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GENETIC ALGORITHMS APPROACH FOR CONTAINERSHIPS FLEET MANAGEMENT DEPENDENT ON CARGO AND THEIR DEADLINES

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Abstract:

This work proposes a method to improve the flexibility of short sea shipping and to increase its competitiveness with other means of freight transport. A logistic model and a mathematical model are developed to manage a fleet of two or more vessels which transport cargo to and from several ports, bearing in mind the cargo distribution and delivery deadlines. At each port, the model determines which port to visit next, which containers to embark, disembark and to shift, as well as how to stow them on board. In fact, this formulation brings together the fleet management problem, the container stowage problem (CSP) and the vehicle routing problem (VRP). An example scenario is set up, using generated but realistic data. The problem is then solved, in a simplified version, using a Genetic Algorithm. The results show that introducing the possibility of route changes, the overall efficiency (and thus competitiveness) of short sea shipping can be improved.

Keywords: short sea shipping, fleet management, containers, logistic model, genetic algorithm

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1. INTRODUCTION

Vessels have always been used as means of transport between European ports and, to this day, short sea shipping is responsible for a significant part of all freight moved within the European Union borders.

The advantages of short sea shipping are well known and recognized by EU member states: it is environmentally sound; it contributes to road safety; it has low infrastructure costs (the sea itself is the "motorway"); and it can reach most of Europe's "peripheral" regions. Nonetheless, there are also some downsides, namely: the bureaucracy attached to customs; port services costs and efficiency; travel duration; inflexibility of routes; and dependency on environmental factors. In the last decades, containerization has revolutionized cargo shipping. According to Drewry Shipping Consultants, over 70% of the value of the world international seaborne trade today is being moved in containers. The world container fleet expanded at an average annual growth rate of 9% over the period 2002-2006 and the total fleet amounted to about 23.2 million TEUs (Twenty-foot Equivalent Units) in 2006. Today, a significant part of all freight moved within the European Union travels by sea. In fact EU statistics state that 3800 million tons were transported by ship in 2006 and it is hoped that in 2018, after the economical crisis has passed, the 5300 million tons mark will be reached.

This paper intends contribute to a better management of small fleets of containerships in order to reduce transport time and increase flexibility. The main goal of this work is to produce a logistic model for a fleet of containerships with no pre-defined routes, being these routes defined dynamically, depending on cargo arrival at ports and delivery deadlines.

To achieve this, three different challenges will be addressed. These are: (i) how to select navigation routes for the fleet; (ii) how to distribute the cargo by the available vessels; and (iii) how to stow cargo on the vessel. According to these challenges, the main issue is that two different kinds of optimization problems must be dealt with, in an integrated way: the Vehicle Routing Problem (VRP) and the Container Stowage Problem (CSP).

The paper starts (section 2) by presenting a review of the subject, including available approaches to solve the CSP and applications of VRP to supply chains.

In section 3, the conceptual model is presented informally, with the help of figures to represent its increasing complexity. The problem is explained evolving from the need to deliver freight to several ports taking into consideration deadlines to a problem where ports and containerships characteristics, costs and constraints are considered. Moreover, based on this description, a mathematical model is presented (section 4). In section 5, a genetic-inspired algorithm is proposed as a possible approach to obtain good solutions. Finally (section 6), a possible scenario is analyzed where several containers arrive at different ports with a pre-defined distribution and, depending on that, the containerships' routes and stacking plans are determined. In this process, port costs are taken into account, as well as the aim to reduce voyages with empty containers. For the sake of simplicity, in this simulation, optimization of loading/unloading operations to reduce overstows and to maintain the vessels' stability is not yet considered. Finally in section 7, some conclusions are drawn and the future work is discussed.

2. STATE OF THE ART

All the intra-European movement of freight by sea is considered by EU as short sea shipping, keeping in mind that for door-to-door transport other modes of transport are also necessary. In spite of all these reasons and the reasons mentioned in section 1, up to the beginning of this century and even now, the *CSP* has been given little attention in the literature. However, since the late 80's several works on this area were published. To the best of our knowledge Aslidis (1989) was the first author to solve the stack overstowage problem using a dynamic programming algorithm with the kernel of the arrangement policy which is widely adopted in later works. Avriel *et al.* (1993) presents a binary linear programming formulation to find the optimal solution for stowage in a single rectangular bay with only accessibility constraints. This method is limited because of the large number of binary variables and constraints needed to the formulation. As Avriel *et al* (1998) proved, the *CSP* is a NP-Complete problem and for this reason, Avriel *et al.* (2000) developed the *Suspensory Heuristic Procedure* which is a dynamic slot-assignment scheme that terminates with a stowage plan. This procedure was tested with very satisfactory results and computing time. Nonetheless, the method proved to be very inflexible as far as the implementation of constraints is concerned. Binary Linear Programming formulation for *CSP* with stability constraints, weight constraints, accessibility constraints, etc., can be found in Botter (1992), Ambrosino *et al.* (2004) and Ambrosino *et al.* (2006). Various searching methods such as Genetic Algorithms (*GA*) (Martins *et al.* 2009c), Branch and Bound (Wilson and Roach 2000), Simulated Annealing (Dubrovsky *et al.* 2002) have also been applied. The ability to use genetic algorithms to solve this kind of problem, the ability to incorporate any kind of constraints and its robustness was also proven in Nobre *et al.* (2007) when studying the use of containerships as means of force projection. Wilson and Roach (1999) present a two-phase method based on the normal procedure followed by the containership operators and interpreting it step by step. In the first stage containers are grouped by destination using a *Branch and bound search*, aiming to reduce *overstows* and hatch movements at the next port-of-desination (*POD)*, constrained by stability and segregation of cargo requirements. After that, *Tabu search* is applied to the generalised solution, trying to move the containers and assigning them to a specific slot, in order to reduce *re-handles*, bearing yet in mind the stability constraints. One drawback of this approach is that it allows the container stacking over bay hatches.

As far as ship routing and scheduling are concerned, Christiansen and Nygreen (1998) present an optimization-based solution approach for a real ship planning problem which the authors called inventory pickup and delivery problem with time windows (*IPDPTW*). The mathematical programming model of this problem was solved using a Dantzig –Wolfe decomposition approach. For this approach the IPDPTW was decomposed into a sub problem for each harbor and each ship. The LP-relaxation of the master problem is solved by column generation, where the columns represent ship routes or harbor visit sequences. In order to make the integer solution optimal, the iterative solution process is embedded in a branch-and-bound search to make the solution integer optimal. Later on, Agarwal and Ergun (2008) presented an integrated model with a mixed integer linear program to solve the ship scheduling and the cargo routing problems simultaneously. In this method a greedy heuristic, a column generation based algorithm and a two phase Benders decomposition based algorithm were developed and then proposed as an efficient interactive search algorithm that is able to generate good schedules for ships.

On the other hand, very little has been done in the area of integrating routing problems (*VRP*) with container stowage (*CSP*), despite the fact that those two problems are naturally related.

When we integrate the *VRP* with the *CSP* we have a similar problem to *VRLP* that is an integration of Vehicle Routing Problem with Time Windows (*VRPTW*) and Three-dimensional loading problems. Those two problems are widely handled in literature. For example Moura and Oliveira (2004) presented an original algorithm to solve the *VRPTW* and Moura and Oliveira (2005) presented several non-populational meta-heuristics applied to the loading problem and comparisons of the results. Nevertheless, the study of *VRLP* problems only started in 2006. Since then some work has been done. Gendrau *et al.* (2006) and Moura and Oliveira (2009) were the first to formulate the three-dimensional *VRLP*, to suggest solution methods and to introduce benchmark instances. Additionally, Moura (2008) presented a multi-objective GA applied to the *VRLP* with time windows.
Despite the previous mentioned works, the challenge of combining routing with container stowage considerations and applying them to real problems has not yet been tackled. Our work intends to do so.

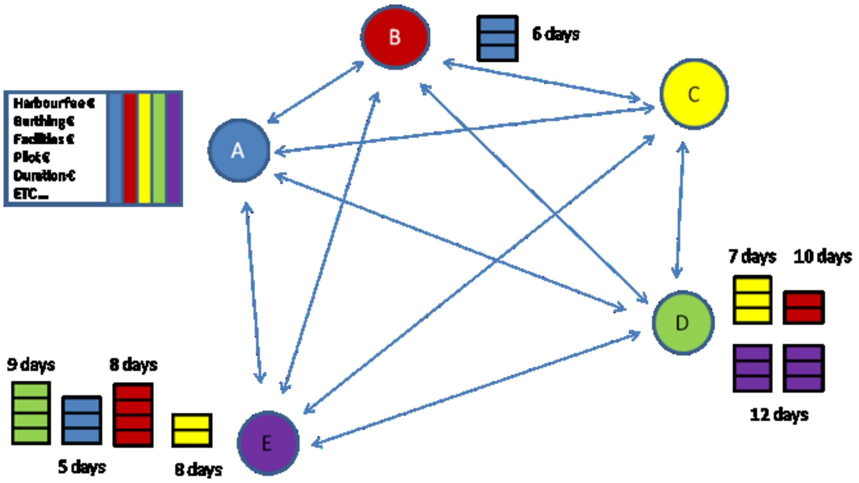
3. PROBLEM DEFINITION

A conceptual definition will be made to explain the problem. In this section a step-by-step evolution from a basic *VRP* into a more complex problem (*VRP* integrated with *CSP*) will be presented.

3.1. Scenario definition

Let us assume that there are several containers in different *ports* (five) to be delivered to other destinations within a given time limit.
Each port is at a different geographical location. The distances between them are known and are less than 1000 nautical miles. For each port the *tariffs* and the number of containers (20 foot - TEU) to be transported are also known. The data that characterizes each container is: (i) *weight*, (ii) *port of origin*; (iii) *port of destination* and (iv) *deadline to be delivered*.
Figure 1 represents one possible scenario, where the circles represent the ports, the rectangles represent a number of containers, the rectangles' colour identifies the destination port and the delivery deadlines are placed bellow each container column.

Figure 1 – Scenario representation



Some other complexities could be added to the scenario, such as the hypothesis that a port may be closed due to environmental conditions or that not all ports have cranes, etc.. However, for simplicity's sake, for the moment, none of them are going to be considered.

3.2. Route selection and cargo distribution

As in the vehicle routing and loading problem with time windows (*VRLP*) of Moura and Oliveira (2009), in this problem (*CSP*) the cargo at each port must be delivered considering a time limit and the vehicles that are going to be used to deliver the cargo are containerships (two). Each one of the containerships has the following different characteristics: (i) *dimensions*, (ii) *stability characteristics*, (iii) *deadweight*, (iv) *speed* and (v) *specific fuel consumption*.

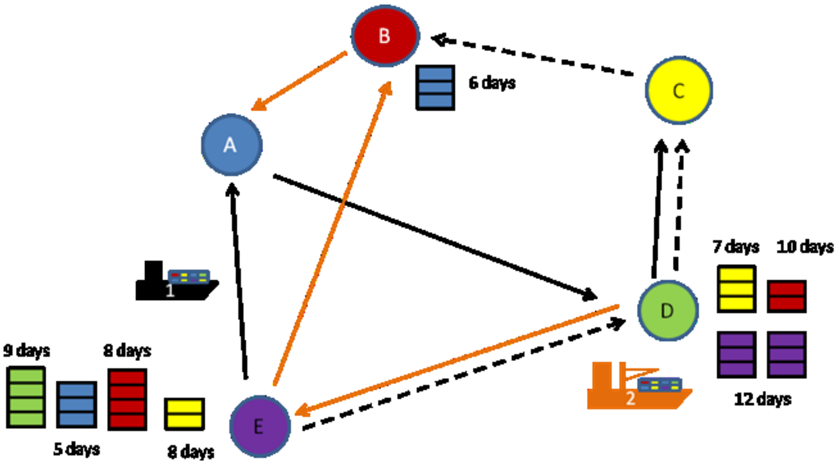
Based upon this information two major decision must be made:

(a) what containers should be carried by each ship;
(b) which ports should be visited by each ship and the visit sequence.

The solutions will have associated costs and depending on the solution the relaxation of the deadline constraint will be allowed. With these assumptions, we face an optimization problem for the route selection and cargo distribution.

Figure 2 shows two different solutions to distribute all the containers taking into account that vessels *1* and *2* depart from port *E* and port *D* respectively. While in both solutions vessel *2* routes are the same, the routes for vessel *1* and cargo distribution are not. Looking carefully, in one of the solutions (lines in full) vessel *1* departs from *E* to *A* fulfilling the deadline of the containers in blue while if this cargo had to wait for vessel *2* the deadline most probably wouldn't be accomplished.

Figure 2 – Route selection



When the route is decided, *operation costs* according the distances between ports and fuel consumption of each ship are computed.

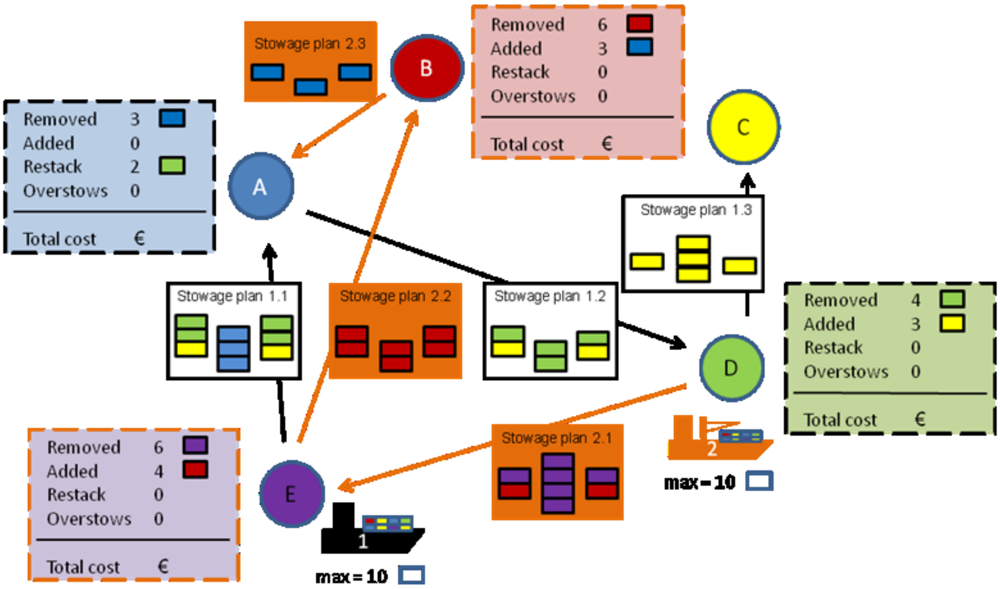
3.3. Container stowage

Another main subject of this problem is the way how containers are stowed on vessels. It is well known that the ship's stowage plan influences port handling and the vessel's stability.
In fact, the cost and time consumed in each port depends on the stowage plan. At each port several containers are moved and the stowage plan is normally rearranged, since there are:

- containers that are unloaded because they reached their destination;
- containers that have to be moved because they block the access to others that have to be unloaded (overstows);
- containers that are stacked on the top of the cargo hatches and that have to be moved to allow the access to the cargo bay (a particular case of the previous ones);
- containers that are re-positioned to improve the overall stowage and make the next port handling easier, which are known as re-handles;
- new containers that are brought on board to send to another port.

Figure 3 presents the stowage plans between ports for each vessel (stowage plans are identified by vessel number and run). At each port of call the large squares specify the container handling operations and their associated costs, though they are not represented at ports *A* and *C* where vessels *1* and *2* finish their journey.

Figure 3 – Cargo handling and stowage plans



After the containers stowage and handling characteristics are presented, the problem is completely defined. It is now possible to produce a unified cost function that includes all different types of tariffs and costs, namely: (i) *operation costs including fuel consumption*, (ii) *crew costs*, (iii) *ports tariffs*, and (iv) *handling costs at each port*.
Other costs, such as insurance costs, are also relevant for the owner but, for now, are not included since it is thought that they have no relevance for the intended optimization process.

4. MATHEMATICAL FORMULATION

As far as we know the VRP integrated with CSP has been dealt very little in literature (see section 2). In particular, with the several constraints considered in this work, a mathematical formulation of this problem does not exist. This particular integration of *VRP* and *CSP* models can be mathematically formulated as shown below. This formulation is a simplified version since several constraints are not considered (e.g. stability constraints). The mathematical formulation of this model, could be defined as:

Input variables:

$G(P,A)$ - A directed graph;

$P=\{1,...,p\}$ - G's set of nodes. The nodes 1 to p represent the ports that could be visited;

$A=\{(i,j):i,j\in P,i\neq j\}$ - G's set of arcs joint node i to j that represents a journey performed by a vessel;

$V=\{1,...,k_{\max}\}$ - Set of vessels (*k*) that may be used;

$C=\{1,...,\alpha_{\max}\}$ - Set of containers *c* were $\alpha_{\max}$ is the total number of containers to delivery;

Ω_k - Matrix (z_x,z_y,z_z) of slots placed in vessel k. A slot is equal to 1 if it is possible to load a container and 0 if not;

$\Phi=\{1,...,\phi_{\max}\}$ - Set of journeys (ϕ) for any vessel that represents the number of arcs (i,j) traveled by a vessel in a route.

Further, assuming that: $\forall i,j\in P:i\neq j$, $\forall k\in V$, $\forall\phi\in\Phi$, $\forall\alpha\in C$ and $\forall(z_x,z_y,z_z)\in\Omega_k$.

d_{ij} - Length of arc (i,j) corresponding to the distance between port i and j in miles;

$L_k,B_k,T_k,D_k,\Delta_k,GT,Q_k,s\_fuel_k$ - Vessel's k characteristics: Length, Beam, Draught, Depth, Displacement, Gross Tonnage, Maximum pay load weight, Specific fuel consumption;

vel_k - Vessel's k travel velocity (assumed constant throughout all the travel distance);

q_α - Total weight of container *α*;

a_α - Deadline delivery time of container *α*;

$o_\alpha;e_\alpha$ - Origin and destination port of container *α,* respectively;

$l_\alpha,w_\alpha,h_\alpha$ - TEU dimensions of container α (length with and height);

f_i - Port i fixed tariffs in Euros;

$r_{ik\alpha\phi}$ - Cost of a movement (load or unload) of a container α placed in vessel k in port i and journey ϕ;

$b_{ik\alpha\phi}$ - Time of a movement (load or unload) of a container α placed in vessel k in port i and journey ϕ;

Auxiliary variables:

$u_{ik\phi} = u_{crew} + u_{port}$ - Visiting cost in Euros by time unit (hours) of port i in journey ϕ by vessel k that depends of, the cost of the crew and the taxes cost of each port;

$c_k = c_{fuelk} + c_{crewk}$ - Cost travel operation (per unit distance, in Euros) of vessel k that depends of, the cost of the fuel and the cost of the crew;

$\mu_{ik\alpha\phi} = 2 * r_{ik\alpha\phi}$ - Total cost to shift a container placed in vessel k in port i and journey ϕ, that depends of the cost of a movement $r_{ik\phi}$;

$\tau_{ik\alpha\phi} = 2 * b_{ik\alpha\phi}$ - Total time to shift a container placed in vessel k in port i and journey ϕ, that depends of the time needed to perform a movement $b_{ik\phi}$;

$Corig_{ik\phi} = \# \left\{ \alpha : o_\alpha = i \wedge \sum_{(i,z_x,z_y,z_z)}^{\Omega_k} \gamma_{ik\phi\alpha(z_x,z_y,z_z)} = 1 \right\}$ - number of containers α to loaded in vessel k at port i in journey ϕ;

$Cdest_{jk\phi} = \# \left\{ \alpha : e_\alpha = j \wedge \sum_{(i,j,z_x,z_y,z_z)}^{\Omega_k} \gamma_{ik\phi\alpha(z_x,z_y,z_z)} x_{ijk\phi} = 1 \right\}$ - number of containers α to unloaded in vessel k at port j in journey ϕ;

$\beta_{ik\phi}$ - Number of shifts performed by vessel k in port i at journey ϕ;

$move_{ik\phi} = Corig_{ik\phi} + Cdest_{ik\phi}$ - Number of movements performed by vessel k in port i at journey ϕ;

$s_{ik\phi}$ - Time at which vessel k arrives port i in journey ϕ;

$t_{ik\phi} = \tau_{ik\alpha\phi} * \beta_{ik\phi} + b_{ik\alpha\phi} * move_{ik\phi}$ - Service time of vessel k in port i at journey ϕ;

Decisions variables:

$x_{ijk\phi}$ - Equals 1 if vessel k visits port j immediately after port i in journey ϕ and 0 otherwise;

$\gamma_{ik\phi\alpha(z_x,z_y,z_z)}$ - Equals 1 if, after vessel k leaves port i the slot (z_x, z_y, z_z) is occupied by the container α and 0 otherwise;

The objective function (1) is the minimization of: total route cost, total shifts cost and total movement cost. A weight is assigned to each one of these objective function's components: W_1, W_2, W_3. The concrete values of these weights will depend on the practical application under consideration and on the importance given by the decision-maker to each component. In most cases, since total cost is usually the objective, these constants will simply be 1.

$$\begin{aligned}\min\ & W_1\sum_{i=1}^{p}\ \sum_{j=1\wedge j\neq i}^{p}\ \sum_{k=1}^{v}\sum_{\phi=1}^{\phi_{\max}}(d_{ij}c_k x_{ijk\phi}+x_{ijk\phi}f_i) \qquad + \\ & W_2\sum_{i=1}^{p}\sum_{k=1}^{v}\sum_{\phi=1}^{\phi_{\max}}\beta_{ik\phi}\mu_{ik\phi} \qquad + \\ & W_3\sum_{i=1}^{p}\ \sum_{j=1\wedge j\neq i}^{p}\ \sum_{k=1}^{v}\sum_{\phi=1}^{\phi_{\max}}\sum_{\alpha=1}^{c}(Corig_{ik\phi}r_{jk\alpha\phi}+Cdest_{jk\phi}r_{ik\alpha\phi})\end{aligned} \tag{1}$$

This problem is subject to several constraints. The first one (equation 2) is the flow conservation constraint and, therefore, if a vessel arrives at a node then it has to leave from that node to another one.

$$\sum_{i=1}^{p-1}x_{ilk\phi}-\sum_{j=2}^{p}x_{ljk\phi}=0,\quad i\neq j\neq l\,,\ \forall k\in V\,,\ \forall\phi\in\Phi \tag{2}$$

Equation 3 guarantees that the port's service does not begin before the vessel arrives into the port. M$_1$ is a Big-M constant. The service time depends on the time and distance travelled by the vessel and the summation of the service time in each previously visited port by the same vessel (if the actual port is not the first port visited).

$$s_{ik\phi}+t_{ik\phi}+d_{ij}\times vel_k-s_{jk\phi}\le M_1\left(1-x_{ijk\phi}\right),\ \forall i,j\in P\wedge i\neq j\,,\ \forall k\in V\,,\ \forall\phi\in\Phi \tag{3}$$

The following constraints (equations 4, 5 and 6) are related to the containers. The first one guarantees that the containers deadline is not violated and the second one the weight capacity of the vessels is not exceeded. In equation 6, it is guaranteed that each container is transported by one and just one vessel between ports.

$$s_{ik\phi}\gamma_{(i-1)k\phi\alpha(z_x,z_y,z_z)}\le a_\alpha\,,\quad \forall i\in P,\ \forall k\in V\,,\ \forall\phi\in\Phi\,,\forall\alpha\in C\,,\forall(z_x,z_y,z_z)\in\Omega_k \tag{4}$$

$$\sum_{z_x,z_y,z_z}\ \sum_{\alpha=1}^{\alpha\max}q_\alpha\gamma_{ik\phi\alpha(z_x,z_y,z_z)}\le Q_k\,,\quad \forall k\in V\,,\ \forall\phi<\Phi\,,\forall i\in P \tag{5}$$

$$\sum_{z_x,z_y,z_z}\ \sum_{k=1}^{k\max}\gamma_{ik\phi\alpha(z_x,z_y,z_z)}=1,\quad \exists^1 i\in P,\ \exists^1\phi\in\Phi,\ \forall\alpha\in C \tag{6}$$

Constraint of equation 7 binds the container loading variables to the vehicle routing problem variables, *i.e.* if a container is placed inside a vessel then that vessel has to visit the port to which the contained is destined to go.

$$\sum_{z_x,z_y,z_z}\ \sum_{i=1}^{p}\gamma_{ik\phi\alpha(z_x,z_y,z_z)}x_{ijk\phi}\ge 1,\quad j=e_\alpha\,,\forall k\in V\,,\forall\phi\in\Phi\,,\ \forall\alpha\in C \tag{7}$$

For physical reasons, the next constraint guarantees that if a slot is occupied with a container then all the slots below are also occupied.

$$\gamma_{ik\phi\alpha(z_x,z_y,z_z)}-\gamma_{ik\phi\alpha(z_x,z_y,z_z+1)}\ge 0\,,\forall i\in P,\ \forall\phi\in\Phi\,,\ \forall\alpha\in C\,,\forall(z_x,z_y,z_z)\in\Omega_k \tag{8}$$

The mathematical formulation represents this particular routing and container stowage problem that is a NP-Hard problem. The size of the above formulation shows that its use in real life problems will be prohibitive due to the time needed to get an admissible solution. Therefore, in order to solve this problem in reasonable computing time, some algorithms and heuristics must be developed and applied. Those algorithms are presented in the next sections together with simulation results.

5. A PRELIMINARY GENETIC ALGORITHM APPROACH

A Genetic Algorithm (*GA*) is a programming technique that imitates biological evolution as a problem-solving strategy (Fogel 1999). Given a specific problem to solve, the input to the GA is a set of potential solutions encoded in some fashion (chromosomes). Then, a fitness function is defined in order to allow each candidate to be quantitatively evaluated. The algorithm then applies genetic operators such as mutation and crossover to "evolve" the solutions in order to find the best one(s). The promising candidates are kept and allowed to reproduce. These offspring then go on to the next generation, forming a new pool of candidate solutions, and are subjected to a second round of fitness evaluation. Those candidate solutions which do not improve are not considered for the final solution.

In this section, some details of the containerships fleet management problem (solved as an integration of *VRP* and *CSP*) solutions representation, fitness evaluation, selection strategy and other *GA* features used are described.

5.1. Implementation stategy

As presented in the formulation (section 4), in order to solve the purposed problem, three different decisions have to be made:

(a) the port sequence; } 1st stage
(b) what containers to carry; }
(c) how to stow the cargo onboard (common CSP problem). } 2nd stage

Following the same approach as in Martins and Lobo (2009b) for solving the pipe routing problem, in the first stage of the problem, *GA*'s are used together with an heuristic method that is incorporated in the fitness function.

In the second stage the *CSP* can be solved using any of the previously mentioned methods, either *GA* or any metaheuristic model (this step has not been implemented).

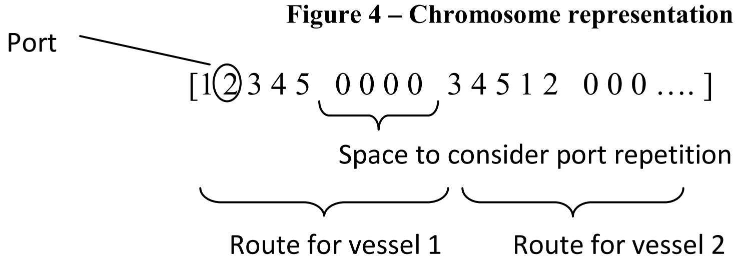
5.2 Chromosome coding, initial population and operators

The implementation starts by considering an *initial population* of routes that were brought together analysing what would be a normal containership route.

First it was considered that all ships should visit all ports and that no port would be visited more than once. These solutions were then complemented by other routes were the vessels visited all ports, and after doing so once, would continue in a circular manner.

Each potential solution was encoded into a chromosome, which comprises all the necessary information to apply the *GA*. The structure of each chromosome (set of genes) is a string of numbers that is going to be built containing the routes for all ships, using the procedure represented in figure 4.

Figure 4 – Chromosome representation



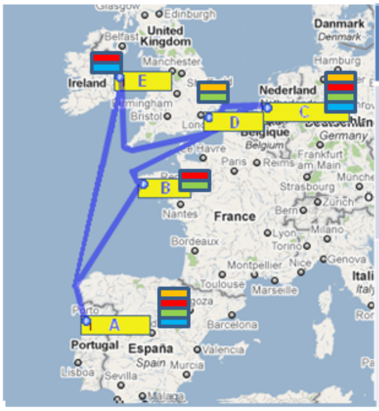
In order to select the potential solution to be encoded, the chromosome fitness function is evaluated. The fitness function and the selection phase are described in the next section.

For crossover and mutation operators, the standard methods available in MATLAB ™ where used in the first formulations and in the second one we used a method based on a Poisson distribution developed in the University of Aveiro. Since these use real numbers (instead of integers), and do not guarantee a feasible solution a preprocessing step was used to generate only integer genes.

6. VALIDATION AND RESULTS

To validate the model previously developed, an example problem has been put together. In this example, available data from real ships and ports has been used. Some simplifications have been made, such as: (i) all tariffs are the same, independent on the port; (ii) the fuel consumption and speed is always the same and independent of the cargo.
Let us considered that *AXE* and *HEAVY* are the two different kinds of vessels considered ($V = \{AXE, HEAVY\}$). Figure 5, represents the scenario of five ports $P = \{A, B, C, D, E\}$ with known distances (d_{ijk}) and with known set of containers ($C = \{1,...,3500\}$) to be delivered (one rectangle stands for 50 or 100 TEU). Further, the containerships' characteristics are also presented and it is known that at instant zero the origin ports of *AXE* and *HEAVY* are *A* and *C*, respectively.

Figure 5 – Scenario for the validation example
(each rectangle = x 50 or x 100 containers)



Ships	Length (m)	Beam (m)	Draught (m)	Speed (knots)	N.º TEU	Gross tonnage (GT)	Fuel (t/h)
AXE	95	15.6	6.15	12.5	348	3814	0.378
HEAVY	132.2	20	7.7	16.5	641	8445	0.945

At each port, the existing containers have the following distribution as far as the different container properties are considered:

i. Containers weight (q_{α}): 80% of the containers have a weight of 10t, 10% a weight of 8 t and the last 10% a weight of 12 t;

ii. Containers delivering deadlines (a_α): 80% with a deadline of 15 days, 10% with a deadline of 8 days and the last 10% a deadline of 20 days;

iii. Containers destination: for each port 50% of the containers must be delivered to the port furthest away ($Cdest_j$), 30% of the containers to next furthest ($Cdest_l$), and 10% each to the other two ports ($Cdest_f$ and $Cdest_g$).

As far as handling and stowage is concerned, the example does not consider any shift nor stowage constraints. Thus, only what was previously mentioned as *stage 1* of the problem was addressed in the simulation. In this scenario, at each port, the medium handling time of one movement ($b_{ik\alpha}$), is considered to be 3 minutes (0.05 hours).

The costs considered in the example are showed in table 1, where, as mentioned before, some costs, such as insurance costs and others, were neglected.

Table 1 – Costs used in the example

Port tarifs (ship related costs)	Containers related costs	Voyage costs
• pilot charges; • berthing; • space; • tugs and towing;	• port tariff p/ TEU; • container embarkation; • container disembarkation; • container shift;	• fuel; • crew related;

6.1. Results comparison

The scenario was used considering two different initial freight distributions at the ports. For both of them, the genetic algorithm implementation was used to determine a good route that would allow delivering every container within the deadlines. A third case considered has as main goal the delivery of all containers in the lowest cost.

In tables 2 and 3, the routes found using *GA*'s are compared with two other predefined routes. The first simulates a passage of the containerships by every port without repeating any of them. In the second, the vessel visits every port twice except for the last one.

Table 2 – First cargo distribution comparison table

Containers distribution:		A – 200 B – 100 C – 200 D – 100 E – 100				
	Ship	Route	Travelled miles	Time interval	Deadlines surpassed	Total cost
Pre - defined	Axe	A – B – C – D – E	100 containers not delivered			
	Heavy	C – D – E – A – B				
	Axe	A – B – C – D – E – A – B – C – D	3372	300 h	9	469500
	Heavy	C – D – E – A – B – C – D – E – A	3164	232 h		
GA	Axe	A – B – E – D – B – A – B – E – D	3083	271 h	32	446060
	Heavy	C – D – B – A – E – B – D – C	2693	209 h		

In this first case, the GA-based method shows an improvement of 10% over the predefined solution. This is not very impressive, but due to the small number of containers being considered the problem is simple and thus the predefined solution achieves a satisfactory result and a much better one would probably not be possible.

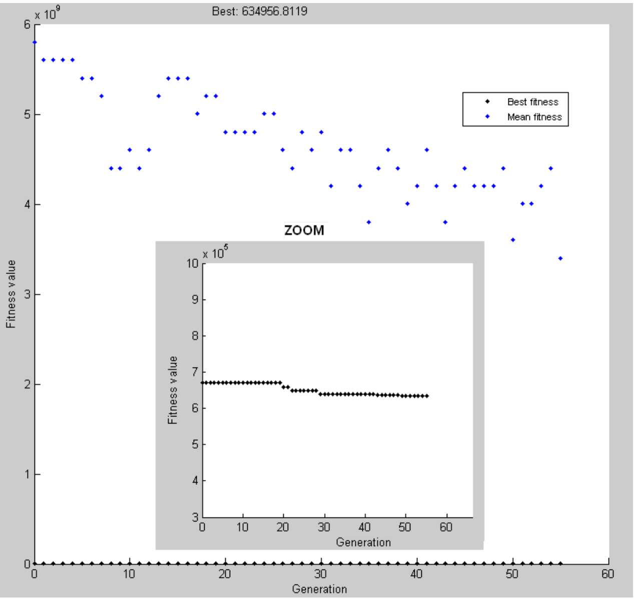
On the other hand, in the second example (Table 3), only the GA implementation is able to deliver all containers, though 5% of them are not delivered on time.

Table 3 – Second cargo distribution GA results

Containers distribution:			A – 400 D – 200	B – 200 E – 200	C – 400	
	Ship	Route	Travelled miles	Time interval	Deadlines surpassed	Total cost
Pre - defined	Axe	A – B – C – D – E	No solution was found			
	Heavy	C – D – E – A – B				
	Axe	A – B – C – D – E – A – B – C – D	100 containers not delivered			
	Heavy	C – D – E – A – B – C – D – E – A				
GA	Axe	A – B – D – E – B – A – B – D – E	3134	315.5 h	68	634960
	Heavy	C – B – A – B – E – B – D – C	2653	236 h		

These results (trajectories for the vessels), as is known, are probably not the optimal solution. However, it is a good one, as may be seen from the analysis of the graph in figure 6, where the evolution of the cost function is presented.

Figure 6 – Genetic algorithm fitness value evolution for second cargo distribution



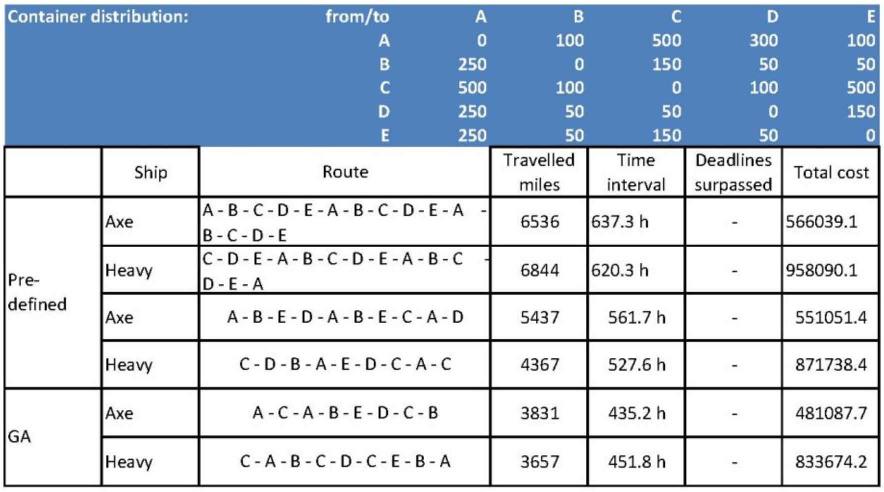
6.2. Scenario change

In order to test the *GA*'s flexibility and different implementations, another scenario was used to workout results. In this case, the same ports were used, but the containers distribution was different (table 4). As far as restrictions are concerned, there were no pre-determined limit number of port visits, neither have deadlines been considered. However, all containers should be delivered at the lowest cost and time. Further, the pre-defined routes were chosen considering that all containers could be delivered in 15 containership journeys.

Table 4 compares the results found for some pre-defined routes and the routes found by the GA's implementation. Using the *GA*'s solution, all containers can be delivered within 9 port visits, with a medium cost lower than 400 unit/ TEU.

Figure 7 shows the evolution of the objective function (fitness) during the GA optimization process and their 3500 generations. It can be seen that the GA evolution is not constant, showing a stagnation of the process after the 600th generation and during more than 1000 generations.

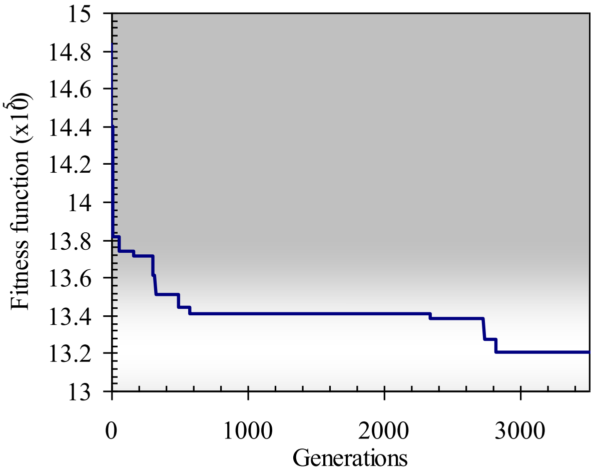
Table 4 – Third cargo distribution GA results



Container distribution:	from/to	A	B	C	D	E
	A	0	100	500	300	100
	B	250	0	150	50	50
	C	500	100	0	100	500
	D	250	50	50	0	150
	E	250	50	150	50	0

	Ship	Route	Travelled miles	Time interval	Deadlines surpassed	Total cost
Pre-defined	Axe	A - B - C - D - E - A - B - C - D - E - A - B - C - D - E	6536	637.3 h	-	566039.1
	Heavy	C - D - E - A - B - C - D - E - A - B - C - D - E - A	6844	620.3 h	-	958090.1
	Axe	A - B - E - D - A - B - E - C - A - D	5437	561.7 h	-	551051.4
	Heavy	C - D - B - A - E - D - C - A - C	4367	527.6 h	-	871738.4
GA	Axe	A - C - A - B - E - D - C - B	3831	435.2 h	-	481087.7
	Heavy	C - A - B - C - D - C - E - B - A	3657	451.8 h	-	833674.2

Figure 7 – Genetic algorithm fitness value evolution for third cargo distribution



7. CONCLUSIONS

This paper starts by defining short sea shipping and naming several of its advantages and disadvantages. Some considerations are made on the reduction of some of these disadvantages and on the increase of competitiveness of short sea shipping with other means of freight transport.

First, a review of past work related to cargo transport optimization is done, identifying two main classical problems that are related to the subject: (i) vehicle route planning (*VRP*) and (ii) containers stowage plan (*CSP*). While the first deals with the route selection and cargo distribution problem for each ship, the second is related with how the cargo is distributed on board.

Based upon this approach, a conceptual model is built up for several containers placed in different ports to be delivered by a small fleet of containerships within time constraints for each container. At this stage, using simple examples, it was concluded that, apart from the known dependency from CSP, the process efficiency and the ability to fulfill all cargo deadlines also depends upon the routes and cargo distribution selected for each vessel.

In order to apply this conceptual model to real life applications, a rigorous mathematical model is formulated, whose complexity is evident by the number of variables considered. The optimization process consists upon minimizing the total operation cost, dependent upon two input matrices that are related to the containerships' characteristics and each container's characteristics, such as the port of origin and destination, whose vessel is going to carry it, where it is going to be stacked, etc. The decision variables concern the route taken by each ship, the distribution and, when necessary, stowage of each container in each journey of the routes. Within the solution finding process, many constraints have to be considered, though in the presented work several of them have been neglected for the sake of simplicity.

Since using direct calculations to solve the optimization is clearly an extremely difficult task, a genetic algorithm was implemented to solve the routing and cargo distribution problem, leaving the implementation for the containers stowage for a later stage. At each iteration (generation) the concurrent solutions were evaluated against the constraints and then the best ones were selected.

Finally, the procedure is put to proof in a real scenario in which two vessels had to visit five different ports and change cargo between them. In this example it is proven that the method brings advantages when compared with circular routes (which are nowadays the norm), as far as fulfilling cargo deadlines, in delivering all cargo and reducing operation cost.

In this paper, an uncommon approach to improve short sea shipping has been proposed, showing promising results for the initial implementation case studies. Nevertheless, a large amount of work, as far as analysis of different scenarios and validation are concerned, has yet to be done. However, it can be stated that once these improvements have been implemented, this approach could be considered in containerships fleet management processes, with great benefits.

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