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REVIEW

# A survey on computational intelligence approaches for intelligent marine terminal operations

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**Abstract**

Marine container terminals (MCTs) play a crucial role in intelligent maritime transportation (IMT) systems. Since the number of containers handled by MCTs has been increasing over the years, there is a need for developing effective and efficient approaches to enhance the productivity of IMT systems. The berth allocation problem (BAP) and the quay crane allocation problem (QCAP) are two well-known optimization problems in seaside operations of MCTs. The primary aim is to minimize the vessel service cost and maximize the performance of MCTs by optimally allocating berths and quay cranes to arriving vessels subject to practical constraints. This study presents an in-depth review of computational intelligence (CI) approaches developed to enhance the performance of MCTs. First, an introduction to MCTs and their key operations is presented, primarily focusing on seaside operations. A detailed overview of recent CI methods and solutions developed for the BAP is presented, considering various berthing layouts. Subsequently, a review of solutions related to the QCAP is presented. The datasets used in the current literature are also discussed, enabling future researchers to identify appropriate datasets to use in their work. Eventually, a detailed discussion is presented to highlight key opportunities along with foreseeable future challenges in the area.

## 1 | INTRODUCTION

Sea transportation is considered one of the crucial modes for the delivery of goods around the globe. According to the UNCTAD report published in 2022 [1], more than 80% of global trade is carried out through ships and handled by ports worldwide. The report further says that the total number of containers handled per year has increased steadily every year (with the exception of 2020 due to the COVID19 pandemic). For instance, in 2021, global container throughput reached 165 million twenty-foot equivalent units, an 11.1% increase over the previous year and 22.3% increase since 2016 [1]. Furthermore, it is expected to grow 2.1% annually from 2023-2027. Since maritime trade is increasing, the number of marine container terminals (MCTs) and the competition among them, in terms of throughput capacity maximization and vessel turnaround time minimization, is also increasing. Therefore, the MCTs have high importance and are considered one of the major nodes in sea transportation systems. 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.

One of the major operations at the MCTs is the allocation of incoming vessels to berths, which is known as the berth allocation problem (BAP). On the fleet side, the berth allocation schedule establishes berthing times along with berthing positions for arriving vessels with the objectives of achieving reduced costs, waiting times, handling times, and delays in departure. However, on the port side, an efficient berth allocation plan indicates how many ships can be handled in a scheduling period with the objectives of maximum profit and proper utilization of port resources. Berth allocation is considered a heavy cost operation and the ports pay a high penalty when ships start their mooring process late due to congestion, low tides, or any other problem [2]. Figure 1 describes the

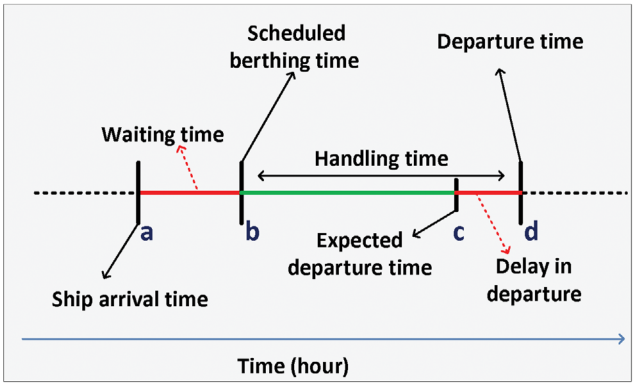


**FIGURE 1** Timing of berth operations at an MCT.

timing of typical berth operations at the MCT. After berth allocation, the efficient loading/unloading of containers to/from ships is needed, which is performed with special types of cranes located alongside the quay, known as quay cranes (QC). The allocation of these QCs to moored ships for unloading/loading and the determination of a work plan lead to a further problem named quay crane allocation problem (QCAP). The QCAP is often combined with the BAP as it is immediately needed after berth allocation; however, a solution to the QCAP must follow the BAP characteristics, such as length of vessel, berth allocation time, expected departure time, and the total number of containers that need to be loaded or unloaded [3].

In recent literature, various computational intelligence (CI) methods have been proposed to address the BAP and QCAP. CI is a collection of computational approaches and methodologies that are influenced by nature [4]. For example evolutionary algorithms (EAs) work based on the evolution process of nature, swarm intelligence (SI) approaches mimic social behaviours of animals, and neural networks (NN) work based on the architecture of the human brain. The fundamental characteristic of the CI family is the capability to find (near) optimal solutions to complex problems, while guaranteeing low computational complexity and tractability [5]. Such large and complex problems cannot typically be addressed by traditional or exact mathematical approaches [6].

The fundamental objective of this study is to present an in-depth survey of the application of CI approaches in intelligent maritime transportation (IMT) systems. IMT systems incorporate advanced technologies including data communication, sensor, intelligent navigation, and intelligent control technologies to the maritime transportation systems. Although both IMT systems and CI are quite vibrant research areas, they are rarely discussed together in a comprehensive way. To the best of our knowledge, this is the first study that systematically discusses CI applications to the BAP and QCAP, as well as presents benchmark datasets that were employed in the surveyed studies. The latest general survey on the BAP and QCAP was published in 2015 [7], and was a follow-up of a previously published survey in 2009 from the same authors [8]. A more recent survey on BAP and QCAP only considers specific studies related to uncertainty [9], while a previous survey focused on transshipment operations [10]. In another study [11], a general overview is provided of applications of artificial intelligence (AI) in the maritime industry: energy efficiency, digital transformation, big data analytics applications, and predictive analysis. Furthermore, general AI applications in the maritime industry are also presented in [12], e.g. vessel path planning, trajectory prediction, vehicle routing problem, traffic prediction, vessel movement analysis, rail scheduling problem, anomaly detection, load planning etc. They also review a couple of studies that solve BAP and QCAP, but without in-depth analysis and categorization of the related problems. Unlike our study, the datasets used for experiments in the various studies are not considered by the above-mentioned survey works. Between 2014 and 2023, over 60 distinct approaches have been developed to enhance the performance of MCTs by employing recent CI approaches and showing great benefits over older approaches. This aspect motivates us to explore these new solutions along with critical review and future research directions.

## 1.1 | Survey methodology

The methodology for conducting this survey is based on the systematic literature review proposed by [13] and includes three main steps. 1) Keyword-based search: In the first step, we performed a keyword-based search using Google Scholar (keywords include MCTs, ports, BAP, QCAP, CI methods for BAP and QCAP, exact methods for BAP and QCAP etc.). 2) Screening and identification of additional articles (a.k.a. snowballing): In this phase, we excluded some irrelevant articles and included new articles that we found from citations of relevant articles. 3) Review and analysis of results: Finally, we reviewed and analyzed the results of the selected studies from the previous phase.

## 1.2 | Contributions

This manuscript focuses on discovering new research avenues based on emerging patterns and innovations in seaside container terminal operations. For this, we provide a survey of the latest studies related to the stand-alone BAP and the combined BAP with QCAP following CI-based approaches. In this survey, most of the reviewed studies are very recent, which helps in visualizing the trends and directions of current research efforts. This work also presents an overview and categorization of CI techniques that were developed for the same problems. Furthermore, unlike previous studies [7, 8], this survey discloses various datasets reported in the literature for solving the BAP and QCAP, which has a huge research value. Eventually, our survey sheds light on the current challenges and research avenues in the field of IMT systems, including the need for standardized environments, online berth allocation, integrated uncertainties, day-ahead forecasting, and spatiotemporal berth planning.

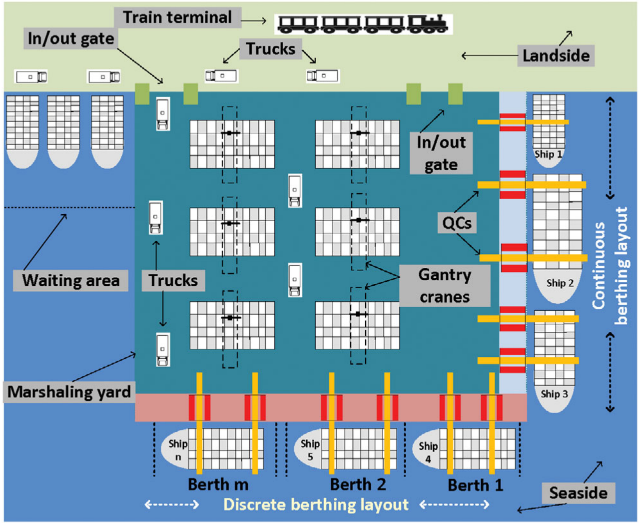


**FIGURE 2** An illustration of the different areas of an MCT.

## 1.3 | Outline

The remainder of the manuscript is organized as follows. The MCT and its key operations are described in the next section. A preliminary on the BAP and QCAP is presented in Section 3. Sections 4 and 5 review recent literature related to the BAP and the combined BAP with QCAP, respectively. Section 6 discusses and summarizes the key observations from the literature review. Section 7 provides a categorization of the CI approaches used to address the BAP and QCAP. Section 8 describes the benchmark datasets used in the described studies. Finally, Section 9 presents research challenges and future opportunities for improving the performance of MCTs, before concluding this survey.

# 2 | MARINE CONTAINER TERMINAL AND ITS KEY OPERATIONS

The marine container terminals (MCTs) have been essential towards low-cost and efficient sea transportation along with economic growth worldwide. The MCTs handle a huge volume of containers per year, which is expected to increase in the future [14]. Hence, the MCTs are continuously challenged to enhance their productivity by adapting many software and hardware innovations, such as terminal design, goods handling equipment, automatic berthing, and operations research applications. The MCTs can be partitioned into three major areas, namely, seaside, marshalling yard, and landside [15], as depicted in Figure 2. The berth, quay, and waiting areas are included in the seaside area, the arriving and departing containers are stored in the yard area, and internal/external transport connects various areas of MCTs [14, 16]. Furthermore, current literature focuses on various MCT operations, which are primarily divided into three major research areas [14, 17]: 1) seaside operations, 2) marshalling yard operations, and 3) landside operations, which are further discussed below. Figure 3 presents different fundamental operational problems of MCTs for each of these areas.

## 2.1 | Seaside operations

Seaside operations typically include loading and unloading containers to/from arrived vessels at the port, by employing on-shore quay cranes. These containers are then transferred to the marshalling yard area by using internal transport vehicles (ITV), e.g. automated lifting vehicles, automated guided vehicles, yard trucks etc. The seaside operations face three fundamental scheduling problems, namely, the BAP, the QCAP, and the QC scheduling problem (QCSP) [18]. In the seaside operations, berth allocation is considered one of the major operations and an available berthing position can be allocated to an arrived ship based on various ship and berth characteristics. For instance, the vessels arrival pattern, berthing layout, and ships handling time are the major considerations for vessel berthing, as discussed in Section 3.

The QCAP deals with assigning QCs to berthed vessels, while QCSP deals with how the QCs assigned to a particular vessel will be used for loading/unloading containers from that vessel [18]. The ship's cargo along with loading and unloading information can be collected from a stowage plan. Based on this information, QCs are assigned to vessels.

Concerning QCs specifications, the QC assignment and scheduling operations can be classified in various ways. The first classification refers to how QCs handle loading/unloading tasks, where each QC has particular constraints while operating. All containers that are unloaded or loaded to a ship belong to a specific bay (i.e. a space in the vessel to store containers), each corresponding to a task [19]. The number of bays is used to determine the maximum number of QCs that can be assigned to a vessel and work in parallel [19]. The second classification is based on QCs restrictions. Based on the current literature, the QCs restrictions include safety distance between two QCs, movement limitations, and interference among QCs [20]. The QCs are rubber-tired at some MCTs and rail-mounted on others [21]. The rubber-tired QCs (also known as moveable QCs) can move freely and cross each other, while the latter cannot [22]. Hence, there is a need for some non-crossing constraints for models that consider rail-mounted QCs. Furthermore, the constraints related to safety distance are also considered to avoid interference with other QCs. The last classification involves initial positions of QCs, ready times of QCs, and availability/unavailability of QCs [19].

## 2.2 | Marshaling yard operations

The major operations in the marshalling yard include vehicle routing [23], transport vehicle dispatching [24], yard cranes scheduling and yard truck scheduling [25, 26], yard cranes and yard truck utilization [27, 28], storage blocks allocation [29], yard transshipment problem, also known as yard allocation problem [30], and traffic control [16].

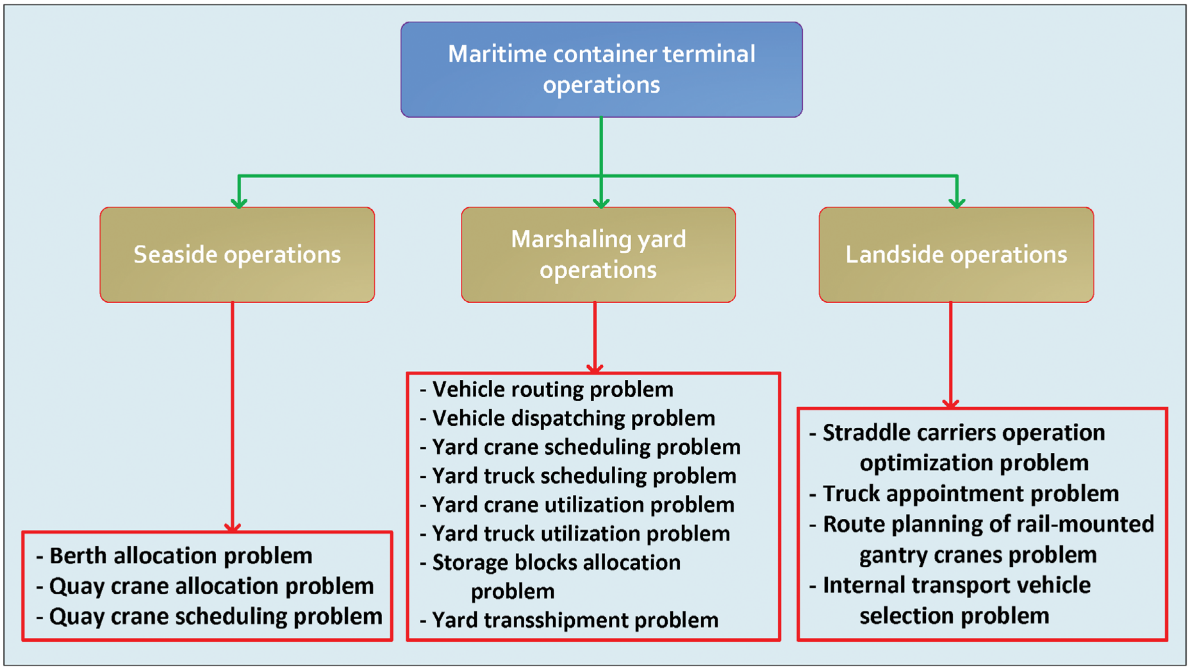


**FIGURE 3** Primary operational problems considered under the marine container terminal umbrella.

Typically, all containers are stored at the MCT for a particular time period before delivering them to trucks or trains for inland transportation or loading them to vessels for water transportation. In the marshalling yard operations, yard cranes, also known as gantry cranes, are employed to handle unloaded containers. The yard cranes are responsible for placing the containers in the yard blocks. Furthermore, housekeeping operations (e.g. container relocation and pre-marshalling) are also performed by yard cranes. Thus, efficient yard crane scheduling is key to the enhanced performance of the MCTs. Furthermore, transshipment containers often need to be reallocated to a yard position close to the vessel's berthing position. Therefore, an optimal allocation of transshipment containers can largely contribute towards reducing the operational costs [31], the service time [32, 33], and consequently the environmental impact [34]. In particular, it could help in reducing travel distances between quayside and yardside in order to reduce service costs and enhance terminal productivity. In addition, yard trucks are employed to transport the inbound and outbound containers within the terminal. Hence, yard trucks dispatching, scheduling, and routing operations affect the traffic congestion inside the terminal and the overall progress of operations in MCTs.

## 2.3 | Landside operations

MCTs offer several services as an intermediator between landside and seaside operations. For landside operations, trains, trucks, or barges are employed to either pick up or deliver containers. The trucks or trains enter the MCT through specific terminal gates and wait in a dedicated area until loaded on or loaded off. Furthermore, the MCTs can have various interfaces for landside operations, e.g. rail terminals for trains, transfer points where trucks are loaded or unloaded, and barges service center [35]. The major problems in the landside operations include: straddle carriers (SCs) operation optimization [36], truck appointment optimization to avoid truck congestion and reduce truck turnaround time [37], double cycling (i.e. loading and unloading simultaneously to enhance productivity) scheduling [38], route and schedule planning of rail-mounted gantry cranes for efficient exchange of containers between the terminal and road [39], scheduling appointments of container trucks [40], and internal transport vehicle selection to avoid delays and enhance terminal performance [41].

# 3 | INTRODUCTION TO BAP AND QCAP

In this section, we introduce the two major problems of seaside operations (i.e. the BAP and the QCAP), which have been extensively investigated in the last two decades.

## 3.1 | Preliminaries on BAP

Allocating available berthing slots to arriving vessels based on ship properties (e.g. dimensions, draft etc.), berth characteristics (e.g. length, depth etc.), and various constraints, is considered the first decision problem, known as BAP (a few studies also refer to BAP as the berth scheduling problem).

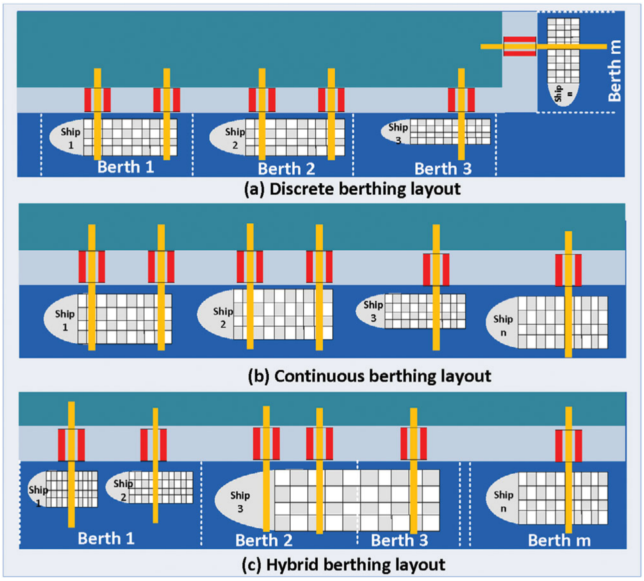


**FIGURE 4** Different berthing layouts.

The goal of the BAP is to specify which berthing position is suitable for which arriving ship while considering the various types of constraints, both physical and operational. For developing solutions for a typical BAP, the possible inputs include: expected time of arrival for ships, preferred berthing position, length of ship, number of containers loaded on each ship, handling time, cranes productivity, and expected time of departure. The typical outputs of the BAP include: scheduled berthing position for each ship, berthing time for each ship, and scheduled departure times. BAPs can be classified on the bases of two key aspects, namely berthing layout and arrival times [8, 14].

#### 3.1.1 | Berthing layout

Several berthing layouts are assumed in the literature in order to provide feasible berthing positions to arriving ships, which are explained below.

*Discrete layout*
In a discrete berthing layout, the wharf is divided into various sections, called berths, and only a single ship can be moored at any berth at a particular time period [8, 42]. It is important to note that the extra length of the berth is wasted if the assigned ship's length is less than the length of the berth. Furthermore, the quay is partitioned either based on the quay construction or divided in order to ease the planning problem, as presented in Figure 4(a).

*Continuous layout*
In a continuous berthing layout, as shown in Figure 4(b), ships can be moored at any arbitrary location along the wharf, i.e. the quay is not partitioned into a discrete number of berths. The quay can be better utilized because it is not partitioned into a discrete number of berths. However, berth planning for continuous berthing layout is more complex than a discrete berthing layout due to the much higher number of available berthing positions.

*Hybrid layout*
Hybrid berthing layout is a combination of both discrete and continuous berthing layouts, where the wharf is partitioned into a number of berths. However, a large ship can occupy more than one berth, and sometimes two small ships can be moored at a single berthing slot, as depicted in Figure 4(c). Furthermore, indented berths are also possible when two opposing berths exist, which can be utilized to unload/load one large ship from both sides [43].

#### 3.1.2 | Vessel arrivals

As for the ships' arrivals, the BAP can be distinguished as static arrival and dynamic arrival.

*Static arrival*
In static ship arrival, no arrival times are given against incoming ships. Instead, it is assumed that all ships have already arrived at the MCT, towed to the waiting area, and can be moored immediately based on berth planning.

*Dynamic arrival*
In the dynamic ship arrival, ships are not assumed to be present at the MCT during the planning horizon. Instead, the expected time of arrival (ETA) for each ship is provided to the MCT for the sake of better berth planning. A ship may arrive before its ETA, but for the purposes of planning, the ship cannot be moored before its ETA.

### 3.2 | Mathematical modelling of stand-alone BAP

The performance measure is an important aspect of the BAP and it explains the objective function (OF) to be maximized or minimized, such as throughput maximization, cost reduction etc. Based on current literature, most studies use an OF that aims to minimize the total time vessels spend at the MCT. Other OFs are associated with the minimization of the total weighted handling time [44, 45], the total waiting time [46, 47], and the total services (processing) cost for all arriving ships at the MCT [42]. The selection of the OF is mainly driven by the business and operational characteristics of the MCT and is typically independent from the CI method employed to solve the optimization problem.

In the BAP, a set of ships $S = \{1, 2, \ldots, N\}$ arriving at the MCT must be scheduled for berthing over a set of time intervals $T = \{1, 2, \ldots, K\}$ (representing a time horizon of interest) at berthing positions from the set of all possible berthing positions $B = \{1, 2, \ldots, M\}$ on the wharf. For each arriving ship $s$, a BAP solver will assign a berthing time $\mathrm{BT}_s$ and a berthing position $\mathrm{BP}_s$. If berthing is scheduled for after the ship's ETA, then the ship will incur a waiting time $\mathrm{WT}_s$ with a per-unit waiting cost $\mathrm{WC}_s$. The ship $s$ is moored at berthing position $\mathrm{BP}_s$ for a particular time, known as handling time $\mathrm{HT}_s$, to perform loading/unloading operations, and the total handling cost depends on the per-unit handling cost $\mathrm{HC}_s$. Furthermore, if the ship's berthing position $\mathrm{BP}_s$ is other than its preferred berthing position $\mathrm{PBP}_s$, additional penalty will be added into the total handling cost, typically based on how far $\mathrm{BP}_s$ is from $\mathrm{PBP}_s$. Finally, a late departure penalty cost is incurred if the ship $s$ is departed late, which is calculated based on $s$' late departure time $\mathrm{LDT}_s$ (i.e. difference between actual and estimated time of departure) and a per-unit late departure penalty cost $\mathrm{LDC}_s$. All mathematical notations used in this manuscript are listed in Table 1.

The most comprehensive BAP formulation aims to minimize the total processing cost of all arriving ships, which includes waiting, handling, and late departure penalty costs [48]. The corresponding OF for BAP is:

$$\textbf{minimize} \sum_{s \in S} \sum_{b \in B} \sum_{t \in T} x_{sbt} \cdot \mathrm{Cost}(s, \mathrm{BP}_s, \mathrm{BT}_s) \tag{1}$$

**TABLE 1** Mathematical notations.

| Name | Explanation |
|---|---|
| AQP | Average QC productivity (container or tons per unit time) |
| $\mathrm{BP}_s$ | Berthing position of ship $s$ (metres) |
| $\mathrm{BT}_s$ | Berthing time of ship $s$ |
| $\mathrm{ETA}_s$ | Expected time of arrival of ship $s$ |
| $\mathrm{ETD}_s$ | Expected time of departure of ship $s$ |
| $\mathrm{HC}_s$ | Handling cost of ship $s$ per time period |
| $\mathrm{HT}_s$ | Handling time of ship $s$ |
| $L_b$ | Length of berth $b$ (metres) |
| $L_s$ | Length of ship $s$ (metres) |
| $\mathrm{LDC}_s$ | Late departure cost of ship $s$ per time period |
| $\mathrm{LDT}_s$ | Late departure time of ship $s$ |
| $\mathrm{PBP}_s$ | Preferred berthing position of ship $s$ (metres) |
| $Q$ | Total number of quay cranes available on the wharf |
| $q_s^{\max}$ | Maximum number of cranes that can be assigned to ship $s$ |
| $q_s^{\min}$ | Minimum number of cranes that can be assigned to ship $s$ |
| $W$ | Length of wharf (metres) |
| $\mathrm{WC}_s$ | Waiting cost of $s$ per time period |
| $\mathrm{WT}_s$ | Waiting time of ship $s$ |
| **Sets and Indices** | |
| $B$ | Set of available berth positions; $b \in B$ a berth position |
| $S$ | Set of arriving ships; $s \in S$ a ship |
| $T$ | Set of time periods (planning horizon); $t \in T$ a time period |

where the total processing cost for ship $s$ is calculated as:

$$\begin{aligned}\mathrm{Cost}(s, \mathrm{BP}_s, \mathrm{BT}_s) &= \mathrm{WT}_s \cdot \mathrm{WC}_s \\ &+ \mathrm{HT}_s \cdot [\mathrm{HC}_s + f(|\mathrm{BP}_s - \mathrm{PBP}_s|)] \\ &+ \mathrm{LDT}_s \cdot \mathrm{LDC}_s\end{aligned} \tag{2}$$

In Equation (2), $f(|\mathrm{BP}_s - \mathrm{PBP}_s|)$ calculates a term that may increase the handling cost depending on the difference between the actual and preferred berthing positions of ship $s$. Some previous works assign a fixed penalty cost when $\mathrm{BP}_s$ is different than $\mathrm{PBP}_s$ [48], while others compute a cost that is proportional to the difference between $\mathrm{BP}_s$ and $\mathrm{PBP}_s$ [19].

The above objective is subject to various constraints outlined in Table 2. In constraint (3), the variable $x_{sbt}$ is 1 if ship $s$ is assigned to berthing position $b$ at time interval $t$, and 0 otherwise. Constraint (4) guarantees that each arrived ship will be assigned at a particular berthing position only once during the planning horizon. Constraint (5) ensures that the scheduled berthing time $\mathrm{BT}_s$ of ship $s$ must always be later than or equal to its expected time of arrival $ETA_s$. The following two constraints only apply when a continuous berthing layout is considered. Constraint (6) guarantees that two ships never overlap in terms of both berthing time and berthing positions. Constraint (7) warrants that the berthing position $\mathrm{BP}_s$ of ship $s$ plus its length $L_s$ will always be less than or equal to the total length $W$ of the wharf. When the berthing layout is discrete, each berthing position $b$ represents a specific berth and constraint (8) ensures that the same berth is not assigned to two ships during the same time intervals. Finally, constraint (9) checks that the length of ship $s$ is less than or equal to the length of berth $L_b$ assigned to ship $s$.

**TABLE 2** Constraints related to stand-alone BAP.

**General constraints**

$$x_{sbt} \in \{0,\ 1\}, \quad \forall\, s \in S,\ b \in B,\ t \in T \tag{3}$$

$$\sum_{b \in B} \sum_{t \in T} x_{sbt} = 1, \quad \forall\, s \in S \tag{4}$$

$$\mathrm{ETA}_s \le \mathrm{BT}_s, \quad \forall\, s \in S \tag{5}$$

**Constraints for continuous berthing layout**

$$\sum_{s' \neq s \in S} \sum_{b=\mathrm{BP}_s - L_{s'}+1}^{\mathrm{BP}_s + L_s} \sum_{t=\mathrm{BT}_s - \mathrm{HT}_{s'}+1}^{\mathrm{BT}_s+\mathrm{HT}_s} x_{s'bt} = 0, \quad \forall\, s \in S \tag{6}$$

$$\mathrm{BP}_s + L_s \le W, \quad \forall\, s \in S \tag{7}$$

**Constraints for discrete berthing layout**

$$\sum_{s' \neq s \in S} \sum_{t=\mathrm{BT}_s - \mathrm{HT}_{s'}+1}^{\mathrm{BT}_s+\mathrm{HT}_s} x_{s'bt} = 0, \qquad \forall\, s \in S,\ b = \mathrm{BP}_s \tag{8}$$

$$L_s \le L_b, \quad \forall\, s \in S,\ b = \mathrm{BP}_s \tag{9}$$

### 3.3 | Preliminaries on QCAP

The important decisions that need to be made immediately after berth allocation concern the type and number of handling equipment to be employed for loading/unloading the containers to/from vessels. Quay cranes (QCs) are employed at the MCTs to load/unload containers from vessels and are typically manned because automation in this process creates multiple challenges, such as inaccurate positioning of containers [49]. The cranes contain trolleys that can move along the QC arm to transfer the containers from transport vehicles to vessels and vice-versa. A trolley is equipped with the spreader, a pick-up device that is used to pick the containers. Furthermore, loading and unloading operations on a single ship can also be done simultaneously, i.e. one crane can be employed for loading and the other for unloading [49]. Hence, the number of QCs allocated to vessels is a crucial decision for arriving vessels.

For unloading/loading vessels, there exist two types of QCs, movable (dynamic) and non-movable (static). The first type of cranes can shift from one berth to another berth during the process of loading/unloading cargo from the currently assigned ships, which makes their use more flexible [3]. The latter type of QCs cannot move from one berth to another before completion of the process on currently assigned ships.

### 3.4 | Mathematical modelling of combined BAP and QCAP

The combined BAP and QCAP, also known as tactical BAP, considers the allocation of berths to arriving ships as well as the assignment of QCs to each ship for loading/unloading containers. Since the main objective of several studies is to minimize vessels' processing times [50], turnaround times [51], late departure times [52], and weighted handling cost [45, 53, 54], it is necessary to perform the process of unloading/loading very efficiently in order to meet the requirements of the customers. For the convenience of the readers and following the mathematical BAP model presented in Section 3.2, this section extends the discussion to the combined BAP and QCAP model (BAP+QCAP). The key difference is that, when considering QCAP, the handling cost of a ship $s$ depends also on the number of quay cranes $\mathrm{NQ}_s$ assigned to $s$. The objective remains the same, i.e. to minimize the total processing cost of all vessels. The OF is:

$$\min \sum_{s \in S} \sum_{b \in B} \sum_{t \in T} \sum_{q \in [1,Q]} x_{sbtq} \cdot \mathrm{Cost}(s, \mathrm{BP}_s, \mathrm{BT}_s, \mathrm{NQ}_s) \tag{10}$$

where the total processing cost for ship $s$ is calculated as:

$$\begin{aligned} \mathrm{Cost}(s, \mathrm{BP}_s, \mathrm{BT}_s, \mathrm{NQ}_s) &= \mathrm{WT}_s \cdot \mathrm{WC}_s \\ &+ \mathrm{HT}_s \cdot \left[\mathrm{HC}_s + f(|\mathrm{BP}_s - \mathrm{PBP}_s|)\right] \\ &+ \mathrm{LDT}_s \cdot \mathrm{LDC}_s \end{aligned} \tag{11}$$

The handling time $\mathrm{HT}_s$ depends on the total load $\mathrm{Load}_s$ (number of containers or tons), the number of assigned quay cranes $\mathrm{NQ}_s$, and the average productivity of the cranes AQP (number of containers or tons per unit time), and can be calculated as:

$$\mathrm{HT}_s = \frac{\mathrm{Load}_s}{\mathrm{AQP} \cdot \mathrm{NQ}_s} \tag{12}$$

The objective in Equation (10) is subject to various constraints listed in Table 3. In constraint (13), the variable $x_{sbtq}$ is 1 if ship $s$ is assigned to berthing position $b$ at time interval $t$ with $q$ number of QCs, and 0 otherwise. Constraint (14) guarantees that each arrived ship will be assigned at a particular berthing position with $q$ number of cranes only once during the planning horizon. Constraints (5)–(9) (see Table 2) presented for the stand-alone BAP model in Section 3.2 also apply in the combined BAP+QCAP model as they involve constraints related to berthing positions and times. Constraint (15) guarantees that each arriving ship $s$ must be assigned an appropriate number of cranes for loading and unloading, which is between the minimum $q_s^{\min}$ and maximum $q_s^{\max}$ cranes that can be allocated for ship $s$. Finally, constraint (16) ensures that at any time interval $t$, the number of QCs assigned to all ships is less than or equal to $Q$, the total number of available QCs.

## 4 | CURRENT LITERATURE ON STAND-ALONE BAP

This section deals with the latest efforts of the researchers to cope with various types of stand-alone BAP, namely, discrete dynamic BAP (DD-BAP), continuous dynamic BAP (CD-BAP), and hybrid dynamic BAP (HD-BAP). A tabular summary presentation is given in Table 4.

### 4.1 | Discrete and dynamic BAP

This section reviews recent literature on discrete and dynamic BAP (DD-BAP), which considers discrete berthing layout and dynamic vessel arrivals as described in Section 3. Table A.1 presents an analysis of the recent literature on discrete and

**TABLE 3** Constraints related to BAP+QCAP.

$$x_{sbtq} \in \{0, 1\}, \quad \forall\, s \in S,\ b \in B,\ t \in T,\ q \in [1, Q] \tag{13}$$

$$\sum_{b \in B} \sum_{t \in T} \sum_{q \in [1,Q]} x_{sbtq} = 1, \qquad \forall\, s \in S \tag{14}$$

$$q_s^{\min} \le NQ_s \le q_s^{\max}, \qquad \forall s \in S \tag{15}$$

$$\sum_{s \in S} \sum_{t'=\max(\mathrm{BT}_s, t-\mathrm{HT}_s(q)+1)}^{t} x_{sbt'q} \cdot q \le Q, \quad \forall t \in T, b = \mathrm{BP}_s, q = \mathrm{NQ}_s \tag{16}$$

**TABLE 4** Summary of current literature related to BAP. [ED: employed dataset, PY: published year, RD: random data, RPD: real port data, UF: uncertain factor, VA: vessel arrivals, VO: vessel operational times, WC: weather conditions].

| Ref. | PY | Method | Compared method(s) | UF(s) | ED |
|---|---|---|---|---|---|
| **DD-BAP** | | | | | |
| [55] | 2014 | PSO | GSSP, LP, and clustering search | – | [84], RPD |
| [56] | 2015 | GA | CPLEX | – | RD |
| [57] | 2015 | GA | – | – | RD |
| [58] | 2015 | EDE | GSPP, TS, CS, and PSO | – | [84] |
| [59] | 2015 | BMO | GSSP, PSO, and CPLEX | – | [84] |
| [61] | 2016 | POPMUSIC | PSO | – | [14, 85] |
| [62] | 2016 | ALNS | PSO, CS, GSPP, GRASP, SA, CPLEX, and TS | – | [84, 85] |
| [63] | 2018 | MA | FCFS and EA | – | [14, 86] |
| [64] | 2018 | SAEA | Standard EA, AEA, DPCEA | – | [14, 86, 87] |
| [65] | 2019 | ITS | TS, and stochastic DP | VA | [84] |
| [2] | 2019 | Lèvy Flight | PSO, CPLEX, and IG | – | [88, 89] |
| [66] | 2020 | CRO | GA, block-based GA, PSO, and exact approach | – | RPD |
| [67] | 2020 | MILP | – | – | RPD |
| [60] | 2022 | AACS | ACO and exact method | – | [42] |
| **CD-BAP** | | | | | |
| [68] | 2015 | GA | CPLEX, GRASP, TS, and SBS | – | [90] |
| [47] | 2016 | DE | SA, MIP, IA, and GRASP | – | [91] |
| [69] | 2016 | Hybrid GA | Standard GA and CPLEX | VA, VO | RD |
| [70] | 2017 | GWO | CPLEX and GA | VA, VO | [92] |
| [71] | 2017 | MNSGA-II | GA, NSGA-II-III, and ALNS | – | [93] |
| [72] | 2017 | GA | – | – | RPD |
| [75] | 2018 | SA | GA and CPLEX | – | [94] |
| [73] | 2018 | HSA | CPLEX and Greedy | – | RPD [95] |
| [74] | 2018 | SA | GRASP, TS, SBS, and GA | – | [84, 96] |
| [76] | 2018 | SA | – | – | RD |
| [77] | 2019 | IDE | DE, GA, TS, and IP | – | [97] |
| [78] | 2020 | ERO, RCRO | MILP and S-MILP | VA, VO | [92] |
| [79] | 2020 | Fuzzy logic | – | VA, VO | RD |
| [81] | 2021 | PSO | MILP | VO, WC | RPD |
| [82] | 2021 | ML | – | VA | RD |
| [80] | 2022 | CSA | MILP and GA | – | [47] |
| [83] | 2023 | ML | – | VA | [98] |
| **HD-BAP** | | | | | |
| [99] | 2014 | SWO | MILP, FCFS, and GSPP | – | RPD |
| [100] | 2015 | EA | CPLEX | – | [101] |
| [102] | 2015 | VND | EA and BCO | – | [101] |
| [103] | 2016 | SEDA | CPLEX | – | [97] |
| [104] | 2018 | GVNS | EA, VND, BCO, and CPLEX | – | [101] |
| [105] | 2018 | Bat-inspired | CPLEX | – | [84, 106] |
| [107] | 2019 | ILS | MILP | – | RPD |
| [66] | 2020 | CRO | GA and PSO | – | RPD |
| [108] | 2020 | ILP | – | – | RPD, [109] |
| [110] | 2020 | HGA | CPLEX | – | RPD |

dynamic BAP including dataset explanation and key achievements of each paper.

A heuristic-based approach is presented in [55] to deal with discrete and dynamic BAP. The key objectives of this study are twofold: minimization of waiting time of serving vessels at MCT and minimization of total handling time. The problem is modelled as a mixed-integer linear programming (MILP) model and solved by a particle swarm optimization (PSO) algorithm. The proposed method is tested with several datasets of different sizes and compared with state-of-the-art methods. Results indicate higher performance over counterparts in terms of better berth allocation with low computation time.

Simrin et al. employed a genetic algorithm (GA) to solve the same BAP [56]. The main aim of this study is to alleviate total vessels' service time that they have divided into two parts, (i) waiting time and (ii) handling time. Unlike other works, this paper assumes that each berth has different handling productivity and showed that GA can handle much larger problem sizes compared to a CPLEX-based approach.

Another work employed GA for near-optimal berth allocation [57]. Specifically, the authors formulate a mixed-integer programming (MIP) model considering a discrete berthing layout and dynamic vessel arrivals. Their key objective is to minimize total weighted late departures and workload in night times. Simulations have been carried out for 1 and 2 weeks in order to validate the proposed GA-based solution.

The work presented in [58] proposed an enhanced differential evolution (DE) algorithm-based solution for DD-BAP, where the enhanced DE uses game theory to control the selection of mutation operator. The objectives of this work are twofold: minimization of late departure penalties and minimization of handling times at an MCT. GSSP, TS (Tabu search), CS (clustering search), and PSO are also employed to solve the same problem and results denote that enhanced DE outperforms over counterparts in terms of both objectives.

Another DD-BAP is discussed in [59], where a novel EA, namely bird mating optimizer (BMO) algorithm is developed. The problem is modelled as a vehicle routing problem with time windows and solved by the BMO algorithm. The authors of the study [59] also implement PSO and exact approaches for the sake of comparison. Results demonstrate the effectiveness of the BMO method in terms of minimum turnaround time.

The author of [60] solves the DD-BAP while proposing an adaptive ant colony system (AACS) by hybridizing three various methods: (i) adaptive heuristic information (AHI) is used to deal with real-time difficulties of DD-BAP, (ii) variable range receding horizon is employed to divide the complete space into small parts, and (iii) partial memory unit is developed to quicken the convergence speed of whole system (AACS). An exact method and two metaheuristics are also implemented for comparison purposes. Simulation results show that the proposed method is more efficient than its counterparts in handling uncertainties.

An approach called POPMUSIC is proposed in [61] to solve DD-BAP. The proposed method is partially metaheuristic (and inspired by Tabu search) and partially mathematical, which solves the problem and allocates berths to arriving vessels in a reasonable time. Experimental results show the efficacy of the proposed method over a PSO-based alternative.

Another study [62] exploits a heuristic-based adaptive large neighbourhood search (ALNS) algorithm in order to solve DD-BAP. The BAP is formulated as an MILP problem and the key objective is to achieve minimum cost that occurred due to late departures within minimum computational time. They also use priorities for various vessels based on different factors, e.g. total load, a vessel belonging to a specific linear company etc. In this way, vessels with higher priority get served and departed sooner than low priority ships. The proposed model is evaluated against seven existing models (see Table 4).

A memetic algorithm (MA)-based method is adopted in [63] to solve DD-BAP, where the BAP is formulated as a nonlinear MIP model. This study also proposes a new policy, where demand can be shifted from normal MCT to an external MCT at an extra cost. A large number of simulations have been performed to affirm the productiveness of the proposed MA-based approach. Results from simulations indicate the efficacy of the newly developed algorithm in terms of its key objective to minimize handling cost.

Another research presented in [64] proposes a self-adaptive EA (SAEA), which, unlike other EAs, employs a self-adaptive parameter control strategy for efficient planning of berth allocation. The primary objectives are to minimize the total weighted turnaround time of all the docked vessels as well as delays in departures. The problem is also formulated as an MILP model and extensive experiments have been carried out to affirm the performance of the proposed SAEA approach. Compared algorithms include standard EA, deterministic parameter control EA (DPCEA), and adaptive EA (AEA).

The authors of [65] also investigate the discrete BAP along with stochastic vessels arrivals. The primary objective of this study is to mitigate the total turnaround time of vessels that they spend between arrival and departure. For optimal berth allocation, various proactive and reactive approaches are developed, a metaheuristic iterated tabu search (ITS) is proposed as a proactive method for berth allocation, while stochastic dynamic programming method as a reactive approach is modelled for real-time ship arrivals. Here it is important to note that the study also considers uncertainty in ships' arrival. Simulation results indicate that the ITS has higher efficiency in terms of minimum turnaround time with affordable computation time.

Wang et al. developed a novel metaheuristic based approach to solve DD-BAP, where the proposed method combines the nature-inspired Lèvy Flight random walk with local search [2]. The primary goals of this study are twofold: minimize the total cost of ships' handling cost and provide optimal berth allocation of arriving vessels while considering a multi-tidal planning horizon. They also perform a comparative study to investigate the performance of the proposed Lèvy flight based algorithm. Results demonstrate the effectiveness of the proposed method when comparing it with state-of-the-art approaches, i.e. PSO, CPLEX (exact approach), and iterated greedy (IG) heuristic algorithms.

The work presented in [66] focuses on dynamic BAP, where waiting time along with fuel consumption of vessels when they are in the anchorage area is also investigated. The problem is first formulated as an MILP model. In their proposed model, the fuel cost is associated with the waiting times of arriving vessels. The key reason for including fuel cost/consumed fuel is to address the sustainability aspects of the BAP. Later, this study proposes a chemical reaction optimization (CRO) algorithm to solve the BAP and real-time instances are employed for experiments. Eventually, a comparative study has been taken into account in order to validate the newly proposed CRO algorithm, where GA, block-based GA, and PSO methods are considered as benchmarks. Results show the efficacy of the proposed CRO method in terms of efficient utilization of MCT resources.

Sheikholeslami et al. in [67] investigate dynamic and discrete BAP, where the key objective is to mitigate the late departure of vessels. They utilized a real-time dataset from the Port of Shahid Rajaee situated in Iran, where tide effects are also investigated during implementation. The problem is modelled as an MILP model and solved by the exact approach. Experimental results reveal that late departures are reduced while implementing the proposed solution.

## 4.2 | Continuous and dynamic BAP

In the continuous and dynamic BAP (CD-BAP) formulation, continuous berthing layout (Section 3.1.1) and dynamic vessel arrivals (Section 3.1.2) are considered. Table A.2 summarizes recent literature on CD-BAP, including dataset explanation and key achievements of each paper.

Frojan et al. in [68] consider three wharves with lengths 800, 600, and 1000 m, and 12 vessels that arrive dynamically for mooring. To tackle this CD-BAP with multiple quays, an integer linear model has been developed to describe the elements of the problem and interactions, and then the problem is solved with GA. Furthermore, the authors perform extensive simulations by employing several real time instances as well as past datasets used in the existing literature. Results demonstrate that the proposed method provides a high quality solution in terms of total operational cost that includes waiting and late departure costs.

The study presented in [47] applies an evolutionary method, namely a differential evolution (DE) algorithm. The authors also explore the impact of DE's user-defined parameters on the solution of the problem and conduct a statistical analysis for establishing the optimal values for DE. Finally, extensive simulations have been carried to affirm the productiveness of the proposed DE based solution, and results are compared with several state-of-the-art approaches, i.e. mixed integer programming (MIP), simulated annealing (SA), immune algorithm (IA), and greedy randomized adaptive search procedure (GRASP) algorithms.

The work presented in [69] discusses CD-BAP, where the major objective is to mitigate the late departures of vessels by efficient berth allocation. For near-optimal berth position searching, this study develops a hybrid of GA and branch and cut (B&C) methods, which assigns the best berthing location based on vessels' arrival and departure times and other constraints. Furthermore, the proposed method is tested on both small and large datasets, and compared with standard GA and CPLEX methods. Results indicate the effectiveness of the proposed solution to the BAP over counterparts.

Another study investigates the CD-BAP in [70], where the primary objective is to achieve a berth allocation strategy with minimum turnaround time. A heuristic-based grey wolf optimization (GWO) algorithm is developed to solve the BAP. Furthermore, this study also considers uncertainties in vessels' arrival and operational time of vessels, and the proposed GWO based method shows efficiency in solving the BAP with uncertainties over existing solutions such as GA and CPLEX.

The authors of [71] also examine the CD-BAP intending to reduce the total time that vessels stay at the port for loading/unloading operations. They transformed constrained single-objective BAP to unconstrained multi-objective BAP model by converting constraint violations to objectives. Next, the multi-objective continuous BAP is solved by modified non-dominated sorting genetic algorithm II (MNSGA-II). Furthermore, the newly proposed unconstrained multi-objective model along with the proposed method is tested on benchmark instances. The results indicate the effectiveness of the proposed model and MNSGA-II method over the original NSGA-II-III method as well as GA and ALNS.

A GA based solution of the CD-BAP is presented in [72]. The key concerns of this work are to attain port efficiency and reduce late departures and in this way, the penalty cost will be reduced. The GA-based solution of the BAP is tested on real-time instances and results show the effectiveness of the proposed method.

Xu et al. developed a hybrid SA-based heuristic method to deal with the BAP while considering traffic limitations in the navigation channel [73]. The primary aim of this work is to propose cost-efficient berth allocation while enhancing the performance of MCT. The problem is formulated using the MILP model and then solved by the hybrid SA (HSA) method that combines SA and reheat treatment methods. In order to validate the newly proposed method, real time instances from two container terminals of Tianjin, China are used and CPLEX and Greedy methods are also applied for comparative study. Results demonstrate the effectiveness of the proposed HSA method in terms of lower cost and MCT efficiency.

Another study presented in [74] examines the CD-BAP where the major objective is to minimize total weighted handling time along with deviation cost that occurs by not assigning vessels to their preferred berthing positions. Different variants of the SA algorithm are proposed to solve the BAP and then mathematical and other heuristics are also implemented for comparison purposes. They test the proposed method on several datasets including small and large instances, and results indicate the effectiveness of the proposed SA method in terms of the above-mentioned primary objectives.

Another study [75] focuses on the CD-BAP with the aim of reducing total waiting cost, handling costs, and late departures penalties. An SA-based hybrid algorithm is developed to solve the problem, where one algorithm deals with berthing positions, and the other algorithm determines berthing times. Eventually, several experiments were performed and results are compared with existing methods. It is validated from comparison that the proposed method provides efficient berth allocation within acceptable computational time.

The work presented in [76] deals with the BAP where a continuous wharf is assumed and various priorities are taken into account, e.g. priori berthing of VIP customers. The objective of this work is to improve robustness and attain minimum handling cost. A heuristic-based SA is developed and tested on data instances taken from past literature. Results denote that the proposed method is able to find the optimal solutions with minimum cost and maximum robustness.

Song et al. also focus on the CD-BAP while considering time-varying water depths [77]. The primary objective of this study is to mitigate the total turnaround time of arriving vessels. They develop improved DE-based solution and implement on small and medium scale instances. It is affirmed from simulation results that the proposed DE-based method is appropriate for optimal berth allocation over simple DE, GA, Tabu search, and integer programming.

Liu et al. focus on the CD-BAP [78], where the mooring schedule of arriving vessels at continuous berthing layout is provided by employing a two-stage robust optimization (RO) method. This study also deals with uncertainty, which includes uncertainty in vessels' arrival and handling time. Extensive simulations have been carried out to affirm the productiveness of newly proposed approaches, i.e. expanded RO-BAP (ERO-BAP) and risk constrained RO-BAP (RCRO-BAP).

A fuzzy logic-based solution is developed in [79] to deal with CD-BAP, where the primary objective is to minimize vessels' waiting time. In addition, this paper also models uncertainty in vessels' arrivals. They performed simulations on randomly generated data and results show the productiveness of the proposed method.

The authors of [48, 80] formulate the CD-BAP as an MILP model and adopt, for the first time in the BAP literature, the recently-developed metaheuristic cuckoo search algorithm (CSA) to solve the CD-BAP. For validating the performance of the proposed CSA method, the authors used a benchmark case study from [47] and compared their results against a genetic algorithm solution and the optimal MILP solution.

The authors of [81] deal with CD-BAP considering uncertainty in vessels handling time due to weather conditions. They have formulated the problem as integer linear programming and solved it using the CPLEX solver. However, they also have developed a hybrid of a metaheuristic-based PSO and a machine learning (ML) model to solve large-scale problems. The data was obtained from United Metro Co. Ltd. (http://www.meteochina.com) for experimental purposes.

A study [82] develops a ML-based vessel arrival time prediction (ATP) method for efficient berth allocation using k-nearest neighbours, linear regression, and regression trees. This study considers continuous berthing layout and dynamic vessel arrival along with a robust optimization approach based on dynamic time buffers. Another study presented in [83] also employs ML models (namely, linear regression, k-nearest neighbour, decision tree regressor, and artificial neural networks) for actual ATP of vessels, and then an exact optimization method is utilized to solve the continuous BAP. Based on extensive simulations, it is concluded that ML-based ATP of vessels could improve the optimization results, as accurate prediction helps a lot to minimize uncertainty in vessel arrivals.

## 4.3 | Hybrid and dynamic BAP

This section presents a detailed review of current works that investigate the BAP with hybrid berthing layout and dynamic arrivals of vessels as discussed in Section 3. Table A.3 summarizes recent literature on the hybrid and dynamic BAP (HD-BAP), including dataset explanation and key achievements.

Umang et al. studied the HD-BAP with the objective of minimizing total service time of arriving vessels [99]. The problem is first modelled as an ILP problem and then it is solved by the exact approach as well as by a metaheuristic method, namely squeaky wheel optimization (SWO). The SWO method works on the principle of a construct, analyze, and prioritize, where, at each iteration, possible solutions are constructed and analyzed, and results are used to build a new priority order to attain new solutions in the next iteration. In order to affirm the productiveness of the proposed SWO algorithm, several experiments are performed on real-time data taken from the container terminal at Port of Mina SAQR, UAE. Results are also compared with other methods, i.e. MILP, FCFS, and generalized set partitioning problem (GSPP).

Another study examines the hybrid BAP and an EA is proposed to solve the problem [100]. The objective of this study is to minimize the total cost, which includes handling cost, waiting cost, and cost occurred due to delays in departures. In order to check the productiveness of the proposed EA method, several simulations have been performed and results show the efficiency of the proposed algorithm over CPLEX.

The authors of [102] investigate the hybrid BAP where the key objective is to mitigate total cost that includes waiting and handling costs. They developed a heuristic-based deterministic variant of variable neighbourhood search (VNS) named variable neighbourhood descent (VND). In order to test the performance of the proposed VND method, simulations have been performed on two datasets and results show the effectiveness of the proposed algorithm over other metaheuristics, namely, bee colony optimization (BCO) and EA.

The authors of [103] investigate the BAP with the objective of minimum vessels' handling cost, where hybrid berthing layout is taken into account. They developed two methods to solve the hybrid BAP, namely sedimentation algorithm (SEDA) and SEDA with an estimation & rearrangement heuristic (SEDA+ERH). The first method is an exact combinatorial optimization algorithm and the latter method employs a heuristic as a pre-processing step to alleviate the computational complexity. The proposed methods are tested on three different instances taken from the literature. Experimental results denote the effectiveness of SEDA+ERH in terms of minimum cost in affordable computation time.

Kovavc et al. extended their previous work on the hybrid BAP [102] and proposed a new method namely general variable neighbourhood search (GVNS) [104]. The problem is formulated as MILP and then solved by GVNS along with other three metaheuristics that were proposed in their previous work, i.e. EA, BCO, and VND. The proposed method and other compared methods are tested on randomly generated datasets and results denote that the newly proposed GVNS outperformed EA, BCO, and VND in terms of computation times while maintaining better quality of solutions.

Azza et al. developed a metaheuristic based bat-inspired algorithm to deal with the hybrid BAP [105]. The major objective of this work is to reduce vessels' stay time at the terminal. Furthermore, they performed extensive simulations to validate the efficacy of the proposed algorithm, and the results are compared with the CPLEX solver. The results from simulations are evident that the proposed method is efficient over counterparts in terms of providing good solutions in minimum computation time.

Another study also deals with the BAP while assuming various irregular berthing layouts [107]. The primary objective is to minimize the total stay times of vessels at the port. Basically, they solved discrete and dynamic BAP; however, due to considering irregular berthing layouts, it becomes hybrid BAP, where one vessel can take two berths if its length exceeds one berth. In order to solve this type of problem, first, an exact MILP-based method is developed for small instances and then a heuristic-based iterated local search (ILS) is developed for large scale problems. For simulations, they employ data from a tank terminal and the results from experiments indicate the effectiveness of the proposed method.

The work presented in [66] examines two variants of BAP, i.e. the DD-BAP and hybrid dynamic BAP. In their proposed hybrid BAP formulations, a large vessel can take more than one berth and two or more vessels can take one berth if they are small. In this study, the problem is first formulated as a mixed-integer non-linear programming (MINLP) model, then it is solved by the CRO algorithm. The primary objectives of this work are to alleviate handling and fuel costs. Extensive simulations are carried out to affirm the productiveness of the proposed CRO-based method and results show its higher performance over two variants of GA and PSO.

Bouzekri et al. developed an integer linear programming (ILP) based solution for the hybrid BAP [108], where they tested their proposed method on a real-time dataset taken from the Port of Jorf Lasfar, Morocco. Extensive simulations have been carried out and results denote that the ILP based method can solve the hybrid BAP considering up to 40 vessels within reasonable computation time.

The HD-BAP is also investigated in [110], where a hybrid GA (HGA) algorithm is developed. In order to affirm the productiveness of the proposed HGA method, several simulations have been conducted on various datasets, i.e. small, medium, and large datasets, where ten vessels with two berths, 30 vessels with seven berths, and 50 vessels with 12 berths are taken into account. Simulation results show the effectiveness of the proposed HGA method over CPLEX in terms of minimum computation time.

## 5 | CURRENT LITERATURE ON COMBINED BAP+QCAP

This section examines in detail current studies that deal with the combined BAP and QCAP, summarized in in Table 5.

### 5.1 | Discrete and dynamic BAP with QCAP

This section reviews discrete and dynamic BAP, while the QCAP is also taken into account. Table A.4 summarizes recent literature on this problem formulation, including dataset explanation and key achievements per paper.

Lalla et al. examine the combined BAP and QCAP in [50] for reducing the total weighted service time of ships and propose a new heuristic method named migrating birds optimization (MBO). The MBO is a newly developed nature-inspired technique that is based on the V-formation flight of migrating birds. Furthermore, the proposed MBO method is tested on five datasets, with different numbers of vessels and berths, taken from recent literature [84]. Simulation results show that MBO beats existing approaches, i.e. CPLEX and PSO, in terms of lower computation times.

A study presented in [45] solves the BAP along with the QCAP by proposing a model predictive control (MPC)-based method, where the primary concerns of this work are to reduce total handling and waiting costs. In order to affirm the productiveness of the proposed MPC-based method for berth and QC allocation, several experiments are performed on a real-time dataset taken from Indonesian Seaport. The results from simulations validate the performance of the proposed technique over FCFS and a density-based strategy.

A multi-objective berth and QC allocation model is developed in [52], where the major objectives are to ensure the earliest departure time of vessels and enhance terminal efficiency. The problem is formulated as an MIP model and solved by the newly-developed chaos cloud PSO (CCPSO) method. A comparison study was also carried out to verify the productiveness of the proposed optimization algorithm. Experimental results indicate the effectiveness of the proposed method over GA in terms of the earliest departure times.

Lu et al. developed improved NSGA-II for solving the combined BAP and QCAP in [111], where discrete berthing layout is assumed. In this work, the authors also consider uncertainties in ships' arrival times and container handling times. Additionally, movable QCs (that can move to other berths/ships before completing the process of an assigned ship) are examined to enhance the flexibility of the MCT. The problem is formulated as a non-linear MIP problem and then solved by improved NSGA-II. Several experiments are carried out to affirm the benefits over standard NSGA-II.

The paper presented in [53] investigates both the BAP and the QCAP problems of MCT while employing discrete berth allocation. The primary objective of this study is to mitigate the total handling costs. First, the problem is formulated

**TABLE 5** Summary of current literature related to combined BAP+QCAP. [ED: employed dataset, MA: maintenance activities, PY: published year, RD: random data, RPD: real port data, UF: uncertain factor, VA: vessel arrivals, VO: vessel operational times].

| Ref. | PY | Method | Compared method(s) | UF(s) | ED |
|---|---|---|---|---|---|
| **DD-BAP+QCAP** | | | | | |
| [50] | 2015 | MBO | CPLEX and PSO | – | [84] |
| [45] | 2015 | MPC | FCFS & density-based strategy | – | RPD |
| [52] | 2017 | CCPSO | GA | – | RD |
| [111] | 2018 | Improved NSGA-II | Standard NSGA-II | – | RPD |
| [53] | 2018 | RH method | CPLEX and greedy | AT, VO | RD, [70] |
| [51] | 2019 | S-ILP | – | MA | RD |
| [113] | 2019 | Exact model | Existing operational practices | – | RD |
| [112] | 2019 | HGAs | Standard GA | – | RD |
| [132] | 2019 | MPA | FCFS & density-based strategy, GA, and hybrid PSO | VA | RD, [45] |
| [114] | 2020 | GRASP, FBS | Iterative approach | – | RPD |
| [116] | 2020 | Deep neural network | – | – | RD |
| [115] | 2021 | Decomposition Algorithm | CPLEX | VA | RD |
| [117] | 2023 | Reinforcement learning | FCFS | VA | RD |
| **CD-BAP+QCAP** | | | | | |
| [118] | 2015 | PSO | CPLEX | – | RPD |
| [119] | 2017 | ALNS | GA, TS, and SWO | – | [94] |
| [54] | 2017 | GA | Discrete DE | – | [92] |
| [120] | 2018 | Branch & bound | CPLEX | – | [101] |
| [46] | 2018 | RH method | Exact approach | – | RD |
| [123] | 2019 | LRVM and improved GA | RH and CPLEX | MA | [133] |
| [121] | 2019 | IGA | Standard GA, CPLEX | – | – |
| [122] | 2019 | ILS | MILP and B&C | – | [92] |
| [124] | 2020 | RTPSO | PSO and exact approach | – | RD |
| [125] | 2020 | Two-phase IM | CPLEX | MA | RPD |
| [126] | 2020 | GVNS | CPLEX | – | RD |
| [127] | 2021 | SBH | MIP | – | [92, 94] |
| **HD-BAP+QCAP** | | | | | |
| [129] | 2016 | GAMS | – | – | RD |
| [130] | 2016 | GAMS | – | – | RD |
| [131] | 2019 | SA method | – | VO | RD |

as an MIP model that also deals with several disruptions in vessels' handling, i.e. deviation of ships' arrivals, uncertainties in vessels' unloading/loading times, and failure of QCs or other handling equipment. Then, a heuristic-based rolling horizon (RH) algorithm is developed to find a feasible solution under disruptions, which is further tested on real-time instances. The results from experiments affirm the efficacy of the proposed reactive method over the proactive technique.

Another study presented in [51] investigates the same problem and develops a stochastic ILP (S-ILP) model to solve it. This study also considers uncertainties in QCs maintenance activities and the primary aim of this work is to minimize total turnaround time. In order to verify the productiveness of the proposed model, the authors perform simulations on 90 instances and the results verify the proposed model in terms of higher efficiency and accuracy.

The paper presented in [112] investigates the discrete and dynamic combined BAP and QCAP. In order to make the problem more realistic, this study considers variable QCs assignment that makes MCT more flexible. Furthermore, three hybrids of GA are developed to solve the problem, where three different mutations are employed for three algorithms, i.e. swap mutation, thoros mutation, and thoras mutation. Finally, extensive simulations have been carried out to validate the proposed methods. The results from simulations affirm the productiveness of proposed techniques over GA.

Abou et al. also investigated a similar problem with the objective of minimizing the total service time of arriving vessels [113]. This study considers both QCs allocations, i.e. static and dynamic allocations. Furthermore, the problem is mathematically formulated and an exact solution is proposed. For experimental purposes, the authors perform a case study on Abu Dhabi's container terminal and the proposed solution is implemented on the same terminal. The results from experiments indicate that the proposed method attained decreased service times over the current operational approach.

The work presented in [114] also deals with the combined BAP and QCAP. Their formulation allows the reassignment of ships to other terminals in a multi-user terminal. The primary objective of this study is to reduce the total service cost and this work claims that unnecessary movements of QCs reduce MCT efficiency. To tackle this issue, heuristic-based GRASP and filtered beam search (FBS) are developed. Furthermore, real-time datasets from Busan Terminal, Republic of Korea, are employed for experiments in order to validate the productiveness of the proposed method.

In [115], an exact method, namely a decomposition algorithm, is developed to deal with combined BAP and QCAP, where the basic objective is to minimize the total cost incurred due to deviations from departure times and berth positions. In addition, the authors also consider two uncertainty factors, namely the increase/decrease in the number of containers and the late arrival of ships. They conduct several experiments with randomly generated data and the results confirm the effectiveness of the decomposition method.

A study [116] develops a deep learning-based model for solving the combined BAP and QCAP. They propose a deep neural network for berthing time prediction in order to support berth planning. From the presented simulation results it becomes evident that the proposed model can help in achieving efficient berth and quay crane allocation. The authors of [117] propose a greedy insert-based offline model to optimize BAP when vessel information is available. They further propose an online strategy based on a reinforcement-learning algorithm to solve the problem when vessel information is uncertain. The proposed model is capable of learning from feedback and of adapting quickly in real time. The experimental results demonstrate the effectiveness of both offline and online methods.

## 5.2 | Continuous and dynamic BAP with QCAP

In this section, current studies on another form of BAP and QCAP are investigated, where continuous berthing layout and dynamic vessels arrivals are taken into account. Table A.5 summarizes recent literature on the combined continuous and dynamic BAP with QCAP, including dataset explanation and key achievements of each paper.

A two-phase model of BAP and QCAP is developed in [118], where the major aims are to improve port resources savings and reduce QCs movements to enhance MCT efficiency. As a first step, BAP is solved with a metaheuristic-based PSO algorithm and then QCAP is addressed by a CPLEX solver. In order to confirm the productiveness of proposed solutions for the combined problem, experiments are performed on real-time datasets that were adapted from the Ningbo Beilun container terminal, China.

The work presented in [119] also cope with the combined problem. For increasing handling productivity of the MCT, an ALNS-based heuristic is proposed to mitigate overall cost, which includes penalty cost due to late departures and QCs assignment cost. The output of the ALNS method is compared with GA, TS, and SWO algorithms, where comparison analysis demonstrates the efficacy of the proposed method.

Correcher et al. studied the continuous BAP and QCAP with time-invariant crane assignment in [54], where the primary objective was to reduce total handling cost along with vessel service times. They proposed biased random-key GA with memetic improvement and local search to solve the problem and the proposed method is tested on several real-time instances to verify its performance. Experimental results demonstrate that the biased random-key GA provides optimal solution considering up to 40 vessels; however, it can also provide near-optimal solutions considering up to 100 ships within reasonable computation time.

[120] consider carbon emission policies in order to reduce total carbon emission at the port along with the primary objectives of the study, i.e. reduction in penalty costs and operating costs. Basically, total operating and carbon emission costs both depend on the operating hours of QCs and unnecessary operations of QCs because inefficient berth and cranes allocation lead to high carbon and handling cost. In order to solve this joint problem, a branch and bound algorithm was developed, which was tested on several real-time instances, taken from [101]. The results from experiments affirm the benefits of the proposed method over the CPLEX solver.

The authors of [46] investigate the combined BAP and QCAP. First, the problem is mathematically formulated based on relative position formulation and then solved by two approaches, the exact approach and using the RH method. In addition, this work considers several uncertainties and various inequality constraints. In order to assure the effectiveness of developed methods, experiments are performed on real-time instances extracted from a multi-user terminal that was primarily used for bulk cargo operations. The results from experiments denote that the exact approach easily solves small-scale instances and RH is a more suitable algorithm for large-scale instances.

An MIP model is developed in [121] to deal with the BAP and the QCAP simultaneously, where the GA and its variant, improved GA (IGA), are developed for minimizing total service cost, which includes handling cost, waiting cost, and QCs conversion cost. In order to validate the proposed method, several experiments are carried out and results show the efficacy of IGA over standard GA and CPLEX.

Correcher et al. also deal with the same problem in [122]. The continuous BAP with QCAP is modelled as an MILP problem, where arriving vessels can be moored at any location throughout the quay. Next, the problem is solved following an iterated local search (ILS) approach. Simulation results denote that the proposed method efficiently solves the problem considering 50 vessels in a week.

Zheng et al. also studied the same problem while considering QCs maintenance [123]. The problem is formulated as the ILP model and solved by the exact approach; however, it can solve the problem considering up to only 18 vessels. Then, this study develops improved GA and a novel heuristic named left and right vessel move (LRVM) algorithm. Furthermore, this study is also compared with the previous work presented in [46] while ignoring QCs maintenance constraints. Results from simulations affirm the productiveness of the proposed method over counterparts.

A combined BAP and QCAP is investigated in [124], where the primary objective is to enhance the performance of MCT by efficiently allocating berths and QCs to arriving ships. The authors of this study developed a novel variant of the PSO algorithm, namely random topology PSO (RTPSO). Unlike standard PSO, the proposed RTPSO works on two basic rules while assuming there are $k$ neighbourhoods: each particle is connected to itself and it is also linked to $k-1$ particle. The problem is formulated as an MIP model and several tide constraints are also considered in the formulations. In addition, several simulations on self-generated instances are performed to validate the performance of the proposed RTPSO method.

The authors of the study presented in [125] investigated a new bi-objective optimization model of BAP and QCAP while considering QCs maintenance activities. The objectives of this work are twofold: reducing the total turnaround time of serving ships and minimizing the total penalty costs of QCs maintenance tardiness and earliness. The problem is first formulated as an ILP model and then it is solved by a heuristic-based two-phase iterative method (IM). The authors tested their newly designed method on real-time and randomly generated instances to affirm their productiveness and effectiveness.

Krimi et al. studied the same problem in [126] while considering several uncertainties, e.g. bad weather conditions, QCs maintenance activities etc. In order to improve the performance of the container terminal located at a port in Morocco, the joint problem is formulated as an MIP model. Later, it is solved with a GVNS-based heuristic algorithm. Furthermore, various experiments are performed on a real dataset taken from the practical problem of the port in Morocco. Experimental results demonstrate that the compared method, a CPLEX solver, takes higher computation time and in many cases cannot solve the problem in a given time frame. However, the proposed GVNS guarantees optimal or near-optimal solutions in reasonable computation time.

In [127], a search-based (remove & reinsert) heuristic (SBH) is developed for the combined BAP and QCAP, where the authors' goal is to reduce the costs involved in container handling. The problem is formulated as a MIP that can handle both fixed and flexible departure time settings. To confirm the effectiveness of the proposed method, several simulations are performed with small, medium, and large data instances.

## 5.3 | Hybrid and dynamic BAP with QCAP

This section examines the recent status of literature that deals with one of the most challenging problem of seaside operations, i.e. the combined hybrid and dynamic BAP with QCAP [99, 128]. Table A.6 summarizes recent literature on the combined hybrid and dynamic BAP with QCAP, including dataset explanation and key achievements of each paper.

A study presented in [129] examines the combined hybrid BAP and QCAP. Its objective is to minimize the total service times of arriving vessels. A GAMS solver is employed to solve the modelled integrated problem with an exact solution. Data instances are generated randomly that assume three ships with four berthing positions. Simulation results affirm its effectiveness in terms of optimal berth and QCs allocations.

Alnaqabi et al. have studied the combined problem of BAP and QCAP [130] while assuming a fixed number of QCs at each berthing position and a safety distance between adjacent QCs. The ultimate objective of this work is to reduce the total processing time of ships. The problem is modelled as MILP and then solved by a GAMS solver. Simulations are also carried out to validate the productiveness of the proposed solution and results show that the proposed method gave an optimal solution in reasonable computation time.

The authors of [131] also deal with the combined hybrid BAP and QCAP, where hybrid berthing layout and dynamic vessel arrivals are assumed. Furthermore, the non-crossing constraints of QCs are assumed in this study. Finally, a simulated annealing (SA) based heuristic algorithm is developed to minimize late departures of vessels. In order to test the proposed SA-based approach, simulations are performed on a randomly generated dataset that includes 40 vessels, seven berths, and 18 QCs. Simulation results indicate that the proposed heuristic-based can easily solve large-scale instances.

# 6 | DISCUSSION AND OBSERVATIONS

In this survey, we review recent studies addressing the single-BAP and combined BAP with QCAP, where most of the studies propose a solution using CI approaches. Each CI-based approach has its own set of advantages and disadvantages when it comes to solving a BAP; as a result, determining which model is the best is challenging. Since there is no benchmark data and most of the researchers use their own data (in many cases randomly generated), and codes of their research are unavailable online, it is difficult to compare the performance of the algorithms. However, based on the reviewed studies, we offer the following key observations related to single-BAP. Many studies use some variant of GA for single-BAP, as it is the most popular algorithm from the metaheuristic family and easy to implement due to having fewer parameters compared to other heuristics. Furthermore, almost all studies implement mathematical models and some form of linear programming for solving single-BAP; these are efficient in small-scale problems but cannot solve large-scale problems in affordable computation time. CI approaches are able to solve small and large scale problems, however, with an optimality gap of 10–40% compared to an optimal solution.

Furthermore, when we analyze and discuss the performance of methods developed for combined BAP and QCAP, we observe almost the same trends when CI and mathematical methods are compared. Mathematical models provide an optimal solution but can only be used for small-scale problems, even smaller compared to the single-BAP case. On the contrary, CI approaches can solve the combined problem in low computation time, but relatively higher compared to single-BAP. As for hybrid algorithms, especially, when metaheuristics are combined with mathematical approaches, e.g. [22, 61], they often provide high quality solutions in terms of low computation time due to metaheuristics and high accuracy due to mathematical methods. Hence, more combinations of different algorithms with different settings need to be explored for better solutions. For example different schemes for initial population generation in an algorithm should be tested instead of using a random population as done by almost all reviewed methods.

The current analysis also highlights the scarcity of studies (as evident from Tables 4 and 5) that address BAP or BAP+QCAP with various uncertainties, such as uncertainty in vessel arrival times, operational times, weather conditions and maintenance activities. The lack of such studies reveals a research gap in understanding the complexities and subtleties associated with uncertainties in algorithm development. Based on the current analysis, we found that only 19% (11 out of 58) of the reviewed studies consider some form of uncertainty. Consequently, future researchers must strive for a comprehensive approach that incorporates a broader range of uncertainties in both seaside problems, i.e. standalone BAP and combined BAP+QCAP, allowing for a more holistic understanding and interpretation of research findings. Considering uncertainties, would also lead to a more fair comparison of existing approaches and improved resilience for real-world implementations.

Overall, only a few studies develop metaheuristics that can self-adapt, self-evolve, and self-tune to deal with large scale and complex problems [64, 119]. There is still a need to develop these types of methods to deal with different variants of BAP, such as multiple quay BAP, combined BAP and QCAP with hybrid berthing layout, and BAP with real-world constraints and practical settings.

## 7 | CATEGORIZATION OF CI APPROACHES

In this section, we unfold the architectures and workings of the CI approaches that are commonly proposed or employed in recent literature for solving the stand-alone BAP and the combined BAP with QCAP. The Computational Intelligence Society of IEEE defines CI in their constitution, Article I, Section 5 as "the theory, design, application, and development of biologically and linguistically motivated computational paradigms emphasizing neural networks, connectionist systems, genetic algorithms, evolutionary programming, fuzzy systems, and hybrid intelligent systems in which these paradigms are contained" [5, 134].

The present study considers three primary categories of CI approaches, namely, fuzzy logic, metaheuristics, and control systems [5, 135, 136]. In addition, metaheuristics are further divided into single individual and population-based approaches, with the latter further divided into swarm intelligence (SI) and evolutionary approaches. Since the BAP is an NP-hard problem, metaheuristics are considered more efficient than exact approaches, as they solve these problems with low computational complexity. In this section, we review the three main categories of metaheuristic approaches based on their wider application for optimizing MCTs' operations and discuss various methods belonging to the metaheuristic family. Figure 5 showcases all CI approaches found in the surveyed studies at a glance.

### 7.1 | Single individual approaches

Single individual methods solve an optimization problem by iteratively applying generation and modification procedures for improving a single candidate solution [137]. They typically perform a random walk through search trajectories or neighbourhoods in the problem search space, where an iterative process is employed to perform a walk for moving from the current solution to the next one. A set of candidate solutions is produced from the existing solution in the generation step. In the selection or replacement step, a new solution is chosen based on a fitness function. The process repeats until some stopping criteria are met, e.g. maximum iterations, specific fitness value, or maximum computation time. Although there are several popular approaches that belong to a single individual metaheuristic family, this section elaborates on simulated annealing (SA) because of its wider use in the BAP and QCAP.

SA is one of the most popular algorithms from the single individual metaheuristic family, which has been widely adapted for optimization problems. Kirkpatrick et al. developed the SA algorithm in [138], which is based on the metropolis algorithm. In the SA algorithm, the term "annealing" means a process of crystallization by cooling. Slow cooling of metals typically generates reliable crystallization, while poor crystallization is produced by rapid cooling. SA starts searching with an initial solution that is created randomly. In each iteration, it seeks a novel solution in the current solution's neighbourhood, known as an algorithm move. There exists various types of moves, such as single and double swap move, insertion move, and single and double shift move [75]. In order to decide if the new solution is good or not, the fitness value of the new solution is calculated and compared with the existing solution. If the new solution is better, it becomes the current solution for the continuation of the search. On the contrary, if the fitness value of a new solution is lower compared to an existing solution, it can also be considered as a new current solution; however, it can be done with a probability calculated by the application of criteria presented in [139]. The aim is not only to limit the movement of the search algorithm in directions that enhance the fitness value but also

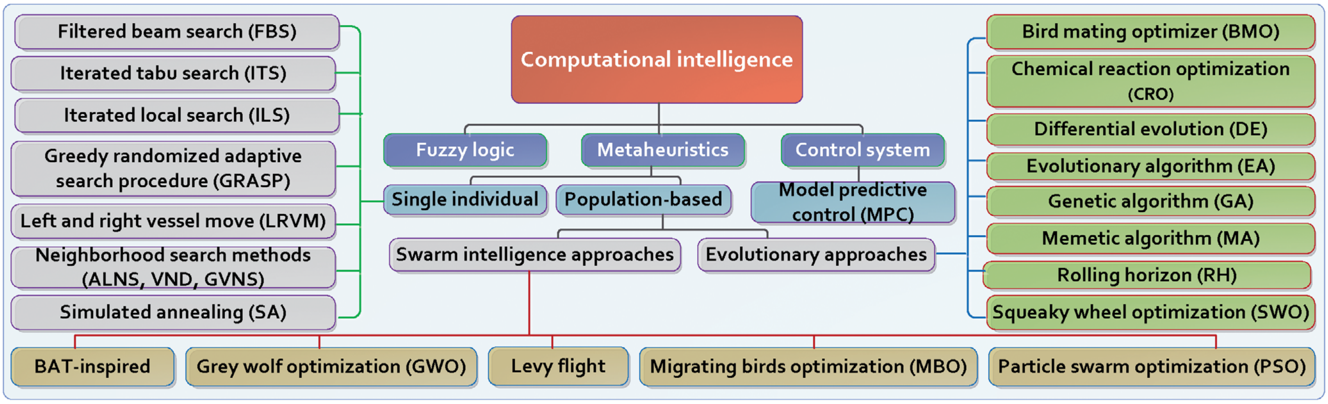


**FIGURE 5** CI approaches proposed/adopted in the literature for solving the stand-alone BAP or the combined BAP with QCAP [5, 135, 136].

to permit movements that decrease the fitness value with small probabilities, as this can, in principle, minimize the chances that the search procedure is stuck in local optima. The search process continues until the criteria of termination have been met.

## 7.2 | Swarm intelligence approaches

The SI approaches are nature-inspired that work on the basis of interaction between living organisms [134]. The key inspiration for SI is the social behaviours of various animals, insects, or birds, often referred as swarms. There exist several similarities between SI and evolutionary approaches, for instance, both types of methods maintain population and employ iterative optimization process based on single or multiple objective functions (OFs). In addition, SI approaches operate on the principle that several individuals may be able to accomplish a greater objective together, acting independently but cooperatively [5]. Unlike evolutionary approaches, gradient-based optimization principles do not drive SI methods. They employ other strategies to explore the search space. In both numerical and combinatorial optimization problems, these algorithms are primarily used to explore combinations of values that optimize a particular OF. There exist many techniques that work on the SI principle; however, in this section, particle swarm optimization (PSO), one of the most widely adopted SI approaches, is discussed in detail.

PSO is a swarm-based metaheuristic approach that has earned huge attention in the last two decades because of its simple application in various optimization problems. It was first proposed by [140], which is based on the social behaviours of animals. Various animal species adopt a cooperative mechanism for searching for food in the form of groups, and each member keeps altering the search pattern based on its own and other members' learning experiences. The initial kind of PSO algorithm was only able to solve nonlinear continuous optimization problems; however, a lot of improvements were made in PSO for enhancing its abilities to solve a wide variety of complex problems [141].

In the standard PSO algorithm, all possible solutions are called particles. In the total search space, each particle is associated with two vectors, the velocity vector and the position vector. Each particle updates its position on the bases of its previous experience and velocity vector. A random population of possible solutions (particles) is generated and random velocity and position vectors are assigned to each particle. The population size depends on the problem dimension. The fitness value of each particle is evaluated based on the objective function and the particle with the best value is stored. Next, the velocity and position of each particle is updated based on their values from the previous iteration along with some model parameters. The fitness evaluation and vector updates repeat until the termination criteria (e.g. maximum number of iterations or computation time) are met.

## 7.3 | Evolutionary algorithms

Evolutionary algorithms are population-based metaheuristics that work on the basis of certain phenomena of nature, such as recombination, selection, mutation, and reproduction [142]. A typical evolutionary method has a population of several individuals (chromosomes). All possible solutions are mapped onto chromosomes that consist of multiple genes. The population is modified over time, the quality of chromosomes is measured, and the fittest are chosen for the next generation. This leads to the population of superior quality solutions. In this way, the OF can be minimized or maximized. This section presents the details of GA, which is most widely adopted in the literature when dealing with the BAP and QCAP.

GA has a high convergence rate compared to most metaheuristics, and thus can solve big and high-complexity problems. It was developed by Holland [143] and is based on the evolution process in natural systems, i.e. Darwin's principles of survival of the fittest individuals. GA is a population-based approach that finds a better solution by managing a population that contains various possible solutions, which are revised generation to generation by employing several genetic operators, including selection, crossover, and mutation. Initially, a random population of different possible solutions is generated. A single solution is known as a gene, a solution set is known as a chromosome, and all solution sets form a population. Next, fitness values of all solution sets are calculated to evaluate the goodness of solutions. A subset of the fittest individuals (solutions sets) are selected as parents for the next generation. Crossover is then employed to produce offsprings, where a child adopts portions of its parents. A mutation operator is also applied to some portion of the solutions in the new generation to avoid premature convergence and maintain diversity in the population. The fitness values of the new population are calculated and the same process repeats until conditions of termination are met. Typical termination conditions include maximum available computation time, maximum iterations, and a maximum number of generations.

## 8 | BENCHMARK DATASETS

Since datasets are considered important assets of any research field, it is necessary to present them in a comprehensive way. In this manner, researchers can easily find details and characteristics of benchmark datasets instead of spending time and effort in finding or creating new datasets. To facilitate the research community, this section unfolds various datasets that were used in recent literature.

### 8.1 | Datasets for stand-alone BAP

*Dataset 1*

Cordeau et al. generated a dataset based on real-time berth allocation and traffic data collected from the Port of Gioia Tauro, Italy [84]. The Port of Gioia Tauro deals with an average of 60 vessels per week; however, they generated a smaller number of ships due to implementation issues. Regarding berthing positions, even though there are 13 discrete berths, they considered up to 10 berths for dataset generation. Based on a statistical analysis of real-time data, various vessels of different lengths are generated with different handling times. They consider five different problem sizes (i.e. number of ships and berths) and they randomly generate ten data instances for each size. For example, ten data instances are generated for 25 ships with five berths, 25 ships with seven berths, 25 ships with ten berths, 35 ships with seven berths, and 35 ships with ten berths. In addition, the earliest available time of berth is considered the same for each berthing position.

*Dataset 2*

Lalla-ruiz et al. produced a dataset in [85], which is based on instances presented in [84]. Unlike [84], they consider more realistic data instances by considering fewer berthing positions, high traffic, and longer planning horizon. They generate data instances against ten various sizes, for instance, 30 ships with three berths, 30 ships with five berths, 40 ships with five berths, 40 ships with seven berths, 55 ships with five berths, 55 ships with seven berths, 55 ships with ten berths, 60 ships with five berths, 60 ships with seven berths, and 60 ships with ten berths. The planning horizon is set to be 600 h.

*Dataset 3*

The authors of [17] and [144] generate larger instances of the berth allocation problem in the same form. A set of 50 instances of different sizes considering 80–150 ships and 10–15 berths is generated in [17]. For larger problem instances, Kramer et al. generate 20 data instances of two different sizes (10 instances for each size), for example, 200 ships with 15 berths and 250 ships with 20 berths [144]. The planning period is considered as 600 h in both cases.

### 8.2 | Datasets for combined BAP and QCAP

*Dataset 1*

Agra et al. generate a dataset based on real-world data of a terminal devoted for short-sea shipping and deals with bulk cargo operations [46]. The authors obtained physical characteristics of the terminal from real data, including length of vessels, number of QCs and their initial positions, and handling productivity of QCs. For data instances generation, 34 berths and seven QCs are considered, where six cranes have the same handling productivity and the last one has greater productivity. Based on historical data, the first type of QCs can handle 263.6 tons/h and for the greater productivity QC, the handling rate is 319 tons/h. Each berthing position is set to 25 meters and ships' lengths are equal to six to nine berth segments. The load on ships vary between 3000 to 8800 tons. The total number of arriving ships ranges between 7 to 15 per day and the planning horizon is 1 day.

*Dataset 2*

Correcher et al. [122] present data instances that are generated based on a mechanism presented by Park et al. [90]. They consider a wharf of length 1200 m divided into portions of 10 m. The total planning horizon is set to 300 h discretized in 1-h intervals. There are 11 QCs considered for all instances (minimum of two and maximum of five QCs can be assigned to 1 ship for berthing). The developed instances contain various number of vessels: 20, 25, 30, 35, and 40 vessels. In this way, ten instances are generated for each number of vessels and the total instances equal to 50. The values related to ships are generated by uniform distribution, for instance, ship length $U[15, 35]$, arrival time $U[1, 170]$, number of QCs hours required $U[10, 48]$, and the planned berthing position for each ship is generated as $U[1, 120]$.

## 9 | CURRENT CHALLENGES AND FUTURE DIRECTIONS

Up to this point, we have focused on understanding and reviewing the literature on seaside operations, i.e. various variants of the BAP and QCAP, including the current progress in terms of developments and latest trends. Even though this field has attracted huge attention from the research community in the last decade, there are still many topics/gaps in this field that need to be investigated as future research. In this section, this study presents a list of current challenges along with future directions for using computational intelligence approaches to enhance the performance of marine container terminals.

## 9.1 | Standardized benchmarking environment

In this work, a lot of studies develop berth and quay crane allocation solutions by employing several CI techniques. However, in the IMT era, one of the most challenging tasks is to develop a standardized environment of algorithm development, where researchers can directly compare their proposed methods for the BAP and QCAP with other state-of-the-art methods. For instance, Brockman et al. developed a standardized environment, named OpenAI, for reinforcement learning research [145]. It contains a number of current benchmark problems along with state-of-the-art results, where researchers can propose new methods and compare their results with existing solutions. Since there is no standardized environment in IMT, there is an urgent need for this type of environment that will help in the development of new and efficient solutions for the berth and QC allocation problems.

## 9.2 | Online berth allocation

Based on the surveyed literature, it is concluded that there is a need for developing CI-based solutions that deal with online berth allocation. Although a lot of research works solve the BAP and QCAP dynamically (in terms of vessels' arrivals), most of the techniques still solve the problems offline [14]. However, online methods must consider the real-time operational situation of berths and vessels as well as other practical constraints (e.g. tidal constraints), and handle last-minute changes when the ships routes and arrival schedules are altered without prior warning to the MCT for optimal utilization of terminal resources. Therefore, there is a need to develop online approaches that can alter previous decisions in a timely manner.

## 9.3 | Integrated uncertainties

The handling of uncertainties in berth and QC allocation problems has earned huge attention in the last couple of years, which include uncertainty in vessels arrival, uncertainty in vessel unloading/loading times, uncertainty due to weather conditions, uncertainty in handling time, uncertainty due to the failure of equipment and maintenance activities, and other unforeseen events [70, 146–148]. However, most of the studies only deal with a few uncertainties instead of considering all possible uncertainties to make the problem more practical. For instance, Schepler et al. consider only uncertainty in vessels' arrival [65], uncertainty in handling time and vessels' arrival is considered in [78], uncertainty in container handling time is included in [3], and the study presented in [51] deals with uncertainty related to QCs maintenance time. Therefore, there exists a research gap in current literature, which provides a great direction for the research community to develop such types of algorithms that tackle practical problems considering all possible uncertainties.

## 9.4 | Spatiotemporal berth planning

Spatiotemporal berth planning plays a significant role in optimizing operations of the future container terminals. We have noticed from current literature that there are very few studies (e.g. [68, 149]) that deal with the BAP and QCAP while considering multiple quays or terminals. In practice, there exist many MCTs having more than one quays; for instance, the port of Valencia, Spain contains two, Terminal-1 of Jebel-Ali Port, Dubai and Brani and Tanjong Pagar terminals, Singapore have three, and Keppel Terminal, Singapore consists of four. Forjan et al. in [68] proposed a GA-based solution for the BAP while considering three quays. Hence, the development of novel CI-based methods that deal with spatiotemporal dynamics (multiple quays or cooperating terminals) at container terminals will enhance the performance and reduce the computation costs of future terminals.

## 9.5 | Day-ahead forecasting

The need to enhance operational activities at the container terminal has dramatically increased in order to meet the many requirements of industry and customers, as well as to achieve fast delivery of goods around the globe. However, due to inefficient streamlined systems and many other factors, there exists a lack of reliable information about vessel arrivals, departures, and destination ports [150]. Inaccurate information causes congestion at the terminal and wastage of terminal resources [151]. In [152], the effect of time in port is considered by investigating 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 improved prediction of arriving vessels. Day-ahead forecasting using learning systems (e.g. SVM, NN etc.) has gained huge attention in the last decade in various fields, such as load and price forecasting in smart grids [153], energy forecasting in microgrids [154], and workload forecasting in cloud computing [155]. Therefore, an accurate day-ahead forecasting of vessels arrivals and departures also has a great research value, which will help to further enhance the efficiency of MCTs.

## 9.6 | Deployment of advanced CI methods

The maritime industry is still lacking in the development of advanced and adaptable CI approaches to address seaside operational problems, such as BAP and QCAP. A study presented in [156] utilizes an adaptive learning approach to tackle job scheduling problems in the manufacturing supply chain domain. This approach draws inspiration from the training weights of ANN while developing CI-based methods like GA, PSO, and SA. The study's simulation results lead to the conclusion that adaptive CI methods offer more efficient solutions compared to standard CI approaches. Given the success of adaptive CI methods in various fields, it is evident that there is untapped potential for employing such techniques, along with other advanced methods like adaptive critic design algorithm, to resolve well-known seaside operational problems, specifically BAP and QCAP. Additionally, there is an emerging and intriguing area of research in the maritime industry concerning parameter learning within the realm of CI.

## 10 | CONCLUSIONS

In this study, we conducted a comprehensive state-of-the-art literature review on current trends and developments for IMT systems. Since this study focuses on reviewing seaside operations involving two major optimization problems, namely the BAP and QCAP, we have underpinned our discussions with background knowledge of container terminals as well as seaside operational problems. Then, we reviewed current studies that address stand-alone BAP or combined BAP with QCAP. The primary objectives of these studies include reducing vessels' turnaround time, minimizing departure delays, alleviating waiting time before berthing, and reducing overall service costs for arriving ships. Since the literature review revealed that most of the recent studies use new computational intelligence (CI) approaches, this study also sheds light on the background of CI techniques, focusing on broader adopted categories such as single individual, swarm intelligence, and evolutionary approaches. In addition, the characteristics of the datasets that are used to solve the stand-alone BAP or the combined BAP with QCAP are investigated, including the data types (e.g. real-time data, benchmark data, randomly generated data), dataset features (e.g. data origin, data availability), and dataset sizes (e.g. number of vessels, number of berths, wharf size, planning horizon). Finally, this study presents research challenges and open issues related to current IMT systems, including a standardized benchmarking environment, online berth allocation, integrated uncertainties, spatiotemporal berth planning, day-ahead forecasting, and the deployment of advanced CI methods. These challenges need to be resolved in order to realize the full potential of future IMT systems.

## NOMENCLATURE

| | |
|---|---|
| AEA | Adaptive evolutionary algorithm |
| ALNS | Adaptive large neighbourhood search |
| BAP | Berth allocation problem |
| BCO | Bee colony optimization |
| BMO | Bird mating optimizer |
| CCPSO | Chaos cloud particle swarm optimization |
| CD-BAP | Continuous and dynamic BAP |
| CI | Computational intelligence |
| CRO | Chemical reaction optimization |
| CSA | Cuckoo search algorithm |
| DC-BAP | Dynamic and continuous BAP |
| DD-BAP | Discrete and dynamic BAP |
| DE | Differential evolution |
| DPCEA | Deterministic parameter control EA |
| EA | Evolutionary algorithm |
| FBS | Filtered beam search |
| FCFS | First come first serve |
| GA | Genetic algorithm |
| GASSR | GA with state-space reduction |
| GRASP | Greedy randomized adaptive search procedure |
| GSSP | Generalized set partitioning problem |
| GVNS | Generalized variable neighbourhood search |
| GWO | Grey wolf optimization |
| HD-BAP | Hybrid and dynamic BAP |
| HGA | Hybrid GA |
| HSA | Hybrid SA |
| IA | Immune algorithm |
| IG | Iterated greedy |
| ILS | Iterated local search |
| ILP | Integer linear programming |
| IP | Integer programming |
| IMT | Intelligent maritime transportation |
| ITS | Iterated tabu search |
| ITV | Internal transport vehicle |
| LRVM | Left and right vessel move |
| MA | Memetic algorithm |
| MASSR | MA with state-space reduction |
| MBO | Migrating birds optimization |
| MCT | Marine container terminal |
| MIP | Mixed integer programming |
| MILP | Mixed integer linear programming |
| MINLP | Mixed-integer non-linear programming |
| ML | Machine learning |
| MPA | Model predictive allocation |
| MPC | Model predictive control |
| MNSGA-II | Modified non-dominated sorting GA II |
| OF | Objective function |
| PSO | Particle swarm optimization |
| QC | Quay crane |
| QCAP | Quay crane allocation problem |
| QCSP | Quay crane scheduling problem |
| RCRO-BAP | Risk constrained robust optimization BAP |
| RTPSO | Random topology PSO |
| SA | Simulated annealing |
| SEDA | Sedimentation algorithm |
| SEDA+ERH | SEDA estimation & rearrangement heuristic |
| SAEA | Self-adaptive evolutionary algorithm |
| SC | Straddle carrier |
| SI | Swarm intelligence |
| SWO | Squeaky wheel optimization |
| TS | Tabu search |
| VND | Variable neighbourhood descent |
| VNS | Variable neighbourhood search |

## AUTHOR CONTRIBUTIONS

**Sheraz Aslam**: Conceptualization; investigation; methodology; writing—original draft; writing—review and editing. **Michalis P. Michaelides**: Conceptualization; investigation; supervision; writing—original draft; writing—review and editing. **Herodotos Herodotou**: Conceptualization; investigation; supervision; writing—original draft; writing—review and editing.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data sharing not applicable – no new data generated, or the article describes entirely theoretical research.

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# APPENDIX A

**TABLE A.1** Analysis of methodologies adopted for discrete and dynamic BAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [55] | 2014 | PSO | GSSP, LP, and clustering search (CS) | Data instances are generated from real-time traffic and berth allocation data collected from Port of Gioia Tauro, Italy, containing up to 35 vessels and 10 berths. Another dataset is generated based on the mechanism presented in [84], which considers up to 60 vessels with 13 berths. | This work proposes a PSO-based solution to solve the BAP with the objective of minimizing total handling and waiting time of arriving vessels. It provides the best solution in 41%, 91.30%, and 36.12% lesser times than GSSP, LP, and clustering search, respectively. |
| [56] | 2015 | GA | CPLEX | This paper generates 6 random data instances that includes 5 to 80 ships and 3 to 30 berths. | This paper adopts GA for reducing total service and waiting times of arriving vessels. This work assumes that each berth has different handling productivity. Simulation results reveal that CPLEX is only able to solve the problem of having up to 10 vessels and 5 berths. However, the GA-based method can solve the problem of having up to 80 ships and 30 berths. |
| [57] | 2015 | GA | – | Datasets are produced randomly for the planning horizon of 180 h. The ETA and ETD are generated using a uniform distribution. | This work develops a GA-based solution with the objective of reducing workload at night times and delays in departures. This is the first study of its type that considers daytime preference while proposing a solution of BAP. Simulation results show the efficacy of GA in terms of reducing late departures and shifting maximum load in day times. |
| [58] | 2015 | Enhanced DE | GSPP, TS, CS, and PSO | This paper uses the data instances presented in [84]. The benchmark data includes 30 instances while considering 30 vessels with 13 berths. In each instance, ships' length, ETA, departure time, and berth length are assumed differently. | This paper proposes an enhanced version of the DE algorithm for minimizing total service and handling times of all ships. A game theory-based approach is adapted for the best selection of mutation operator. The proposed method achieves the best objective value of 1306.8 in 6.80 s; GSPP, CS, and PSO take 14.98, 12.79, and 8.17 s for the best objective value, respectively. The objective value of TS is 1309.7. |
| [59] | 2015 | BMO algorithm | GSSP, PSO, and CPLEX | This work produces 12 data instances from [84], which include up to 35 ships and 10 berths. | This work developed a novel BMO algorithm in order to enhance MCT's efficiency by mitigating total handling and waiting times of all vessels. The average OF value of the proposed method is 985.62, while the OF values of GSSP, PSO, and CPLEX are 953.66, 953.66, and 1419.58, respectively. |
| [61] | 2016 | POPMUSIC (hybrid of metaheuristic and exact methods) | PSO | This paper generates two datasets based on data instances presented in [14, 85], where up to 60 ships are taken into account. | The objective of this study is to minimize the total service cost of ships. The proposed method is a combination of meta-heuristic and mathematical approaches, which provides efficient berth allocation in a reasonable time. The proposed and compared methods provide the same OF value; however, the average execution time of the proposed method and compared method (PSO) are 10.39s and 12.76s, respectively. |

(Continues)

**TABLE A.1** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [62] | 2016 | ALNS | PSO, CS, GSPP, GRASP, SA, CPLEX, and TS | This study uses three sets of problem instances. The first was developed by [84] and includes 30 instances with 60 vessels and 13 berths. The second was developed by [85] and consists of 90 instances, including 30 to 60 vessels with 3 to 10 berths. The last dataset was generated randomly but based on the above two data instances, while considering a longer planning period and higher traffic. | This work proposed a heuristic-based ALNS method with the objective of minimizing total handling and waiting times along with minimum computational time. Results from simulations show that the ALNS takes a minimum time of 2.31 s; PSO, CS, GSPP, GRASP, SA, CPLEX, and TS take 8.17, 12.79, 14.98, 15.48, 60.26, 3600, and 120 s, respectively. |
| [63] | 2018 | MA | FCFS and EA | This paper generates data randomly by employing mechanism presented in current literature [14, 86, 87]. The total planning horizon is 1 week while ETA, departure times, the total load on the vessels, and the number of berths are generated by UD. | This paper aims to minimize the total service cost of arriving ships and proposes an MA-based approach. A new policy is developed in this study, where demand can be shifted from a normal terminal to an external MCT at an extra cost. Simulation results reveal the effectiveness of the proposed algorithm over counterparts. The objective value of MA is 18.99, while the objective values of FCFS and EA are 20.13 and 19.17, respectively. |
| [64] | 2018 | SAEA | Standard EA, AEA, and DPCEA | This paper also develops random data by UD based on current literature [14, 86, 87]. | This study develops a novel SAEA approach, where a self-adaptive parameter control strategy is adapted to achieve minimum total turnaround time of ships and delays in departures. Results demonstrate that the SAEA method outperformed the EA, DPCEA, and AEA approaches in terms of the OF value at termination on average by 11.84%, 6.83%, and 4.01%, respectively, |
| [65] | 2019 | ITS | Tabu search and stochastic dynamic programming | This paper generates 80 data instances based on mechanism presented in [84], where 5 ship-berth combinations are used to generate 50 instances and a combination of 60 ships with 13 berths is used for the other 30 instances. | This study aims to reduce the total turnaround time of vessels while considering uncertainty in vessels' arrivals. Simulation results show that the proposed method achieves optimal berth allocation over counterparts. The performance gap of ITS is 0.10% to optimal solution; however, the performance gap of TS is 0.20%. |
| [2] | 2019 | Lèvy Flight | PSO, CPLEX, and IG | This paper uses 4 sets of data instances. Set 1 includes 24 vessels with 8 berths from [88]. Set 2 consists of 50 ships with 8 berths from [89]. Set 3 includes 500 ships with 50 berths and set four considers 300 ships with 10 berths. | A novel Lèvy Flight meta-heuristic is developed and the key objective is to reduce the total service cost of all ships. This paper also considers tide impacts on berth allocation, which means that at high and low tides, there are specific ships that can only be moored on a certain berth based on tide characteristics. Simulation results reveal that the OF value of the proposed method is 469.8, and OF value of PSO is 492.9. |
| [66] | 2020 | CRO algorithm | GA, block-based GA, PSO, and exact approach | This study employs real-time data for experiments, taken from a MCT of a port located in the eastern region of India. | The authors propose CRO for minimizing the total waiting time of vessels. They also consider the fuel consumption of vessels during their stay at MCT to check the sustainability aspect of BAP. Results show that the handling cost by CRO is 279454, while costs by GA, block-based GA, PSO, and exact method are 288585, 284161, 287616, and 272197 Indian rupees, respectively. |

(Continues)

**TABLE A.1** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [67] | 2020 | MILP | – | Real-world data is collected from the MCT of Shahid Rajaee port, Iran. The dataset includes ships' ETA, actual time of arrival, departure time, mooring time, start time of unloading and loading, and the volume of unloading and loading. | This paper mitigates late departures at the port of Shahid Rajaee Shallow, Iran by employing an exact MILP approach and considering tide effects. It is affirmed from the results that the proposed solution is better than the existing model at the port. |
| [60] | 2022 | AACS | ACO and exact method | This paper uses the same dataset as [42] | Simulation results show that the proposed method is more efficient than its counterparts in handling uncertainties. |

**TABLE A.2** Analysis of methodologies adopted for continuous and dynamic BAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [68] | 2015 | GA | CPLEX, GRASP, TS, and stochastic beam search (SBS) | This study first employs real-time data from Pusan Eastern Container Terminal in Pusan, South Korea [90], which includes 25 instances (13 to 20 ships) and 1200 m LoW. Another dataset including 75 instances is generated from a real-time dataset and the wharf is split into three quays. | This study deals with a unique type of the CD-BAP for minimizing the total operational cost of all ships, where multiple wharves are considered. A mathematical solution is developed that is only feasible for small instances. Next, GA is developed to deal with BAP. GA shows efficiency in providing the best solutions while using the minimum computational time, which is 76%, 62%, 9.62% lower than SBS, GRASP, and TS, respectively. |
| [47] | 2016 | DE | SA, MIP, IA, and GRASP algorithm | The dataset is generated randomly based on uniform distribution (UD) [91]. Ships' arrivals, processing, and departures times are produced as U(1,15), U(1,5), and U(1,20), respectively. | This work aims to reduce the total service cost, which includes the cost for non-optimal berthing positions and late departure penalty. They generate a random dataset for simulations and perform a comparative study. The average OF value of the proposed method is 514.85, while the OF values of SA, IA, and GRASP are 713.27, 1019.47, and 2568.4, respectively. |
| [69] | 2016 | Hybrid of GA and B&C | Standard GA and CPLEX | This paper generates 20 data instances randomly, that include vessels' lengths, ETA, handling times, ETD, and PBPs. | This study aims to reduce delays in departures. The proposed solution shows efficacy over counterparts in terms of lower computational time, where it also provides a near-optimal solution. For the 30-vessels problem, the OF value of the proposed method is 748; however, the OF values of GA and CPLEX are 860 and 659, respectively. CPLEX takes 1 h and the proposed method only takes 6.51 min. |

(Continues)

**TABLE A.2** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [70] | 2017 | GWO | CPLEX and GA | This paper develops random data instances based on [92]. Furthermore, ships' arrival times, handling times, lengths, and PBPs are generated from U(1,250), U(10,48), U(15,35), and U(1,120), respectively. | The objectives are reducing total operational cost and maximizing customer satisfaction. The problem is formulated as MIP and various uncertainty factors are also modelled, i.e. uncertainty in vessels' arrival and operational time of ships. The results are presented in relative difference (RD) from an optimal solution; the GWO denotes minimum RD=0.8 within reasonable computation time while RD =4.6 using GA. |
| [71] | 2017 | MNSGA-II | GA, NSGA-II, NSGA-III, and ALNS | This study uses three datasets. The first one is taken from [93] and includes 14 small-scale and four large-scale instances. The other two datasets are generated based on the first dataset by changing the number of vessels, the number of berths etc. | The minimization of total stay time of vessels at the port is the primary objective of this study. The authors converted the constrained single objective CD-BAP to unconstrained Multi-objective (MO) CD-BAP. Afterward, an MNSGA-II is proposed and results are compared with current algorithms. The proposed method achieves an average objective value of 322.3, while GA, NSGA-II, NSGA-III, and ALNS provide objective value 456, 325.1, 442.2, and 329.5, respectively. |
| [72] | 2017 | GA | – | The dataset is generated from real port data; however, explanation is not given in the paper. | This paper proposed a GA-based method to solve the CD-BAP while reducing delay in vessels' departures. The proposed method is tested on a real-time dataset and results show there is no vessel late with the proposed solution. |
| [75] | 2018 | SA | GA and CPLEX | The dataset is taken from [94] and includes 30 instances with 20, 30, and 40 vessels. They also generate new random instances with 50, 60, 70, and 80 vessels. | This paper aims at reducing total waiting cost, late departure penalty cost, and non-optimal berthing cost of all vessels. They propose a hybrid SA method to solve the problem. Results show that the proposed method can save up to 21% of the system cost. |
| [73] | 2018 | HSA | CPLEX and Greedy | This work employs a real-time dataset collected from TPCT and FICT terminals, in Tianjin, China [95], which contains 178 arriving ships and LoW is 1200 m. | The OF of this study is to minimize delays in ships' departures. The authors also consider traffic channel limitation (e.g. temporary closure of the channel, one-way navigation rule, and other restrictions) while solving CD-BAP. Experimental results show that the HSA achieves objective value 25.36%, lesser than the Greedy method and equal to CPLEX; however, it takes 90.57% lesser computation time than CPLEX. |

(Continues)

**TABLE A.2** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [74] | 2018 | SA | GRASP, TS, SBS, and GA | Three datasets are employed from previous studies [68, 84, 96]. | This study investigates the CD-BAP with the key objectives of minimizing weighted handling times and penalties (cost) from late departures. The problem is formulated as MILP and later an SA algorithm is developed and compared with several benchmark methods. Results indicate that the SA achieves an improved average objective value of 2.83% and 13.67% than GA and TS, respectively. |
| [76] | 2018 | SA | – | A random dataset is generated that includes ships' length, ETA, workload, PBP, ETD, and priority of VIP customers. | This paper proposed an SA approach to deal with priority-based continuous BAP with the objectives of minimizing total turnaround time and providing priori services to VIP customers. Simulation results reveal the effectiveness of the proposed SA method. |
| [77] | 2019 | Improved DE | DE, GA, TS, and IP | This work uses eight random data instances for 1 week that is developed by generation mechanism presented in [97]. Dataset includes combination of 15, 20, 30, 50, 60, 70, 100, and 110 vessels. | This paper aims to reduce the total weighted service times of vessels and proposes an improved DE method while considering time-varying water depth constraints. Simulation results show that the average performance gap of improved DE is 10.22%; on the contrary, the average performance gaps for DE, GA, TS, and IP are 16.79%, 18.54%, 17.80%, 50.93%, respectively. |
| [78] | 2020 | ERO-BAP and RCRO-BAP | MILP and S-MILP | This paper generates data instances using the mechanism of [92], where the length of wharf (LoW) is 1200 m and total planning horizon is 300h. Ships' arrival times, handling times, lengths, and PBPs are generated from the UD U(1,250), U(10,48), U(15,35), and U(1,120), respectively. | The objective is to minimize total operational cost while considering various uncertainty in vessels' arrival and handling time. The developed exact approach is able to solve small and medium instances in a very short time and it beats compared methods with a minimum performance gap that is 0.45%; however, the MILP and S-MILP have root gaps of 10.02% and 1.18%, respectively. Furthermore, this study also develops benchmark datasets that can be used in future research works. |
| [79] | 2020 | Fuzzy logic | – | This study uses randomly generated data that consider wharf of 700 m and eight ships. Ship lengths, arrival times, and handling times are also generated randomly. | The primary objective of this study is to mitigate total waiting time while considering uncertainty in vessels' arrival and handling times. Simulation results show the effectiveness of the proposed method. |

(Continues)

**TABLE A.2** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [81] | 2021 | PSO | MILP | The data is obtained from United Metro Co. Ltd. (https://www.meteochina.com). | The authors consider uncertainty in vessels handling time due to weather conditions and have developed a hybrid of PSO and a ML model to solve large-scale problems. |
| [82] | 2021 | ML | – | The data is generated randomly. | This study develops ML-based models for vessels' arrival time prediction for efficient berth allocation. |
| [80] | 2022 | CSA | MILP and GA | A problem dataset is taken from a previous study [47]. | The authors propose the most comprehensive BAP formulation that aims to minimize the total processing cost of all arriving ships, which includes waiting, handling, and late departure penalty costs. The recently developed CSA is adapted for the first time to solve the CD-BAP. |
| [83] | 2023 | ML and exact method | – | The data is taken from [98] for experiments. | This study first proposes ML-based method for accurate vessel arrival time prediction (ATP), and then an exact method is deployed to solve BAP. The authors conclude that the accurate ATP helps in achieving higher results for BAP. |

**TABLE A.3** Analysis of methodologies adopted for hybrid and dynamic BAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [99] | 2014 | SWO | MILP, FCFS, and GSPP | A dataset is generated based on real-time data collected from Port of Mina SAQR, UAE, and includes 20 ships over 10 consecutive days in 2011. The data consists of vessels' length, expected and actual times of arrival, expected and actual berthing times and positions, handling times, and departure times. | This study proposed a new metaheuristic method, namely the SWO algorithm for solving the hybrid BAP and the key objective is to reduce total service time for all ships. Results demonstrate that MILP can only solve small-scale instances and it cannot provide an optimal solution for large-scale instances in a given time-span. In the case of 40 vessels, the SWO provides a near-optimal solution in 171.97 seconds. MILP cannot solve this problem size and GSPP takes 1767.57 s for solving the problem. |
| [100] | 2015 | EA | CPLEX | This paper uses the real-time dataset given in [101], which is produced from the example that includes 21 ships, 12 berths, and planning horizon is 54 h. | This work proposes an EA to mitigate the total cost of arriving vessels that includes handling cost, waiting cost, and late departure penalties. A hybrid berthing layout is assumed. The results from simulations denote that the EA provides results in 98.861% lesser time than CPLEX. |

(Continues)

**TABLE A.3** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [102] | 2015 | VND | EA and BCO | A random-generated dataset is taken from from [103] and includes 35 ships and eight berths. A real-time data is taken from [101] and includes 21 ships with 12 berths. | The authors deal with the hybrid BAP for reducing total service cost and late departure penalties, and propose a novel method, namely VND, for optimal berth allocation. Simulation results show that the average execution time of proposed VND through all real-time instances is 0.71 seconds, compared to 180.19 and 10.71 s of average running times of EA and BCO, respectively. |
| [103] | 2016 | SEDA and SEDA+ERH | CPLEX | This study generates three classes of datasets based on mechanism presented in [97], where class 1 consists of 5–30 ships, five berths, and planning horizon is 1 week, class 2 consists of 5–60 ships, eight berths, and planning horizon is 2 weeks, and the last class contains 5–40 ships, 13 berths, and planning horizon is 2 weeks. | The primary objective is to achieve minimum service cost. An exact approach named SEDA is developed to solve the BAP while another variant of SEDA that includes heuristic in the pre-processing phase was also proposed to minimize the objective within reasonable computation time. Simulation results show that SEDA+ERH is 286.91 times faster than its counterparts and solves the problem by having up to 40 vessels in 30 min. On the contrary, SEDA can only solve the problem by having up to 20 vessels in the same time. |
| [104] | 2018 | GVNS | EA, VND, BCO, and CPLEX | This paper uses real-time dataset given in [101], which is produced from the example that includes 21 ships, 12 berths, and planning horizon is 54 h. They also modified the original dataset by increasing the number of vessels up to 28. | This study investigates the hybrid BAP with the objective of minimizing total service cost and penalties due to vessels' late departures. A novel method named the GVNS algorithm is developed and compared with four existing methods. The proposed GVNS method provides an optimal or near-optimal solution in an average time of 0.10 s, while EA, VND, BCO, and CPLEX take 33.80, 0.71, 52.68, and 62.48 seconds, respectively. |
| [105] | 2018 | Bat-inspired algorithm | CPLEX | Real-time problem instances are produced based on arriving ships in the Tangier Container Terminal, Morocco, using data generation mechanism presented in [84, 106]. It includes ships' ETA, ETD, and handling times. The planning horizon is 1 week. | A Bat-inspired algorithm is developed for optimal berth allocation while minimizing the total stay time of vessels at the terminal. The results from experiments are compared with the CPLEX solver. The bat-inspired algorithm provides good results (for 60 ships with four berths) in an average computation time of 6.3 s; on the contrary, CPLEX takes 7200 s for the same problem size. |

(Continues)

**TABLE A.3** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [107] | 2019 | ILS | MILP | A real-time dataset collected from a tank terminal, Port of Antwerp, Belgium, where 10 to 70 ships and eight to 24 berths are considered [157]. It includes ETA, requested departure times, vessels' lengths, and operational time. | The objective of this study is to minimize total stay times of vessels at the terminal and reduce total waiting and late departure penalty costs. This study also includes various restrictions on mooring in problem modeling, such as unavailability of berths due to maintenance, structural restrictions, and adjacency restrictions. An irregular berthing layout is assumed. The results from simulations show that ILS achieves optimal or near-optimal solution in 95.37% lesser time as compared to MILP when using 100 vessels. |
| [66] | 2020 | CRO | GA, block-based GA, and PSO | This study uses real-time data taken from a port located in the eastern part of India, which includes 49 arriving ships, date, month, ETA, number of loaded containers, and ship sizes [66]. | The proposed CRO-based method is developed with the objectives of minimizing total service and waiting costs along with fuel cost reduction during waiting and mooring. Results show that CRO achieves a minimum total cost that is 279,454 (Indian rupees) while the total costs by block-based GA, GA, and PSO are 284,161, 288,585, and 287,616, respectively. |
| [108] | 2020 | ILP | – | This work generates data from real-time data collected from Port of Jorf Lasfar, Morocco [109]. It includes 3 sets of 5 instances each for 20, 30, and 40 ships. The planning horizon is 20 days. | An ILP-based solution is proposed to solve the hybrid BAP for enhancing coordination between berthing and yard activities. This work considers several wharves, various water depths at different berthing positions, routing constraints, and heterogeneous unloading/loading equipment. Simulation results show the efficacy of the proposed model; however, the proposed method can only solve the BAP when arriving vessels are up to 40. |
| [110] | 2020 | HGA | CPLEX | The dataset is generated based on real-time traffic and berth data, observed at Tangier Terminal, Morocco. It includes ten to 50 vessels and two to 12 berths. | This study develops the HGA method to solve the DH-BAP for reducing the total stay cost (at the port) of all ships. The results from simulations denote that the proposed method solves the BAP having 50 vessels with 12 berths within 6 seconds; however, CPLEX takes almost 3600 s to solve the same problem. |

**TABLE A.4** Analysis of methodologies adopted for combined discrete and dynamic BAP with QCAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [50] | 2015 | MBO | CPLEX and PSO | This paper utilizes the dataset presented in [84], which is divided into ten instances considering 25 to 60 ships and five to 13 berths. The data is generated by considering real-time statistics of berth allocation data at MCT of Gioia Tauro, Italy. | A recently developed nature-inspired algorithm is adopted and the major purpose is to mitigate the total weighted service time of all ships. For verifying the productiveness of the MBO algorithm, experiments are performed on different datasets including small, medium, and large instances. The MBO beats two benchmark methods in terms of the lowest computation time and it takes 0.52 s on average for five instances; on the contrary, CPLEX and PSO take 12.38 and 1.54 s, respectively. |
| [45] | 2015 | MPC | FCFS & density-based strategy | A real-time dataset is collected from small terminal of seaport in Indonesia, which includes only two berths with seven QCs. In the planning horizon, the data of 29 ships are recorded and their loads range from 327 to 2156 TEU. | This work employed MPC to solve the BAP and QCAP with the aim of minimizing total handling cost (it includes the cost of operating the QCs that are allocated to a specific vessel) and waiting cost. Simulations are performed on real-time data and results are compared with the existing heuristic-based method, where FCFS is employed for berth allocation and density-based strategy is used for QC allocation. Results affirm that the proposed method saves 20% cost over counterparts. |
| [52] | 2017 | CCPSO | GA | This paper produces random data, considering 12 QCs, four berths having length 400, 400, 300, and 200 m, respectively, and container quantity range is 100 to 1200. Acceptable waiting time is 5 to 10 h, and crane productivity is assumed 35 TEU/h. | A new variant of the PSO algorithm, namely CCPSO, is proposed in this work for minimizing late departure and stay time at the terminal for all ships. Several experiments are performed to validate the performance of the proposed method. Simulation results show that the average stay time of vessels by using the CCPSO method is 9.35 h, while the average stay time is 10.4 h by the compared method, GA. |

(Continues)

**TABLE A.4** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [111] | 2018 | Improved NSGA-II | Standard NSGA-II | This paper uses real-time data instances collected from container freight port in a city of China. The terminal contains only four discrete berths (berth lengths: 200, 200, 300, and 260 m) and 15 QCs. The dataset includes ETA, ETD, and freight capacity of 15 arriving ships. | An NSGA-II heuristic is developed to reduce ships' stay time at port and system cost while considering uncertainties in vessels' arrival times and containers' handling times. In addition, this study considers movable QCs, which can move from one berth to another before completing the current task. Multiple experiments on different datasets have been performed by considering different number of vessels and berths. The results from simulations show that the proposed improved NSGA-II shows 17 times higher performance to standard NSGA-II. |
| [53] | 2018 | RH algorithm | CPLEX and greedy | This study uses two datasets; one is randomly generated based on rules presented in [70] and the other is a real-time example taken from Tianjin terminal, China. The LoW is 1202 m and the total number of QCs is 12. | A heuristic-based RH method is developed to solve the QCAP while minimizing service cost and penalty cost from non-optimal berthing and late departures. This work also considers various uncertainties in the proposed system, i.e. uncertainty in ships' arrival, handling time, and maintenance of QCs. Based on simulations, the RH approach solves the problem with 40 ships in 1235.7 s, while greedy takes 1238.7 s and MIP cannot solve the same problem in 3600 s. |
| [51] | 2019 | Sample average approxima- tion method | – | This work generates 90 random instances based on real data. The instances are divided into three major groups: A) four vessels, eight berths, and eight QCs, B) six vessels, eight berths, and eight QCs, and C) eight vessels, eight berths, and eight QCs. | An exact method based on sample average approximation is developed in this study to deal with the combined BAP and QCAP with the objective of attaining minimum total turnaround time. Several experiments denote the effectiveness and accuracy of the proposed method; however, the proposed method only solves small instances in reasonable computation time. |

(Continues)

**TABLE A.4** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [113] | 2019 | Mathematical model | Existing operational practices | The dataset is generated randomly and divided into four cases: a) Four small ships with eight QCs, b) Three medium ships with 9 QCs, c) Two large ships with eight QCs, and d) three ships (one of each size) with nine QCs. | The authors propose four policies in order to minimize total service time at MCT of Khalifa Port, Abu Dhabi. The four policies are: static allocation with task preemption, static allocation without task preemption, dynamic allocation with task preemption, and dynamic allocation without task preemption. The experimental results affirm that the improvements reached up to 37.5% in investigated cases. |
| [112] | 2019 | HGAs | Standard GA | This work uses a randomly generated dataset for experiments. | The authors develop 3 hybrids of GA to achieve minimum costs by reducing vessels' waiting, handling, and delay times. This study models variable QCs for unloading/loading to make the system more flexible. Results show that all three methods have higher performance over standard GA in terms of fitness value by 53.06% to 58.24%. In terms of computation time, standard GA takes on average 457.2 seconds, while the new approaches 88.8–90.0 s. |
| [132] | 2019 | MPA | FCFS & density-based strategy, GA, and hybrid PSO | This work utilizes the real-time dataset presented in [45]. Another large-scale dataset is also generated, which includes 50 ships and TEU ranges from 3000–10,000. The number of berths range from two to five and QCs from five to 11. | The objective is to reduce the total handling cost along with the waiting cost of arriving vessels at the port of Tanjung Priuk, Indonesia. The results are compared with several existing approaches. It is affirmed from results that the proposed MPA-based algorithm is able to reduce the total cost by 6–9% over FCFS & density-based strategy, 9.57 % over GA, and 4.051% by hybrid PSO. |

(Continues)

**TABLE A.4** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [114] | 2020 | GRASP and FBS | Iterative approach | Real-time datasets are used, which are taken from an MCT located in Busan, Republic of Korea. Data instances contain 30 ships, 11 QCs, and LoW is 1200 m. | This work examines the combined BAP with QCAP for minimizing the total service cost of ships while allowing the reassignment of ships to another terminal. They proposed GRASP and FBS to solve the problem. Simulation results denote that the proposed FBS method shows 2.45% improvement over the iterative approach in terms of total cost. |
| [116] | 2020 | Deep neural network | – | Randomly generated data is employed for simulations. | This work proposes a DL model for accurate berthing time prediction, which is further used for making decisions related to berth and quay crane allocations. After extensive simulations, it is concluded that accurate berthing time prediction can help in solving BAP and QCAP. |
| [115] | 2021 | Decomposition Algorithm | CPLEX | Data were randomly generated from different distributions (e.g. uniform, normal) with up to 50 vessels and generating different scenarios. The planning horizon is 1 week. | The basic objective is to minimize the total cost incurred due to deviations from departure times and berth positions. Two uncertain factors are taken into consideration, namely the increase/decrease in the number of containers and the late arrival of ships. |
| [117] | 2023 | Greedy insert-based method and reinforcement-learning | FCFS | Random data is used. | This study develops both offline and online models for solving combined BAP with QCAP to improve turnaround time. The greedy insert-based algorithm solves the offline problem, while reinforcement learning is employed to solve online BAP and QCAP. Simulation results show the effectiveness of both methods over FCFS. |

**TABLE A.5** Analysis of methodologies adopted for combined continuous and dynamic BAP with QCAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [118] | 2015 | PSO | CPLEX | A real-time dataset is used, collected from a container terminal at Ningbo Beilun China, with a 1248 m wharf. The dataset includes arrival times of 12 ships, their lengths, PBP, and handling time. | This work proposes a two-phase solution of the BAP and QCAP by employing a metaheuristic-based PSO algorithm. The primary objectives are to reduce vessels' stay time at the port and the cost added by late departures. Based on simulations, CPLEX is only able to solve small-scale instances quickly, while PSO can solve both small and large-scale instances. Considering 10 vessels, the PSO takes 39.8 seconds for an optimal or near-optimal solution; in contrast, the CPLEX cannot solve it in 800 s. |
| [119] | 2017 | ALNS | GA, TS, and SWO | The authors utilize 30 instances proposed in [94] considering 20 to 40 ships. Each data instance includes three types of ships, i.e. feeders, medium, and jumbo. The total number of QCs is ten and the LoW is 1000 m, which corresponds to 100 equi-width berthing positions. | This study develops an ALNS solution for increasing container terminal efficiency with the objective of reducing overall service cost, which includes late departure penalty and QCs assignment costs. The problem is first formulated as an MILP model and then solved by the ALNS algorithm. Experiments are performed on real-time instances taken from recent literature and results reveal that the proposed method has higher performance over counterparts. The average performance gap by ALNS is 2.86%, while SWO, TS, and GA have an average gap of 3.85%, 4.94%, and 6.31%, respectively. |
| [54] | 2017 | Biased random-key GA | Discrete DE | This work employs random datasets generated based on UD and criteria given in previous studies [92, 94]. The first dataset contains up to 90 ships, 100 berths (length of each berth is 10 m), ten QCs, planning horizon up to 252 h, and time interval of 1 h. The other dataset consists of 1200 m LoW, up to 50 ships, 11 QCs, and the planning horizon is set to 300 h. | The main concerns of this study are to increase handling productivity of container terminal with reduced overall cost, which consists of waiting, delay in departure, deviation, and exceeding total horizon costs. This study considers various QCs with different characteristics and determines which particular QCs are suitable to serve which ships. A novel variant of GA called biased random-key GA is developed to solve the problem. Several simulations are performed on real-time instances to affirm its performance and results are compared with discrete DE algorithm. The average deviation of the proposed method output from the results of the compared method is −11.05%. |
| [120] | 2018 | Branch & bound | CPLEX | A real-time dataset is taken from [101]. The MCT consists of 11 QCs and LoW is 1100 m. The data instances are split into three classes: small, medium, and large. Small includes six ships and 24 h planning time; medium 15 ships and 72 h planning time; and large 35 ships and 168 h planning time. | A branch & bound method is developed to solve the combined BAP and QCAP, where the primary aims of this study are to achieve minimum handling and penalty costs along with carbon emission reduction. Several experiments on real-time data instances are carried out and results show the effectiveness of the branch & bound method. The branch & bound method provides an optimal solution in 2.36 s; however, CPLEX solver takes 7.98 s for providing optimal output. |
| [46] | 2018 | RH method | Exact approach | This work uses a real-time dataset collected from multi-user terminal of a seaport that deals with short-sea shipping. The data instances include seven QCs, 34 berths, where six QCs have the same working productivity and one QC has a larger one. Arrival times of ships are generated by U(0,150) and ship lengths are generated randomly from set $\{6, 7, 8, 9\}$. | This study also examines the same problem for alleviating total waiting and handling time against all arriving vessels. For this purpose, two algorithms branch & bound and RH are developed, then, both are tested on real-time data collected from MUT at the port that deals with bulk container operations. Results are evident that the RH method is 99% faster than the exact approach. |

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**TABLE A.5** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [123] | 2019 | LRVM and improved GA | RH and CPLEX | This study uses random instances containing 60% feeders, 30% mediums, and 10% jumbo vessels, as presented in [133]. All data instances are generated by UD and the max number of ships and berths are 50 and 25, respectively. | A novel heuristic named LRVM and an enhanced GA are developed to minimize the total turnaround time of arriving ships. This study also considers uncertainty due to QCs maintenance activities. It is affirmed from results that the proposed method LRVM takes 0.08 seconds for providing optimal or near-optimal solutions; however, RH and enhanced GA take 17.44 and 18.38 seconds, respectively. |
| [121] | 2019 | IGA | Standard GA, CPLEX | Dataset explanations are not provided. | A novel variant of GA, IGA, is developed for reducing handling, waiting, and QCs conversion costs. This study also considers time-varying QCs assignment; i.e. the number of cranes assigned to a vessel can vary during the handling process. The IGA achieves an OF value of 13.8 with the computation time of 33.11 seconds. On the contrary, the objective value by GA is 16.4. Compared to CPLEX, the IGA provides an optimal or near-optimal solution in 24.37% lesser time. |
| [122] | 2019 | Iterative method | MILP and B&C | This study produces data instances based on mechanism presented in [92], where LoW is 1200 m, planning horizon is 300 h, the total number of QCs are 11, arriving ships range from 20 to 40. Arrival times are generated by U(1,170), handling times U(10, 48), LoSs U(15,35), and preferred berthing location U(1,120). | The authors of this article developed an iterative method to solve the BAP and QCAP in an integrated way. The main objective of this study is to reduce the total cost that consists of waiting, delay in departure, and non-optimal berthing (deviation) costs. To confirm the effectiveness of the proposed iterative method, several simulations are performed and results are compared with existing approaches. Results show that the iterative method provides an optimal solution in 15.4 seconds while considering 30 vessels; however, MILP and branch&cut take 955.3 and 304.4 seconds, respectively. |
| [124] | 2020 | RTPSO | PSO and exact approach | The dataset contains 20 small-scale instances with 5 to 10 ships, 5 to 20 QCs, and LoW is 40 m. It also contains 30 large-scale instances, where the number of ships is set to 20 to 40, QCs 20 to 40, and LoW is 50 m. The arrival times and length of vessels are generated from intervals (1,20) and (1,5), respectively, in both cases. | This work examines the problem for the objective of performance improvement of MCT by reducing the waiting time of all ships. Water depth and tide conditions at different berths are also taken into account. A novel variant of PSO is developed and compared with standard PSO and exact approach. The results from the simulation show that the RTPSO has minimum GAP (the percentage deviation of the implemented technique compared to the best possible result) of 0.19%. The GAP of standard PSO is 0.83%. Furthermore, the exact approach implemented through the GAMS solver is unable to solve large instances in a reasonable time. |
| [125] | 2020 | Two-phase iterative method | CPLEX | The dataset is collected from a MCT in China with 12 berthing positions and 12 QCs. The total incoming ships are 18 and the planning horizon is set to 42 h. In addition, 400 instances are randomly generated with up to 100 vessels. | A two-phase iterative method is developed in this work to deal with the combined BAP and QCAP. The problem is formulated as the ILP model for minimizing total turnaround times and penalty cost because of QCs maintenance activities. The proposed method was tested on real-time datasets by performing simulations. The computational results show that the proposed heuristic-based method has superior performance, as it takes an average of 53 seconds while solving 6 different datasets. On the contrary, the compared method takes an average of 12,430 s for solving the same size problem. |

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**TABLE A.5** (Continued)

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [126] | 2020 | GVNS | CPLEX | A real-time dataset is used that contains data of 14 ships and planning horizon is 15 days. The terminal contains 4 quays with a length of 400, 200, 200, and 180 m. | The objective of this study is to reduce delay in vessels' departures while assuming various model uncertainties, i.e. bad weather conditions and QCs maintenance activities. The problem is formulated as the MIP model and solved by the GVNS method. In order to affirm the productiveness of the GVNS method, several experiments are performed. The results reveal that CPLEX consumes 120 s for solving 14 vessels problem; however, the GVNS solves the same problem in 1.68 s. |
| [127] | 2021 | Search-based (remove & reinsert) | MIP | Synthetic dataset with up to 144 vessels that considers historical data and real-world characteristics described in other datasets [92, 94]. | A search-based heuristic is proposed based on a developed MIP formulation, and can be employed under both fixed and flexible departure times settings for the arriving vessels. Results demonstrate the ability to improve berthing schedules and reduce container transshipment distances. |

**TABLE A.6** Analysis of methodologies adopted for combined hybrid and dynamic BAP with QCAP.

| Reference | Published year | Method/ algorithm(s) | Compared method(s) | Dataset description | Achievement/ observation(s) |
|---|---|---|---|---|---|
| [129] | 2016 | GAMS | – | This study uses randomly generated data and considers three vessels, four berths, and four QCs. | The proposed work deals with the combined BAP and QCAP to reduce total service time while considering the hybrid berthing layout of the terminal. To achieve the primary objective, the joint problem is first mathematically formulated and then solved by a GAMS solver. The results from simulations indicate that the proposed method can solve this type of problem in reasonable computation time. |
| [130] | 2016 | GAMS | – | This work develops random data instances, considering 15 ships and eight berths. In addition, 17 QCs are considered and the handling productivity for all the QCs is the same. | This study also employed a GAMS solver to minimize total service time while solving the hybrid BAP and QCAP. The problem is first formulated as a MILP model and then solved by GAMS. The effectiveness of the proposed method is affirmed through simulation results. |
| [131] | 2019 | SA method | – | A random dataset based on practical features is generated, which includes 40 arriving ships, seven berths, 18 QCs, and the total wharf is divided into three quays. The complete dataset is presented in the appendix of the paper. | A heuristic-based SA algorithm is developed to mitigate delay in vessels' departure times while considering various real-time constraints such as QCs cannot cross each other. It is validated from simulation results that the proposed method can solve large-scale instances in affordable computation time. |