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A New Meta-Heuristic Approach to Solve the Hybrid Berth Allocation Problem

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Abstract: The Berth Allocation Problem (BAP) is one of the most important operational logistic problems encountered in a container terminal. It aims to assign vessels to berthing areas along the quay and it depends generally on two main factors the type of ships arrival (static or dynamic) and the type of berth space (discrete, continuous or hybrid). In this study, we addressed the problem in the dynamic hybrid case and we developed a recent meta-heuristic Based on the Bat-inspired Algorithm (BA) as a resolution approach. Finally, computational experiments and comparisons are realized to demonstrate the quality of our results.

Key words: Meta-heuristic, container terminal, berth allocation problem, bat-inspired algorithm, planning problems, demonstrate

INTRODUCTION

In the last decade, container terminals have acquired a great importance due to the exponential increase that the world merchant fleet has known. A container terminal is considered as a point of exchange and transshipment of a massive flow of containers. Therefore, the optimal management of port operations is considered as the basis of a container terminal efficiency. Indeed, to serve the arrived ships at the terminal, port operators must plan a series of operations which include the assignment of vessels to berths for their berthing, the quay cranes assignment which are in charge of loading/unloading containers, the allocation of yard trucks which transfer the containers from the quay area to the yard area. Finally, the storage area where containers are stored (Fig. 1).

In this study, we focused on the Berth Allocation Problem (BAP) in a container terminal which is the first critical decision to take by the operational planning service. It consists of planning an allocation of quay to a set of vessels in order to optimize a performance measure which often considered as the minimization of vessel's total stay time at a port. For the purpose of carry out this allocation, vessel-owners calling at a port have to transmit to operators of planning service a dataset concerning their vessels some days before their arrival at the port; namely the length and draft of the vessel, number of containers to be loaded/unloaded as well as the estimated arrival time. According to the previous publications, the BAP depends principally on the two following factors.

The type of berth space which can be resumed in three types (Fig. 2). Discrete where the wharf is divided into a specified number of berths. Continuous where the wharf is not divided; Therefore, the vessels can carry out the berthing conforming their need for space on the quay. Hybrid where the wharf is split in a discrete manner except that the big vessels can be positioned into two or three berths and small vessels can share a single berth. The type of vessel's arrival at the port which is defined in two types Static arrival, it onsiders that all vessels are in the port before starting the assignment. Dynamic arrival, it is necessary to schedule in the beginning of the planning the berthing of vessels that haven't arrived yet at the port. The primary objective of this study is to develop a new meta-heuristic based on the Bat-inspired Algorithm (BA) as an approach for solving the Berth Allocation Problem in the Dynamic and Hybrid case (DHBAP) with the objective of minimizing the staying cost for all vessels at the port. The rest of the study is organized as follows.

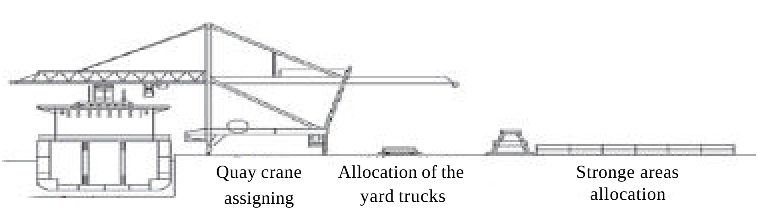

Fig. 1: Operations in container terminals

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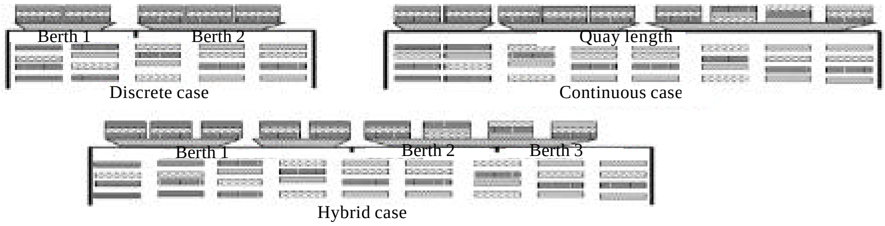

Fig. 2: Type of berth space

Literature review: In the literature, there are many works which have studied the BAP because of its complexity and its practical applicability. In the following, we present a large list of the main works on the Dynamic Berth Allocation Problem (DBAP). Imai *et al*. (2001) was the first, who introduce the dynamic discrete BAP (DDBAP) they solved the problem using a heuristic based on lagrangian relaxation method. The 2 years later Imai *et al*. (2003) improved their model considering different service priorities between ships they resolved the problem using a Genetic Algorithm (GA). Kim and Moon (2003) proposed a meta-heuristic based on Simulated Annealing (SA) method for solving the Dynamic Continuous BAP (DCBAP). By Cordeau *et al*. (2005), the researchers implemented a heuristic based on a tabu search for the DDBAP and DCBAP they assessed solution quality found with their heuristic by making a comparison with the exact solution found by CPLEX.

In a related study, Theofanis *et al*. (2007) studied the DDBAP and proposed a resolution approach based on Genetic Algorithm (GA) to minimize the total weighted service time of all ships. The DDBAP has been proposed as a multi-objective combinatorial optimization problem by Ieropetritou *et al*. (2009) where the service rendered to vessels is based on priority agreements and a GA is developed to solve the resulting problem. They presented also a plan for the berthing of vessels which minimizes delayed departures of ships and emissions from ships in standby mode.

Buhrkal *et al*. (2011) presented three differents mathematical programming models of the DDBAP and proposed a formulation of the problem as a Generalized Set Partition Problem (GSPP). For testing their formulation they used the instances from Cordeau *et al*. (2005) and obtained the optimal solutions using cplex. By De Oliveira *et al*. (2012) a meta-heuristic based on Clustering Search (CS-SA) with Simulated Annealing is presented as an alternative for solving the DDBAP which improves the results presented by Buhrkal *et al*. (2011) and Cordeau *et al*. (2005).

Furthermore, by Umang *et al*. (2013) the researchers used a set partitioning method and a heuristic method based on Squeaky Wheel Optimization (SWO) as a method of resolution of DDBAP in the context of bulk ports. Hu (2015) planned a bi-objective model that considers the preference to research within days with the objective of minimizing workloads late and workloads in the nights a multi-objective Genetic algorithm is developed to solve this model. A conceptual model of the vessel-berth allocation by proposed by Budipriyanto *et al*. (2015), given the variability of vessel arrival and the time of service. The objective of this model is the reduction of the total processing time and the improvement of resources utility (berth, quay crane and container yard).

Recently, Lin *et al*. (2018) developed two simulated annealing methods each one of them is based on different strategies to assign the incoming vessels to available berth along the quay. In this study researchers aim to minimize the total weighted service time and the deviation cost from vessel's preferred berth in a continuous terminal. To minimize the total service time for each vessel in a dynamic and discrete container terminal, a dynamic programming-based meta-heuristic is proposed by Nishi *et al*. (2016). In this research different comparison with others methods of the literature have been realized by the authors to show the performance of the proposed meta-heuristic.

MATERIALS AND METHODS

Model formulation: In this study, a mathematical model of DHBAP is presented. The proposed model is similar to that presented by imai *et al*. (2013) to address the BAP in a conventional terminal which is classified as a hybrid terminal. However, in our formulation, the objective function aims to minimize the staying cost for all vessels which is the sum of their waiting and handling cost. To formulate and adapt the model to a real-life container terminal we considered the following assumptions and notation:

- Length of each berth is 400 m
- The berth allocation ignores the FCFS rule
- The length of each vessel range from 200-400 (m)
- All berths have the same water depths

- The safety distance between moored vessels is included in the length of the vessel
- If a vessel is assigned to a location it will remain in that position until all cargo-handling operations are completed
- Two vessels can be served at the same berth simultaneously, if their total length does not exceed the overall berth length
- The vessel handling time depends on the assigned berth
- The planning horizon is 1 week

The sets:

- j (= 1, ..., T) V set of vessels
- k (= 1, ..., T)U set of service orders
- z (= 1, ..., P) Z set of storage yard

Parameters:

- A_j: Arrival time of vessel j
- BL_i: Length of berth i
- L_j: Length of vessel j
- S_i: Time when berth i becomes idle for the first time in the planning horizon
- q_{jz}: Number of container in vessel j assigned to storage yard z
- Q_j: Number of container in vessel j
- d_{iz}: Distance between berth i and storage yard z
- G_i: Number of quay crane assigned to berth i
- R: The estimated efficiency of each crane
- RT: The rate of container's transfer to the storage yard
- C_1: The waiting Cost per hour for each vessel
- C_2: The handling Cost per hour for each vessel
- H_{ij}: Handling time of vessel j at berth i
- M: A very large number

Regarding the handling time for each vessel which includes the time for loading/unloading containers and the time that take yard trucks to transfer containers towards the storage it has been determined according to the following rule:

$$H_{ij} = \left(Q_j \div \left(G_i * R\right)\right) + \sum_{z \in Z} q_{jz} * d_{iz} * RT \ \forall_i \in B,\ j \in V \quad (1)$$

where, the estimated efficiency of each crane (R) is supposed to be equal to 30 containers per h (according to the data of tangier's container terminal) and the rate of container's transfer to storage yard (RT) is 1/15000 h/m.

Decision variables:

- X_{ijk} = 1 if vessel j is handled as kth vessel at berth and 0, otherwise
- W_{ikk} = 1 if both the kth and kth vessel to be assigned are berthed simultaneously in berth i and 0, otherwise
- b_{ik} = beginning time of handling for kth vessel at berth i
- f_{ik} = Completion time of handling kth vessel at berth i
- WT_{ik} = Waiting time of kth vessel at berth i

Objective function:

$$\text{Minimize} \sum_{i \in B} \sum_{k \in U} C_1 * WT_{ik} + \sum_{i \in B} \sum_{j \in V} \sum_{k \in U} C_2 * H_{ij} * X_{ijk} \quad (2)$$

Subject to:

$$\sum_{i \in B} \sum_{k \in U} X_{ijk} = 1 \quad \forall j \in V \quad (3)$$

$$\sum_{j \in V} X_{ijk} \leq 1 \quad \forall i \in B,\ k \in U \quad (4)$$

$$b_{ik} \geq \sum_{j \in V} \left(\max\left(S_i - A_j\right) * X_{ijk}\right) \quad \forall i \in B,\ k \in U \quad (5)$$

$$f_{ik} = b_{ik} + \sum_{j \in V} H_{ij} * X_{ijk} \quad \forall i \in B,\ k \in U \quad (6)$$

$$b_{ik} \leq b_{ik'} \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (7)$$

$$f_{ik} \leq b_{ik'} + W_{ikk'} * M \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (8)$$

$$b_{ik'} \leq f_{ik} + \left(1 - W_{ikk'}\right) * M \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (9)$$

$$\sum_{j \in V} L_j * X_{ijk} + \sum_{j \in V} L_j * X_{ijk'} + \left(W_{ikk'} - 1\right) * M \leq BL_i \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (10)$$

$$WT_{ik} \leq b_{ik} - \sum_{j \in V} A_j * X_{ijk} \quad \forall i \in B,\ k \in U \quad (11)$$

$$\sum_{k' \in U} W_{ikk'} \leq 1 \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (12)$$

$$X_{ijk} \in \{0, 1\} \quad \forall i \in B,\ j \in V,\ k \in U \quad (13)$$

$$W_{ikk'} \in \{0, 1\} \quad \forall i \in B,\ k,\ k'(>k) \in U \quad (14)$$

$$b_{ik} \geq 0,\ f_{ik} \geq 0,\ WT_{ik} \geq 0 \quad \forall i \in B,\ k \in U \quad (15)$$

The objective Eq. 2 minimizes the total stay cost of vessels at the port. Equation 3 ensures that at any berth and any order of service a vessel must be served. Equation 4 enforces that at the same berth each vessel must be served at an order of service different note that, although, two vessels are simultaneously, at a berth their service orders must be different Eq. 5 determines the starting time of the handling of a vessel j. Equation 6 defines vessel departure time. Equation 7 ensures that if the service order of the vessel j' is greater than that of vessel j then the latter is served earlier than the vessel j'. Equation 8 and 9 guarantee that if two vessels are served simultaneously their services coincide in time. Equation 10 enables two vessels to be served at the same berth, if their total length is equal or less than the berth length. Equation 11 determines the waiting time for each vessel. Equation 12 ensures that the number of vessels served simultaneously to a specific berth does not exceed two. Equation 13-15 define the type of the decision variables (X_{ijk}, W_{ikk}', b_{ik}, f_{ik},).

Solution procedure by bat-inspired algorithm

Principe of the algorithm: By Yang (2010) developed a new meta-heuristic based on the echolocation behavior of bats to find and reach a prey. The general conduct of bats can be summarized as follows: a population of bats flies at a random with the aim of finding food without having any idea about its position. Nevertheless, they can emit calls out to the environment and listen to the echoes that bounce back from it to be able to calculate the distance that separates each one of them from the target.

General procedure of a bat-inspired algorithm: A bat inspired algorithm is based on these three steps.

Initialization: A bat population is initialized randomly to each bat a randomized velocity v_i is assigned, a frequency f_i and a position x_i. Moreover, pulse rates r_i and the loudness A_i are also initialized.

Position update and generation of new solutions: The movement of bats is realized by adjusting frequency f_i and updating velocity v_i. In this way each bat generates a new solution. The bat updates its frequency, velocity and position with the following Eq. 16-18.

$$f_i = f_{min}+(f_{max}-f_{min})*\beta \quad (16)$$

$$\upsilon_i^t = \upsilon_i^{t-1}+(x_i^{t-1}-x^*)*f \quad (17)$$

$$x_i^t = x_i^{t-1}+\upsilon_i^t \quad (18)$$

where f_i, v_i and x_i are the new bat frequency, velocity and position consecutively, β is a number generated randomly between 0 and 1, v_{it}-1 and x_{it}-1 are the current bat frequency and position consecutively. The variable x* represent the current global best solution while the values of fmin and fmax are pre-defined depending on the type of treated problem in our case we will use $f_{min} = 0$ and $f_{max} = 4$.

Table 1:Parameters of bat-inspired algorithm

Parameters	Values
Population size	60
Pulse rate r_i	0.3, r_i [0, 0.7]
Loudness A_i	0.8, A_i [0, 0.8]
Frequency f_{min}	0
Frequency f_{max}	4
γ	0.9
α	0.8
Max number of iterations	150

Updating of pulse rates r_i and the loudness A_i: A_i and r_i are updated by:

$$A_i^{t+1} = \alpha * A_i^t \quad (19)$$

$$r_i^{t+1} = r_i^0 * \left[1\text{-}\exp(-\gamma t)\right] \quad (20)$$

Algorithm 1: Pseudo-code of bat-inspired

Objective function f(x), x = (x1 , …, x d)
- Initialize the bat population xi = (I = 1, 2, 3, ..., n) and v_i
- Define pulse frequency f_i at x_i
- Initialize pulse rates r_i and the loudness A_i

While(t<Max number of iterations)
- Generate new solution by adjusting frequency and updating velocity and locations/solution [Eq. 16-18]
  If (rand >r_i)
    Select a solution among the best solution
    Generate a local solution around the selected best solution
  End if
- Generate a new solution by flying randomly
  If (rand < A_i and f(x_i) < f(x))
    Accept the new solution
    Increase r_i and reduce A_i [Eq. 19 and 20]
  End if
- Rank bats and find the current best x

End while

where, α, γ are constants. The pseudocode of the bat-inspired algorithm for the DHBAP is shown in Algorithm 1.

Parameters: In Table 1, we summarize the main parameters used to start our BA.

Solution representation: Figure 3 shows the representation of a feasible solution found by a bat for a DHBAP with nine vessels and three berth. For each vessel corresponds a real number contained in the interval [1, 4] whose integer part determines the berth of vessel and the fractional part determines the service order for each vessel in a given berth with respect to vessels assigned to the same berth. For example, the vessels {1,

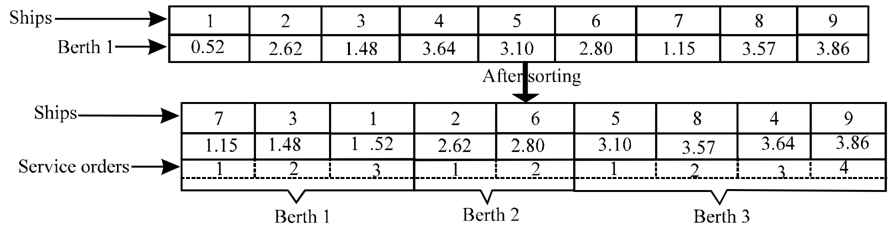

Fig. 3: Solution representation

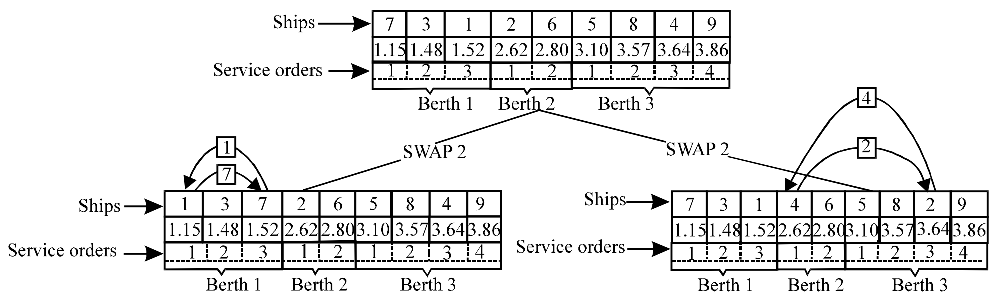

Fig. 4: Local solution: a) Swapping the service order between two vessels within a berth and b) Swapping the berth between two vessels

3, 7} are berthing in berth 1 and according to the sorting in an increasing order of the fractional parts the vessel 7 will be the first to be served followed by the vessel 3 and 1, the same for the other berth.

Correction of the solution: To limit the search only in the feasible solution space, we will proceed as follows. For example, in the solution presented in Fig. 3, if the value in a cell is <1, we will andomly generate a value in [1, 2] for the cell. If the value is >4 (number of berth +1), we will randomly generate a value in [1, 2] and subtract this from 4 (number of berth +1).

Generation of the local solution for BA: In order to generate a local solution according to the best solution found, two permutations are performed as shown in Fig. 4. The first permutation changes the service order of two vessels in the same berth as shown in (Fig. 4a). Whereas, the second changes the berth of two vessels selected randomly as shown in (Fig. 4b).

RESULTS AND DISCUSSION

Computatinal results: The proposed meta-heuristic was implemented with language C on Acer computer with an Intel core i3 (2.30 GHz) and 4 GB RAM. In order to test the performance of our method, we have realized two experiences called exampla 1 and 2. For the example 1, the values of costs C_1 and C_2 have been omitted from the mathematical model, i.e., both C_1 and C_2 are equal to 1 in addition all constraints which ensure the simultaneous service in the mathematical model presented in study 3 have been neglected. In this way, the resulting mathematical model is equivalent to a model for the popular DDBAP. Then, a comparison was carried out between the objective function value and the running time found with our approach and those found using other existing methods; Namely, Tabu Search (T2 S) by De Oliveira *et al.* (2012) and Generalized Set-Partitioning Problem mathematical Model (GSPP) by Imai *et al.* (2003). This comparison is based on the set I3 of the benchmarking instances used by De Oliveira *et al.* (2012) which include 30 instances with 60 vessels and 13 berths. Although, for the example 2, we use a realistic data which comes from Tangier Med port, considered as the biggest port in Africa in transshipment. A comparison was realized between our results and those got with FCFS (First Come First Serve) policy used regularly in the Tangier's container terminal, as well as, between that provided by CPLEX 12.7 (OPL Language) with a running time maximal of 2 h for each experiment. The instances used in example 2 are the same data size observed in the Tangier's container terminal for 7 days where the number ofberths is equal to 4 and the estimated number of arriving vessels at the port is equal to 60 vessels. We should note that in example 2 the value of costs C_1 and C_2 can be equal or different to 1.

Data generation for the example 2: As stated already in the previous section real problems instances were

Table 2 : Comparison of the results found with CPLEX, FCFS and BA

	T^2S	GSPP		BA	
Vessels*Berth	Objective values (h)	Objective values (h)	Time (sec)	Objective values (h)	Time (sec)
60*13 (1)	1415	1409	17.92	1410	15.42
60*13 (2)	1263	1261	15.77	1263	12.20
60*13 (3)	1139	1129	13.54	1132	10.23
60*13 (4)	1303	1302	14.48	1302	9.28
60*13 (5)	1208	1207	17.21	1207	12.92
60*13 (6)	1262	1261	13.85	1264	12.23
60*13 (7)	1279	1279	14.60	1281	13.21
60*13 (8)	1299	1299	14.21	1299	12.59
60*13 (9)	1444	1444	16.51	1446	12.36
60*13 (10)	1213	1213	14.16	1213	8.63
60*13 (11)	1378	1368	14.13	1368	11.59
60*13 (12)	1325	1325	15.60	1325	12.95
60*13 (13)	1360	1360	13.87	1362	12.98
60*13 (14)	1233	1233	15.60	1234	12.63
60*13 (15)	1295	1295	13.52	1298	12.39
60*13 (16)	1375	1364	13.68	1366	12.35
60*13 (17)	1283	1283	13.37	1287	10.10
60*13 (18)	1346	1345	13.51	1350	11.69
60*13 (19)	1370	1367	14.49	1369	12.98
60*13 (20)	1328	1328	16.64	1330	12.45
60*13 (21)	1346	1341	13.37	1341	11.33
60*13 (22)	1346	1341	13.37	1341	11.33
60*13 (23)	1266	1266	13.65	1266	12.69
60*13 (24)	1261	1260	15.58	1260	13.65
60*13 (25)	1379	1376	15.80	1376	12.54
60*13 (26)	1330	1318	15.38	1322	11.36
60*13 (27)	1261	1261	15.52	1266	14.36
60*13 (28)	1365	1359	16.22	1359	12.86
60*13 (29)	1282	1280	15.30	1283	12.65
60*13 (30)	1351	1344	16.52	1344	14.60
Average	1309.7	1306.8	14.98	1308.3	12.32

Table 3: Comparison of the results found with CPLEX, FCFS and BA

	CPLEX			FCFS	BA	
Vessel*Berth	Objective values	Running time (sec)	Gap[a] (%)	Objective values	Objective values	Running time (sec)
60*4 (1)	36985	7200	82.94	38421	27999	11.63
60*4 (2)	52222	7200	87.09	32274	22507	12.36
60*4 (3)	39675	7200	83.70	44147	29246	12.25
60*4 (4)	50062	7200	87.82	42673	30638	12.42
60*4 (5)	87266	7200	92.84	27332	18756	14.32
60*4 (6)	60501	7200	88.61	43374	30186	12.24
60*4 (7)	83289	7200	92.17	34319	23421	12.32
60*4 (8)	35040	7200	82.34	43815	29273	11.20
60*4 (9)	56883	7200	88.28	50521	34151	10.32
60*4 (10)	52246	7200	87.77	46965	31554	12.36
Average	50714.6	7200	87.35	40348.1	27773.1	12.14

Gap is calculated as (feasible solution value-lower bound)*100/lower bound

generated based on the traffic observed in the Tangier container terminal where the number of loaded and unloaded container is range from 16000 to 10000 while the number of cranes for each berth were generated between 2 and 5. The time (S_i) when a berth i becomes idle on the planning horizon was generated according to Budipriyanto *et al*. (2015) and De Oliveira *et al*. (2012) and considered the same for all berths. In order to simplify the calculations, the Costs C_1 and C_2 are supposed to be equal to 2 and 1, respectively. Finally, arrival times of vessels within the week period are randomly generated.

In the Table 2, the column 1 presents the size of the problem. The column 2 shows the value of the objective function found by T2 S while the latest two columns expose the objective function value and the running time found by GSPP and BA, respectively. According to the results presented in the Table 2, we can observe clearly that the proposed BA can improve all resultsfound by T2 S. While in comparison with the GSPP, BA is capable to obtain in 60% of the tested instances the same optimal solution found by GSPP and in 40% leftover, BA can obtain very near solution of the optimum. In other hand, our method overcome the GSPP in each instance tested in term of running time. Therefore, we can conclude that BA is a new good alternative of others methods of the literature to solve the BAP.

In Table 3, column 1 presents the size of the problem while columns 2-4 expose the bjective function value, the running time and the Gap, respectively, found by CPLEX. Column 5 contains the objective function value obtained with FCFS policy. Finally, column 6 and 7 contain the objective function value and running time, respectively, obtained by the BA. So, the results specified in the Table 3 illustrate that the function objective value found by CPLEX as well as the running time are much less reliable in comparison with those obtained with BA. Because of realistic and larger size instances, the CPLEX becomes very limited and unable to find an optimal solution during a running time maximal of 2 h. In addition, according to the table its obviously that HBAP Model gives the better results in comparison to FCFS policy.

CONCLUSION

In this research, a recent meta-heuristic based on bat-algorithm is developed as an alternative to solve the hybrid dynamic berth allocation problem. The comparison realized between our results, found by the at-inspired algorithm and others methods of the literature showed that our method is the interesting alternative for solving the BAP. In the future research on DHBAP, we will take into account the uncertainty of vessel's arrival and handling time. Furthermore, we will deal with the HBAP in other types of terminals as bulk terminals.

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