Chapter 6
Berth Allocation and Quay Crane Assignment

The new concept for integrated seaside operations planning comprises a deep integration of the BAP and the QCAP. The resulting problem, namely the *Berth Allocation and Crane Assignment Problem* (BACAP), is studied within this chapter. The first mathematical formulation of the combined problem of berth allocation and crane assignment has been presented by Park and Kim (2003). A new problem formulation has been provided by Meisel and Bierwirth (2009), which incorporates QC productivity determining effects. This new model is presented in Sect. 6.1 and solution methods are described in Sect. 6.2. Computational tests follow in Sect. 6.3. Section 6.4 concludes the BACAP study.

6.1 Modeling the BACAP

6.1.1 Problem Description and Assumptions

The BACAP bases on the continuous dynamic variant of the BAP. It is formally described as follows. A terminal with a quay of length L, measured in segments of 10 m length, is considered. A number of Q QCs is available to serve vessels. The planning horizon of the BACAP is H hours, where T is a corresponding set of 1-hour 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 $i \in V$ 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 given. Berthing the vessel earlier than ETA_i is possible by a speedup on its journey to the terminal. The realizable speedup, however, is bounded. To model this an earliest starting time $EST_i \leq ETA_i$ is given, i.e., the

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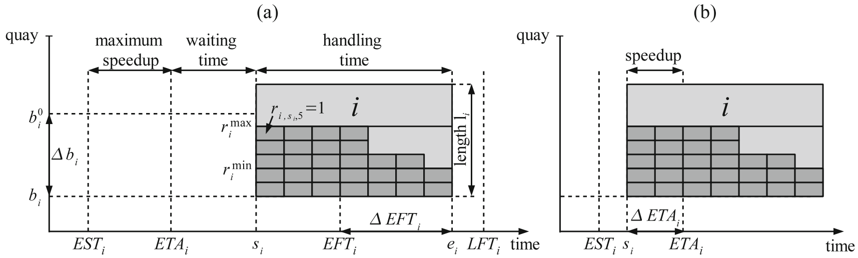

Fig. 6.1 Vessel data – waiting before berthing (**a**) and speedup case (**b**)

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.

The following assumptions are made for the BACAP:

1. Each quay position shows sufficient water depth to berth arbitrary vessels.
2. It takes no time to berth and to unberth vessels.
3. It takes no time to move a QC from one vessel to another vessel.
4. Vessels are served without preemption, i.e., once started to serve a vessel the process is not interrupted until the service is completed.
5. Every crane has the technical capability to serve every vessel. Furthermore, the cranes are identical, i.e., they show the same maximum productivity.

The decisions of the BACAP are to determine a berthing time s_i, a berthing position b_i, and the number of QCs to assign to each vessel $i \in V$ in its service periods such that a cost measure is minimized. The berthing time s_i of a vessel follows from the beginning of the first period with cranes assigned, whereas its departure time e_i is defined by the end of the last period 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 at time 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. Figure 6.1 illustrates the interrelations of the so far introduced vessel data and variables. A description of the cost structure of a vessel follows in Sect. 6.1.3.

6.1.2 Resource Utilization

Different effects influence the productivity of a terminal and thus, the utilization of its resources. For seaside operations, two influencing factors are of importance and need to be incorporated in a BACAP formulation:

- Interference among QCs
- Berthing vessels apart from desired berthing positions

The rail mounted QCs in a CT are unable to pass each other. As a consequence *interference among QCs* can take place 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. For reasons of simplicity Park and Kim (2003) ignore this effect by assuming that the crane productivity is proportional to the number of QCs that simultaneously serve a vessel. To overcome this simplification, crane productivity loss must be formally described. According to Schonfeld and Sharafeldien (1985) an *interference exponent* can be used that reduces the marginal productivity of cranes. For a given interference exponent α ($0 < \alpha \leq 1$), 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 support the allocation of human resources in container terminals and by Dragovic et al. (2006) for a simulation study on the berthing process. Oğuz et al. (2004) transfer a similar idea from machine scheduling to berth allocation and crane assignment where the interference exponent is used to determine handling times of vessels instead of crane productivity. Unfortunately, the solution method adopted from machine scheduling considers time-invariant QC-to-Vessel assignments only. It furthermore necessitates the objective of makespan minimization, which is rarely considered in berth planning due to its low practical relevance.

The productivity of a terminal is also affected by the workload of horizontal transport means. This workload is minimal if a vessel berths at its *desired berthing position* b_i^0. 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 deploying more transport vehicles. Therefore, Park and Kim (2003) propose to penalize apart berthing positions through additional costs. The approach, however, ignores the fact that a larger number of vehicles decelerates the average speed and thus reduces the service rate again. Therefore an apart berthing position of a vessel leads to a productivity loss. This productivity loss is modeled by an increase in the vessel's QC capacity demand. Let $\beta \geq 0$ 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 quay segments away from its desired berthing position requires $(1+\beta\Delta b_i)m_i$ QC-hours to be served.

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

$$d_i^{\min} = \left\lceil \frac{(1+\beta\Delta b_i)m_i}{(r_i^{\max})^{\alpha}} \right\rceil. \tag{6.1}$$

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 $\Delta b_i = 10$ quay segments. Without productivity loss the fastest possible handling requires 3 hours. If the interference exponent and the berth deviation factor are set to $\alpha = 0.85$ and $\beta = 0.02$, respectively, the minimum handling time increases to 5 hours according to (6.1).

6.1.3 Cost Structure

The most frequently pursued objective in berth allocation models is the minimization of waiting and handling times of vessels in order to achieve a high satisfaction of vessel operators. For a precise treatment of the various factors influencing service quality, different cost functions are proposed in the literature, see, e.g., Park and Kim (2003), Golias et al. (2006), and Hansen et al. (2008). In the following, the *service quality cost* of vessel i is the sum of three types of cost:

- Speedup cost for catching a berthing time earlier than ETA_i
- Tardiness cost for exceeding the expected finishing time EFT_i
- 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 speedup cost and tardiness cost grow constantly in time, penalty cost incur only once, if the departure of the vessel is beyond the latest allowed finishing time LFT_i. Figure 6.2 illustrates the cost drivers of 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.

Service quality objectives are certainly of highest importance. Nevertheless, besides offering a competitive service, the CT management also has to pursue low operational costs. Regarding the seaside of a CT, one of the operational cost drivers is the labor force needed to operate the QCs. Therefore, Meisel and Bierwirth (2006) propose to minimize the number of 8-hour gang shifts required to fulfill a berth plan without considering any service objectives. To combine service quality objectives and resource cost objectives, a fourth cost type is added here, called the *QC operational cost*. It evaluates the utilized QC-hours within a berth plan. The objective accounts for the decreasing marginal productivity of QCs and the resulting trade-off between accelerating the handling of a vessel and the operational cost of QCs. The cost rate per QC-hour is denoted as c^4. The QC operational cost plus the service quality costs of the vessels make up the total service costs of a berth plan. In the following all cost rates are given in units of 1,000 USD.

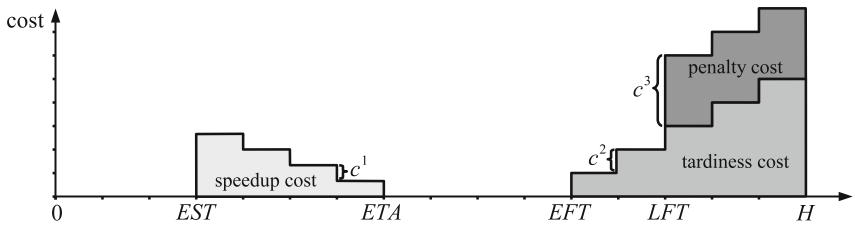

Fig. 6.2 Structure of the service quality cost of a vessel

6.1.4 Optimization Model

Besides the already introduced decision variables s_i, b_i, and r_{itq} the following binary decision variables are denoted to provide a mathematical formulation of the BACAP:

- r_{it} Set to 1 if at least one QC is assigned to vessel i at time t, 0 otherwise
- u_i Set to 1 if the finishing time of vessel i exceeds LFT_i, 0 otherwise
- y_{ij} Set to 1 if vessel i is berthed below of vessel j, i.e., $b_i + l_i \leq b_j$, 0 otherwise
- z_{ij} Set to 1 if the service of vessel i ends not later than the service of vessel j starts, 0 otherwise

The BACAP is formulated as follows:

$$\text{minimize } Z = \sum_{i \in V} \left[c_i^1 \, \Delta ETA_i + c_i^2 \Delta EFT_i + c_i^3 u_i + c^4 \sum_{t \in T} \sum_{q \in R_i} (q \, r_{itq}) \right] \quad (6.2)$$

subject to

$$\sum_{t \in T} \sum_{q \in R_i} (q^{\alpha} r_{itq}) \geq (1 + \beta \Delta b_i) m_i \qquad \forall i \in V, \quad (6.3)$$

$$\sum_{i \in V} \sum_{q \in R_i} (q r_{itq}) \leq Q \qquad \forall t \in T, \quad (6.4)$$

$$\sum_{q \in R_i} r_{itq} = r_{it} \qquad \forall i \in V, \forall t \in T, \quad (6.5)$$

$$\sum_{t \in T} r_{it} = e_i - s_i \qquad \forall i \in V, \quad (6.6)$$

$$(t+1) r_{it} \leq e_i \qquad \forall i \in V, \forall t \in T, \quad (6.7)$$

$$t r_{it} + H(1 - r_{it}) \geq s_i \qquad \forall i \in V, \forall t \in T, \quad (6.8)$$

$$\Delta b_i \geq b_i - b_i^0 \qquad \forall i \in V, \quad (6.9)$$

$$\Delta b_i \geq b_i^0 - b_i \qquad \forall i \in V, \quad (6.10)$$

$$\Delta ETA_i \geq ETA_i - s_i \qquad \forall i \in V, \quad (6.11)$$

$$\Delta EFT_i \geq e_i - EFT_i \qquad \forall i \in V, \quad (6.12)$$

$$M u_i \geq e_i - LFT_i \qquad \forall i \in V, \quad (6.13)$$

$$b_j + M(1 - y_{ij}) \geq b_i + l_i \qquad \forall i, j \in V, i \neq j, \quad (6.14)$$

$$s_j + M(1 - z_{ij}) \geq e_i \qquad \forall i, j \in V, i \neq j, \quad (6.15)$$

$$y_{ij} + y_{ji} + z_{ij} + z_{ji} \geq 1 \qquad \forall i, j \in V, i \neq j, \quad (6.16)$$

$$s_i, e_i \in \{EST_i, \ldots H\} \qquad \forall i \in V, \quad (6.17)$$

$$b_i \in \{0, 1, \ldots L - l_i\} \qquad \forall i \in V, \quad (6.18)$$

$$\Delta ETA_i, \Delta EFT_i \geq 0 \qquad \forall i \in V, \quad (6.19)$$

$$r_{itq}, r_{it}, u_i, y_{ij}, z_{ij} \in \{0, 1\} \qquad \forall i, j \in V, \forall t \in T, \forall q \in R_i. \quad (6.20)$$

This optimization model pursues the minimization of the total cost arising from the service of all vessels within the planning horizon. Constraints (6.3) 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 (6.4) 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 (6.5). Constraints (6.6)–(6.8) set the starting times and ending times for serving vessels without preemption. Constraints (6.9)–(6.12) determine the deviations from the desired berthing position, expected arrival time, and expected finishing time for each vessel. Variable u_i indicates whether the handling of vessel i ends later than LFT_i. It is set by Constraints (6.13) where M denotes a large positive number. Constraints (6.14) and (6.15) set the variables y_{ij} and z_{ij}, which are used to avoid overlapping the handling of vessels in the space–time diagram in Constraints (6.16). The arrival of a vessel can be sped up to at most the earliest starting time EST_i. Moreover, the planning horizon H defines a limit on the departure time of the vessels. Both aspects are reflected in Constraints (6.17). Constraints (6.18) ensure that each vessel is positioned within the quay boundaries. The Constraints (6.19) and (6.20) define domains for the remaining decision variables.

With the above model a linear formulation for the BACAP is provided. Although the BACAP model incorporates the productivity effects of resources, it is formulated more compact than the model of Park and Kim (2003) shown in Appendix A. The number of constraints grows in $O(nH)$ in the BACAP model while it grows in $O(nH^2)$ in the model provided by Park and Kim (2003). Also the number of variables grows less fast if Q is supposed to be much smaller than L. The compactness is based on a suitable formulation of the non-preemption condition in Constraints (6.6)–(6.8) and of the space–time condition in Constraints (6.14)–(6.16). The BACAP model shows that the assumption that QC productivity grows linearly in the number of cranes assigned to a vessel, as used by Park and Kim, can be replaced by a more accurate handling of crane productivity without increasing the complexity of the model.

The following characteristics of the classification scheme of Sect. 4.1.1 apply for the presented BACAP model. For the spatial attribute the value *cont* applies because the model is based on the continuous variant of the BAP. Since speeding up vessels is allowed only within certain bounds, an earliest possible time of arrival is known for every vessel. Due to the dynamic arrival process of vessels, the problem is classified as dynamic. The handling times of vessels depend on their berthing positions and the assignment of QCs as represented by the handling time characteristics *pos* and *QCAP*. The objective is the minimization of service quality costs incurred by speedups of vessels (*speed*) and by tardy departures (*tard*) as well as the operational cost of the utilized QC-hours (*res*). Note that the presented classification scheme does not distinguish between different types of tardiness costs for the sake of clarity. Summarizing, the BACAP is classified by $cont \mid dyn \mid pos, QCAP \mid \sum(w_1\, speed + w_2\, tard + w_3\, res)$.

The provided model can be reformulated to feature other well known BAP characteristics. For instance, discrete and hybrid BACAPs as well as vessel draft consideration can be modeled by eliminating forbidden berthing positions from the domains of the variables b_i. Due dates for the vessels can be represented in turn by an unacceptably large penalty c_i^3 for a tardy departure. The consideration of QC scheduling data within the BACAP, which leads to the handling time characteristic *QCSP*, is investigated by an explicit study later in this thesis.

6.2 Solution Methods

The BACAP as stated by (6.2)–(6.20) is an intractable problem because already the BAP is $\mathcal{NP}$-hard, see, e.g., Lim (1998) and Imai et al. (2005). Therefore, several heuristic solution methods are provided for the BACAP by Meisel and Bierwirth (2009):

- A construction heuristic to obtain an initial feasible solution
- Procedures for locally refining solutions by resource leveling and by shifting of vessel clusters
- Two meta-heuristics, namely Squeaky Wheel Optimization and Tabu Search

6.2.1 Construction Heuristic

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 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 deployed in period t (represented by the variables r_{itq}). As shown in Fig. 6.3, the procedure *Insert(i)* performs eight steps, namely (a)–(h).

In Step (a) the cost for inserting vessel i, denoted here by Z_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 space–time diagram by pursuing the fastest possible handling of the vessel. Using (6.1) the handling time $d_i^{\min}$ 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 (6.3) holds for the vessel to be inserted. To minimize the productivity loss, an almost uniform distribution of QCs over time is realized. Pseudocodes

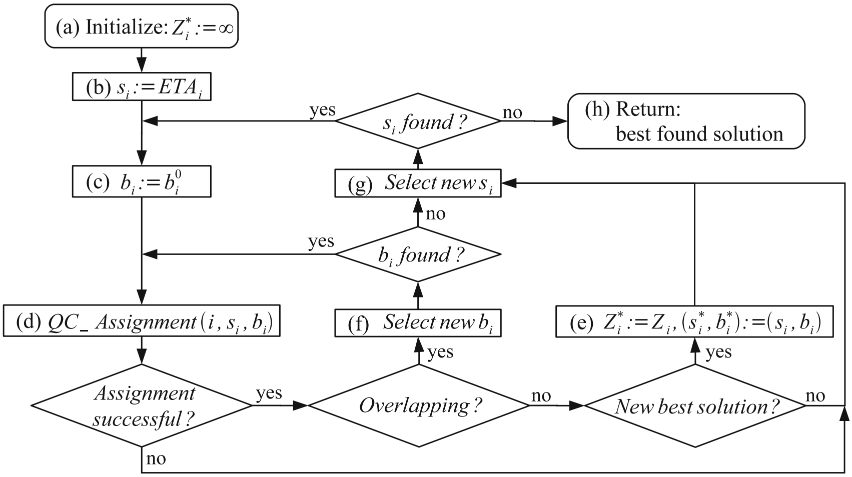

Fig. 6.3 Procedure *Insert(i)* of the constructor

for the crane assignment procedure and the subsequently described procedures are given in Appendix B.

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 is computed according to the objective function (6.2). In the event 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 $[ETA_i - 1, ETA_i + 1, ETA_i - 2, \ldots]$ until s_i has reached EST_i in the one direction and the end of the planning horizon in the other. To speed up the procedure, a lower bound of the cost associated with a starting time is determined using (6.2). 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^*).

Example 6.1: Insertion of a vessel

To illustrate the procedure, 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 $\beta = 0.1$. The data of the vessels is shown in Table 6.1. The partial schedule, already fixed for Vessels 1 and 2, is

Table 6.1 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

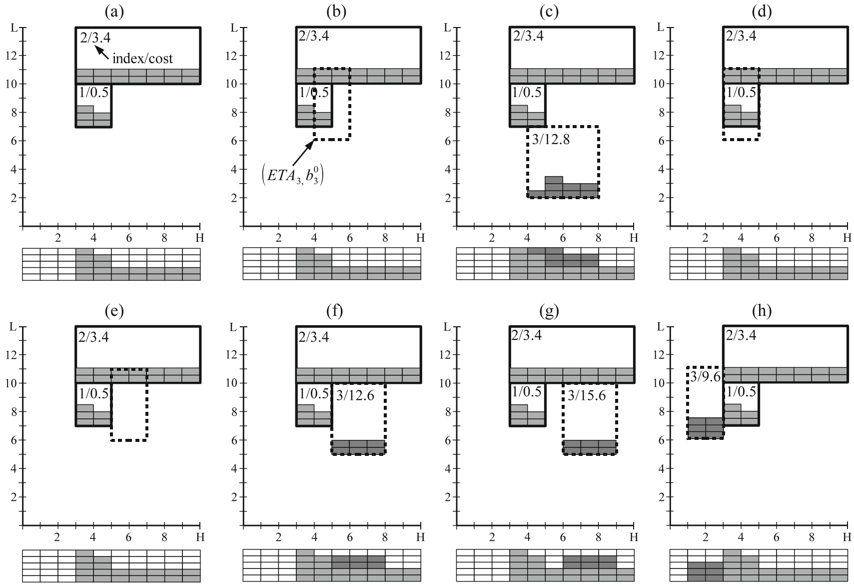

Fig. 6.4 Example positioning of a vessel

shown in Fig. 6.4a. Now, Vessel 3 has to be inserted. According to (6.1) its minimum handling time is $d_3^{\min} = 2$ hours if berthed at its desired berthing position.

At first, procedure $Insert(i = 3)$ selects the preferred coordinates, as shown by the dotted rectangular in Fig. 6.4b. 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 quay segments. Therefore, the number of needed QC-hours increases from $m_3 = 5$ to $(1 + \beta \cdot 4)m_3 = 7$ QC-hours. As shown in Fig. 6.4c, the QC assignment procedure 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 twice within the service. This resource assignment is sufficient because the QC productivity of $1^{0.9} + 3^{0.9} + 2 \times 2^{0.9} = 7.42$ satisfies the needed 7 QC-hours. The projected service of the vessel requires no speedup ($\Delta ETA_3 = 0$), but the finishing time exceeds the expected finishing time ($\Delta EFT_3 = 2$) and also the latest allowed finishing time ($e_3 > LFT_3$). With 8 QC-hours assigned, the corresponding cost of the vessel is $Z_3 = 12.8$. Next, to generate an alternative berth plan, $ETA_3 - 1$ is assigned to the vessel as a new handling start time. Figure 6.4d shows that not enough QCs are available in this period with respect to $r_3^{\min}$. Therefore, the starting time is set to $s_3 = ETA_3 + 1$. As shown in Fig. 6.4e the insertion overlaps the partial berth plan again. This is resolved by repositioning the vessel to $b_3 = 5$ which enlarges the handling time of the vessel by one period leading to a new best solution with $Z_3 = 12.6$, see Fig. 6.4f. 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. 6.4g. 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. 6.4h. Since $s_3 = EST_3$ 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 $(s_3^*, b_3^*) = (1,6)$.

6.2.2 Local Refinements

6.2.2.1 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 inserted early on in the berth plan by the construction heuristic have good prospects for being placed at their desired position in the space–time diagram and for getting 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 $P = (p_1, p_2, \dots, p_n)$ of all vessels $i \in V$. Starting with an empty berth plan, vessel p_1 is inserted once for every resource level $r_{p_1}^{\text{lvl}}$ 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.

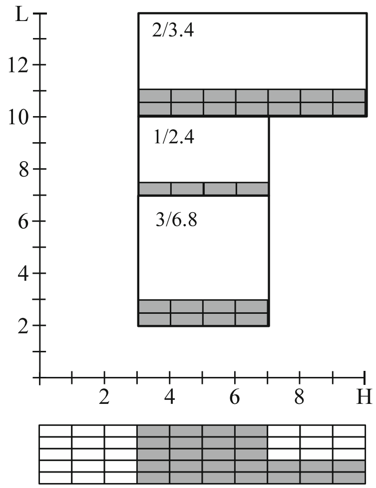

Fig. 6.5 Refinement of a berth plan by resource leveling

Example 6.2: Local refinement by resource leveling (continued Example 6.1)

To illustrate the procedure, a possible local refinement of the berth plan shown in Fig. 6.4h is described. If Vessel 1 is inserted with the resource level $r_1^{\mathrm{lvl}} = 1$, accepting an increase in 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. 6.5. 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.

6.2.2.2 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 that are connected in the space–time diagram because they occupy adjacent quay segments and are served simultaneously for at least one time period. A temporal cluster is a subset of vessels that are connected because they are served immediately one after the other, where subsequent vessels occupy at least one common quay 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 be used for the BACAP. 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 second refinement procedure iteratively performs shifts of all spatial clusters towards the quay'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 quay segment while a shift of a temporal cluster changes the berthing time of each vessel by one time period. If the QC assignment of vessel i becomes infeasible due to 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 shifted no further in the considered direction. Improved solutions are recorded during the second refinement phase. It terminates if no further improvement is possible.

Example 6.3: Local refinement by vessel shifts (continued Example 6.2)

To illustrate the procedure, the spatial cluster $\{1,2,3\}$ shown in Fig. 6.5 is shifted towards the lower quay border. The first shift yields the berth plan of Fig. 6.6a. Now, Vessel 2 requires less QC capacity while the demands 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

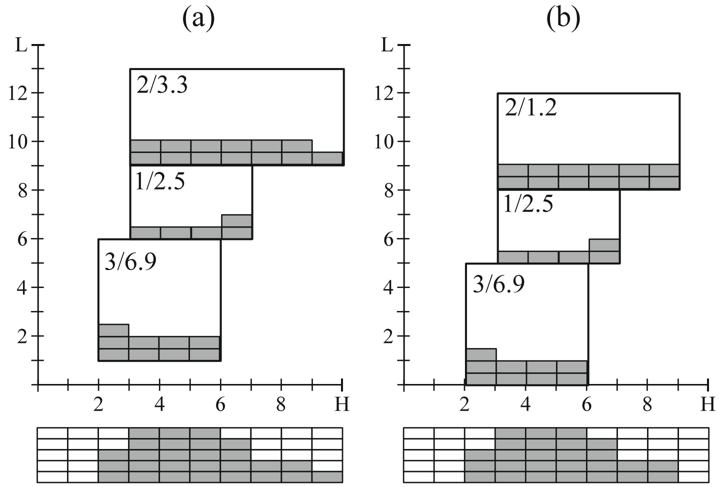

Fig. 6.6 Refinement of a berth plan by vessel shifts

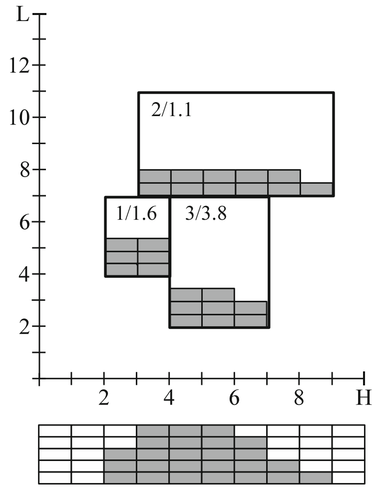

Fig. 6.7 Optimal solution to the BACAP example

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 in the improved berth plan, see Fig. 6.6b.

The optimal berth plan to the problem is shown in Fig. 6.7. This solution cannot be generated by the construction heuristic from the insertion order $(1,2,3)$ of the vessels. Hence, alternative priority lists for inserting vessels have to be taken into consideration.

6.2.3 *Meta-heuristics*

In this section two meta-heuristic approaches are presented, which enable changes in the priority list in order to improve the quality of berth plans.

6.2.3.1 Squeaky Wheel Optimization

Solutions of combinatorial optimization problems are often composed of 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 towards the top of a priority list. The new list serves to build a new solution using a base

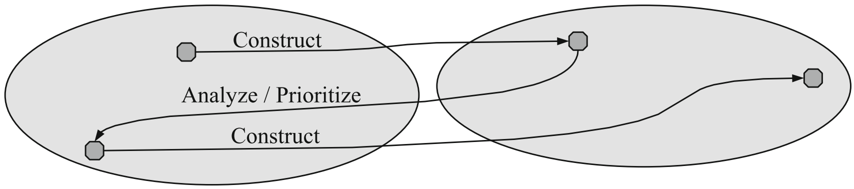

Fig. 6.8 Search spaces explored by SWO

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. 6.8.

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. (2004a,b), 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 whenever the 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 of 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 a 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 in a First-come First-served manner. Afterwards, a local refinement of the berth plan is done as described in Sect. 6.2.2 leading to an individual service quality cost for each single vessel. The operational costs for 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. Regardless 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 may be trapped in a cycle. Usually, this takes place if it generates a priority list that has already been generated in a previous round. A major source of cycling is local refinement, which may effect that a changed priority list leads to an already investigated solution and, thus, the priority list itself is also not influenced by this solution. 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 analyzing a given number of solutions without finding a new best solution.

Example 6.4: Prioritization by SWO (continued Example 6.3)

As an example for an iteration of SWO, the solution obtained after the second local refinement is taken up, see Fig. 6.6b. The original priority list that led to this solution is $P = (1,2,3)$. Since SWO considers service quality cost only, the relevant costs of Vessels 1, 2, and 3 are 2, 0, and 6, respectively. The priority list is changed by pairwise comparison of vessels on the basis of these costs. Hence, Vessels 1 and 2 do not change their position within the priority list because Vessel 1 shows higher service quality cost. The positions of Vessels 2 and 3 are changed because Vessel 3 shows higher service quality cost. A new priority list $P = (1,3,2)$ is derived, which is investigated in the next SWO iteration, and so on.

6.2.3.2 Tabu Search

As a further meta-heuristic approach the well known *Tabu Search* (TS) method, see Glover (1986), is applied to the BACAP. Like SWO, the proposed 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 carried out 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 Criterion is not necessary because a new best solution found cannot be contained in the tabu list.

The TS algorithm terminates after a given number of iterations without finding a new best solution.

6.2.4 *Specific Quay Crane Assignment*

As intended by the provided BACAP model, the solution methods presented so far decide on the berthing times, the berthing positions, and the number of cranes to assign to each vessel within each period of its service interval. So far undecided is the set of *specific* cranes that make up the assigned QCs, see Fig. 3.4 on page 22 for an example. The determination of a specific assignment leads to a subsequent problem as shown by Park and Kim (2003), Ak and Erera (2006), and Imai et al. (2008a). Park and Kim (2003) propose a dynamic programming method to solve this problem. The method minimizes the total number of QC setups at the vessels and ensures that the cranes do not cross. It can be applied to the above BACAP formulation without modifications. The method is computationally inexpensive. For example, it generates a specific QC assignment for a BACAP solution with 40 vessels in less than a second. Therefore, the method is not involved in the computational study.

6.3 Computational Study

The following tests assess the performance of the BACAP solution methods and investigate the sensitivity of the solutions regarding the parameter settings.

- Performance comparison of BACAP solution methods:

  Test 6.1: Capability of CPLEX to deliver optimal solutions
  Test 6.2: Comparison of initial solutions and locally refined solutions
  Test 6.3: Comparison of SWO and TS
  Test 6.4: Comparison with the Park–Kim approach
  Test 6.5: Comparison with a sequential solution approach

- Sensitivity on problem parameter settings:

  Test 6.6: Effectiveness of vessel priorities
  Test 6.7: Estimating cost of productivity losses
  Test 6.8: Effectiveness of QC operational cost consideration
  Test 6.9: Potential of variable-in-time QC-to-Vessel assignments

In order to carry out the tests, all solution methods have been implemented in JAVA. A PC P4 2.4 GHz is used for the computations.

Table 6.2 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

Benchmark Instances

For the tests, appropriate benchmark instances are required. While a set of benchmarks is provided by Park and Kim (2003) the instances are not rich enough to investigate all objectives of the outlined tests. For example, all vessels within these instances show identical cost rates. For this reason the instances are applied only in the comparison in Test 6.4. For all other tests a set of new created test instances is used. In these instances vessels are distinguished by three classes, namely feeder, medium, and jumbo. The classes differ in technical specifications and cost rates as shown in Table 6.2, where 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).

Three sets of test instances have been generated containing 20, 30, and 40 vessels with ten instances each. 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 1 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 at most 10% which determines the earliest starting time $EST_i = \lceil 0.9ETA_i \rceil$. 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. Further model parameters are as follows. The terminal data is $L = 100$ (1,000 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 in the handling effort per quay segment of berthing position deviation.

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

Test 6.1: Capability of CPLEX to deliver optimal solutions

To obtain insight into the difficulty of the three instance sets, ILOG CPLEX 9.1 is applied using the options "emphasize optimality" and "aggressive cut generation". For recommendations of CPLEX parameter settings see Atamtürk and Savelsbergh

Table 6.3 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*	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*	56.8	15	–	136.9	25	–	133.3
6	57.6*	57.6	16	–	106.2	26	–	201.3
7	68.0	67.5	17	–	99.6	27	–	172.2
8	56.1*	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

*Optimal solution

(2005). Table 6.3 reports the objective function value *Z*, representing the total cost of a berth plan, for each of the 30 instances, if found within a limited runtime of 10 h. Additionally, a lower bound *LB* is obtained from the solver and reported in every case. CPLEX always delivers near optimal solutions 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 remain unsolved, while not a single integer feasible solution has been found for the large sized instances. Running CPLEX with the option "emphasize feasibility" did not lead to further feasible solutions. These results indicate that the more congestion is faced at a CT the poorer CPLEX performs. While CPLEX does not provide a suitable solution procedure for the BACAP, the derived lower bounds are valuable for evaluating heuristic solutions in the subsequent tests.

Test 6.2: Comparison of initial solutions and locally refined solutions

This test investigates the quality of solutions obtained by the construction heuristic and by the local refinements. With vessels sorted by increasing expected time of arrival, the construction heuristic is used in First-come First-served manner, referred to as FCFS. To assess the individual contribution of the two local refinement procedures, the FCFS solutions are refined once by applying QC resource leveling ($FCFS_{LR1}$) and once by shifting vessel clusters ($FCFS_{LR2}$). Finally, both refinement procedures are subsequently applied to the initial solutions ($FCFS_{LR}$), where QC resource leveling is performed before shifting vessel clusters. The reverse order is not investigated because refinements of a berth plan obtained by shifts of vessel clusters get lost by a subsequent QC resource leveling. Table 6.4 reports the obtained objective function value *Z* and the relative error *RE* in percent of the heuristics

Table 6.4 Initial solutions and locally refined solutions

n	#	FCFS		$FCFS_{LR1}$		$FCFS_{LR2}$		$FCFS_{LR}$	
		Z	RE	Z	RE	Z	RE	Z	RE
20	1	118.5	41.07	118.5	41.07	86.1	2.50	86.1	2.50
	2	60.1	11.50	60.1	11.50	53.9	0.00	53.9	0.00
	3	97.6	29.79	97.6	29.79	87.3	16.09	87.3	16.09
	4	96.4	27.18	96.4	27.18	79.7	5.15	79.7	5.15
	5	73.1	28.70	65.2	14.79	56.8	0.00	56.8	0.00
	6	57.6	0.00	57.6	0.00	57.6	0.00	57.6	0.00
	7	93.3	38.22	91.6	35.70	71.4	5.78	69.9	3.56
	8	78.9	40.64	69.6	24.06	66.5	18.54	69.6	24.06
	9	96.4	28.53	96.4	28.53	76.3	1.73	76.3	1.73
	10	115.5	30.95	109.7	24.38	98.2	11.34	101.1	14.63
30	11	216.0	56.86	187.5	36.17	148.6	7.92	152.6	10.82
	12	96.7	18.80	94.7	16.34	87.9	7.99	86.4	6.14
	13	135.0	33.80	135.0	33.80	107.6	6.64	107.6	6.64
	14	144.5	49.28	130.9	35.23	117.5	21.38	113.2	16.94
	15	197.5	44.27	181.3	32.43	174.1	27.17	173.8	26.95
	16	137.7	29.66	132.1	24.39	125.8	18.46	127.2	19.77
	17	139.8	40.36	130.8	31.33	106.3	6.73	110.2	10.64
	18	167.8	42.44	167.8	42.44	131.4	11.54	131.4	11.54
	19	268.7	71.80	268.7	71.80	185.0	18.29	185.0	18.29
	20	184.7	47.05	178.1	41.80	144.3	14.89	140.5	11.86
40	21	317.0	91.31	278.3	67.95	298.5	80.14	261.3	57.69
	22	276.9	73.50	247.0	54.76	186.9	17.11	189.0	18.42
	23	550.4	197.51	364.0	96.76	455.0	145.95	325.7	76.05
	24	453.3	102.28	430.9	92.28	367.9	64.17	360.2	60.73
	25	239.1	79.37	208.6	56.49	166.6	24.98	162.0	21.53
	26	398.9	98.16	375.9	86.74	295.7	46.90	273.1	35.67
	27	354.6	105.92	292.7	69.98	245.6	42.62	233.0	35.31
	28	424.2	100.38	424.2	100.38	408.5	92.96	408.5	92.96
	29	334.2	85.36	289.7	60.68	291.2	61.51	268.4	48.86
	30	425.8	150.32	364.2	114.11	327.3	92.42	280.8	65.08
ARE (%)			59.83		46.76		29.03		23.99

against the CPLEX lower bound, i.e., $RE = (Z - LB)/LB \times 100$. To compare the heuristics on an aggregate level, the observed relative error has been averaged over the 30 test instances (*ARE*). Since all procedures terminate within less than a second for each of the instances, no computation times are reported here.

In Table 6.4 it can be seen that the initial solutions show very large relative errors of about 60% on average. For the large-sized instances with $n = 40$, the solutions even show an average error of more than 100%. Applying the local refinement procedures individually reduces the *ARE* considerably. Local refinement through resource leveling decreases the *ARE* by more than 13% compared to FCFS. Local refinement by shifting of vessel clusters decreases the *ARE* by more than 30%. Obviously, the shifting of vessel clusters provides a more effective local refinement of the initial solutions. However, better solution quality is obtained if both refinement procedures are applied sequentially to the initial solutions. Here, the *ARE* is about 36% below the *ARE* of the initial solutions. Taking a closer look at the three instance sets, one can see that for the small-sized instances with $n = 20$ only one instance (#7) is further improved, while for two instances (#8, 10) even worse solutions are returned by the sequentially applied local refinements compared to FCFS_{LR2}. Four of the medium-sized instances are improved (#12, 14, 15, 20), while for three instances (#11, 16, 17) worse solutions are returned compared to FCFS_{LR2}. The major improvements are observed for the large-sized instances with $n = 40$. Here, the sequential application of both refinement procedures improves eight of the ten instances compared to FCFS_{LR2}. These results show that shifting of vessel clusters successfully preserves the refinements obtained by QC resource leveling as encoded in the resource level variables r_i^{lvl}. From a practical point of view it becomes obvious that a higher congestion at a CT calls for the application of both refinement procedures.

Test 6.3: Comparison of SWO and TS

In this test, the two meta-heuristics Squeaky Wheel Optimization (SWO) and Tabu Search (TS) are compared. The initial priority list for the heuristics is derived from sorting the vessels by increasing expected time of arrival, i.e., the FCFS rule is applied. Both algorithms terminate after 200 iterations without gaining an improvement. Further parameters do not exist for the methods. Table 6.5 reports the obtained objective function value Z, the relative error *RE* against the CPLEX lower bound, and the computation times *time* (in seconds) for each of the 30 instances and each of the two meta-heuristics. To ease identification of the improvements realized by the meta-heuristics, the locally refined initial solutions FCFS_{LR} as found within the previous test are reported again.

The results show that SWO and TS deliver much better solutions than the local refinements for the 30 instances. The *ARE* observed for FCFS_{LR} is decreased by about 11% using SWO and by about 9% using TS. For small-sized instances SWO and TS return better solutions for six and seven instances, respectively. Here, the TS solutions for instances #4, 8, 9, 10 are better than the SWO solutions. However, for the instances with $n = 30$ and $n = 40$ SWO is superior to TS. For example, for the large-sized instances with $n = 40$, SWO shows an *ARE* of about 30% but TS shows an *ARE* of 33%. The increase in the *ARE* for medium-sized and large-sized instances shows that the BACAP becomes more difficult to solve if the workload increases in the terminal. This is also reflected by the growth of average cost per vessel under an increasing workload. For instances with 20 vessels, average cost of approximately 3,500 USD per vessel are observed. They increase to 5,900 USD per vessel for instances with 40 vessels.

Regarding the runtimes, SWO is slightly faster than TS within each of the three instance sets. The average runtime per instance significantly increases from smaller to larger instances for both meta-heuristics but stays clearly below 10 min even for

Table 6.5 Performance comparison of meta-heuristics

n	#	$FCFS_{LR}$		SWO			TS		
		Z	RE	Z	RE	*time*	Z	RE	*time*
20	1	86.1	2.50	85.1	1.31	11	85.1	1.31	14
	2	53.9	0.00	53.9	0.00	4	53.9	0.00	8
	3	87.3	16.09	77.4	2.93	11	77.4	2.93	17
	4	79.7	5.15	79.7	5.15	8	77.9	2.77	12
	5	56.8	0.00	56.8	0.00	10	56.8	0.00	15
	6	57.6	0.00	57.6	0.00	4	57.6	0.00	7
	7	69.9	3.56	68.9	2.07	17	68.9	2.07	24
	8	69.6	24.06	57.0	1.60	8	56.1	0.00	13
	9	76.3	1.73	75.9	1.20	18	75.5	0.67	14
	10	101.1	14.63	94.6	7.26	10	93.0	5.44	10
30	11	152.6	10.82	147.8	7.33	51	149.5	8.57	61
	12	86.4	6.14	83.3	2.33	17	82.5	1.35	36
	13	107.6	6.64	105.7	4.76	53	104.5	3.57	41
	14	113.2	16.94	105.8	9.30	22	113.2	16.94	41
	15	173.8	26.95	159.0	16.14	57	157.4	14.97	79
	16	127.2	19.77	118.5	11.58	40	119.5	12.52	51
	17	110.2	10.64	104.5	4.92	38	104.2	4.62	41
	18	131.4	11.54	125.5	6.54	20	131.2	11.38	46
	19	185.0	18.29	173.8	11.13	27	173.8	11.13	41
	20	140.5	11.86	135.2	7.64	58	138.3	10.11	93
40	21	261.3	57.69	215.0	29.75	311	226.7	36.81	209
	22	189.0	18.42	178.8	12.03	163	183.4	14.91	165
	23	325.7	76.05	273.9	48.05	315	264.3	42.86	373
	24	360.2	60.73	326.6	45.74	325	342.2	52.70	351
	25	162.0	21.53	155.1	16.35	206	154.8	16.13	140
	26	273.1	35.67	260.4	29.36	130	259.6	28.96	298
	27	233.0	35.31	200.8	16.61	209	215.8	25.32	282
	28	408.5	92.96	286.2	35.19	373	294.3	39.02	109
	29	268.4	48.86	219.4	21.69	202	223.4	23.90	175
	30	280.8	65.08	240.9	41.62	209	254.7	49.74	395
Avg.			23.99		13.32	98		14.69	105

instances with $n = 40$ vessels. The runtimes indicate that the two meta-heuristics are extremely useful for practice.

Summarizing, SWO and TS deliver solutions of near optimal quality for small-sized instances. While the average errors for medium-sized and large-sized instances still indicate a further optimization potential, the meta-heuristics are the only methods that deliver solutions of acceptable quality for these instances. The slightly better overall performance of SWO against TS in terms of solution quality as well as computation time makes it the preferable solution method for the BACAP. SWO is therefore used as the reference solution method in the following tests.

Test 6.4: Comparison with the Park–Kim approach

In order to further assess the quality of the approach, SWO is compared with the Lagrangean heuristics proposed by Park and Kim (2003). The authors report solutions and lower bounds for a set of 50 test instances with $n \in \{20, 25, 30, 35, 40\}$ vessels. Solving these instances by the new BACAP approach requires slight modifications. The indices for quay segments and for time periods are adapted and the objective function is replaced as defined in the model of Park and Kim (2003). To eliminate the influence of decreasing effects of QC productivity, the interference exponent is set to $\alpha = 1$ and the berth deviation factor is set to $\beta = 0$.

Table 6.6 shows the cost of the best solution found by Park and Kim for each of the test instances in column PK. It is compared with the solutions generated by the SWO heuristic. The table also shows the relative improvement *Impr* in percent as realized by SWO, i.e., $Impr = (\text{PK} - \text{SWO})/\text{PK} \times 100$. As can be seen, SWO always delivers better solutions for the 50 instances. On average, SWO improves

Table 6.6 Comparison of SWO with results of Park and Kim (2003)

$n = 20$				$n = 25$				$n = 30$			
#	PK	SWO	*Impr.*	#	PK	SWO	*Impr.*	#	PK	SWO	*Impr.*
1	53	42	20.75	11	85	80	5.88	21	109	98	10.09
2	93	87	6.45	12	126	113	10.32	22	221	194	12.22
3	161	145	9.94	13	145	135	6.90	23	190	166	12.63
4	91	77	15.38	14	64	58	9.38	24	77	71	7.79
5	78	74	5.13	15	86	73	15.12	25	174	161	7.47
6	31	27	12.90	16	163	147	9.82	26	130	117	10.00
7	93	75	19.35	17	127	118	7.09	27	103	90	12.62
8	47	41	12.77	18	142	134	5.63	28	171	144	15.79
9	65	52	20.00	19	69	60	13.04	29	230	188	18.26
10	156	145	7.05	20	213	199	6.57	30	94	78	17.02
Avg.			12.97				8.97				12.39

$n = 35$				$n = 40$			
#	PK	SWO	*Impr.*	#	PK	SWO	*Impr.*
1	158	136	13.92	11	181	162	10.50
2	138	123	10.87	12	219	200	8.68
3	136	124	8.82	13	313	239	23.64
4	208	181	12.98	14	234	222	5.13
5	245	203	17.14	15	333	301	9.61
6	169	150	11.24	16	269	238	11.52
7	187	167	10.70	17	271	240	11.44
8	196	175	10.71	18	215	188	12.56
9	172	151	12.21	19	250	217	13.20
10	197	168	14.72	20	359	274	23.68
Avg.			12.33				13.00

the objective function value by 12%. Park and Kim also report lower bounds for their test instances. Curiously, many of the solutions obtained by SWO fall below these bounds. Therefore the feasibility of every solution has been checked through a CPLEX analysis of Park and Kim's model by fixing the decision variables according to the SWO solution. CPLEX verifies that the found values of the decision variables are feasible with respect to the model. It also returns the same objective function value as SWO does. For this reason, either the lower bounds reported by Park and Kim are faulty, or their model implementation differs from their published mathematical formulation. Regardless of this open question, the gained results confirm the competitiveness of the new approach.

Test 6.5: Comparison with a sequential solution approach

In practice, BAP and QCAP are usually solved sequentially, whereas the BACAP provides an integrated solution. The following test compares these two alternatives. To simulate the sequential solution process, the procedure $QC\_Assignment(i, s_i, b_i)$ is removed from the procedure $Insert(i)$. Instead, the handling time of each vessel is fixed to the minimum handling time $d_i^{\min}$ as defined in (6.1) on page 57. Note that the terminal planners might apply handling times above $d_i^{\min}$ to anticipate terminal productivity influences. However, this anticipation is rather speculative and therefore not considered here. From the outlined modification, all presented solution procedures solve a BAP with fixed handling times. For the derived berth plan, a QCAP solution needs to be determined. To do so, the vessels are removed from the berth plan one by one and reinserted using the original procedure $Insert(i)$. The derived final solution comprises a berth plan and an assignment of QCs to vessels. The reinsertion ensures that the solution is feasible by revising berthing positions and berthing times whenever the QC assignment causes infeasibility of the original berth plan. Table 6.7 shows the derived objective function values if SWO is applied within the described sequential solution process in column SEQ. Column BACAP shows the objective function values if SWO is applied within the integrated solution process (these values are the same as reported in Table 6.5). Furthermore, the resulting relative improvement $Impr = (\text{SEQ} - \text{BACAP})/\text{SEQ} \times 100$ in percentage of the BACAP approach over the sequential solution approach is given.

As can be seen by the results, the integrated solution of the BACAP clearly dominates the sequential solution of BAP and QCAP. For small-sized and medium-sized instances the average improvement is about 12% and 16%, respectively. For the large-sized instances the average improvement is even larger than 40%. This shows that in a congested terminal the combined consideration of the affected resources quay space and QCs becomes an essential need. Their separate consideration within the BAP (quay space resource) and the QCAP (QC resource) leads to solutions of very poor quality.

The superior solution quality of the BACAP within all three instance sets indicates that deep integration of the BAP and the QCAP represents an advanced planning concept for seaside operations in a CT.

Table 6.7 Comparison with a sequential solution approach

$n=20$				$n=30$				$n=40$			
#	SEQ	BACAP	*Impr.*	#	SEQ	BACAP	*Impr.*	#	SEQ	BACAP	*Impr.*
1	91.1	85.1	6.59	11	218.3	147.8	32.30	21	386.2	215.0	44.33
2	57.8	53.9	6.75	12	98.5	83.3	15.43	22	275.1	178.8	35.01
3	88.7	77.4	12.74	13	143.0	105.7	26.08	23	555.2	273.9	50.67
4	109.3	79.7	27.08	14	131.2	105.8	19.36	24	564.3	326.6	42.12
5	67.3	56.8	15.60	15	177.3	159.0	10.32	25	179.7	155.1	13.69
6	57.6	57.6	0.00	16	122.4	118.5	3.19	26	452.0	260.4	42.39
7	75.5	68.9	8.74	17	113.6	104.5	8.01	27	292.6	200.8	31.37
8	68.0	57.0	16.18	18	140.4	125.5	10.61	28	429.6	286.2	33.38
9	82.4	75.9	7.89	19	203.4	173.8	14.55	29	413.6	219.4	46.95
10	120.1	94.6	21.23	20	160.1	135.2	15.55	30	647.4	240.9	62.79
Avg.			12.28			15.54				40.27	

Test 6.6: Effectiveness of vessel priorities

In the presented BACAP formulation, vessel priorities are modeled by different cost rates per vessel class. The solutions to the BACAP have to reflect these priorities to ensure satisfaction of vessel operators. To assess the effectiveness of the prioritization, the indicators of service quality, i.e., the speedup of vessels, the tardiness of vessels, and the deviations from desired berthing positions, are measured. If priority is given to certain vessels these values should decrease at the expense of vessels with lower priority.

For the test the benchmark suite is solved, once using identical cost rates for all vessel classes, i.e., no vessel receives priority, and once using the vessel class specific cost rates as stated in Table 6.2. The class specific cost rates give low priority to vessels belonging to the feeder class, medium priority to vessels belonging to the medium class, and high priority to vessels belonging to the jumbo class. Table 6.8 reports the average speedup (ΔETA_i), tardiness (ΔEFT_i), and berthing position deviation (Δb_i) of all vessels belonging to the same class as observed within the solutions to the 30 instances.

The results show that the specific cost rates for the vessel classes improve the service quality of jumbo vessels at the expense of feeder and medium vessels. For example, the average tardiness ΔEFT_i of a jumbo vessel decreases from 2.62 h in the solutions with identical cost rates to 1.13 h in the solutions with class specific cost rates. In contrast, the average tardiness of a feeder vessel increases from 0.34 to 0.64 h. Similar results can be observed regarding the speedup ΔETA_i of vessels. Interestingly, values observed for jumbo vessels are still larger than the corresponding values for feeder and medium vessels. An explanation is that speedups and tardiness of smaller vessels are frequently avoided by assigning them apart berthing positions. Due to the shorter vessel length, such alternative positions are often easier to find than for jumbo vessels. This is verified by the average deviation from desired

Table 6.8 Effects of vessel prioritization by cost rates

Cost rates	Identical			Class specific		
Vessel class	Feeder	Medium	Jumbo	Feeder	Medium	Jumbo
Avg. ΔETA_i	0.13	0.51	0.72	0.23	0.54	0.60
Avg. ΔEFT_i	0.34	1.06	2.62	0.64	1.11	1.13
Avg. Δb_i	5.83	4.70	3.68	6.01	4.76	2.23

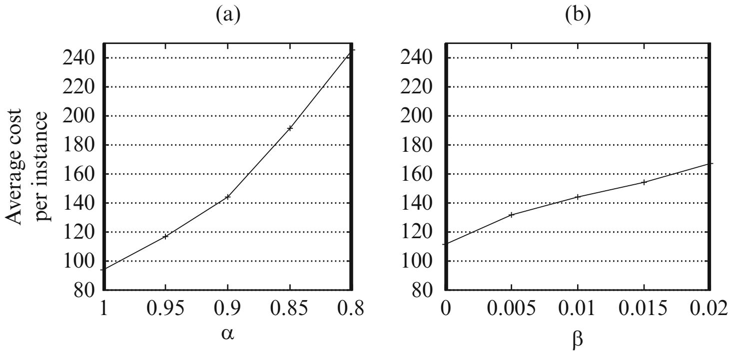

Fig. 6.9 Impact of α and β on average cost per instance

berthing positions which is 6.01 quay segments (≈60 m) for a feeder vessel but only 2.23 segments (≈22 m) for a jumbo vessel. The test shows that the incorporation of different cost rates for vessel classes is an effective way to prioritize vessels within the BACAP solution process.

Test 6.7: Estimating cost of productivity losses

In this test, the influence of QC productivity on the cost of solutions is investigated. To quantify its impact, α and β, previously set to 0.9 and 0.01, are varied separately. SWO is run for every parameter setting over all 30 instances. Figure 6.9a shows the average service cost obtained for the instances 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 loss of crane productivity. The average cost per instance amounts to below 100,000 USD, if QC interference is neglected ($\alpha = 1$). With the still reasonable interference exponent $\alpha = 0.8$ it is more than doubled. Figure 6.9b shows the average cost obtained for the instances, 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 vessels' berthing positions on the crane productivity considerably underestimates costs. 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.

Test 6.8: Effectiveness of QC operational cost consideration

Besides service quality cost of vessels also QC operational cost is included in the objective function of the BACAP. This cost reflects the CT management's desire to avoid productivity losses caused by crane interference and apart berthing positions of vessels. Clearly, the QC operational cost stays in conflict with the service quality objectives. The more demanding the latter are, the more often QCs need to be utilized, even if they show only little marginal productivity. To investigate the reduction potential of productivity losses, different QC-hour cost rates are investigated in combination with different service quality cost structures of vessels. The QC-hour cost rate c^4 is varied in the range [0,0.5], where $c^4 = 0.5$ means that a utilized QC-hour incurs cost of 500 USD. Two scenarios are investigated for the service quality objectives. In the first scenario the original cost rates are used as stated in Table 6.2. The second scenario represents relaxed service quality objectives by neglecting the tardiness cost. Here, $c_i^2 = 0$ is set for all vessels. In this scenario only speedup cost and penalty cost for overshooting the latest allowed finishing times LFT_i remain for the overall cost of service quality. Figure 6.10 shows the total observed productivity loss over all 30 instances for each combination of QC-hour cost rate and service quality scenario. The productivity loss is derived from the total utilized QC-hours in the solutions, minus the requested QC capacity (m_i) over all vessels contained within the instances.

As one would expect, the productivity loss decreases in both scenarios if the QC-hour cost rate c^4 is increased. The most considerable decrease is observed between

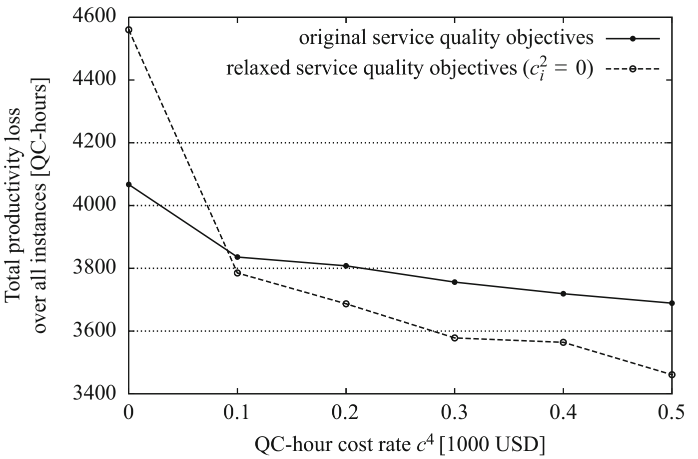

Fig. 6.10 Impact of QC operational cost on productivity loss

$c^4 = 0$ and $c^4 = 0.1$, which shows that even a small c^4 value avoids a waste of QC capacity. A further increase in c^4 leads to a further decrease in the productivity loss at a lower rate.

Focusing on the impact of service quality objectives, the relaxed scenario shows a higher productivity loss than the original scenario in the case of $c^4 = 0$. At first glance this is unexpected because the relaxation of service quality requirements allows to use QC capacity more effectively. However, with $c^4 = 0$ the solution methods do not aspire to minimize QC operational cost at all and thus, a reduction in productivity loss takes place only by chance. If c^4 takes a positive value, the productivity loss in the relaxed scenario is lower than in the scenario with original service quality objectives. This confirms that the service quality objectives and the QC operational cost objectives are in conflict and that the potential to reduce QC productivity loss depends on the service quality requirements.

Summarizing the test, incorporating QC operational cost in the BACAP provides an option to reduce crane productivity loss at a considerable rate. This result even holds in the presence of demanding service quality objectives.

Test 6.9: Potential of variable-in-time QC-to-Vessel assignments

The presented BACAP approach is able to deal with variable-in-time QC-to-Vessel assignments, i.e., the number of cranes serving a vessel may change during the service process. The studies of Oğuz et al. (2004), Liu et al. (2006), and Imai et al. (2008a) consider time-invariant QC-to-Vessel assignments only, i.e., the number of assigned cranes is held constant during the service of a vessel, which eases modeling and solving of seaside operations planning. A final test addresses the improvement potential offered by consideration of variable-in-time assignments. For comparison, SWO is restricted to consider time-invariant assignments only. This is realized by modifying the procedure *QC_Assignment* such that vessel i is served by a *constant* number of $q \in R_i$ cranes during its whole handling interval. This number is determined by the local refinement procedure for QC resource leveling.

Table 6.9 reports the objective function values obtained if SWO considers merely time-invariant QC-to-Vessel assignments in column INVAR. The results for the original SWO variant considering variable-in-time assignments are taken from Test 6.3 and appear in column VAR. The relative percentage improvement of VAR over INVAR is reported as $Impr = (\text{INVAR} - \text{VAR})/\text{INVAR} \times 100$.

The results show that consideration of variable-in-time QC-to-Vessel assignments leads to better solutions for all 30 instances. For small and medium-sized instances, the average improvements are within 6–7%. Interestingly, the instances with $n = 40$ vessels show an average improvement of 15%. This indicates that variable-in-time QC-to-Vessel assignments are of predominant importance in congested terminal situations. In such a situation a simultaneous service of vessels is made possible by removing and reassigning QCs in a flexible fashion. In contrast, under time-invariant QC-to-Vessel assignments, the service of a vessel must be postponed if only a subset of cranes is available.

Table 6.9 Results for time-invariant and for variable-in-time QC-to-Vessel assignments

$n = 20$				$n = 30$				$n = 40$			
#	INVAR	VAR	*Impr.*	#	INVAR	VAR	*Impr.*	#	INVAR	VAR	*Impr.*
1	89.0	85.1	4.38	11	148.0	147.8	0.14	21	293.2	215.0	26.67
2	56.2	53.9	4.09	12	93.4	83.3	10.81	22	193.8	178.8	7.74
3	89.8	77.4	13.81	13	111.2	105.7	4.95	23	331.4	273.9	17.35
4	81.8	79.7	2.57	14	115.8	105.8	8.64	24	366.0	326.6	10.77
5	59.2	56.8	4.05	15	175.8	159.0	9.56	25	171.6	155.1	9.62
6	59.2	57.6	2.70	16	126.6	118.5	6.40	26	278.4	260.4	6.47
7	75.8	68.9	9.10	17	114.6	104.5	8.81	27	235.8	200.8	14.84
8	61.4	57.0	7.17	18	144.4	125.5	13.09	28	412.4	286.2	30.60
9	79.0	75.9	3.92	19	180.8	173.8	3.87	29	255.0	219.4	13.96
10	105.0	94.6	9.90	20	139.8	135.2	3.29	30	284.2	240.9	15.24
Avg.			6.17				6.95				15.32

Summarizing, the improved solution quality offered by variable-in-time QC-to-Vessel assignments makes their consideration an essential need for seaside operations planning.

6.4 Summary

This chapter has provided a study on the combined Berth Allocation and Crane Assignment Problem (BACAP). The proposed mathematical formulation of the problem is able to tackle QC productivity losses caused by crane interference and caused by berthing vessels apart from desired berthing positions. It additionally comprises practical aspects such as the bounding of vessel speedups by earliest service start times and by taking care of QC operational cost in addition to common service quality objectives. Despite these extensions, the proposed mathematical formulation of the problem is more compact than the one presented in the pioneering work of Park and Kim (2003).

Several new heuristics have been presented and intensively tested. The computational results show that the local refinement procedures are effective in improving initial solutions. The two meta-heuristics SWO and TS both lead to further improvements. They deliver solutions of near optimal quality for small-sized instances and of reasonably good quality for medium-sized and large-sized instances. The computation times are acceptable even for large-sized instances. The tests also confirm the superiority of SWO over the solution method proposed in Park and Kim (2003) and the superiority of the integrated solution of BAP and QCAP over a sequential solution process. Further tests have revealed the strong impact of QC productivity effects on the obtained solutions, the effectiveness of the combined service quality and QC operational cost objectives, and the high quality solution potential offered by considering variable-in-time QC-to-Vessel assignments.

From these results, it is concluded that the influence of crane assignment and crane productivity is not marginal and needs to be considered as an essential input for berth planning. The parameters used to model the productivity losses and the cost rates used to model vessel priorities as well as QC operational cost objectives allow the CT management to adapt the BACAP flexibly on terminal specific characteristics such as the workload situation. The deep integration of BAP and QCAP proves to be a successful first step towards an integrated planning of seaside operations.