Scheduling of Berthing Resources at a Marine Container Terminal via the use of Genetic Algorithms: Current and Future Research

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1. Introduction

The tremendous increase of containerized trade over the last several years, the resulting congestion in container terminals worldwide, the remarkable increase in containership size and capacity, the increased operating cost of container vessels and the adoption by liner shipping companies of yield management techniques strain the relationships between ocean carriers and container terminal operators. Shipping lines want their vessels to be served upon arrival or according to a favorable priority pattern and complete their loading/unloading operations within a prearranged time window, irrespective of the problems and shortage of resources terminal operators are facing. Therefore, allocating scarce seaside resources is considered to be a problem deserving both practical and theoretical attention. Scientific research has focused on scheduling problems dealing primarily with two of the most important seaside resources: berth space and quay cranes. Comprehensive reviews of applications and optimization models in the field of marine container terminal operations are given by Meersmans and Dekker (2001), Vis and de Koster (2003), Steenken et al. (2004), Vacca et al. (2007), and Stahlbock and Voß (2008).

Scheduling of berth space, also called the berth scheduling problem (BSP), can be simply described as the problem of allocating space to vessels at the quay in a container terminal. The quay crane scheduling problem (QSP) can be described as the problem of allocating quay cranes to each vessel and vessel section. Vessels arrive at a container terminal over time and the terminal operator assigns them to berths to be served. To unload/load the containers from/onboard the vessel a number of quay cranes are assigned to each vessel. Ocean carriers, and therefore vessels, compete over the available berths and quay cranes, and different factors affect the berthing position, the start time of service, and the number of quay cranes assigned to each vessel. Several formulations have been presented for the BSP, the QSP, and recently for the combination of the BSP and QSP, the berth and quay crane scheduling problem (BQSP). Most of the model formulations have been single objective and it was not until recently that researchers recognized the multi-objective and multi-level character of these problems and introduced formulations that capture berth scheduling policies using the latter two formulations. The formulations that have appeared in the literature, in most cases, lead to NP-hard problems that require a heuristic or meta-heuristic algorithm to be developed in order to obtain a solution within computationally acceptable

times. Evolutionary algorithms, and more specifically Genetic Algorithms, have been used in some of these studies and are increasingly gaining popularity as main resolution approaches for these problems due to their flexibility and robustness as global search methods.

The topic of this Chapter is the application of Genetic Algorithms (GAs) based heuristics as resolution approaches to problems relating to the seaside operations at marine container terminals; namely the BSP, the QSP, and the BQSP. The first part of this Chapter presents a critical, up-to-date, review of the existing research efforts relating to the application of GAs based heuristics to these three classes of problems. Strengths and limitations of the existing algorithms to address the resolution of these problems are discussed in a systemic and coherent manner. The second part of the chapter summarizes and groups the different chromosome representations, genetic operations, and fitness function selection techniques presented in the published scientific research. It provides generic guidelines of how these components can be implemented as resolution approaches to different formulation types (i.e. single objective, single level multi-objective, and multi-level multi-objective) and the berth and quay crane scheduling policies the latter represent (e.g. minimum service time, minimum vessel delay, minimum quay crane idle time etc). In addition, the second part provides an in-depth analysis and proposed improvements on how these components may address two main "weak spots" of GAs based heuristics: a) the lack of optimality criteria of the final solution, and b) how to exploit the special characteristics of the physical problem and construct improved approximations of the feasible search space. The Chapter concludes with a critical review of the issues that need to be addressed to make GAs more relevant, applicable and efficient to berth scheduling real world applications, and provides some insights for future research directions.

2. Literature review

In this section we present a critical, up-to-date review of the existing research efforts relating to the application of GAs based heuristics to problems relating to the seaside operations at marine container terminals (namely the berth scheduling problem, the quay crane scheduling problem, and the combination of the two problems). For a more comprehensive literature review on the berth scheduling and quay crane scheduling problem and the different terminal operator policies we refer to Bierwirth and Miesel (2009a) and Theofanis et al. (2009). Strengths and limitations of the existing algorithms to address the resolution of these problems are discussed in a systemic and coherent manner.

2.1 Berth scheduling
As we mentioned earlier, the berth scheduling problem (BSP) can be simply described as the problem of allocating berth space to vessels in a container terminal. Vessels usually arrive over time and the terminal operator needs to assign them to berths to be served (unload and load containers) in a timely manner. Ocean carriers and therefore vessels compete over the available berths and different factors, discussed in detail later, affect the berth and time assignment. The BSP has three planning/control levels: the strategic, the tactical, and the operational. At the strategic level, the number and length of berths/quays that should be available at the port are determined. This is done either at the initial development of the port or when an expansion is considered. At the tactical level, usually midterm decisions are taken, e.g. the exclusive allocation of a group of berths to a certain ocean carrier. At the

operational level, the allocation of berthing space to a set of vessels scheduled to call at the port within a few days time horizon has to be decided upon. Normally, this planning horizon does not exceed seven to ten days. Since ocean carrier vessels follow a regular schedule, in most cases the assignment of a berth to the vessel has to be decided upon on a regular and usually periodical basis. At the operational level the BSP is typically formulated as combinatorial optimization problem. After the BSP has been solved, the resulting Berth Scheduling Plan is usually presented using a time-space diagram.

The BSP has been formulated according to the following variations: a) Discrete versus Continuous Berthing Space, b) Static versus Dynamic Vessel Arrivals, and c) Static versus Dynamic Service Time, involving different assumptions on the utilization of the space of the quay, the estimation of the handling time of the vessels and the arrival time of the vessels as compared to the beginning of the planning horizon. Time-space representations of BSP variations are shown in Figure 1. The BSP can be modeled as a discrete problem if the quay is viewed as a finite set of berths, where each berth is described by fixed-length segments or as points. Typically, however, vessels are of different length and dividing the quay into a set of predefined segments is difficult, mainly due to the dynamic change of the length requirements for each vessel. One solution to this problem is to use longer segments (a solution resulting in poor space utilization), or short segments (an approach leading in infeasible solutions). To overcome these drawbacks continuous models have appeared in the literature, where vessels can berth anywhere along the quay. In the former case, the BSP can be, and in the majority of the cases has been, modeled as an unrelated parallel machine-scheduling problem (Pinedo, 2008) whereas in the latter case as a packaging problem. The BSP can also be modeled as a static problem (SBSP), if all the vessels to be served are already at the port when scheduling begins or as a dynamic problem (DBSP), if all vessels to be scheduled for berthing have not yet arrived but arrival times are known in advance. Service time at each berth depends on several factors; with the two most important being the number of cranes operating on each vessel and the distance from the preferred berthing position, i.e. from the berth with the minimum distance from the storage yard blocks, where containers to be (un)loaded from/onboard the vessel are stored. If the model does not take under consideration the number of cranes operating at each vessel, then the problem can be considered as static in terms of the handling time. On the other hand, if this number is decided upon from the model, the formulation can be considered as dynamic in terms of the vessel service time. Finally, technical restrictions such as berthing draft, inter-vessel and end-berth clearance distance are further assumptions that have been considered. The model formulations that have appeared in the literature combine two or more of these assumptions and, in most cases, lead to NP-hard problems that require heuristic algorithms to be developed for computationally acceptable solution times.

The first paper to appear in the literature that applied Genetic Algorithms as a resolution approach to the berth scheduling problem was by Go and Lim (2000). In their paper the authors represent the continuous space and dynamic vessel arrival time berth scheduling problem (CDBSP) using a directed acyclic graph and investigate the efficiency of several variants of the Randomized Local Search, Tabu Search and Genetic Algorithms. The authors based their representation of the problem on the work by Brown et al. (1997) and their objective was to determine the minimum length of the wharf to serve all the vessels. The authors observed that a combination of the different methods (i.e. Tabu Search and GAs) can have improved results as compared to each method being applied individually. In the

next section we will expand on this observation and critically discuss why this phenomenon is to be expected.

a. Static-Discrete   b. Dynamic-Discrete

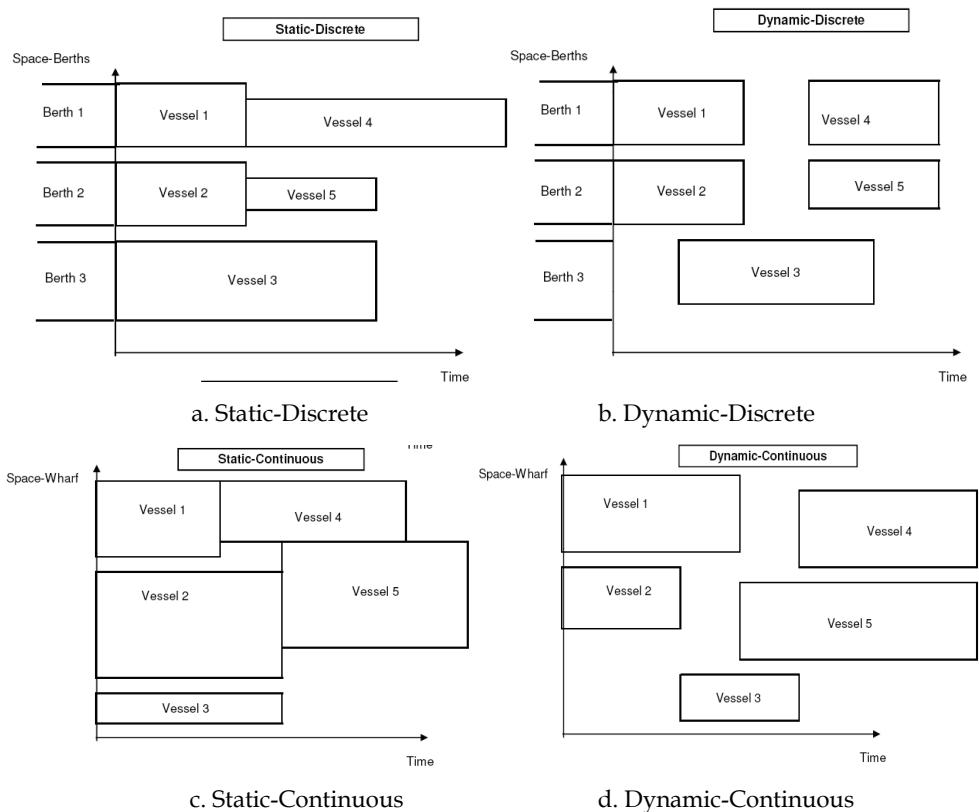c. Static-Continuous   d. Dynamic-Continuous

Fig. 1. Berth Scheduling Problem (BSP) Variations

In 2001, Nishimura et al. (2001) extended the work by Imai et al. (1997) and Imai et al. (2001) and presented a GAs heuristic for a discrete space and dynamic vessel arrival time BSP (DDBSP) at a public berth system. The objective was to minimize the total service time of all the vessels served. A one-dimensional representation with genetic operations of reproduction, crossover and mutation and a fitness function defined by the reciprocal of the actual objective function were implemented. No justification was provided for the use of the selected genetic operations or fitness function. The proposed GAs heuristic was compared against results from a Lagrangian relaxation heuristic, with the latter performing better but without significant differences. Following this work, Imai et al. (2003) presented a formulation for the DDBSP, based on the unrelated machine scheduling problem, where vessel service was differentiated based on weights assigned to each vessel. The authors initially proposed a Lagrangian relaxation based approach, which then was replaced by the GAs based heuristic proposed by Nishimura et al. (2001), due to the difficulty of applying the sub-gradient method to the relaxed problem. The authors commented only on the berth scheduling policy and not on the efficiency or consistency of the proposed GAs heuristic,

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which cannot be assumed to have the same behavior as the one observed for the policy presented in Nishimura et al. (2001). Imai et al. (2006) presented a formulation for the DDBAP at a terminal with indented berths. The authors used the GAs based heuristic presented by Nishimura et al. (2001) with the addition of a procedure to obtain feasible solutions. In a similar fashion to the previous research by the authors (Imai et al. 2003) the experimental results focused on the evaluation of the proposed policy and terminal design, as compared to a conventional terminal without indented berths, and no results were provided as to the efficiency of the GAs based heuristic.

Han et al. (2006) studied the DDBSP with the objective of minimizing the total service time of all the vessels (similar to Imai et al., 2001; and Nishimura et al., 2001) and presented a hybrid optimization strategy of a combination of a GAs and a Simulated Annealing (SA) based heuristic. This is the first time that GAs were combined explicitly with another heuristic (which is part of the new area of research called Memetic Algorithms, see Goh et al., 2009) for the berth scheduling problem. The authors used the same GAs characteristics (i.e. representation and fitness function) as in Nishimura et al. (2001) and applied a Metropolis based stochastic process based on parameters given by the SA approach to select the individuals of the next generation. The proposed heuristic was compared to results obtained from the GAs heuristic without the stochastic component and, as expected, it performs better.

For the first time in 2006 the DDBSP was formulated as a stochastic machine scheduling problem by Zhou et al. (2006), with the objective of minimizing the expected values of the vessels waiting times. The authors assumed that the vessel arrival and handling times at the berths are stochastic parameters, resulting in a binary problem with stochastic parameters in the objective function as well as in the constraints. A GAs based heuristic was proposed as a resolution algorithm using the representation introduced by Nishimura et al. (2001), two simple crossover and mutation operations, and a fitness function based on the actual value of the objective function and a penalty for violating the waiting time constraint. Experimental results focused on the CPU time and convergence patterns of the proposed algorithm and to a brief comparison with a first come first served (FCFS) policy The next year, Golias et al. (2007) studied the DDBSP where vessel arrival and handling times were considered as stochastic variables. They presented and conceptually compared three different heuristic solution approaches: a) a Markov Chain Monte Carlo simulation based heuristic b) an Online Stochastic Optimization based heuristic, and c) a deterministic solution based heuristic. A generic Genetic Algorithms based heuristic that can be used within the former two heuristics was also proposed. Computational results were not provided.

Imai et al. (2007a) studied the DDBSP and presented a bi-objective formulation to minimize the total service time and delayed vessel departures. The GAs proposed in Nishmiura et al. (2001) and the Subgradient Optimization procedure proposed in Imai et al. (2001) were used as resolution approaches. The two procedures were compared and it was shown that the former outperformed the latter. We should note that the proposed GAs heuristic can only solve single objective problems and cannot be compared to GAs that are used in multi-objective optimization problems, which will be presented later on in this Chapter. In the same year Theofanis et al. (2007) were the first to present an optimization based GAs heuristic for the DDBSP. The proposed resolution algorithm could be applied to any linear formulation of the BSP (i.e. different berth scheduling policies). The authors applied the GAs

based heuristic proposed by Golias (2007) and followed the same representation to Nishimura et al. (2001), but differentiated the genetic operations using four different types of mutation (presented by Eiben and Smith, 2003) without applying crossover. This approach was justified by the large number of infeasible solutions that crossover operations produce and the increase in CPU time that would be required to deal with this issue. The authors also used the objective function value as the fitness function and the roulette wheel selection algorithms (Goldberg, 1989). Similar to the research presented so far, the proposed heuristic was only compared to the GAs heuristic without the optimization component, and results showed that the former outperformed the later in terms of variance and minimum values of the objective function, especially as the problem size increased. The increase in computational time due to the optimization component was negligible.

Imai et al. (2008) extended their previous work and presented a formulation for the DDBSP where ships which would normally be served at a terminal but their expected wait time exceeds a time limit are assigned to an external terminal. Similar to their previous work, the GAs based heuristic proposed as a resolution approach used the fitness function proposed by Kim and Kim (1996), a two-point crossover and a tournament process proposed by Ahuja et al. (2000). The proposed heuristic was not evaluated in terms of obtaining optimality, as it was the case with their previous published work. In the same year, Boile et al. (2008) proposed a 2-opt based heuristic for the DDBSP where the GAs heuristic proposed in Golias (2007) was used to reduce the computational time required. Finally, in 2008, Hansen et al. (2008) presented a new berth scheduling policy for the DDBSP and proposed a variable neighborhood search heuristic as the resolution approach. The proposed heuristic was compared to the GAs heuristic by Nishimura et al. (2001), Multi-Start Algorthm, and a Memetic Search algorithm. The latter was an extension of the GAs heuristic with local Variable Neighborhood Descent search instead of mutation. Results showed that their proposed heuristic outperformed the latter three.

In 2009, Golias et al. (2009a) were the first to formulate and solve the DDBSP as a multi-objective combinatorial optimization problem. A GAs based heuristic was developed to solve the resulting problem. Results showed that the proposed resolution algorithm outperformed a state of the art metaheuristic and provided improved results when compared to the weighted approach. The authors used the same chromosomal representation, reproduction, and selection as in Golias (2007) but used a different fitness function equal to the difference of the maximum objective function among all the chromosomes and the objective function value of the chromosome. Similar to Boile et al. (2008), Golias et al. (2009b) used the GAs heuristic in Golias (2007) as an internal heuristic to an adaptive time window partitioning based algorithm for the DDBSP. In the same year Golias et al. (2009c) presented a new formulation for the DDBSP where vessel arrival times are optimized in order to accommodate an environmentally friendly berth scheduling policy and increase the opportunities for vessel berthing upon arrival. The problem was formulated as a bi-level optimization model and a stochastic GAs based heuristic was proposed as the resolution algorithm. The same year Theofanis et al. (2009b), solved the same problem but as a multi-objective optimization problem using a variant of the GAs heuristic presented in Golias et al. (2009c). Finally, Saharidis et al. (2009) presented a concrete methodology on the bi-level multi-objective DDBSP and proposed an innovative GAs based heuristic that followed the example of the k-best algorithm (Bialas and Karwan, 1978, 1984).
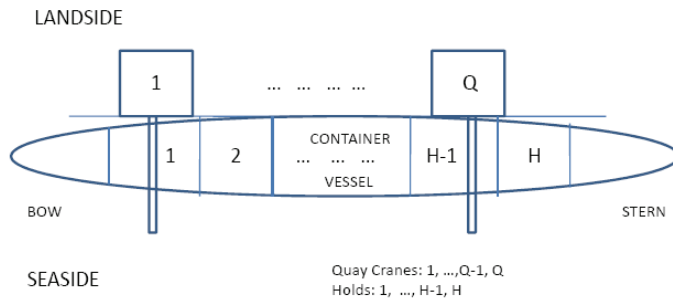
2.2 Berth and Quay Crane scheduling

The goal of studying the QC scheduling problem is to determine the sequence of discharging and loading operations that quay cranes will perform so that the completion time of a vessel operation is minimized. This problem assumes that a berth schedule has already been provided. In practice though, the BSP is mainly affected by the vessel handling times which are dependent on three key parameters: a) the distance between the berthing position of the vessel and the storage area allocated to the containers to be unloaded from/loaded onboard the vessel, b) the number of QCs assigned to the vessel, and c) the number of internal transport vehicles (ITVs) assigned to the vessels' quay cranes. For example, the further away a vessel is berthed from its assigned storage yard area, the largest the distance that the ITVs will travel between the QCs serving the vessel and the storage yard, increasing the ITVs turnaround time. If the number of ITVs assigned is not adequate this may result in QC idle time. Proximity of the vessel's berth location to its assigned yard area would potentially reduce the number of ITVs required. In another instance, when the number of ITVs assigned to a vessel is fairly large, a different case may occur, in which ITVs may remain idle waiting to be served by a QC. These simple examples indicate that there is a need to simultaneously optimize vessel berthing with QC and ITV assignments to achieve better seaside operation efficiencies. We refer to Steenken et al. (2004) and Mastrogiannidou et al. (2008) for more details. To our knowledge, the complex relationship between the vessel handling time and these parameters (i.e. number of QCs and ITVs assigned to a vessel, and the vessels' preferred storage yard location and berth allocation) has not been addressed in the literature.

Some researchers have attempted to formulate and solve the combination of the quay crane and berth scheduling problem. There is no unique objective for optimization when dealing with the QSP or the BQSP. Minimization of the sum of the delays of all vessels; maximization of one vessel's performance; or a well-balanced or economic utilization of the cranes, are some indicative objectives. The most general case of the QSP or the BQSP is the case in which ships arrive at different times at the port and wait for berthing space if all berths are occupied. The objective in this case is to serve all the ships while minimizing their total delay. Crane to ship allocation has to reflect several constraints like technical limitations and the accessibility of cranes at various berths. Crane split allocates a respective number of cranes to a ship and its bays/sections (on hold and deck) and decides on which schedule the bays have to be operated. The QSP or the BQSP problem can be considered as a machine-scheduling or project-scheduling problem (Peterkofsky & Daganzo, 1990), usually formulated as a MIP, either studied independent from the other processes or as part of the berth planning, container allocation to the yard and vehicle dispatching. One of the decisions that have to be made is the exact number of QCs that work simultaneously on one ship to minimize vessel delays. Decisions at the operational level (which crane loads which container onboard the vessel and which container should be taken out of the hold first) are in practice determined by the vessel loading and unloading plan and are typically followed by the crane operator. Figure 2 shows graphical representations of BQSP and QSP problems. Very few papers applied GAs based heuristics as resolution approaches to the QSP or the BQSP. Interest in using this type of heuristics began in 2006 and based on the number of publications, is increasing ever since. In 2006, Lee et al. (2006) presented a bi-level formulation of the BQSP where the upper level schedules the vessels and the lower level schedules the quay cranes. In the upper level the total service time for all the vessels is minimized, while the lower level minimizes the total makespan of all the vessels and the

Note: C: Quay Crane
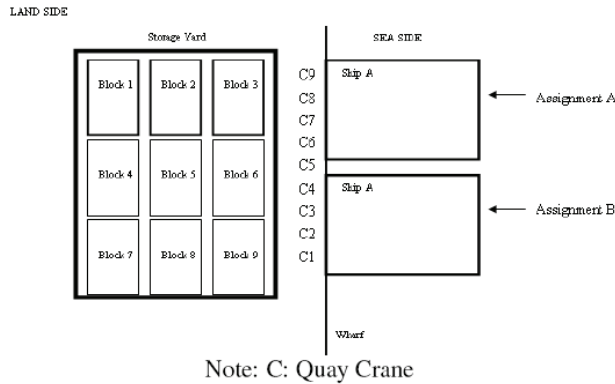
Source: Golias et al. (2007)

Fig. 2a. Berth and Quay Crane Scheduling Problem (BQSP)

Source: Adapted from Lee et al. (2008)

Fig. 2b. Quay Crane Scheduling Problem (QSP)

Fig. 2. BQSP and QSP Illustrative Examples

completion time of all the QCs. A GAs based heuristic with a similar representation to the one by Nishimura et al. (2001) is used to solve the upper level problem, while LINDO is used to solve the lower level problem. The authors adopt order-based crossover and mutation for the genetic operations, a fitness function equal to the objective function of the upper level problem, while the selection process is confined in the 100 best chromosomes. Computational examples where very limited and no conclusion could be drawn for the efficiency of the heuristic. The following year, Theofanis et al. (2007) and Golias et al. (2007) formulated the BQSP as an integer programming model with the objective to minimize costs resulting from the vessels delayed departures and inadequate berth productivity service levels. These models simultaneously assign quay cranes and dynamically allocate vessels along a wharf, assuming that the handling time of each vessel is a function of the number of cranes assigned and the location along the wharf, and include wharf length constraints. Rectangular chromosome GA based heuristic and tabu mutation based heuristic procedures were developed to solve the resulting problem. The fitness function was set equal to the objective function of each chromosome, while no crossover was performed. The roulette wheel selection routine was used to select the new generations. As in Lee et al. (2006), the

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computational examples performed to evaluate the proposed heuristic were not substantial to produce robust conclusions on the efficiency of the GAs heuristic.

Imai et al. (2008) introduced a formulation for the simultaneous berth and crane allocation problem with the objective to minimize the total vessel service time. A GAs based heuristic was employed to find an approximate solution to the berth scheduling problem without consideration of the QCs. The QC assignment was performed by a maximum flow problem-based algorithm. The proposed GAs heuristic was very interesting as the chromosomes only produced the vessel-to-berth service order and before reproduction, crane scheduling was performed. A two-point crossover was used for reproduction, and selection was based on the fitness function presented in Nishimura et al. (2001). Based on trend analysis of the results of numerical experiments, the authors concluded that the proposed heuristic is applicable to solve the problem.

Lee et al. (2008a) and Lee et al. (2008b) studied the QSP with and without vesssel priority in order to determine a handling sequence of holds for quay cranes assigned to a container vessel considering interference between quay cranes with the objective of minimizing the vessel completion time. The GAs based heuristic proposed in both papers as the resolution algorithm had very similar chromosome representation to the one presented in the berth scheduling problem by several researchers. The fitness value was set equal to the reciprocal of the objective function value and the roulette wheel selection routine was applied as the selection algorithm. Order crossover and swap mutation were adopted for reproduction of new chromosomes. CPLEX was used to obtain lower bounds of an exact solution to a relaxed formulation of the same problem and computational examples showed that the proposed heuristic produces near-optimal results. Liang et al. (2009) studied the BQSP with the objective to minimize service time and delays for all the vessels. A GAs based heuristic was proposed with a three layer chromosome. The first layer provided vessel priority, the second the berth to vessel assignment and the third the assignment of QCs to the vessels. One-cut point crossover and swap mutation where applied to reproduce future generations of chromosomes.

Finally, Tavakkoli-Moghaddam et al. (2009) presented possibly the most interesting QSP formulation capturing a very practical container terminal operators policy (also described in Golias 2007) of maximizing premiums from early departures and minimizing costs from late departures and variable vessel handling cost. In the proposed GA, a chromosome consisted of a rectangular matrix, different from the one in Theofanis et al. (2007). The authors proposed a heuristic approach to initial the chromosome, while arithmetic and extended patch crossover were used as reproduction operations. The authors use swap mutation to retain diversity in the solutions as the GAs heuristic proceeds and similar to other research they use the roullete wheel selection technique to sample future generations, based on a semi-greedy strategy. The fitness value is derived directly from the values of the objective function of each chromosome. Computational results showed that the proposed resolution algorithm produces results with reasonable gaps as compared to the optimal solutions found using an exact resolution algorithm within reasonable computational time.

3. Resolution algorithms details

This section of the Chapter attempts to summarize the different chromosome representations, genetic operations, and fitness function selection techniques presented in the published scientific research. From the presented literature it is obvious that the papers

by Go and Lim (2000) and Nishimura et al. (2001) initiated the use of GAs based heuristics as resolution algorithms for seaside related operational problems at marine container terminals. In general GAs based heuristics consist mainly of four parts: a) the chromosomal representation, b) the reproduction operations, c) the fitness function evaluation and d) the selection process. In the following subsections we discuss in depth f each one of the four components.

3.1 Representation

For scheduling problems (like the BSP, the QSP, and the BQSP) integer chromosomal representation is more efficient, since the classical binary representation can obscure the nature of the search. Most of the papers presented to date dealing with the BSP and the QSP used an integer chromosomal representation to exploit the characteristics of the problem. An illustration of the typical chromosome structure for the BSP and QSP is given in figure 3 for a small instance of the problem with 6 vessels and 2 berths. As seen in figure 3a the chromosome has twelve cells. The first 6 cells represent the 6 possible service orders at berth1 and the last 6 cells the 6 possible service orders at berth 2. In the assignment illustrated in figure 3a vessels 2, 4, and 5 are served at berth 1 as the first, second and third vessel respectively, while vessels 1, 3, and 6 are served at berth 2 as the first, second, and third vessel respectively. Fig. 3b shows a somewhat typical chromosomal representation for the QSP where there are two QCs. The first QC will work on holds 1, 3, 6, and 7 (in this order) and the second QC will work on holds 8, 9, 12, and 10 (in this order). This representation has the advantage of including QC interference constraints in a natural way.

Berth	1						2					
Vessel	2	4	5	0	0	0	1	3	6	0	0	0

Source: Golias et al. (2009a)

Fig. 3a. Chromosome Representation for the BSP

Quay Crane	QC 1				QC 2			
Hold	1	3	6	7	8	9	12	10
Sequence	1	2	3	4	1	2	3	4

Fig. 3b. Chromosome Representation for the QSP

Fig. 3. Illustration of Chromosomal Representations for the BSP and the QSP

For the BQSP we cannot claim that there is a typical chromosome representation, as the number of publications that have appeared is rather small (as compared to the BSP). Some authors used a variation of the chromosome representation shown in figure 3. In figure 4 we show the two representations found in the literature that deviate from the one string representation shown in figure 3. The chromosome on the left of figure 4 consist of a rectangular matrix with (V x (A + 1)) genes, where V and A represent number of vessels and the greatest number of jobs on the vessels, respectively. In each column for each vessel, the first gene represents the number of QCs assigned to that vessel. The rows in the chromosome represent the number of QCs assigned to vessels. The chromosome on the right of figure 4 also consists of a rectangular matrix with (QxT) cells where Q and T represent the total number of Quay Cranes and T is the total planning period. In this chromosome vessel 1 is serviced by quay cranes 1 through 3, starts service at the beginning

of the planning horizon, finishing service 3 hours later. Cells with zero value indicate that no vessel is serviced at that time.

Source: Tavakkoli-Moghaddam et al. (2009)   Source: Golias et al. (2007)

Fig. 4. Illustration of Chromosomal Represenations for BQSP

3.2 Reproduction

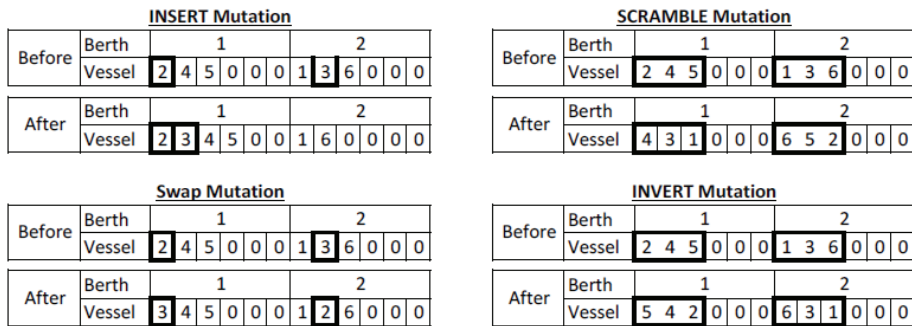GAs reproduction operations can be distinguished into two broad categories: a) crossover, and b) mutation. Crossover is explorative; it makes a big jump to an area somewhere "in between" two parent areas. On the other hand, mutation is exploitative; it creates random diversions of a single parent. There is a debate on the use of crossover and mutation and which approach is the best to use. In fact, the performance of either mutation or crossover is highly affected by the problems' domain. In the reviewed literature most of the researchers applied both differernt types of crossover and mutation with the exception of a few papers that claimed that at each generation the crossover operation will generate a large number of infeasible children. The latter chose to apply more complex mutation and did not include crossover operations. Unfortunately, no experimental results have been presented to direct research to the use of either one approach. It is worthnoting though that crossover operations, where applied, usually implemented simple crossover techniques and where dominated by the one or two point crossover reproduction technique (fig. 5).
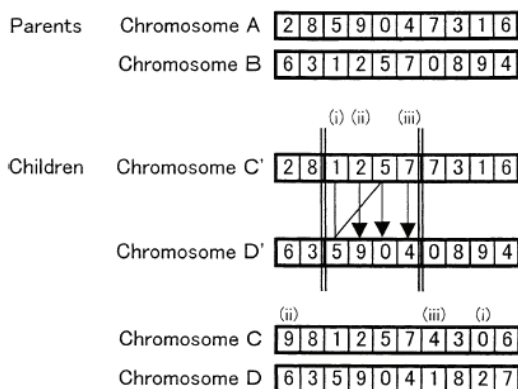
Source: Nishimura et al. (2001)

Fig. 5. Schematic Representation of the Crossover Operations

Figure 6 shows the main four different types of mutation that were identified during the literature review. Each of the four types of mutations has its own characteristics, in terms of preserving the order and adjacency information. Insert mutation picks two cells at random and moves the second one to follow the first, thus preserving most of the order and adjacency information. Inverse mutation picks two cells at random and then inverts the substring between them preserving most adjacency information (only breaks two links), but disrupting the order information. Swap mutation picks two cells from a chromosome and swaps their positions preserving most of the adjacency information but disrupting the order. Finally, scramble mutation scrambles the position of a subset of cells of the chromosome. Each of the four types of mutations has its own characteristics in terms of preserving the order and adjacency information (Eiden and Smith, 2003).

INSERT Mutation

	Berth	1		2								
Before	Vessel	2	4	5	0	0	0	1	3	6	0	0	0

	Berth	1		2								
After	Vessel	2	3	4	5	0	0	1	6	0	0	0	0

SCRAMBLE Mutation

	Berth	1		2								
Before	Vessel	2	4	5	0	0	0	1	3	6	0	0	0

	Berth	1		2								
After	Vessel	4	3	1	0	0	0	6	5	2	0	0	0

Swap Mutation

	Berth	1		2								
Before	Vessel	2	4	5	0	0	0	1	3	6	0	0	0

	Berth	1		2								
After	Vessel	3	4	5	0	0	0	1	2	6	0	0	0

INVERT Mutation

	Berth	1		2								
Before	Vessel	2	4	5	0	0	0	1	3	6	0	0	0

	Berth	1		2								
After	Vessel	5	4	2	0	0	0	6	3	1	0	0	0

Source: Boile et al. (2008)

Fig. 6. Schematic Representation of the Mutation Operations

3.3 Fitness function and evaluation

Fitness evaluation and selection refers to the evaluation of the strength of each chromosome and the selection of the next generation based on the fitness. Usually, the BSP, the QSP, and BQSP are minimization problems; thus the smaller the objective function value is, the higher the fitness value must be. The best solutions are likely to have an extremely good fitness value among solutions obtained, where there is no significant difference between them in the objective function value. The most common fitness functions found in the literature were the reciprocal of the actual objective function (Nishimura et al., 2001), or the actual value of the objective function. Unfortunately, no experimental results exist to justify or suggest the use of one fitness function over the other.

3.4 Selection

Although several selection algorithms exist in the literature (Taboada, 2007), the most common one found to be implemented in almost all the literature reviewed is the so-called roulette wheel selection (Goldberg, 1989). This selection approach has the benefit of combining elitism (by selecting the best chromosome from each generation) and a semi-greedy strategy (when solutions of lower fitness are included), which has shown to reduce the computational time of the genetic algorithms performance (Tavakkoli-Moghaddam et al., 2009).

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3.5 General guidelines of GAs implementation

From the literature presented in the second section of this Chapter it becomes apparent that GAs have been shown to be very efficient and effective in scheduling problems that arise at the seaside operations of a container terminal. As most of these problems are NP-hard or NP-complete, GAs have the advantage of flexibility over other more traditional search techniques as they impose no requirement for a problem to be formulated in a particular way, and there is no needfor the objective function to be differentiable, continuous, linear, separable, or of any particular data-type. They can be applied to any problem (e.g. single or multi-objective, single or multi-level, linear or non-linear etc) for which there is a way to encode and compute the quality of a solution to the problem. This flexibility provides GAs with an important advantage over traditional optimization techniques. Using the latter techniques, the problem at hand is usually simplified to fit the requirements of the chosen search method, whereas GAs do not make any simplification of the problems' original form and produce solutions that describe the system as is. To that extend we can observe that the reproduction and evaluation techniques, as well as the fitness functions, presented to date are very simplistic, and can be easily tranferable to different objectives for the same problem, i.e. the GAs heuristic presented in Nishimura et al. (2001) has been used as a resolution algorithm to accomodate a large number of different berth scheduling policies (Imai et al., 2003; Imai et al., 2007 etc).

To this end we would like to emphasize that as the need to tackle real world applications increases, multi-objective problem formulations tend to be more suitable. GAs have been the main a posteriori methods adopted for solving multi-objective optimization problems and generating the set of Pareto optimal solutions from which a decision maker will decide upon the best solution. Although, very few papers have been presented in the literature with multi-objective formulations of seaside operations policies, the trend towards adoption of this modeling approach seems more likely in the near future, which will lead to an increasing use of GAs based heuristics as resolution approaches.

An additional advantage, that will increase the popularity of GAs as resolution algorithms in container terminal operations, is the recent focus of researchers to the use of hybrid GAs combining exact resolution algorithms (e.g. branch and bound), local search (i.e. Memetic Algorithms), and/or other (meta)heuristics (e.g. tabu search) to guarantee at least local optimality of the solution (single or Pareto set) or improve the convergence patterns.

Despite these advantages the GAs based heuristics presented to date suffer from two main weaknesses: a) optimality guarantees of the final solution, and b) the selection of a direction during the search to avoid trapping the algorithm at local optimal/feasible locations of the solution space. Very few researchers tried so far to combine local search heuristics or other (meta)heuristics to guide the search of the feasible space and even fewer applied exact resolution algorithms, within the GAs to provide guarantees of optimality of the final solution. It is the authors' opinion that this is an area that will attract more attention in the future, as we will move from ad-hoc search of the feasible space to a more guided search.

In addition, most of the GAs presented for the seaside operations take full advantage of the special characteristics of the problem in the representation phase of the GA only in the case of the BSP, and lack in the representation phase of the QSP and the BQSP. Furthermore, for all three problems the GAs presetned to date lack in the design of sophisticated reproduction techniques, as they rely on existing methodologies (e.g. simple swap and instert techniques). Several methods that can be used and enhance the search procedure in the reproduction phase including optimization or problem based heuristic techniques, such

as valid inequalities or tabu mutation, have yet to be presented. The same remark applies to the limited fitness functions and evaluation techniques presented to date,where a very interesting research direction would be the use of Game Theoretical Equilibrium techniques, especially in the cases of multi-objective problems.

As a final comment, we would like to note that to date there are rather few research groups focusing on using GAs to solve container terminal seaside operational problems and consequently there are rather limited research results published (i.e. Boile et al. 2008; Imai et al., 2001, 2003, 2007, 2008; Golias et al., 2007, 2009a, 2009b, 2009c; Lee et al. 2006, 2008a, 2008b; Theofanis et al. 2007, 2009a, 2009b), a fact which might explain the limited variety of chromosomal represenations, reproduction operations and fitness functions. As more researchers are becoming interested in marine container terminal operations and as we look into the near future, we see that there is potential for more investigation as to the effects of new reproduction and fitness selection schemes as well as into the application of multi-dimensional chromosomal representations for the BQSP that will better capture and represent the problem at hand.

4. Conclusions

In this Chapter we presented a critical, up-to-date, literature review of existing research efforts relating to the application of GAs based heuristics as resolution algorithms to three operational problems of seaside operations at marine container terminals: the BSP, the QSP, and the BQSP. We presented the different chromosome representations, genetic operations, and fitness function selection techniques in the published scientific research and provided an analysis of how these components can be improved to address two main "weak spots" of GAs based heuristics: a) the lack of optimality criteria of the final solution, and b) the relatively poor exploitation of the special characteristics of the physical problem and how to construct improved approximations of the feasible search space. From the existing literature it became apparent that the future of GAs based heuristic as resolution algorithms to marine container terminal seaside operational problems is quite promising, especially if the GAs will be combined with exact resolution, heuristic or local search algorithms. Although we have yet to see how these research directions will be tackled, even in problems outside this research area, the future looks certainly very exciting and it is expected that more researchers will dwell into this field of research.

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