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A Framework for Container Terminal Operations: Metaheuristic Optimization and Simulation Analysis

Reza Haddad[1], Mahdi Hamisheh Bahar[2,*], Mohsen Varmazyar[3]

[1] Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran; Reza_haddad@ie.sharif.edu; Mahdi.hamishebahar77@sharif.edu; Varmazyar@sharif.edu.

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Abstract

Container unloading and loading operations in ports are addressed through the Berth Allocation Problem (BAP). Developing container terminal models and methods that enhance operational efficiency is crucial for supporting maritime ports in managing the increasing volume of container flows within global supply chains. Consequently, recent years have witnessed a growing body of research literature aimed at advancing quayside operations. This study first examines the theoretical framework of the Quay Crane Scheduling Problem (QCSP) and Quay Crane Assignment Problem (QCAP) as presented in existing literature. We then formally define these problems within deterministic and sequencing contexts. The research employs berth modeling alongside Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) for deterministic scenarios, while stochastic conditions are addressed through berth simulation. Given the NP-hard nature of the problem, obtaining optimal solutions within reasonable time frames is infeasible. Thus, we implement metaheuristic approaches—GA, PSO, and simulation of the model—to efficiently allocate vessels to berths.

Keywords: Simulation, Mathematical modelling, Quay crane scheduling problem, Quay crane assignment problem, Genetic algorithm, Particle swarm optimization, Metaheuristic.

1 | Introduction

The exponential growth in global containerized trade has intensified competition among ports, transforming terminal operations into complex optimization challenges requiring sophisticated management approaches [1]. Container terminals serve as crucial interfaces between maritime and terrestrial transportation networks, where the efficient coordination of berths, cranes, and storage facilities fundamentally determines overall port

Corresponding Author: Mahdi.hamishebahar77@sharif.edu
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performance and competitive advantage. A significant operational challenge stems from the increasing size of container vessels, which substantially prolongs berthing durations and strains terminal resources. As Quay Cranes (QCs) are the primary equipment for handling container unloading and loading operations, enhancing QC efficiency has become a critical imperative for both researchers and practitioners seeking to improve terminal productivity. Consequently, optimizing the integrated planning of berth allocation and QC scheduling has emerged as a vital strategy, as these decisions directly interface with maritime and landside operations and significantly impact key performance metrics, such as vessel turnaround time [2].

The Berth Allocation Problem (BAP) involves determining optimal mooring positions and times for arriving vessels, considering constraints such as vessel length, draft, arrival time, container volumes, and storage requirements. Terminals may employ discrete models, segmenting the berth into fixed positions, or continuous models, allowing vessels to moor across berth boundaries to maximize utilization. Simultaneously, the Quay Crane Scheduling Problem (QCSP) focuses on efficiently sequencing container handling tasks for the QCs assigned to each vessel to minimize service time. Given the inherent interdependence between where and when a vessel berths and how its assigned QCs operate, integrated optimization of BAP and QCSP offers significant potential for efficiency gains over sequential planning, despite the increased computational complexity. This project, therefore, investigates integrated berth allocation and QC scheduling to enhance operational efficiency at Shahid Beheshti Port, Chabahar. The recent installation of new gantry cranes at this port informs the modeling context. The research employs metaheuristic optimization techniques and simulation approaches to address vessel sequencing, allocation, and crane scheduling.

2 | Literature Review

Efficient quayside operations planning is fundamental to container terminal competitiveness, fundamentally integrating three interrelated optimization problems: the BAP, the Quay Crane Assignment Problem (QCAP), and the QCSP. Decisions within these domains collectively determine vessel turnaround times—a critical service quality metric [3]. The sustained growth of maritime transport, particularly containerized shipping, due to its security, efficiency, and standardization advantages [4], has intensified operational challenges. Minimizing vessel service time is paramount for ports, as reducing loading/unloading durations critically improves terminal throughput and container cycle times [5]. Consequently, optimal berth allocation and QC deployment directly influence operational throughput and profitability [6], necessitating sophisticated resource optimization (labor, berths, equipment) alongside service quality improvements [7].

2.1 | Quayside Optimization Problems

I. BAP: The BAP assigns mooring positions and times to vessels within a planning horizon while respecting berth capacity constraints. Foundational work by Imai et al. [8] established the discrete BAP framework, later expanded to continuous models where vessels can berth at any quay position [9]. Problem complexity escalates with dynamic arrivals, heterogeneous vessels, and multiple objectives. Metaheuristics like Tabu Search [10] and Variable Neighborhood Search [11] have proven effective for large-scale, realistic BAP instances, outperforming exact methods.

II. QCSP: The QCSP schedules container handling tasks (typically grouped by bay) for the QCs assigned to a single vessel, aiming to minimize the vessel's service time (makespan) while respecting precedence and safety constraints (e.g., non-crossing, interference). Early exact approaches like branch-and-cut highlighted the problem's computational difficulty [12]. Incorporating practical constraints like crane interference further complicates the problem [13]. Heuristics [14] and advanced methods like branch-and-bound for multi-objective cases [15] and surrogate models [16] continue to be developed.

III. Integrated planning (BAP + QCAP + QCSP): Recognizing the strong interdependencies between berthing decisions and crane productivity, research has increasingly focused on integrated models. Liu et al. [17] demonstrated that isolated optimization leads to suboptimal performance, emphasizing the need for integration. However, the computational complexity of full integration remains a significant challenge, often necessitating partial integration strategies or hierarchical decomposition approaches to balance solution quality and tractability [18]. Integration can extend further to include yard operations [19] or automated guided vehicles [20].

2.2|Solution Methodologies

Metaheuristic optimization: Given the NP-hard nature of BAP, QCSP, and especially integrated problems, metaheuristics are the predominant solution approach for realistic problem sizes. Genetic Algorithms (GAs) have shown effectiveness for BAP since early applications [21] and remain versatile for multi-objective problems [22]. Particle Swarm Optimization (PSO) is valued for its convergence speed and has demonstrated superior performance over GAs in some integrated BAP-QCAP studies [23]. Other metaheuristics applied include estimation of distribution algorithms [24] and novel human-inspired algorithms [25]. Hybrid metaheuristics and multi-objective approaches like NSGA-II are increasingly common to address complex, real-world scenarios [26], [27].

Simulation-based approaches: Discrete-event simulation is powerful for modeling the stochastic elements of terminal operations (e.g., vessel arrivals, handling times, equipment breakdowns) under various policies and scenarios [28]. Simulation-Optimization (SO) frameworks integrate simulation for evaluation with metaheuristics for search, providing robust solutions under uncertainty [29]. Simulation is also crucial for validating and assessing the robustness of solutions derived from optimization models [30].

This research contributes to this field by developing and applying metaheuristic approaches (PSO, GA, NSGA-II) to deterministic mathematical models for integrated berth allocation and QC scheduling, complemented by stochastic simulation modeling using empirical distributions to capture real-world uncertainties at Shahid Beheshti Port. A comparative analysis of metaheuristic performance will be conducted.

3|Methodology

3.1|Problem Formulation and Assumptions

Berth allocation involves determining the berthing time and position for each container ship, considering factors such as ship length, cargo volume, arrival time, and the required number of cranes. The port is divided into several berths, making the allocation problem discrete. Sometimes, ships are allowed to berth along the entire quay to maximize capacity, leading to a continuous BAP.

This study uses Shahid Rajaee Port, equipped with gantry cranes, as a case study. The modeled problem is solved in two stages using three algorithms: first, ship allocation, then sequencing, employing both heuristic and metaheuristic methods.

Seaside operations planning in container terminals fundamentally encompasses three interrelated problems: The BAP, the QCAP, and the QCSP. The decisions made in addressing these problems collectively determine the duration of container vessels' stay at the port, which directly reflects the quality of service offered to shipping lines and influences the overall competitiveness of the terminal. Consequently, integrated planning of these operations has become a central focus within operations research and transportation studies. Typically, a port consists of multiple quays, each designated for specific types of ships. The processing speed for loading and unloading varies depending on the ship's length and type, with preparation time accounted for between consecutive ships to ensure smooth transitions. The number of cranes allocated per berth is fixed, comprising various types such as gantry and QCs, which function as processing machines. The general terminal layout includes berths, cranes, storage yards (both open and closed), and a fleet of trucks responsible for transporting containers to urban centers or airports. Ships are categorized by capacity into three main types: Feeders, which carry fewer than 1,000 containers and primarily transfer cargo from central hub ports to smaller ports; Handy-size vessels, with capacities ranging from 1,000 to 3,000 Twenty Equivalent Unit (TEU); and Panamax ships, accommodating between 3,000 and 4,000 TEU. Container units adhere to standardized measurements, primarily the TEU and the Forty Equivalent Unit (FEU), facilitating uniform handling and transport across the global shipping network.

In this study, three ship types (Feeder, Handy size, Panamax) are considered, all arriving with 20-foot containers. Input distributions and crane processing speeds are obtained from expert surveys. The arrival distribution is: 50% Feeder, 15% Panamax, and the rest Handy size. Five out of ten berths are active, each with at least one and at most three cranes. The channel is about 2,700 meters, with an average ship speed of 60 km/h (about 3 minutes, variance 1). Only four ships can pass through the channel simultaneously. Ships are prioritized solely by arrival time and are assigned to berths with the most available length. Gantry cranes unload at a rate of 50–80 containers/hour, increasing with more cranes. Trucks can carry about five containers (10 tons), with loading and transport times following a triangular distribution (average 2 hours, max 4 hours, mode 3 hours). The shortest queue at each terminal determines the ship order. A total of 100 ships of the three types, based on the given percentages, enter the port.

4 | Solution Method

This study addresses quay scheduling and sequencing, reviewing existing problems and methods. Two solution approaches are used: deterministic modeling and probabilistic modeling. For mathematical modeling, metaheuristic algorithms such as NSGA, GA, and PSO are used, and results are compared. For simulation, input and service distributions are derived from relevant data, and two-stage modeling is performed: Unloading ships at the quay and transporting goods to warehouses by trucks, followed by analysis and sensitivity tests.

4.1 | Quay Mathematical Modelling

First, we consider deterministic modelling as mentioned earlier.

Table 1. The notations.

Sets	
i	Index for ships
j, j'	Index for quays
M_j	Set of ships assigned to berth j
Variables	
x_{ijk}	One if ship j is scheduled at berth i in sequence k, Zero otherwise
St_{ijk}	Start time of ship j at berth i in sequence k
C_{ijk}	Completion time of ship j at berth i in sequence k
Parameters	
P_{ij}	Processing time of ship j at berth i
r_j	Arrival time of ship j
$S_{jj'}$	Setup time for ship j after ship j'

Based on *Table 1, the* mathematical formulation is as follows:

$$\text{Min } Z_1 = C_{max}, \text{Min } Z_2 = L_{max},$$

$$\text{s.t.}$$

(1)

$$\sum_k \sum_j x_{ijk} = 1, \qquad \text{for all } i \in M_j,$$

$$\sum_j \sum_i x_{ijk} = 1, \qquad \text{for all } k,$$

(2)

$$-x_{ijk} \le My^1_{ijk}, \qquad \text{for all } i \in M_j \text{ . for all } k. j,$$

$$
\begin{aligned}
&St_{ijk} - r_j \le M\left(1 - y^1_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&r_j - St_{ijk} \le M y^1_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&x_{ijk} \le M\left(1 - y^1_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&-x_{ijk} \le M y_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&St_{ijk} - P_{ij} - C_{ijk} \le M\left(1 - y_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&-St_{ijk} + P_{ij} + C_{ijk} \le M y_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&x_{ijk} \le M\left(1 - y_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&-x_{ijk} \le M y_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&-St_{ijk} + P_{ij} + C_{ijk} \le M\left(1 - y_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&St_{ijk} - P_{ij} - C_{ijk} \le M y_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&x_{ijk} \le M\left(1 - y_{ijk}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j,
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
&-\alpha_{ijj'k(k-1)} \le M w_{ijj'k(k-1)}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&St_{ijk} - C_{ij'(k-1)} - S_{jj'} \le M\left(1 - w_{ijj'k(k-1)}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&-St_{ijk} + C_{ij'(k-1)} + S_{jj'} \le M w_{ijj'k(k-1)}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&\alpha_{ijj'k(k-1)} \le M\left(1 - w_{ijj'k(k-1)}\right), \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&A_{ijj'k(k-1)} \le x_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&\alpha_{ijj'k(k-1)} \le x_{ij'(k-1)}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \\
&\alpha_{ijj'k(k-1)} \ge x_{ijk} + x_{ij'(k-1)} - 1, \quad \text{for all } i \in M_j \text{ . for all } k.\, j,
\end{aligned}
\tag{4}
$$

$$
L_{max} \ge l_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \tag{5}
$$

$$
C_{max} \ge C_{ijk}, \quad \text{for all } i \in M_j \text{ . for all } k.\, j, \tag{6}
$$

$$
x.\, y.\, w.\, \alpha \in \{0.1\}. \tag{7}
$$

Each set of constraints implies a specific assumption as follows:

In *Eq. (1)*, the first objective minimizes the maximum completion time (C_{max}), and the second objective minimizes the maximum lateness/delay time (L_{max}).

In *Eq. (2)*, each ship must be assigned to exactly one berth in a unique sequence. Every ship gets allocated to one specific berth and one specific position in the processing order.

Constraints (3) and *(4)* control the start time of each ship's operation, which must be after its arrival time at the port. The completion time of each ship equals its start time plus the processing time on the assigned berth.

Based on *Eq. (5),* each job must start after the completion of the previous job plus the required setup time. The start time of work on a specific machine requires that the job be assigned to that machine.

Eq. (6) shows that C_{max} must be greater than or equal to all individual job completion times L_{max} must be greater than or equal to all individual job delays/lateness values.

Eq. (7) All decision variables (x, y, w, α) are binary variables taking values in {0,1}.

4.2 | Quay Simulation Model

As mentioned in the introduction, in this study, three types of ships—Liner, Handy Size, and Panamax—are considered, all of which enter the docks with 20-foot container units. The arrival distribution for each type of ship is determined based on collected data, and the processing speed of the cranes is obtained through research and consultation with experts. Among the ship arrivals, 50% are Feeder, 15% are Panamax, and the remainder are Handy Size. Each ship has technical specifications such as the number of containers, ship length (for berthing purposes), and a different tag color for each type.

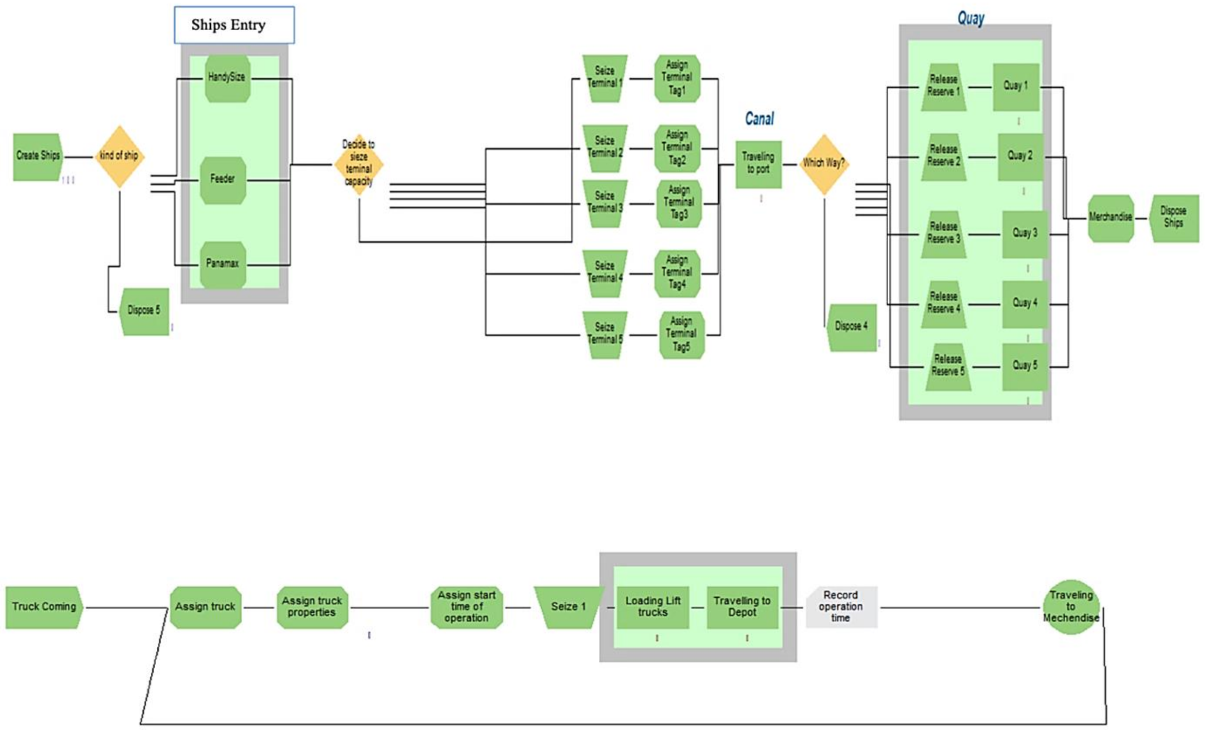

Fig. 1. Simulated port schema.

In this model, five active docks out of a total of ten are considered, with each dock equipped with at least one and at most three cranes. The channel length is approximately 2,700 meters, and the average speed of the ships is assumed to be 60 km/h, which is roughly equivalent to 3 minutes with a variance of one. Furthermore, only four ships can pass through the channel simultaneously. The ships do not have any priority over one another, and the only determining priority is their arrival time at the dock. Ships are assigned to the dock with the most available berthing length. The unloading speed of each gantry crane is estimated to be uniformly between 50 and 80 containers per hour, and naturally, this speed increases with the addition of more cranes. Loading and unloading operations are carried out based on the stated assumptions. Finally, the containers are transported to customs warehouses, or if those are full, to city warehouses by small trucks. Each truck can carry about five containers, equivalent to 10 tons, and the loading and transport time follows a triangular distribution with a minimum of 2 hours, a maximum of 4 hours, and a most likely value of 3 hours. The arrangement of ships is determined based on the shortest queue at each terminal. In total, 100 ships of the three mentioned types enter the anchorage according to the specified percentages. The overall simulation, along with its diagram, is presented in *Fig. 1*. In the next stage, all containers are transferred to the warehouse by 20 ten-ton trucks, each capable of carrying five containers.

5 | Results and Analysis

5.1 | Metaheuristic-Based Solution for the Quay Problem

The above problem is an NP-hard problem, and to solve it, we employ GA and PSO. The working methodology with these algorithms is as follows: first, the allocation of ships to berths is determined. This process transforms the parallel machine problem into a single machine problem.

To compare the performance of the PSO and GA, we considered one of the main objective functions, namely the maximum completion time (C_{max}). Both algorithms were tested under identical conditions, and the results are summarized in *Table 2*. In our model, we considered a model with 100 jobs (ships) and 10 machines (berths). The algorithms were executed five times, each with an initial population of 1000 and 200 generations.

Table 2. Comparison of genetic algorithm and PSO performance on C_{max}.

Iteration	1	2	3	4	5
GA	26	25	26	26	25
PSO	44	41	41	39	35

As observed in *Table 2*, the PSO algorithm consistently yielded weaker results compared to the GA. Therefore, based on these findings, the GA demonstrates superior performance and is selected for further analysis in subsequent stages of this research.

After determining the allocation, the sequence of operations must be established. For this purpose, we used several heuristic approaches to determine the sequence:

I. Shortest Processing Time (SPT): Arrange processing times in ascending order based on processing time.

II. $p_i - r_i$ rule: Arrange in ascending order based on the relationship $p_i - r_i$.

III. $r_i + \max_k(s_{ki}) - p_i$ rule: Arrange in ascending order based on the relationship $r_i + \max_k(s_{ki}) - p_i$.

Table 3. Maximum completion time objective values for different methods.

Iteration	1	2	3	4	5	6	7	8	9	10
SPT	28	27	29	27	27	27	28	29	25	28
$p_i - r_i$	28	28	29	27	27	27	27	25	26	26
$r_i + \max_k(s_{ki}) - p_i$	26	27	25	25	26	26	25	26	25	25

Experimentally, each of the above methods was tested ten times on sample data. The best reported values for minimum completion time and delay time were selected. This process helps identify the optimal method. The values are reported in *Tables 3* and *4*.

Table 4. Maximum delay time objective values for different methods.

Iteration	1	2	3	4	5	6	7	8	9	10
SPT	5049	5073	5247	5272	5304	5066	5230	5265	4961	5038
$p_i - r_i$	5020	4954	5285	5108	5203	5189	5089	5009	5214	5289
$r_i + \max_k(s_{ki}) - p_i$	4995	5054	5038	4996	5040	5091	5088	4979	5059	4983

The results of each method based on mean and variance are presented in *Table 5*. By observing the results, we can see that sorting based on $r_i + \max_k(s_{ki}) - p_i$ has both a lower mean and standard deviation. Therefore, it is a suitable method for creating sequences in metaheuristic algorithms.

Table 5. Mean and standard deviation of the reported results.

Method	Objective Function	Mean	std
SPT	C_{max}	27.5	1.18
	L_{max}	5163	125.01
$p_i - r_i$	C_{max}	27	1.16
	L_{max}	5119	111.07
$r_i + max_k(s_{ki}) - p_i$	C_{max}	25.6	0.70
	L_{max}	5037.778	40.47

The problem with 100 ships and 10 berths was solved using the GA. The algorithm population size was set to 500, and the number of iterations to 200. The Pareto chart is shown as *Fig. 2*. The obtained Pareto frontier contains 63 different sequences. These sequences were positioned at four points in terms of objective functions.

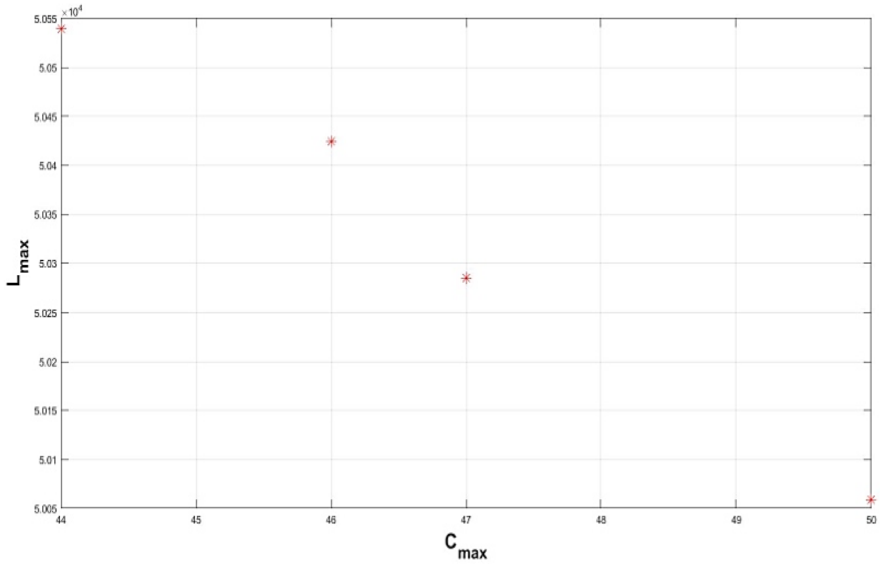

Fig. 2. Pareto of GA.

For one of the sequences, the Gantt chart of the problem scheduling is shown in *Fig. 3*. In this figure, each vertical axis represents a berth and the horizontal axis represents time.

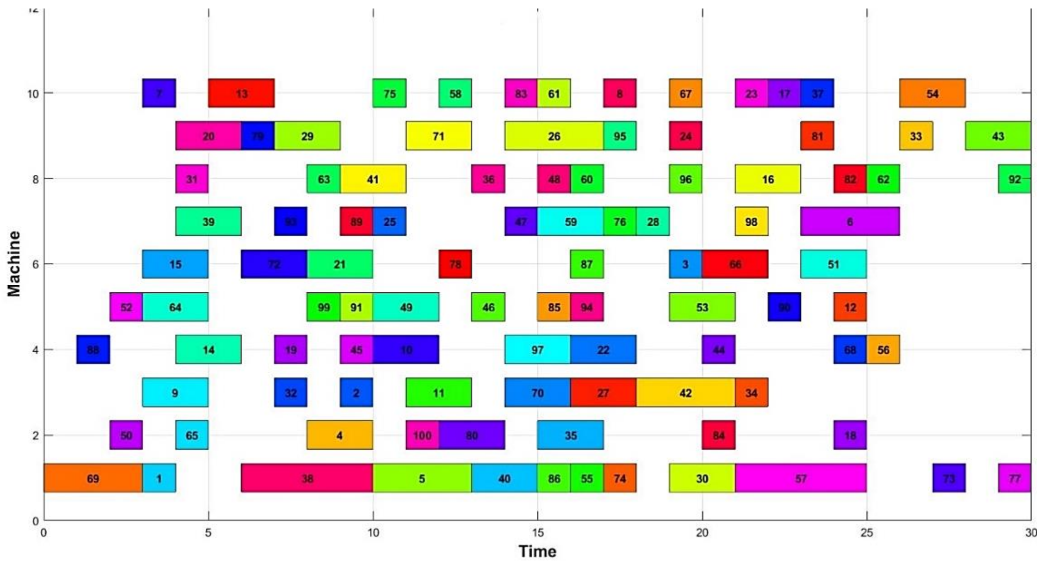

Fig. 3. Gantt of one of the optimal solutions.

5.2|Simulation-Based Solution for the Quay Problem

The first part of the simulation model focuses on the loading and unloading operations at five berths, with a particular emphasis on evaluating the productivity of cranes stationed at each berth. The rationale for examining crane productivity per berth stems from the operational practice that, upon the arrival of a ship, all cranes at that berth work concurrently on it. Consequently, the productivity of the cranes effectively represents the overall productivity of the berth itself. The simulation outputs indicate that over a period of approximately six months, a total of 142,459 containers were handled across 100 scheduled ship arrivals, demonstrating the system's capacity to manage substantial throughput efficiently. The second part of the model addresses the inland transportation of containers from the berths to warehouses via trucks. Assuming the availability of 20 trucks, the simulation estimates that approximately eight months are required to transfer the entire container volume. This two-stage simulation framework provides a comprehensive view of terminal operations, from quayside handling to inland logistics.

Over a period of approximately six months, 142,459 containers were handled and transferred according to the planned schedule, with all containers processed from the depot. The measures of each crane are presented in *Table 5*.

Table 5. Output measures.

Crane Num.	Utility	Ave. Queue
Crane1	49%	0.09
Crane2	32%	1.6
Crane3	56%	0.32
Crane4	96%	22.28
Crane5	37%	2.27

To assess the robustness of the simulation model, sensitivity analyses were conducted on ten test data sets, examining the impact of varying input parameters on multiple objective functions. Specifically, sensitivity analysis for the quay operations simulation included three key factors: 1) increasing berth length, 2) modifying the access channel width, and 3) adjusting berth prioritization. For the inland transportation model, analyses focused on: 1) increasing the number of trucks, and 2) optimizing transport and unloading times. For instance, extending the berth length at Shahid Beheshti port from 1,280 meters to 1,600 meters—effectively widening the quay and adding new berths while maintaining the number of cranes—resulted in a significant increase in crane utilization rates (*Table 6*). This expansion reduced crane idle times and capital wastage, enabling the port to handle a higher number of ships and approximately 20,000 additional containers within a shorter timeframe. Correspondingly, average queue lengths at the berths decreased markedly, indicating improved operational flow.

Table 6. Output measures after length modification.

Crane Num.	Utility	Ave. Queue
Crane1	94%	0.94
Crane2	97%	0.97
Crane3	96%	0.95
Crane4	99%	0.992
Crane5	100%	0.999

Adjustments to the access channel width were also examined to address low vessel throughput, with findings suggesting that optimizing berth length and truck availability yields better system performance than merely increasing channel width unnecessarily.

Furthermore, prioritizing berth 2 in *Table 7*, which initially exhibited low efficiency, helped balance ship traffic across berths, improving crane utilizations and reducing queue lengths relative to the baseline scenario (*Table 5*). Increasing the truck fleet size from 20 to 30 reduced container transfer times by approximately three months. Alternatively, optimizing transport and unloading times by halving their variance also improved overall system efficiency.

Table 7. Output measures after berth prioritization adjustment.

Crane Num.	Utility	Ave. Queue
Crane1	48%	0.64
Crane2	58%	4.78
Crane3	58%	0.52
Crane4	96%	13.22
Crane5	62%	4.96

6 | Discussion and Conclusion

We presented a comprehensive approach to optimizing container terminal operations by integrating berth allocation, QCs scheduling, and inland transportation through both mathematical modeling and simulation techniques. The use of metaheuristic algorithms, GA and PSO, allowed effective handling of the NP-hard nature of the quay scheduling problem. Comparative analysis showed that GA outperformed PSO in terms of solution quality and stability, making it the preferred method for further optimization. Then, the simulation model provided valuable insights into the operational dynamics of the port, capturing the complex interactions between ship arrivals, crane utilization, and container movement to warehouses. The productivity of cranes at each berth was identified as a key performance indicator, reflecting the overall efficiency of quay operations. The results indicated that increasing berth length significantly improves crane utilization and reduces vessel waiting times, thereby enhancing throughput. Moreover, prioritizing underperforming berths helped balance workload distribution, further optimizing resource use. Inland transportation, modeled via truck movements, was found to be a critical bottleneck affecting total container handling time. Sensitivity analyses demonstrated that increasing the truck fleet size or optimizing loading and transport times can substantially reduce delays, highlighting the importance of integrated planning across terminal operations.

This research successfully developed and validated an integrated framework for optimizing container terminal operations, combining metaheuristic optimization and discrete-event simulation. The GA proved to be a robust and effective tool for solving the quay scheduling problem, outperforming PSO in both accuracy and consistency. Simulation results revealed that strategic investments in berth expansion and truck fleet augmentation can lead to significant improvements in terminal throughput and resource utilization. Additionally, dynamic berth prioritization emerged as a practical approach to balancing workloads and minimizing vessel queues. Furthermore, emphasizes the necessity of an integrated perspective, considering both seaside and landside operations, to achieve comprehensive efficiency gains in container terminals. Future research could extend this work by incorporating real-time data analytics and exploring the impact of emerging technologies such as automation and digital twins on terminal performance.

Author Contribution

The author contributed to the study design, theoretical formulation, computational coding, testing of the algorithm, performance evaluation, and preparation of the manuscript.

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Data Availability

The datasets used and analyzed in this study are fully presented within the article.

Conflicts of Interest

The author reports no potential conflict of interest.

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