

# Minimizing fuel usage of straddle carriers in container terminals

M.P.M. Hendriks<sup>a</sup>, A.A.J.Lefebber<sup>a</sup>, J.E. Rooda<sup>a</sup>, J.T.Udding<sup>a</sup>

<sup>a</sup>*Department of Mechanical Engineering, Eindhoven University of Technology, The Netherlands  
(M.P.M.Hendriks@tue.nl, A.A.J.Lefebber@tue.nl, J.E.Rooda@tue.nl, J.T.Udding@tue.nl)*

---

**Abstract:** We consider a container port, which consists of multiple terminals all run by the same terminal operator. The terminal operator provides a number of vessel lines with the logistics services of container unloading, loading, transporting and storing. He faces the combined decisions on strategic, tactical, and operational level to provide a certain service level while running its operations with the smallest possible amount of resources. Since these combined decisions are often too complex to be solved at once, the problem is often divided into a number of subproblems, which are then solved subsequently, or alternately where possible. Existing studies subdivide the combined problems in container operations according to the common categorization and subsequently solve strategic, tactical and operational problems. In this research however, we propose a typically different subdivision, such that each subproblem i) can be solved within the time allowed, ii) has not yet been addressed in literature, and iii) is practically interesting in its own right. In this paper, we address this unique subdivision in general and one of the resulting subproblems in particular: minimizing the fuel usage of the straddle carriers by intelligent berth and terminal planning. This research has financially been supported by the terminal operator PSA HNN in Antwerp, Belgium. Results of a case study suggest significant reductions in the fuel usage of the straddle carriers. Currently, results of this research have actually been implemented in one of the terminals in Antwerp.

*Key words:* berth planning, yard planning, linear programming

---

## 1. Introduction

Since 1960, containerization has grown rapidly and nowadays, annually over 150 million TEU's (1 TEU, Twenty feet Equivalent Unit, is a container of length 20 feet, width 8 feet and height 8 feet) are transported worldwide. In this worldwide network, a container port not only serves as a connection between land and sea container transportation, but also as a transshipment hub for forwarding containers between vessels.

A terminal operator coordinates and performs the facility logistics of discharging, loading, transporting and storing containers of various vessel lines in a particular terminal. Each vessel line owns a vessel fleet to maintain several repetitive loops along ports all over the world. Commonly, the number and phasing of the vessels of one loop are such that one vessel calls on each of its ports exactly once a week. Hence, the terminal operator has to service each customer (line) according to a timetable, which is repeated cycle after cycle. One can compare such a timetable with a bus or train schedule. The general levels of decision making in logistics networks can be applied to a multi-terminal container port as follows:

Dependent on its assets, a terminal operator provides its services at a certain number of terminals around the world. Once a new terminal is to be built or an

existing one is to be overtaken, a terminal operator can take part in a competitive bidding procedure for operating this terminal in the future. These are long term decisions and have a large impact on the overall turnover of the operator. The expansion of the number of terminals is very expensive, but necessary to cope with the exponential growth of container transport. Hence, an operator has to continuously anticipate on the future market while considering the services in another terminal. Next, strategic decisions have to be made on the way to operate a terminal, e.g. which kind of resources (straddle carriers vs. trucks and stacking cranes) are used to transport the containers between quay and yard and how many quay cranes are required at the quay.

In many multi-terminal container ports, various operators take care of the logistics processes for container handling. Commonly, the tasks are divided such that one terminal operator is responsible for one terminal (or at least for the major share of one terminal). In an increasing number of ports (e.g. Singapore, Rotterdam and Antwerp) however, one terminal operator is responsible for multiple terminals. Given the quay lengths and storage capacities of the terminals, and given the load compositions of the calling loops, the first tactical problem is then to allocate i) a terminal and ii) a berthing time interval to each of the loops. Secondly, a berth position

has to be allocated to each loop and an appropriate yard layout (which containers to stack where) has to be constructed. Together this results in a tactical timetable, which is reconsidered on the medium term time scale.

The tactical timetable depicts the allocation if all vessels arrive perfectly in time. However in practice, vessels are sometimes early or late (e.g. due to breakdown or bad weather conditions), and may have different call sizes and/or compositions each week. Moreover, quay cranes and other resources may brake down for an unknown period of time. The daily operational tasks of a port operator involve the management of the disrupted system to serve the vessel lines as good as possible at minimal costs. First, each vessel has to be allocated to a specific berth position within its terminal. The reference berth position of a vessel is usually taken closest to the position of its export containers in the stack. In this way, the travel distance of container carriers between vessels and stacks is reduced. Second, a schedule for quay cranes along with resources and its drivers has to be constructed to process a vessel within the agreed service time. These decisions are usually made every eight hours (one shift), and sometimes even a replanning takes place after four hours (half a shift). The detailed sequence of actual discharging, loading, transporting and stacking containers is updated at every container pick-up and drop-off.

The combined decisions are too complex to be solved at once. A possible approach is to subdivide the problem into subproblems, which are then solved subsequently. Existing studies subdivide the combined problems according to the general classification (strategic, tactical, and operational), as depicted left in Figure 1. We, however, apply a subdivision that is typically different Hendriks (2009) and from the traditional one. This subdivision is shown right in Figure 1. First of all, we incorporate the, traditionally strategic decision on the quay crane capacity, while making the tactical decisions on the terminal and berth time allocation. The goal in this first subproblem is to equally spread the vessel lines over the different terminals for a certain amount of time while the amount of inter-terminal transport is minimal. In the next subproblem, we slightly adapt the resulting timetable to increase its robustness to disturbances on vessel arrivals. Only in the third subproblem, an actual berth position is allocated to each of the vessel lines. This problem is solved in combination with the yard planning problem, i.e. the allocation of the different container types to the yard blocks. The results of the first three steps lead to a tactical timetable, that can be repeated cycle after cycle. In practice however, all kinds of disturbances cause the system to deviate from this tactically preferred timetable. In the fourth step, we therefore

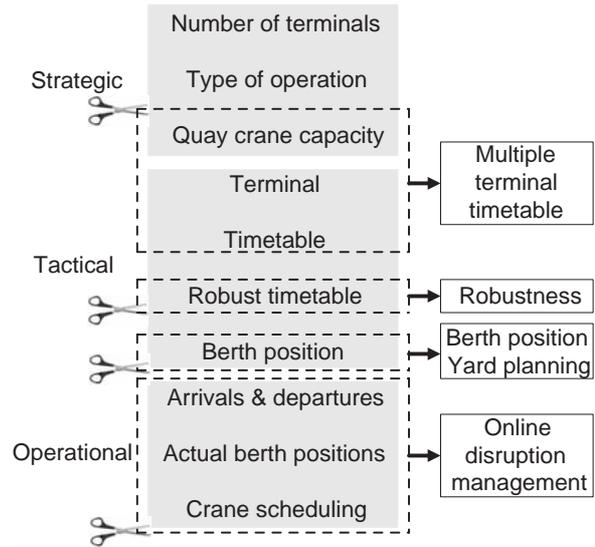


Figure 1: Traditional (left) and proposed subdivision (right) of decision making in container terminals.

develop an online rolling horizon approach that acts upon (forecasts of) these disturbances to make cost-efficient operational decisions.

In this paper, we address the third of these subproblems, being the berth position and yard planning problem. We assume the (robust) timetable of a terminal to be derived during the previous substeps. Hence, the arrival and departure times of the vessels are given and cannot be controlled. Given the timetable, the terminal operator has to run its operations with the smallest possible amount of resources needed. In this case, we consider the resources of straddle carriers (Figure 2) that transport containers between quay and yard. Goal is i) to allocate berth positions and ii) to plan the yard, such that the travel distance and, with that, the fuel usage of the straddle carriers is minimized.

## 2. Related work

The well-known berth allocation problem (BAP) is one of the key issues in container operations and has been investigated extensively over the last decades. The problem involves the allocation of container vessels in time and space in order to minimize a certain objective function. In most of the reported studies, the objective is to minimize the vessels' turnaround times Guan and Cheung (2004), Monaco and Sammarra (2007), Imai et al. (2005), Cordeau et al. (2005), Kim and Moon (2003). A limited number of studies, considers a multi-objective problem, where besides the turnaround times, the weighted deviations from predetermined berth positions are minimized Hansen et al. (2008), Wang and Lim (2007). The authors in these studies consider predetermined,



Figure 2: Straddle carrier.

reference berth positions, which are chosen closest to given positions of containers in the yard. In this way, the distance that has to be covered by container carriers between quay and yard is tried to be reduced.

Of particular interest is the study in Moorthy and Teo (2006). The authors mention that the total travel distance strongly depends on the stack positions of containers in the yard. They assume that all containers to/from a certain vessel are stacked closest to the position where the particular vessel berths and approximate the total carrier travel distance by the travel distances for transshipment containers between connecting vessels. In practice however, two main reasons exist to contradict that all containers can be stacked close to a vessel's berth position. First of all, special container types (like refrigerated, dangerous goods, and empty containers) have designated areas in the yard and hence cannot be stacked arbitrarily. Second of all, once a stack is filled up to its capacity, containers have to be allocated to surrounding stacks, unavoidably inducing additional travel distances for carriers.

The above mentioned studies all address the allocation of vessels in space and time. According to our specific subdivisions (see Figure 1) however, the time allocation has already been determined in previous steps. Hence, we assume the time allocation to be given and solve the berth position problem in combination with another problem, the yard planning problem. The yard planning problem involves the allocation of container types to different stacking

blocks in the yard for temporary storage. The combined decisions on berth positions and yard planning determine the carrier travel distance. In this study we aim to minimize the total carrier travel distance.

The problem is different from the known capacitated location allocation problem Brimberg et al. (2000), Aras et al. (2008) and Durmaz et al. (2009) in two ways: i) in our model vessels have to be allocated to a berth position such that they do not overlap, while in the mentioned studies it is allowed that multiple facilities and customers are allocated to the same location, and ii) the traditional capacitated location allocation problem is static, while we consider a dynamic version, i.e. the berth allocation and yard plan evolve over time. To the best of our knowledge, the capacitated location allocation problem has not yet found its application in container terminals, while it is very relevant from a practical point of view.

We propose an appropriate mixed integer quadratic program, which turns out to be non-convex and consequently complex from a computational point of view. The constraints however are separable in the two decision variables being i) the berth position of a vessel and ii) the amount of containers flowing between a vessel and a block. Since we consider a linear (Manhattan) distance function, the problem can be decoupled into two linear problems, an MILP and an LP, being i) a vessel berth position problem and ii) a yard planning problem, respectively. These problems are coupled in the objective function. A solution technique, that continues alternating between both linear programs, is proven to converge to a local optimum Cooper (1972). Several other heuristics for the location allocation problem can be found in Aras et al. (2008) and Durmaz et al. (2009).

Although the alternating method is very fast, the converged solution heavily depends on the initial condition (see also Aras et al. (2008) and Durmaz et al. (2009)) and a proper guess for this initial condition is required to yield a satisfactory solution. To find a proper initial guess, we propose an MILP, which allocates fixed-sized container groups to blocks, rather than considering the groups sizes as a decision variable. The found initial condition leads to a solution that outperforms results obtained from numerous random initial conditions. This approach of finding a proper initial condition by considering fixed-sized groups is slightly different from the well-known quadratic assignment problem Cordeau et al. (2006), in the sense that we consider a dynamic scenario rather than a static one. A case study on a handmade berth allocation and yard plan, provided by the terminal operator PSA HNN, learns that the proposed method is very efficient and suggests a reduction of more than 20% in the total carrier travel distance.

The outline of this paper is as follows: in Section 3, problem is formally phrased and an MIQP is proposed. Additionally, the alternating solution approach is addressed and the approach to find a proper initial guess is discussed. Section 4 presents a case study and shows results for random initial conditions and the sophisticated initial conditions. We end with conclusions and recommendations in Section 5.

### 3. Approach

#### 3.1. Problem description

A simplified illustration of the problem can be seen in Figure 3. Vessels have to be allocated to a position at the quay, and containers to the blocks in the yard. Straddle carriers have to travel a rectilinear distance (between the blocks) to transport containers from vessels to yard and vice versa. The combined decisions on i) the position of a vessel at the quay, and ii) the block(s) its corresponding containers in the yard determine the straddle carrier travel distance and with that its fuel usage. Given the timetable, the goal is to find vessel positions and container blocks such that the total straddle carrier fuel usage is minimal.

Due to space limitation in this paper, we only present a simplified, static version of the model. Nevertheless, the simplification incorporates all phenomena necessary to explain our approach.

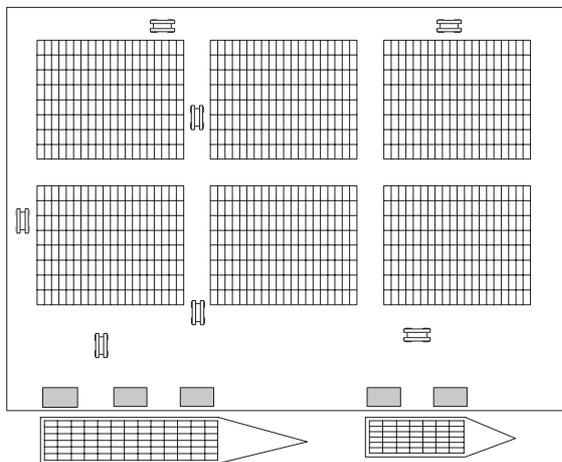


Figure 3: Illustration of the considered problem.

#### 3.2. MIQP

To model the problem, we define two decision variables, i)  $p_v$  to be the position of vessel  $v$  at the quay, and ii)  $y_{vn}$  to be the amount of containers transported between vessel  $v$  and block  $n$ . Additionally, we introduce an auxiliary variable  $z_{vn}$ , being the rectilinear distance between vessel  $v$  and block  $n$ , which can directly be derived from the position of vessel

$v$ . The straddle carrier travel distance can then be defined as the product of  $y_{vn}$  and  $z_{vn}$ , which is the objective function in model. Furthermore, there are a number of (in)equality constraints for each of the two decision variables  $p_v$ , and  $y_{vn}$ , which we do not elaborate on due to space limitations. The left hand-sides of these constraints are represented by the functions  $g_1(p_v)$ ,  $g_2(y_{vn})$ ,  $f_1(p_v)$ , and  $f_2(y_{vn})$ . The corresponding mixed integer quadratic problem (MIQP) formulation is depicted in Figure 4. An analysis of this formulation learns that it is very complex from a computational point of view due to the non-convexity of its objective function.

$$\begin{array}{ll}
 \min_{p_v, y_{vn}} & \sum_{v \in \mathcal{V}} \sum_{n \in \mathcal{N}} y_{vn} \cdot z_{vn} \\
 \text{s.t.} & g_1(p_v) \leq 0 \\
 & g_2(y_{vn}) \leq 0 \\
 & f_1(p_v) = 0 \\
 & f_2(y_{vn}) = 0
 \end{array}$$

Figure 4: MIQP for the simplified model.

#### 3.3. Alternating procedure

A second analysis however learns that the formulation has a typical structure: the constraints are decoupled in the decision variables  $p_v$ , and  $y_{vn}$ . The model can thus be decoupled into two separate linear programs, which are coupled in the objective function. This is presented in Figure 5. We start from a (random) initial solution  $y_{vn}^*$  for the yard planning problem and solve the vessel position problem for these parameters. Next, the optimal values  $p_v^*$  are passed to the yard planning problem, which is then solved to optimality. The updated values of  $y_{vn}^*$  are again passed to the vessel position problem, and so on and so on. It can readily be seen that this iteration method yields a convergent monotone non-increasing sequence of values, which are bounded by zero (see also Cooper (1972)). The algorithm is stopped if the difference between the objective values of two successive iterations is less than  $\epsilon$ ,  $\epsilon > 0$ .

Although the alternating approach can be solved within minutes for real-life problems, its performance heavily depends on the chosen initial condition. In the next section, this dependency is shown in an experiment with a large number of random initial conditions. Additionally, we propose a method to find a proper guess for the initial condition. Finally, we show results of a real-life case study initiated by PSA HNN. Results suggest that starting from the sophisticated initial guess results in a solution that outperforms all results from random initial conditions. Furthermore, these results suggest that the straddle carriers' fuel usage can be reduced by over 20%.

Again we have to stress that this is a simplified version of the model. In the complete model, we explicitly distinguish between inbound and outbound containers, and between different container types (full, empty, refrigerated, hazardous) and lengths (20 and 40 ft.). Furthermore, we take the time-evolution of (dwell-time distributions) of arriving and departing containers into account to prevent the exceeding of the blocks' storages at any moment in time.

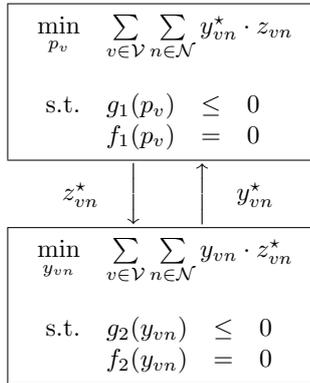


Figure 5: Alternating solution approach.

### 3.4. Sophisticated initial guess

The performance of the alternating approach heavily depends on the chosen initial condition. In this subsection, we discuss a mixed integer linear program (MILP) that finds a good initial guess. The principle of the MILP is that the decision on the amount of containers from a certain vessel to a certain block is no longer a decision variable. Instead, we assume fixed-sized container groups, and hence as decision variable (besides the vessel position) we introduce binary variables to indicate whether a group is allocated to a block or not. Each container group has to be allocated to exactly one block. The number of containers from a vessel to a block is no longer a variable, but a parameter instead. This turns the objective function into a linear relation rather than a non-convex quadratic objective function as in section 3.2. Basically, by solving this MILP, we solve a coarse version of the MIQP of section 3.2.

## 4. Results

In this section, we present results for the alternating approach starting from both a random initial condition and a sophisticated initial condition.

### 4.1. Random initial conditions

Results for one hundred experiments with random initial conditions are depicted in Figure 6, where a triangle represents the carrier travel distance for

quasi-randomly chosen blocks and variable berth positions (objective from the first step of the alternating procedure), and the circle straight below represents the carrier travel distance after convergence of the alternating procedure for that particular initial condition. The carrier travel distances are scaled to the carrier travel distance corresponding to the provided data set by PSA HNN (grey dotted line). From Figure 6 we learn the following:

- In each experiment, the alternating procedure yields significant reductions in the carrier travel distance starting from the initial condition.
- A good, randomly selected, initial condition does not necessarily provide a good end solution. One of the possible reasons might be that, while allocating the groups, the blocks' capacities are not taken into consideration. Hence, several groups of containers might be allocated to the same block, inducing a small travel distance, however exceeding the actual capacity. Since the alternating optimization does take the block capacities into account, the converged solution might end up not being that good.
- The major part (about 80% of all triangles in Figure 6) of the quasi-randomly generated initial conditions leads to an allocation with a larger carrier travel distance than in the allocation provided by PSA HNN.
- For each of the hundred performed experiments, the alternating procedure yields a solution that is at worst about 10% better than the provided allocation.
- The best solution found (black marked circle) outperforms the current allocation by almost 20%.

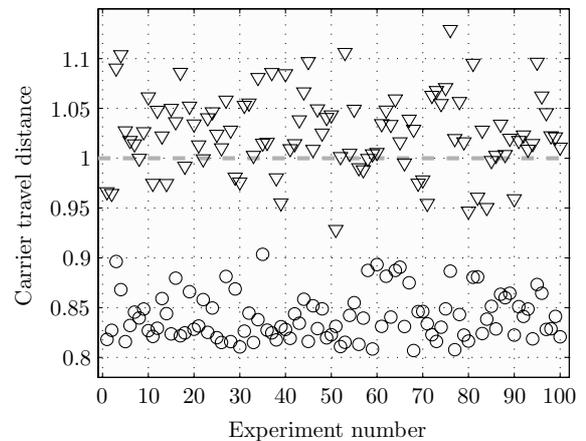


Figure 6: Results of the alternating procedure for one hundred random initial conditions.

#### 4.2. Sophisticated initial conditions

In this section, we apply the alternating optimization for the initial condition generated by the MILP discussed in Section 3.4. Since the MILP consists of a relatively large number of binary variables (whether a container group is allocated to a certain block or not), it cannot be solved to optimality within satisfactory time. Hence, the following is proposed: the provided allocation is reconstructed by fixing all variables accordingly. The objective function evaluates the corresponding straddle carrier travel distance. Next, the groups of containers are ordered according to their contributions to the total carrier travel distance. From this ordered set, we take the first  $G$  container groups with the largest distance contributions, declare the corresponding binary variables (concerning the group to block allocation) and  $p_v, \forall v$  to be variables again, and run the MILP discussed in section 3.4. Subsequently, the generated solution is fed into the alternating optimization procedure of Section 3.3 as an initial condition. Figure 7 shows the results of the found initial condition and corresponding converged solution as a function of  $G$ . From the experiments shown in this Figure we conclude the following:

- In each experiment, the alternating procedure yields significant reductions in the carrier travel distance starting from the initial condition. The reduction however decreases as  $G$  increases. A reason for this might be that for relatively large values of  $G$ , the initial guess is that good that less improvements can be obtained by the alternating procedure.
- Each generated initial condition already outperforms the allocation in the data set provided by PSA HNN.
- For  $G = 0$  (zero groups can be modified) the initial condition already outperforms the allocation in the data set provided by PSA HNN. Although the container block allocation is fixed and cannot be changed for  $G = 0$  while generating this initial condition, the berth positions of the vessels are variable. Apparently, a modification of only the vessels' berth positions already yields a reduction of about 3% in carrier travel distance.
- As  $G$  increases, the found objective value for the initial conditions (triangles) decreases. This makes sense since if more container groups are variable, no larger travel distance will result from the optimization.
- A better initial condition (triangle) never yields a worse converged solution (circle). This disagrees with the observation made for Figure 6,

where a better initial condition not necessarily led to a better converged solution. Apparently, the reason we gave for this observation in the first place is a crucial one. Namely, the method to construct a proper initial guess does take the blocks' capacities into consideration right away.

- The modification of only the eight largest contributions (and possible all vessels' berth positions) already leads to a better solution than the best found solution for a hundred random initial conditions. The corresponding reduction in travel distance with respect to the travel distance in the representative allocation is more than 20%.

From these results we conclude that it pays off to generate a proper initial condition rather than executing an extensive number of experiments for random initial conditions.

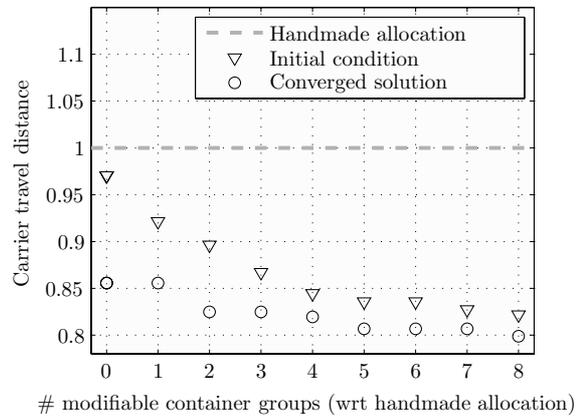


Figure 7: Results of the alternating approach for sophisticated initial conditions.

## 5. Conclusions

In this paper we considered the joint problem of finding berth positions for vessels at the quay and stack positions for containers in the yard. The well-known berth allocation problem concerns the allocation of vessels in space and time. In practice however, the arrival and departure times of vessels are often imposed by the vessel lines' schedules. In this paper, the berth position problem is therefore addressed jointly with the allocation of containers to blocks in the yard to minimize the total travel distance and with that the fuel usage of carriers operating between vessels and yard.

First, an appropriate MIQP is formulated, which chooses berth positions for vessels and amounts of containers for blocks to minimize the carrier travel distance. Since the objective is non-convex and consequently real-life instances run forever, the problem is separated into an MILP, which represents the

berth position allocation, and an LP, which presents the container amounts to different blocks. These problems are coupled in the objective function and solved in an alternating fashion. The method converges to a local optimum very fast, however appears to be very sensitive to the initial condition.

Hence an MILP is proposed to find a proper initial condition by allocating berth positions to vessels and fixed-sized groups of containers to blocks. The solution found by this MILP is passed to the alternating method as an initial condition. The alternating optimization now finds a solution, which outperforms all solutions resulting from an extensive number of randomly generated initial conditions. Applying the alternating optimization on a representative data set provided by PSA HNN suggests that a reduction of more than 20% in the carrier travel distance can be obtained. These results suggest that the same amount of work can be done with less straddle carriers and less fuel.

## References

- Aras, N., Orbay, M., Altinel, I., 2008. Efficient heuristics for the rectilinear distance capacitated multi-facility Weber problem. *Journal of the Operational Research Society* 59, 64–79.
- Brimberg, J., Hansen, P., Mladenovic, N., Taillard, T., 2000. Improvements and comparison of heuristics for solving the uncapacitated multi-source Weber problem. *Operations Research* 48, 444–460.
- Cooper, L., 1972. The transportation location problem. *Operations Research* 20 (1), 94–108.
- Cordeau, J., Gaudioso, M., Laporte, G., Moccia, L., 2006. A memetic heuristic for the generalized quadratic assignment problem. *INFORMS Journal on Computing* 18 (4), 433–443.
- Cordeau, J., Laporte, G., Legato, P., Motta, L., 2005. Models and tabu search heuristics for the berth-allocation problem. *Transportation Science* 39, 526–538.
- Durmaz, E., Aras, N., Altinel, İ., 2009. Discrete approximation heuristics for the capacitated continuous location allocation problem with probabilistic customer locations. *Computers and Operations Research* 36, 2139–2148.
- Guan, Y., Cheung, R., 2004. The berth allocation problem: Models and solutions methods. *OR Spectrum* 26, 75–92.
- Hansen, P., Öguz, C., Mladenović, N., 2008. Variable neighborhood search for minimum cost berth allocation. *European Journal of Operational Research* 191 (3), 636–649.
- Hendriks, M., 2009. Multi-step optimization of logistics networks. strategic, tactical, and operational decisions. Ph.D. thesis, Eindhoven University of Technology.
- Imai, A., Nishimura, E., Papadimitriou, S., 2005. Berth allocation in a container port: using a continuous location space approach. *Transportation Research Part B* 39, 199–221.
- Kim, K., Moon, K., 2003. Berth scheduling by simulated annealing. *Transportation Research Part B* 37, 541–560.
- Monaco, M., Sammarra, M., May 2007. The berth allocation problem: A strong formulation solved by a Lagrangean approach. *Transportation Science* 41 (2), 265–280.
- Moorthy, R., Teo, C., October 2006. Berth management in container terminal: the template design problem. *OR Spectrum* 28 (4), 495–518.
- Wang, F., Lim, A., 2007. A stochastic beam search for the berth allocation problem. *Decision Support Systems* 42, 2186–2196.