Optimizing Multi-Quay Berth Allocation using the Cuckoo Search Algorithm

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Abstract: Proper utilization of port resources and efficient berth planning play a crucial role in minimizing port congestion and overall handling costs. Therefore, this study focuses on efficient berth planning in maritime container terminals composed of multiple quays. In particular, this study addresses the Multi-Quay Berth Allocation Problem (MQ-BAP), where a continuous berthing layout is considered along with dynamic ship arrivals and practical constraints such as safety time windows and safety distances between ships. Since MQ-BAP is an NP-hard problem, this study proposes a metaheuristic-based approach, the Cuckoo Search Algorithm (CSA) for solving the problem. A comparative study is also performed using real data instances collected from the Port of Limassol, Cyprus, against a genetic algorithm solution proposed in the recent literature, as well as the optimal exact solution implemented using MILP. The results of the experiments show the effectiveness of our proposed CSA approach in handling real-world berth allocation in ports with multiple quays while also considering practical constraints.

1 INTRODUCTION

Maritime transport accounts for 90% of the world's seaborne trade and 74% of all goods imported in, or exported from Europe are carried by ships (Aslam et al., 2020). According to a recent report on maritime transport conducted by the United Nations Conference on Trade and Development (UNCTAD) in 2021 (UNCTAD, 2021), total global containerized trade has increased by 45.45%, with Twenty-Foot Equivalent Units (TEUs) totaling 110 million in 2010 and rising to 160 million TEUs in 2021. The container traffic has also increased in 2021, even though it was reduced in 2020 compared to 2019 due to the pandemic situation.

Maritime Container Terminals (MCTs) play a critical role in meeting the growing demand for seaborne trade. To deal with the growing demand for MCTs, there is a need to optimize their operations, benefiting from current technologies and optimization-based approaches. Following this practical need, the development of novel and efficient methods for optimizing terminal operations has attracted immense attention from academia and industry (Lind et al., 2020, 2021; STEAM, 2022; STM, 2022). Michaelides et al. (2019) have investigated the factors influencing the various waiting times at the Port of Limassol, Cyprus, both from a quantitative and a qualitative perspective. For shipping, and particularly for short sea shipping, there are obvious and immediate benefits from improving efficiency by supporting all actors involved in the port call process to engage more easily, to give shipping companies, port service providers, and ship agents better information and decision support systems to boost their efficiency and that of their port (Lind et al., 2019). Hence, MCTs' operators need to employ suitable strategies and approaches for proper utilization of the port resources and to avoid the aforementioned issues.

As MCTs handle huge volumes of containers, they are constantly challenged to increase their productivity by introducing numerous software and hardware innovations, e.g., in terminal design, cargo handling equipment, automated/efficient berthing operations, and operations research. MCTs can be divided into three main areas, namely seaside, marshaling yard, and landside areas, with each area having its own set of terminal operations (Hsu and Chi-

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ang, 2019). The main problems in the seaside operations include the Berth Allocation Problem (BAP), the Quay Crane Assignment Problem (QCAP), and the Quay Crane Scheduling Problem (QCSP) (Aslam et al., 2021). In this study, we address the first decision problem, namely the allocation of berths to arriving ships, known as BAP. On the fleet side, the berth allocation plan determines both the berthing position and the berthing time for arriving vessels to reduce costs, waiting times, handling times, and departure delays. On the port side, on the other hand, an efficient berth allocation plan determines how many ships can be handled in a planning period, with the goal of maximizing profit and making appropriate use of port resources.

The BAP has attracted a lot of attention from the research community and several approaches/techniques have been developed to optimize seaside operations. For example, in Dulebenets (2020), an evolutionary algorithm is proposed to deal with BAP, where the main objective is to reduce the weighted total service cost. Another study also deals with BAP, while additionally considering uncertainties in the operational time of ships (Xiang and Liu, 2021). In particular, an exact approach is developed and K-means clustering is used to model the uncertainty. The proposed method performs well; however, it is only suitable for small data instances. A hybrid heuristic-based Genetic Algorithm (GA) is developed in Bacalhau et al. (2021) to solve the BAP to avoid the issue of high computation time in exact approaches. The authors combine Dynamic Programming (DP) with the standard GA to solve large-scale problems that minimize service cost. Guo et al. (2021) deal with BAP, taking into account the uncertainty in handling times of vessels. They develop an optimization method to solve the BAP, combining particle swarm optimization and machine learning. Here, machine learning is used to check the relationship between handling time and weather conditions to model the uncertainty in handling time. They conduct several experiments and the results confirm the effectiveness of the proposed method compared to its counterparts. A study presented in Cheimanoff et al. (2021) also addresses continuous and dynamic BAP, in which a metaheuristic-based reduced variable neighborhood search method is developed to optimally allocate berths to arriving vessels. The study also considers tidal constraints for optimal berth assignment, and the main objective of this study is to reduce the total service time of vessels. In addition, a machine learning algorithm is used to tune the parameters of the metaheuristic. The proposed method has been tested on several datasets (small and large scale) and the results were compared with the exact method. The comparative study shows the effectiveness of the metaheuristic approach over other methods proposed in the literature.

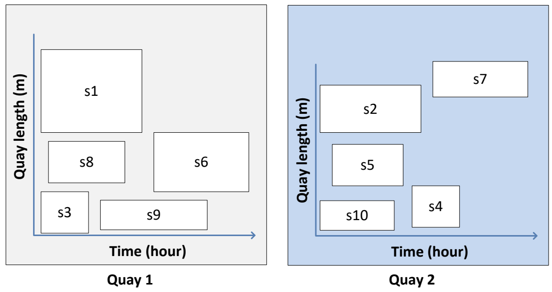


Figure 1: An illustration of two continuous berthing quays with 10 arriving ships.

Most of the aforementioned studies deal only with the allocation of berths at a single quay, assuming that it forms one straight line in which vessels can be berthed according to their length and the positions of other vessels. However, this assumption is not realistic for several ports around the globe, which consist of multiple separate line segments or quays for berthing (Frojan et al., 2015). For example, the Port of Limassol in Cyprus has seven continuous berthing quays. Considering multiple quays adds a new dimension to the BAP; the problem of assigning vessels to quays in addition to assigning berthing positions and times for each separate quay. This requires a multiple space-time representation, as can be seen in Figure 1. Very few studies have dealt with the Multi-Quay BAP (MQ-BAP). One study presented in Frojan et al. (2015) proposes a set of priority rules and uses GA to address the MQ-BAP. However, in their problem formulation, the total length of the quay is evenly distributed among the number of quays, while the evaluation is only performed over random data. Another study proposes a set of heuristics based on general variable neighborhood search (Krimi et al., 2020). Even though this approach is shown to be very efficient in solving this problem, in certain cases it proposes solutions that are far (up to 40%) from the optimal.

The motivation of this study is to develop a Multi-Quay BAP model and solution that can be applied in a real port, such as the Port of Limassol, Cyprus. As such, we consider additional practical constraints of the port, including the preferred berthing quay of each arriving ship, a safety time interval between consecutive vessels entering the port, as well as a safety time and distance between vessels berthed at a particular quay. First, the MQ-BAP is modeled as a mixed-integer linear model and then solved by the metaheuristic-based cuckoo search algorithm (CSA). Furthermore, we also implement the exact method using MILP and a popular heuristic method using GA for comparison. We conduct experiments using real data from one week of operations at the Port of Limassol and the results confirm the effectiveness of our proposed method.

The remaining paper is organized as follows. Problem definition and formulation are presented in Section 2. Next, Section 3 presents the details of the proposed CSA method and Section 4 discloses simulation setting, data instances, and simulation results. Finally, Section 5 concludes this study.

2 PROBLEM DESCRIPTION

In this section, we first introduce the MQ-BAP along with assumptions, and then we formulate the problem as a mixed-integer linear problem.

2.1 Problem Definition

In contrast to existing studies, and to make the problem more practical, this work considers MCT with multiple quays (having continuous berthing layouts) to berth arriving vessels, i.e., $Q = \{1,...|Q|\}$. A continuous quay $q \in Q$ consists of a section of the berth line at the MCT and arriving ships can be moored at any point along the berth line, representing the available berthing positions at q, i.e., $B_q = \{1,...|B_q|\}$. The set T indicates the set of time intervals considered for planning, i.e., $T = \{1,2,3,...|T|\}$. There is a set of arriving ships $S = \{1,2,3,...|S|\}$ and each ship $s \in S$ has multiple known characteristics, including Length of Ship (LoS), Expected Time of Arrival (ETA), Expected Time of Departure (ETD), Handling Time (HT), and Preferred Berthing Quay (PBQ). Table 1 presents the mathematical notations that are used in this section.

The objective of this study is to determine the berthing quay, berthing position, and berthing time for all arriving ships in S in order to minimize the total cost associated with the berthing process. The cost against ship s includes handling cost C_s^h, waiting cost C_s^w, penalty cost due to late departures C_s^{ld}, and penalty cost due to allocation of ships to non-optimal berthing quay C_s^{noq}. The handling cost includes the cost of loading and unloading of containers and depends on the handling time T_s^h of ship s. The waiting cost is calculated based on the waiting time T_s^w, which is the difference between the estimated arrival time T_s^{ea} and the berthing time T_s^b. The late departure penalty cost C_s^{ld} depends on the late departure time T_s^{ld}, which is defined as the difference between the operations finishing time T_s^f and the requested departure time T_s^{rd} of each ship. The last penalty cost C_s^{noq} is added if the ship s is not moored to its preferred berthing quay (PBQ) but rather it is moored to an alternative berthing quay (ABQ), since more resources are needed to move containers over a longer distance. ABQs are introduced in this study to constraint the algorithm to select only appropriate quays (i.e., either the preferred or alternative quays) for berthing a vessel since in practical scenarios, not all quays can handle all vessels (e.g., due to lack of proper equipment).

2.2 Assumptions

The problem under consideration and the solution are based on the following assumptions:

- The number of incoming ships in the planning period is known;
- When a vessel commences operations at a particular quay, it cannot be interrupted until the operations are completed;
- Berths from any quay become available immediately after a ship completes its operations;
- The number and length of the quays are known;
- The ETA along with ETD for all arriving ships are known;
- The handling time for each vessel is known;
- Each vessel has a PBQ and an optional list of ABQs that are known in advance;
- All berths are assumed to be free at the beginning of the time horizon (time = 0);
- All penalty costs for all vessels are known;

2.3 Mathematical Formulation

The total handling cost of a ship s that is planned for berthing at position B_s of a particular quay Q_s at time T_s^b includes a waiting cost, a handling cost, and a penalty for late departure, presented as:

$$\begin{aligned} Cost(s, Q_s, B_s, T_s^b) &= T_s^w \cdot C_s^w \\ &+ T_s^h \cdot C_s^h \cdot f(Q_s, B_s, PBQ_s, ABQ_s, C_s^{noq}) \\ &+ T_s^{ld} \cdot C_s^{ld} \end{aligned} \quad (1)$$

The first term in Equation (1), $T_s^w \cdot C_s^w$, shows the waiting cost when a ship s has to wait for mooring. The waiting time T_s^w of ship s is calculated as the difference between the ETA T_s^{ea} and berthing time T_s^b,

Table 1: Mathematical Notations.

Name	Explanation
ABQ_s	Alternative berthing quays for ship s
B_s	Berthing position of ship s at quay Q_s
C_s^h	Handling cost per time unit (hour) for ship s
C_s^w	Waiting cost per time unit (hour) for ship s
C_s^{noq}	Penalty cost against non-optimal berthing quay (fixed cost) for ship s
C_s^{ld}	Penalty cost against late departure per time unit (hour) for ship s
L_s	Length of ship s
L_q	Length of quay q
PBQ_s	Preferred berthing quay of ship s
Q_s	Berthing quay of ship s
SD	Safety distance (in meters) between two ships during berthing
SE	Safety entrance time between two ships
ST	Safety time between two ships during berthing on the same quay
T_s^b	Berthing time of ship s
T_s^{ea}	Expected/estimated arrival time of ship s
T_s^f	Finish time of operations (loading and/or unloading) of ship s
T_s^h	Handling time of ship s
T_s^{ld}	Late departure time of ship s
T_s^{rd}	Requested departure time of ship s
T_s^w	Waiting time of ship s
$s \in S = \{1,2,...,\lvert S\rvert\}$	Individual ship
$q \in Q = \{1,2,...,\lvert Q\rvert\}$	Berthing quay
$b \in B_q = \{1,2,...,\lvert B_q\rvert\}$	Berthing position in quay q
$t \in T = \{1,2,...,\lvert T\rvert\}$	Single time period

$$T_s^w = T_s^b - T_s^{ea}, \quad \forall s \in S \tag{2}$$

The second term in Equation (1), $T_s^h \cdot C_s^h \cdot f(Q_s, B_s, PBQ_s, ABQ_s, C_s^{noq})$ represents the total processing cost of ship s that was incurred by unloading and loading containers from/to ship s, where T_s^h and C_s^h denote handling time for ship s and handling cost per unit time, respectively.

Without loss of generality, this work also introduces the penalty function $f(Q_s, B_s, PBQ_s, ABQ_s, C_s^{noq})$, which penalizes the handling cost due to non-optimal quay assignment, as presented in Equation (3). The penalty cost equals 0 if ship s is moored at its preferred berthing quay PBQ_s and C_s^{noq} if s is moored at one of the alternative berthing quays ABQ_s. Otherwise, the penalty is set to infinite to ensure the algorithm will never perform such an assignment.

$$f(Q_s, B_s, PBQ_s, ABQ_s, C_s^{noq}) = \begin{cases} 0 & \text{, if } Q_s = PBQ_s \\ C_s^{noq} & \text{, else if } Q_s \in ABQ_s \\ \infty & \text{, otherwise} \end{cases} \tag{3}$$

The final term $T_s^{ld} \cdot C_s^{ld}$ in Equation (1) calculates the late departure penalty cost against ship s when it departs after a requested departure time. The delay in departure time T_s^{ld} of ship s is computed as the difference between the time of operations completion T_s^f and the requested time of departure T_s^{rd}.

$$T_s^{ld} = max\{T_s^f - T_s^{rd}, 0\}, \quad \forall s \in S \tag{4}$$

where, T_s^f can be calculated as,

$$T_s^f = T_s^b + T_s^h, \quad \forall s \in S \tag{5}$$

The primary objective of the MQ-BAP is to allocate optimal quays and berthing positions along with berthing times to arriving ships such that the total processing cost (that includes waiting cost, handling cost, and various penalties) can be minimized, as presented by the following objective function:

$$\textbf{minimize} \sum_{s \in S} \sum_{q \in Q} \sum_{b \in B_q} \sum_{t \in T} Cost(s,q,b,t) \cdot x_{sqbt} \tag{6}$$

subject to the following constraints.

$$x_{sqbt} \in \{0,\ 1\}, \quad \forall s \in S,\ q \in Q,\ b \in B_q,\ t \in T \tag{7}$$

The variable x_{sqbt} is 1 if ship s is assigned to berthing position b of quay q at berthing time slot t, and 0 otherwise.

$$\sum_{q \in Q} \sum_{b \in B_q} \sum_{t \in T} x_{sqbt} = 1, \quad \forall s \in S, \tag{8}$$

Constraint (8) states that each ship is assigned to a particular quay q and berthing position b only once (at time t) during the planning period T.

$$T_s^b \geq T_s^{ea}, \quad \forall s \in S. \tag{9}$$

Constraint (9) defines that the proposed berthing time T_s^b for particular ship s must be equal or greater than its expected arrival time T_s^{ea}.

$$B_s + L_s \leq L_{Q_s}, \quad \forall s \in S, \tag{10}$$

Constraint (10) ensures that the summation of the proposed berthing position B_s and the ship length L_s must always be equal to or less than the quay length L_{Q_s}.

$$\sum_{j \neq s \in S} \sum_{b=B_s-L_j-SD+1}^{B_s+L_s+SD} \sum_{t=T_s^b-T_j^h-ST+1}^{T_s^b+T_s^h+ST} x_{jqbt} = 0, \quad \forall s, j \in S, q \in Q_s \tag{11}$$

Constraint (11) avoids scheduling overlapping of two or more ships. For example, suppose ship s is scheduled to berth at time $6h$, has a processing time of $5h$, uses berth position $600m$, and its length is $300m$. As per constraint (11), no other vessel can use position from $600m$ to $900m$ (as length of ship s is $300m$) in the time interval $6h$ to $11h$. Furthermore, another vessel j with a length of $200m$ and a processing time of $4h$ cannot be berthed at positions from $401m$ to $900m$ (ignoring the safety distance) in the time interval $3h$ to $11h$ (ignoring the safety time) because it would overlap with previous vessel s. Furthermore, constraint (11) is also responsible for keeping the safety distance SD and safety time ST between two ships in order to avoid any dangers during berthing. Visually, this constraint ensures that any two rectangles (denoting the time intervals and berthing positions allocated to vessels) shown in Figure 1 can never overlap.

$$T_s^b - T_j^b \geq SE \quad \forall s \neq j \in S, \tag{12}$$

Finally, constraint (12) ensures a minimum safety entrance time period SE between sequential berthings, regardless of berthing quay, since at the Port of Limassol, like many other ports around the world, there is a single port entrance that all ships must sequentially enter to berth (see the red triangle in Figure 2).

3 PROPOSED METHOD

In this study, we employ the Cuckoo Search Algorithm (CSA) to address MQ-BAP. CSA is a metaheuristic optimization algorithm developed by (Yang and Deb, 2009). The CSA is inspired by the breeding mechanism of some cuckoo species, which are fascinating because of their beautiful sounds and aggressive reproduction mechanism. Some cuckoos lay their eggs in communal nests of other species, where they try to remove the eggs of other birds in order to improve the hatching probability of their own eggs. Then, other birds, probably from other species, known as host birds take care of cuckoo eggs. However, if the host birds realize that some eggs do not belong to them, then the cuckoo eggs are disposed of or current nests are destroyed and built elsewhere. In particular, some cuckoo species (e.g., new world brood-parasitic Tapera) specialize in the mimicry of the pattern or color of eggs and they lay their eggs in nests of relevant species in order to reduce the probability of their eggs being thrown or destroyed (Gandomi et al., 2013). Overall, the CSA works based on the behavior of cuckoos for laying eggs and adopts three idealized rules (Yang and Deb, 2009):

1. each cuckoo bird dumps only one egg at a time in a random nest;
2. the best nests having high quality eggs are kept and used for the next generation;
3. the number of host nests is fixed and the egg laid by a cuckoo is detected by a host bird with probability $p_\alpha \in (0,1)$.

The mapping of CSA to MQ-BAP is as follows. A single nest shows a set of solutions containing the mooring positions and mooring times of all arriving ships. An egg in a nest denotes a berthing time or berthing position in a berthing quay for an arriving ship, whereas, a cuckoo egg shows a novel (or better) solution (i.e., a berthing time or position in a quay). The total search space of the problem at each iteration is reflected by the total number of host nests, which is fixed (100 host nests are assumed in this study). In addition, each nest includes $2N$ eggs, where N shows the number of ships that have arrived at a given time. Therefore, the total number of eggs in a nest is twice the total number of ships arriving. This is because we need two solutions for each ship (i.e., one is the berthing time and the other is the berthing position). The overall goal of the algorithm is to use cuckoo eggs (better solutions) to replace the not-so-good eggs in the various nests.

4 SIMULATION RESULTS

In this section, we present the simulation setup along with the simulation results. We propose and implement metaheuristic-based CSA for the berth allocation problem when considering multiple quays (MQ-BAP). We also implement the GA, a popular metaheuristic approach proposed in Salhi et al. (2019), and the exact solution using MILP for comparison purposes. Simulations are performed on a PC with Core i7 using MATLAB 2018b. Regarding the dataset, we employ real-world data collected from the Port of Limassol, Cyprus, which contains information about each arriving ship, i.e., ETA, ETD, LoS, processing time of ship, and preferred berthing quay (as the Port of Limassol has multiple quays). The data are collected directly from a port calls database and are converted into a more suitable format for processing. For example, time is discretized into fixed-time intervals for easier processing by the scheduling algorithms. In

Table 2: Example data for 10 ships (out of the 28 ships) in our dataset that arrived at the Port of Limassol, Cyprus).

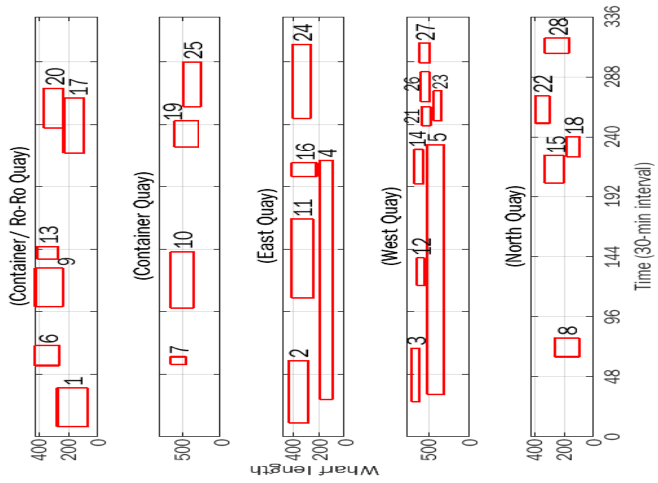
Ship #	ETA (day\time)	HT (min.)	ETD (day\time)	PBQ	LoS (meters)
1	1\04:00	919	1\22:30	Container/ Ro-Ro Quay	194
2	1\05:30	1490	2\06:50	East Quay	139
3	1\14:00	1285	2\12:50	West Quay	84
4	1\15:00	5700	5\14:03	East Quay	89
5	1\17:00	5970	5\21:00	West Quay	190
6	2\04:30	470	2\13:50	Container/ Ro-Ro Quay	159
7	2\05:00	168	2\09:30	Container Quay	196
8	2\08:00	440	2\15:55	North Quay	155
9	3\04:00	905	3\20:50	Container/ Ro-Ro Quay	175
10	3\03:30	1331	4\06:15	Container Quay	277

Figure 2: A satellite view of the Port of Limassol, Cyprus illustrating its seven berthing quays (taken from ais.cut.ac.cy (2022)).

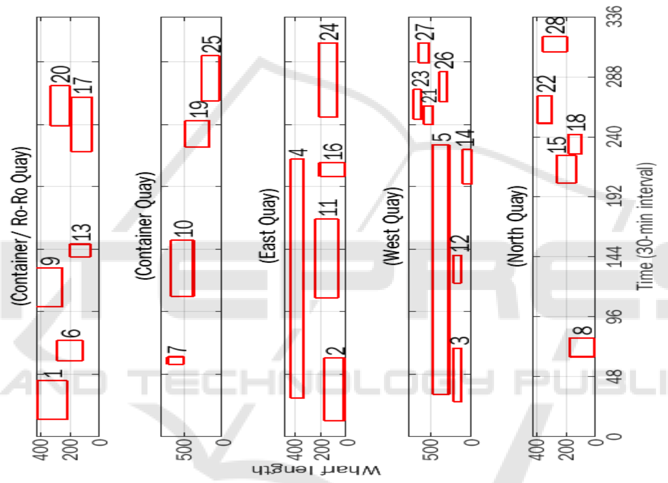
the future, we plan to implement a graphical user interface for visualizing the output of the algorithm to the berth planner in a user-friendly manner. Table 2 shows a sample of the collected data for 10 arriving ships. The full dataset contains a total of 28 ships that arrived at the port during a period of one week. We implement the proposed and compared methods on the same dataset and the results are presented later in this section. As for cost calculations, we assume the handling cost is 10 euro/hour, the waiting cost is 20 euro/hour, and the late departure cost is 20 euro/hour.

A satellite view of the Port of Limassol is shown in Figure 2. There are a total of seven quays in the Port of Limassol but only five appear in the dataset (i.e., only the ones that handle commercial traffic), namely Container/ Ro-Ro Quay, Container Quay, East Quay, West Quay, and North Quay, and are all of different lengths, as shown in Table 3. Note that all arriving ships have a preferred berthing quay for performing loading and unloading operations, but currently, the dataset does not include a preferred berthing position or alternative berthing quays.

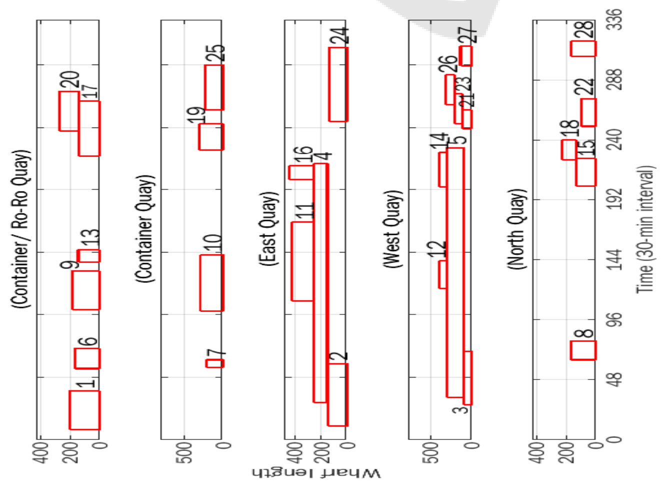
Figure 3 shows the berth allocation plan obtained by the 3 implemented solutions: (a) CSA, (b) GA, and (c) MILP. The berthing plan is developed according to the objective function of this study (given in Equation (6)) and considering all constraints. In this figure, the horizontal axis shows the berthing time divided into 30-minute intervals, and the vertical axis shows the berthing positions of the arriving vessels.



(a) Solution by CSA



(b) Solution by GA



(c) Solution by MILP

Figure 3: Berth allocation solutions over one week for five quays at the Port of Limassol, Cyprus.

Table 3: Quays at the Port of Limassol, Cyprus.

Quay #	Quay name	Length (m)
1	Container/ Ro-Ro Quay	450
2	Container Quay	800
3	East Quay	480
4	West Quay	770
5	North Quay	430

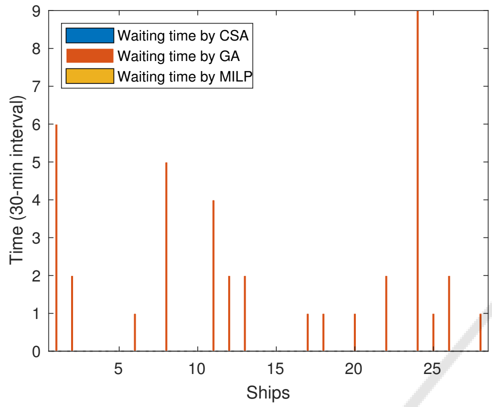


Figure 4: Waiting time for all arriving ships when using all three algorithms, i.e., CSA, GA, and MILP. The only induced waiting times are reported when using GA.

Each rectangle demonstrates the berthing positions and berthing time intervals assigned to each ship.

Furthermore, the label next to the rectangle corresponds to the vessel index. For example, ship 8 arrives at 8:00 on the second day and the PBQ is 'North Quay'. It can be observed that the CSA (see Figure 3a) efficiently assigns a berth (without any waiting time) to ship 8 at its PBQ. However, if we look at the berth allocation for ship 8 for GA (see Figure 3b), we can observe that ship 8 has to wait for an optimal berthing and the waiting time is 5 time slots (2.5 hours). However, despite the delay of 5 time slots in berthing, ship 8 can reach the desired departure time. Figure 3c shows the optimal berth allocation plan computed using the exact method, i.e., MILP.

Figure 4 clearly shows that MILP and CSA always provide an optimal solution with regards to minimizing waiting times because there is no waiting time before berthing. However, using GA, 14 out of the 28 ships have to wait, with a maximum waiting time of 9 slots (4.5 hours) before they can berth. As for the departure time, we can see from Figure 5 that no ship departs late when using any of the three algorithms, i.e., CSA, GA, and MILP. Even with GA, several ships are late in docking, but they can still achieve the desired departure time. In this case, penalty cost for waiting time is calculated, and therefore the total handling cost (shown in Equation 1) using GA is higher than our proposed CSA and MILP methods. Note that the total handling cost is the sum of the total waiting cost, the handling cost (including the penalty for non-optimal quay assignment), and the penalty for late departure.

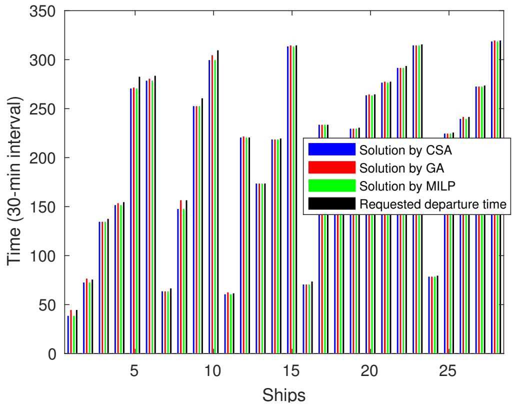


Figure 5: Requested and proposed departure times when using all three algorithms, i.e., CSA, GA, and MILP.

Table 4 shows the total handling cost for the 28 vessels and the computational time for all three algorithms. From this table, it can be seen that the total costs of the CSA and MILP methods are the same, which shows that CSA achieves an optimal solution for all arriving ships for this particular dataset. However, for GA, the total cost is 11.2% higher because some of the ships have to wait for a long time before berthing. As for the computation time, MILP takes 910.76 seconds and, as expected, its computation time is orders of magnitude higher than the other two algorithms. However, our proposed CSA method and GA solve the same problem in near real time, with only 4.49 and 1.79 seconds, respectively. Even though GA achieves the minimum computation time (1.79 seconds) to handle a week's worth of data, it fails to provide an optimal solution.

It is worth noting that for larger problems, the exact method (MILP) cannot be used because it reportedly requires over 100 hours CPU time for large datasets (Aslam et al., 2021). Such times are certainly not acceptable in the context of MCT operations. From the above discussion, it appears that CSA can provide an optimal or near-optimal solution within an acceptable computation time.

Table 4: Comparison of proposed and benchmark methods.

	Total Cost (Euro)			Comp. Time (Sec)		
Method:	CSA	GA	MILP	CSA	GA	MILP
1-week	5385	6025	5385	4.49	1.79	910.76

5 CONCLUSION

Over the past decade, international maritime trade has increased dramatically. In order to serve the growing number of vessels arriving at the terminal for loading and unloading, MCTs need to increase their efficiency by using various technologies and methods. This study focuses on the Multi-Quay BAP and proposes a metaheuristic-based CSA method to solve the problem. A continuous berthing layout is considered and the ships arrive dynamically. The problem is first formulated as a mixed-integer linear problem and then solved by CSA. In addition, two benchmark methods (i.e., GA and MILP) are also implemented in this study for comparison. To confirm the performance of our proposed method, simulations are conducted using real data from the Port of Limassol, Cyprus. The data contains 28 ships arriving in a period of one week and intending to dock at five different quays. The results of the experiments confirm the benefits of the proposed method with 11.2% lower cost than GA and 200x lower computation time than MILP.

In the future, we plan to examine the performance of the proposed CSA method on larger real-world datasets, containing several vessels and spanning longer planning time periods (days to weeks). We also plan to extend the modeling to incorporate a hybrid berthing layout that includes both discrete and continuous berthing layouts. Finally, we plan to investigate the application of the CSA in solving the berth allocation problem combined with the related quay crane assignment and scheduling problems.

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