ADDRESSING ROBUST BERTH PLANNING UNDER UNCERTAINTY VIA SIMULATION BASED OPTIMIZATION

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ABSTRACT
Decisions of allocating berth segments to incoming vessels, in maritime container terminals, has been extensively modeled in the scientific literature by resorting to formulations of mathematical programming with integer variables. Both vessel arrival times and processing times are usually considered as a deterministic input to the mathematical model despite of the uncertainty affecting berth decisions at the operational level, when several unpredictable events and operation delays occur and require to be managed. In this paper, we propose to apply the methodology of simulation based optimization to cope with uncertainty: a constructive algorithm is used to obtain a weekly plan at the tactical level; the allocation decisions are then adjusted at the operational level. Randomness in events and operations is taken into account by Monte Carlo simulation, while moving-average sample mean estimators are used to reduce the number of simulation runs required. Preliminary numerical results are also given.

Keywords: Simulation Optimization, statistical selection, port logistics, berth planning

1. INTRODUCTION
Many modern day systems providing products and services in the fields of logistics, manufacturing, transportation, network-centric computing, etc., are event-driven and, thus, can be modeled as discrete-event systems with the objective of carrying-out performance analysis and optimization. When pursuing decision integration and performance optimization in similar complex systems, the idea of inserting a simulation engine in an optimization algorithm is often the only practical solution method available in order to deal with difficult-to-solve combinatorial problems, embedded in realistic and dynamic processes characterized by several elements of randomness. The optimization algorithm is aimed at first generating an initial feasible solution and then exploring the whole feasible region (search process) until no further improvements of the performance results are obtained or until computation time is exhausted. The use of the simulation engine is required (evaluation process) since an estimate of the objective function cannot be returned by simply fitting a set of possible decision variables into a simple closed-form formula.

In the resulting methodology, known as Simulation Optimization (SO) (Andradottir 2007), the trade-off between the amount of computational time needed to find improved alternative solutions on the optimization side versus the effort in estimating via simulation the performance of a particular solution has always been a key issue in most SO techniques and general frameworks (Lee et al. 2006). (Fu 2001) divides these techniques in the following main categories:

- statistical procedures (e.g. ranking & selection procedures and multiple comparison for the comparison of two or more alternative system configurations);
- metaheuristics (methods directly adopted from deterministic optimization search strategies such as simulated annealing);
- stochastic optimization (random search, stochastic optimization);
- other, including ordinal optimization and sample path optimization.

In this paper we propose a Simulation Optimization scheme to manage both tactical and operational planning issues when facing the berth allocation problem (BAP) in port logistics. The object of the scheme is to enable the tuning of the tactical solution returned for the above problem when unforeseen and/or unwanted conditions overcome in the operational stage. In doing so, the SO scheme may benefit of a minor computational effort by employing a moving-average estimator for the sample mean in the procedures used to compare alternative solutions for the problem. The scheme, in fact, is based on a procedure belonging to the first category (i.e. ranking & selection) to estimate the best among a set of alternative berth allocation solutions, as well as metaheuristics that take care of solution generation and improvement at both the tactical and operational level.

The paper is organized as follows. In Section 2 an integrated tactical-operational view of the berth allocation problem is given, followed by considerations on how this problem is dealt with at the real container terminal of our interest. In Section 3 the Simulation Optimization scheme is described by focusing on the constructive algorithm used to find the tactical solution and the simulation approach used to find the operational solution. In particular, in the latter case a low-variance sample mean is proposed for use in ranking & selection techniques when selecting the best berth allocation solution. Some numerical examples that explain the concept of robustness of the final berth allocation solution provided via Simulation Optimization are presented in Section 4, while conclusions are drawn in Section 5.

2. THE BERTH ALLOCATION PROBLEM

Deciding which berthing position to assign to an incoming vessel is certainly the first and most important step of the overall resource and activity planning process in a maritime container terminal. Besides the (obvious) physical constraints that must be satisfied with respect to vessel size, draft and security measures, the assignment must take into account the distance lying between the candidate berthing position and the yard area where containers for the incoming vessel are to be stacked/retrieved. The ideal berthing position, meaning the position which minimizes the above distance, is also known as "home berthing". As one may observe from Figure 1, with respect to the yard block in the dotted lines, berthing option n°1 is a more suitable choice than berthing option n°2. Indeed, the first option leads to shorter container transfer times and, thus, to greater throughput and higher revenues for the maritime terminal and improved customer satisfaction for the shipping companies calling the port.

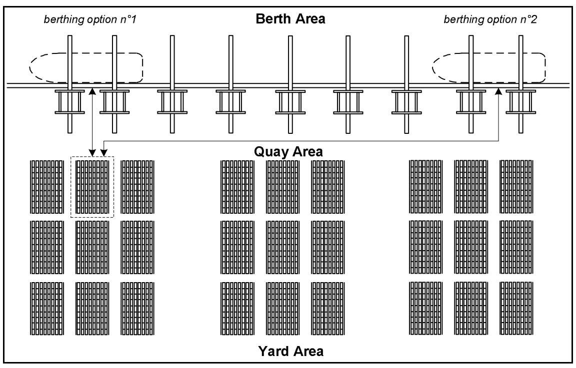

Figure 1: An example of how different positions yield different distances to be covered when performing vessel discharge/loading

A great number of factors may affect the vessel's sojourn time in the assigned berthing position, among which resource availability (i.e. cranes, transfer vehicles and manpower), number of container moves to be performed, congestion due to other traffic, weather conditions, equipment failure, lack of synchronization in operations performed across bordering terminal areas involved in the D/L operations and so on. Therefore, when dealing with the BAP, both deterministic and stochastic models of Operations Research can give a valuable support. Decision models pertaining to the BAP are often integrated in solution methodologies designed for wider logistic processes (Steenken et al. 2004; Meisel and Bierwirth 2006; Stahlbock and Voß 2008). Moreover, BAP decisions have also been included in discrete-event simulation models of port logistics according to global outer views to evaluate the global performance of the terminal in terms of productivity and vessel turnaround time (Yun and Choi 1999; Legato and Mazza 2001; Bielli et al. 2006).

As was well pointed out by (Moorty and Teo 2006), the BAP may be suitably viewed at both a tactical and operational level. In the former case it pertains to the definition of a "weekly plan", i.e. a berth template where arriving vessels are expected to be moored at some preferable berth segments, under the assumption that (1) incoming vessels enter the port at a forecasted, but deterministic time instant and (2) a specific but fixed, average service rate should be guaranteed in discharging-loading each berthed vessel, whatever be the availability of the quay cranes when the operations start. Vice versa, at the operational level, the terminal manager is asked to face delays on vessel arrival time, actual availability in time of each crane and manpower gang to be assigned, plus delays within operations, physical obstacles such as draft and work in progress that restrict mooring locations and so on. This calls for adjusting the tactical weekly plan in real time. At this level of the planning process, a finer representation of the berth segment and handling equipment (e.g. position of quay cranes, shift constraints for manpower, etc.), together with a finer reproduction of the complex discharge/loading process by means of a discrete-event simulator is well appreciated. To this purpose (Legato et al. 2010) developed a simulator where the effect of container transfer from the yard to the berth and vice versa is also highlighted when simulating container discharge/loading processes under a given assignment profile of some cranes to a vessel and a given schedule of container moves.

Coming back to the tactical level of decisions, the whole berth may be viewed as a discrete set of small berthing segments or a continuous, unique long segment and each vessel is represented as a space-time rectangle to reflect it space-time occupancy within the berth template. Whatever the berth representation, the planning goal is to achieve a good matching between container storage positions on the yard versus container discharge/loading positions on the berth. This is a prerequisite before organizing the container picking, transfer and delivery process back and forth between the yard and quay. In previous literature both the discrete and the continuous approaches to berth modeling at a tactical level have been pursued (Lim 1998; Imai et al.

2001; Kim and Moon 2003; Guan and Cheung 2004; Imai et al. 2005, Cordeau et al. 2005) under the common assumption that both the arrival time and processing time per ship are known without any uncertainty.

More recent papers concentrate on improving computational performance of the heuristic methods proposed for problem solution (Wang and Lim 2007; Hansen et al. 2008; Lee and Chen 2009; Buhrkal et al. 2009), while others are devoted to integrate berth allocation with the subsequent decision of assigning the right number of cranes, hour by hour, to each vessel during discharge-loading operations (see Bierwith and Meisel 2010 for an extensive survey). Observe that just couple of papers (Zhou and Kang 2008; Hendriks et al 2010) focus on the problem of managing the uncertainty in vessel arrival times and service times. Precisely, (Zhou and Kang 2008) adopt a discrete berth representation, with a given number of service points along the quay, and propose an integrated berth & quay-crane model by using a stochastic 0-1 programming model aiming to minimize the waiting time for both berth and crane assignment. Vice versa, (Hendriks et al. 2010) remark that container terminal operators and shipping lines agree upon arrival time windows and develop a planning model that explicitly takes this arrival time window into account. The concept of robustness in berth planning is implemented as the capability of returning a feasible solution for each arrival scenario where all vessels arrive within their arrival time window. This window is obtained by simply shifting the arrival time of each vessel with the goal of minimizing the maximal crane capacity reservation that would result from adopting a plan based on fixed arrival times.

The major limit of the stochastic programming approach pursued in recent literature for managing uncertainty lies in the prohibitive computational costs of representing and analyzing all possible scenarios arising from the joint variations of both vessel arrivals and time duration of discharge/loading operations. In such a case, a simulation based approach to the optimization of berthing decisions is preferable.

In the work at hand, we refer to the container terminal at the port of Gioia Tauro in Southern Italy. The generation of their weekly plan is supported by CaLeMa: a simulation environment designed to reproduce ship berthing, with a particular focus on contention of the entrance channel and the management of berthing points (Canonaco et al. 2007). Besides being used in scenario analysis, CaLeMa is under further development to include quay crane management by taking into account the uncertainty in quay crane availability and durations of discharge/loading operations.

3. THE SIMULATION-OPTIMIZATION SCHEME

To model and solve the berth allocation problem we propose the Simulation Optimization scheme illustrated in Figure 2 that bridges the natural gap between the related tactical and operational solution methodologies.

As for the tactical level, the scheme responds to the quest of producing a berth template by applying a constructive algorithm. This template specifies the position in time and space of single berth windows by taking into account both the contractual agreements defined between the terminal and the shipping companies and the physical constraints imposed by vessel drafts. Although this solution is obtained in a fast and accurate way, it still corresponds to a static representation that is unable to embody the uncertainty of the major activities taking place in the terminal facility such as the vessel arrival process and the container discharge/loading (D/L) process, as well as the actual availability of the resources required to carry out the above processes.

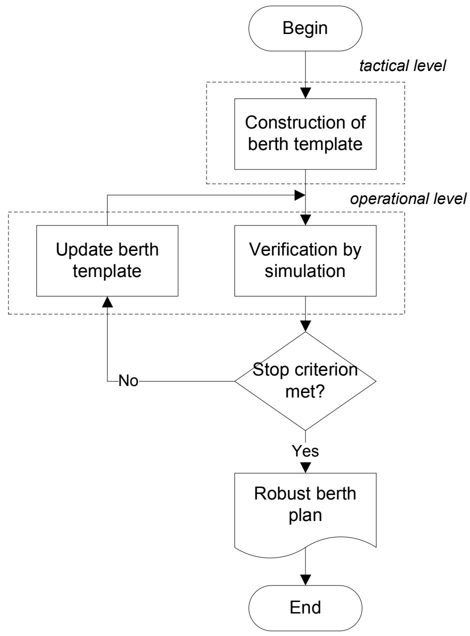

Figure 2: The SO scheme for robust berth planning

As a result, the performance of this initial solution needs to be tested at the operational level with respect to a wide range of additional conditions that, in our view, offer a measure of the so-called robustness of the solution found. In other words, in the SO scheme the goodness of the solution found at the tactical level is later assessed and compared with alternative berthing plans on the operational level generated by a heuristic algorithm for neighborhood exploration. The overall aim of the scheme consists in minimizing the waiting time suffered by vessels due to untimely arrivals, non-deterministic service times and/or unavailable resources.

3.1. View at the tactical level

Constructing a solution for the BAP at the tactical level may certainly vary from one facility to another, although the information used to do so is practically the same (e.g. vessel size and draft, expected vessel arrival/departure, workload, resource availability). As reported in Section 2, mathematical programming models are often used for this purpose. In particular, the work by (Kim and Moon 2003), which minimizes the cost for berthing a vessel far from its home berthing and the cost for delaying vessel departure, may be considered the starting point for most models based on the continuous location space approach to the BAP.

Unfortunately, despite it being very useful, a few practical requirements prevent us from applying this model. First of all, the commercial solvers normally used for this purpose can only solve small instances. Secondly, whatever the dimension of the problem, commercial solvers cannot be embedded in the software applications already in use at most container terminals. As a consequence, the SO scheme in Figure 2 has been designed to use a constructive algorithm in order to provide a tactical solution for the BAP. In companion papers we experimented and analyzed the properties of metaheuristics used to cope with similar complex logistic problems (Legato et al. 2008; Legato et al. 2010). However, we recognize that in this particular case obtaining a fast and accurate solution at the tactical level calls for the use of a constructive approach, rather than feeding randomly-generated initial solutions that almost certainly do not resemble those provided by the terminal operators in real-life planning.

This stated, we designed a constructive solution algorithm that extends the model proposed by (Kim and Moon 2003) in order to include restrictions on vessel berthing along certain segments due to the lack of compliance between vessel draft and berth depth. The algorithm, which minimizes the additional cost sustained by the terminal operator when vessels are berthed in non-optimal conditions (i.e. delay in berthing and far from its ideal berth position), is described by the pseudo-code given below.

Initialization
1: *Parameter setting (Δ, m)*
2: *Generation vessel and order by arrival time*
Berth definition for current vessel
3: *Extract vessel with smallest arrival time*
4: *Define all feasible berth segments*
5: *Determine all vessel berthing positions*
Berth definition for next Δ vessels
6: *Define all feasible berth segments for the next Δ vessels*
7: *Select best berthing position for each of Δ vessels*
Selection
8: *Evaluate objective function* f_Δ
9: *Order solution and select of top m*
10: *Eliminate of non-selected solutions*
Exit condition
11: *Return to step 3 if berthing of all incoming vessels is not completed*

In the above algorithm, just as in real-life company practice, all vessels arriving to the port are bound to be berthed, so the problem is highly combinatorial. However, a natural pruning stage is delivered by the limited number of feasible berthing positions (step 4) and, thus, the number of possible combinations is reduced. As a matter of fact, a vessel can be berthed along a segment only if the size of the segment matches the length of the vessel measured in bollards, followed by an extra bollard for security matters. Furthermore, as previously mentioned, water depth in free berth areas need to comply with vessel draft. If both of these conditions are met, then one of the following two rules applies: the vessel can be berthed in the upper or lower angle of a free area, as illustrated for berthing options 1 to 4 for vessel 4 in Figure 3; in contrast, the vessel can be berthed in the same positions as previously berthed vessels once these have completed their D/L operations and have been unberthed, as illustrated by berthing option 5 in Figure 3.

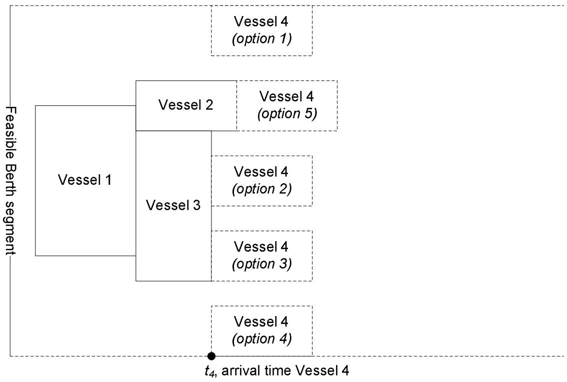

Figure 3: Five possible berthing solutions for Vessel 4

The estimation of the objective function f_Δ associated with any of the above berth allocation decisions is performed in the *Selection* section by taking into account two contributions. One term represents the cost of the first i vessels already berthed and, thus, it returns an immediate evaluation based on the previously made berth assignments. The other is an estimate of the cost required to berth the next Δ vessels ($i+1, i+2, \ldots, i+\Delta$) based on a greedy-operating logic (steps 6 and 7). Thanks to this estimation, node sampling aimed at selecting the best partial solutions to be fed as input to the next solution-building iterations of the algorithm is performed according to the classic top m criterion (step 9). The entire mechanism is cycled until all incoming vessels are berthed and, thus, the algorithm returns a final solution for the BAP.

3.2. View at the operational level

A discrete-event simulator has been designed to test the solution returned by the tactical level with respect to its so-called robustness at the operational level. As a result, the weekly template may not hold because of the randomness featured by the terminal activities in which process initiation and duration change over time. In our experience, the major sources of randomness, for which the simulator must account for, are given by:

- vessel arrival times;
- quay crane availability and deployment;
- D/L service times.

Vessel arrival generally occurs within a fixed time window in a week for oceanic vessels or on the basis of a probabilistic profile as in the case of common feeders. An example of a similar profile is given in Figure 4, according to which the real interarrival times of 1030 common feeder vessels (in one year) can be suitably modeled by an exponential law with mean value equal to 505 minutes. So, while the periodic arrivals of the oceanic vessels are of limited impact on the berth planning activities, the simulator is necessary to account for the random arrivals of the common feeders.

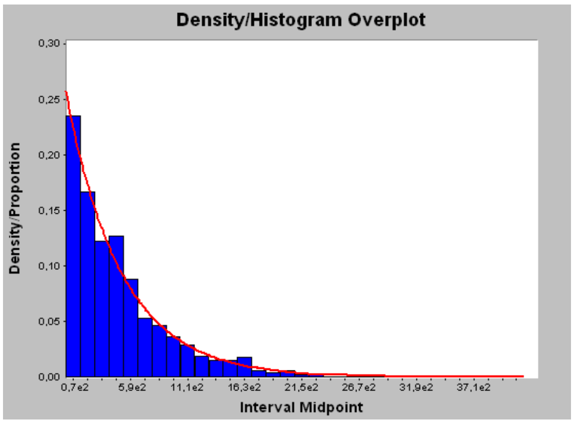

Figure 4: Profile of common feeder interarrival times

The use of quay cranes is another source of randomness for which the simulator is meant to cope with. As a matter of fact, the terminal's operations manager must first verify the overall availability of the cranes and then provide for assigning specific cranes to a specific vessel and deploying these cranes along the quay according to an hourly profile.

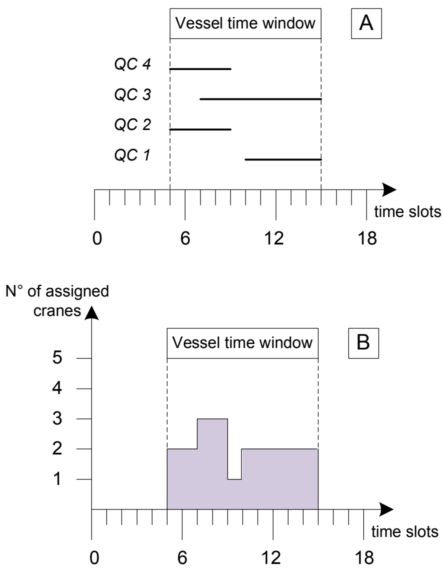

Figure 5: Crane availability and crane intensity

Frame A of Figure 5 illustrates both the availability of 4 quay cranes and the length of the time window during which a vessel requires crane assignment. Specifically, the average number of cranes to be assigned to a vessel during its time window, a.k.a. *crane intensity* (*CI*), is usually fixed by contractual agreements. The actual value of the crane intensity for a given vessel, which ought to match the target value of the crane intensity, can be determined from the corresponding quay crane hourly deployment profile as, for example, the one illustrated in frame B of Figure 5, and computed according to the following

$$CI = \frac{1}{tw_f - tw_s}\sum_{i=1}^{n} aQC_i \qquad (1)$$

where tw_f, tw_s, n and aQC_i are the time window's start and finish times, the number of quay cranes deployed and the availability (in hours) of each quay crane, respectively. As a result, since the berth template is built according to the target value of the crane intensity for each vessel bearing a time window, it should be clear how any kind of change in quay crane availability and/or deployment at the operational level may affect the goodness of the entire template.

As for the final, yet most important source of randomness, the simulator must account for the D/L service times by considering eventual disruptions due to *i*) failure in the container handling and/or transfer equipment and *ii*) congestion and/or starvation phenomena arising from the lack of synchronization among the equipment involved in container transfer from the quay area to the yard area and vice versa. In other words, if the transfer activity carried-out by transfer vehicles from the quay to the yard is too slow, then the quay crane discharge activity is prone to be affected by *blocking* during operations due to container space that will be likely unavailable in the buffer area under the crane. Vice versa, because of an empty buffer area, crane *starvation* is likely to occur during container loading operations on the vessel if the transfer vehicles from the yard to the quay are too slow.

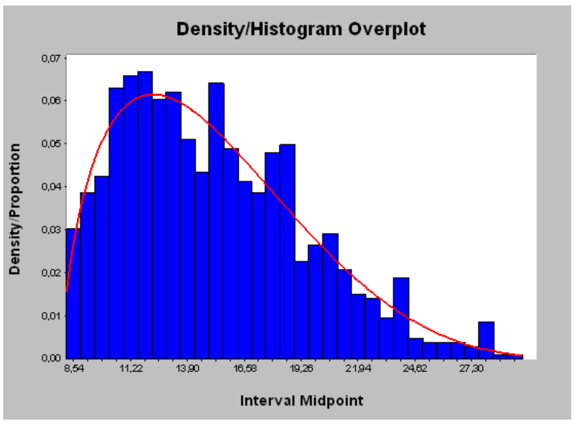

Figure 6: Profile of common feeder overall D/L times

An example of the randomness in the overall D/L times of the same real 1030 common feeder vessels previously mentioned is represented by the Beta-like profile in Figure 6 bearing mean=15.12, variance=18.96 and skewness=0.66.

This stated, at every iteration of the scheme in Figure 2, the simulator is meant to play its role by feeding to the SO procedure a sample mean that represents an estimate of the expected value of the objective function for the current solution (berth template). In turn, the SO procedure is asked to compare alternative competing solutions. To guarantee the correct selection of the "best" sample mean under a fixed level of confidence, a great computational effort may be required in terms of number of observations upon which each sample mean is defined: the greater the variance of the sample mean, the greater the number of observations required. The most common procedures of ranking and selection (R&S) work with the standard sample mean (Kim and Nelson 2006), which, in our context is computed across multiple simulation replications (sample size). Here a moving-window based logic, inspired by Welch's procedure for estimating the length of the transient in simulation, is adopted. Thus, we first organize n independent, simulated output observations into b groups and then compute the average value of the *ith* observation across these groups according to the width w of the moving window. Let Y_{ji} be the *ith* observation within group b, then

$$\overline{Y}_i = \frac{1}{b}\sum_{j=1}^{b} Y_{ji}. \tag{2}$$

Hence, the set of values, $\overline{Y}_1, \overline{Y}_2, ..., \overline{Y}_m$, is used to define the moving average (MA) $\overline{Y}_i(w)$ with a window length of w as follows:

$$\overline{Y}_i(w) = \frac{\sum_{s=-w}^{w} \overline{Y}_{i+s}}{2w+1} \qquad i = w+1, ..., m-w. \tag{3}$$

Observe that the neighboring moving averages (say $\overline{Y}_i(w)$ and $\overline{Y}_{i+1}(w)$) are still unbiased estimators of the mean of the output observations but they are (positively) correlated due to those common observations shared when averaging over the fixed w values. As a result, the variance of the moving-average estimator $\overline{Y}_i(w)$ is smaller than the variance associated to the standard estimator (with $w = 0$) and, thus, less simulation effort is expected to be required. Clearly, the MA estimator can be used in any type of R&S procedure whether it be one-stage (Bechhofer 1954), two-stage (Rinott 1978) or *n*-stage (Goldsman et al. 2002).

Turning the attention to the optimization part of the SO procedure, observe that the main component at the operational level is based on a neighborhood structure that allows to move from one BAP solution to another. In particular, a vessel is selected from the BAP solution currently proposed and meant to be swapped with that of another vessel. The swap is considered feasible if, on one side, the vessel's future position is compliant with vessel size and draft and, on the other, if the vessel's arrival and departure is covered by that of the other vessel. Obviously, for the other nearby vessels the swapping activity may require an "adjustment" along the berth. All the vessels fulfilling the above conditions are inserted in a set of so-called swappable vessels and the corresponding BAP solutions represent new neighboring solutions for the current berth plan. One (or more than one) neighbor will be chosen from this set and, then, verified via simulation. When deciding which solution to choose between the current and the new BAP solutions, a simulated annealing (SA) metaheuristics (Kim and Moon 2003) is used.

The pseudo-code describing this part of the SO scheme is given below.

Initialization
1: *Parameter setting (T, α, threshold, n)*
2: *Assign tactical template to current BAP solution*
Definition of swappable vessels for current vessel
3: *Select vessel from current BAP solution*
4: *Create a set of swappable vessels and select a vessel*
5: *Swap vessels and perform adjustments*
Solution comparison
6: *Compare new solution with current solution*
7: *Accept new solution with probability p=1 if value of objective function is best or with probability* $p = e^{\Delta/T}$ *if value of objective function is worst*
8: *Decrease T according to α*
Exit condition
9: *T<threshold or no improvements in last n iterations (else return to step 3)*

At this point, it is possible to discuss how solution robustness is conceived and accomplished by the above SA-based search for the optimal operational BAP template. When the tactical template is simulated, the stochastic operational conditions unavoidably affect the value of the objective function returned by the tactical planning phase. In particular, the delays in the vessel handling time highlighted by the simulation must be recovered by rearranging the space-time windows pertaining to every single vessel, at the price of settling for a new berthing position that is distant from the home berthing. As a result, the value of the objective function is expected to deteriorate. Therefore, the aim of the overall SO scheme consists in keeping deterioration within a limited range from the initial value corresponding to the tactical template. This stated, a solution is said to be robust when, under the uncertainty of the operational level, it is able to limit its deviation from optimality - for instance, given a final operational template, in 90% of the cases vessels already berthed are able to complete their operations without triggering delay propagations on the incoming vessels waiting to be berthed.

4. NUMERICAL EXAMPLES

The aim of this section is twofold: on one hand, we expect to show how under the previously described conditions of uncertainty the tactical solution returned for the BAP requires tuning at the operational level; on the other, we wish to verify to what extent the SO scheme proposed may benefit of a minor computational expense when comparing simulated solutions by means of a moving-average estimator for the sample means within R&S procedures, rather than the straightforward sample means based on independent observations.

As for the first aim, preliminary experiments mainly devoted to illustrative purposes focus on a few vessels (i.e. 2 oceanic vessels and 3 feeders which both share a common and dedicated berth segment) belonging to a major service for which real data is provided by the company that runs the container terminal located at the port of Gioia Tauro in Southern Italy. Considering the small number of vessels to be berthed and under the hypothesis that all problem data is deterministic, the corresponding integer programming based formulation of the BAP has been solved under Excel, thus obtaining the tactical solution required as initial step of the SO scheme. A graphical representation of the tactical solution for the problem instance at hand is given in the left side of Figure 7.

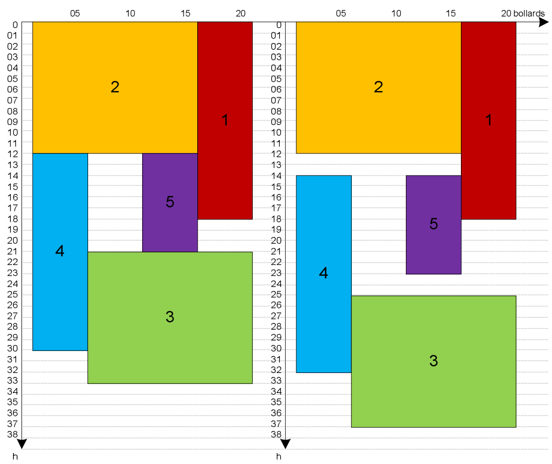

Figure 7: Tactical vs operational berth template

Now, according to company records, the delay in vessel operations is distributed according to the Pearson Type VI profile illustrated in Figure 8 (scale I, shape 1.945) for oceanic vessels and the Log-Logistic profile illustrated in Figure 9 (scale 0.586, shape 0.262) for feeder vessels. Unfortunately, as one may observe from Figure 7, the template on the left does not tolerate any kind of delay on oceanic vessel 2 and feeder vessel 5. Vice versa, since the time gap of two hours left in the right side template in Figure 7 for vessels 2 and 5 is sufficient to prevent delay propagation in 72% and 85% of the cases, respectively, then the operational template on the right in Figure 7 may be viewed as the robust counterpart of the tactical template. In other words, the degree of robustness lies in the time gap located after every single window which is delay-tolerant, i.e. unpredictable delays in operations do not immediately affect the operations scheduled on the vessels planned to be berthed afterwards. A robust template is also valuable for its managerial implications: the number of vessels delayed beyond their time windows is reduced and, therefore, the senior management reduces the payment of extra charges to shipping companies for not achieving the level of service stipulated in their contracts.

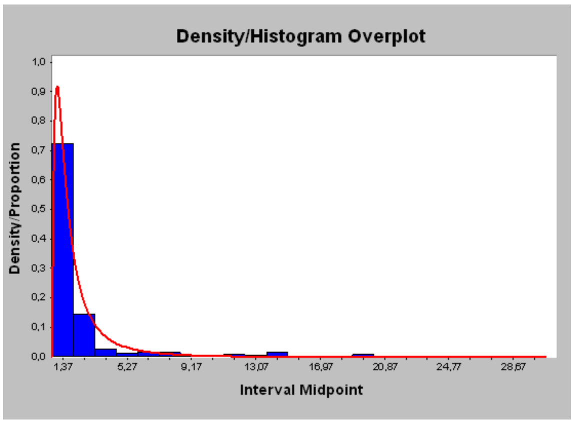

Figure 8: Profile of delays for oceanic vessels

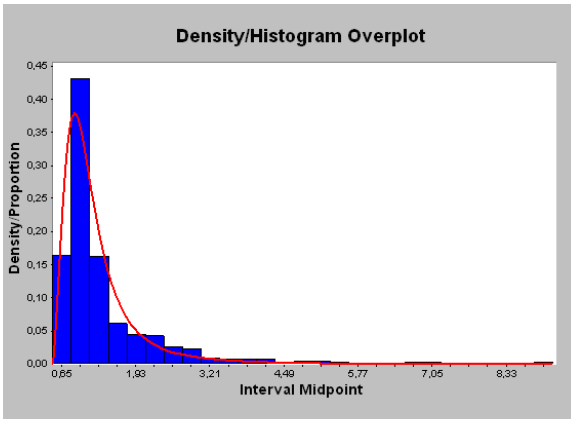

Figure 9: Profile of delays for feeder vessels

As for the second aim of the preliminary numerical experiments, to investigate the effect of using R&S procedures based on a moving-average, rather than standard estimator for the sample mean, we organized the n simulated output observations into b groups, each of size m, and then computed the average value of the *ith* observation across these groups according to the width *w* of the moving window. We then focused on the computational results returned when increasing the value of *w* from 1 to 5. In Table 1 for five selected instances we recorded the number of simulated observations (runs) required by the moving-average

(MA) sample mean (3) against the standard sample mean (S) estimator for the expected value of the objective function associated with each berth allocation plan.

Table 1: Average simulation runs required by different estimators for the sample mean in R&S procedures

W	E/I	#1	#2	#3	#4	#5
1	MA	110	283	459	195	145
	S	828	3771	6835	2571	1952
2	MA	104	192	233	133	117
	S	847	3840	7026	2448	1952
3	MA	104	142	195	119	103
	S	834	3836	7025	2544	1964
4	MA	100	139	184	119	101
	S	832	3925	7124	2641	1963
5	MA	100	118	141	105	100
	S	829	3765	7107	2507	1975
indifference zone parameter					δ=1‰	

In the above examples, both estimators were used to determine the number of additional runs required according to a classic two-stage indifference-zone ranking and selection procedure, under a fixed probability of correct selection $1-\alpha=0.95$ and $\delta=1$‰. To this purpose, we remark the effectiveness of the MA estimator since it reduces the sample size from intolerable to tolerable, especially if one considers the number of runs cumulated over all the neighbor solutions to be compared (consider that in the above five instances neighborhood size may reach 100). Furthermore, MA also delivers a growing variance reduction effect as the width of the window increases. In Table 1, this may be appreciated by reading the MA vertical values for each instance.

5. CONCLUSIONS

Simulation Optimization has been shown to be well suitable in addressing the solution of the berth allocation problem under uncertainty. It has allowed to integrate the proper deterministic model formulation at the tactical level with discrete-event simulation, used at the operational level, to cope with uncertainty in the duration of vessel discharge/loading activities and other sources of random occurring events and availability of resources in time. Real-size BAP instances may be solved by combining constructive heuristics and a simulated annealing based search process, where a discrete-event simulator is called to evaluate competing solutions. The computational burden due to the number of simulation runs required for the ranking and selection of solutions is kept tolerable by resorting to window-based moving sample means within a classic two-stage procedure. The SO scheme proposed has returned "robust" BAP solutions that well contain delay propagation at the operational level. Results of extensive numerical experiments on large-size instances will be presented in a companion paper.

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