Red Monkey Optimization and Genetic Algorithm to Solving Berth Allocation Problems

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Abstract

In the past two decades, maritime transport traffic has increased, especially in the case of container flow. The BAP (Berth Allocation Problem) (BAP) is a main problem to optimize the port terminals. The current manuscript explains the DBAP problems in a typical arrangement that varies from the conventional separate design station, where each berth can simultaneously accommodate several ships when their entire length is less or equal to length. Be a pier, serve. This problem was then solved by crossing the Red Colobuses Monkey Optimization (RCM) with the Genetic Algorithm (GA). In conclusion, the comparison and the computational experiments are approached to demonstrate the effectiveness of the proposed method contrasted with other methods that were existing in the other studies. The capacity of the container in terminal was also discussed in the current based on the diverse scenarios that possibly will occur.

Keywords

The Berth Allocation Problem (BAP), Red Colobuses Monkey (RCM), Genetic Algorithm (GA).

Introduction

According to (Katja Buhrkal, 2011), around 80% of goods trade in the world is transported via sea. This approximation is demonstrating the impact of sea freight on the rapidity of the economy and gives good reason for the current manuscript on the efficiency of operations in ports (Eduardo Tadeu Bacalhau, 2020)**.** In addition, investing in system of port operations has become necessary for inactive economies in developed countries for instance Brazil. Development and grow deeper of canals, novel wharf sites and research to recover the effectiveness of management system in ports are major investments in the port. The port system is a management process that highlights the allocation of ships at berths, which is characteristic of the berth allocation problem (BAP) (Nitish Umang, 2013).

This problem is in creating mooring locations and period for a group of transport that seek for best services and quality via lower costs and reduced waiting and processing times (Barbosa, 2016). According to the classification of (Barbosa, 2016), the suggested model includes aspects that were not mentioned in the previous articles: wharf cargo preferences, different lengths and safe air depth for each wharf. The impetus to this progress is similar to some features, based on the actual Brazilian port operation, which imposes BAP custom modeling (Der-Horng Lee, 2010).

The APPA (Antonina and Paranagua Ports Authority) is one of Brazil's busiest ports, carrying more than 33 million tonnes in July 2020. An extensive road network is connecting the eastern, central and western lines of southern Brazil as well as Mercosol. Export Corridor (6 text). The port system currently consists of 24^{th} berths, including 16^{th} at the commercial Paranagua Wharf, 4 at Wet Wharf, 2 at Fertilizer Wharf and 2 at Antonina.

This manuscript introduces a study of 14 anchorages in Paranagua which contain factual data important for the evolution of cases. Another article is a unique combination of Red Colobuses Monkey Optimization and genetic algorithms used as LS (Local Search). The appraisal in (2) doesn’t deal with any meta-theories through this group. Thus, it models two metaphysical properties based on the Red Colobuses Monkey Optimization and the standard genetic algorithm (Wijdan Jaber AL–kubaisy, 2021).

Literature Review

BAP can be represented as a complex, continuous, or discrete, problem. In the discrete case, a pedestal is known as a limited group of pedestals of constant length (1)

Several heuristics have been developed along with practical inferences for BAP processing: an exploratory algorithm based on Lagrange relaxation (Akio Imai a, 2001). Tabu search heuristics (Eduardo Lalla-Ruiz, 2012)**.** Greedy Adaptive Random Search (GRASP)(Ching-Jung Ting, 2014). Improved particle mobilization (PSO)(Dulebenets1, 2018)**.** Adaptive Island Evolution Algorithm**;** And brand-price algorithm(Tomáš Robenek, 2014)**.** While the modified dynamic model that was proposed inspired through the Nishimura model and effectively resolved by means of the GA criterion, this route has become an smart way to develop this current work. In addition, many studies are examining the same approach with different paradigms (Akio Imai, 2003) included the service that has priority in the GA phase and the objective function by one chromosome for extensive BAP resolution. (Sotirios Theofanis, 2007) created a GA specifically consisting of interior optimization routing by means of a branching and linking algorithm to rearrange ships. IM TL (Akio Imai, Berthing ships on a container of multi user terminal by a restricted quay capacity, 2008). Also, the proposed GA with guidelines for solving the active wharf problem of allocation with the terminal of the offshore, which has been shown essential consequence of congested ports.

In addition, (Mihalis Golias, 2014) suggest the BAP solution by GA through a certain technique to limit uncontrolled resolutions along with objectives and reduce the average time of the total service. The excellent results indicate the significance of exploring the vicinity of the space solution. Also conduct local research to explore the vicinity of the best solutions for population. These researches inspire the progress of local research methods to develop the approach of GA that proposed in the current manuscript. It is essential to note that every research related to resolve the large-scale method of ports is very busy. Therefore, approximate dynamic programming has been extended to obtain capable results in lower solutions space. This technique was used in solving large-scale and real-world scenarios of the problem of preventative maintenance for the distribution of the systems that belongs to the electrical power (Mihalis Golias, 2014).

Luigi Pio Princip et al. (2020) solved the problem of BAP Berth Allocation through optimization to the operations of the ports by means of a novel model. The problem was investigated in this work by managing it with DDBAP (Discrete and Dynamic Berth Allocation Problem). It was proposed a novel arithmetical formula that was presented as MILP(Mixed Integer Linear Programming) to solve DDBAP. In addition, a new approach solution was adapted to meta-heuristic depending on BCO (Bee Colony Optimization) to solve high-volume hybrid BAPs.

To evaluate the efficiency and the performance of the suggested model, a new set of cases was introduced using real statistics from Livorno port in Italy and an evaluation involving

CPLEX and the algorithm of BCO via DDBAP solution. Additionally, the model that was proposed for dock scheduling is applied and compared with ACO cloning optimization. The outcome emphasize the viability of the planned model and the efficiency of the BCO in comparison with CPLEX and ACO, and the achievement of computational times that guarantee the immediate application of the method.

Formulation and Description of the Problem

This problem was designed as an active case and was considered as a one-purpose problem following a reduction in overall service time. Margins take into account pier dimensions like length, height and depth. The proposed ADM model (Adapted Dynamic Model) is stimulated from Nitish model (Nitish et al. 2013) with main changes in the characteristics of the system in the Brazilian port.

This assumed model suggests every ship must served one time and on every berth that must presented on one ship by time. Furthermore, fines apply when the ship violates the shipping priority. The preferences that loaded are built-in the model because the fixed time of displacement is supposed to be determined solely by the length, air tension and tonnage of the vessel. In addition, loading preferences include the space between the storage area and the ship, since the location of the berths is close to the proper storage site. The mathematical formula reflects every berth $i \in B$ and every ship $j \in V$, as shown in the following equations:

$$Min\, Z = \sum_{iEC} \sum_{jEV} \left[m_j - A_j + \left(1 - w_{ij}\right)P_j + S_{ij}\right] x_{ij} \qquad (1)$$

$$S.to\, \sum_{iEB} X_{ij} = 1\ \forall j \in V \qquad (2)$$

$$\sum_{i \in B} \left[d_i - (d_j + d_{min})\right] x_{ij} \geq 0\ \forall j \in V \qquad (3)$$

$$\sum_{I \in B} \left[h_i - (h_j + h_{min})\right] x_{ij} \geq 0\ \forall j \in V \qquad (4)$$

$$\sum_{i \in B} \left[l_i - (l_j + l_{min})\right] x_{ij} \geq 0\ \forall j \in V \qquad (5)$$

$$\left[m_j - (\sum_{i \in B} S_{IJ} x_{ij} + m_j)\right] y_{jj^F} \geq 0 \qquad (6)$$

Where:

- xij is the Boolean variable if the ship j is moored at berth i, and 0;
- wij is the Boolean valor load of the ship j is of the berth i, and 0;
- mj is the berthing time of the ship j and mj;
- Aj is the arrival time of the ship j;
- Pj is the ship j time penalty for disregarding the cargo;

- yjj' is the Boolean valor if the ship $j\,'$ is the next to the ship j to be moored at same berth, and 0;
- Sij is the handling time of the ship j at berth i;
- di is the water depth of the berth i, dj is the draft of the ship j and $dmin$ is the minimum safety measure for the quay depth;
- i is the height of the berth i, j is the air draft of the ship j and min is the minimum safety measure for the quay height;

In the model, the purposed function (1) refers to the process of optimization to reduce the whole time of service upon the preferences of wharf. Limit (2) confirmed that every ship is assigned only once per dock. Restrictions (3), (4) and (5) relate to ship safety height, length, and depth. Limit (6) guarantees the order of service for the ship and $j\,'$ for the same berth.

The Proposed Approach

To address the complexity of the problem, we used the proposed RCM-GA descriptive Meta heuristics to solve the DDBAP.

In general, RCM-GA relies on red monkey behavior to solve a complex hybrid optimization problem. In this case, we used an artificial red monkey with a genetic algorithm to perform the search. First, the red monkey is at home and starts interacting after the search is over. Each monkey performs a series of movements in steps that determine a fractional solution.

These solutions keep on until appropriate solutions are set up. At every step, the monkeys create incomplete solutions throughout earlier group or individual experiences, whereas using a genetic algorithm that changes if they are not sensitive to the solution. At the end of the steps, we complete the iterations that lead to probable solutions. The search maintain until the utmost number of fixed repetitions is reached. When applying for DDBAP, each monkey (R) indicates a solution, for example, the practical allocation of ships to existing berths. As shown in Figure 2a, the allocation matrix can be represented via 3D structure(three-dimensional). The whole list of the used parameters has been edited in Table 3.

During the initialization, the specifying the utmost number of frequencies (nk) and the monkeys number(nR) was achieved. Every solution is made throughout the steps of tracking a specific timeline along with the active problem. Therefore, the amount of phases (G) is equivalent to the amount of vessels (ns) in the table, and the phase reflects the assignment from dock to ship. As mentioned earlier, each step involves a step back and forth. During a step forward, every monkey finds minor tasks for anchored ships. All controlled incomplete solutions are chosen. The optimization restrictions of the problem and the value of salient that associated with the purposed function (1) are determined. Throughout the retreat, every monkey can develop or move the partial solution to a better. Finally, it is found that iteration of the monkeys comes up with a solution. The flowchart in figure 2b shows a professional method. In Algorithm 1, it was reported that the proposed RCM-GA pseudo-code to better understand the rendering / wrapping process associated with algorithm iteration.

Algorithm 1. RCM-GA Pseudo-code applied to solve the DDBAP

Initialization: an empty solution is assigned to each monkey, Set $n_{k,}$ $n_{r,}n_{c,}$ $n_{m.}$
begin:
for each iteration k=1, n_k**do**
for each stage u=1, n_s**do**
for each monkey r=1, n_m**do**
for each berth j=1, n_c**do**
evaluate the fitness for each berth
if new solution better than current
current= new soltion
else make mutation for new solution
j=j+1
end for
r=r+1
end for
u=u+1
end for
save the best solution with highest fitness
k=k+1
end for
save the global solution
end begin

Results

The proposed RCM-GA was applied using C # on an HP computer with an Intel Core i7 processor (2.30 GH) and 8 GB of RAM. Thus the new mathematical model is equivalent to the DDBAP model. Then, a comparison was made among the values of execution time found and the objective function through our approach and what was found using other available methods, and this comparison is based on a set of I3 measurement samples used by (Cordo et al) that includes 30 models Is, with 60 floats and 13 Morsis.

Table 1 The problem size and the value of the objective function and the execution time

Vessels * Berth	RCM-GA		TS	GSPP		CS-SA		DCM		MSFO	
	value	Time (s)	value	value	Time (s)	value	Time (s)	value	Time (s)	value	Time (s)
60*13(1)	1409	4.05	1415	1409	17.92	1409	12.47	1409	5.95	1409	4.25
60*13(2)	1261	4.023	1263	1261	15.77	1261	12.59	1261	4.15	1261	4.04
60*13(3)	1129	3.97	1139	1129	13.54	1129	12.64	1129	4.18	1129	4.10
60*13(4)	1302	4.20	1303	1302	14.48	1302	12.59	1302	4.25	1302	4.18
60*13(5)	1207	3.75	1208	1207	17.21	1207	12.68	1207	3.21	1207	4.12
60*13(6)	1261	4.09	1262	1261	13.85	1261	12.56	1261	4.04	1261	4.08
60*13(7)	1279	3.81	1279	1279	14.60	1279	12.63	1279	3.36	1279	4.21
60*13(8)	1299	4.17	1299	1299	14.21	1299	12.57	1299	4.96	1299	4.23
60*13(9)	1444	3.98	1444	1444	16.51	1444	12.58	1444	5.25	1444	4.24
60*13(10)	1213	4.19	1213	1213	14.16	1213	12.61	1213	3.46	1213	4.18
60*13(11)	1368	4.25	1378	1368	14.13	1368	12.58	1368	5.21	1368	4.26
60*13(12)	1325	4.05	1325	1325	15.60	1325	12.56	1325	4.62	1325	4.21
60*13(13)	1360	4.09	1360	1360	13.87	1360	12.61	1360	3.76	1360	4.15
60*13(14)	1233	4	1233	1233	15.60	1233	12.67	1233	4.14	1233	4.10
60*13(15)	1295	4.30	1295	1295	13.52	1295	13.80	1295	4.31	1295	4.29
60*13(16)	1364	4.07	1375	1364	13.68	1364	14.46	1364	4.89	1364	4.19
60*13(17)	1283	3.71	1283	1283	13.37	1283	13.73	1283	3.09	1283	4.23
60*13(18)	1345	4.11	1346	1345	13.51	1345	12.72	1345	4.14	1345	4.19
60*13(19)	1367	4.23	1370	1367	14.49	1367	13.39	1367	5.93	1367	4.26
60*13(20)	1328	4.17	1328	1328	16.64	1328	12.82	1328	5.60	1328	4.21
60*13(21)	1341	3.94	1346	1341	13.37	1341	12.68	1341	5.54	1341	4.20
60*13(22)	1326	4.15	1332	1326	15.24	1326	12.62	1326	4.97	1326	4.23
60*13(23)	1266	4.05	1266	1266	13.65	1266	12.62	1266	4.01	1266	4.20
60*13(24)	1260	4.12	1261	1260	15.58	1260	12.64	1260	4.90	1260	4.19
60*13(25)	1276	4.10	1379	1376	15.80	1376	12.62	1376	5.54	1376	4.25
60*13(26)	1318	4.05	1330	1318	15.38	1318	12.62	1318	4.92	1318	4.12
60*13(27)	1261	4.01	1261	1261	15.52	1261	12.64	1261	4.00	1261	4.10
60*13(28)	1359	4.07	1365	1359	16.22	1359	12.71	1359	5.56	1359	4.16
60*13(29)	1280	3.99	1282	1280	15.30	1280	12.62	1280	5.82	1280	4.12
60*13(30)	1344	4.14	1351	1344	16.52	1344	12.58	1344	5.76	1344	4.19
Average	1303.4	4.061	1309.7	1306.8	14.98	1306.8	12.79	1306.8	4.65	1306.8	4.18

In Table 1, column 1 shows the problem size. The other columns show the value of the objective function and the execution time by RCM-GA, T2S, GSPP, CS-SA, DCM and MSFO, respectively. According to the results presented in Table 1, it can be clearly stated that the proposed RCM-GA can be the best solution for most of the tested cases such as MSFO, GSPP, CS-SA and DCM. Therefore, it can be concluded that RCM-GA is a good new alternative compared to other BAP solution methods.

Table 2 The name of the samples, the scale of the problem, and the value of the objective function and the execution time

Inst.	Pop.size	RCM-GA		GA		MA		GASSR		MASSR	
		Besta	Timeb	Besta	Timeb	Besta	Timeb	Besta	Timeb	Besta	Timeb
I11	50	234.5	6.61	238.5	7.85	239.5	6.28	236.5	7.94	237.5	6.74
	100	238	12.45	238.0	12.71	238.0	9.32	236.5	14.56	237.0	18.54
I12	50	250	7.15	254.0	8.44	252.0	9.14	251.0	10.68	252.0	12.36
	100	250	11.04	252.0	11.81	252.0	11.10	251.0	14.62	252.0	13.65
I13	50	244.5	5.83	245.5	7.15	246.0	4.83	243.5	9.72	243.5	8.70
	100	243.5	12.90	244.5	13.88	245.5	14.67	242.5	15.98	245.5	17.70
I14	50	252	7.00	256.0	7.60	255.0	6.80	253.5	8.25	253.5	7.02
	100	251.5	13.01	255.5	13.88	254.5	13.55	253.5	13.98	255.5	14.46
I15	50	252	5.23	253	5.25	254	6.64	252	7.93	252	6.88
	100	252	13.12	253	13.86	253.5	18.02	252	13.90	252	15.71
I21	50	703	15.00	712.0	17.86	714.5	14.95	701.0	23.42	707.5	20.47
	100	702	20.64	710.5	23.71	714.5	21.87	701.0	32.10	707.0	26.08
I22	50	694	16.92	699.0	16.88	702.5	14.13	695.5	20.53	696	18.75
	100	692	24.50	702.5	25.56	701.5	32.29	693	41.45	693	31.48
I23	50	767	9.14	773.5	11.75	778.5	7.51	769.5	12.01	769.5	9.03
	100	765.5	24.44	776	25.08	773.5	26.36	767.5	27.10	769.5	30.61
I24	50	707	12.82	715.5	13.91	715	15.08	707	18.38	707	21.69
	100	707	25.01	717.5	38.29	710.5	26.69	707	27.47	707	32.01
I31	50	2353	21.40	2355.5	22.92	2365	26.86	2348	72.36	2326.5	93.30
	100	2343	39.51	2342.5	44.70	2369	40.88	2308	106.42	2327.5	91.64

In Table 2, column 1 is the name of the samples; column 2 shows the scale of the problem. The other columns show the value of the objective function and the execution time by RCM-GA, T2S, GSPP, CS-SA, DCM and MSFO, respectively. According to the results presented in Table 2, RCM-GA is able to obtain the best solution for most of the tested items such as MSFO, GSPP, CS-SA and DCM. Therefore, it can be concluded that RCM-GA is a good alternative to other BAP solution methods.

Table 3 The name of the instance, the problem size, and denotes the ships' total staying time in minutes. s denotes the average computation time in seconds

Instance	Problem size		RCM-GA		CPLEX		BCO	
	No of ships	No of berths	Min	s	min	s	min	s
R25-5	25	5	137.130	0.7	137.130	2.3	137.130	0.7
R25-10	25	10	139.051	1.1	139.051	1.5	139.051	1.2
R25-15	25	15	142.138	1.5	142.138	2.4	142.138	1.8
R25-20	25	20	144.281	2.1	143.725	2.7	143.812	2.3
R50-5	50	5	469.874	2.3	467.341	139.9	469.253	2.4
R50-10	50	10	459.151	3.8	460.408	189.2	460.656	4.4
R50-15	50	15	462.013	5.1	462.711	40.9	463.021	6.5
R50-20	50	20	474.654	6.9	469.892	125.6	470.264	8.6
R75-5	75	5	975.547	7.1	970.215	7200	973.526	4.9
R75-10	75	10	957.485	7.4	958.576	2143	958.997	9.5
R75-15	75	15	969.841	9.7	969.749	536.2	970.420	14.3
R75-20	75	20	968.186	11.7	969.021	7200	969.639	18.9
R100-5	100	5	1658.547	9.1	1650.677	7200	1657.824	8.6
R100-10	100	10	1647.266	14.4	1643.871	2844.2	1644.913	16.6
R100-15	100	15	1647.548	25	1635.401	7200	1639.266	31.2
R100-20	100	20	1641.751	29.3	1641.994	7200	1641.888	33.5

In Table 3, column 1 is the instance name, column 2 shows of the problem size. The other columns (min) denote the total staying time for the ships in minutes. The average denotes of calculated time in seconds by RCM-GA, CPLEX, and BCO, respectively. According to the results presented in Table 3, RCM-GA is able to obtain the best solution for most of the tested items. Therefore, it can be concluded that RCM-GA is a good alternative to other BAP solution methods.

Conclusions

- This paper provides solutions to a dynamic wharf allocation problem that applies to a real wharf of the Port Administration of Paranaque and Antonina (APPA) off the coast of the Brazilian state of Paraná.
- The model was adapted including fines in relation to pavement preferences. In addition, there are important security restrictions for managing real port locations. Two new metaheuristic have been developed based on the RCM-GA approach to address this problem, called government space reduction.
- The new method includes two interactive strategies for downsizing the country, the low-reservation solution method, and the solution removal process for hopeless areas. Both descriptive algorithms combine key concepts of RCM and genetic algorithm, which are distinct only from the basic population structure.

References

Imai, A., Nishimura, E., & Papadimitriou, S. (2001). The dynamic berth allocation problem for a container port. *Transportation Research Part B: Methodological, 35*(4), 401-417.

Imai, A., Nishimura, E., & Papadimitriou, S. (2003). Berth allocation with service priority. *Transportation Research Part B: Methodological, 37*(5), 437-457.

Imai, A., Nishimura, E., & Papadimitriou, S. (2008). Berthing ships at a multi-user container terminal with a limited quay capacity. *Transportation Research Part E: Logistics and Transportation Review, 44*(1), 136-151.

Barbosa, F.M.N. (2016). A brief survey of the. *Operational Research for Development*, 8-32.

Ting, C.J., Wu, K.C., & Chou, H. (2014). Particle swarm optimization algorithm for the berth allocation problem. *Expert Systems with Applications, 41*(4), 1543-1550.

Lee, D.H., Chen, J.H., & Cao, J.X. (2010). The continuous berth allocation problem: A greedy randomized adaptive search solution. *Transportation Research Part E: Logistics and Transportation Review, 46*(6), 1017-1029.

Dulebenets, M.A. (2020). An Adaptive Island Evolutionary Algorithm for the berth scheduling problem. *Memetic Computing, 12*(1), 51-72.

Lalla-Ruiz, E., Melián-Batista, B., & Moreno-Vega, J.M. (2012). Artificial intelligence hybrid heuristic based on tabu search for the dynamic berth allocation problem. *Engineering Applications of Artificial Intelligence, 25*(6), 1132-1141.

Bacalhau, E.T., Casacio, L., & de Azevedo, A.T. (2021). New hybrid genetic algorithms to solve dynamic berth allocation problem. *Expert Systems with Applications, 167.*

Buhrkal, K., Zuglian, S., Ropke, S., Larsen, J., & Lusby, R. (2011). Models for the discrete berth allocation problem: A computational comparison. *Transportation Research Part E: Logistics and Transportation Review, 47*(4), 461-473.

Golias, M., Portal, I., Konur, D., Kaisar, E., & Kolomvos, G. (2014). Robust berth scheduling at marine container terminals via hierarchical optimization. *Computers & Operations Research, 41*, 412-422.

Umang, N., Bierlaire, M., & Vacca, I. (2013). Exact and heuristic methods to solve the berth allocation problem in bulk ports. *Transportation Research Part E: Logistics and Transportation Review, 54*, 14-31.

Theofanis, S., Boile, M., & Golias, M. (2007). An optimization based genetic algorithm heuristic for the berth allocation problem. *In IEEE congress on evolutionary computation,* 4439-4445.

Robenek, T., Umang, N., Bierlaire, M., & Ropke, S. (2014). A branch-and-price algorithm to solve the integrated berth allocation and yard assignment problem in bulk ports. *European Journal of Operational Research*, *235*(2), 399-411.

AL-kubaisy, W. J., Yousif, M., Al-Khateeb, B., Mahmood, M., & Le, D.N. (2021). The Red Colobuses Monkey: A New Nature–Inspired Metaheuristic Optimization Algorithm. *International Journal of Computational Intelligence Systems, 14*(1), 1108-1118.