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A Metaheuristic for the Containership Feeder Routing Problem with Port Choice Process

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ABSTRACT

In this paper, we focus on understanding the joint problem of container ship route generation and consolidation center selection, two important sub-problems influencing the effectiveness of the liners shipping industry, which addresses the ship-routing problem. Two different metaheuristics procedures are presented that both consist of two stages: a solution construction phase (either nearest neighborhood with greedy randomize and Clark and Wright with greedy randomize selection) and a solution improvement phase, based on local search. Both metaheuristics are compared in terms of quality of solution, robustness analysis and computing time under variety of instances, ranging from small to large. A thorough comparison evaluation uncovers that both metaheuristics are close-to-each other. An argument in favor of the nearest neighborhood with greedy randomize approach is that it produces better performance than Clark and Wright configuration. Additionally, through sensitivity analysis, we investigate and test two hypotheses in this paper.

1. Introduction

International liner shipping facilitates transferring goods at low cost and with greater energy efficiency than any other form of international transportation. Due to their ability to transport a large amount of cargo and containerization of cargo, the liner container ship is the most efficient transportation mode in the world. Thus, they play a very important role in the transportation and logistics industry. Here below are some of factors that indicate the efficiency of Liner shipping:

The capacity of container ships has noticeably increased during the previous years, which has increased profit making, based on the economy of scales principle (Pearson 1988).

Increasing the number of services to keep liner shipping in a better position compared to competitors in the market is a commercially strategic decision that major liner firms need to make (e.g. Daily Maersk 2012).

Additionally, the ability of a Liner to visit as many ports as possible by itself or by providing a feeder network.

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Among the points mentioned above, one of the most important elements that has influenced the effectiveness of the shipping industry is the design of an efficient distribution system over a certain period of time. As economy-of-scale is reducing transportation costs per box, the demand for ever bigger vessels is continuing. The high demand volumes of main and hub ports and long distances between regions allow trunk lines to benefit from the effectiveness of mega container-ships. The demand volume and operating scale of short sea shipping make it necessary to operate with small sized ships in feeder service. In order to optimize operation costs, subsidiary feeder lines generally operate less frequent service to feeder ports. (Chang et al. 2008).

Also, a shipping line has to service its customers with fixed sailing schedules in order to make containers available to ensure loading of the containers into the ships. In liner shipping, it could be expected that a ship will serve various ports on its route. As in public transport bus service, liner shipping service has to follow regular service frequencies in order to meet periodic demands of customers. Further analyses on determinants of container liner shipping are recently provided by Ducruet and Notteboom (2010). Also, trunk lines have usually less affected from seasonal demand fluctuations. On the other hand, the demand patterns of regional ports are rather unstable and seasonal. Hence, feeder lines limited scales; they have rather affected from seasonal demand fluctuations. On the other hand, feeder lines are more flexible to adapt their self to changes on market environment. (Notteboom 2006)

Our study focusses on but among coping with higher acceleration and gravitational forces, ultra-large vessels would also be constrained by port and seaways limitations, such as crane outreach and drafts. Therefore, major ports are usually selected as hub ports based on their location and the demands of freight shipping, while the other ports serve as feeders. Large mother ships are used on main lines to provide services among hub ports, while small feeder ships are used on feeder lines to provide the services between a hub port and its feeder ports. (Shen et al., 2007) In a certain period (preferably on a daily basis), containers are delivered from feeder centres to major consolidation centres. Container ships will pick them up in its periodic visit to consolidation centres. A set of suppliers whose cargoes need to be picked up and transported by container ships apply feeders to reach the consolidation centers. The term “Consolidation centers” here is defined as major ports among several minor ports, which are directly served by liner container ships as a loading center. Appropriately, we will apply the term “feeder port” for minor ports, which are served by feeders and are not direct destinations of the container vessels.

The purpose of major liner companies is to set up the daily services, while deploying the fewest number of vessels. This purpose is reached by distance optimization and improving the trade-off between a number of consolidation centers and a number of feeder ports and, in addition to mentioned procedures, the number of routes is of the highest importance. Feeders are applied to decrease the number of consolidation centers for a liner vessel and, accordingly, decrease the route distance for container ships. As is obvious here, the favourable distribution deals with the exact application of port selection; establishing consolidation centers, route design and feeders for port assignments. Thereby, it is interesting for transport companies to optimize the total cost while submitting some restrictions such as capacity of container ship, distance of feeders from their base to the consolidation center and so on. This efficient planning allows picking up the demands from various consolidation centers and dropping them off at the hub center on schedule. To meet this concept, creating a set of potential consolidation centers in advance is necessary, which need to have the least and minimum distance from location of existing feeder ports. At the same time, feeder ports will be assigned to an appropriate consolidation center while satisfying the maximum capacity of the container ship.

Although the distance and appropriately the fuel consumption and in general voyage cost is highly effective in a ship management, the shipping business uses the market mechanism to regulate supply and demand and consequently the freight rates. Thus, in our model, the objective is solely to optimize the total voyage distance, and the purchase cost is presented in the form of a constraint. Basically, our problem is similar to the traveling purchaser problem (TPP), the problem of determining a tour of a purchaser who needs to buy several items in different shops, so that the total amount of travel and purchase costs is minimized. However, in this paper, we apply (VPR) and SRP, as the variation in our model that we study here incorporates several constraints, motivated by VPR scheduling application and by TPP to set the variants. The approach that we propose in this paper is specifically tailored to this variant only, and only within shipping's high market conditions. As far as we know, none of the previous studies on the TPP have considered the variant of distance as the sole constraints, considering the dynamic of the competitive market in a short sea trade. On the other hand, the limited number of feeder ports in a short sea trade route, for instance within the Mediterranean Sea or the far-east, the distance is the most influential and competitive factor. In a practical way and in a high market, we assume that the feeders fleet run at full capacity, as long as the demand in the market remains high.

2. Literature Review

There are some common and unique factors in port choice behaviors of trunk liners and feeder service providers. The phenomenal growth of port throughput significantly contributes to government decisions on seaport capacity expansion. Local cargo volume, terminal handling charge, land connection, service reliability and port location are most common important factors for trunk and feeder service. (Notteboom 2006) On the trunk liners side, water draft, feeder connection, and port due are also determining factors. On the other hand, berth availability, transshipment volume and cargo profitability are the other determining factor for feeder service providers (Chang et al. 2008). According to the above mentioned description, demand pattern and volume of cargo throughput can vary from one port to another in the same geographical region. Demand for freight transport is determined by demand for physical commodities in a given location. Because of the uneven distribution of natural resources and specialization of production, some areas experience an oversupply of certain commodities, whereas other areas suffer from a deficit. In this paper, we assume that geographical imbalance does not give rise to fluctuation in demand for freight transport in a short sea market. Therefore, in this paper, we only focus on minimizing the distance cost (Coyle et al.,2000). Ship routing is defined as the allocation of the sequences of ports to be met by a ship (Ronen, 1993). Contrary to previous work on the ship-routing problem and several of its extensions, there are a number of studies presented in review papers by Ronen (1983, 1993). Christiansen et al., (2004) mentions that ship routing highly relies on the type of shipping operations parameters, including industrial and linear shipping. Interestingly, they present the model that optimum order of ship in port is visited, resulting in minimizing the operating cost. Additionally, some researchers have done some studies on container ship routing and scheduling (e.g. Shintani et al., 2007; Rana and Vickson, 1991); Perakis and Jaramillo (1991) present the linear programming approach, allocating container ships to a predefined set of routes; Cho and Perakis (1996) present the LP formulation to obtain optimal set of routes; Bendall and Stent (2001) provide a scheduling model for a high-speed container ship service and Hsieh and Chang (2001) develop the hub network model for routing the ship linear. Many recent studies have concentrated on VRPBTW and, using the local search meta heuristic, Cho and Parakis (1996) Sambracos et al. (2004), Sigurt et al. (2008) G.Clarck et al.(2012) develop a capacitated vehicle routing problem approach for identifying containership routes in the Aegean Sea. Meanwhile, Shintani et al. (2007) report on the implementation of a genetic algorithm for optimizing containership routes in which the repositioning of empty containers is considered. Many scheduling applications are described in literature: Multiple ship pickup and delivery problem with time windows, such as those studied by Fagerholt (2001), Sigurt et al (2005), and Hsu and Hsieh (2007). Just as in a simple vehicle routing problem, the concept proposed in this paper intends to minimize the total traveling distance while following certain restrictions as the capacity of container ship. This is performed considering three inner relational problems in the same level as follows:

a) A location problem for determining consolidation center facilities
b) An allocation problem for allocating feeders to the located consolidation centers
c) A routing problem for generating the routes that visit the consolidation center and return to the hub center

The sub-problems a) and c) directly affect the objective functions, whereas sub-problem b) has an indirect effect on the objective function.

3. Statement of the Problem

The ship-routing problem stated in this paper is a generalization of the well-known vehicle routing problem (VRP), where a single hub port, one type of feeder center, and identical ships, each of them with fixed capacity, are employed. The objective here is to optimize the total traveling distance as in the traditional VRP. Since the SRP extends the VRP, it can be considered as NP-hard as well. Table 1 summarizes the symbols included in the model.

Table 1
Symbols used in mathematical model

Data	
C	Ship capacity
V	Set of potential consolidation centers
S	Set of feeders
c_{ij}	Cost of travelling from consolidation center i to consolidation center j
Td	Travelled distance from the feeder starting point to consolidation center
S_{il}	$S_{il=1}$if Binary variable equal to 1 if feeder l can reach consolidation center I, 0 otherwise
Decision variable	
x_{ijk}	1 if ship k traverses the arc from consolidation center i to j, 0 otherwise
y_{ik}	1 if the ship k meets consolidation center i, 0 otherwise
z_{ilk}	1 if demand in feeder l is picked up by ship k at consolidation center i, 0 otherwise

The following formulae are made based on the formula of Toth and Vigo (2001, p. 15).

$$\min \sum_{i\in v}\sum_{j\in v}\sum_{k=1}^{n} c_{ij}\, x_{ijk} \tag{1}$$

s.t.

$$\sum_{j\in V} X_{ijk} = \sum_{j\in V} X_{jik} = y_{ik} \qquad \forall\, i \in V, K = 1, \dots..n \tag{2}$$

$$\textstyle\sum_{k=1}^{n} y_{ik} \le 1 \qquad \forall\, i \in V/\,(0) \tag{3}$$

$$\sum_{k=1}^{n} z_{ilk} \le S_{il} \qquad \forall\, L \in S, \forall\, i \in V \tag{4}$$

$$\sum_{i\in V}\sum_{l\in S} z_{ilk} \le C \qquad k = 1, \dots\dots..n \tag{5}$$

$$z_{ilk} \le y_{ik} \qquad \forall\, i, l, k \tag{6}$$

$$\sum_{k=1}^{n} z_{ilk} = 1 \qquad \forall\, l \in S \tag{7}$$

$$y_{ik} \in (0,1) \qquad \forall\, i \in V, k = 1, \dots..n \tag{8}$$

$$x_{ijk} \in (0,1) \qquad \forall\, i, j \in V, k = 1, \dots..n \tag{9}$$

$$z_{ilk} \in (0,1) \qquad \forall\, i, j \in V, i \ne j, k = 1, \dots..n \tag{10}$$

The objective function (1) minimizes the total travel distance covered by all ships and, due to Constraint (2), for each consolidation center i, the number of arcs entering is exactly the same as the number of arcs leaving; Constraint (3) guarantees that the ship serves each consolidation center only once, except for the consolidation center associated to the hub port; Constraint (4) enforces that each demand in the feeder is picked up at the consolidation center it moves onto; Constraint (5) guarantees that the capacity of the ships is not exceeded; inequalities (6) impose that picking up a demand in port in a non-visited consolidation center by ship k is not possible; Constraint (7) states that each feeder is picked up exactly once; finally, constraints (8), (9) and (10) define the domain of the decision variable, which is binary.

The formulation presented here has been solved using a CPLEX solver in GAMS and tested on a set of instances. It was observed here that while the size of increases rises, the computing time rises, which could be problem in solving large instances in a reasonable computing time. As a result, we have implemented a metaheuristic approach described in the following section.

4. Metaheuristic Approach

In this paper, two kinds of Metaheuristics are proposed to solve liner container ship-routing problem. Both proposed heuristics here are embedded by two phases: a constructive solution phase and an improvement phase. In the constructive solution phase, it tries to generate a feasible initial solution, which is followed by the improvement phase, where an effort is made to reduce the number of routes and, thereby, improve the solution. The two kinds of Meta Heuristics proposed here are different in the initial solution, but they are the same at the improvement phase. The first Meta heuristic uses the idea of 'nearest neighborhood' with 'Greedy randomized selection' to generate route selection, whereas the second Meta Heuristic is performed based on the Clark and Wright greedy randomized selection method. These two phases (constructive and improvement) are executed sequentially until maximum iterations are met. The innovation of this paper is that it applies a heuristic in order to allocate a feeder to a consolidation center. It is important to note here that applying allocation of feeder to the consolidation center is carried out separately by means of heuristic. In fact, the feeder allocation sub problem is performed to check the feasibility of the solution.

Proposed Meta heuristics are employed to obtain total traversing cost and computation time. Additionally, we will apply our findings to state the following hypotheses:

Hypothesis I: an increase in the capacity of the container ship vessel will decrease the number of routes and, accordingly, the total traverse distance.

Hypothesis II: among our variables (vessel capacity, number of consolidation centers and number of feeder centers), vessel capacity has the most significant effect on the CPU Time.

4.1. *Construction Phase*

The main goal of this phase is to provide a solution in a constructive way, step by step. In general, constructive heuristics start from an empty solution and end in a complete solution. According to the literature, constructive heuristics have been effectively employed to solve a variety of related problems in the routing field.

In this paper, two different constructive heuristics are used to generate an initial solution for the SBRP. These heuristics are represented by: (i) which is a variant of the Clarke and Wright's heuristic in which a greedy randomized selection mechanism is used to select and implement the savings and (ii) which is a variant of the nearest neighborhood heuristic, with greedy randomized selection procedures of the nearest nodes to be added in the current route.

4.1.1. Clarke and Wright with Greedy Randomized Selection Mechanism

The Clarke and Wright's heuristic is one of the most well-known methods employed to solve the VRP and its variant (Clarcke and Wright 1969). The standard of Clarcke and Wright starts with a solution in which each consolidation center is visited in separate routes (in which each consolidation center is assigned to only one vehicle) and iteratively merges two routes, making a saving in the travel costs. To speed up the solution approach, a saving matrix is created at the beginning of the algorithm containing the savings, which can be achieved by connecting two consolidation centers, thus resulting in combining two routes into one. Following this, these savings are ordered in a decreasing order. Merging to routes that contains the consolidation center s, and associated to the saving is which ??? is only feasible if (1) both consolidation centers are connected to the depot and (2) the total capacity associated to the new merged route, including consolidation centers, cannot exceed the vehicle capacity.

For SBRP, the original algorithm of Clarcke and Wright is modified as follows: (i) after the initial setup (in which each consolidation center is visited separately) allocated to the consolidation center according to a feeder allocation sub-problem (see section 4-4) and (ii) a greedy randomized selection mechanism is used in order to take the advantages of a proper balance between greediness and randomness. To this end, a restricted candidate list (RCL) is used at each iteration of the Clarke and Wright heuristic by selecting a subset of all the savings, sorted in a decreasing order. Next, from the RCL, one element is selected randomly and the associated merge operation is put in place in order to achieve the corresponding saving. Afterward, the RCL is updated, depending on the configuration of the new solution.

The process of selecting one element from the RCL and updating, the list of the RCL is repeated sequentially until RCL is empty and a complete solution is built. The size of the RCL list is denoted by letter and the construction of the solution is completely greedy, and is the largest available saving selected while building the current solution. If it becomes large; for example, equal to the number of available saving elements given the current solution, the construction will be completely random. Its value is a parameter that allows for the generation of a different initial solution for the SBRP at each restart of the heuristic.

It should be noted that, if the feeder allocation problem is infeasible, no feasible solution will exist for the SBRP. In the other case, where the allocation sub-problem is feasible, consolidation centers are selected randomly from RCL to be merged.

Unlike the original Clarke and Wright's, in our modified version of this heuristic, checking the feasibility performance at each iteration also involves the feeders in allocation to the consolidation centers, so it significantly affects he computation time. To save time, when the feeder allocation problem is solved, after connecting two routes, the feeder allocation sub-problem is resolved from scratch to check whether the selected saving is feasible. In fact, savings result in an unfeasible feeder allocation problem, after which the savings are removed from the RCL. This procedure allows us to save computation time in an efficient way.

4.1.2. A Nearest Neighborhood with Greedy Randomized Selection Mechanism

A nearest neighborhood heuristic including a greedy randomized selection process represents the second constructive heuristic developed in this paper. Just as the modified Clacke and Wright constructive heuristic at the beginning of the algorithm, a feeder allocation problem is solved for each consolidation center. If an unfeasible solution was found, no feasible solution would exist for the SBRP. On the other hand, if a feasible solution is found, a variant of the nearest neighbored constructive heuristic is applied. This heuristic is modified as follows: a greedy randomized selection process is applied instead of a greedy selection process. As a consequence, the next consolidation center in the current route is randomly chosen from the restricted candidate list, including the first; the closest unvisited consolidation centers. It should be noted here that, as in the modified adapted Clarke and Wright heuristic mentioned before, the allocation of feeder to the consolidation centers is not executed every time a consolidation center is added to the current solution to speed up the algorithm. Then, after selecting an unvisited consolidation center, the capacity constraint is checked. If a feasible solution for the feeder allocation problem is found, the addition of a new consolidation center is evaluated. If it is not the case, the route will be closed and the ship will return back to the hub port and a new route generated from the hub port to new unvisited consolidation centers. A pseudocode for both constructive heuristics is presented in Figure 1.

4.2. *Local Search*

Once an initial solution is generated, the solution is subjected to an improvement phase by using local search. The improvement phase is based on variable neighborhood descent (VND). Our VND heuristic uses five different neighborhood structures, from which there are (i) three intra routes operators: Remove-insert, Relocate and Replace and (ii) two inter route operators, Remove-Insert and Swap. Intra route operators attempt to improve the current solution by making changes within one route, whereas Inter-route operators modify more than one route, simultaneously. The inter-route operators tend to be more computationally expensive, due to a large neighborhood which has to be explored when the number of consolidation centers and feeders increase. Before applying any kind of intra and inter local search operator, both the cost of the solution and its feasibility in regard to the ship capacity has to be checked. If the local search operator finds better solutions and, as the capacity constraint is satisfied, the corresponding move is executed, or otherwise discarded. The local search terminates when the solution is stuck at a local optimum, and cannot be further improved by executing any of the local search operators. The neighborhoods are employed in order, presented below.

Remove Insert within a route and remove insert between routes

According to this operator, one consolidation center is randomly selected and removed from its current position, and inserted in a different position within the same route (for the inter route operator) or in a different route (for the inter-route operator). The main difference between the intra and the inter route operators is that, where moving involves only a single route, the capacity check or feeder allocation sub-problem is not taken into account, which can speed up the application of the operator.

Replace

This operator selects an unvisited consolidation center from the list of unvisited consolidation centers and, subsequently, includes it in a route by replacing it with a consolidation center contained in that route. The list of unvisited consolidation centers is sorted in a decreasing order of number of feeders that can reach that consolidation center. The cost check needs to be performed before the application of the move, while the feeder allocation sub-problem (section 4-4) has to be solved.

Remove

This operator attempts to remove a consolidation center in order to decrease the cost of the route to maintain the feasibility of the solution. For this reason, before applying the move, a feeder allocation sub-problem must be solved. If the latter produces a feasible solution, the move will be carried out. Due to triangular inequality, it is not necessary to perform a cost check, since a consolidation center removal will always produce a reduction in travel costs.

4.3. *The Allocation Sub-Problem Heuristic Approach*

As mentioned before, the SBRP can be solved by decomposing it in a master and a sub-problem. The master problem addresses the minimization of total travel distance, while the sub-problem copes with the allocation of feeders to consolidation centers, and thus impacts on the feasibility of the SBRP problem. If the master problem is run first and, on top of this, the feeder allocation sub-problem is run, the consolidation centers are initially determined and fix the ship and, then, the sub-problem is constructed in order to allocate the feeder to the selected consolidation centers. In this case, if all feeders are assigned to the selected consolidation centers, a feasible SBRP solution is found. Otherwise, the SBRP results will be unfeasible.

In our solution approach, the master problem and the allocation problem are integrated into a single optimization approach. More specifically, the feeder allocations are considered in the constructive phase, while the consolidation centers are selected and the routes are built while preserving the feasibility of the solution under the viewpoint of the feeder allocations. Moreover, during the intensification stage, where the current solution is improved, feasibility is preserved, exploring neighborhoods in which all feeders can be efficiently assigned to the consolidation centers included in the routes contained within the solution. In this respect, the heuristic procedure used to assign the feeders to consolidation centers during the constructive heuristic works as follows:

For each student, one needs to decide which consolidation centers are reachable. In other words, the list of consolidation centers from which the distance is not greater than the maximum travel distance is generated in a preliminary stage. Then, the list of feeders is sorted following an increasing order of the number of allowable consolidation centers. The heuristic first starts allocation of the feeders from the top of the list to the first available consolidation center that is at a reachable distance, and the list of feeders is explored sequentially. This simple rule allows critical feeders that have only one or few allowable consolidation centers to be assigned first to the available consolidation centers. The drawback of this procedure is that it might happen during the heuristic that, for some of the feeders in the list, no consolidation center with available capacity is available. If this happens, a repair procedure is put in place to allocate the unassigned students. The congested consolidation centers here have no remaining capacity, where hosting an unassigned feeder are identified.
In order to make room in these congested consolidation centers, a list of feeders that are assigned to these consolidation centers has been made, which presents the highest number of non-congested alternative consolidation centers where they can theoretically reallocate.

Then, a feeder is randomly is selected from this list and reallocated to another alternative non-congested consolidation center. After reallocation, a room to assign the unassigned feeder to the congested consolidation center is created, and the unassigned feeder assigned to the congested consolidation center. Thus, the heuristic can continue until the whole list of unassigned feeders is empty. It is important to note here that, at this stage, if an infeasible solution is found, no feasible solution will exist for the SBRP. Feeder reallocation procedure before applying local search is a little different from feeder allocation in the initial solution. Figures 1 and 2 here show the allocation heuristic in more details during the construction of the initial SBRP solution and before applying the improvement stage.

5. Problem Instance Generation

An instance generator for the ship routing problem presented here is a combination of real and random cases. The generator needs five parameters per instance: np (the number of potential consolidation centre), ns (the number of feeder per consolidation center), xd, yd (the x and y-coordinates of the consolidation center) and wmax (the maximum distance).

It is important to note that the coordinates of the consolidation center are taken from the port of Piraeus to a set of 25 consolidation centers in the Aegean Sea. In this way, the value of the consolidation centre is real. For each generated consolidation center, ns feeder location is generated in distance of wmax from consolidation center, which is conducted by creating distance wj from the consolidation center for each feeder and angle and for the first time Then, to this end, the feeder is generated as coordinates it is equal to.

6. Experimental Analysis

In this section, an experimental analysis is set up, in which the two meta heuristics for the SBRP presented in Section 4 are analysed. In the first stage, the key components of each meta heuristic are investigated and examined in such a way that each meta heuristic generates the best solutions, on average. In the second stage, once the optimal value for each of the components has been obtained, the comparison between the two metaheuristics is performed. The first and the second phases of the experiments are presented in sections 6-1 and 6-2, respectively.

6.1 *Analysis of Metaheuristics*

Both metaheuristics presented in section 4 have several components. In this section, we present statistical analysis in order to achieve a better understanding about the behaviour of both proposed metaheuristics. The main idea underlying this analysis is to identify the best components that influence the performance of the metaheuristic. In this way, the components of metaheuristics make no contribution towards the quality of the solution, and can be discarded. The same experiments have been performed for both metaheuristics, related to the local search block and initial solution part. The different parameters that have been tested are displayed in Table 2, as well as the number of tested values.

The algorithm is performed five times using each combination parameter setting (presented in table 1). To solve the instances presented in this section, the full factorial experiment is used for both metaheuristics configurations by means of a multi-way ANOVA method., which means this analysis considers some run where all proposed neighbourhoods are deactivated for both metaheuristics. In that case, we only have a constructive phase.

Table 2
Parameters and levels tested

Parameters	Description	Value	Number of of levels
N1=Remove_ Insert	Remove –Insert inter neighbourhood	On, off	2
N2=Replace	Replace inter neighbourhood	On, off	2
N3=Remove	Remove inter neighbourhood	On, off	2
N4=Remove-Insert	Remove –Insert intra neighbourhood	On, off	2
β	Maximum worsening of the objective function	0% , 10%, 15%,20%, 25%, 30%	6
α	Size of restricted candidate list	1,2,3,4,5	4

Table 3
Optimal setting for two kinds of metahueristics configuration

Parameters	M-cwg	M-NNg	ILS-cwg	ILS –nng
N1=Remove_ Insert	On	On	On	On
N2=Replace	On	On	On	On
N3=Remove	On	On	On	On
N4=Swap	On	On	On	On
N5=Remove-Insert	On	On	On	On
N6=Swap	On	On	On	On
β	---	-----	10%	15%
α	3	3	2	1

6.2 *Metaheuristic Comparison*

After reaching the optimal parameter settings for the solution approach, we compare both metaheuristics in terms of the quality of the solutions, time computing and robustness analysis, ranging from small, medium and large instances. To test and compare the ILS and multi- start metaheuristic, each configuration runs 10 times for all samples. The experiment is performed on 50 instances consisting of three subsets named, respectively: Set S, Set M and Set L, where Set S contains 25 instances, with the number of consolidation center ranging from 5 to 10; set M consists of 35 instances with the number of consolidation center, ranging from 15 to 20; and set L consists of 30 instances with 25 consolidation centers. Additionally, four maximum distances are included in this problem: 15, 20, 25, and 30. In Table 6, 7 (See Appendix A), the results of experiments are reported for each metaheuristic configuration. All the solutions in these tables have been created using the same parameter setting obtained in section 6-1, where each table presents details on the problem instances, and also results of each meta heuristic in 10 columns: the number of consolidation center (column con), the number of feeder (column feeder), ship capacity (column cap), maximum distance (column wd), the best known solution (column Best), best solution (column best sol), average solution (column ave sol), percentage gap from the optimal solution (column percentage gap) and average computing time (column ave time). Additionally, we will apply our findings to indicate two hypotheses. Finally, the summation of results for each sub testing set is presented in Table 4 and one gap is reported: Table 4 (a) denotes the percentage average gap from the best solution so far. In Table 4 (a), the first column depicts the type of metaheuristics, and the next three columns note the ranging of instances, from small to large.

Table 4(a)
Robustness of each metaheuristic on small, medium and large sized instances

Metaheuristic	SET S	SET M	Set L
m-cwg	1.25%	0.71%	3.69%
m-NNg	0.39%	0.68%	0.51%

Table 4(b)
Total computing time of each metaheuristic on small, medium and large sized instances (second)

Metaheuristic	SET S	SET M	Set L
m-cwg	688.22	5834.16	8869.85
m-NNg	272.43	2334.29	3852.92

In Table 4 (b), the results show two things: according to the kinds of metaheuristic configuration, we can conclude that m-NNg gives a lower percentage gap from the optimum solution over all instances. The m-NNG is the second best and generates better solutions for small and medium instances. Moreover, in the medium-sized, the percentage gap for m-NNg is not far from the m-CWg.

In terms of computing time, it could be said from the tables 5(c) that the m-CWg is slower than m-NNg configuration. Additionally, the m-CWG needed an average of 2.93 times more computing time than the m-NNG configuration.

It can be concluded that m-CWg gives poor performance in both robustness analysis and computing time. In addition to investigating the first hypothesis, the sensitive analysis is mostly carried out for ship capacity. Figure 3 shows the number of route for different ship capacities

(75,100,125,150,175). As expected, while the capacity of ship rises, the number of routes decreases, which supports the first hypothesis

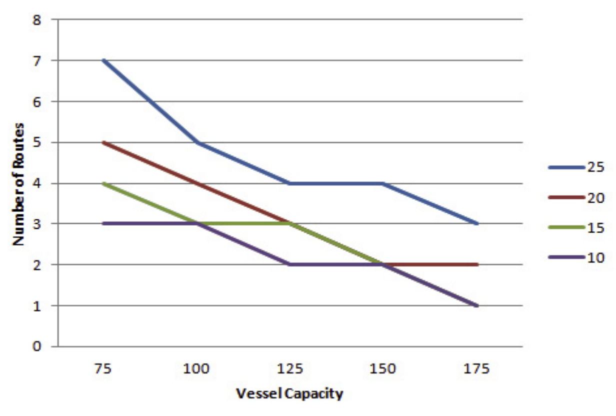

Fig. 1. Sensitivity analysis for various vessel capacities

Table 5
Model CPU time

Source	m-Cwg	m-NNg
Consolidation center	<0.001	0.00086
Feeder center	0.0025	0.0036
Capacity	0.04	0.08
Maximum Travelling distance	0.735	0.893

7. Conclusions and Future Research

In this paper, we present ship-routing problems, combining ship consolidation center selection and route generation, picking up demand from the potential locations, and generating ship routes that visit the selected consolidation center to carry the demand to the hub port.

To solve small presented instances in a reasonable time, we test two different metaheuristics configurations. Experiments conducted on 50 consolidation centers show that the proposed nearest neighbourhood is found faster than other metaheuristic configurations, in respect to computing time. In terms of robustness analysis, the nearest neighbourhood with a multi-start configuration is able to find a better percentage gap for an optimal solution, meaning that nearest neighbourhood gives a better performance. Future research can be aimed at two directions: Firstly, the additive objective function, where constraints and features may be included in the problem of increasing its realism. For example, the time window constraint. Secondly, it is interesting to try solving this problem through a better heuristic configuration, as well as efficient neighbourhood operators. Thirdly: it is understood that the most important part of our metaheuristic configuration is that it takes a longer time, related to the applying local search operators, as well as checking the feasible allocation, whether in the initial solution, or before applying each improvement operator. To this end, further research aims at investigating this topic in two categories: 1: using the strategy to reduce the computational complexity of a local search. To efficiently investigate this approach, the data structure will be proposed in such a way that saves the information about the set of a neighbouring solution. 2: applying strategic oscillation that allows a crossing to the boundary of a feasible region, which is the transition between feasible and infeasible solution regions.

Appendices

A. Detailed computational results for both m-CWg,m NNg configuration

Table 6
Results obtained solving the instances using the m-CWg and m-NNg heuristic in their optimal setting

ID	consolidation center	Feeder center	capacity	TD(Travelled distance)	Quality of solution m-CWg	Quality of solution m-NNg
1	5	10	100	10	433.50	437.88
2	5	10	150	10	559.94	565.60
3	5	10	100	20	343.24	346.71
4	5	10	150	20	23.46	23.69
5	5	10	100	40	881.33	890.23
6	5	10	150	40	595.02	601.03
7	5	10	100	80	401.28	405.34
8	5	10	150	80	39.63	40.03
9	5	15	100	10	1107.81	1191.19
10	5	15	150	10	904.48	972.55
11	5	15	100	20	414.87	446.10
12	5	15	150	20	181.23	194.87
13	5	15	100	40	452.50	486.56
14	5	15	150	40	751.78	808.36
15	5	15	100	80	335.03	360.25
16	5	15	150	80	99.14	106.61
17	10	20	100	10	707.20	760.43
18	10	20	150	10	1950.28	2097.07
19	10	20	100	20	894.12	961.42
20	10	20	150	20	288.38	310.08
21	10	20	100	40	3687.56	3965.12
22	10	20	150	40	2572.82	2737.04
23	10	20	100	80	1741.75	1852.92
24	15	30	100	10	1056.55	1123.99
25	15	30	150	10	3163.51	3365.43
26	15	30	100	20	1836.99	1954.25
27	15	30	150	20	393.52	418.64
28	15	30	100	40	3498.00	3721.28
29	15	30	150	40	3247.20	3454.47
30	15	30	100	80	2796.36	2974.85
31	15	30	150	80	696.90	741.38
32	20	40	100	10	1306.45	1360.89
33	20	40	150	10	1143.92	1191.58
34	20	40	100	20	609.34	634.73
35	20	40	150	20	295.21	307.51
36	20	40	100	40	4786.50	4985.94
37	20	40	150	40	827.31	861.79
38	20	40	100	80	859.64	914.51
39	20	40	150	80	435.26	463.04
40	25	50	100	10	1612.45	1662.32
41	25	50	150	10	1411.85	1455.51
42	25	50	100	20	752.06	775.32
43	25	50	150	20	364.35	375.62
44	25	50	100	40	4212.20	4342.47
45	25	50	150	40	1021.09	1052.67
46	25	50	100	80	1060.99	1093.80
47	25	50	150	80	537.21	553.82

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Allocation heuristic to find an initial feasible solution

Input: allowed capacity for each consolidation center (ACS), List of unassigned feeders(L), list of feeder sorted in increasing number of allowable consolidation center (K), list of allowable feeder for each feeder (M), Sort unfilled consolidation center based on the capacity, in increasing order in the list (S), matrix of allocation feeder to consolidation center (Sil), list of all allowable consolidation centers for each unassigned feeder (A), List of possible consolidation centers for each feeder (B), list of the unfilled consolidation center sorted in increasing order of number of filled capacity (p),

Create the list of (K) : all students, sorted in increasing order of the number of allowable consolidation centers
For each feeder € K do, sequentially from the top of the list, M=0,
Select the feeder from the list (K),
Select the feeder from the list (K),
Identify the number of allowable consolidation center for selected feeder and add it to the list M,
While allocation =false **do**
    One consolidation center is selected from the List (M),
    Check the capacity of consolidation center
If the filled capacity of selected consolidation center is lower than allowed capacity **then**
    Allocation = true, assign the feeder to the consolidation center , ACS =ACS-1, Remove the feeder from the list (K)
Else
    Remove the consolidation center from the list M and update the list M
End if
  End while
      If the feeder cannot assign to allowed consolidation center in the list M **then**
       Add the feeder to the unassigned feeder list (L)
End if
End for
If the List L=0,then
        allocation is true and allocation is terminated, meaning initial feasible solution is found
Else
        Sort the unfilled consolidation center based on the capacity in increasing order in the list (P)
For each unassigned feeder€ L **Do**,
A=0 & B=0 & p1=0
            Select the allowable consolidation centers for the UN assigned feeder from the matrix of feeder–consolidation center (Sil) and added in the list A
            Identify all other feederswhich are already assigned to these consolidation centers and add them to the list B
While allocation 1=false **do**,
                One feeder is selected from the list B, randomly
                Corresponding, the list B, identifying allowable consolidation center from Matrix of (Sil) and added in the list P1
For each consolidation center in the list of P1 Do,
if the capacity of selected consolidation center from the list P1 is lower than allowable capacity, **then**
Try to move the feeder to the consolidation center in the list of P1, as well as allocate the unassigned feedersin the list A
End if
if unassigned feeder can assign in the consolidation center in the list A, **then**
  Allocation 1= true, Remove the unassigned feeder from the list (L)
Else, remove the feeder from the List B and update the list B
End if
End for
                End while
          End for
     End if
If the list L=0, **then**
                        Final allocation is true
Else, the initial Infeasible solution is found
End if

Fig. 1. Allocation heuristic during the generation of an initial solution

Allocation heuristic before applying local search

Input List of excess feeder per route (E), list of all possible consolidation centers for each feeder (A), List of possible routes for selected consolidation centers (B), List of route that local search should be performed (R), List of existing feedersin the selected route, sorted in increasing order of allowable consolidation centers
(K1), allowed capacity for each consolidation center and route (AC)
For each route € R (first a route is selected in which there are more exceed students) do,
Create the list of K1: all feedersin selected route, sorted in increasing order of the number of allowable consolidation centers
Remove the Feedersthat are only allowable to move one consolidation center from the list K1 and update the list K1
While feasibility =true do,
For each feeder€ K1 do, sequentially from the top of the list
A=0 & B=0
Select the allowable consolidation centers for the feeder from the matrix of feeder–consolidation center (Sil) and add them to the list A
Remove the consolidation center that exists in route from the list A and update the list A
Concerning allowable consolidation center in the list A, select routes containing allowable consolidation centers and add them to the list B,
For each consolidation center from the list A
If the capacity of consolidation center is lower than AC and if the capacity of route containing selected consolidation center is lower than AC then
Allowable Feeder is allocated in this consolidation center and remaining capacity of consolidation center and route are updated,
Exceed=exceed-1
if exceed=0 **then**
feasibility = true
Else, remove the consolidation center from the list A and update the list A
End if
End if
End for
End for
End while
End for
If exceed =0 **then**
feasible solution exist
Else infeasible solution is found
End if

Fig. 2. allocation heuristic before applying local search operator