LogForum

> Scientific Journal of Logistics <

2022, 18 (4), 505-515

http://doi.org/10.17270/J.LOG.2022.786

http://www.logforum.net p-ISSN 1895-2038 e-ISSN 1734-459X

ORIGINAL PAPER

GENETIC BASED ALGORITHMS TO SOLVING MULTI-QUAYS BERTH ALLOCATION PROBLEM WITH SETUP TIME CONSTRAINTS

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ABSTRACT. Background: This study focuses on efficient berth planning in multi-purpose terminal composed of multiple quays. A multi-quay berth offers infrastructure, equipment, and services for different types of cargo and vessels to meet the needs of users from various freight markets. Moreover, each berth from any quay can be dedicated for one or two different types of cargo and vessels. To improve port efficiency in terms of reducing the waiting time of ships, this study addresses the Multi-Quay Berth Allocation Problem (MQ-BAP), where discrete berthing layout is considered along with setup time constraints and practical constraints such as time windows and safety distances between ships. Sequence dependent setup times may arise due to the berth can convert from dedicated function to another function according to the variance of cargo demand. This problem was inspired by a real case of a multi-purpose port in Thailand.

Methods: To solve the problem, we propose a mixed-integer programming model to find the optimal solutions for small instances. Furthermore, we adapted a metaheuristic solution approach based on Genetic algorithm (GA) to solving the MQ-BAP model in large-scale problem cases.

Results: Numerical experiments are carried out on randomly generated instances for multi-purpose terminals to assess the effectiveness of the proposed model and the efficiency of the proposed algorithm. The results show that our proposed GA provides a near-optimal solution by average 4.77% from the optimal and show a higher efficiency over Particle swarm optimization (PSO) and current practice situation, which are first come first serve (FCFS) rule by 1.38% and 5.61%, respectively.

Conclusions: We conclude that our proposed GA is an efficient algorithm for near-optimal MQ-BAP with setup time constraint at acceptable of computation time. The computational results reveal that the reliability of the metaheuristics to deal with large instances is very efficient in solving the problem considered.

Keywords: Multi-Quay, Berth Allocation Problem, Genetic algorithm, Sequence-Dependent Setup Times

INTRODUCTION

Maritime transport contributes to more than 80% of the world's seaborne trade and is considered significant transportation for global trade and the economy. In 2020, sea freight accounted for 10.7 billion tons. The value is slightly lower than the total transportation of sea freight in 2019, resulting from the COVID-19 epidemic around the world. In the past 10 years, the ocean freight volume has continuously increased. In addition, in 2022, the average growth rate is expected to be 2.4% per year [UNCTAD, 2021].

Due to the increased volume of ocean freight volume, the demand for port services has increased accordingly. Therefore, each port must develop strategies to compete or attract customers to use their ports. The key strategy is to enable it to provide integrated services. Especially the berth expansion and adjust according to demand trend for loading and unloading changes over time. As a result of the strategies mentioned above, the current port has become more extensive. There is a more complicated operation, including more flexibility to use highly competent port management methods to maximize port efficiency.

Citation: *Sangsawang C., Longploypad C., 2022. Genetic based algorithms to solving multi-quays berth allocation problem with setup time constraints. LogForum 18 (4), 505-515,* http://doi.org/10.17270/J.LOG.2022.786

Received: 20.10.2022, Accepted: 05.12.2022, on-line: 30.12.2022

The Berth Allocation Problem (BAP) is a critical problem of seaside port operations and is affected by the change in the competitive port strategy. BAP are related to the allocation of berths for each ship that will use the service. Included allocation of the berth position and the berthing time for the arriving vessel. Regarding spatial dimension, there are three types of berth layouts: discrete layout, continuous layout, and hybrid layout. The discrete layout is the most basic layout where the quay area is clearly divided into several berths, and each berth can be serviced by only one vessel at any time. For the continuous layout, the quay area is not divided into several berths and the arriving vessel can berth in any quay area without overlapping. The hybrid layout is similar to discrete layout but ships can occupy one or more berths if necessary [Bierwirth and Meisel, 2010]. In addition, the BAP problem can also be divided into 2 types of the ship's arrival time dimension: static arrival and dynamic arrival. Static arrival requires that each ship arrive at the port and be ready for service before the planning horizon. In the dynamic arrival, arrival times are scheduled and assigned to each ship. The ship may arrive before or after the planned time [Imai et al., 2001].

BAP is a problem that has been studied by several researchers using different solutions. The static variant of the discrete BAP was first formulated by Imai et al. [1997], while the dynamic variant was addressed by Imai et al. [2001]. Mostly, the purpose of berth allocation is to focus on the service level and reliability of the port. Each research has different objectives, for example, to minimize the waiting time for docking services, to reduce the workload of terminal resources, and to minimize the number of service rejections. Bierwirth and Meisel, [2010, 2015] and Carlo et al. [2015] are the most recent reviews of the literature regarding seaside operations, including the BAP. In recent years, researchers have proposed new solution methods to address BAP which respect more realistic conditions and characteristics. For example, Mauri et al. [2016] developed a variant of the neighborhood search method called adaptive large neighborhood search (ALNS) to deal with the dynamic and continuous berth allocation problem (DCBAP). The objectives of this study are to minimize the total service cost and the total time at port. Another study [Chen and Huang, 2017] also develops a GA-based approach to deal with the DCBAP to minimize penalty costs for late departures. The study presented in Xu et al. [2018] proposed a simulated annealing (SA) algorithm to deal with BAP with traffic limitations in the consideration of the navigation channel. In 2019, Jos et al. [2019] developed a new mixed-integer linear programming (MILP) model to deal with the BAP to minimize operation costs and Hsu et al. [2019] developed a hybrid genetic algorithm (HGA) to solve the BAP and Quay Crane Assignment Problem Simultaneously. Prencipe and Marinelli. [2021] proposed a novel arithmetical formula that was presented as MILP model to deal with the Discrete and Dynamic Berth Allocation Problem (DDBAP). In addition, a new approach solution was adapted to meta-heuristic based on Bee Colony Optimization (BCO) to solve a large scale BAPs. Bacalhau et al. [2021] developed a hybrid heuristic-based genetic algorithm (GA) with dynamic programming (DP) to solve the dynamic and discrete berth allocation problem (DDBAP) to avoid the problem of high computation time in exact approaches. Several approaches are reported in the literature dealing with the BAP. However, metaheuristics approaches are more popular over exact methods due to their efficiency in terms of computational complexity. Among the heuristic approaches, Genetic Algorithms and Evolutionary Algorithms take the by far largest share with 40%; see Bierwirth and Meisel [2015] and Prencipe and M. Marinelli [2021].

Academic work has primarily focused on the problem of BAP in a single quay. Currently, ports are expanding in terms of area and service. Some ports will consist of multiple quays that can be configured to serve different types of vessels. So, considering quay as a single is inconsistent with the current situation. Considering the nature of multiple quays in the BAP problem, it means the problem of assigning vessels to the quay and assigning berthing positions and times for each separate berth. Very few studies have researched Multi-quay BAP (MQ-BAP), For example, Frojan et al. [2015] deals with an updated form of BAP, where multiple quays and continuous berth layouts are considered. They proposed a first formulated as an integer linear model and then solved using GA. Another study by Krimi et al. [2020] studied a multi-quays berth allocation and crane assignment problem under availability restrictions on bulk terminals. They proposed a mixed-integer programming model and investigated a set of heuristics based on the general variable neighborhood search (GVNS) approach. The proposed GVNS heuristic turns out to be very efficient in solving the problem considered. Moreover, a study presented in Cheimanoff et al. [2021] also addresses multiple continuous quays and dynamic BAP. The study also considers tidal constraints for optimal berth assignment, and the main objective of this study is to reduce the total service time of the vessels. They presented a mixed-integer linear model and adapted Iterated Local Search (ILS) approach to solve industrial-sized instances.

This research aims to study the problem of Multi-quay BAP to find an effective method for berth allocation. This problem was inspired by a real case of a multi-purpose port in Thailand that considered special conditions in addition to practical conditions, as seen in Figure 1. This includes changing the type of cargo that the berth can provide for more than one type of cargo, known as a multipurpose berth, to increase flexibility in port operation management in case of increased cargo handling demand or decreases in each product type. Furthermore, the setup time conditions are also considered when adjusting the types of cargo capable of each berth. Setup times may arise due to the berth can convert from dedicated function to another function according to the variance of cargo demand, known as sequence-dependent setup time. However, the study of the MQ-BAP solution with multi-purpose berth and sequence-dependent setup time constraints has not been considered previously in the literature.

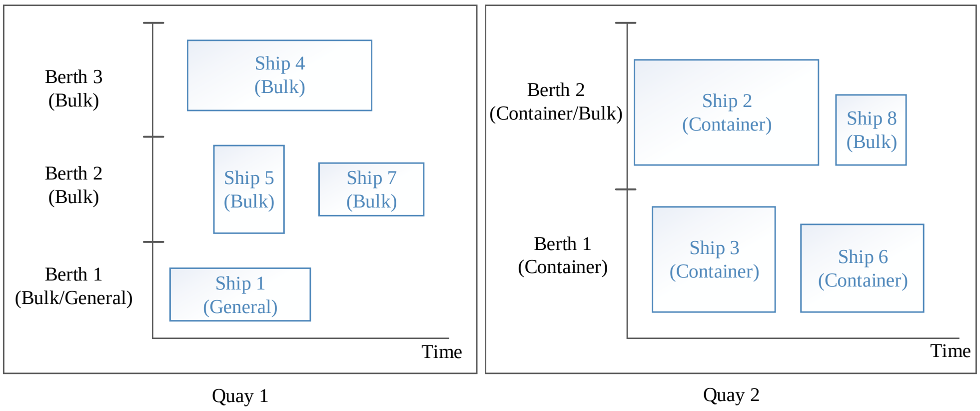

Fig. 1. An illustration of two discrete berthing quays with 8 arriving ships and 3 types of cargo

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This paper proposes a mixed-integer programming model to find the optimal solutions for small instances and adapted a metaheuristic solution approach based on Genetic algorithm (GA) to solving the MQ-BAP model in large-scale problem cases. Furthermore, numerical experiments are carried on randomly generated instances for multipurpose terminals to assess the effectiveness of the proposed model and the efficiency of the proposed algorithm. The remainder of this article is organized as follows. The problem description and formulation are presented in the next section. Then, we present the detail of the proposed metaheuristic based on the GA algorithm. While, the result and conclusion are described.

PROBLEM DESCRIPTION AND FORMULATION

Problem Definition

This study addresses the Multi-Quay Berth Allocation Problem (MQ-BAP), where the discrete berthing layout is considered. The quay is divided into a number of berth $i \in I$ and berth can service one vessel at a time. In each berth, there is an eligibility constraint Cij, which means the compatibility between berths and ships (i.e., cargo type, length of berth, depth of berth). Moreover, setup times for ST_{hj} may arise due to the changing of berth type according to the sequence of assigning ships. There is a set of arriving ships J = {1,2,3,…J} along with the attribute of cargo type and each ship $j \in J$ has multiple known characteristics, including Length of Ship (*LS*), Draft of Ship (*DS*) Expected Time of Arrival (*AT*) and Handling Time (*HT*). The objective of this study is to determine the berthing position and berthing time for all arriving ships in J in order to minimize the maximum waiting time of all ships. The waiting time is defined as the time that a ship in waiting for the previous ship to leave the same berth.

Assumptions

- All berths are assumed to be free in the initial state.
- Each ship corresponds to at least one compatible berth due to the discrete layout of the quays.
- A berth is considered as a specific point on the quay (referred to by a number).
- Each berth can be dedicated to one or two different types of cargo and vessels.
- The compatibility between ships and berths is related to geometric and cargo-type constraints.
- One ship can occupy only one berth and is not allowed to interrupt the operations when a vessel starts operations at a particular berth.
- The berths of any quay become available immediately after a ship completes its operations.
- Ships arrive at the port in the harbour area according to scheduled arrival times and not in delay.
- The arrival times and handling times for all arriving ships are known.

Mathematical Formulation

The notation used in the MIP model for Multi-Quay Berth Allocation Problem is presented in Table 1 and the model is presented in Table 2.

Table 1. Notation used in the MIP model for Multi-Quay Berth Allocation Problem

Sets and indices
I : Set of berths, indexed by i=1, 2, 3,…, I
J : Set of ships, indexed by j,h = 1, 2, 3,…, J
K : Set of service orders, indexed by k,p = 1, 2, 3,…, K
P_k : Subset of K such that $P_k = \{p \mid p < k \in K\}$
W_i : Subset of ships with $AT_j \geq BA_i$
Parameters
CB_{ij} : $\begin{cases} 1 & \text{if berth } i \text{ is capable of berthing ship } j \\ 0 & \text{Otherwise} \end{cases}$
ST_{hj} : Setup time to berthing ship j after ship h on the same berth
AT_j : Arrival time of ship j
LB_i : Length of berth i
LS_j : Length of ship j
DB_i : Depth of berth i
DS_j : Draft of ship j
HT_{ij} : Handling time of ship j at berth i
BA_i : Initial available time of berth i
M : Very large positive number
Decision variables
R_{ijk} : $\begin{cases} 1 & \text{if ship j is berthing as the } k\text{th ship at berth } i \\ 0 & \text{Otherwise} \end{cases}$
ID_{ijk} : Idle time of berth i between the departure of the k-1th ship and the arrival of the kth ship when ship j is berthing as the kth ship
ATB_{ik} : Arrival time of the kth ship at berth i
SH_{ik} : Start time of handling the kth ship at berth i
FH_{ik} : Completion time of the kth ship at berth i
$MaxW$: Maximize waiting time of all ships

Table 2. MIP model for Multi-Quay Berth Allocation Problem

Objective function		
$Min\ Z = MaxW$		(1)
Constraints		
$MaxW \le SH_{ik} - ATB_{ik}$	$\forall I \in I, k \in K$	(2)
$\sum_{i\epsilon I}\sum_{k\epsilon K} R_{ijk} = 1$	$\forall j \in J$	(3)
$\sum_{j\epsilon J} R_{ijk} \le 1$	$\forall i \in I, k \in K$	(4)
$LS_j \le LB_i + M\,(1-R_{ijk})$	$\forall i \in I, j \in J, k \in K$	(5)
$DS_j \le DB_i + M\,(1-R_{ijk})$	$\forall i \in I, j \in J, k \in K$	(6)
$R_{ijk} \le CB_{ij}$	$\forall i \in I, j \in J, k \in K$	(7)
$\sum_{j\epsilon J} R_{ijk+1} \le \sum_{j\epsilon J} R_{ijk}$	$\forall i \in I, k \in 1 \ldots K-1$	(8)
$ATB_{ik} = \sum_{j\epsilon J} R_{ijk} * AT_j$	$\forall i \in I, k \in K$	(9)
$SH_{ik} \ge \sum_{j\epsilon J} R_{ijk} * BA_i$	$\forall i \in I, k \in K$	(10)
$SH_{ik} \ge \sum_{j\epsilon J} R_{ijk} * AT_i$	$\forall i \in I, k \in K$	(11)
$SH_{ik+1} \le M * \sum_{j\epsilon J} R_{ijk+1}$	$\forall i \in I, k \in 1 \ldots K-1$	(12)
$\sum_{l\epsilon J}\sum_{m\epsilon P_k}(HT_{il}R_{ilm} + ID_{ilm}) + ID_{ijk} - (AT_j - BA_i)R_{ijk} \ge 0$	$\forall i \in I, j \in W_i, k \in K$	(13)
$FH_{ik} = SH_{ik} + \sum_{j\epsilon J} R_{ijk} HT_{ij}$	$\forall i \in I, k \in K$	(14)
$FH_{ik-1} + ST_{hj} - SH_{ik} \le M * (2 - R_{ijk} - R_{ihk-1})$	$\forall i \in I, h, j \in J, k \in 2 \ldots K$	(15)
$R_{ijk} \in \{0,1\}$	$\forall i \in I, j \in J, k \in K$	(16)
$ID_{ijk} \ge 0, \in int$	$\forall i \in I, j \in J, k \in K$	(17)
$ATB_{ik}, SH_{ik}, FH_{ik} \ge 0, \in int$	$\forall i \in I, k \in K$	(18)

In this model, the objective function (1) and constraints (2) denote the optimization process to minimize the Maximum waiting time of all ships. Constraints (3) and (4) ensure the uniqueness of the assignment. Constraints (5), (6), and (7) ensure the compatibility between the length, the draft of the ships, and the cargo type of ship with respect to those of the berths. Constraints (8) ensure the service order *k* and *k*+1 for the same berth. Constraints (9), (10), (11) and (12) evaluate the start time of handling the *k-th* ship at berth *i*. Constraints (13) ensure that ships must be serviced after their arrival. Constraints (14) and (15) define the completion time of handling the *k*th ship at berth *i* that consists of handling time of the the ship and setup time of berth in any case. Constraints (16) define the binary nature of the decision variable. Finally, constraints (17) and (18) define the decision variable as greater than or equal 0.

GENETIC BASED ALGORITHMS FOR MULTI-QUAYS BERTH ALLOCATION PROBLEM

The MIP model presented in the previous section is not tractable for the MQ-BAP because it is a typical combinatorial optimization problem. Thus, we focus instead on developing effective metaheuristic approaches, and the Genetic Algorithm proposed by Holland [1992] is modified. The general pseudocode of the proposed GA is presented in Figure 2.

Chromosome representation

The chromosome can be seen as the assignment of each ship for berth on any quay, considering the berth sequence. Table 3. shows a sample of data for a problem with three berths and ten ships. The chromosome used to represent the solution in this study consists of N (number of ships) genes, as shown in Figure 3. A pair of numbers [berth, ship] in each gene represents an assignment of a berth and the sequence of the ships on each berth.

```
Procedure: the proposed GA
Inputs: crossover rate: P_C, mutation rate: P_M, population size: popSize, and maximum generation: maxGen.
Output: the near optimal solution
Begin
   Let generation index T = 0.
   Randomly generate an initial population.
   While (T ≤ maxGen)
         Let population index P = 1.
         While (P ≤ popSize)
               Randomly select two chromosomes from current population.
               If (random number ≤ P_C)
                  Do ordered crossover operations.
               End If
               If (random number ≤ P_M)
                  Do swap mutation operations.
               End If
               Evaluation and calculate the fitness value of each schedule.
               P = P + 1:
         End While
         Construct the next generation by a roulette-wheel and elitism from the children.
         T = T + 1:
   End While
End
```

Fig. 2. The pseudo code of the genetic based algorithms to solving multi-quays berth allocation problem.

Table 3. Example of a multi-purpose port problem data

Ship no.	1	2	3	4	5	6	7	8	9	10
Ship Type	1	2	3	1	1	2	3	2	1	2
Berth capable	1/2	2/3	3	1/2	1/2	2/3	3	2/3	1/2	2/3
Handling time (hrs.)	5	15	20	10	30	10	25	10	15	25

Notes. Ship type 1: Container, 2: General, 3: Bulk. Berth capable 1: Container, 2: Container/General, 3: General/Bulk.

Encoding

[2,2]	[3,3]	[1,1]	[1,5]	[1,4]	[2,8]	[2,10]	[3,6]	[3,7]	[1,9]

Decoding

Berth1	Ship1	Ship5	Ship4	Ship9
Berth2	Ship2	Ship8	Ship10	
Berth3	Ship3	Ship6	Ship7	

Fig. 3. An illustrative example of chromosome representation.

Population and selection

For the present study, we propose to construct the population that has been created based on the constraint (7). After producing solutions, constraints (10), (11), (13), (14) and (15), which show evaluate the start time of handling and the completion time of handling of ships at berth, are considered. At each generation, the roulette wheel selection method and elitism are used for selection method. With elitism, the best performing chromosome of the population will automatically carry over to the next generation, ensuring that the most successful chromosome persists.

Crossover and Mutation

Crossover exchanges a certain portion of the chromosome between two chromosomes. Figure 4. shows an example of ordered crossover, in which the parents are generated based on the data in Table 1. In the example, two genes are randomly selected (the fourth and seventh) for crossover.

For each GA iteration, the swap mutation is applied for this study. Mutation changes the sequence of genes, related to sequencing of ship. An example of the swap mutation is shown in Figure 5.

P1	[2,2]	[3,3]	[1,1]	[1,5]	[1,4]	[2,8]	[2,10]	[3,6]	[3,7]	[1,9]
P2	[1,4]	[1,5]	[2,1]	[2,6]	[3,2]	[1,9]	[2,8]	[3,3]	[3,7]	[1,10]

O1	[3,3]	[1,1]	[1,5]	[2,6]	[3,2]	[1,9]	[2,8]	[1,4]	[2,10]	[3,7]
O2	[2,1]	[2,6]	[3,2]	[1,5]	[1,4]	[2,8]	[2,10]	[1,9]	[3,3]	[3,7]

Fig. 4. Example of ordered crossover operations

Before Mutation

[2,2]	[3,3]	[1,1]	[1,5]	[1,4]	[2,8]	[2,10]	[3,6]	[3,7]	[1,9]

Berth1	Ship1	Ship5	Ship4	Ship9
Berth2	Ship2	Ship8	Ship10	
Berth3	Ship3	Ship6	Ship7	

After Mutation

[2,2]	[3,3]	[2,10]	[1,5]	[1,4]	[2,8]	[1,1]	[3,6]	[3,7]	[1,9]

Berth1	Ship5	Ship4	Ship1	Ship9
Berth2	Ship2	Ship10	Ship8	
Berth3	Ship3	Ship6	Ship7	

Fig. 5. Example of swap mutation

COMPUTATIONAL RESULTS

In this section, we conducted computational experiments using randomly generated test problems to evaluate the performance of proposed method in this article. All experiments using CPLEX and GA are executed on a PC Intel® Core™ i5 2.30 GHz with 8 GB of RAM. The GA algorithm was developed in Python 3.7.0, while ILOG CPLEX 12.10 is used to obtain the optimal solution through MIP as presented in Section 3.

The computational results of the proposed GA on two MQ-BAP groups are reported. A small- sized problem group, involving problem instances with the number of ships (*S*) as 10, 15, 20 and 25 and number of quays (*Q*) as 1 and 2 with 3 and 5 berths (*B*), is for comparing solution obtained by GA with the optimal solution. A large-size problem group, involving problem instances with the number of ships as 50, 70, 90 and 110 and number of quays as 2, 3, 4 and 5 with 5, 7, 10, and 15 berths, is for comparing the performance of GA with current practice situation which are first come first serve (FCFS) rule. Moreover, we also implement PSO, a wildly popular metaheuristic approach proposed by Kennedy and Eberhart [1995], for performance comparison purposes. All cases comprise lengths of ships, draft of ships, lengths of berths, depth of berths, Number of cargo types, Ship handling times, Setup time of berth, and Inter-arrival time of ships as shown in table 4. Moreover, according to the problem constraint, at least one berth must be compatible with each ship in terms of length and draft.

Table 4. Test problem data

Lengths of ships	100, 150, 200, and 250 m.
Lengths of berths	100, 150, 200, and 250 m.
Draft of ships and	8, 10 and 15 m.
Depth of berths	8, 10 and 15 m.
Number of cargo type	3 Types
Ship handling times	5 to 24 hrs.
Setup time of berth	1, 2 and 3 hrs.
Inter-arrival time of ships	0 to 3 hrs.

Concerning the GA algorithm, the parameters of the algorithm are fixed and determined as 50 and 100 individuals for both population size and maximum iterations for small-size instance, and large-size instance respectively, 90% of crossover rate, 5% of elitism rate, and 2% of mutation rate. For the control parameters of PSO, the particle numbers were set to 100, the acceleration coefficients *c*1 and $c2$ are set to 2 and set the inertia weight (w) to 0.4. The computation times (t) are related to the average CPU time over 10 runs. The PSO stops when the computation time reaches the same time spent by the proposed GA for the problem instance. Regarding CPLEX, we set the time limit for finding the global optimum equal to 21600 s.

The results of the comparison in the small-size problem are reported in Table 5. We found that the GA algorithm is achieved by the exact solution in many cases and shows that the results in terms of the objective function gap, compared with CPLEX, give a low value on average 4.77%. The objective function gap between FCFS and CPLEX gives a value by average 19.10%. Moreover, the results of the comparison in large-size problem instances are reported in Table 6. We can observe that the average percentage of improvement in terms of the minimizing of maximum ship's waiting time is 5.61% when compared to the FCFS rule. While, the average percentage of improvement between GA and PSO gives a value of average 1.38%. A statistical analysis is also performed by applying a paired-t test at a significant level of $\alpha = 0.05$ to confirm whether there are significant differences between algorithms. Table 7 shows that the p-values for the two-tailed form of the t-test are 0.004 and < 0.001 for both GA-PSO and GA-FCFS respectively. They are less than the significance level of 0.05. Therefore, the differences between means are statistically significant, and the results also confirm that the proposed GA algorithm guarantees a near-optimal solution in low computation time and gives a better performance than both PSO and FCFS.

Table 5. Result comparison for small-sized problems.

Instance	**Problem size**	**CPLEX**		**GA**			**FCFS**	**Gap (%)**	
	S×Q×B	*f*	*t*	*f* Best	*f* Avg.	*t*	*f*	GA- CPLEX	FCFS - CPLEX
S1	10×1×3	26	0.30	26	26.00	0.92	33	0.00	26.92
S2	10×1×3	12	1.86	12	12.10	1.00	21	0.83	75.00
S3	10×1×3	42	0.48	42	42.00	1.01	42	0.00	0.00
S4	10×2×5	2	2.72	2	2.10	0.93	2	5.00	0.00
S5	10×2×5	12	1.41	12	12.10	0.89	12	0.83	0.00
S6	10×2×5	8	2.39	8	8.00	0.84	8	0.00	0.00
S7	10×1×3	17	14.95	17	17.00	0.98	24	0.00	41.18
S8	10×1×3	9	5.28	9	9.00	0.98	9	0.00	0.00
S9	10×1×3	16	14.13	17	17.00	0.98	18	6.25	12.50
S10	10×2×5	10	176.44	10	10.00	1.01	14	0.00	40.00
S11	10×2×5	10	8.49	10	10.40	1.00	10	4.00	0.00
S12	10×2×5	12	113.17	12	12.00	1.00	12	0.00	0.00
S13	20×1×3	37*	21,622.38	37	37.70	1.12	45	1.89	21.62
S14	20×1×3	26	5,830.97	27	27.00	1.01	33	3.85	26.92
S15	20×1×3	35*	21,620.98	35	37.10	1.09	40	6.00	14.29
S16	20×2×5	15	3,612.17	17	18.20	1.11	24	21.33	60.00
S17	20×2×5	13	4,627.81	15	17.10	1.09	19	31.54	46.15
S18	20×2×5	9*	21,620.98	12	13.30	1.10	13	47.78	44.44
S19	25×1×3	62**	4,811.00	63	63.60	1.23	65	2.58	4.84
S20	25×1×3	61*	21,620.20	59	60.00	1.20	65	-1.64	6.56
S21	25×1×3	51	335.20	51	51.00	1.22	51	0.00	0.00
S22	25×2×5	20**	3,662.05	13	15.30	1.21	23	-23.50	15.00
S23	25×2×5	13**	7,970.45	12	14.80	1.22	16	13.85	23.08
S24	25×2×5	25**	3,856.19	22	23.50	1.22	25	-6.00	0.00

Notes. *f* denotes the maximize ship's waiting time in hours. *t* denotes the average computation time in seconds. * Best found before time limitation at 6 hours. **Best found before out of memory.

Table 6. Result comparison for large-sized problems.

Instance	Problem size S×Q×B	GA			PSO		FCFS	Gap (%)	
		f Best	*f* Avg.	*t*	*f* Best	*f* Avg.	*f*	GA-FCFS	GA-PSO
L1	50×2×5	97	99.10	10.05	101	102.30	114	-13.07	-3.13
L2	50×2×5	115	117.80	9.47	116	118.10	124	-5.00	-0.25
L3	50×3×7	87	93.60	9.64	91	94.70	107	-12.52	-1.16
L4	50×3×7	188	188.00	9.54	193	193.00	193	-2.59	-2.59
L5	50×4×10	66	72.50	11.20	39	73.30	78	-7.05	-1.09
L6	50×4×10	65	67.70	9.80	66	69.20	72	-5.97	-2.17
L7	70×2×5	162	165.30	12.26	162	165.30	173	-4.45	0.00
L8	70×2×5	197	197.00	12.30	207	207.00	207	-4.83	-4.83
L9	70×3×7	192	192.70	13.13	192	192.40	198	-2.68	0.16
L10	70×3×7	149	154.30	11.98	150	155.00	172	-10.29	-0.45
L11	70×4×10	103	106.00	14.05	104	107.40	115	-7.83	-1.30
L12	70×4×10	92	98.80	13.57	97	104.60	110	-10.18	-5.54
L13	90×3×7	140	141.00	15.26	140	142.60	150	-6.00	-1.12
L14	90×3×7	193	193.40	15.41	193	193.40	201	-3.78	0.00
L15	90×4×10	139	141.90	16.23	142	146.20	151	-6.03	-2.94
L16	90×4×10	143	150.80	14.97	144	151.20	157	-3.95	-0.26
L17	90×5×15	192	192.80	17.81	193	193.00	198	-2.63	-0.10
L18	90×5×15	123	125.50	16.65	121	125.40	133	-5.64	0.08
L19	110×3×7	225	257.10	18.24	257	258.20	269	-4.42	-0.43
L20	110×3×7	288	288.70	17.99	288	288.20	293	-1.47	0.17
L21	110×4×10	261	262.70	20.45	261	262.80	263	-0.11	-0.04
L22	110×4×10	154	162.00	20.42	163	171.70	178	-8.99	-5.65
L23	110×5×15	180	181.20	18.89	180	180.50	183	-0.98	0.39
L24	110×5×15	176	177.20	19.63	177	178.50	185	-4.22	-0.73

Notes. *f* denotes the maximize ship's waiting time in hours. *t* denotes the average computation time in seconds.

Table 7. Results of Statistical Test

Pair algorithm	Mean Difference	p-Value
GA-PSO	-1.95417	.004
GA-FCFS	-8.20417	<0.001

CONCLUSIONS

This paper has investigated MQ-BAP with multi-purpose berth and sequence-dependent setup time constraints. We develop metaheuristics based on the Genetic Algorithm approach to address the problem, which focuses on the minimizing of the maximum ship waiting time. Furthermore, three benchmark schemes, an exact approach (MIP), a current practice (FCFS) solution, and PSO have also been implemented for comparison purposes. The computational results of the proposed GA on two MQ-BAP groups are reported. A small problem group is for comparing solution obtained by GA with the optimal solution. A large problem group is for comparing the performance of GA with the PSO and current practice situation. The results show that our proposed algorithm has higher efficiency over PSO and FCFS by 1.38% and 5.61% respectively. Compared to MIP, our proposed GA provides a near-optimal solution by average 4.77% from the optimal at acceptable computation time. Hence, we conclude that our proposed GA is an efficient algorithm for near-optimal multiple quays berth allocation in very low computation time and shows a better performance than both PSO and FCFS considerably.

There are some works we will investigate in the future. We plan to extend the modeling to incorporate continuous berthing layouts and investigate the application of GA in solving the berth allocation problem combined with the related quay crane assignment problems. Finally, we plan to improve the performance of the proposed GA in solving the MQ-BAP by integrating with other metaheuristics such as PSO or adding a self-adaptation concept.

ACKNOWLEDGMENTS

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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