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Heuristics for the integration of crane productivity in the berth allocation problem

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ABSTRACT

In this paper, the combined problem of berth allocation and crane assignment in container terminals is investigated. The proposed problem formulation includes important real world aspects such as the decrease of marginal productivity of quay cranes assigned to a vessel and the increase in handling time if vessels are not berthed at their desired position at the quay. To solve the problem a construction heuristic, local refinement procedures, and two meta-heuristics are presented. These methods perform well on a set of real world like instances. The results emphasize the important role of quay crane productivity in berth planning.

1. Introduction

The core competence of a container terminal (CT) in a seaport is to serve container vessels by discharging and charging containers. Vessel operators expect this service to be as fast as possible. Fast service operations require a careful disposition of the seaside resources, namely the quay space and the quay cranes.

The Berth Allocation Problem (BAP) is one of the major CT operations planning problems, cf. Steenken et al. (2004). It consists of assigning a berthing position and a berthing time to every vessel projected to be served within a given planning horizon. Typically, these decisions are made with respect to the different priorities, lengths, and handling times of vessels. The handling times are usually assumed to be fixed and known in advance. As shown in Fig. 1a, a solution to a BAP can be depicted in a space–time-diagram. It divides the quay in segments of 10 m length and the time in periods of 1 h. The height of each of the rectangles corresponds to the length of a vessel (including clearance) and the width corresponds to the needed handling time. The lower-left vertex of a rectangle gives the vessel's berthing position and berthing time. In a feasible berth plan the rectangles do not overlap.

Besides quay space also quay cranes (QCs) are a scarce resource at a CT. Typically, if several vessels moor simultaneously at the quay, the Quay Crane Assignment Problem (QCAP) arises. The number of QCs serving a vessel simultaneously is often restricted by a minimum number (contracted between the vessel operator and the CT operator) and a technically allowable maximum number. In practice, the QC-to-Vessel assignment can change during the handling process of a vessel. Fig. 1b shows one possible crane assignment for the given berth plan with four QCs available at the quay. As can be seen by Vessel 2, assigning more QCs to a vessel can accelerate its handling time at the expense of other vessels (here Vessel 3). For this

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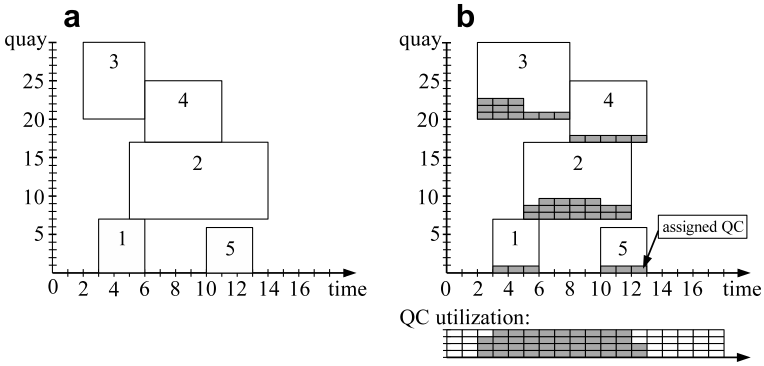

Fig. 1. An example of a berth plan (a) precised by a quay crane assignment (b).

reason, the determination of reliable handling times is disturbed within a sequential planning process. Berthing times may be required to change too (Vessel 4).

An integrated solution to the BAP and the QCAP leads to the Berth Allocation and Crane Assignment Problem (BACAP). It has been pioneered by Park and Kim (2003) under simplifying assumptions regarding the productivity of QCs. The utilization of the crane resource, however, needs to be considered under more realistic circumstances. This issue is approached in this paper by a new model formulation for the BACAP. It is organized as follows. The relevant literature is reviewed in the next section. Section 3 addresses the crane productivity and provides a suitable cost structure for handling a vessel as well as a MIP formulation of the underlying optimization problem. Sections 4 and 5 describe a basic construction heuristic and some refinement procedures. To further improve the solution quality obtained for the BACAP two meta-heuristic approaches, namely Squeaky Wheel Optimization and Tabu Search, are investigated in Section 6. The proposed methods are compared by a computational study in Section 7 verifying the need to incorporate effects influencing the QC productivity. Finally, Section 8 concludes the paper.

2. Literature review

Berth allocation models are classified into discrete and continuous problems and into static and dynamic problems, cf. Imai et al. (2001, 2005). In the discrete case, the quay is partitioned into a number of sections, called berths, where one vessel can be served at a time. In the continuous case no partitioning exists and a calling vessel can be moored at an arbitrary position provided enough space is available. In a static BAP the arrival times of vessels can be ignored while they impose a constraint on the earliest possible berthing time in a dynamic BAP.

The BAP receives much attention in the literature. In the majority of research fixed handling times are assumed by ignoring the crane resource, cf. Kim and Moon (2003), Guan and Cheung (2004) and Wang and Lim (2007). In the following, we briefly review that part of the literature, which puts focus on berthing position dependent handling times and crane resources.

Considering discrete problems, individual handling times are typically given for each vessel at each berth. Static and dynamic variants of the discrete problem are studied by Imai et al. (2001) and Nishimura et al. (2001), leading to an assignment and sequencing problem with minimum waiting and handling times of vessels as objective. A Genetic Algorithm and a Lagrangean relaxation based heuristic are proposed to solve the problems. Further objectives are discussed for these problems by Golias et al. (2006). Imai et al. (2007) study a BAP for indented berths, where large vessels can be served from two sides. Cordeau et al. (2005) study the dynamic discrete BAP and a continuous variant, where they consider a quay, partitioned into berths of variable lengths. A Tabu Search method is proposed that outperforms CPLEX and the First-Come-First-Served heuristic. In the problem considered by Hansen et al. (in press) not only handling times but also service costs of vessels depend on the berth they are assigned to. A Variable Neighborhood Search is used to solve the problem which is superior to the Genetic Algorithm of Nishimura et al. (2001).

In addition to berth dependent handling times, Lee et al. (2006) consider the QC operations within the discrete BAP. Given a number of QCs available at a berth, no crane assignment is necessary. A Genetic Algorithm is used to obtain berth plans which are evaluated by generating a feasible work plan for the cranes that serve a vessel. In lack of a suitable scheduling algorithm for the generation of work plans only a single problem instance of small size is investigated. The QC resource is also considered in a recent paper of Imai et al. (in press), where the referable number of QCs is given for each vessel. The task is to determine the specific QCs that are used for the handling of each vessel. The objective is to minimize the movements of QCs between the berths.

The incorporation of berthing position dependent handling times in the continuous BAP is treated by Imai et al. (2005). They suggest a heuristic solution method which solves a discrete BAP. Afterwards, the obtained solution is improved by shifting vessels along the quay as allowed in the continuous BAP. The isolated problem of assigning QCs to vessels has been considered by Liu et al. (2006). With respect to a given berth plan, the objective is to minimize the maximum tardiness of vessel departures while the number of QCs assigned to a vessel is held constant throughout the handling process.

The integration of the continuous BAP and the QCAP was first considered by Park and Kim (2003). In their BACAP the arrival times of vessels impose no hard constraints on the berthing times. According to the classification of Imai et al. (2005) it is therefore a static problem. A MIP and a heuristic solution method based on a Lagrangean relaxation are proposed to determine the berthing positions, berthing times, and the QC assignments. In the approach, the QC-to-Vessel assignment is made up by single QC-hours. This assignment is allowed to change during the handling process. Time variable crane assignments are very common in practice but did not receive attention by research until then. For reasons of simplicity Park and Kim (2003) assume that the crane productivity is proportional to the number of QCs that simultaneously serve a vessel. This has been criticized by Cordeau et al. (2005) and Hansen et al. (in press), because QCs are exposed to interference effects decreasing the marginal productivity. Moreover, the crane productivity also decreases if a vessel is berthed apart from its desired berthing position. Park and Kim (2003) treat such difficulties through additional cost which is again rather unrealistic because the productivity loss is not reflected in the crane assignments.

The static continuous BACAP is also studied by Oğuz et al. (2004). They consider the problem as a parallel machine scheduling problem and pursue to minimize the makespan, i.e. the latest finishing time among the vessels. The approach differs from the one of Park and Kim (2003) in two points. It merely considers time invariant QC-to-Vessel assignments, but is able to cope with the decreasing marginal productivity of QCs by introducing an interference coefficient. Unfortunately, the way berthing positions and berthing times are determined is not described in the paper. A dynamic variant of the BACAP is discussed by Meisel and Bierwirth (2006). The problem is treated as a multi-mode resource-constrained project scheduling problem where each vessel is represented by an activity. Activities can be performed in different modes, each one representing a certain QC-to-Vessel assignment over time. A priority rule based method is used to decide on the mode, the berthing time, and the berthing position of each vessel. The goal is to minimize the cost for manning QCs, which is one of the primary objectives for terminal operators. On this basis, several real world berth plans are considerably improved without deteriorating the service quality much.

3. Modeling the BACAP

This section provides a new mathematical formulation for the BACAP with QC productivity reducing effects and a suitable cost structure.

3.1. Notation

Input data

V	set of vessels to be served, $V = \{1,2,\ldots,n\}$
Q	number of available QCs
L	number of 10-m berth segments (length of the quay)
T	set of 1-h periods, $T = \{0,1\ldots,H-1\}$, H is the planning horizon
l_i	length of vessel $i \in V$ given as a number of 10-m segments
b_i^0	desired berthing position of vessel i
m_i	crane capacity demand of vessel i given as a number of QC-hours
$r_i^{\min}$	minimum number of QCs agreed to serve vessel i simultaneously
$r_i^{\max}$	maximum number of QCs allowed to serve vessel i simultaneously
R_i	feasible range of QCs assignable to vessel i, $R_i = [r_i^{\min}, r_i^{\max}]$
ETA_i	expected time of arrival of vessel i
EST_i	earliest starting time if journey of vessel i is speeded up, $\mathrm{EST}_i \leqslant \mathrm{ETA}_i$
EFT_i	expected finishing time of vessel i
LFT_i	latest finishing time of vessel i without penalty cost arising
$c_i^1,\ c_i^2,\ c_i^3$	service cost rates for vessel i given in units of 1000 USD per hour
c^4	operation cost rate given in units of 1000 USD per QC-hour
α	interference exponent
β	berth deviation factor
M	a large positive number

Decision variables

b_i	integer, berthing position of vessel i
s_i	integer, time of starting the handling of vessel i (berthing time)
e_i	integer, time of ending the handling of vessel i (finishing time)
r_{it}	binary, set to 1 if at least one QC is assigned to vessel i at time t, 0 otherwise
r_{itq}	binary, set to 1 if exactly q QCs are assigned to vessel i at time t, $q \in R_i$, 0 otherwise
Δb_i	integer, deviation between the desired and the actually chosen berthing position of vessel i, $\Delta b_i = \lvert b_i^0 - b_i \rvert$

ΔETA_i integer, required speed up of vessel i to reach its berthing time, $\Delta\text{ETA}_i = (\text{ETA}_i - s_i)^+$
ΔEFT_i integer, tardiness of vessel i, $\Delta\text{EFT}_i = (e_i - \text{EFT}_i)^+$
u_i binary, set to 1 if the finishing time of vessel i exceeds LFT_i, 0 otherwise
y_{ij} binary, set to 1 if vessel i is berthed below of vessel j, i.e. $b_i + l_i \leqslant b_j$, 0 otherwise
z_{ij} binary, set to 1 if handling of vessel i ends not later than handling of vessel j starts, 0 otherwise

3.2. Resource utilization

The productivity of a terminal is strongly affected by interference among QCs. According to Schonfeld and Sharafeldien (1985) the productivity loss is described through an interference exponent that reduces the marginal productivity of QCs. For a given interference exponent α ($0 < \alpha \leqslant 1$), the productivity obtained from assigning q cranes to a vessel for one hour is given by a total of q^α QC-hours. This idea was taken up by Silberholz et al. (1991) to improve the allocation of human resources in container terminals and by Oğuz et al. (2004) and Dragovic et al. (2006) to describe the berthing process with respect to the QC assignment.

The productivity of a terminal is also affected by the workload of horizontal transport means. It depends on the distance between the berthing position of the vessel and the dedicated yard areas for import and export containers. Generally, a desired berthing position b_i^0 is specified for a vessel i within the vicinity of these yard areas. If the actually chosen berthing position is apart from the desired position, the load of the horizontal transport increases. This effect can be partially alleviated by employing more transport vehicles. Therefore, Park and Kim (2003) propose to penalize apart berthing positions by additional cost. This approach however ignores that a larger number of vehicles decelerates the average speed and thus reduces the service rate again. Therefore, in our model, an apart berthing position of a vessel leads to an increase of its QC capacity demand. Let $\beta \geqslant 0$ denote the relative increase of QC capacity demand per unit of berthing position deviation, called the berth deviation factor. Hence, a vessel positioned Δb_i berth segments away from its desired berthing position requires $(1 + \beta \cdot \Delta b_i) \cdot m_i$ QC-hours to be served.

With respect to both effects described above, the minimum duration needed to serve vessel i is given as

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

As an example, let the handling of vessel i require a total of 15 QC-hours. The vessel can be served by at most five QCs simultaneously. Assume further that the vessel is berthed 100 m away from its desired position, which corresponds to $\Delta b_i = 10$ berth segments in our model. Without productivity loss the fastest possible handling requires 3 h. If the interference exponent and the berth deviation factor are set to $\alpha = 0.85$ and $\beta = 0.02$, respectively, the minimum handling duration increases to 5 h according to Eq. (1).

3.3. Cost structure

The most frequently pursued objective in berth allocation models is the minimization of port stay times. Short port stay times are desirable because they generally increase vessel operators satisfaction. For a precise treatment of the various factors influencing service quality, different cost functions are proposed in the literature, cf. Park and Kim (2003), Golias et al. (2006) and Hansen et al. (in press). We distinguish three types of cost, namely the cost to speed up a vessel on its journey to catch a berthing time earlier than ETA_i, the cost for exceeding the expected finishing time EFT_i, and penalty cost for exceeding the latest allowed finishing time LFT_i. The corresponding cost rates are denoted as c_i^1, c_i^2 and c_i^3. While speed up cost and delay cost grow constantly in time, penalty cost incur only once, if the departure of the vessel is beyond LFT_i. We refer to these three cost as the service quality cost of a vessel. Fig. 2 illustrates the cost drivers of the service quality on a discrete time basis. If the vessel is completely served in the time span between ETA_i and EFT_i, the perfect service quality is reached and no cost is incurred.

Due to the decreasing marginal productivity of QCs there exists a trade-off between accelerating the handling time of a vessel and the corresponding operation cost. We model this effect by incorporating a fourth cost type which evaluates the QC-hours utilized in a berth plan. The cost rate per QC-hour is denoted as c^4. These operation cost plus the service quality cost of the vessels make up the total service cost of a berth plan.

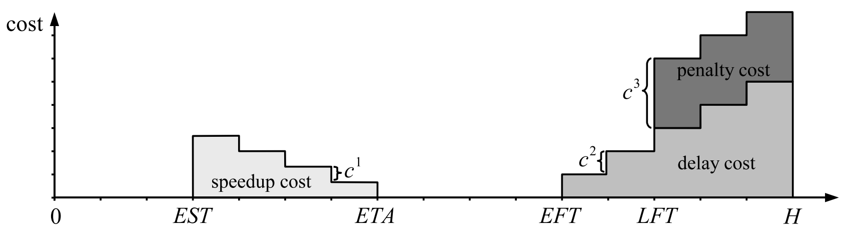

Fig. 2. Structure of the service quality cost of a vessel.

3.4. Optimization model

We formulate the BACAP as follows:

$$\text{minimize } Z = \sum_{i\in V}\left(c_i^1 \cdot \Delta\text{ETA}_i + c_i^2 \cdot \Delta\text{EFT}_i + c_i^3 \cdot u_i + c^4 \cdot \sum_{t\in T}\sum_{q\in R_i} q \cdot r_{itq}\right) \tag{2}$$

$$\sum_{t\in T}\sum_{q\in R_i} q^{\alpha} \cdot r_{itq} \geqslant (1+\beta\cdot\Delta b_i)\cdot m_i \quad \forall i\in V \tag{3}$$

$$\sum_{i\in V}\sum_{q\in R_i} q \cdot r_{itq} \leqslant Q \quad \forall t\in T \tag{4}$$

$$\sum_{q\in R_i} r_{itq} = r_{it} \quad \forall i\in V \ \forall t\in T \tag{5}$$

$$\sum_{t\in T} r_{it} = e_i - s_i \quad \forall i\in V \tag{6}$$

$$(t+1)\cdot r_{it} \leqslant e_i \quad \forall i\in V \ \forall t\in T \tag{7}$$

$$t\cdot r_{it} + H\cdot(1-r_{it}) \geqslant s_i \quad \forall i\in V \ \forall t\in T \tag{8}$$

$$\Delta b_i \geqslant b_i - b_i^0 \quad \forall i\in V \tag{9}$$

$$\Delta b_i \geqslant b_i^0 - b_i \quad \forall i\in V \tag{10}$$

$$\Delta\text{ETA}_i \geqslant \text{ETA}_i - s_i \quad \forall i\in V \tag{11}$$

$$\Delta\text{EFT}_i \geqslant e_i - \text{EFT}_i \quad \forall i\in V \tag{12}$$

$$M\cdot u_i \geqslant e_i - \text{LFT}_i \quad \forall i\in V \tag{13}$$

$$b_j + M\cdot(1-y_{ij}) \geqslant b_i + l_i \quad \forall i,j\in V,\ i\neq j \tag{14}$$

$$s_j + M\cdot(1-z_{ij}) \geqslant e_i \quad \forall i,j\in V,\ i\neq j \tag{15}$$

$$y_{ij} + y_{ji} + z_{ij} + z_{ji} \geqslant 1 \quad \forall i,j\in V,\ i\neq j \tag{16}$$

$$s_i, e_i \in \{EST_i, \ldots H\} \quad \forall i\in V \tag{17}$$

$$b_i \in \{0,1,\ldots L-l_i\} \quad \forall i\in V \tag{18}$$

$$\Delta\text{ETA}_i, \Delta\text{EFT}_i \geqslant 0 \quad \forall i\in V \tag{19}$$

$$r_{itq}, r_{it}, u_i, y_{ij}, z_{ij} \in \{0,1\} \quad \forall i,j\in V \ \forall t\in T \ \forall q\in R_i \tag{20}$$

This model decides on the berthing position, the berthing time, and the number of cranes that serve a vessel within the handling period. Determining the specific QCs that fulfill the service leads to a subsequent problem with respect to the non-crossing of cranes. This problem can be solved separately as shown by Park and Kim (2003) and Imai et al. (in press).

Our optimization model pursues the minimization of the total service cost arising for all vessels within the planning horizon. Constraints (3) ensure that every vessel receives the required QC capacity with respect to productivity losses by QC interference and the chosen berthing position. Note that the number of cranes q assigned to a vessel is no decision variable in order to ensure the linearity of this constraint. Instead, the number of cranes assigned to a vessel is described by binary variables r_{itq}, indicating whether exactly q QCs are assigned to vessel i at time t. Constraints (4) enforce that at most Q cranes are utilized in a period. In every period a certain number of QCs is assigned to every vessel which is either zero or taken from the range R_i. A consistent setting of the corresponding variables r_{it} and r_{itq} is ensured by (5). Constraints (6)–(8) set the starting times and ending times for serving vessels without preemption. Constraints (9)–(12) determine the deviations from the desired berthing position, expected arrival time and expected finishing time for each vessel. Ending the handling of a vessel later than LFT_i is indicated by variable u_i as defined in (13). Constraints (14) and (15) set the variables y_{ij} and z_{ij} which are used in Constraints (16) to avoid overlapping the handling of vessels in the space–time-diagram. The arrival of a vessel can be speed up to at most the earliest starting time EST_i, which makes the BACAP a dynamic problem according to the classification of Imai et al. (2005). Moreover the planning horizon H defines a limit on the departure time of the vessels. Both aspects are reflected in Constraints (17). Constraints (18) ensure that each vessel is positioned within the berth boundaries. The further constraints define domains for the remaining decision variables.

With the above model we provide a linear formulation of the BACAP. It incorporates the productivity effects of resources which are ignored in the model provided by Park and Kim (2003). Moreover, the new model is more compact as the number of constraints grows in $O(nH)$ instead of $O(nH^2)$. Also the number of variables is not growing that fast in our model if Q is supposed to be smaller than L.

4. Construction heuristic

The BACAP is an intractable problem because already the BAP is NP-hard, cf. Lim (1998). To obtain an initial solution for this problem, a straightforward construction heuristic is used. It schedules the vessels one by one in the order of a given priority list. Vessel $i\in V$ is inserted into the partial berth plan by assigning it a berthing time s_i, a berthing position b_i, and the number q of cranes employed at period t (r_{itq}). As shown in Fig. 3 the procedure *Insert(i)* performs eight steps.

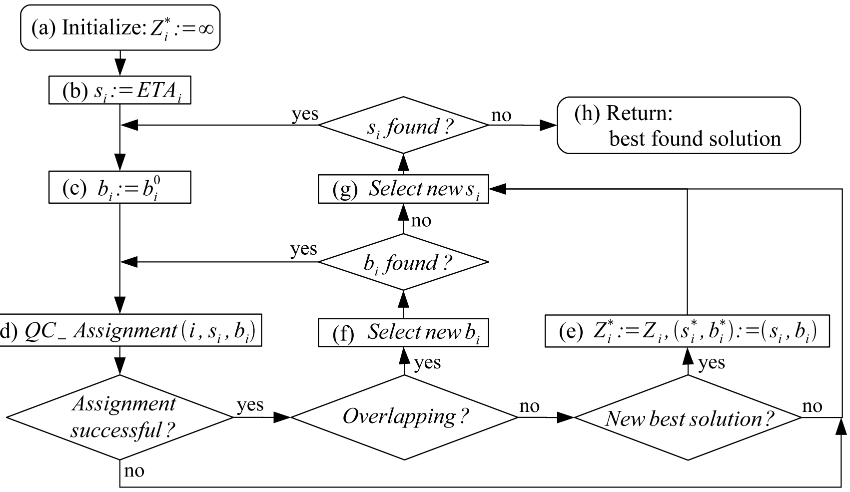

Fig. 3. Procedure *Insert(i)* of the constructor.

In Step (a) the cost Z_i^* for inserting vessel i is initially set to infinity. In Steps (b) and (c) the berthing time for vessel i is set to the ideal berthing time ETA_i and the berthing position is set to the desired berthing position b_i^0.

In Step (d) an assignment of QCs is generated for the current position (s_i, b_i) in the time–space-diagram by pursuing the fastest possible handling of the vessel. Using Eq. (1) the handling duration $d_i^{\min}$ is computed leading to the ending time e_i. If the available number of QC-hours within this interval is insufficient to serve the vessel, respecting that no more than $r_i^{\max}$ QCs can be assigned to it within a period, e_i is increased until the capacity is sufficient. If either $e_i > H$ is observed or less than $r_i^{\min}$ QCs are available within at least one of the periods $[s_i, s_i + 1, \ldots e_i - 1]$ the QC assignment fails. Otherwise, a feasible QC assignment is obtained by assigning the available QCs within the determined handling interval respecting $r_i^{\min}$ and $r_i^{\max}$ until Constraint (3) holds for the vessel to be inserted. To minimize the productivity loss an almost uniform distribution of QCs over time is realized.

If QCs have been assigned to a vessel, an ending time for its handling is fixed. To ensure consistency with the partial schedule, it is checked whether the vessel overlaps with other vessels in the space–time representation. If the attempted insertion is feasible, the cost of vessel $i \in V$ is computed according to the objective function (2). In case that a new best solution has been found, its coordinates (s_i^*, b_i^*) and the corresponding cost Z_i^* are updated in Step (e). In case of an infeasible insertion, a new berthing position $b_i \in [0, L - l_i]$ is selected in Step (f). The new position is the closest not yet inspected position to the desired position b_i^0 such that the overlapping conflict is resolved. If such a position is found Step (d) is repeated. Otherwise, the procedure continues in Step (g), as it does if Step (d) has not delivered a successful QC assignment or if a feasible schedule has been obtained.

In Step (g) a new starting time s_i for serving vessel i is taken one after the other from the list $[\mathrm{ETA}_i - 1, \mathrm{ETA}_i + 1, \mathrm{ETA}_i - 2, \ldots]$ until s_i has reached EST_i in the one direction and the end of the planning horizon in the other. To fasten the procedure, a lower bound of the cost associated with a starting time is determined using Eq. (2). If the estimate overshoots the cost of the best known solution Z_i^* the iteration of earlier or later starting times is suppressed. The new starting time s_i is evaluated as described above. If no new starting time can be assigned to a vessel, the procedure *Insert(i)* terminates in Step (h) returning the best found solution (s_i^*, b_i^*).

To illustrate the procedure we consider three vessels to be served at a terminal with $L = 14$, $H = 10$, $Q = 5$, $c^4 = 0.1$, $\alpha = 0.9$, and $\beta = 0.1$. The data of the vessels is shown in Table 1. The partial schedule, already fixed for Vessels 1 and 2, is shown in Fig. 4a. Now, Vessel 3 has to be inserted. According to Eq. (1) its minimum handling duration is $d_3^{\min} = 2$ periods if berthed at its desired position.

At first, procedure *Insert*$(i = 3)$ selects the preferred coordinates, as shown by the dotted rectangular in Fig. 4b. Since this insertion is overlapping with the given partial schedule, Vessel 3 is repositioned to $b_3 = 2$. This berthing position deviates from the desired position by four berth segments. Therefore, the number of needed QC-hours increases from

Table 1
Example vessel 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

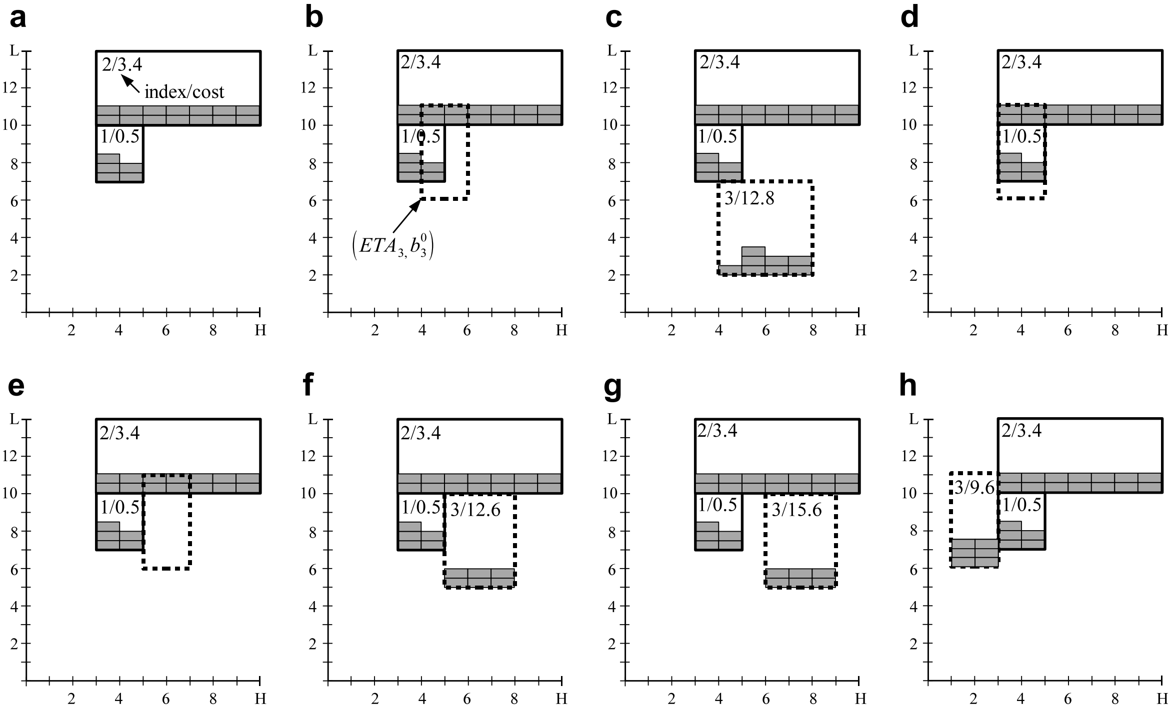

Fig. 4. Example positioning of a vessel.

$m_3 = 5$ to $(1+\beta\cdot 4)\cdot m_3 = 7$ QC-hours. As depicted in Fig. 4c, the QC assignment delivers $r_{3,4,1} = r_{3,5,3} = r_{3,6,2} = r_{3,7,2} = 1$, indicating that the number of assigned QCs changes two times within the handling interval. This resource assignment is sufficient because the QC productivity of $1^{0.9} + 3^{0.9} + 2\cdot 2^{0.9} = 7.42$ satisfies the needed 7 QC-hours. The projected service of the vessel requires no speed up ($\Delta\mathrm{ETA}_3 = 0$), but the finishing time exceeds the expected finishing time ($\Delta\mathrm{EFT}_3 = 2$) and also the latest allowed finishing time ($e_3 > \mathrm{LFT}_3$). With 8 QC-hours assigned, the corresponding cost of the vessel is $Z_3 = 12.8$. Next, to generate an alternative berth plan, $\mathrm{ETA}_3 - 1$ is assigned to the vessel as new handling start time. Fig. 4d shows that not enough QCs are available in this period with respect to $r_3^{\min}$. Therefore, the starting time is set to $s_3 = \mathrm{ETA}_3 + 1$. As shown in Fig. 4e the insertion overlaps the partial berth plan again. This is resolved by repositioning the vessel to $b_3 = 5$ which enlarges the handling duration of the vessel by one period leading to a new best solution with $Z_3 = 12.6$, see Fig. 4f. The generation of the next berth plan for $s_3 = 2$ fails due to short QC capacity in period 3. Continuing with $s_3 = 6$ delivers the solution shown in Fig. 4g. Next, $s_3 = 1$ is assigned to the vessel at its desired berthing position. This leads again to a feasible and new best solution with $Z_3 = 9.6$, shown in Fig. 4h. Since $s_3 = \mathrm{EST}_3$ and berthing times later than time 6 cannot lead to a better solution, no other berthing times need to be inspected. The algorithm terminates returning the best found solution $(s_3^*, b_3^*) = (1, 6)$.

5. Local refinements

5.1. Quay crane resource leveling

The construction heuristic generates a feasible berth plan with respect to a given priority list of the vessels. Vessels which are early inserted in the berth plan by the construction heuristic have good prospects to be placed at their desired position in the space–time-diagram and to get full QC capacity. To alleviate the double preferential treatment of early inserted vessels, one can restrict the maximum assignable number of QCs to a level r_i^{lvl} below $r_i^{\max}$. This, in turn, saves QC capacity that can be assigned to vessels inserted with lower priority in the berth plan. Technically, this is realized by using the procedure *Insert(i)* in combination with a given resource level r_i^{lvl} which plays the role of $r_i^{\max}$.

The first refinement procedure considers the vessels one by one according to the given priority list $P = (p_1, p_2, \ldots p_n)$ of all vessels $i \in V$. Starting with an empty berth plan, vessel p_1 is inserted once for every resource level $r_{p_1}^{\mathrm{lvl}}$ within the range R_{p_1}. Each of these incomplete berth plans is completed by subsequently inserting the remaining vessels p_2 to p_n using the insertion procedure without a restricting resource level. Due to the resource restriction for vessel p_1, other vessels have received higher priority regarding the QC assignment in the completed berth plans. Possibly, the saved QC capacity has not been completely exhausted by these vessels and can therefore be reassigned to vessel p_1. For this purpose, p_1 is removed again in all completed berth plans and inserted once again without a resource restriction. Afterwards, a partial berth plan containing vessel p_1 is obtained from the best of the generated solutions. Next, the partial berth plan of p_1 is extended by inserting vessel p_2 in the same manner. This process is continued for every vessel up to p_{n-1}. The vessel with the lowest priority is simply inserted in the almost completed berth plan with respect to the remaining QC capacity.

To illustrate the procedure we describe one possible local refinement of the berth plan shown in Fig. 4h. If Vessel 1 is inserted with the resource level $r_1^{lvl} = 1$, accepting an increase of the handling time, Vessel 3 benefits from the saved QC capacity because its berthing time approaches its expected time of arrival. Vessel 2 is inserted as before leading to the improved berth plan shown in Fig. 5a. While in this small example all vessels show a time invariant QC-to-Vessel assignment resource leveling also supports changes in the number of assigned QCs.

5.2. Spatial and temporal shifts

A further refinement aims at reducing cost by shifting clusters of vessels in the space–time-diagram. According to Kim and Moon (2003) a spatial cluster is a subset of vessels which are connected in the space–time-diagram because they occupy adjacent berth segments and are served simultaneously for at least one time period. A temporal cluster is a subset of vessels which are connected because they are served immediately one after the other, where subsequent vessels occupy at least one common berth segment.

In the approach of Kim and Moon (2003), the sets of spatial and temporal clusters are identified for a given berth plan. Afterwards, spatial clusters are shifted in the spatial dimension and temporal clusters in the temporal dimension, each as long as no further cost reduction is reachable. A similar concept is applied in Imai et al. (2005) where two conflicting vessels are shifted together like a single vessel. Both approaches do not take the QC assignment into consideration and require adaptation to our needs. Since a spatial shift of a vessel changes its QC capacity demand, its crane assignment and probably its space–time positioning have to be revised. Shifting of a temporal cluster requires comparable revisions to respect the available QC capacity of the affected time periods. Since the impact of a spatial or a temporal shift on the cost is unforeseeable, it must be executed in order to identify improvements.

The refinement procedure iteratively performs shifts of all spatial clusters toward the berth's borders and shifts of all temporal clusters within the entire planning interval. A shift of a spatial cluster changes the berthing position of each vessel by one berth segment while a shift of a temporal cluster changes the handling start time of each vessel by one time period. If the QC assignment of vessel i gets infeasible by a shift operation, the vessel is removed from the berth plan and reinserted with the resource level r_i^{lvl}, fixed in the first refinement phase. If all vessels of a cluster are scheduled feasible, the saved but unused QC capacity is reassigned to the reinserted vessels as described above. If all vessels require reinsertion, the structure of the cluster is supposed to be lost and the cluster is not further shifted in the considered direction. Improved solutions are recorded during the second refinement phase. It terminates if no further improvement is possible.

To illustrate the procedure, the spatial cluster {1,2,3} shown in Fig. 5a is shifted toward the lower berth border. The first shift yields the berth plan of Fig. 5b. Now, Vessel 2 requires less QC capacity while the capacity demand of Vessels 1 and 3 increase because they are shifted away from their desired positions. The existing QC assignments become infeasible. In the following reinsertion, Vessel 3 is assigned an earlier berthing time, and Vessel 1 receives a released capacity unit, although its resource level r_1^{lvl} has been set to one by the previous refinement. With the next shift, the changed QC assignments of Vessels 1 and 3 are still feasible. The capacity demand of Vessel 2 decreases again and leads to cost 1.2 as shown by the improved berth plan in Fig. 5c.

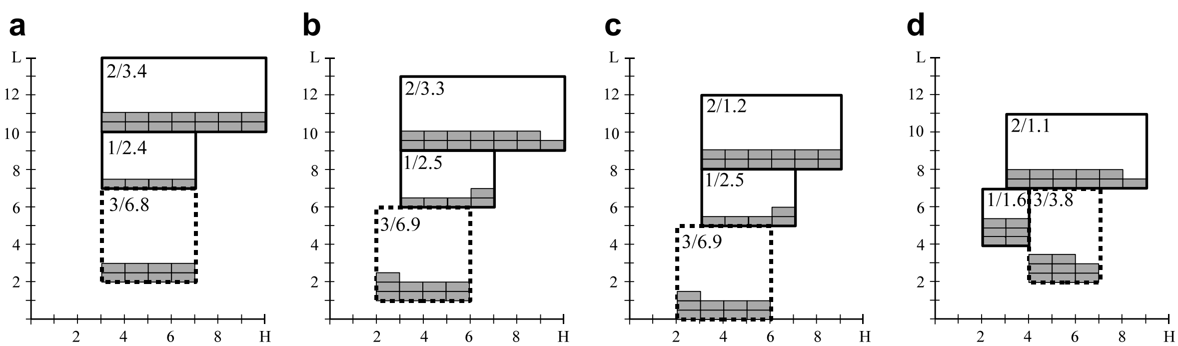

Fig. 5. Refinement of a berth plan by resource leveling and space–time adjustments.

The optimal berth plan to the problem is shown in Fig. 5d. This solution can not be generated by the construction heuristic from the insertion order (1, 2, 3) of the vessels. In order to search the solution space of the BACAP effectively one needs to take alternative priority lists for inserting vessels into consideration.

6. Meta-heuristics

In this Section, we propose two meta-heuristic approaches, which enable changes of the priority list in order to improve the quality of berth plans.

6.1. Squeaky wheel optimization

Solutions of combinatorial optimization problems are often composed from elements with individual contributions to the overall solution quality. The idea of Squeaky Wheel Optimization (SWO), as introduced by Clements et al. (1997), is to exploit this information. In SWO a given solution is analyzed regarding the performance of its elements. In order to strengthen the overall performance, weak performing elements are assigned higher priority in the solution process by moving them toward the top of a priority list. The new list serves to build a new solution using a base heuristic of the problem. According to Joslin and Clements (1999), SWO searches two spaces, namely the priority space and the solution space, as shown in Fig. 6. For a given priority list, the base heuristic constructs a corresponding point in the solution space. The analysis of this solution effects again a modification of the priorities of the contained elements, which leads to a new point in the priority space. The underlying strategy of SWO is to explore new solutions by large coherent moves in the priority space, which have only little chance to be reached through sequential moves in the solution space.

SWO has been used in a number of recent approaches to different combinatorial optimization problems, see Smith and Pyle (2004), Lim et al. (2004), Fu et al. (2007). However, in these approaches SWO is rarely competitive to other meta-heuristics such as Genetic Algorithms and Tabu Search. It fails because these problems do not allow for a quantification of the individual contribution of each single problem element to the overall solution quality.

In the BACAP a berth plan (solution) is composed from vessels (elements) with individual cost contributing to the overall solution quality. The objective of the BACAP is to minimize the total service cost of the set of vessels. Therefore, SWO is straightforward applicable. Weak performing vessels are easily identified because they contribute relatively large proportions to the observed total cost. To generate new promising solutions, SWO increases the priority of these vessels at the expense of vessels with lower service quality cost.

Initially, the priority list P of the vessels is ordered with respect to increasing arrival times. Ties are broken arbitrarily. The construction heuristic serves as a base heuristic in the SWO procedure to generate a berth plan for a given priority list. Hence, for the initial list, a berth plan is generated on a First-Come-First-Served basis. Afterwards, a local refinement of the berth plan is done as described in Section 5 leading to individual service quality cost for each single vessel. The operation cost of QCs are neglected in the solution analysis to avoid the bias that stems from the different QC capacity demand of vessels.

Following this solution analysis, the priorities of vessels are changed by a modification of the priority list. Two consecutive vessels in the priority list are swapped, if the cost incurred by the first vessel is lower than the cost incurred by the second vessel. Starting from the top, the priority list P is partially sorted by applying the swap operation $n-1$ times which may lead to a multiple of changes. For a new priority list the corresponding berth plan is generated by the construction heuristic and the local refinements. Independent of its quality, the obtained berth plan is accepted as a new solution and the SWO procedure starts a new round by analyzing the new solution. This time, the priorities are changed according to each vessel's total service quality cost of the first and the second solution. Doing so, vessels are prioritized according to their performance in all solutions generated so far.

SWO is trapped in a cycle if it generates a priority list that has already been generated in a previous round. A major source of cycling is local refinement. Therefore, if a cycle is detected the local refinement procedures are deactivated in SWO. The berth plans generated next will show worse quality and lead to changes in the priority list. Local refinements are reactivated if a not yet investigated priority list is found. The SWO procedure terminates after analysing a given number of solutions without finding a new best solution.

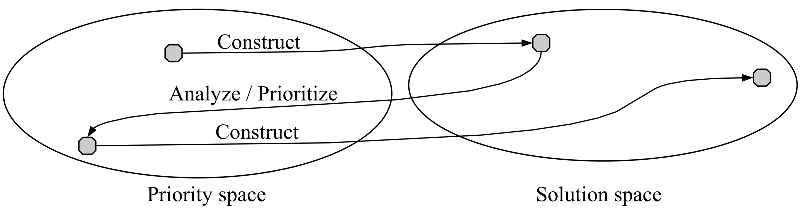

Fig. 6. Search spaces explored by SWO.

6.2. Tabu Search

As a further meta-heuristic approach the well known Tabu Search (TS) method is applied to the BACAP. Like SWO, our TS algorithm works on the priority list P of the vessels. Contrasting SWO, TS employs pairwise-exchanges of vessels in the priority list to obtain new solutions instead of adjacent swaps. The pairwise-exchange neighborhood of a solution is completely explored within each TS iteration. Every neighbor of the current solution, i.e. every modified priority list, is evaluated by the construction heuristic. If the obtained berth plan is an element of the tabu list it is not considered any further. In order to save computation time, a local refinement is done only for the best performing neighbor of the current solution. This solution replaces the current solution even if it shows larger cost. The tabu list is managed as follows. The current berth plan is stored without the local refinement in the tabu list. In doing so, the totality of priority lists leading to this berth plan is set tabu at one strike. Since, by this effect, TS cannot benefit from removing any berth plan from the tabu list again, all berth plans are kept within the tabu list throughout the solution process. Using an Aspiration Criteria is not necessary because a new best solution found can not be contained in the tabu list. The TS algorithm terminates after a given number of iterations without finding a new best solution.

7. Computational investigations

We demonstrate the strengths of the sketched approach by comparing it with results reported by Park and Kim (2003), by evaluating the contribution of each of the involved heuristic components, and finally by analyzing the impact of QC productivity on the obtainable solution quality. All algorithms have been implemented in Java. The initial priority list for SWO and TS is derived from sorting the vessels by increasing expected time of arrival. Both algorithms terminate after 200 iterations without gaining further improvement. The tests were run on a PC P-IV 2.4 GHz.

7.1. Comparison with the Park–Kim approach

In order to assess the quality of our approach we compare it with the Lagrangean heuristics proposed by Park and Kim (2003). They report solutions and lower bounds for a set of 50 test instances with $n \in \{20, 25, 30, 35, 40\}$ vessels. Solving these instances with our approach requires slight modifications. We adapt the indices for berth segments and for time periods and replace the objective function as defined by Park and Kim (2003). Furthermore, the interference exponent is set to $\alpha = 1$ and the berth deviation factor is set to $\beta = 0$.

Table 2 shows the best solution PK found by the Lagrangean heuristics for each of the test instances. It is compared with the solutions generated by the SWO heuristic. For all instances SWO delivers better solutions. On average SWO improves the objective function value by 12%. Additionally, Park and Kim report lower bounds for their test instances. Curiously, many of our solutions fall below these bounds. Therefore we have checked the feasibility of every SWO solution through a CPLEX analysis of Park and Kim's model. It verifies that either the reported lower bounds are faulty, or that their model implementation differs from the published mathematical formulation. Regardless of this open question, the gained results confirm the competitiveness of the SWO algorithm.

7.2. Test instance generation

The benchmarks provided by Park and Kim are not rich enough to demonstrate the power of our solution approach. For this reason we have created new test instances in which we distinguish between three vessel classes, namely Feeder, Medium, and Jumbo. The classes differ in technical specifications and cost rates as shown in Table 3. The denotation U expresses a uniform distribution of integer values in the specified interval. The given ranges are in accordance with empirical data provided by ISL (2003). We have generated three sets of test instances containing 20, 30, and 40 vessels with ten instances each.

Table 2
Comparison of SWO with results of Park and Kim (2003)

$n = 20$			$n = 25$			$n = 30$			$n = 35$			$n = 40$		
#	PK	SWO	#	PK	SWO	#	PK	SWO	#	PK	SWO	#	PK	SWO
1	53	42	11	85	80	21	109	98	31	158	136	41	181	162
2	93	87	12	126	113	22	221	194	32	138	123	42	219	200
3	161	145	13	145	135	23	190	166	33	136	124	43	313	239
4	91	77	14	64	58	24	77	71	34	208	181	44	234	222
5	78	74	15	86	73	25	174	161	35	245	203	45	333	301
6	31	27	16	163	147	26	130	117	36	169	150	46	269	238
7	93	75	17	127	118	27	103	90	37	187	167	47	271	240
8	47	41	18	142	134	28	171	144	38	196	175	48	215	188
9	65	52	19	69	60	29	230	188	39	172	151	49	250	217
10	156	145	20	213	199	30	94	78	40	197	168	50	359	274

Table 3
Technical specifications and cost rates for different vessel classes

Class	l_i	m_i	r_i^{min}	r_i^{max}	c_i^1	c_i^2	c_i^3
Feeder	$U[8,21]$	$U[5,15]$	1	2	1	1	3
Medium	$U[21,30]$	$U[15,50]$	2	4	2	2	6
Jumbo	$U[30,40]$	$U[50,65]$	4	6	3	3	9

Within each instance, 60% of the vessels belong to the class Feeder, 30% belong to the class Medium, and 10% belong to the class Jumbo. The planning horizon H is set to one week (168 h). The expected times of arrival ETA of vessels are uniformly distributed in the planning horizon. It is assumed that a vessel can be speed up at most 10% which determines the earliest starting time EST = $\lceil 0.9 \cdot \text{ETA} \rceil$. The latest finishing time LFT of a vessel is derived by adding 1.5 times a vessel's minimum handling time to ETA_i. Further model parameters are as follows. The terminal data is $L = 100$ (1000 m), $Q = 10$ QCs, and $c^4 = 0.1$ thousand USD per QC-hour. The desired berthing position is drawn for vessel i using $U[0, L - l_i]$. 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 effects a 1% increase of the handling effort per segment of berthing position deviation.

Since the planning horizon H imposes a hard constraint in our BACAP model the generated instances are not necessarily solvable. To ensure solvability, we check for every generated instance whether the construction heuristic returns a feasible solution. Only in this case the instance is included in an instance set.

To get insight into the difficulty of the three instance sets, CPLEX 9.1 is applied using the options 'emphasize optimality' and 'aggressive cut generation', cf. Atamtürk and Savelsbergh (2005). Table 4 reports the objective function value Z for each of the 30 instances, if found within a computation time limit of 10 h. Additionally, a lower bound LB is obtained from the solver and reported in every case. CPLEX delivers near optimal solutions only for small sized instances with 20 vessels. Note that these instances represent situations with low workload in a CT. Merely four instances (#2, 5, 6, 8) were proven to be solved to optimality within the given runtime limit. Most of the medium sized instances #11–#20 remain unsolved while not a single integer feasible solution has been found for the large sized instances #21–#30. Obviously, the more congestion is faced at a CT, the poorer CPLEX performs. These results indicate that it does not provide a suitable solution procedure for the BACAP.

7.3. Comparison of heuristics

The heuristics are compared in four configurations. According to the vessels' arrival times, the construction heuristic is used in First-Come-First-Served manner, referred to as FCFS. Additionally, FCFS is combined with the local refinement procedures (FCFS_{LR}). Finally, Squeaky Wheel Optimization (SWO) and Tabu Search (TS) are applied as described above. Table 5 reports the obtained objective function value Z, representing the total service cost of a berth plan, and the relative error RE of the heuristics against the CPLEX lower bound $\left(\text{RE} = \frac{Z-\text{LB}}{\text{LB}}\right)$. Since FCFS and FCFS_{LR} are executed in less than a second for every instance, computation times are reported (in seconds) for SWO and TS only.

To compare the heuristics on an aggregate level, we have averaged the observed relative error over the thirty test instances. It can be seen that already local refinement decreases the average relative error of FCFS from 60% to 24%. However, much better solutions are delivered by SWO and TS. The average relative error of both meta-heuristics is approximately 10% below FCFS_{LR}. It appears that SWO performs slightly better than TS with respect to the produced relative error and the needed runtime. Considering the small sized instances with $n = 20$ it turns out that solutions of FCFS and FCFS_{LR} are significantly weaker than those delivered by CPLEX, while both meta-heuristics consistently generate near optimal solutions. For the medium and large sized instances they are the only methods that produce an acceptable solution quality. Within each of

Table 4
CPLEX results for the test instances

$n = 20$			$n = 30$			$n = 40$		
#	Z	LB	#	Z	LB	#	Z	LB
1	84.1	84.0	11	–	137.7	21	–	165.7
2	53.9[a]	53.9	12	81.8	81.4	22	–	159.6
3	77.4	75.2	13	104.9	100.9	23	–	185.0
4	76.2	75.8	14	–	96.8	24	–	224.1
5	56.8[a]	56.8	15	–	136.9	25	–	133.3
6	57.6[a]	57.6	16	–	106.2	26	–	201.3
7	68.0	67.5	17	–	99.6	27	–	172.2
8	56.1[a]	56.1	18	–	117.8	28	–	211.7
9	75.1	75.0	19	–	156.4	29	–	180.3
10	90.9	88.2	20	–	125.6	30	–	170.1

[a] Optimal solution.

Table 5
Performance comparison of heuristics for the new instance sets

n	#	FCFS		$FCFS_{LR}$		SWO			TS		
		Z	RE	Z	RE	Z	RE	Time	Z	RE	Time
20	1	118.5	0.41	86.1	0.02	85.1	0.01	11	85.1	0.01	14
	2	60.1	0.12	53.9	0.00	53.9	0.00	4	53.9	0.00	8
	3	97.6	0.30	87.3	0.16	77.4	0.03	11	77.4	0.03	17
	4	96.4	0.27	79.7	0.05	79.7	0.05	8	77.9	0.03	12
	5	73.1	0.29	56.8	0.00	56.8	0.00	10	56.8	0.00	15
	6	57.6	0.00	57.6	0.00	57.6	0.00	4	57.6	0.00	7
	7	93.3	0.38	69.9	0.04	68.9	0.02	17	68.9	0.02	24
	8	78.9	0.41	69.6	0.24	57.0	0.02	8	56.1	0.00	13
	9	96.4	0.29	76.3	0.02	75.9	0.01	18	75.5	0.01	14
	10	115.5	0.31	101.1	0.15	94.6	0.07	10	93.0	0.05	10
30	11	216.0	0.57	152.6	0.11	147.8	0.07	51	149.5	0.09	61
	12	96.7	0.19	86.4	0.06	83.3	0.02	17	82.5	0.01	36
	13	135.0	0.34	107.6	0.07	105.7	0.05	53	104.5	0.04	41
	14	144.5	0.49	113.2	0.17	105.8	0.09	22	113.2	0.17	41
	15	197.5	0.44	173.8	0.27	159.0	0.16	57	157.4	0.15	79
	16	137.7	0.30	127.2	0.20	118.5	0.12	40	119.5	0.13	51
	17	139.8	0.40	110.2	0.11	104.5	0.05	38	104.2	0.05	41
	18	167.8	0.42	131.4	0.12	125.5	0.07	20	131.2	0.11	46
	19	268.7	0.72	185.0	0.18	173.8	0.11	27	173.8	0.11	41
	20	184.7	0.47	140.5	0.12	135.2	0.08	58	138.3	0.10	93
40	21	317.0	0.91	261.3	0.58	215.0	0.30	311	226.7	0.37	209
	22	276.9	0.73	189.0	0.18	178.8	0.12	163	183.4	0.15	165
	23	550.4	1.98	325.7	0.76	273.9	0.48	315	264.3	0.43	373
	24	453.3	1.02	360.2	0.61	326.6	0.46	325	342.2	0.53	351
	25	239.1	0.79	162.0	0.22	155.1	0.16	206	154.8	0.16	140
	26	398.9	0.98	273.1	0.36	260.4	0.29	130	259.6	0.29	298
	27	354.6	1.06	233.0	0.35	200.8	0.17	209	215.8	0.25	282
	28	424.2	1.00	408.5	0.93	286.2	0.35	373	294.3	0.39	109
	29	334.2	0.85	268.4	0.49	219.4	0.22	202	223.4	0.24	175
	30	425.8	1.50	280.8	0.65	240.9	0.42	209	254.7	0.50	395
Average				0.60		0.24	0.13	98		0.15	105

the three instance sets, the meta-heuristics show a comparable runtime demand. The runtime demand significantly increases from smaller to larger instances but is clearly below ten minutes in every case.

This study shows that the BACAP gets increasingly difficult to solve if the workload increases in the terminal. This is also reflected by the growth of average cost per vessel under increasing workload. For instances with 20 vessels we observe average cost of approximately 3500 USD per vessel. They grow up to 5900 USD per vessel for instances with 40 vessels.

7.4. Estimating cost of productivity losses

In a final study we investigate the QC productivity which is also supposed to influence cost strongly. To quantify its impact we separately vary α and β, previously set to 0.9 and 0.01. In this test SWO is run for every parameter setting over all thirty instances. Fig. 7a shows the average service cost obtained for an instance if α is varied from 1.0 to 0.8 and $\beta = 0.01$ is held constant. The inverse range is chosen to indicate that larger values of α correspond to smaller losses of crane productivity. The average cost obtained for an instance amounts below 100 000 USD if QC interference is neglected ($\alpha = 1$). With the

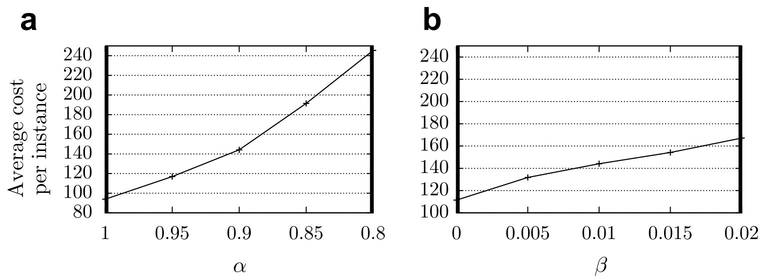

Fig. 7. Impact of α and β on average cost per instance.

still reasonable interference exponent $\alpha = 0.8$ it is more than doubled. Fig. 7b shows the average cost obtained for an instance if β is varied in the range from 0.00 to 0.02 and $\alpha = 0.9$ is held constant. Again, neglecting the impact of berthing position on the crane productivity considerably underestimates cost. For $\beta = 0.02$ average cost are approximately 50% higher.

This result verifies the strong impact of crane productivity on the terminal cost. Incorporating or neglecting productivity losses in the berth planning is by no means a marginal difference. Providing reasonable productivity measures is therefore an important aspect of planning seaside operations in CTs.

8. Conclusions

The paper contributes to recent research in container terminal operations planning by providing a rich model for the Berth Allocation and Crane Assignment Problem (BACAP) as well as new heuristic solution methods which allow treating instances of practical size. While most studies on the Berth Allocation Problem assume fixed handling times of vessels, we have explicitly incorporated the impact of the 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 to speed up vessels and to care for the cost of operating cranes besides the traditional service quality cost. For the resulting dynamic continuous BACAP, new heuristics have been presented. Computational comparisons show that the meta-heuristics Squeaky Wheel Optimization (SWO) and Tabu Search deliver solutions of good quality in a reasonable computation time. The heuristics do not significantly differ in solution quality. Nevertheless, we expect SWO to be of particular interest for future research because it perfectly fits the cost structure of the BACAP. Other topics of future research may deal with the inclusion of stochastic aspects to investigate the robustness of the solutions with respect to changes of the input data. This is of interest because we have seen that the influence of crane productivity is not marginal. It should be considered as an essential input for berth planning.

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