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ORIGINAL ARTICLE

A heuristics-based solution to the continuous berth allocation and crane assignment problem

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Abstract Effective utilization plans for various resources at a container terminal are essential to reducing the turnaround time of cargo vessels. Among the scarcest resources are the berth and its associated cranes. Thus, two important optimization problems arise, which are the berth allocation and quay crane assignment problems. The berth allocation problem deals with the generation of a berth plan, which determines where and when a ship has to berth alongside the quay. The quay crane assignment problem addresses the problem of determining how many and which quay crane(s) will serve each vessel. In this paper, an integrated heuristics-based solution methodology is proposed that tackles both problems simultaneously. The preliminary experimental results show that the proposed approach yields high quality solutions to such an NP-hard problem in a reasonable computational time suggesting its suitability for practical use.

1. Introduction

Since the introduction of standardized containers in freight transport in the 1960s, its use has been in continuous growth, especially with the enormous growth in world trade in the past 20 years. This growth in container transport led to increased service demands at container terminals who now have to serve tens of vessels per day, load and unload thousands of containers per day, and they have to do so in a timely manner in order to reduce the time that ships have to spend at the terminal and thus gaining a competitive advantage over its neighboring ports in the region. This competitive advantage would help the terminal increase its customers and thus its profit.

Container terminals use a large variety of resources and equipment to serve incoming vessels. Berth and Quay Cranes (QCs) are the scarcest and most expensive resources for container terminals because of the large investment needed to increase the capacity of any of these two resources, if the expansion of these two resources is physically feasible in the first place. Consequently, achieving maximum utilization for these two resources through better planning is critical to

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achieve the overall maximum productivity for the whole terminal.

Two important planning problems thus arise, which are the Berth Allocation Problem (BAP) and the Quay Crane Assignment Problem (QCAP). In the former, a berthing time and a berthing position at the quay for each vessel to be served within a given planning horizon are determined. In the latter, a set of specific cranes is assigned to serve each vessel. The strong interrelationship between the utilization of the quay space resource and the quay cranes motivates an integrated solution approach to the two problems. The driving force of this approach is to anticipate vessel handling times on the basis of crane assignment and crane scheduling decisions. These specified handling times are used within the berth planning step to decide on the berthing times and berthing positions of vessels. The resulting problem is referred to as the Berth Allocation and Crane Assignment Problem (BACAP).

Although many studies considered berths as discrete resources that can be allocated to vessels, some studies have considered the quay as a continuous line that multiple vessels can share with each other at the same time. Thus, when the quay is considered as a continuous line, more vessels can be served simultaneously at a quay of a particular length – of course, if the vessels are shorter in length than the quayside [1–4].

There are many different types of constraints that must be considered when determining the berthing positions of vessels. Examples include the depth of water along the quay and the maximum outreach of QCs installed at specific positions on the quay. If the depth of the water of a part of the quay is not enough, or the outreach of QCs installed at a part of the quay is shorter than that necessary, the corresponding vessel cannot be assigned to that part of the quay.

Temporal constraints can restrict the berthing times and the departure times of vessels. According to Frank Meisel [5], the following cases could be distinguished: static arrivals and dynamic arrivals. In the former case, there are no arrival times given for the vessels and it is assumed that vessels already wait at the port and can berth immediately. In the case of dynamic arrivals, either fixed arrival times are given for the vessels and they cannot berth before the expected arrival time, or arrival times impose merely a soft constraint on the berthing times and it is assumed that a vessel can speed up at a certain cost in order to meet a berthing time earlier than the expected arrival time.

In this paper, the problem of allocating vessels with dynamic arrivals to a continuous quay is considered – which is a more challenging problem compared to the discrete variant of the problem. Moreover, variable water depth constraints have been accounted for. A heuristics-based approach is proposed to solve the BACAP.

The rest of this paper is organized as follows. In the next section, a literature review on the berth allocation and crane assignment problems is presented. Section 3 includes the detailed problem definition and the related assumptions. In Section 4, the proposed solution technique is described. The results of implementing our solution strategy to a set of benchmark instances are shown in Section 5. Section 6 discusses an interesting special case, which is referred to as a tightly packed problem, and proposes a methodology to handle it. Finally, Section 7 concludes the paper.

2. Related work

In literature, mathematical formulations have been developed to model the berth allocation and quay crane assignment problems. In general, the resulting models are mixed integer programming formulations and thus, cannot be solved for instances of practical size. Hence, heuristic solution methods have been tailored to handle such problems. In what follows, light is shed on some of these methods.

A genetic algorithm has been applied in [6] to solve the berth allocation problem with dynamic arrivals and discrete berths that can be shared by more than one vessel. The objective is to minimize the total time spent at the CT which includes the ship handling (or service time) and the waiting time for berth availability. Moreover, it has been assumed that the service time is dependent on the berth where a vessel is assigned. Furthermore, variable water depth constraints have been incorporated in the developed mathematical model.

Park and Kim developed a mathematical formulation for the continuous BACAP with dynamic arrivals [7]. They proposed a two phase solution procedure for their formulation. In the first phase, the berthing times and positions as well as the number of cranes assigned to a vessel during its service are determined. In this phase, a Lagrangian relaxation of the problem is solved using a sub-gradient optimization technique where the problem is decomposed into several independent sub-problems. This step may yield infeasible berth plans. Therefore, a heuristic has been proposed to transform infeasible solutions into feasible ones. In the second phase, the specific set of cranes assigned to each vessel is determined using dynamic programming.

Kim and Moon considered the BAP with dynamic arrivals [8]. They proposed a heuristic solution strategy that inserts vessels in the space–time diagram according to a given priority list. Vessels at the top of the list are more likely to be moored close to their desired berthing positions. Simulated annealing is then used to explore the space of priority lists in order to search for improvements in the objective function value. The objective function included terms penalizing non-optimal berthing locations and delayed departures of vessels.

Meisel and Bierwirth in [9] have explicitly incorporated the impact of the quay crane resources as a determinant of the handling time. Factors influencing the crane productivity have been modeled as well as practical aspects of the problem like speeding up vessels and considering the cost of operating cranes besides the traditional service quality cost. Moreover, they considered dynamic arrivals of vessels. For the resulting dynamic continuous BACAP, new heuristics have been presented to solve this problem again according to a given priority list. They considered an initial priority list in which vessels are sorted in ascending order according to their expected time of arrival; that is, on a FCFS basis. They also suggested the use of meta-heuristics; namely, Squeaky Wheel Optimization (SWO) and Tabu Search (TS) to improve the results initially obtained based on their proposed heuristics. Computational comparisons showed that both SWO and TS deliver solutions of good quality in a reasonable computational time. In this paper, their interesting work is extended by considering an alternative initial priority list and by incorporating water depth constraints into our model.

3. Problem definition and related assumptions

In this section, various aspects of the problem addressed in this paper are discussed in detail.

3.1. Basic assumptions

The following assumptions are made for the continuous BACAP with dynamic arrivals dealt with in this paper:

1. It takes no time to berth and to unberth vessels.
2. It takes no time to move a QC from one vessel to another vessel.
3. Vessels are served without preemption, i.e., once started to serve a vessel the process is not interrupted until the service is completed.
4. Every crane has the technical capability to serve any vessel. Furthermore, the cranes are identical, i.e., they show the same maximum productivity.
5. The water depth is not fixed for all berthing positions and hence special consideration is given to respecting the required draft associated with each incoming vessel.
6. All input parameters (such as unloading time) and decision variables (such as the berthing time) are deterministic.

3.2. Input parameters

A terminal with a quay of length L, measured in segments of 10 m length, is considered. The water depth alongside the quay is provided for each segment. A number of Q QCs are available to serve the vessels. The planning horizon of the BACAP is H hours, where T is a corresponding set of 1-h time periods; i.e., $T = \{0, 1, \ldots, H-1\}$. Within the planning horizon, a set of vessels $V = \{1, 2, \ldots, n\}$ is projected to be served, where n is the total number of vessels.

For each vessel i, its length l_i measured in segments of 10 m length is given. The crane capacity demand of vessel i to fulfill all loading and unloading operations is m_i QC-hours. The minimum and maximum number of QCs to assign to the vessel are denoted by $r_i^{\min}$ and $r_i^{\max}$, yielding the range $R_i = [r_i^{\min}, r_i^{\max}]$. Furthermore, an expected time of arrival ETA_i is known. Berthing the vessel earlier than ETA_i is possible by a speedup on its journey to the terminal. The realizable speedup, however, is limited. To model this, an earliest starting time $EST_i \leqslant ETA_i$ is estimated; i.e., the vessel cannot be berthed earlier than EST_i. Finally, an expected finishing time EFT_i and a latest finishing time LFT_i are given for the vessel. Import and export containers of a vessel are stored in dedicated yard areas. A desired berthing position b_i^0 is specified for vessel i within the vicinity of these yard areas. In addition, the vessel draft D_i is provided so that the choice of a berthing position must be made such that the quay shows a sufficient water depth along the vessel's length.

3.3. Decision variables

The decisions to be made to derive a solution of the BACAP are to determine for each vessel i: a berthing time s_i, a berthing position b_i, and the number of QCs to assign to it during each of its service time-slots such that a cost measure is minimized. The berthing time s_i of a vessel is marked by the beginning of the first time-slot with cranes assigned, whereas its departure time e_i is defined by the end of the last time-slot with cranes assigned. The time span between s_i and e_i defines the handling time of vessel i. The assignment of cranes to vessels is represented by a binary decision variable r_{itq}. It is set to 1, if and only if exactly q QCs are assigned to vessel i during time-slot t. To evaluate a solution to the BACAP, the deviation from the desired berthing position $\Delta b_i = |b_i^0 - b_i|$, the necessary speedup $\Delta ETA_i = (ETA_i - s_i)^+$, and the tardiness $\Delta EFT_i = (e_i - EFT_i)^+$ are determined for each vessel i, where $x^+ = \max\{0, x\}$. In Fig. 1, an example of a complete berth plan with quay crane assignment is shown. Each rectangle represents the region occupied in the time–space domain by some vessel i, where the lower left corner corresponds to the obtained optimal pair of berthing time and berthing position (s_i^*, b_i^*).

3.4. Objective function

The same objective function employed by Meisel and Bierwirth in [9] is adopted in this paper, which incorporates both service quality costs and operational costs. It is the sum of the costs arising from four factors:

1. Assigning a vessel a berthing time earlier than its expected time of arrival adds a cost for speeding up the vessel due to excess in fuel consumption (c_i^1 per unit time).
2. Tardiness cost incurred for exceeding the expected finishing time (c_i^2 per unit time).
3. Being unable to finish serving a vessel before its latest finishing time incurs a penalty (c_i^3).
4. The cost of the required QC-hours for serving the incoming vessel, which is the operational cost term (c^4 per QC-hour).

3.5. Productivity of quay resources

The rail mounted QCs in a container terminal are unable to pass each other. As a consequence interference among QCs can be modeled in the form of unproductive crane waiting time. In general, the more cranes are assigned to a vessel the more interference will take place leading to reduced marginal productivity of cranes. According to Schonfeld and Sharafeldien, an *interference exponent* can be used to model the reduction in marginal productivity of cranes [10]. For a given interference exponent α ($0 < \alpha \leqslant 1$), the productivity obtained from

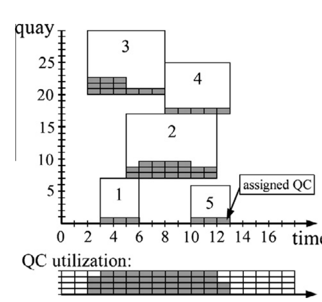

Figure 1 An example of a berth plan with QC assignment [5].

assigning q cranes to a vessel for one hour is given by a total of q^{α} QC-hours.

The productivity of a terminal is also affected by the workload on horizontal transport means; that is, the trucks that deliver/receive containers to/from the yard areas. This workload is minimal if a vessel berths at its *desired berthing position* b_i^0. Therefore, if a vessel moors away from this desired position, this leads to lower productivity. This productivity loss is modeled by an increase in the vessel's QC capacity demand. Let $\beta \geqslant 0$ denote the relative increase in QC capacity demand per unit of berthing position deviation, called the berth deviation factor. Hence, a vessel mooring Δb_i quay segments away from its desired berthing position requires $(1 + \beta\Delta b_i)m_i$ QC-hours to be served, as suggested in [5].

Considering both effects described above, the minimum handling time needed to serve a vessel i is given as

$$d_i^{\min} = \left\lceil \frac{(1+\beta\Delta b_i)m_i}{(r_i^{\max})^{\alpha}} \right\rceil \tag{1}$$

The complete mathematical model for the variant of the BACAP in hand appeared in an earlier publication [11].

4. The proposed solution technique

In this section, a detailed description of the proposed heuristics-based approach to solve the continuous BACAP with dynamic arrivals and variable water depth alongside the quay is provided. The solution iteratively proceeds in three steps. In the first step, a priority list for the vessels is generated. In the next step, a heuristic procedure is applied to the generated list to construct an initial feasible solution. In the third step, two refinement procedures are invoked to seek further improvements in the objective function value.

4.1. Priority list generation

Given the full information on the vessels that are to be handled during the planning horizon, a priority list determines the order in which vessels are inserted in the berth plan (time–space domain). The vessels at the top of the list have a better chance of being placed at or at least close to the desired berthing position.

Initially, the vessels are sorted in descending order of the value of the expression $\gamma l_i/L + (1-\gamma)EFT_i/H$, where $0 < \gamma < 1$. Applying this criterion gives a higher priority to large vessels which usually incur higher costs if delayed in the port. This criterion also gives higher priority to vessels with later EFT. This preference results in constructing the berth plan from right to left in the planning horizon, and thus, when a vessel finds its preferred berthing spot taken by another ship, it could be asked to berth earlier instead of being forced to wait. This behavior of the construction heuristic is preferred because the cost of speeding a vessel up is lower than forcing a vessel to wait beyond its EFT or LFT. The resulting priority list is denoted as LVF (Largest Vessel First). However, a FCFS priority list is also attempted and the results of the two priority lists are compared together. The one that yields a lower cost is set as the initial priority list.

In the subsequent iterations, simulated annealing is used to explore the space of priority lists. In the simulated annealing method, the quality of the solution depends on the control parameters and the schedule of the temperature. In typical implementations, the simulated annealing approach involves a pair of nested loops and three additional parameters, an initial temperature T_0, a cooling rate $0 < r < 1$, and a maximum number of iterations for which the temperature is held fixed, R (see the algorithm below). The following describes the procedure for obtaining a priority list using simulated annealing:

- *Step 1*. Choose an initial priority list P and obtain the corresponding initial solution by applying the construction heuristic and local refinements (discussed below). Set the temperature $T = T_0$.
- *Step 2*. Repeat the following steps until one of the stopping conditions becomes true, for example the temperature drops beyond a threshold or no improvement is obtained for some number of iterations.
  - *Step 2.1*. Perform the following loop R times.
    - *Step 2.1.1*. Pick a random neighboring priority list P' of P.
    - *Step 2.1.2*. Let $\delta = \text{cost}(P') - \text{cost}(P)$. (The cost is evaluated by applying the construction heuristic step and the two local refinement procedures).
    - *Step 2.1.3*. If $\delta < 0$ (downhill move), set $P = P'$.
    - *Step 2.1.4*. If $\delta \geqslant 0$ (uphill move), generate a random number, x, from the interval, $(0, 1)$; if $x < \exp(-\delta/T)$, then set $P = P'$.
  - *Step 2.2*. Set $T = r\,T$ (Reduce the temperature).

A neighboring priority list is generated by randomly choosing two successive vessels and interchanging their ranks in the list.

4.2. Construction heuristic

In this stage of the solution, a feasible berth plan for the incoming vessels is generated according to the given priority list. The vessels are inserted into the berth plan one by one. The procedure attempts to position a vessel at its preferred berthing position and its expected time of arrival. If this is impossible because it would cause an overlap with a previously inserted vessel or due to an insufficient number of QCs available at this time slot to serve the vessel or inappropriate water depth, then the vessel is shifted across the quay length in order to find a feasible berthing spot. Moreover, the vessel is shifted across the planning horizon seeking a better feasible berthing spot in the time–space domain. The finishing time is computed according to Eq. (1) and the number of cranes available to serve a vessel during each time slot within its handling time is determined. The handling time may be extended if the required crane capacity is not fulfilled. An almost uniform quay crane assignment is realized to avoid crane interference problems likely to occur if the number of cranes serving a vessel is altered from one time slot to another [5].

4.3. Quay crane resource leveling

Vessels at the top of the priority list are likely to be berthed at their preferred berthing position and to be served by the maximum number of QCs. Resource leveling tries to overcome this double preferential treatment. It inserts the vessels one by one into the berth plan after applying a restriction on the maximum number of QCs serving the vessel (applying all values between $r_i^{\min}$ and $r_i^{\max}$ iteratively). The rest of the vessels are then inserted to generate a partial berth plan. The current vessel of interest is temporarily deleted from the berth plan and subsequently re-inserted after removing the imposed restriction. The resource level is then fixed at the value that generates the best partial berth plan and the next vessel is handled in the same manner. The procedure is completed after all vessels have been dealt with [5].

4.4. Spatial and temporal shifts

This stage begins with identifying spatial and temporal clusters. Spatial clusters in a berth plan are defined as vessels that are positioned adjacent to each other alongside the quay and are served simultaneously during at least one time slot. Temporal clusters are defined as vessels that are served right after each other and each pair of consecutive ships are assigned to at least one common quay slot. After identifying these clusters, the spatial clusters are moved along the quay toward the lower border and then toward the other border. Moreover, the temporal clusters are moved across the planning horizon; once toward the starting time of the planning horizon and a second time toward the other extreme. This is done in order to further search for berth plans with lower cost [5].

The following flowchart summarizes the whole algorithm, see Fig. 2.

5. Implementation and experimental results

In this section, the test instances and the algorithm parameters setting used to assess the effectiveness of the proposed solution strategy are described. Moreover, a sample of the obtained results is shown.

5.1. Test instances

For testing, appropriate benchmark instances are required. The set of test instances used were provided by Dr. Frank Meisel upon request. In these instances, vessels are distinguished by three classes: namely, feeder, medium, and jumbo. The classes differ in their technical specifications and cost rates as shown in Table 1, where U designates a uniform distribution of integer values in the specified interval. The only modification to his test instances that has been made is adding the draft for each vessel.

Table 1 Technical specifications of different vessel classes.

Class	l_i	m_i	D_i	$r_i^{\min}$	$r_i^{\max}$
Feeder	U[8, 21]	U[5, 15]	U[4, 8]	1	2
Medium	U[21, 30]	U[15, 50]	U[8, 12]	2	4
Jumbo	U[30, 40]	U[50, 60]	U[12, 18]	4	6

Meisel suggested the following methodology in generating suitable test instances [5]. Within each instance, 60% of the vessels belong to the feeder class, 30% belong to the medium class, and 10% belong to the jumbo class. The planning horizon H is set to one week (168 h). The expected times of arrival ETA_i of vessels are uniformly distributed in the planning horizon. It is assumed that a vessel can speed up by at most 10%, which determines the earliest starting time $EST_i = 0.9ETA_i$. The expected finishing time EFT_i is derived by adding a vessel's minimum handling time to ETA_i. The latest finishing time LFT_i is derived by adding 1.5 times a vessel's minimum handling time to ETA_i. The desired berthing position is drawn for vessel i using $U\ [0, L - l_i]$. The terminal data include the quay length $L = 100$ (1,000 m) and the number of QCs $Q = 10$. To attain moderate QC productivity losses, the interference exponent is set to $\alpha = 0.9$ and the berth deviation factor is set to $\beta = 0.01$. The latter causes a 1% increase in the handling effort per quay segment of berthing position deviation. The assumed water depth alongside the quay is shown in Fig. 3.

5.2. Algorithm parameters setting

Each problem is solved 5 times with different streams of random numbers used in the simulated annealing module. The cooling schedule parameters are set to $T_0 = 40$, $r = 0.65$, and $R = 5$. The parameter γ used in the initial priority list generation is set equal to 0.5.

5.3. Results sanity checks

The consistency of the obtained results is verified by plotting the berth plan and visually checking that no overlap between

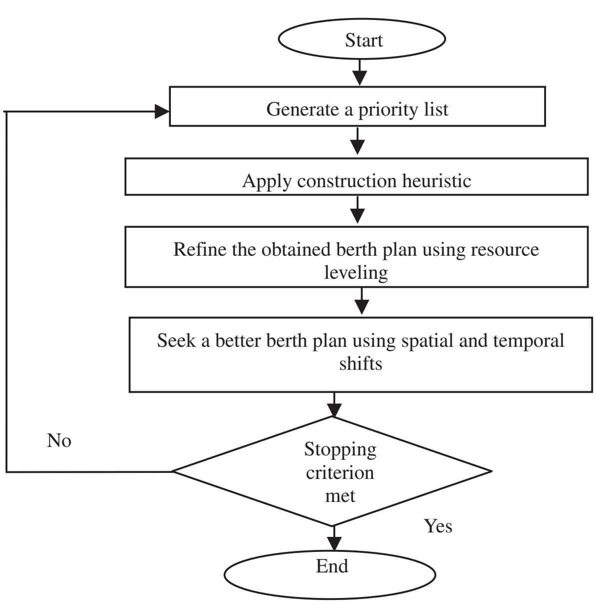

Figure 2 Proposed heuristics-based solution procedure.

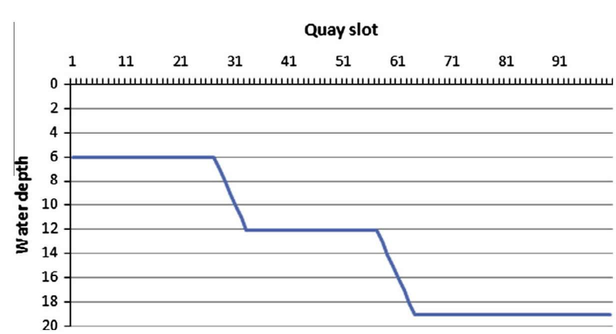

Figure 3 Water depth alongside the quay.

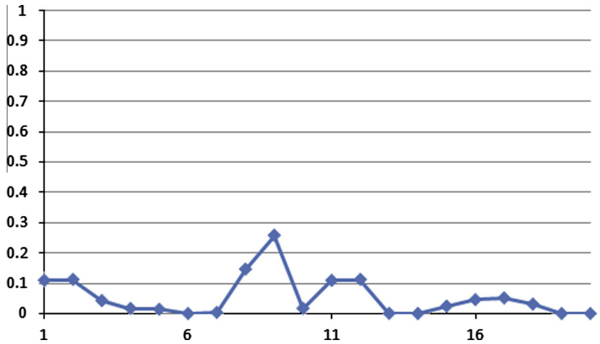

Figure 4 Ratio of the range for the test instances.

vessel rectangles exists and an Excel sheet has been used to assure the validity of the resulting quay crane assignment.

Moreover, for each problem, the ratio of the range of objective values for the five trials to the lowest objective value (which is expressed as the highest objective value during the five trials minus the lowest objective value during the five trials divided by the lowest objective value during the five trials), is calculated. Fig. 4 shows the ratio of the range of the objective values for five trials to the lowest objective value as obtained for the set of 20 test instances used. The results show that the average ratio is 5.4%, then it can be concluded that the objective values obtained by the simulated annealing method are consistent for different trials.

Furthermore, the mathematical model developed in [5] has been extended to incorporate water depth constraints and it has been implemented using LINGO optimization software package. However, it only yielded a solution in instances of very small size. In such restricted problems, it has been checked that both the LINGO model and the proposed heuristics-based approach give identical results. Unfortunately, the version employed of LINGO software had limited capabilities and thus even a lower bound for our test instances of practical size could not have been obtained.

With the aim of validating our implementation and the soundness of the obtained results, the lower bounds for the test instances provided by Dr. Frank Meisel that were indicated in his dissertation [5] are used. In these instances, the water depth constraints are not considered. A sample of the obtained results is shown in Table 2. It is clear that the results in most instances are in close agreement with the lower bounds.

Furthermore, the effectiveness of the proposed initial priority list selection criterion has been tested. This is demonstrated by the results of applying the construction heuristic to the test instances provided by Dr. Frank Meisel, as shown in Table 3.

Table 2 Benchmark instances results.

Number of vessels	CPLEX (LB)	Objective value (minimum)
20	84.0	85.1
	53.9	54.9
	75.2	80.2
	75.8	79.7
	56.8	56.8
	57.6	57.6
	67.5	75.4
	56.1	57
	75.0	77.3
	88.2	92.3
30	137.7	161.6
	81.4	87
	100.9	107.8
	96.8	113.3
	136.9	161.2
40	165.7	217.2
	159.6	185.9
	185.0	300.8
	224.1	357.5
	133.3	168.7

Table 3 Construction heuristic results for different initial priority lists.

Problem number	No. Vessels	Objective value (FCFS)	Objective value (LVF)
1	20	118.5	90.2
2		60.1	56.1
3		97.6	94.9
4		96.4	96.4
5		73.1	57.9
6		57.6	57.6
7		93.3	85.3
8		78.9	78.9
9		96.4	94
10		115.5	115.5
11	30	216	216
12		96.7	93.1
13		135	119.7
14		144.5	134.7
15		197.5	197.5
16		137.7	127.8
17		139.8	113.9
18		167.8	142.6
19		268.7	228.6
20		184.7	115.8
21	40	317	317
22		276.9	276.9
23		550.4	432.7
24		453.3	453.3
25		239.1	239.1
26		398.9	398.9
27		354.6	300.5
28		424.2	424.2
29		334.2	334.2
30		425.8	425.8

6. Tightly packed problems and planning horizon fictitious extension

Consider the following problem. Three vessels are assumed to be served at a terminal with $L = 14$, $H = 10$, $Q = 5$, $c^4 = 0.1$, $\alpha = 0.9$, and $\beta = 0.1$. Table 4 includes the vessel data associated with the studied example. The vessel drafts are $D_1 = 5$, $D_2 = 8$, and $D_3 = 9$. The water depth is set to 6 for the first 5 quay segments, while it reaches 10 for the last six segments. The water depth for the sixth, seventh and eighth segments is 7, 8 and 9, respectively.

There is no problem solving the above test instance using LINGO to optimality without changing the planning horizon.

Table 4 Tightly packed test instance vessels data.

i	l_i	b_i^0	m_i	r_i^{min}	r_i^{max}	EST_i	ETA_i	EFT_i	LFT_i	c_i^1	c_i^2	c_i^3
1	3	7	4	1	3	2	3	5	8	1	1	2
2	4	7	10	1	2	2	3	9	10	2	2	4
3	5	6	5	1	3	1	4	6	7	3	3	6

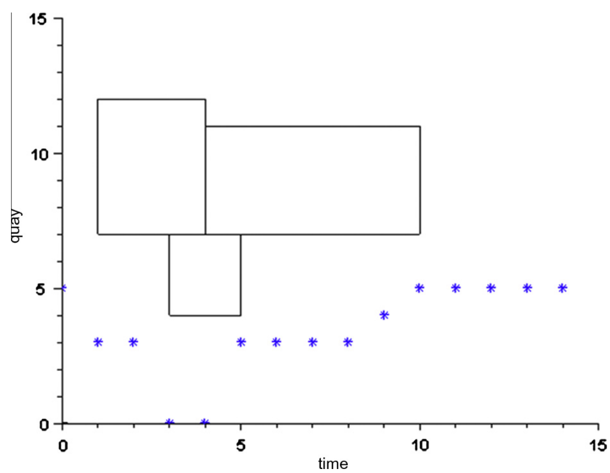

Figure 5 Optimal berth plan of a tightly packed instance.

But trying to solve it using our heuristic approach, a problem has been encountered which will be referred to as the 'startup problem'. This problem might occur in problems with tightly packed berth plans. In these cases, the construction heuristic fails to generate a starting feasible solution when it places the vessels at the top of the priority list in berthing spots that do not leave room for later vessels to be inserted in the first place no matter how the priority list is changed. A proposed remedy for this problem is to increase the planning horizon with a dummy period just to allow all the vessels to be inserted in an initial berth plan, and by imposing a large cost penalty on berthing vessels during this dummy period the subsequent local refinements always try to shift the vessels within the allowed planning horizon.

In the particular example described in this section, to alleviate the aforementioned problem, the planning horizon is increased to 15 h and then it was possible to reproduce the same results obtained using the LINGO® model. The resulting berth plan is shown in Fig. 5. The asterisks appearing in this figure represent the number of unused quay cranes during various time-slots in our planning horizon.

7. Conclusion

In this paper, an integrated heuristics-based solution methodology to solve the two most important optimization problems related to seaside operations at a container terminal; namely, the berth allocation and quay crane assignment problems, has been presented. The problem tackled in this paper assumes a continuous berth with variable water depth along the quay side under the assumption of dynamic vessels arrivals. The proposed technique begins with finding an initial feasible solution which handles vessels according to a given priority list and then seeks further enhancements by applying two local refinement procedures. Finally, simulated annealing is used to search the space of priority lists. An effective initial prioritizing criterion has been proposed, which accelerates the convergence of the employed heuristics to the optimal solution.

The proposed solution algorithm has been applied to several test instances and the consistency of the obtained results with all problem constraints has been verified. The quality of the solutions has been assessed by comparing them to lower bounds provided by CPLEX optimization package and thus it is concluded that the employed heuristics-based methodology succeeded to achieve high quality berth plans. Yet, an important practical aspect remains to be considered. This is the stochastic nature of some of the decision variables and input design parameters. An action plan is required to determine how the berth plan generated by the proposed algorithm is to be modified in case a vessel fails to meet its berthing time or departure time.

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