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Artificial bee colony to solve the berth allocation and crane assignment problem.

Sara SOUAINI*, Jamal BENHRA, Salma MOUATASSIM

* *LARILE Laboratory, TEAM OSIL Hassan II University of Casablanca, Morocco*

*Corresponding author Email address: souainisara@gmail.com

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Abstract

The efficient operation of container terminals hinges on two crucial aspects: vessel scheduling and resource allocation. These tasks, considered NP-hard optimization problems, aim to minimize the total processing time of vessels at docks.
While prior research predominantly focused on optimizing vessel arrival and departure times, recent studies emphasize the significance of addressing resource allocation challenges to enhance overall port efficiency. Recognizing this, our study employs a mathematical model to deepen understanding and elucidate inherent constraints.
To effectively resolve the model, we employ the Artificial Bee Colony (ABC) algorithm. This algorithm is chosen for its efficacy in addressing scheduling problems characterized by limited identical resources, unitary processing, and non-repetitive tasks.
By utilizing the mathematical model and ABC algorithm, our research aims to optimize vessel scheduling and resource allocation in container terminals. Ultimately, the goal is to minimize the total processing time of vessels at docks, thereby streamlining operations and improving port efficiency.
This research contributes to the field by offering a comprehensive approach to address the intertwined issues of vessel scheduling and resource allocation. Its findings hold significance for stakeholders in maritime logistics, providing strategies to enhance service delivery and operational performance in container terminals.

Keywords: Optimization – Scheduling - Berth Allocation - Crane Assignment – Artificial bee colony

1. Introduction

A terminal in a port is formed by a quay, or a group of berths, allowing the berthing and operation of ships assigned to a particular traffic, and completed by the land-based facilities necessary for the exploitation of this traffic. A good illustration of this terminal concept for containerized traffic is that almost every port now has one or more container terminals, reflecting the port's adaptation to the trend towards increased 'containerization [10]. Although today there are still many conventional vessels carrying a variety of goods, particularly on routes serving developing countries, it can be estimated that in the future there will be only three main categories of cargo vessels: bulk carriers (solid/liquid), container ships and conventional or ro-ro specialized vessels (heavy lift, bulky, special products, cars, neo-bulk, i.e., non-containerizable goods) [16].

Container terminals are specifically designed for containerships, serving as locations where various handling equipment is employed to transport containers between different points. The significance of these terminals is on the rise, especially in the face of new challenges posed by advancing shipping technologies, pushing for the construction of larger vessels. Given the sustained growth in containerized traffic, the operation of container terminals has evolved into a pivotal activity. Efficient management is crucial for these terminals to compete successfully in this dynamic environment. [1]. In our context, good terminal management means minimizing the time spent by a container or a ship in the port. More precisely, the fine management of container handling for loading/unloading appears to be a problem that must be studied. This handling represents the first link in the chain for imports and the last one for exports. The integration of the two components berth allocation and crane assignment plays a pivotal role in the import process, serving as the initial link in the logistics chain

within a port terminal. When adequately optimized, it ensures a level of efficiency crucial to the terminal's overall operation. Both berth allocation and crane assignment represent critical resources in the terminal due to their inherent limitation. The criticality stems from their finite nature, underscoring the necessity for efficient and optimized management to maintain competitiveness in a container terminal. [13].
Previous research in vessel scheduling has primarily focused on optimizing arrival and departure times, but recent studies highlight the critical importance of addressing resource allocation challenges to enhance overall port efficiency [3].
Various mathematical models and optimization techniques have been explored to tackle the complex problem of allocating handling resources in maritime transportation, aiming to minimize berth congestion and maximize utilization while considering various operational constraints.
The studies published on this subject highlight the importance of resource allocation in vessel scheduling to improve port efficiency. However, some of these approaches may have limitations in terms of complexity or adaptability to dynamic port variations. and they may not have explored in depth the specific application of the artificial bee colony algorithm to solve this problem. By including this method in our research, we will provide a new perspective on solving this complex challenge.
This research focuses on leveraging approximate optimization methods, particularly meta-heuristics, to address the problem at hand.
Initially, a mathematical model was formulated, and the artificial bee colony algorithm was employed to solve it. The effectiveness of this approach was validated through performance comparisons with other metaheuristic algorithms.

2. Literature review

2.1. Berth Allocation and Crane Assignment Problem

1. Process in a container terminal

In a container terminal, we are interested in the different activities starting with the unloading of the ships until their loading. We are also interested in the different handling equipment associated with them and discuss the different problems that are associated with them, figure (1).

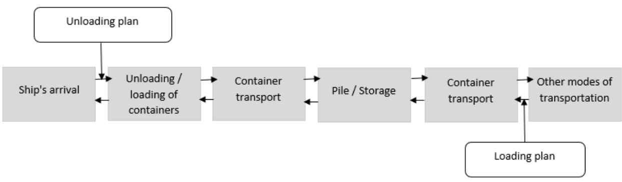


Fig. 1: Process in a container terminal.

2. Berth Allocation

The objective is to assign incoming ships to the available berths within a container terminal, catering to various ship types, ranging from deep-sea vessels capable of carrying up to 13,000 container units (TEU) to conventional ships with a 4,000 TEU capacity. Upon the ship's arrival at the port, it needs to dock at the quay, and the port operators have a specific number of berths on the quay at their disposal. The capacity of a quay to accommodate ships depends on its length [9].
Before the ship arrives, terminal operators receive information about the ship's type, the number of containers to be loaded or unloaded, and the expected arrival and departure times. During the berth allocation planning, details such as berthing time, the precise position of each ship at the quay, and the availability of various resources on the quayside are determined.
Berth Allocation Planning (BAP) is a critical operation in the terminal and berth planning process, directly impacting the ship's turnaround time and the flow of containers in the port [12]. Traditionally, terminal operators employed a first-come, first-served (FCFS) policy for berth allocation, but this approach is no longer viable today.
BAP is defined as the challenge of allocating berth space for incoming ships in a port, considering multiple realistic constraints. As vessels arrive sequentially, the port operator must efficiently allocate berths to ensure prompt service, involving the loading and unloading of containers.

3. Classification of the BAP

The BAP can be considered and formulated according to discrete or continuous, static or dynamic variations.
Static BAP: BAP can be modeled as a static problem (SBAP), if all ships are in port before the planning starts. Several research works on BAP have considered this theory with a discrete berth distribution.
Dynamic BAP: If the SBAP assumption is relaxed, i.e., some ships may arrive after the start of the planning plan, the dynamic berth allocation problem arises (DBAP). This problem is difficult to solve even if there is only one berth available. Most of the research that deals with BAP focuses on this assumption, as it better represents the way terminals operate today.
Discrete or Continuous BAP: Whether BAP is characterized as a discrete or continuous problem hinges on the conceptualization of the quay. If the quay is envisioned as a finite set of berths, with each berth represented as a segment of fixed length [17] [14], then BAP can be appropriately modeled as a discrete problem.

4. BAP-CAP integration

In this perspective, the targeted problem is a berthing area scheduling problem with resource allocation. The reason for the choice of integrating these two problems at the same time comes from their real and effective interaction in a port. Indeed, the primary objective of the CAP is to define the service time for loading/unloading, a crucial input variable for the BAP problem. Consequently, simultaneously modeling both problems brings us closer to the operational reality of a port. Therefore, solving the combined problem holds immediate applicability for a port manager. The integration of the two components, BAP and QCAP (Quay Crane Allocation Problem), gives rise to the BACAP (Berth Allocation and Crane Assignment Problem). This amalgamation has been a focal point of interest among researchers in the field for the past decade [17] [14].

2.2. Artificial bee colony

The Artificial Bee Colony (ABC) algorithm, developed based on the intelligent behavior of a bee swarm by Karaboga and Basturk in 2007, has become one of the most extensively used intelligent swarm algorithms in various applications in recent years [5] [4]. This population-based combinatorial optimization algorithm takes inspiration from the foraging behavior of real bees, employing a collective approach to imitate the actions of a bee colony in locating the optimal food source [11].
Adhering to the minimal selection model observed in real bee foraging, the artificial bee colony in ABC consists of three distinct groups of bees. Firstly, there are employed bees that are associated with specific food sources. Secondly, onlooker bees play a crucial role by observing and interpreting the dance of employed bees, enabling them to select a food source. Lastly, scout bees are tasked with conducting random searches to explore alternative food sources. Onlookers and scouts are also colloquially referred to as unemployed bees. At the outset, scout bees identify all food source positions [6].
Subsequently, employed and onlooker bees exploit nectar from the food sources, leading to their eventual exhaustion. A worker bee, having depleted a food source, transitions to becoming a scout bee searching for new food sources [5].
In the ABC framework, the position of a food source serves as a potential solution, representing an initial feasible solution to the problem. The quantity of nectar associated with a food source indicates the quality or fitness of the corresponding solution. In its basic structure, the number of employed bees aligns with the number of food sources or solutions. Each employed bee is dedicated to and associated with a specific food source [5] [4] [6]. This organization reflects the algorithm's approach to exploring and optimizing solutions through the collective efforts of the employed bee population.

2.3. Related works

In my previous research, I delved into the task scheduling problem, a primarily non-deterministic polynomial (NP-hard) challenge that entails organizing a sequence of tasks temporally while considering real constraints. I addressed this problem by employing various meta-heuristic algorithms, with a particular focus on comparing the performance of the genetic algorithm and the artificial bee colony in a scheduling scenario characterized by identical limited resources, unitary processing, and non-repetitive tasks. The study's findings revealed that the ABC algorithm surpassed the genetic algorithm, yielding superior results in the specific context of task scheduling [15].

3. Contextualization of the study

Efficient scheduling of sea-side operations in container terminals significantly influences their competitiveness, serving as a critical bottleneck operation in terminals worldwide. One of the contemporary challenges in planning these operations involves integrating quay space and allocating cranes to vessels for loading/unloading, with the aim of optimizing service time [2].
The CAP is focused on determining the total berthing time at the quay, which includes both service time (loading/unloading) and waiting time. This cumulative berthing time is a vital input for the BAP. The CAP essentially contributes critical information to the broader challenge of optimizing berthing and crane assignments within a container terminal. The simultaneous modeling of this integrated problem provides a more realistic portrayal of port operations. Consequently, solving these problems jointly offers immediate practical applicability for a port manager. The amalgamation of BAP and CAP results in the intriguing problem known as BACAP, the focal point of our paper. We aim to formulate a new mathematical model and apply a solution approach to address this combined challenge.

3.1. Mathematical model

Within the non-linear framework of BACAP, the model takes into account both the discrete typology of berths and the dynamic temporal aspect of the ship arrival process [7][8].

To formulate BACAP, our proposed objective is to minimize the waiting and handling times of container ships, as depicted in the following expression:

$$MinZ = \sum_{k=1}^{n} \text{waiting time} + \sum_{k=1}^{n} \text{handling time} \qquad \text{n = num of vessels}$$

And explained by the chronology of the berthing operations in the figure.

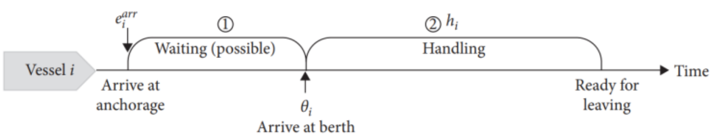


Fig. 2: Berthing operations

In what follows, we present the new mathematical formulation for the time-invariant assignment, referred to as BACAP (Berth Allocation and Crane Assignment Problem).

Model's notations & parameters:
Input

i = 1, … , I set of vessels ;
j = 1, … , J set of discrete berths ;
k = 1, … , K set of ship services at the same berth ;
a_i = ship arrival time ; i ∈ I
c_i = ship container capacity ; i ∈ I
v = crane speed (cont/hour)
H = number of available mobile Crane

Decision Variables:

xijk $\begin{cases} = \text{ if the ship i is served at berth j as the kth ship.} \\ = 0 \text{ else} \end{cases}$

xil $\begin{cases} = 1 \text{ if the ship i is served before the completion} \\ \text{time of ship l} \\ = 0 \text{ else} \end{cases}$

h_i = integer: {0,1,2}, number of cranes affected to ship i, i ∈ I
s_i = starting service time of ship i, i ∈ I
f_i = finishing service time of ship i, i ∈ I
The mathematical nonlinear model is formulated as:

$$Min\ Z = \sum_i \sum_j \sum_k (s_i - a_i)\, x_{ijk} + \sum_i \sum_j \sum_k (f_i - s_i)\, x_{ijk} \quad (2)$$

$$\sum_j \sum_k x_{ijk} = 1 \quad (3)$$

$$\sum_i x_{ijk} \leq 1 \quad \forall j\ \forall k \quad (4)$$

$$s_i \geq a_i \quad (5)$$

$$h_i \leq 2 \quad \forall\, i \in I \quad (6)$$

$$\sum_i s_i x_{ijk} \geq \sum_l \left(s_l + \frac{s_l}{vh_l} \right) x_{ij(k-1)} \quad \forall j\ \forall k \quad (7)$$

$$h_i + \sum_{l \neq i} h_l y_{il} \leq H \quad \forall\, i \in I \quad (8)$$

$$e_i = s_i + \frac{C_i}{vh_i} \quad (9)$$

The objective function (2) is designed to minimize the total of waiting time and handling service duration for container ships. The formulated constraints are as follows:
Constraint (3) ensures that only one vessel can be served at a berth concurrently.
Constraint (4) limits each berth to hosting only one vessel at any specific time.
Constraint (5) dictates that the initiation of service must commence either precisely at or after the arrival of the vessel.
Constraint (6) governs the maximum number of cranes that can be concurrently assigned to a single vessel.
Constraint (7) stipulates that a vessel may not be served at any berth after the departure of the preceding vessel.
Constraint (8) ensures that the allocation of cranes does not surpass the available crane capacity at any given time.
Constraint (9) sets the end times for loading/unloading containers.

3.2. Solving approach

The initial step in the heuristic solution approach involves generating an initial solution in the first phase, where berth and crane assignments are made for relevant vessels across the planning horizon, adhering to constraints (3) through (5). As mentioned earlier, two cranes can be assigned to container ships for handling operations. Consequently, constraint (10) is verified after each assignment attempt to ensure that the allotted number of cranes is not exceeded. If it is, the heuristic adapts by removing one crane for certain vessels. The presented structure for the construction heuristic is depicted in Figure 3.

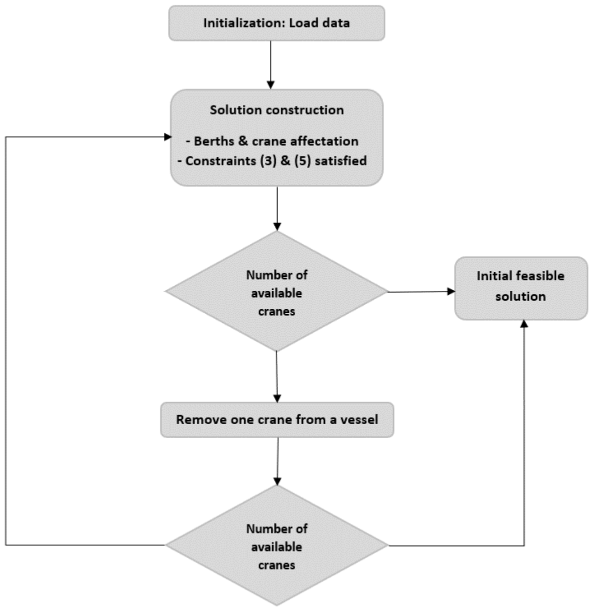


Fig. 3: Framework for the construction heuristic

3.3. Artificial Bee Colony (ABC) to solve BACAP

The implemented ABC algorithm for resolving the BACAP encompasses the following main steps:

1. Initialize Parameters in ABC
2. Generation on the initial population
3. Evaluate the fitness function of all solution in the population.

$$\text{fit}(x_i) = \frac{1}{1+Total\ Services\ (xi)}$$

4. Memorize best solution
5. Set cycle=1
6. Repeat
7. Employed bee phase
8. Evaluate the fitness function
9. Greedy selection
10. Probability Pi

$$P_i = \frac{fit(x_i)}{\sum_{k=1}^{SN} fit(x_k)}$$

11. Onlooker bee phase
12. calculate fitness
13. Greedy selection
14. Scout bee phase
15. Store the best food source found so far in memory.
UNTIL (T is reached).

3.4. Experiments and Results

The formulated mathematical model was implemented using the MATLAB programming language. Experimental trials were conducted on problem instances of varying sizes, spanning from 12 to 40 ships. This diverse range of scenarios aimed to draw conclusions regarding the performance of the instances. Additionally, the parameters of the Artificial Bee Colony (ABC) algorithm were adjusted to assess the influence of these modifications on the obtained results.

1. Initial solution

The input of the heuristic to build an initial solution is presented in Table 1. The scope of work is 6 ships, 3 discrete berths, 8 available mobile Crane. The handling speed is 10 containers/time unit.

Table 1:
Input of the heuristic

Containership	Arrival	Containers
1	10	400
2	12	400
3	20	600
4	15	400
5	8	300
6	10	200

The output represented by Figure 4 shows the assignment of berths and cranes.

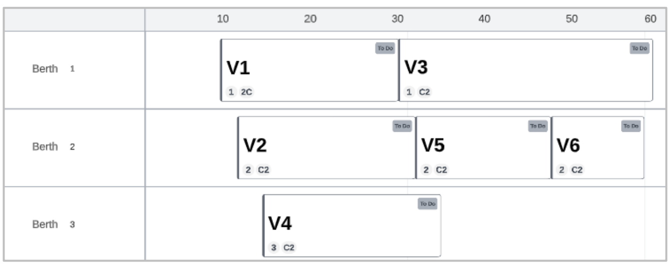


Fig. 4: Output of the heuristic (Initial solution)

In this preliminary solution, the cumulative service time amounts to 186 units.

2. Neighborhood

To generate a neighbor solution, we perform some disruptions on the initial solution. For this example, the ship 6 initially assigned to berth 2 will change to berth 3. This has been done to take account of arrival time constraints.
Adjusting the start of handling operations can be employed to meet the constraint of utilizing the maximum number of available cranes. In this instance, the alternative solution from the neighboring adjustments yields a more favorable result for the total service time, reducing it to 155 units.

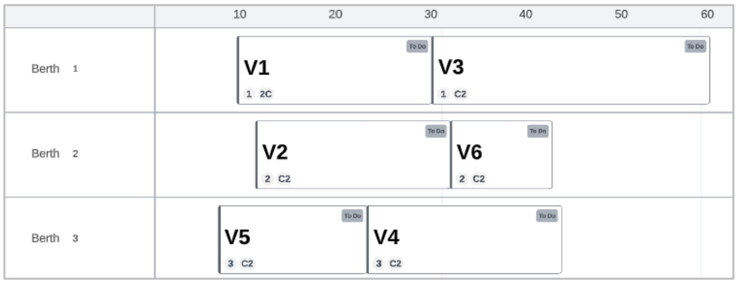


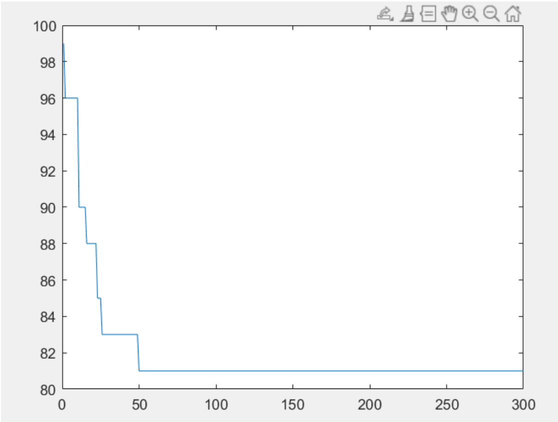
Fig. 5: Output of the heuristic (Neighbor solution)

3. Generating data

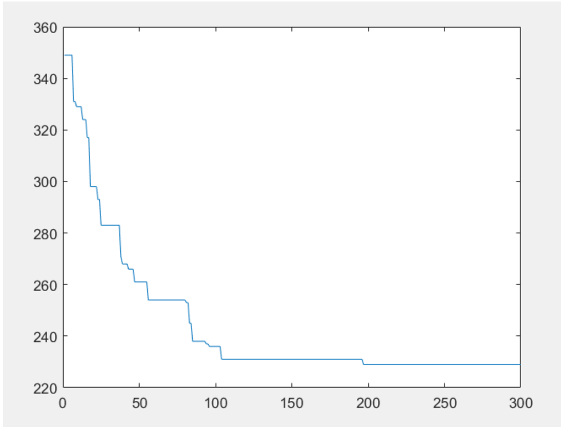
To model the berth and crane assignment process across various horizons of time, we executed our program on instances of different sizes, generating data randomly for each scenario.

4. Results and Discussions

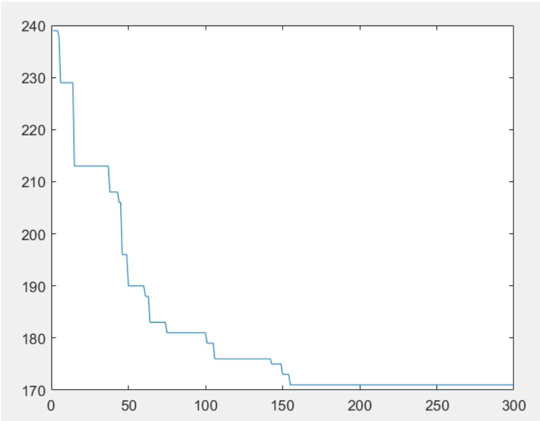
To evaluate the efficacy of the BACAP model in more extensive instances, additional test scenarios were randomly generated, preserving the constant number of berths and available cranes as in previous cases. The number of ships varied from 12 to 40 through adjustments in the ABC parameters.
Throughout the search process, the final optimal solution was achieved after around 200 cycles and remained consistent in subsequent iterations.



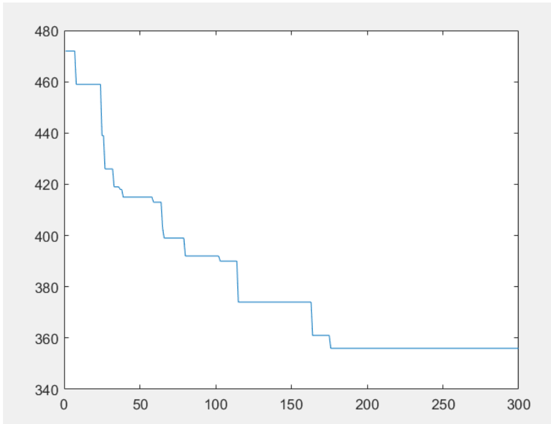
12 vessels



30 vessels



24 vessels



40 vessels

Instance Size	Algorithm parameters (population, limit, Cmax)	Running time	Deviation of the initial solution	Deviation of the final solution
12 ships	10,15,50	15s	0,11	0
	50,100,200	22s	0,01	0
24 ships	20,50,100	21s	0,13	0
	50,200,300	25s	0	0
30 ships	50,250,300	22s	0,05	0
	100,500,1000	40s	0	0
40 ships	50,250,300	22s	0,07	0
	100,500,1000	55s	0,03	0

The presented graphs are the result of simulating each experiment through 10 runs, and the final solutions from these simulations for the identical instance consistently converge to an identical outcome, demonstrating algorithm's efficiency.
The initial solutions in each of the simulations exhibit limited dispersion, attributed to the population, in the algorithm ABC. The heuristic selects the best solution from this population of initial feasible solutions.
Notably, even for the most extensive instance involving 40 ships, the algorithm achieves global optimality in approximately 1 minute, indicating a highly satisfactory time performance for ABC.
The increase in Cyclemax occurs when the convergence graph indicates ongoing minimization of the total service time. This suggests that better results may be achievable with a higher number of iterations.
It's worth highlighting that the NS parameter influences the initial solution significantly, playing a crucial role in the search process. Conversely, the Cyclemax parameter impacts the final solution, serving as a limit to enable the algorithm to explore different feasible solution areas. For smaller instances (12 vessels), the solution approach rapidly reaches the global optimum, whereas it takes longer for larger instances, particularly with increased tuning parameters.

4. Conclusion

In this paper, we have investigated a container terminal scheduling problem that involves the efficient scheduling of ships at berths and the allocation of cranes. Given the inherent complexity of this problem, known for its NP-hard nature, we have proposed a solution approach based on an ABC metaheuristic. The results demonstrate the efficacy of the proposed solving approach, showcasing its potential to obtain optimal solutions rapidly in simulation. The ABC algorithm proposed in this study exhibits remarkable efficiency in solving problems of both small and large scales. Notably, the algorithm consistently identifies optimal solutions, demonstrating its robustness across various simulation instances.
Combining our findings with the broader context of optimizing vessel scheduling and resource allocation in container terminals, our research offers practical solutions to address the challenges faced by maritime logistics. By leveraging the mathematical model and ABC algorithm, we aim to streamline operations and improve port efficiency, ultimately contributing to enhanced service delivery and operational performance in container terminals. Our study provides valuable insights into addressing the intertwined issues of vessel scheduling and resource allocation, offering stakeholders in maritime logistics strategies to navigate this complex landscape effectively.

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