Simulation-optimisation models for the dynamic berth allocation problem

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Abstract: *Container terminals are designed to provide support for the continuous changes in container ships. The most common schemes used for dock management are based on discrete and continuous locations. In view of the steadily growing trend in increasing container ship size, more flexible berth allocation planning is mandatory. The consideration of continuous location in the container terminal is a good option. This paper addresses the berth allocation problem with continuous dock, which is called dynamic berth allocation problem (DBAP). We propose a mathematical model and develop a heuristic procedure, based on a genetic algorithm, to solve the corresponding mixed integer problem. Allocation planning aims to minimise distances travelled by the forklifts and the quay crane, for container loading and unloading operations for each ship, according to the quay crane scheduling. Simulations are undertaken using Arena software, and experimental analysis is carried out for the most important container terminal in Spain.*

1 INTRODUCTION

Container terminals (CT) are important nodes in intermodal transport networks. According to the International Maritime Organization, more than 90% of world trade is transported by sea, and almost 80% is transported in containers. This is a substantive reason to conduct all the operations of a container terminal in an optimised way (Ambrosino et al., 2006).

Container ships are a major aspect in the development of the CT (Notteboom, 2007). The first ships that carried containers were known as barges, which had a capacity of 250 TEUs, and were replaced by the first generation of container ships that could carry around 800 TEUs, a big change in the progress of shipping. Currently, the largest container ship in the world is the Emma Maersk. This ship is capable of carrying 12,508 TEUs, and its dimensions are: length 398 m, breadth 56.4 m, service speed 25 knots (aprox. 50 km/hour), allowing a travel time of 4 days between China and the US west coast. Polo and Díaz (2006) research concludes that the current situation makes the design and operation of CT very complicated.

The CT cannot forget about smaller vessels which make short trips; this type of transportation is called short sea shipping (SSS). This transport is promoted by many governments and international institutions, in order to reduce the environmental impact. Several works can be found in the literature showing the strengths and weaknesses of SSS (Paixao and Marlow, 2002), while other authors discuss specific opportunities for SSS (Martinez and Olivella, 2005).

The CTs are adapting their resources and facilities to support the different sizes of ships arriving at them. The most important adaptation has been carried out in the dock design, especially in the berths where containers are loaded and unloaded. Imai et al. (2005) and Cordeau et al. (2005) consider two types of docks, according to the scheme design: the first with a discrete location with fixed points for berths; and the second with a continuous location, which has no fixed points for berths. In this paper, we opted for the second scheme owing to its versatility, and proceeded to divide the dock into segments, allowing each ship to take the required amount. This approach allows higher flexibility for the CT, and permits the docking of very different types of ships in the port. This approach is different and superior to that considered in Arango et al. (2011).

In this work, we propose a mixed integer model, to solve the dynamic berth allocation problem that considers the minimization of the distances travelled by the forklifts and the quay crane, for container loading and unloading operations as optimisation criteria. These distances are directly linked to the operation times of each ship over a specific time period. Also, we propose a simulation model, to carry out the validation of the models and develop a genetic algorithm to solve the optimization model in three different situations. We use the port of Algeciras that is one of the main ports in Spain and Southern Europe as the simulation scenario. In Section 2, we explain the dynamic berth allocation problem. Section 3 tackles the optimisation model, detailing the required mathematical notation and formulation. Section 4 depicts the characteristics of the implemented genetic algorithm. Section 5 tackles the simulation model. The experimentation and simulation results are detailed in Section 6. Finally, the main conclusions and future work are addressed in Section 7.

2 THE DYNAMIC BERTH ALLOCATION PROBLEM

When a ship arrives at a CT the planners must take into account its basic characteristics, such as size, number of containers to unload and load, and the locations of these in the storage area (SA), to decide the best berth allocation. This information is used in advance to plan the berth allocation, and considers:

- Location of export containers in the SA that will be loaded on to the ship (loading operations). This must be as close as possible to the allocated berth, and also must include a reserve of space for container to be stored in the SA. (Unloading operations).
- Required time for each dock segment according to the ship's arrival.

The objective of this problem is to minimise the total service time, which includes waiting time of the ship to come into the port, and loading and unloading operation time.

Several authors have approached different forms of this berth allocation concept. So, Imai et al. (2001), Imai et al., (2005) and Nishimura et al. (2001) determine the berth allocation, defining a dynamic berth allocation problem (DBAP), which is a generalisation of the static berth allocation problem (SBAP). They propose a genetic algorithm in public berth systems, which can be adapted to real-world applications. Lim (1997), Park and Kim (2003), and Liu et al. (2005) consider the berth allocation and quay crane scheduling problem (QCSP) as a single problem, making berth scheduling dependent on the crane number that is assigned to the ship. They consider the docks to be a critical resource that determines the capacity of CT. This is because the cost of building a dock is a larger investment than the investment undertaken in other facilities. So, they claim the planning of tasks at terminals as necessary, to optimise the use of the docks in order to increase their productivity.

Most of the above authors solved the DBAP with the assumption that CT only considered the information sent by the maritime companies to the CT; that is: time of arrival for each ship; quantity of containers to be loaded and unloaded; containers' location inside each ship etc. All these data are forecasts, but include a considerable degree of uncertainty owing to the presence of many maritime companies arriving at the CT.

Discrete-event simulation provides an excellent tool in systems dynamics (Alvanchi et al., 2011). This tool is a good option for the evaluation of different allocation strategies, location of containers, crane scheduling and too aid to decision-making in the subsystems involved in CT. Authors such as Fu (2002) say that until the 1990s, the simulation and optimisation were used separately, but in the last decade, various studies have been conducted using these tools together as a powerful methodology.

In the literature, there are some works combining simulation and optimisation approaches for the management of CTs, such as Cortés et al. (2007) who conducted case studies of the Seville inland port. Liu et al. (2002) analysed the productivity of automated container terminals, and more recently, Lagana et al. (2006) and Legato et al. (2009) developed optimisation and simulation models for scheduling the yard crane use at Gioia Tauro port.

In this paper, we propose a mixed integer optimisation model, solved by a genetic algorithm that is integrated into a simulation model, to test the efficiency of the provided allocation by the algorithm. The model minimises the time that ship is in the CT carrying out operations with the containers. Most of the research in the literature considers forecast information only, leads to a high degree of uncertainty. In this work, we develop a simulation model together with an optimisation model that are run every time a ship arrives at the port. This moment is represented by a ship's arrival to the CT canal. This place is where ships wait for the tugboats to be transported to the docks. The simulation model considers the system's current information, as well as the information coming from the other processes that participate in the container loading and unloading operations.

3 THE OPTIMISATION MODEL

In this section, we explain the model proposed to solve the DBAP. The model is adapted for the Algeciras port, which is considered as a hub container terminal. Figure 1 shows the layout for the case of study depicting the most important areas: A) train area; b) truck area, c) storage area and d) ship operation area.

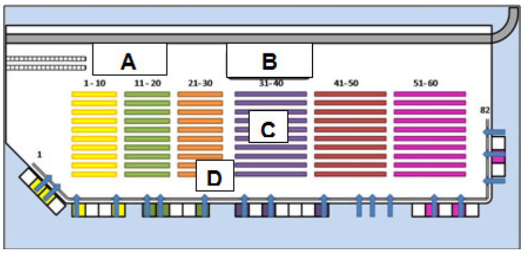

Figure 1 Layout of the Algeciras port

Every time that a ship arrives in the system, the model searches the best berth allocation for loading and unloading its containers, and determines the amount of quay cranes to be assigned to it. It takes into account the location of the container, the amount of loading and unloading in the storage area, and the availability of resources. The model takes into account the following assumptions:

- The dock is divided into 82 segments of 24 metres each.
- Three types of ships are considered: small vessels, whose length does not exceed 8

segments; medium-sized ships with a length between 8 and 14 segments; and large ships with a length between 15 and 17 segments.

• As quay cranes move on the same railway, possible interferences between displacements are considered.

• Only a standard 40-feet container size is considered.

• The maximum number of working sections per ship is three.

• The container's stacking plan is known.

• One free segment is considered as a minimum between two ships in operation.

• The optimisation model will decide which containers block (place) will store the containers unloaded. The precise location (micro-simulation) is not considered in this work.

Given the previous considerations, the DBAP may be formulated as follows:

Sets

B Number of ships where $b \in B$.
M Segments of docks.
T Time horizon where $t \in T$.
S Storage sections in the ship where $s \in S$
G Number of quay cranes where $j \in G$.
C Number of container blocks in the storage area where $c \in C$

Parameters:

h_b Quay crane time needed for ship *b* in minutes.
L_b Length of ship *b*.
A_{bs} Vector with a length equal to *s* for each ship *b*. It shows integer figures if ship section has containers for loading/unloading, and zero otherwise. The integer number corresponds to the section number.
m_b Maximum limit of available quay crane for ship *b*. Limit is equal to work sections in the ship *b.*
g_{jt} Position of the quay crane *j* in the time *t*.
CI_{bs} Containers to be imported in the section *s* of the ship *b*.
CE_{bs} Containers to be exported in the section *s* of the ship *b*.
d_{mc} Distance between the container block *c* and the dock segment *m*.
PE_{bc} Binary vector with a length equal to *c* for each ship *b*. It takes a value equal to 1 to show the block *c* where containers are being stored to be exported in ship *b*.
K_c Available space for containers in the block *c*.
W Quay crane containers output. This time corresponds to each handling operations.
N High constant number

Decision Variables:

X_b Dock segment assigned to ship *b*, the ship prow is located in this segment
Z_{bmt} Binary variable. It takes a value equal to 1 if ship *b* is located in segment *m* in the time *t,* and 0 otherwise.
Y_{bsjt} Binary variable. It takes a value equal to 1 if the section *s* of the ship *b* is operated with the quay crane *j* in the time *t,* and 0 otherwise.
PI_{bc} Binary variable. It takes a value equal to 1 if the containers of ship *b* are located in the block *c,* and 0 otherwise.
F_{bsjt} Auxiliary variable.
U_{bsj} Auxiliary variable.
V_{bsj} Auxiliary variable.

Minimise

$$\sum_{b=1}^{B}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{c=1}^{C}\left[(Z_{bmt} * CE_{bs} * d_{mc} * PE_{bc}) + (Z_{bmt} * CI_{bs} * d_{mc} * PI_{bc}) + Y_{bsjt} * \left(U_{bsjt} + V_{bsjt}\right)\right] \tag{1}$$

Subject to:

$$\sum_{b=1}^{B} Z_{bmt} \leq 1 \quad \forall m = 1 \ldots M, \forall t = 1 \ldots T \qquad (2)$$

$$\sum_{m=1}^{M} Z_{bmt} = L_b \quad \forall b = 1 \ldots B, \forall t = 1 \ldots T \qquad (3)$$

$$Z_{bmt} \leq Z_{b(m+1)t} \quad \forall m = 1 \ldots (X_b + L_b - 1), \forall t = 1 \ldots T, \forall b = 1, \ldots, B \qquad (4)$$

$$\sum_{b=1}^{B}\sum_{s=1}^{S}\sum_{j=1}^{G} \mathrm{Y}_{bsjt} \leq G \quad \forall t = 1 \ldots T \qquad (5)$$

$$X_b + L_b \leq M \quad \forall b = 1 \ldots B \qquad (6)$$

$$\mathrm{K_c} \geq \left(\sum_{\mathrm{S}=1}^{3} \mathrm{CI_{bS}}\right) * \mathrm{PI_{bc}} - \left(\sum_{\mathrm{S}=1}^{3} \mathrm{CE_{bS}}\right) * \mathrm{PE_{bc}} \quad \forall \mathrm{b} = 1 \ldots \mathrm{B}, \forall \mathrm{c} = 1 \ldots \mathrm{C} \qquad (7)$$

$$\sum_{j=1}^{G}\sum_{s=1}^{S} Y_{bsjt} \geq 1 \quad \forall b = 1 \ldots B, \forall t = 1 \ldots T \qquad (8)$$

$$\sum_{j=1}^{G}\sum_{s=1}^{S} Y_{bsjt} \leq m_{\mathrm{b}} \quad \forall b = 1 \ldots B, \forall t = 1 \ldots T \qquad (9)$$

$$\sum_{j=1}^{G}\sum_{t=0}^{T} Y_{bjt} * \mathrm{W} \geq h_b \quad \forall b = 1 \ldots B \qquad (10)$$

$$Y_{bs\,j\,t} - Y_{bs\,(j+1)\,t} \leq N\left(Y_{bs\,(j+1)\,t} - Y_{bs\,(j+2)t}\right) \quad \forall b = 1 \ldots B, \forall j = 1 \ldots G, \forall s = 1 \ldots S, \forall t = 1 \ldots T \qquad (11)$$

$$F_{bsjt} = g_{jt} - [X_b + (\mathrm{A_{bs}} - 1)] \quad \forall b = 1 \ldots B, \forall j = 1 \ldots G, \forall s = 1 \ldots S, \forall t = 1 \ldots T \qquad (12)$$

$$F_{bsjt} = \mathrm{U}_{bsjt} - V_{bsjt} \quad \forall b = 1 \ldots B, \forall j = 1 \ldots G, \forall s = 1 \ldots S, \forall t = 1 \ldots T \qquad (13)$$

$$F_{bsjt} = (\mathrm{free}) \qquad (14)$$

$$\mathrm{U}_{bsjt} \geq 0 \qquad (15)$$

$$V_{bsjt} \geq 0 \qquad (16)$$

$$Z_{bmt} = \{0,1\} \qquad (17)$$

$$\mathrm{PI_{bc}} = \{0,1\} \qquad (18)$$

$$X_b \geq 0 \; integer \qquad (19)$$

$$Y_{bsjt} = \{0,1\} \qquad (20)$$

The objective function (equation 1) minimises the distances travelled by the forklifts and the quay crane, for container loading and unloading operations. These distances are linked directly to the times travel owing to the handling operations carried out in each ship arriving at the CT. Therefore, the expression minimises three aspects: a) travelled distances carrying the export containers between the dock segments and the container blocks; b) travelled distances carrying the import containers between the container blocks and the dock segments; and c) travelled distances by quay cranes displacements in the work sections. It has to be taken into account that the third term of the objective function includes a non-linearity due to the fact of multiplying the binary variable Y_{jbst} by the absolute value related to crane displacement. Non-linearities are reduced exclusively to this term of the objective function.

Constraint number (2) ensures that each segment m can only be assigned to a ship b in the time t. Constraint (3) guarantees that the number of segments used by each ship is equal to its length during the operation time. Constraint (4) ensures that the segments assigned to each ship will be consecutive.

Constraint (5) ensures that the sum of assigned quay cranes depends on the maximum amount of available quay cranes in the port. Constraint (6) guarantees the amount of dock segments allocated to each ship, with respect to maximum limit. Constraint (7) guarantees that the available capacity in block c, that has been assigned for storing the containers of ship b, has to be greater than the number of containers to be stored in this block.

Constraints (8) and (9) ensure the minimum and maximum limits, with respect to the amount of allocated quay cranes for each ship. Constraint (10) guarantees that the quay cranes assigned to each ship complete their workload. Constraint (11) ensures that the quay cranes assigned to the each ship will be consecutive. Constraints (12) and (13) are constraints' simplification that don´t include the absolute value in the objective function. Finally equations (14–20) determine the specifications for the variables.

4 GENETIC ALGORITHM: THE OPTIMISATION MODEL SOLUTION

Non-linear mixed integer models, such the described section 3, are difficult to be solved. Soft computing based approaches have been commonly used to deal with them. That is the case of swarm intelligence or bio-inspired computation (Adeli et al. 1995a), (Chabuk et al., 2012), (Petitjean et al., 2011), (Tao et al., 2012). In this paper, we propose a genetic algorithm (GA) to solve the model described in the previous section. A genetic algorithm is a search heuristic that reproduces the process of natural evolution. This heuristic is used routinely to generate feasible solutions to optimisation and search problems. Many authors in different industry areas have used this approach, such as Marano et al. (2011) in statistical studies, Baraldi et al. (2012) for nuclear power plants, Jiang (2008) and Hsiao et al. (2012) in telecommunications industries, and Sgambi et al. (2012) in the design and control of big infrastructures. Also this metaheuristic has been succesfully used for structural optimization models (Sarma et al., 2001), (Adeli et al., 1995b) and its powerful is validated by many authors (Putha et al., 2012), (Hung and Kumar 1994), (Kim H. and Adeli H. 2001). They put in comparison different metaheuristics such as ant colony, fuzzy logic, tabu search, etc. with genetic algorithms. Also, the use of genetic algorithms together with other methodologies has very commonly proposed (Adeli et al., 1995c), (Adeli et al., 2006). Our solution approach based on genetic algorithms allows dealing with the non-linear term appearing in the objective function in an easier way by simply evaluating the feasible solutions to assess its fitness. Genetic algorithms belong to the larger class of evolutionary algorithm, which generates solutions to optimisation problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

The genetic algorithm is run every time that a container ship arrives in the CT; more exactly every time a container ship arrives at the VBA modules. Each obtained solution applies to the ship that has just arrived and to the rest of ships waiting in queue for free segments of dock, because re-allocations are still possible while ships are waiting to dock.

4.1 Solution encoding

Instead of using the traditional binary bit representation, chromosomes are represented by charter strings. Figure 2 shows a generic chromosome representation for berth allocation.

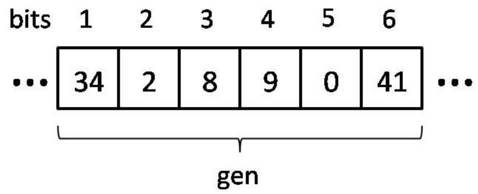

Figure 2 Chromosome representation

The chromosome used for berth programming is composed of 60 bits, which are grouped into 6 representing a gene (ship in the port). Bit 1 of each group represents the location of the dock where the ship's initial section is going to be located. Bit 2 shows the number of assigned cranes, which is complemented by bits 3, 4 and 5, which state which specific cranes are assigned. Finally, bit 6 determines the block number in the storage area where the unloaded containers are stored. So, an individual of the population of the genetic algorithm is a feasible solution to the problem, and such an individual is characterised by its chromosome.

4.2 Fitness

The fitness of every individual is calculated as the sum of the operation times each ship waiting in queue for free segments of the dock. The total time corresponds to: a) times as a result of the required transport for carrying the export containers between the container blocks and the dock segments; b) times as a result the required transport for carrying the import containers between the container blocks and the dock segments; and c) times as a result of required travel by quay crane displacements in the work sections (see equation 1 in the optimisation model).

The DBAP is a minimisation problem; thus, lower fitness values lead to lower objective function values. To deal with this fact, the fitness function is defined as the reciprocal of the objective function as suggested by (Kim and Kim 1996).

4.3 Selection of parents and genetic operators

The selection criteria to choose the parents in the population are based on the fitness of the individuals. Fitter individuals have a higher priority of being selected, with a discrete probability. This mechanism allows a faster convergence of the GA.

The implemented genetic operators were crossover and mutation operators. Tests were carried out with different probabilities for crossover and mutation operators. In the case of mutation, it was found that varying the probability from 50% to 100% had little effect on performance, with a value of 80% to 90% being marginally optimal for tests carried out. A value of 90% is used in the main replications. For crossover, values between 10% and 20% were seen to give better results than typically smaller values. A value of 10% is used in the main replications, in order to enrich the genetic variety of the population.

The genetic algorithm is used to solve the optimisation model immediately a ship arrives at the port. After iterating, the algorithm provides the better found solution; that is, the individual with a better fitness value within the population.

Next, the main characteristics of the genetic operators are detailed as follows:

4.3.1 Mutation

The reproduced chromosomes constitute a new population, and mutation is performed to introduce new chromosomes. The process is divided into two steps: step 1 takes a single individual from the population making a random selection. Then its information is stored in the array offspring; step 2 changes the information in bits 1, 2 and 6 (location of the dock, quay cranes and block respectively). Settings remain subject to various relevant constraints of the model that are conditioned by bits 1, 2 and 6. Figure 3 shows the mutation operation.

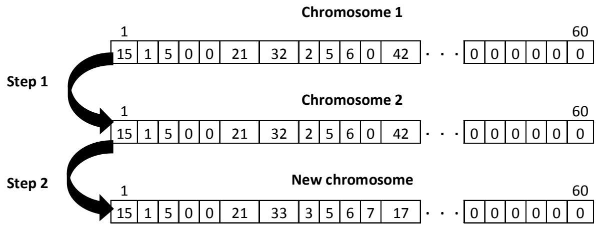

Figure 3 Mutation Operation

4.3.2 Crossover

The chromosome representation states 6 bits (a gene stating the ship in the port). So, the crossover operation can be undertaken only over those individuals with at least two genes different from zero. In other words, when there are at least two container ships in the waiting queue. Figure 4 shows an example of a crossover operator.

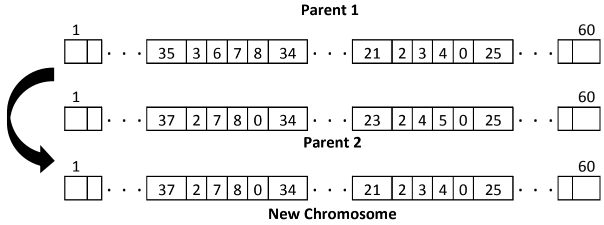

Figure 4 Mutation Operation

4.4 Genetic algorithm structure

The optimisation model is solved as many times as ships arrive at the port. The algorithm provides the better solution than one that has reached a better fitness value within the population.

5 THE SIMULATION MODEL

Some of the main operations carried out at a container terminal are: the container pre-marshalling problem; the landside transport; the stowage planning problem; the yard allocation problem etc. (Steenken et al., 2004) and (Stahlbock and Voß 2008) have done complete and important reviews on the problems arising in a container terminal. The use of simulation models turns into a suitable tool to evaluate and assess the different decisions that have to be taken for the previously exposed problems.

Figure 5 depicts the concept diagram for the starting, optimisation and simulation integrated modules.

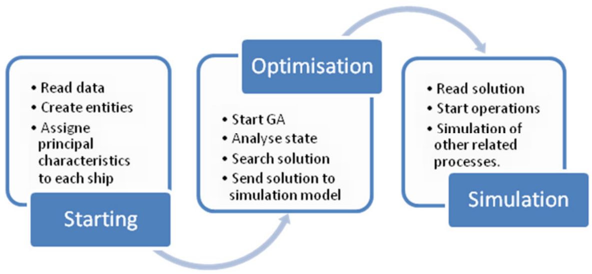

Figure 5 Models interaction

5.1 The data

The arrival times are obtained from a battery of data in an external file. These data were extracted from the Algeciras port real database in October 2010 (available at the Algeciras port website, www.apba.es/). To schedule the ship arrivals according to the real database, we introduce the set of modules, the most important of which is the ReadWrite, which reads or writes values in an external document type txt, dat, xls.

After reading the external file, an entity is created, representing a container ship, and includes attributes information such as: length of the ship; number of sections with containers; number of containers to be loaded and unloaded; location of these containers in the storage area etc.

5.2 The integration with the optimisation model

When a ship is created (arriving at the CT), it is sent to a VBA module, which contains a genetic algorithm (GA), designed in Visual Basic language, and provides a solution to the proposed optimisation model. This module is shown in figure 6. The genetic algorithm is run every time an entity enters into the VBA module. The algorithm provides results for the ship entering, and for the rest of ships waiting in the queue for available resources.

Once a ship leaves the VBA module the optimisation process has provided the best possible found solution, and this information is sent to the simulation model, which determines the quay crane scheduling, berth allocation and the container block, that is being carried by that ship, to be unloaded.

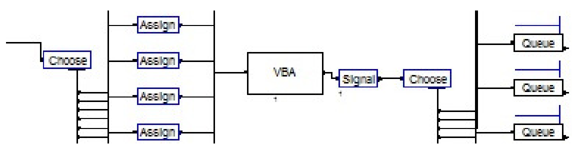

Figure 6 VBA Module

5.3 The virtual dock

Each ship has an attribute which states the assigned segments. We designed a virtual dock in the simulation model, which is used to take and represent the segments that each ship will need. So, this virtual dock moves along the dock line, representing the specific group of segments where the operations are being carried out. Thus, these modules simulate the process of unloading, loading and transport of all the containers. These modules are shown in figure 7. Figure 7 provides a global view of the virtual dock. Its global vision shows the main three constructive building blocks and explains their interrelation and interconnectivity amongst them. Three main constructive building blocks depict the operation of the whole virtual dock system. That is: 1) ship operations; 2) unloading and loading containers operations; and 3) counter for statics.

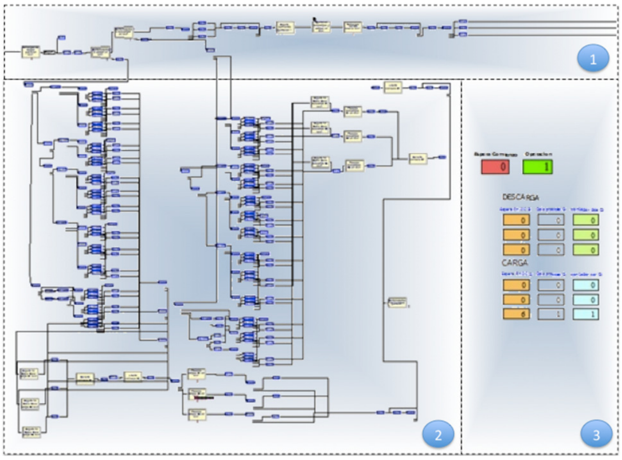

Figure 7 Virtual dock modules

Distances are considered by means of a matrix that stores the distances between all the points of the storage area and each location (segment) of the dock line. The ship will berth in the virtual dock until it has completed the handling operations. Then, the ship will be ready to leave the dock, entering the towing process output. In this way, the ship releases the dock segments, quay crane and virtual dock for other ships on leaving the simulation model.

The quay crane scheduling is simulated in the virtual dock, by assigning the quay cranes by means of the optimisation model. Later, the simulation model distributes the workload between these quay cranes. In accordance with these assumptions, a ship will have between 1 and 3 sections of work (with containers), and therefore 1, 2 or 3 quay cranes could be assigned to each ship. Figure 8 depicts three different examples of ships operations: the first ship has three sections of work and one assigned quay crane; the second ship has three sections of work and two assigned quay cranes; and the third ship has two sections of work and two assigned quay cranes.

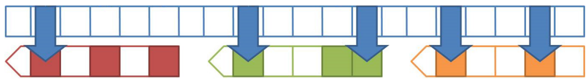

Figure 8 Ships in operations

6 RESULTS AND ANALYSIS

Computational experiments have been carried out in one of the most relevant Southern Europe ports, i.e. the Algeciras port and its container terminal. To do so, we have introduced two specifics constraints (equations 21 and 22), in addition to the general model equations presented in Section 2. These constraints are as follows.

$$Z_{b8t} + Z_{b9t} = 1 \quad \forall b = 1 \ldots B, \forall t = 1 \ldots T \qquad (21)$$

$$Z_{b70t} + Z_{b71t} = 1 \quad \forall b = 1 \ldots B, \forall t = 1 \ldots T \qquad (22)$$

These constraints complement constraints 3 and 4. The aim is to guarantee that the segments 8–9 and 70–71 cannot be allocated consecutively, because these segments are in corners, owing to the particular shape of the Algeciras port.

We produced three different scenarios to verify and validate the optimisation model proposal. The first scenario uses the historical input data recorded by the Algeciras terminal arrivals in October 2010 (which is available at the Algeciras port website, www.apba.es). The information includes the arrival times and lengths of ships. The remaining information, such as the number of sections of work and containers to load and unload, is calculated according to the real freight traffic.

For the second scenario, the parameters that determine the arrival times per ship are constant with respect to the initial scenario, but the number of containers carried by each ship increases. For the third scenario, the parameters that determine the number of containers and sections by ship are constant with respect to the initial scenario, but it increases the number of ship arrivals to the CT by 20, which represents an increase of 12.5%. The time of arrival of these vessels has been taken randomly, within a time frame set at one month, as well as ships' length.

We undertook thirty model replications for each considered scenario, resulting in a total of ninety replications. In this section we analyse the results obtained for the three scenarios.

Table 1 summarises the freight traffic for each scenario in a 30-day period, appreciating that the increase of containers moved in Scenario 2 with respect to 1 is almost 21%; a value that is near to the increase provided by scenario 3 (20%). In addition, scenario 3 increases the ship arrivals by 12.5%.

The objective of the optimisation model is to minimise the operation time for each ship. Table 2 shows the minimum, maximum and average times for the handling operations, as well as the waiting times (the sum of both terms represents the total service time).

Table 1 Ships and containers by scenario

Counters	Scenario 1	Scenario 2	Scenario 3
Unloaded containers	33,940	40,855	40,610
Loaded containers	34,049	41,309	40,917
Total containers	67,989	82,164	81,527
Average number of containers by ship	427	516	513
Ships with fewer than 300 containers	24	27	37
Ships with 300–500 containers	88	68	90
Ships with 500–700containers	16	18	15
Ships with more than 700 containers	32	47	38
Ship arrivals	160	160	180
Average containers handled by quay crane	3,399	4,108	4,076

Table 2 Service time in hours

Time	Data	Min	Max	Average
Waiting	Real	0	6.25	0.29
	Scenario 1	0	4.15	0.25
	Scenario 2	0	10.48	0.30
	Scenario 3	0	3.21	0.27
Operation	Real	5.16	17.23	7.64
	Scenario 1	4.96	15.96	6.85
	Scenario 2	5.04	19.03	7.42
	Scenario 3	5.24	19.07	6.31
Total	Real	5.16	18.05	7,96
	Scenario 1	4.96	16.16	7.10
	Scenario 2	5.04	21.4	7.72
	Scenario 3	5.24	20.71	6.58

We can observe the results obtained in the optimisation model in scenario 1, with respect to real data, reduced the average operations times by 10%, and the maximum operation times by 7%. The minimum operation time has similar values in every scenario, because the probability that a ship has few containers to unload/load is the same for all. So the model reduced the average waiting time by 13%, and the maximum waiting time by 33%. The main reasons for this is because of better assignment management, as the ships unload/load the containers in the berths closest to the container block where the containers are stored.

The results show that although container traffic was increased in scenarios 2 and 3 by 21%, the average operations time in scenario 3 was reduced by 8% with respect to scenario 2 with the same increment. This reduction was a result of the allocation of new container traffic from 20 new ships arriving at the CT.

Figures 9, 10 and 11 show the total hours of operation by dock segment. The sections with a higher number of hours worked are grouped into the centre of the docks. This is owing to the special layout of the Algeciras port that is shown in Figure 1.

In figures 9–11 we can see that certain sections present the highest workload because these sections are located very close to the paths between the container blocks in the storage area. These paths are used by all the vehicles, in order to transport the containers within the container terminal.

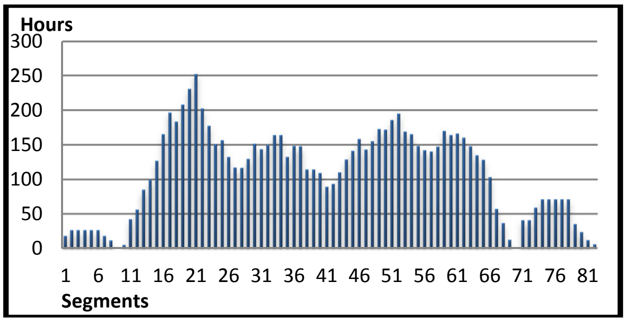

Figure 9 Workload by each segment in hours for scenario 1

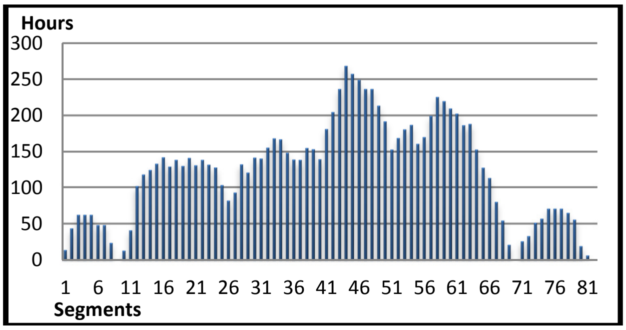

Figure 10 Workload by each segment in hours for scenario 2

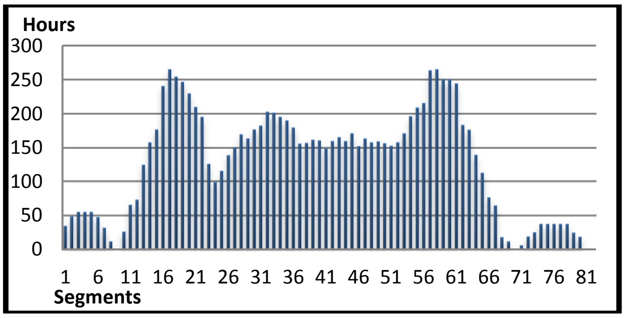

Figure 11 Workload by each segment in hours for scenario 3

To complement the service timetable, figure 12 shows the number of ships classified into 7 time ranges, according to the service time. The first range is for those with less than 6 hours, and the second range is for those within 6 to 7 hours. It can be appreciated that these two ranges represent more than 70% of arrivals to the container terminal.

Finally, attending to the computational time figures of the simulation and optimisation models, and taking into account that numerical experimentations were performed on a personal computer equipped with 3 GB of RAM and 2.1 GHz. Intel dual-core processor, we have to say that the results were feasible for a near-real time problem such as the DBAP. It has to be taken into account that the process of docking a ship implies a time scale of around half an hour from its first arrival into the port, so computational times in this magnitude order are adequate.

The average run-time in simulation models was 17 minutes and 57 seconds. The simulation includes ship arrivals between 160 and 180, corresponding to the number of times that the genetic algorithm (VBA module) was run. The average run-time for the algorithm was approximately 2.07 seconds, with a maximum of 4.12, and a minimum of 1.17 seconds.

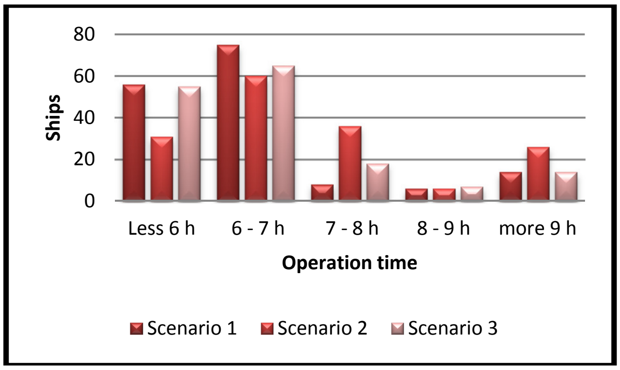

Figure 12 Ships according to the service time

7 CONCLUSIONS

Shipping lines are looking constantly for ways to reduce costs. One of its lines of action is to improve the capacity and speed of their ships in port. This fact leads the port to design dock lines with greater flexibility. At the same time, transport networks are being redesigned, considering two types of ports: hub ports and destination/source ports. In our paper, we considered a well-established hub port — Algeciras port — and analysed the container traffic for such a port. Three scenarios were considered. The first scenario took into account the container ship traffic in October 2010; the second scenario was constructed considering an increase in the container traffic; and, finally we considered an increase of ship arrivals for the third scenario.

By analysing such a hub port, our work focuses on efficient planning and use of the docks to increase the competitiveness and status of the port. An optimisation model supporting berth allocation has been constructed and presented, and allows the improvement of internal organisation and operations management.

The results allow us to affirm that our optimization model improves the performance of the port's container terminal. The reduction of operation times at berths has been valued at 10% respect to the real data. The other scenarios also show good results with respect to a future traffic increase, with a reduction in the maximum waiting time of 33%. These reductions in the operation time and waiting time are perceived directly by the shipping lines.

The results obtained in the paper allow us to affirm that the combined use of simulation and optimisation tools is a valuable asset, with great potential for the scheduling and assignment of resources in ports in general, and particularly for this study about container terminals. The proposed genetic algorithm is also shown as a suitable approach to deal with this type of problem, to find a good solution in less than 3 seconds. Now, our future work focuses on managing the handling equipment, such as forklifts and reach-stackers, as well as other equipment in ports. This equipment is used mainly by the quayside transport and the landside transport, and should be considered in order to minimise costs, handling operations time, bottlenecks etc.

Another interesting research line falls into the definition of stochastic models covering all the port performance. This approach will allow to identify stochastic variables associated to vessel arrivals, docks' occupancy, crane performance, etc., and the model solutions would allow to analyse very different vessel and container traffic situations. This can be viewed as a new promising research line for future works.

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