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RESEARCH ARTICLE

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An integrated container terminal scheduling problem with different-berth sizes via multiobjective hydrologic cycle optimization

Huifen Zhong[1,2] | **Zhaotong Lian**[2] | **Bowen Xue**[1] | **Ben Niu**[1,3] | **Rong Qu**[4] | **Tianwei Zhou**[1]

[1]College of Management, Shenzhen University, Shenzhen, China

[2]Faculty of Business Administration, University of Macau, Macau, China

[3]Institute of Big Data Intelligent Management and Decision, Shenzhen University, Shenzhen, China

[4]School of Computer Science, University of Nottingham, Nottingham, UK

Correspondence

Ben Niu, College of Management, Shenzhen University, 518060 Shenzhen, China.
Email: drniuben@gmail.com

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Abstract

Integrated berth and quay crane allocation problem (BQCAP) are two essential seaside operational problems in container terminal scheduling. Most existing works consider only one objective on operation and partition of quay into berths of the same lengths. In this study, BQCAP is modeled in a multiobjective setting that aims to minimize total equipment used and overall operational time and the quay is partitioned into berths of different lengths, to make the model practical in the real-world and complex quay layout setting. To solve the new BQCAP efficiently, a multiobjective hydrologic cycle optimization algorithm is devised considering problem characteristics and historical Pareto-optimal solutions. Specifically, the quay crane of the large vessel in all Pareto-optimal solutions is rearranged to increase the chance of finding a good solution. Besides, worse solutions are probabilistic retained to maintain diversity. The proposed algorithm is applied to a real-world terminal scheduling problem with different sizes from a container terminal company. Experimental results show that our algorithm generally outperforms the other

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well-known peer algorithms and its variants on solving BQCAP, especially in finding the Pareto-optimal solutions range.

KEYWORDS

evolutionary computing algorithm, hydrologic cycle optimization, integrated berth and quay crane allocation problem, multiobjective optimization, scheduling

1 | INTRODUCTION

Container terminals serve as important nodes in global sea-cargo transportation. According to Sirimanne et al.,[1] in 2018, its trade volume reached 11.08 billion tons, which urges effective resource utilization during the whole operational process. Various scheduling problems in container terminals have attracted attention in the engineering industry and academia to maximize economic benefits.

Berth allocation problem (BAP) and quay crane assignment problem (QCAP) are the first two essential scheduling subproblems, which determine the berthing time, mooring position, optimal quay cranes (QC) arrangement to all incoming vessels (readers are recommended to the latest related survey Rodrigues and Agra[2]). Due to problem complexity, these two subproblems are generally treated separately. Although independence helps in considering dynamic or improving solution efficiency, however, it neglects the close interaction between the two subproblems, which often hinders obtaining an optimal system performance.

To overcome the suboptimal problem, Park and Kim[3] pioneered an integration model for the BAP and QCAP then extended by Raa et al.,[4] Wang et al.,[5] Malekahmadi et al.,[6] and among many others. In the most recent related works, intensive researches focus on constructing a more practical model in container terminal scheduling. For example, Rodrigues and Agra[7] considered an integrated problem with uncertain vessel arrival times, Xiang and Liu[8] studied a robust optimization model case, and Hsu et al.[9] extended to an integrated model considering yard truck scheduling. In many cases, the objective is onefold, such as cost minimization, time minimization, or deviation minimization.

Although the multiobjective nature has been recognized recently, their objectives focused on the average port time of vessels, the difference between the actual berth and preferred berth, total turnaround time of vessels, total operating costs, average waiting time, and total carbon emissions,[10–12] which reckoned without QC equipment that greatly affects port system performance. Besides, the quay was partitioned into a certain number of fixed-length berths. However, the quay utilization efficiency can be improved with berths of flexible and varying lengths—an approach that supports serving more vessels simultaneously, although with increased problem complexity. This motivates us to reformulate the problem into a new integrated berth and quay crane allocation problem with berths of different lengths and multiple objectives (N-BQCAP, for short) to help port managers finish work faster, using minimum equipment.

The N-BQCAP is a complex multiobjective problem, which causes traditional exact methods to be not applicable. Popular solution schemes to date are combining the multiple objectives into a single scalar value by the weighted-sum method,[13] or restricting optimization to one of the objectives by the ε-constraint method.[14] These two approaches rely on statistical estimation and only generate an optimal solution rather than a set of nondominated solutions, which cannot satisfy the various preferences of port managers in reality.

Multiobjective optimization algorithms have revealed good advantages in acquiring solution sets efficiently and suffered extensive development. Such as, Ben Ammar et al.[15] proposed new versions of multiobjective binary particle swarm optimization, Niu et al.[16] gave multiobjective bacterial colony optimization algorithm, Nourmohammadzadeh and Voss[17] declared multi-objective simulated annealing, and so on. These algorithms mostly adopted convergence first and diversity second principle, which may get stuck at an easy-to-find part of the Pareto front, especially in problems with disconnected feasible regions. Multiobjective hydrologic cycle optimization (MOHCO) proposed by Song et al.[18] shows great advantages in both local exploitation and global exploration abilities, exhibiting the potential to deal with our proposed NP-hard N-BQCAP model, which has complex feasible regions. To satisfy more port managers with different preferences in a single run, we are motivated to further improve the solutions range by designing some efficient strategies.

On the basis of the analysis mentioned above, an N-BQCAP model considering varying berth sizes and adhoc algorithm (archive exploration multiobjective hydrologic cycle optimization, AEMOHCO for short) are novelly designed. To match the mixed integer optimization problem, we devise a specific mixed coding strategy for the algorithm. Some main contributions of this study are as follows:

- An N-BQCAP mathematical model considering more practical characteristics where berths of different lengths with multiple objectives are constructed.
- An AEMOHCO algorithm is devised considering the problem characteristics and historical good solutions, achieving improved scalability, stability, and convergence in solving the N-BQCAP.
- A discrete coding strategy is developed in the new problem model to facilitate the effective performance of the proposed algorithm and provide specific scheduling results.

The remainder of this paper is structured into four sections. The problem description and formulation of the N-BQCAP are given in Section 2. The approach based on the MOHCO algorithm for solving the N-BQCAP is introduced in Section 3, and then experiments are followed in Section 4. Section 5 concludes the study with avenues for future work.

2 | PROBLEM DESCRIPTION AND FORMULATION

The predefined N-BQCAP is formulated as an integrated constrained multiobjective model, which reflects the practical concerns of port managers. To have a comprehensively understanding, we will first introduce the problem description followed by its model formulation, including variables, objectives, and constraints with detailed explanations.

2.1 | Problem description

In daily coastal operation, berth allocation, QC assignment, and yard decision (including truck scheduling and warehouse storage problems) shall be solved sequentially as Figure 1A presented. Since the coastal decision affects port operation efficiency greatly and the complexity of integrating

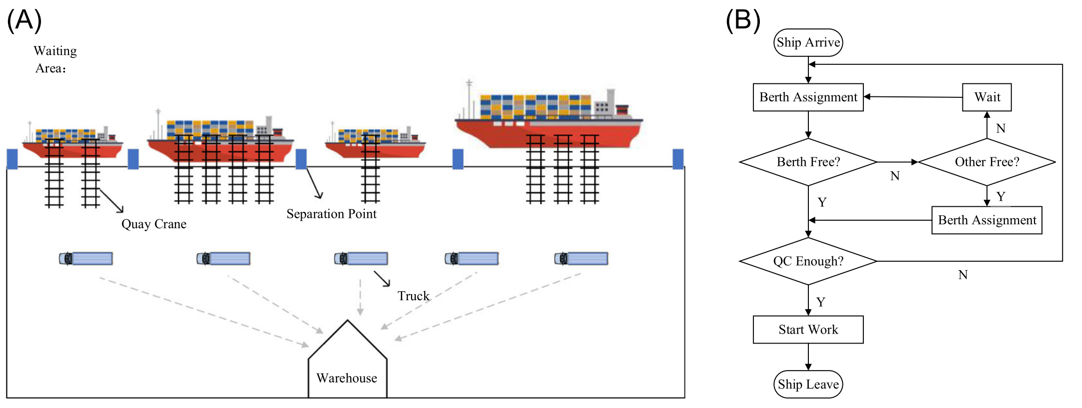

FIGURE 1 Sketched process. (A) Vessel service with multilength berths and (B) integrated decision process. QC, quay crane. [Color figure can be viewed at wileyonlinelibrary.com]

many subproblems, the last yard decision is not considered here. To increase resource utilization, the quay is divided into varying berth lengths (as blue separation points in Figure 1A shown) instead of classical fixed length with a certain number and the QC quantity available for each vessel is also different. To fulfill the overall performance benefits the integrated N-BQCAP brought, we design a berth reassignment strategy, which will be triggered for the vessel when its scheduled berth is occupied or its QC arrangement is not allowed. Specifically, Figure 1B sketches the whole decision process of the integrated multiobjective model with multilength berths.

2.2 | Model formulation

Since the N-BQCAP is a complex constrained multiobjective problem involving multiple resources, for reading convenience, Table 1 first summarizes the assumptions, sets, parameters, and variables used in the model construction. Then we introduce the model formulations, followed by a step-by-step explanation:

$$\min f_1 = \sum_{i \in V} q_i, \tag{1}$$

$$\min f_2 = \sum_{i \in V} \left[(s_i - a_i) + \frac{n_i}{v q_i} \right] \tag{2}$$

subject to

$$\sum_{j \in B} \sum_{k \in O} x_{i,j,k} = 1, \qquad \forall i \in V, \tag{3}$$

$$\sum_{i \in V} x_{i,j,k} \leq 1, \qquad \forall j \in B, \quad \forall k \in O, \tag{4}$$

$$a_1 = s_1, \tag{5}$$

TABLE 1 Definition of assumptions, sets, parameters, and variables

Assumptions			
Consider unloading process only		Vessel arrival time is known in advance	
Considers QC capacity only		All vessels can find a suitable berth	
Sets			
Set	**Definition**	**Set**	**Definition**
$B = \{1, ..., m\}$	Berths, indexed by j	$O = \{1, ..., o\}$	Service order, indexed by k
$V = \{1, ..., n\}$	Vessels, indexed by i	$W = \{1, ..., z\}$	Working vessel, indexed by l
Parameters			
Denotation	**Definition**	**Denotation**	**Definition**
Q	QC quantity capacity	n_i	Containers on vessel i
L_i	Length of the vessel i	a_i	Arrival time of the vessel i
L_j	Length of the berth j	v	QC unit working efficiency
$q_{\max,i}$	Maximum QC quantities assigned for vessel i		
Decision variables			
Denotation	**Definition**	**Denotation**	**Definition**
b_i	Berth allocation for i	s_i	Start working time of i
q_i	QC quantity assigned to the vessel i		
$x_{i,j,k} = \begin{cases} 1 & \text{if vessel } i \text{ is served at } k\text{th in the service order at berth } j, \\ 0 & \text{otherwise} \end{cases}$			

Abbreviation: QC, quay crane.

$$a_i \le s_i, \quad \forall i \in V \ne 1, \tag{6}$$

$$\sum_{j \in B} \sum_{k \in O} \left(s_l + \frac{n_l}{v q_l} \right) x_{l,j,k-1} \le s_i \sum_{j \in B} \sum_{k \in O} x_{i,j,k}, \quad \forall i \in V, \quad \forall l \in W, \tag{7}$$

$$q_i + \sum_{l \in W} q_l \le Q, \quad \forall i \in V, \tag{8}$$

$$x_{i,j,k} L_i \le L_j, \quad \forall i \in V, \quad \forall j \in B, \quad \forall k \in O, \tag{9}$$

$$1 \le q_i \sum_{j \in B} \sum_{k \in O} x_{i,j,k} \le q_{\max,i}, \quad \forall i \in V, \tag{10}$$

$$b_i \in [1, m], \tag{11}$$

$$s_i \in [a_i, +\infty], \tag{12}$$

$$q_i \in [1, q_{\max,i}], \tag{13}$$

$$x_{i,j,k} \in \{0, 1\}, \tag{14}$$

where Equations (1) and (2) are two conflicting objective functions, where f_1 aims to minimize the total equipment used (i.e., QC) while f_2 aims to minimize the sum of the waiting and working time of every vessel. Constraint (3) indicates that each vessel must be served only once at a berth in any order. Constraint (4) requires that, at most, one vessel can be serviced at any berth in any order. Constraint (5) stipulates the first vessel will be served as soon as its arrival. Constraint (6) defines that a vessel cannot be served before its arrival. In each berth, constraint (7) prevents the subsequent vessel from working before the completion of its antecedent vessel. Constraint (8) ensures that the total working QCs do not exceed the total capacity. Constraint (9) ensures that the vessel can be accommodated in its selected berth. Constraint (10) stipulates the maximum QCs arrangement for each vessel, which is determined by the vessel length. The last two constraints define the multilength berths setting in this paper. Constraints (11)–(14) are the value range for all decision variables, respectively.

3 | SOLUTION PROCEDURE BASED ON AEMOHCO ALGORITHM

In this section, we propose an improved MOHCO considering problem characteristics and historical Pareto-optimal information called AEMOHCO for solving the N-BQCAP. It originates from the hydrological cycle phenomenon on Earth and includes three main operators. The remainder of this section presents the basic MOHCO, improved strategies with algorithm analysis, AEMOHCO's detailed steps, and coding mechanisms for solving the N-BQCAP.

3.1 | Basic MOHCO

To clearly understand the improvements of our AEMOHCO compared with the basic MOHCO, we first describe the general process of the MOHCO algorithm in Figure 2. The gray rectangles are three key operations in an evolutionary loop (AEMOHCO maintains the same operators). Specifically, the flow operator guides the solution towards a better region in the search space. Infiltration adjusts search direction by random-dimension neighborhood search. The last operator either facilitates the escape from the local optimum (evaporation) or exploits the local region (precipitation). These designs although can guarantee solution accuracy and diversity at a certain, they execute random mutation and always follow the best direction only, which makes the basic MOHCO effectiveness not efficient enough. Especially when need to be applied to some complex real problems. Thus, we are motivated to propose a more dedicated algorithm for the N-BQCAP model solution.

3.2 | AEMOHCO framework

To solve the N-BQCAP specially, the following two improvements considering problem characteristics and historical Pareto-optimal solutions are designed to increase the solution efficiency and solution range. The modifications proposed to the original MOHCO are concentrated on the green dashed rectangle in Figure 2.

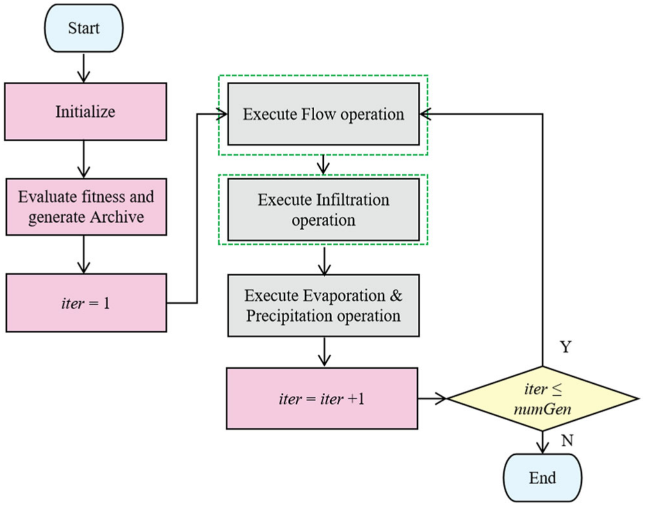

FIGURE 2 General process of the multiobjective hydrologic cycle optimization [Color figure can be viewed at wileyonlinelibrary.com]

1) *Large vessel's QC rearrangement strategy (applied in the flow process)*: For the acquired Pareto-optimal solutions in the flow process, large vessel's QC rearrangement is executed instead of moving to a random position as basic MOHCO does. And the new position will be accepted only when the rearrangement solution performs well. This QC-related detection strategy absorbs the useful problem characteristics (both equipment and berth size information) to generate the favorable and drastic changes, and makes the full use of the contemporary Pareto-optimal solutions, contributing to effective exploitation and improved accuracy. The corresponding formulation is given as follows.

$$\mathbf{x}_{\text{Flow}} = \begin{cases} \mathbf{x}_i + (\mathbf{x}_j - \mathbf{x}_i).\times rand(1,d), & \text{if } i \text{ is not a Pareto-optimal solution,} \\ \text{Execute QC rearrangement for large vessel,} & \text{otherwise,} \end{cases} \tag{15}$$

where the particle j has better fitness than i, $rand()$ is a random generation function to generate a d-dimension vector, and $\mathbf{x} = (x_1, \ldots, x_d)$.

2) *Probabilistic worse-solution acceptance strategy (applied in the solution preservation)*: The strategy proposed in 1) increases the chance of finding a good solution. In this strategy, all better solutions and a half of worse solutions generated from the Infiltration process are maintained to increase swarm diversity while retaining a fast convergence. In fact, keeping few bad solutions may help discover some unexpected potential regions. Formulation (16) expresses the detailed method.

$$\mathbf{x}_i = \begin{cases} \mathbf{x}_{\text{Infiltration}}, & \text{if } f(\mathbf{x}_{\text{Infiltration}}) \prec f(\mathbf{x}_i), \\ \mathbf{x}_{\text{Infiltration}}, & \text{if } f(\mathbf{x}_i) \prec f(\mathbf{x}_{\text{Infiltration}}) \text{ and } rand > 0.5, \\ \mathbf{x}_i, & \text{otherwise,} \end{cases} \tag{16}$$

where $f()$ is the corresponding objective value and $\prec$ represents the dominated notation generally used in multiobjective algorithms.

On the base of the aforementioned introduction, the detailed steps of the AEMOHCO are presented in Algorithm 1.

Algorithm 1. Detailed steps of the AEMOHCO

Input: Parameters including population size, flow times, and termination criteria
Output: Archive set G containing all approximated Pareto-optimal solutions
1: Initial feasible population
2: Evaluate solutions and construct the initial G
3: **while** the termination criterion is not fulfilled **do**
4:     **for** each individual i in the population **do**
5:         Execute the Flow operation by Equation (15)
6:         **while** $f(\mathbf{x}_{\text{Flow}})$ is Pareto-dominated && flow times are not reached **do**
7:             $\mathbf{x}_i = \mathbf{x}_{\text{Flow}}$
8:             Flow another time on the base of $\mathbf{x}_{\text{Flow}}$
9:         **end while**
10:     **end for**
11:     Update G
12:     **for** each individual i in the population **do**
13:         $\mathbf{x}_{\text{Infiltration}} = \mathbf{x}_i$
14:         Execute Infiltration operation:

$$\mathbf{X}_{\text{Infiltration},SD} = \mathbf{X}_{\text{Infiltration},SD} + (\mathbf{X}_{\text{Infiltration},SD} - \mathbf{X}_{j,SD}).\times 2 \times (rand(1, sd) - 0.5),$$

where j is randomly chosen and SD is a vector with random sd dimensions
15:     Execute solution keeping strategy as improvement 2) mentioned
16:     **end for**
17:     Update G
18:     **for** each individual i in the population **do**
19:         Execute the Evaporation or Precipitation operation:

$$\begin{cases} \mathbf{x}_i \text{ moves to another position randomly} & \text{if } rand < P_e \text{ and } rand < 0.5, \\ \mathbf{x}_i \text{ moves to best solution's neighbourhood} & \text{if } rand < P_e \text{ and } rand < 0.5, \end{cases}$$

where P_e is a preset probability and neighborhood is generated by Gauss mutation
20:     **end for**
21:     Update G
22: **end while**

3.3 | Coding rule for N-BQCAP model

To illustrate the coding schema of the model, in Figure 3, an example comprising 4 vessels, 4 QCs, and 3 berth sizes (berths 1, 2, and 3 are small-, middle-, and large-berth, respectively) is presented. Figure 3A presents vessel information—vessel sizes (S, M, and L), arrival time, and unloading containers, which are used to generate service orders by adopting the first-in-first-service and more-container-first-service principles. The latter principle is used when multiple vessels arrive at the same time. Figure 3B,C, whose elements are sorted in ascending order as

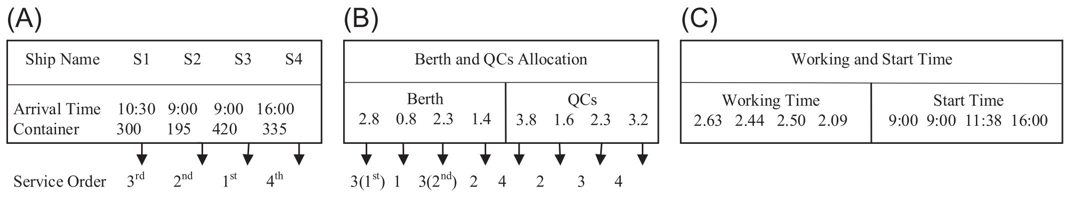

FIGURE 3 Illustrative example of the problem encoding and decoding processes. (A) Examples of generating service orders, (B) encoding strategy, and (C) decoding results. QC, quay crane.

being served, shows the encoding and decoding processes in an evolutionary loop. The rounding-off method is utilized to obtain the discrete values of the decision variables in the problem. For example, the first element of the Berth and QCs column in Figure 3B (2.3 and 3.8) collectively represents that the first-serviced vessel S3(L) will be served in the first order at Berth 3 with 4 QCs. In the decoding process, the first element 2.63 ($n_{S3}/vq_{S3} = 420/40*4 \approx 2.63$) and 9:00 in Figure 3C mean that it costs the first-served vessel S3 2.63 h to unload its containers and it will be served as soon as it arrives at 9:00. Note that this example only demonstrates the essential steps in the coding process. We assume that all vessels' working QCs do not exceed their allowed capacity; if this does not hold, then the Berth Reassignment and Berth Free Judgment strategies will be triggered so as to realize the integrative decision, as mentioned in Figure 1B.

4 | EXPERIMENTS AND RESULT ANALYSES

In this section, real-world instances with different scales are tested to demonstrate the adaptability and superiority of our proposed AEMOHCO in solving the considered N-BQCAP model. In the following parts, the instance details, evaluation metrics, compared algorithms, improved strategies efficiency, and final scheduling schemes are given, respectively.

4.1 | Case instances and evaluation metrics

The basic instance provided by Liang et al.[19] addressing a real-world problem at Shanghai's container terminal company has been extended to a large-scale containing 18 vessels, 17 QCs, and 6 berths (berths 1 and 2, 3 and 4, and 5 and 6 are small-, middle-, and large-berth, respectively). Table 2 shows the detailed vessel information of both test instances.

To evaluate the performance of the multiobjective evolutionary algorithms from various aspects, several performance metrics, that is, generational distance (GD), space (SP), and inverted generational distance (IGD),[20] which are widely recognized in the literature are applied (For concise, the specific formulations are omitted here). They mainly consider proximity, diversity, and distribution of the algorithm-found-Pareto front (F) convergence to the true Pareto-optimal front (PF). For any algorithm, smaller GD and SP values reflect better closeness and inhomogeneity performance and a smaller IGD value reflects better overall performance. Since the PF of the realistic N-BQCAP is unknown, a widely used estimated method is to obtain the PF by collecting all solutions from a large number of experiments on all the compared algorithms.

TABLE 2 Vessel information of both instances

	Instance 1			Instance 2	
Vessel (type)	Arrival time	Container	Vessel (type)	Arrival time	Container
MSG(L)	9:00	428	MSG(L)	9:00	428
NTD(L)	9:00	455	NTD(L)	9:00	455
CG(M)	9:00	259	CG(M)	9:00	259
NT(S)	21:00	172	NT(S)	21:00	172
LZ(L)	0:30	684	LZ(L)	0:30	684
XY(M)	8:30	356	XY(M)	8:30	356
LZI(L)	7:00	435	LZI(L)	7:00	435
GC(M)	11:30	350	GC(M)	11:30	350
LP(S)	21:30	150	LP(S)	21:30	150
LYQ(S)	22:00	150	LYQ(S)	22:00	150
CCG(M)	9:00	333	CCG(M)	9:00	333
			NT(S)	10:00	165
			LP(S)	15:00	180
			LYQ(S)	11:00	193
			XY(M)	14:00	222
			CG(M)	16:00	380
			MSG(L)	17:00	550
			LZI(L)	20:30	500

4.2 | Performance analysis for AEMOHCO algorithm

4.2.1 | Comparisons with peer algorithms

To make the results convincing, AEMOHCO is first compared against six peer multiobjective algorithms (i.e., SPEA2,[21] MOPSO,[22] NSGA-II,[23] MOEA/D,[24] MORBCO,[16] and CMOPSO[25]) on solving the N-BQCAP model defined in Section 2. The first four are classical multiobjective algorithms with different evolutionary principles, and the last two are novel algorithms. All experiments are implemented in MATLAB R2014b. For a fair comparison, population sizes $N = 50$ and maximum generations $T = 3000$ are implemented and each algorithm runs 30 times independently and the best average results obtained by all compared algorithms are highlighted in boldface. All algorithm parameters follow their original settings and the main details, including our AEMOHCO algorithm, are listed as follows:

- In SPEA2, probabilities $P_{\text{crossover}} = 0.1$ and $P_{\text{mutation}} = 0.2$.
- Regarding MOPSO, learning factors $c_1 = 1$, $c_2 = 2$, and the inertia weight $w_0 = 0.9$, $w_1 = 0.5$.
- Considering NSGA-II, $P_{\text{crossover}} = 0.1$ and $P_{\text{mutation}} = 0.5$.
- About MOEA/D, probability $P_{\text{neighbor}} = 0.15$.

- Concerning MORBCO, $N_{\mathrm{swim}} = 4$, $c_1 = 3$, $c_2 = 3$, $\mathrm{Elite}_{\mathrm{num}} = 20$, and chemotaxis step $C = 0.001$.
- Regard to CMOPSO, $\mathrm{Elite}_{\mathrm{num}} = 10$.
- In AEMOHCO, maximum flow time $N_{\mathrm{flow}} = 3$ and probability $P_{\mathrm{e\&d}} = 0.25$.

Table 3 presents the mean, standard deviation, and best result of GD, SP, and IGD metrics among all compared algorithms, for solving the new N-BQCAP under both instances. It is clear that AEMOHCO exhibits good performance since most of its mean values are minimal and it always finds the best result, which means that AEMOHCO can approximate the *PF* with a set of well-converged and well-distributed feasible solutions than other algorithms. This is due to that the problem characteristic incorporated in the AEMOHCO can increase the chance of finding a good solution. Although the standard deviations obtained by the MORBCO are lower than that by the AEMOHCO, there is no significant difference in both instances. This is because that MORBCO focuses on certain elite information, which may easily be trapped in local optimal.

TABLE 3 Metric results obtained by comparing algorithms for solving the N-BQCAP

	Metrics								
	GD			**SP**			**IGD**		
Algorithms	**Mean**	**Std**	**Best**	**Mean**	**Std**	**Best**	**Mean**	**Std**	**Best**
Instance 1									
SPEA2	$0.505^{\approx}$	0.344	0.306	1.498^{-}	0.089	1.599	6.209^{-}	2.519	2.772
MOPSO	0.796^{-}	0.053	0.752	0.772^{-}	0.025	0.783	2.513^{-}	0.724	1.582
NSGA-II	0.929^{-}	0.175	0.874	0.778^{-}	0.037	0.770	4.344^{-}	2.667	2.516
MOEA/D	0.717^{-}	0.278	0.554	0.789^{-}	0.080	0.922	4.890^{-}	1.546	2.578
MORBCO	1.502^{-}	**0.008**	1.500	0.893^{-}	**0.011**	0.885	9.221^{-}	**0.176**	9.116
CMOPSO	1.190^{-}	0.126	1.342	0.883^{-}	0.048	0.962	11.66^{-}	0.879	10.23
AEMOHCO	**0.230**	0.054	**0.214**	**0.611**	0.044	**0.638**	**1.280**	0.456	**0.670**
+/−/≈	0/1/5	–	–	0/0/6	–	–	0/0/6	–	–
Instance 2									
SPEA2	$0.247^{\approx}$	0.150	0.147	1.324^{-}	0.088	1.317	6.076^{-}	2.106	3.193
MOPSO	0.400^{-}	0.064	0.322	$0.827^{\approx}$	0.047	0.886	2.352^{-}	0.266	3.193
NSGA-II	$0.260^{\approx}$	0.135	0.197	$\mathbf{0.820}^{\approx}$	0.045	0.822	1.384^{-}	0.344	0.836
MOEA/D	0.369^{-}	0.135	0.161	0.870^{-}	0.086	0.833	3.494^{-}	1.115	1.536
MORBCO	0.256^{-}	**0.025**	0.243	$0.822^{\approx}$	**0.017**	0.808	1.269^{-}	0.292	0.960
CMOPSO	0.388^{-}	0.049	0.341	0.857^{-}	0.042	0.835	6.131^{-}	1.601	3.035
AEMOHCO	**0.228**	0.059	**0.083**	0.826	0.028	**0.781**	**1.065**	**0.232**	**0.524**
+/−/≈	0/2/4	–	–	0/3/3	–	–	0/0/6	–	–

Abbreviations: AEMOHCO, archive exploration multiobjective hydrologic cycle optimization; GD, generational distance; IGD, inverted generational distance; N-BQCAP, new integrated berth and quay crane allocation problem; SP, space; Std, standard deviation.

Furthermore, we apply Wilcoxon's rank-sum test[26] at a significant level of 5% to statistically compare the mean of all metrics of AEMOHCO with peer algorithms. Signals +, −, and ≈ in the upper right corner of the Mean columns indicate that the compared algorithm has better/worse performance than AEMOHCO, or similar performance as AEMOHCO, respectively. AEMOHCO is statistically no worse than that of any comparison algorithm in terms of distribution and convergence, as indicated by the results that no signal + exists in the last rows under both instances.

4.2.2 | Effectiveness demonstration of the proposed improved strategies

To demonstrate the effectiveness of the aforementioned modified strategies in AEMOHCO, this part conducts comparisons between AEMOHCO and the basic MOHCO in terms of solution quality, algorithm performance stability, and convergence.

Table 4 shows the comparison results among the variant algorithms considering the metrics previously described. From the results, AEMOHCO always achieves smaller metric results, and nearly 25% improvement on IGD is acquired in both N-BQCAP instances, which means that the improved strategies help in enhancing algorithm-solving ability. In addition, the algorithm-found-Pareto fronts by the two algorithms in Instance 1 are visually shown in Figure 4A,B. The simulated Pareto front *PF* of the problem is shown as a red dotted line. It can be seen that AEMOHCO converges to the simulated *PF* better than MOHCO and its solution covers a wider range, which can provide decision-makers with more diverse decision-making schemes. A similar conclusion can be acquired in large-scale Instance 2, as shown in Figure 5.

To demonstrate the Pareto-optimal solution convergence capability enhanced strategies brought, the mean numbers of Pareto-optimal solutions found by AEMOHCO and MOHCO under every 100 generations are recorded in Table 5. The mean numbers found in the 50th generation are also preserved to detect the initial response speed of the algorithms. The results show that AEMOHCO can quickly find more considerable solution numbers at the very execution beginning than MOHCO regardless of the instance scale. And AEMOHCO always finds more Pareto-optimal solutions than MOHCO in the same search environment.

TABLE 4 Metric results obtained by different HCO variants

	AEMOHCO			MOHCO		
Index	**GD**	**SP**	**IGD**	**GD**	**SP**	**IGD**
Instance 1						
Average	**0.167**	**0.804**	**1.224**	0.227	0.819	1.667
Std	**0.066**	**0.043**	**0.345**	0.117	0.050	0.811
Instance 2						
Average	**0.246**	**0.770**	**2.928**	0.258	0.772	3.931
Std	**0.050**	**0.055**	**0.819**	0.123	0.075	0.897

Abbreviations: AEMOHCO, archive exploration multiobjective hydrologic cycle optimization; GD, generational distance; HCO, hydrologic cycle optimization; IGD, inverted generational distance; MOHCO, multiobjective hydrologic cycle optimization; SP, space; Std, standard deviation.

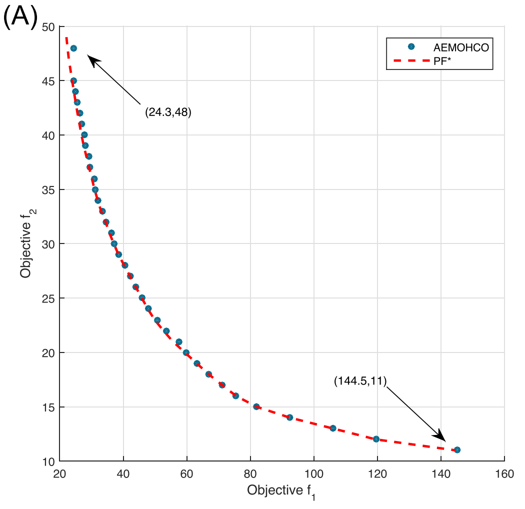

FIGURE 4 Pareto fronts produced by algorithms for the Instance 1. (A) AEMOHCO algorithm and (B) MOHCO algorithm. AEMOHCO, archive exploration multiobjective hydrologic cycle optimization; MOHCO, multiobjective hydrologic cycle optimization; PF, Pareto front. [Color figure can be viewed at wileyonlinelibrary.com]

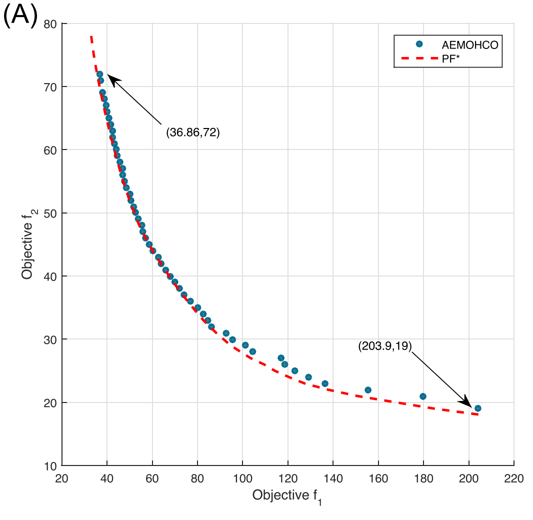

FIGURE 5 Pareto fronts produced by algorithms for Instance 2. (A) AEMOHCO algorithm and (B) MOHCO algorithm. AEMOHCO, archive exploration multiobjective hydrologic cycle optimization; MOHCO, multiobjective hydrologic cycle optimization; PF, Pareto front. [Color figure can be viewed at wileyonlinelibrary.com]

4.2.3 | Scheduling scheme exhibition

One illustrative example solution on Instance 1 given by AEMOHCO is presented in Figure 6. The figure clearly shows that vessels CG(M) and LZ(L), which arrive at 0:30 at the same time, are arranged at Berth 2 and Berth 4, respectively, and two QCs are scheduled for their unloading operation. The red arrow pointing from Berth 4 to Berth 3 indicates that the vessel

TABLE 5 Pareto-optimal solution quantities found with an increase in generations

	Instance 1		Instance 2	
Iterations (time)	AEMOHCO	MOHCO	AEMOHCO	MOHCO
50	23.25	18.00	27.45	21.15
100	26.00	21.40	30.60	24.80
200	28.85	23.70	35.25	29.90
300	30.50	25.55	37.35	32.70
400	31.10	26.65	39.15	34.65
500	32.00	27.80	40.35	36.20
600	32.70	28.85	42.30	37.55
700	33.20	29.65	42.85	39.50
800	34.00	30.25	44.30	40.60
900	34.25	31.20	45.15	41.25
1000	34.70	31.65	46.20	41.90

Abbreviations: AEMOHCO, archive exploration multiobjective hydrologic cycle optimization; MOHCO, multiobjective hydrologic cycle optimization.

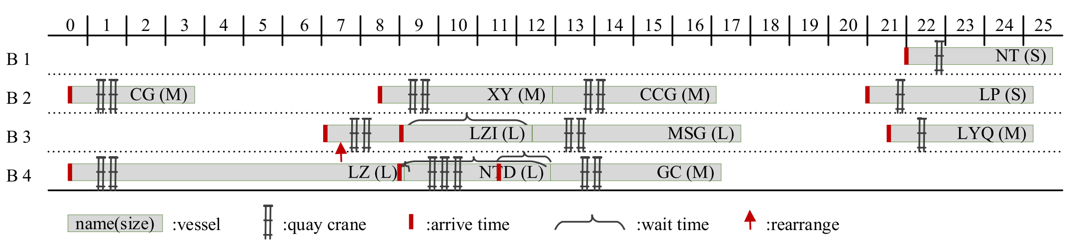

FIGURE 6 Example scheduling solution for Instance 1 [Color figure can be viewed at wileyonlinelibrary.com]

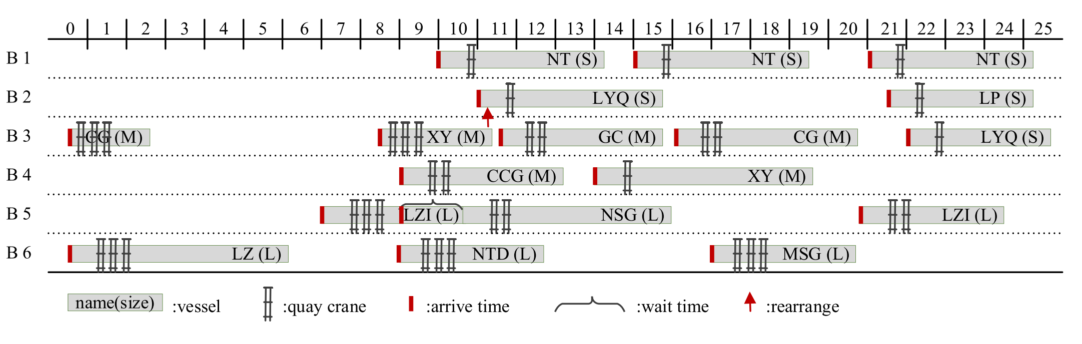

FIGURE 7 Example scheduling solution for Instance 2 [Color figure can be viewed at wileyonlinelibrary.com]

LZI(L), which is originally arranged at Berth 4, is rescheduled to another vacant and suitable Berth 3 since its original berth is occupied at 7:00. The second serviced vessel MSG(L) at Berth 3 cannot be serviced until its antecedent vessel LZI(L) finishes its work at 12:44. This waiting can be attributed to the lack of a vacant and suitable berth for MSG(L) at 9:00. We can conclude all the waiting information from the brace in the figure directly. Similarly, one allocation scheme for the large-scale instance is presented in Figure 7.

5 | CONCLUSION

Contrasting from the existing models that ignore flexible multilength berths and QC utilization on the integrated BQCAP, this study contributes to establishing a more realistic integrated multiobjective model (i.e., N-BQCAP), which defines the total equipment used as independent objective. Thereafter, inspired by the advantages of keeping few bad solutions and equipment rearrangement characteristics, a tailored AEMOHCO algorithm is proposed to solve the N-BQCAP and its effectiveness has been demonstrated comprehensively by some real-world instances. We also can find that AEMOHCO can quickly find more considerable solution numbers at the very beginning regardless of the instance scale.

In the future, yard truck allocation problem also deserves consideration in conjunction with this study to provide the scheduling scheme for the whole process. Besides, our proposed AEMOHCO algorithm is only suitable for the static integrated BQCAP, we will try to design a comprehensive algorithm that fits into more general decision environments, such as for dynamic or emergent situations.

AUTHOR CONTRIBUTIONS

Huifen Zhong: Conceptualization, software, and writing—original draft. **Zhaotong Lian**: Methodology and validation. **Bowen Xue**: Writing—review and editing, visualization. **Ben Niu**: Writing—review and editing, funding acquisition, project administration, and supervision. **Rong Qu**: Writing—review and editing. **Tianwei Zhou**: Conceptualization and methodology. All authors have read and agreed to the published version of the manuscript.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All relevant data are within the paper.

ORCID

Ben Niu http://orcid.org/0000-0001-5822-8743

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