7	2.387	7.641	12.608	20.037	24.768	27.598	34.114	40.81	47.99	54.185
	Computation time (Seconds)	8.79	11.92	17.55	38.08	41.95	84.87	110.58	198.63	218.97	236.81

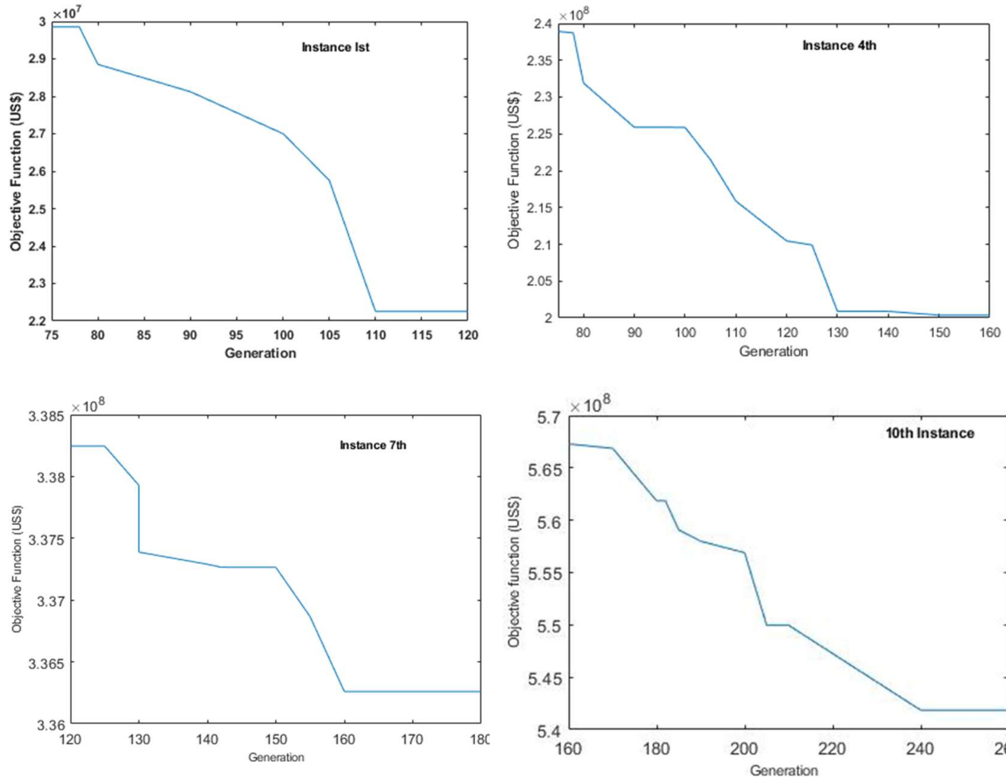

Figure 6:1 Convergence Graphs of Elite Genetic Algorithm (For Instance 1st, 4th, 7th and 10th)

6.4.1 Sensitivity Analysis

Conducting sensitivity analysis serves as a means to assess the model's robustness, providing decision-makers with valuable insights. It involves systematically altering input parameters to analyse the resulting variations in the model's objectives and other pertinent outputs. Therefore, sensitivity analysis has been performed over some crucial parameters like; unitary tax rate, operational cost, time required to handle a single container, and number of containers. Unitary tax rate has gained the popularity in several studies, reflects the environmental and regulatory considerations associated with maritime industry (Wang et al., 2018).

By varying the unit tax rate, the sensitivity analysis assesses how changes in carbon taxation policies impact the model. Understanding this impact is crucial for compliance with environmental regulations and managing the financial implications of carbon emissions. Operational cost is a fundamental aspect of port management. By analysing this parameter, decision-makers can evaluate the financial feasibility of different operational strategies. Similarly, the time required to handle a container directly affects the efficiency of port operations. Variation in this parameter helps in optimizing the allocation of quay cranes and berths to minimize vessel turnaround time. Faster handling times can lead to increased throughput and reduced congestion, while longer times may require adjustments to resource allocation. The sensitivity analysis on container volume is essential because it directly influences resource allocation and capacity planning. Understanding how changes in cargo volume affect the model allows for proactive decision-making in response to fluctuations in demand.

Sensitivity analysis of the unitary tax rate on carbon emissions reveals valuable insights into the relationship between environmental taxation and optimum cost within the context of the maritime industry (refer to Figure 6:2). By systematically varying the unitary tax rate by -25%, -10%, +10%, and +25%, we can observe its direct impact on the optimal cost of sea-side port operations.

As the unit tax rate increases, moving from -25% to +25%, the corresponding trend in optimal cost demonstrates a proportional response. Specifically, when the unit tax rate is reduced by 25%, the optimal cost experiences a decrease of 10.54%. Conversely, a 25% increase in the unit tax rate leads to a corresponding 10.54% increase in optimal cost. This indicates that the unit tax rate and optimal cost share a direct and linear relationship. The study quantifies a 10.54% cost change for every ±25% variation in the unit tax rate, providing empirical evidence to support the relationship between tax rates and operational costs. This approach moves beyond theoretical predictions, offering concrete data that can be used for policy decisions.

The findings suggest the importance of striking a balance when setting carbon tax rates. Excessive taxes can lead to higher operational costs, potentially burdening the industry. On the other hand, lower taxes might reduce the financial pressure but could also weaken incentives for reducing emissions. Through sensitivity analysis, the study highlights how operational costs are highly sensitive to changes in tax rates. This information is crucial for policymakers and port authorities, as it allows them to set tax rates that optimize both environmental goals and economic performance without overburdening the maritime industry. These insights help guide a data-driven approach to carbon taxation, enabling the formulation of policies that promote sustainability while ensuring economic feasibility within the maritime sector.

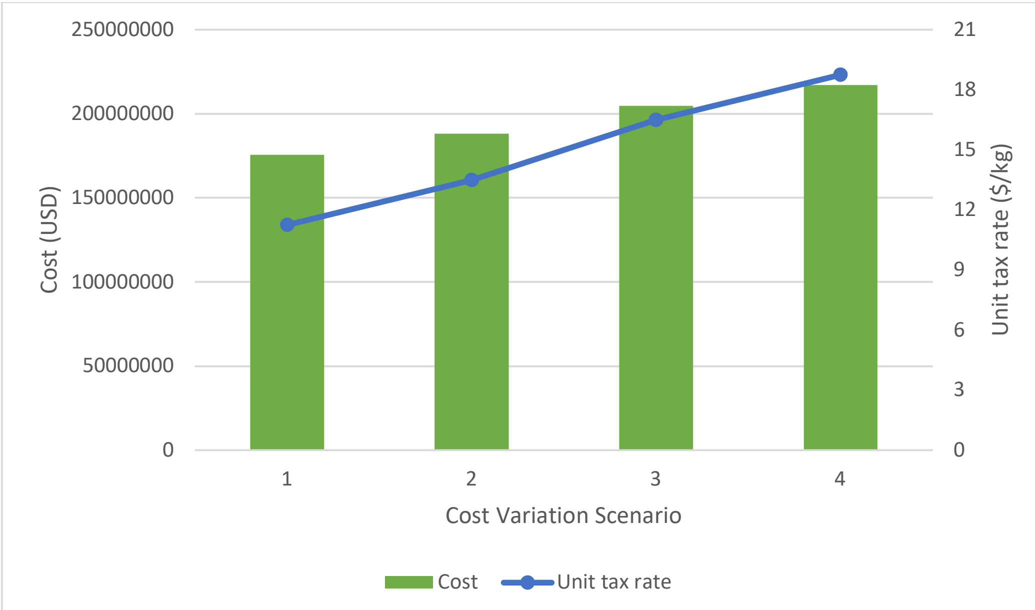

Figure 6:2Variation in unit tax rate

Similarly, variation in operational costs as shown via. Figure 6:3 provides valuable insights into the relationship between cost structure and the overall efficiency of port operations. By systematically varying operational costs by -25%, -10%, +10%, and +25%, we can observe the corresponding impact on the optimal cost of sea-side port operations. The results of this analysis reveal a clear and consistent trend: as operational costs increase or decrease, there is a proportional response in the optimal cost. When operational costs are reduced by 25%, the optimal cost experiences a significant decrease of 14.22%. Conversely, a 25% increase in operational costs leads to a corresponding 14.22% increase in optimal cost. This finding underscores the direct and linear relationship between operational costs and the efficiency of port operations.

The implications of this sensitivity analysis are substantial. It highlights the critical role that cost management plays in determining the overall competitiveness and financial performance of port facilities. While reducing operational costs can lead to significant savings, increasing costs may result in higher overall expenses. Striking a balance between cost efficiency and maintaining the quality and effectiveness of port services is essential for sustainable and competitive port operations. This analysis underscores the need for careful cost management and strategic decision-making within the maritime industry.

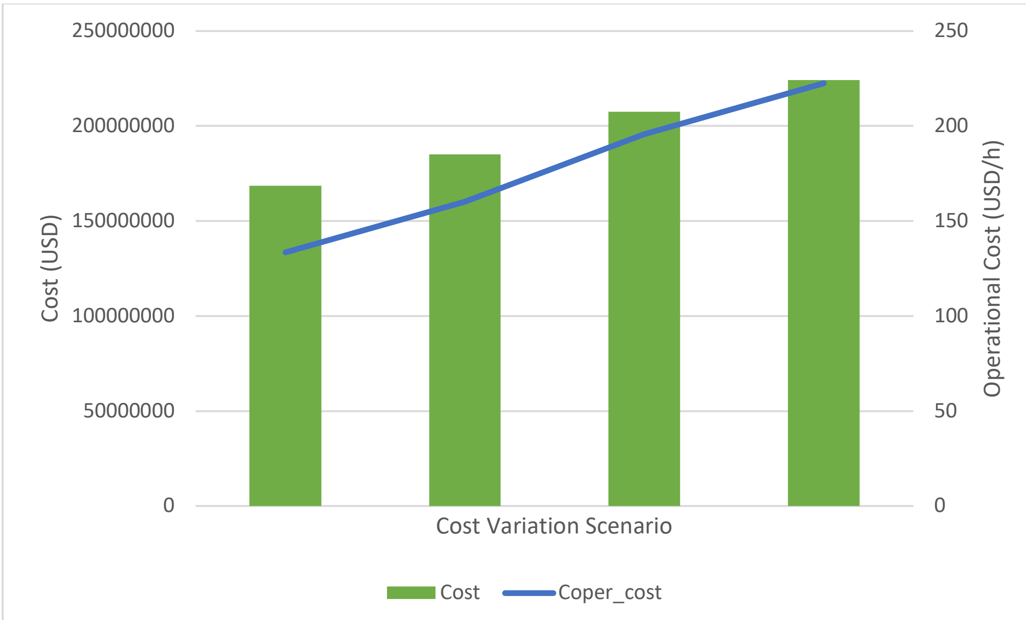

Figure 6:3Variation in operation cost

In the same vein, the changes in 'time required to handle a single container' parameter depicted in Figure 6:4 offer valuable insights into the interplay between handling efficiency and optimal cost. By systematically varying the time required to handle a container by -25%, -10%, +10%, and +25%, we can observe the corresponding impact on the optimal cost of port operations. The results of this analysis reveal a consistent and significant trend: variations in the time required to handle a single container directly correlate with proportional adjustments in the optimal cost. When the handling time is reduced by 25%, the optimal cost experiences a substantial decrease of 24.72%. Conversely, a 25% increase in the handling time leads to a corresponding 25.06% increase in optimal cost.

These findings underscore the critical role that container handling efficiency plays in the financial performance of port facilities. Faster container handling times can lead to cost reductions, while slower handling times can result in increased operational expenses. Port operators must carefully manage their operational processes and invest in technologies and practices that enhance efficiency to achieve cost-effective and competitive port operations. This sensitivity analysis highlights the strategic significance of optimizing container handling times for sustainable and economically viable port operations.

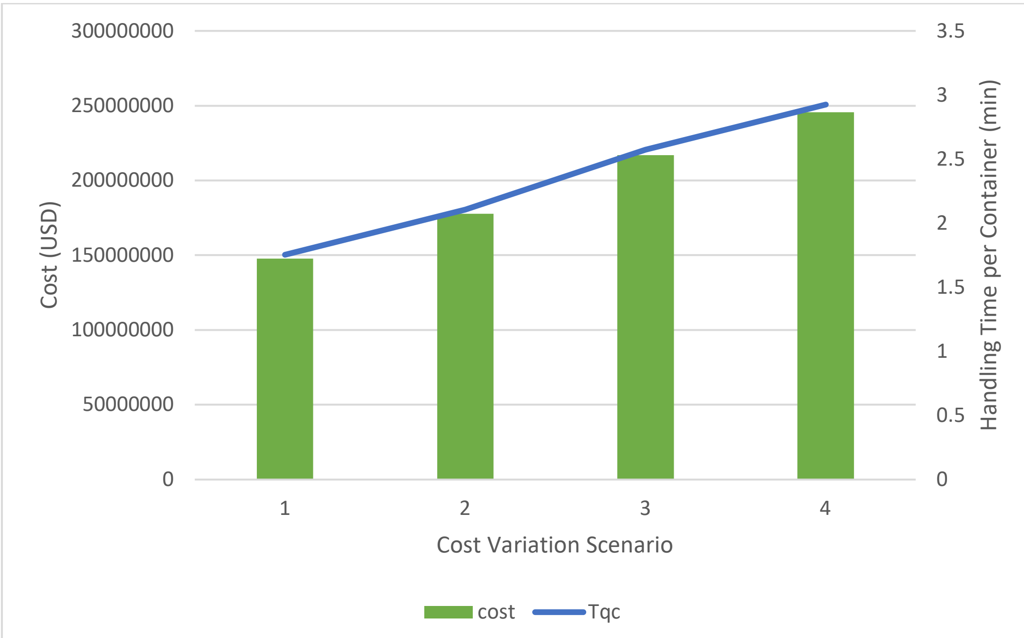

Figure 6:4Variation in time required to handle a single container

Examining the influence of the 'number of containers' parameter on optimal costs within the proposed model illuminates the significant role that container volume plays in the efficiency and financial performance of port operations (refer to Figure 6:5). By systematically varying the number of containers by -25%, -10%, +10%, and +25%, we can observe the corresponding effect on the optimal cost of port operations. The results of this analysis unveil a notable and consistent trend: changes in the number of containers are directly associated with proportional adjustments in the optimal cost. When the number of containers is reduced by 25%, the optimal cost experiences a substantial decrease of 24.72%. Conversely, a 25% increase in the number of containers leads to a corresponding 25.06% increase in optimal cost.

These findings underscore the strong relationship between container volume and operational costs in port facilities. Higher container volumes can result in increased operational expenses, while lower volumes can lead to cost reductions. Port operators must carefully manage their resources and capacity to strike a balance between efficiently handling container traffic and controlling costs. This sensitivity analysis emphasizes the strategic importance of container volume management in achieving cost-effective and competitive port operations.

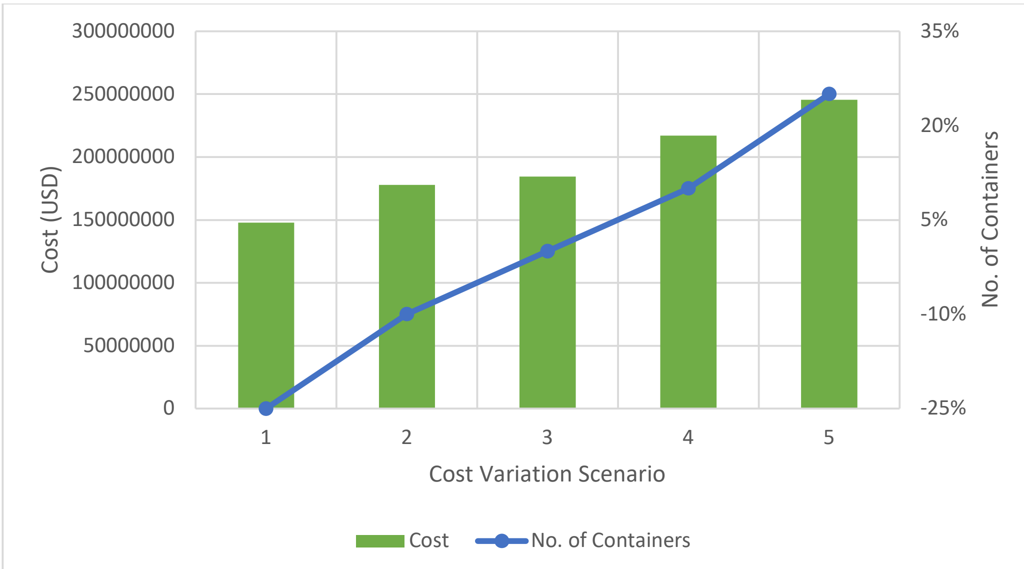

Figure 6:5Variation in no. of containers

6.5 Conclusions

This research has addressed two critical challenges in optimizing container terminals: Berth Allocation Problem (BAP) and Quay Crane Assignment Problem (QCAP). Specifically, current work focus has been on the static allocation of berths, where we consider a discrete set of berths for vessels. To tackle the inherent complexity of this problem, we developed a Mixed-Integer Non-Linear Programming (MINLP) model to represent the system. To find solutions, we employed two approaches: Gurobi, an exact solver, and Genetic Algorithms (GA) combined with an elitist mechanism. These approaches were applied across a range of instances, encompassing small, medium, and large scenarios, to ensure compliance with all constraints. When comparing these approaches, we evaluated them based on two key criteria: computational time and optimal value. Gurobi excelled in achieving optimal values with higher computational time, while Elite GA demonstrated superior computational efficiency, providing near-optimal solutions. Notably, Elite Genetic Algorithms offer near-optimal solutions with considerably reduced computation times compared to the Exact Solution Approach, highlighting the trade-off between solution quality and computational efficiency.