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An integrated optimization of routing and scheduling of liner ships in offshore logistics management

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Abstract

The magnitude of maritime transportation in the offshore logistics, has been increasing over time. As such, container's demand has been growing dramatically. Shipping lines have been using different strategies to efficiently serve the existing customers. One of the common strategies is the deployment of large ships. The current practice in the liner shipping industry is to deploy a combination of ships of different types with different carrying capacities, especially at the routes with a significant demand. However, heterogeneous fleets of ships have been investigated by a very few studies addressing the tactical-level decisions in liner shipping of offshore logistics. Moreover, little research efforts have been carried out to simultaneously capture all the major tactical-level decisions in liner shipping using a single solution methodology. The proposed model is also multi-period and multi-product which make it much complex than existing ones. Based on these challenges and contributions, this research deploys an integrated optimization of routing and scheduling of liner ships for offshore logistics. This paper deals with a combinatorial optimization model which is NP-hard and very difficult to solve. Hence, another main contribution of this work is to develop a hybrid metaheuristic with regards to a set of well-known and recent efficient metaheuristics. The results confirm the applicability and efficiency of the proposed hybrid algorithm in comparison with individual ones in this context and encourage to add more elements for our integrated optimization model more broadly.

Keywords

Routing and scheduling of liner ships; offshore logistics; integrated optimization model; hybrid metaheuristic

1. Introduction

Nowadays, one of the most challenging issues to design an efficient offshore logistics network is to consider the harmful effects of the fuel consumption that cause the environmental pollution in view

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of environmental sustainability (Bazan, Jaber, & El Saadany, 2015; Fathollahi-Fard, Ahmadi, & Al-e-Hashem, 2020; Fathollahi-Fard, Govindan, Hajiaghaei-Keshteli, & Ahmadi, 2019). Without a doubt, the research on the shipping lines is very challengeable with regards to the environmental considerations of ships planning. Another challenge is the continuous growth in container demand, since more and more companies are outsourcing their operations and moving their production activities offshore (Fathollahi-Fard, Hajiaghaei-Keshteli, Tian, & Li, 2020; X. Liu, Tian, Fathollahi-Fard, & Mojtahedi, 2020). However, the COVID-19 pandemic may slow down this trend in container demand for some time. In order to address the demand growth and efficiently serve the existing customers, shipping lines have adopted various strategies (e.g., formation of alliances, operations optimization, and deployment of large ships). One of the common strategies is the deployment of large ships. The largest container ships in the world now have capacities close to 24,000 twenty-foot equivalent units (TEUs), as compared with the capacity of 500-1,000 TEUs that was common in 1956 (Prokopowicz & Berg-Andreassen, 2016). Large ships assist shipping lines with economies of scale, savings in fuel consumption, emission reduction, and lower transportation cost per unit (M. Dulebenets, 2018). Due to economies of scale, large ships enable shipping lines to reduce freight rates and effectively share the existing capacity with other shipping lines(X. Liu et al., 2020; Prokopowicz & Berg-Andreassen, 2016).

Tactical-level decisions in liner shipping include: (i) determination of service frequency; (Ozcan, Eliiyi, & Reinhardt) fleet deployment; (iii) optimization of ship sailing speed; and design of ship schedules. Many studies focusing on the aforementioned decisions have been conducted to date(Meng, Wang, Andersson, & Thun, 2014). Service frequency refers to the time interval between consecutive ship visits at a port of call. For example, Lam and Voorde(Lam & Van De Voorde, 2011) indicated that maintaining the common practice of weekly service frequency, when interconnected with unreliability in ship schedules, could lead to difficulties associated with timely production and distribution. Tai and Lin (Tai & Lin, 2013) assessed the impact of daily service frequency and slow steaming on emissions produced from liner shipping. It was found that daily frequency could reduce emissions, even when the strategy of slow steaming was not adopted. The study that was conducted by Lin and Tsai(Lin & Tsai, 2014) outlined different aspects of daily service frequency. Zhang and Lam(A. Zhang & Lam, 2014) examined the Daily Maersk service that adopted daily service frequency as well. Recently, Giovannini and Psaraftis (Giovannini & Psaraftis, 2019) integrated determination of service frequency with the design of ship schedules. The study assessed variable service frequency with the aim of maximizing the total profit.

The fleet deployment problem, on the other hand, deals with the assignment of ships to port rotations. Moura et al. (Mourão, Pato, & Paixão, 2002) studied the assignment of a heterogeneous fleet of ships in a hub-and-spoke environment. An integer programming model was proposed in order to minimize the total annual trade cost. Results from the executed computational experiments favored to assign a small fleet of ships. Álvarez (Alvarez, 2009) studied fleet deployment and routing of container ships. For short-term fleet deployment, Meng and Wang (Meng & Wang, 2010) devised a chance-constrained model that considered container demand uncertainty. In order to model container demand uncertainty, the study assumed a normal distribution of container demand between two ports of call under a port rotation. Gelareh and Pisinger(Gelareh & Pisinger, 2011) developed a mathematical model for the problem of simultaneous fleet deployment and network design. A methodology for repositioning of empty containers, while addressing fleet deployment, was proposed by Huang et al. (Huang, Hu, & Yang, 2015). In another study, Zheng et al. (Zheng, Gao, Yang, & Sun, 2015) proposed a network design model for liner shipping alliances, which accounted for fleet deployment decisions. Since the proposed model was for liner shipping alliances, the carrying capacities of ships were exchanged between different alliance partners. Several other aspects were integrated as well, such as container routing and variable container demand. Thun et al. (Thun, Andersson, & Christiansen, 2017) tackled the network design problem and considered assigning one type of ship to each port rotation. The study promoted multiple visits to a single port of call in order to incorporate various route structures.

Design of ship schedules covers a wide array of decisions regarding port waiting times, arrival times, departure times, sailing times, and so on. This is the most complicated of the problems at the tactical level of liner shipping. Qi and Song (Qi & Song, 2012) assessed uncertainties in port times and considered ship sailing speed constraints. While capturing uncertainties in port times, Song et al., (Song, Li, & Drake, 2015) determined the required quantity of ships, ship sailing speeds, and ship schedules. Several studies modeled availability of multiple handling rates (HRs) at ports and/or availability of multiple port arrival time windows (TWs) throughout scheduling of ships (Alharbi, Wang, & Davy, 2015; M. A. Dulebenets, 2018; Dulebenets, Pasha, Abioye, & Kavoosi, 2019; Z. Liu, Wang, Du, & Wang, 2016)Wang (Wang, 2015) acknowledged the fact that the capacities of ships, allocated for service of a given port rotation, might vary. Their study proposed some rules for the optimal ship sequencing in a string.

More recently, Gürel and Shadmand (Gürel & Shadmand, 2019) studied the design of ship schedules, while addressing uncertainties in port handling times and waiting times. The study also facilitated heterogeneous fleets of ships, which involved different fuel consumption functions for different types of ships. Ozcan et al., (Ozcan et al., 2020) designed ship schedules, while addressing the cargo allocation problem and considering transshipment operations and transit times. Zhang et al. (B. Zhang, Zheng, & Wang, 2020) studied the design of ship schedules for a two-way tidal channel, whose depth was impacted by tides. Zhuge et al. (Zhuge, Wang, Zhen, & Laporte, 2020) reported that a number of ports adopted voluntary speed reduction initiatives. Hence, the study examined ship schedules under such initiatives.

At last but not least, an integrated optimization model to support the tactical decisions is established by this paper. In addition to several decision variables, the proposed model has the features of multi-period and multi-product models which increases its complexity. Therefore, the proposed model is a combinatorial optimization problem to solve the routing and scheduling of liner ships, simultaneously and can be classified as an NP-hard model which has a high computational time. In this regard, one of the main innovations of this study is to propose a novel hybrid metaheuristic based on the advantages of genetic algorithm (GA) (Whitley, 1994), Keshtel algorithm (KA) (Hajiaghaei-Keshteli & Aminnayeri, 2013) and red deer algorithm (RDA) (Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2020) as a recent developed metaheuristic. The proposed hybrid metaheuristic is novel and firstly applied to the area of routing and scheduling of the liner ships.

This paper follows four sections. Section 2 explains the framework of the proposed problem and formulates it. Section 3 shows the solution algorithms and our proposed novel hybrid metaheuristic. Section 4 provides a comprehensive comparison and analysis based on the parameters of the model and the quality of solutions as well as some sensitivity analyses. Finally, conclusion and future remarks are conducted in Section 5.

2. Proposed integrated optimization model

Maritime transport in the offshore logistics, is an active research topic and the use of optimization models in this area is rarely contributed in comparison with other transportation types like trains, cars, and planes. That is why many studies recently have considered different and practical optimization model to evaluate the routing and scheduling of ships. However, attention to maritime transport has increased in recent decades and gained more importance.

Here, an integrated optimization method is introduced to cover all the tactical decisions in the offshore logistics. The decision variables of the proposed integrated model cover all the tactical decisions including determination of service frequency, the fleet deployment, optimization of ship sailing speed, and the design of ship schedules and routing optimization. Most significantly, the proposed model is multi-period and multi-product which make the proposed optimization model more complex than majority of existing works (Qi & Song, 2012; Thun et al., 2017; Zheng et al., 2015).

The main contribution is to provide a comprehensive plan for the liner ships. The shipping line has to make several considerations to set the ship sailing speed for a voyage leg of a given port rotation. The lower bound on the ship sailing speed is generally set to reduce the deterioration of the ship engines. The upper bound, on the other hand, is mostly influenced by engine capacities. Several other factors affect ship sailing speeds, such as transit time of ships, unit cost of emissions, unit cost of fuel, unit cost of ship operating, unit cost of inventory, etc. Decreasing the ship sailing speed reduces the fuel consumption along with the emissions produced in sea. However, it will increase the total container transit time in sea, and, therefore, will necessitate the deployment of more ships in order to maintain the frequency of service, which will ultimately increase the cost of ship operating or chartering. As a multi-period model, each day is a period. Regarding the multi-product supposition, there are many products and the case of shortage is existed when the demand in the port has not been satisfied. At the same time, reducing the ship sailing speed to a certain level may cause violation of the requirements imposed on the transit time. For selecting ship sailing speeds for different types of ships, this study supports aforementioned assumptions similar to recent studies (Z. Liu et al., 2016; Wang, 2015).

It goes without saying that a significant portion of the mathematical models addressing the tactical-level decision problems in liner shipping, especially the ship scheduling models, use the total route service cost in their objective functions (M. A. Dulebenets, 2018; Dulebenets et al., 2019). This study, however, uses the total turnaround cost in the objective function of its mathematical model, as heterogeneous fleets of ships are facilitated by this study. Generally, in our objective function, we have considered all the costs existing for an offshore logistics with regards to the tactical decisions.

First the notations of the proposed model is provided and then a case by case explanation is conducted to address the details of the proposed integrated optimization model.

Indices and sets:

N	Total number of nodes
H	Total number of hubs
D	Total number of ports
H_v	A hub which is used for planning of ship v at the beginning of the period
$i, i'j$	Index of nodes
P	Total number of products
p	Index of product
V	Total number of ships
v	Index of ships
R	Total number of motion counters for ships
r, r'	Index of motion counters for ships
T	Total number of time periods
t, t', t''	Index of time periods
P_i	Total number of products in port i

Parameters:

Cap_v	Capacity of ship v

W_p	Weight of product p
Dem_{pit}	Demand of port i for product p in period t
Tra_{ij}	Travelling time from node i to j
TC_{ij}	Travelling cost from node i to j
RC_{vit}	Cost of staying ship v in node i in period t
VC_{vt}	Cost of renting ship v in period t
IC_{pi}	Inventory cost for product type p in port i
ICV_{pv}	Inventory cost for handling product type p in ship v
SC_{pi}	Shortage cost for product p in port i
UC_{vp}	Cost of used capacity of ship v for product p
Ul_i	Time of loading and unloading in port i
a_i	Earliest availability time in node i
b_i	Latest availability time in node i
$Fuel_{ij}$	Rate of fuel consumption to travel from node i to j
FC_v	Capacity of fuel for ship v
FT_v	Time of fuel loading for ship v
CT_v	Cost of fuel for ship v

Decision variables:

X_{ijvrt}	If ship v with motion counter r goes from node i to j in the period t, it gets 1; otherwise, 0;
Z_{vrt}	If the last travel of ship v with motion counter r is done in period t, it gets 1; otherwise, 0;
α_{vt}	If ship v is available in period t, it gets 1; otherwise, 0;
U_{ivrt}	If ship v in period t loads the fuel in node i before motion counter r
Y_{ivrt}	A time which ship v with motion counter r goes to node i in period t
Q_{pivrt}	Amount of product p handled by ship v with motion counter r goes to port i in period t
L_{pivrt}	Used capacity of ship v from product p once motion counter r goes to node i in period t
G_{ivrt}	Amount of consumed fuel of ship v when it goes out from motion counter r to node i in period t
Inv_{pit}	Inventory status of port i from product p in period t
Sh_{pit}	Amount of shortage from product p in port i in period t

Now, with the use of aforementioned notations, the objective function is established as follows:

$$Min\ (\sum_{i\in N}\sum_{\substack{j\in N:\\ j\neq i}}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} TC_{ij}X_{ijrvt} + \sum_{i\in D}\sum_{p\in P_i}\sum_{t\in T} SC_{pi}Sh_{pit} + \sum_{i\in D}\sum_{p\in P_i}\sum_{t\in T} IC_{pi}Inv_{pit}$$
$$+ \sum_{i\in N}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} RC_{vit}Y_{ivrt} + \sum_{v\in V}\sum_{t\in T} VC_{vt}\alpha_{vt}$$
$$+ \sum_{i\in N}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} CT_v U_{ivrt} + \sum_{p\in P}\sum_{i\in N}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} ICV_{pv}Q_{pirvt}$$
$$+ \sum_{p\in P}\sum_{i\in N}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} UC_{vp}L_{pirvt}) \quad (1)$$

Eq. (1) is the objective function of our integrated optimization model which aims to minimize the total cost in the network of offshore logistics. The first term considers the total transportation cost and the second term is the shortage cost. The third term is the inventory costs in ports. Next, the cost of staying the ships in each node is computed. As such, for each period, we need to pay a fixed cost to rent the ships as given in the fifth term. The main source of environmental pollution in the offshore logistics, is the fuel consumption and the cost of fuel for each ship is computed in the sixth term. The inventory cost for handling products in each ship is addressed in seventh term and finally, the cost of used capacity of ships for the products, is computed in the last term.

This objective function is limited by a set of following constraints to close the real suppositions of an offshore logistic. Eq. (2) confirms that if the ship is to be used in a period of time, it must make its initial move in that period.

$$\alpha_{vt} = \sum_{i \in N} \sum_{\substack{j \in N: \\ j \neq i}} X_{ijvrt} \quad \forall v \in V, r = 1, t \in T \tag{2}$$

Eq. (3) shows that each ship must start its first voyage in all periods in seven periods of its hub.

$$\alpha_{vt} - \sum_{t'=1}^{t-1} \alpha_{vt'} \leq \sum_{\substack{j \in N: \\ j \neq i}} X_{ijvrt} \quad \forall v \in V, i = H_v, r = 1, t \in T$$

Eq. (4) explains that if a ship makes a voyage in one period and that voyage is not the last voyage of that day, it must make the next voyage that day.

$$\sum_{\substack{i \in N: \\ i \neq j}} X_{ijvrt} - Z_{vrt} \leq \sum_{\substack{i \in N: \\ i \neq j}} X_{jiv(r+1)t} \quad \forall j \in N, v \in V, r \in R, t \in T$$

Eq. (5) illustrates that if a ship makes a move in a period and does not move after this period, that move is considered its last move.

$$\sum_{i \in N} \sum_{\substack{j \in N: \\ j \neq i}} X_{ijvrt} = \sum_{i \in N} \sum_{\substack{j \in N: \\ j \neq i}} X_{ijv(r+1)t} + Z_{vrt} \quad \forall v \in V, r \in R, t \in T$$

Eq. (6) guarantees that each ship can only go from one origin to another in each movement (two trips are not made in one movement).

$$\sum_{i \in N} \sum_{\substack{j \in N: \\ j \neq i}} X_{ijvrt} \leq 1 \quad \forall v \in V, r \in R, t \in T$$

Eq. (7) shows that if the ship is not used in a course, the previous course must have entered a hub on the last move (the ship cannot stay in the rig on a day without a plan).

$$\alpha_{vt} - \alpha_{v(t+1)} \leq \sum_{i \in N} \sum_{\substack{j \in H: \\ j \neq i}} X_{ijvrt} + M(1 - Z_{vrt}) \quad \forall v \in V, r \in R, t \in T$$

Eq. (8) confirms that each ship must reach each node in the last voyage of its course, the next working day must start from that node.

$$\sum_{\substack{i \in N: \\ i \neq j}} X_{ijvrt} + Z_{vrt} \leq \sum_{\substack{i \in N: \\ i \neq j}} X_{jivr't'} + 1 + M(1 - \alpha_{vt'}) + M \sum_{t''=t+1}^{t'-1} \alpha_{vt''} \ \forall j \in N, v \in V, r \in R, r' = 1, t, t' \in T: t < t' \tag{8}$$

Eq. (9) shows the balance of demand. It means that the demand of each product should be provided. Otherwise, the shortage is considered.

$$\textstyle\sum_{v \in V} \sum_{r \in R} Q_{pivrt} + Inv_{pi(t-1)} + Sh_{pit} = Dem_{pit} + Sh_{pi(t-1)} + Inv_{pit} \ \forall i \in D, p \in P_i, t \in T \tag{9}$$

Eq. (10) explains the capacity limitation for each ship. It means that the used capacity of each ship in per period is limited by a maximum amount.

$$\sum_{p\in P} W_p L_{pivrt} \leq Cap_v \quad \forall i \in D, v \in V, r \in R, t \in T$$

Eq. (11) shows that the arrival time in the current node is directly related to the next node if the route between them exists.

$$Y_{jvrt} \geq Y_{iv(r-1)t} + UL_i + Tra_{ij} + FT_v U_{ivrt} - M\left(1 - X_{ijvrt}\right) \quad \forall i, j \in N: i \neq j, v \in V, r \in R, t \in T$$

Eq. (12) confirms that if the ship is to enter a node in a period, do not exceed the total hours of that period.

$$Y_{ivrt} \leq 1440 \qquad i \in N, v \in V, r \in R, t \in T$$

Eqs. (13) and (14) are the time windows limitation. It means that each port is available for each ship in allowable bounds.

$$Y_{jvrt} \geq a_j - M(1 - \sum_{\substack{i\in N:\\ i\neq j}} X_{ijvrt}) \quad \forall j \in D, v \in V, r \in R, t \in T$$

$$Y_{jvrt} \leq b_j + M(1 - \sum_{\substack{i\in N:\\ i\neq j}} X_{ijvrt}) \quad \forall j \in D, v \in V, r \in R, t \in T$$

Eq. (15) shows the relationship between the amounts of ships in two consecutive movements in a period.

Eq. (16) confirms the relationship between the amount of ship loads between the first move of a period and the last move of the previous period.

$$L_{pjvrt} \leq L_{pivr'(t-1)} - Q_{pivr'(t-1)} + M(3 - \textstyle\sum_{\substack{i'\in N:\\ i'\neq i}} X_{i'ivr'(t-1)} - Z_{vr'(t-1)} - X_{ijvrt}) \tag{16}$$

$$\forall i \in D, j \in N: i \neq j, p \in P, v \in V, r = 1, r' \in R, t \in T$$

Eq. (17) illustrates that the amount of products handled by the ship delivered to each port is not more than the ship's inventory.

$$Q_{pivrt} \leq L_{pivrt} \qquad \forall i \in N, p \in P, v \in V, r \in R, t \in T \tag{17}$$

Eqs. (18) and (19) are the correlation of decision variables to provide a link with each type of variables.

$$Y_{ivrt} + \sum_{p\in P} Q_{pivrt} + \sum_{p\in P} L_{pivrt} \leq M * \sum_{\substack{j\in N:\\ j\neq i}} X_{jivrt} \qquad \forall i \in N, v \in V, r \in R, t \in T \tag{18}$$

$$G_{ivrt} \leq M \sum_{\substack{j\in N:\\ j\neq i}} X_{ijvrt} \qquad \forall i \in N, v \in V, r \in R, t \in T \tag{19}$$

Eq. (20) investigates that each ship must have enough fuel to travel among each node.

$$G_{ivrt} \geq Fuel_{ij} - M(1 - X_{ijvrt}) \quad \forall i, j \in N: i \neq j, v \in V, r \in R, t \in T \tag{20}$$

Eqs. (21) and (22) are the correlation between two nodes if a route between them exists in a period.

$$G_{jvrt} \leq G_{iv(r-1)t} - Fuel_{ij} + M(1 - X_{ijv(r-1)t}) + MU_{jvrt} \quad \forall i, j \in N: i \neq j, v \in V, r > 1, t \in T \tag{21}$$

$$G_{jvrt} \leq FC_v + M(1 - X_{ijv(r-1)t}) + M(1 - U_{jvrt}) \;\forall i,j \in N: i \neq j, v \in V, r > 1, t \in T \tag{22}$$

Eqs. (23) and (24) are the relationships between the amount of ship fuel in the last node which should met in this period and the first node in the next period.

$$G_{jvrt} \leq G_{ivr'(t'-1)} - Fuel_{ij} + M(2 - X_{ijvr'(t'-1)} - Z_{vr'(t'-1)}) + MU_{jvrt} + M \textstyle\sum_{t''=t'}^{t-1} \alpha_{vt''} \quad \forall i,j \in N: i \neq j, v \in V, r = 1, r' \in R, t, t' \in T: t' \leq t \tag{23}$$

$$G_{jvrt} \leq FC_v + M(2 - X_{ijvr'(t'-1)} - Z_{vr'(t'-1)}) + M(1 - U_{jvrt}) + M \textstyle\sum_{t''=t'}^{t-1} \alpha_{vt''} \quad \forall i,j \in N: i \neq j, v \in V, r = 1, r' \in R, t, t' \in T: t' \leq t \tag{24}$$

Eq. (25) shows that the ship do not refuel in the port.

$$\sum_{i \in D} \sum_{v \in V} \sum_{r \in R} \sum_{t \in T} U_{ivrt} = 0 \tag{25}$$

Eq. (26) confirms that the fuel of ship is limited by its maximum capacity of fuel in each ship.

$$G_{ivrt} \leq FC_v \qquad \forall i \in N, v \in V, r \in R, t \in T \tag{26}$$

Eqs. (27) and (28) show that the decision variables must be feasible.

$$X_{ijvrt}, Z_{vrt}, \alpha_{vt}, U_{ivrt} \in \{0,1\} \tag{27}$$

$$Y_{ivrt}, Q_{pivrt}, L_{pivrt}, G_{ivrt}, Inv_{pit}, Sh_{pit} \geq 0 \tag{28}$$

3. Proposed solution

The literature approved that the routing and scheduling of ships models are classified as NP-hard problems (Alharbi et al., 2015; Song et al., 2015). This issue confirms the needs and benefits of the metaheuristics for solving these combinatorial models. The high complexity of the routing and scheduling of liner ships in large-scale instances motivate several researchers to propose novel metaheuristics (Ozcan et al., 2020). This study in addition to GA, applies two recent nature-inspired metaheuristics including KA and RDA. To improve the benefits of these recent and old metaheuristics, a novel hybrid algorithm is also developed to better address the proposed problem and to provide a comparison among these algorithms based on the solution time and quality.

First, we need to provide the encoding scheme to show that how a feasible solution can be generated. An encoding scheme of our model is given in Fig. 1. With this matrix, all possible routes are created according to the problem conditions. The dimension of this matrix is $1 \times 2P$, and P denotes the number of nodes in which the loading is done, and the numbers 1 through 2P are randomly permutated there. Since each loading node has its corresponding discharge node, in some routes, the problem conditions are not met, so unjustified solutions are eliminated using a heuristic algorithm.

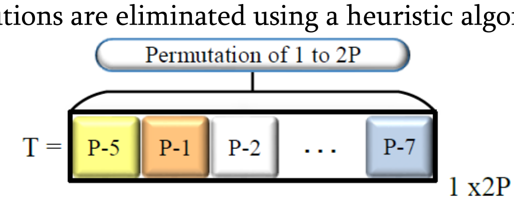

Fig. 1. Encoding scheme for establishing the route

For example, if there are 5 loading ports and 5 discharge ports and the random path created by the string chromosome T, then, a suggested route is the heuristic algorithm operates as follows:

8→9→1→2→7→3→5→10→4→6

First, nodes 8 and then 9 are checked. Since both nodes are discharge nodes and their prerequisites have not been met, they are not transferred to this matrix. Then node 1 is transferred to it, since it is a loading node. Each time that a node is moved to the matrix, the first matrix is checked from the beginning of the route, so after moving port 1 to the modified matrix, ports 8 and 9 are re-examined, and because their prerequisites have not been met, they remain in their positions. In the next step, node 2 is moved to the matrix, and still prerequisites of nodes 8 and 9 have remained unfulfilled. Node 7 is a discharge port, and its corresponding loading port (port 2) has already been serviced, so it is added to the continuation of the modified matrix. Port 3 has no prerequisite, and then discharge port 8 is added to the modified matrix because its prerequisite (port 3) has been serviced. This process repeats until all the ports are transferred. The modified route is as follows:

1→2→7→3→8→5→10→4→9→6

Based on the above encoding scheme, we run the metaheuristics. Following, the description of KA, RDA and the proposed novel hybrid algorithm, is studied. Note that as the GA is an old algorithm, many studies are existed for the interested readers to study on the details of this metaheuristic (Fathollahi-Fard, Ahmadi, Goodarzian, & Cheikhrouhou, 2020; Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2018, 2020; Hajiaghaei-Keshteli & Aminnayeri, 2013; Whitley, 1994).

3.1. Keshtel Algorithm (KA)

Swam intelligence is one of the main inspirations for the metaheuristics. Considering the swarm behavior of birds, bees and ants, is being a hot topic for metaheuristics studies. The Keshtel Algorithm (KA) is another swarm intelligence-based metaheuristic. This algorithm was firstly developed by developed by Hjiaghaei-Keshteli and Aminnayeri (Hajiaghaei-Keshteli & Aminnayeri, 2013). The KA is inspired by the feeding behavior of a dabbling dock, namely Keshtel, in *Anas* family.

With regards to behaviors of this type of birds, there live in Asia and normally in northern countries like Russia, Azerbaijan and Iran. They always migrate from northern lands in Russia to the north parts of Iran and Azerbaijan near the Caspian see. The Keshtels have an amazing behavior in their feeding. When they find a source food in the lake, other Keshtels approach to this luck Keshtel who firstly found a good food and they swirl together in a circle. Other Kehstels who cannot find a good source of the food, move to other parts of the lake or fly to another lake.

To model these behaviors of Keshtels, Hjiaghaei-Keshteli and Aminnayeri proposed a nature-inspired metaheuristic for solving optimization problems. They generated the initial Keshtels as a set of random solution in the lake. They divided this population into three groups (i.e. N_1, N_2 and N_3) with regards to the fitness or the cost of the objective function. N_1 is the group of the luck Keshtels who have found a good source of the food in the lake. $N2$ moves fast between the luck Keshtels to search the source foods. In fact, the best source food is the global solution and each Keshtel is able to find it is the best solution in all iterations. Finally the last group, i.e., N_3 population, is generated randomly in each iteration. They are new Keshtels which may land in the lake(Hajiaghaei-Keshteli & Aminnayeri, 2013).

As a metaheuristic, it is very important to find an interaction between two main search phases, i.e., intensification and diversification. In this metaheuristic, this classification of three groups, is very useful to explore the new search areas. The first group ($N1$) does the exploitation or intensification phases. Other groups help the algorithm to perform the diversification phase. Most importantly, $N3$ group finds a way for the algorithm to escape from the local solutions. To the best of our knowledge

[34-37], no paper contributes the KA in this research area. To have a conclusion about the steps of KA, a pseudo-code is addressed in Fig. 2.

```
Initialize Keshtels population.
Calculate the fitness and sort them in three types: N1, N2 and N3
X*=the best solution.
while (t< maximum number of iterations)
    for each N1
      Calculate the distance between this lucky Keshtel and all Keshtels.
      Select the closest neighbor.
      S=0;
      while (S< maximum number of swirling)
        Do the swirling.
        if the fitness (at least, one of objective functions has been improved) of this new position is better than prior
          Update this lucky Keshtel.
            break
        endif
        S=S+1
      endwhile
    endfor
    for each N2
      Move the Keshtel between the two Keshtels, randomly.
    endfor
    for each N3
      Create a random solution.
    endfor
    Merge the N1, N2 and N3 .
    Sort the Keshtels and form N1, N2 and N3 for next iteration.
    Update the X* if there is better solution.
     t=t+1;
end while
return X*
```

Fig. 2. The pseudo-code of KA

3.2. Red Deer Algorithm (RDA)

Evolutionary algorithms are another well-known classification of the metaheuristics. These algorithms are also nature-inspired algorithms. However, from the current to the next generation, only a group of animals who are probably stronger than other ones, will keep and other agents will be removed. As another evolutionary metaheuristic, Fathollahi-Fard et al., (Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2020) recently proposed the Red Deer Algorithm (RDA) inspired by an amazing behaviors of males and females in a breeding season.

This algorithm studies the behavior of red deers with regards to roaring, fighting and mating behaviors. These animals are naturally living in British Isles mainly in Scotland. In this regard, the scientists called them as Scottish Red Deer (*Cervus Elaphus Scoticus*) (Fathollahi-Fard et al., 2018). In a breeding season, the males which are also known as stags roar loudly and repeatedly to attract the females so-called hinds. Based on this feature of the males, the hinds select their preferable stag and he will create his territory and harem. The harem is a group of hinds and a commander as the head of this group manage and control them. The fighting act is always existed among males. Stags and commanders do a fighting and the winner will achieve the territory and harem. This competition among males is the main activity. The last part of this season is the mating behaviors among males and hinds and as a result, the new red deers will born for the next breeding season. Among all roaring, fighting and mating processes, the evolutionary concept to confirm that only strangest will always keep in nature and this rule is existed among red deers.

Fathollahi-Fard et al.,(Fathollahi-Fard, Hajiaghaei-Keshteli, & Tavakkoli-Moghaddam, 2020) modeled these facts as another evolutionary algorithm. They generated the first population of red deers as the random solutions. This population is divided into males and hinds. Then, males roar and based on their power, a group of them will be selected as the commanders and the others are stags. Next, a fight between commanders and stags occurs. After that for each commander, a harem will be generated by some random hinds. The number of hinds in a harem is directly related to the power of the commander. After that the commoner has this ability to mate with a number of his hinds in the harem and a few hinds in another harem. The stags which have not this chance to be a commander can mate with one hind which is closest to him geographically. After the mating, an offspring is created for each mating. Finally, for the next generation, the males will be selected as the best solutions among all available solutions and the hinds will be selected by an evolutionary mechanism like the roulette wheel selection method.

With these features, the authors developed an interesting and successful metaheuristic and called it RDA. According to the best of our knowledge(Fathollahi-Fard, Ahmadi, Goodarzian, et al., 2020), no paper uses the RDA in the area of the ships routing and scheduling problems. To have a brief illustration of RDA, its pseudo-code is available as seen in Fig. 3.

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
X*=the best solution.
while (t< maximum number of iterations)
    for each male RD
      A local search near his position.
      Update the position if better than the prior ones.
    end for
    Sort the males and also form the stags and the commanders.
    for each male commander
        Fight between male commander and stag.
        Update the position of male commander and stag.
    end for
    Form harems.
    for each male commander
        Mate male commander with the selected hinds of his harem randomly.
        Select a harem randomly and name it k.
        Mate male commander with some of the selected hinds of the harem.
    end for
    for each stag
        Calculate the distance between the stag and all hinds and select the nearest hind.
        Mate stag with the selected hind.
    end for
    Select the next generation with roulette wheel selection.
    Update the X* if there is better solution.
    t=t+1;
end while
return X*
```

Fig. 3. The pseudo-code of RDA

3.3. Proposed novel hybrid metaheuristic (H-RDKGA)

Based on the aforementioned description, it is approved that the KA uses a high exploitive behavior. The RDA is good at the exploration phase. The GA has also a classical crossover operator to do the explorative behavior. The proposed novel hybrid metaheuristic called as H-RDKAGA uses the aforementioned benefits.

In the proposed hybrid algorithm, the RDA acts as the main loop and two other algorithms improve the sub-loop of this algorithm. This hybrid metaheuristic uses the swirling process instead of roaring and fighting operators in the RDA. In this regard, each male performs the swirling process with its closest neighbor. The proposed hybrid algorithm also considers the crossover of the GA instead of the mating operator. Other steps are similar to the main RDA. Given more details of proposed H-RDKGA, a pseudo-code is provided as seen in Fig. 4.

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
X*=the best solution.
while (t< maximum number of iterations)
    for each male RD
        Calculate the distance between this male and all males.
        Select the closest neighbor.
        S=0;
        while (S< maximum number of swirling)
          Do the swirling.
          if the fitness of this new position is better than prior
            Update this lucky male.
              break
          endif
          S=S+1
        endwhile
    endfor
    Sort the males and also form the stags and the commanders.
    for each male commander
        Select a hind by roulette wheel selection.
        Mate (Crossover) male commander with the selected hind.
     end for
    for each stag
        Select a hind randomly.
        Mate (Crossover) stag with the selected hind.
    end for
    Select the next generation via roulette wheel selection.
    Update the X* if there is better solution.
    t=t+1;
end while
return X*
```

Fig. 4. The pseudo-code of H-RDKGA

4. Computational Results

Here, firstly, the performance of the metaheuristics is improved by a tuning approach to have a fair comparison. A full factorial design method is applied. Next, a comparative study is done to evaluate the efficiency and performance of algorithms in different criteria. Finally, some sensitivity analysis are done to assess the efficiency of the proposed model.

4.1. Tuning of metaheuristics

As all metaheuristics has a number of controlling parameters, the tuning is needed satisfactorily. Here, based on the concept of the Design of Experiment (DOE), all algorithms have been calibrated. This method is able to analyze the impact of different candidate values on the parameters of the algorithms and to evaluate the behavior of the algorithms. Without a good calibration of the parameters, the behavior of the metaheuristics are not reliable.

To do the tuning, the parameters of the given metaheuristics are considered. With regards to the DOE method, a full factorial method to analyze all possible experiments with regards to the levels, is done. The levels and tuned value for each parameter are given in Table 1. It should be noted that all candidate levels values are taken from similar studies in the literature (Fathollahi-Fard, Ahmadi, Goodarzian, et al., 2020).

Table (1): Tuning of metaheuristics.

Metaheuristic	Parameters	Levels			Tuned value
KA	Population size	100	150	200	100
	Maximum number of iterations	300	500	700	300
	Percentage of N1	0.1	0.2	0.3	0.1
	Percentage of N2	0.4	0.5	0.6	0.6
	Maximum number of swirling	5	10	15	10
RDA	Population size	100	150	200	150
	Maximum number of iterations	300	500	700	700
	Number of males	15	25	30	25
	Alpha	0.5	0.6	0.7	0.6
	Beta	0.7	0.8	0.9	0.7
	Gamma	0.8	0.9	1	0.8
GA	Population size	100	150	200	200
	Maximum number of iterations	300	500	700	500
	Rate of mutation	0.05	0.15	0.25	0.15
	Rate of crossover	0.6	0.7	0.8	0.8
H-RDKGA	Population size	100	150	200	150
	Maximum number of iterations	300	500	700	500
	Number of males	15	25	30	30
	Maximum number of swirling	5	10	15	15

4.2. Comparison among the employed metaheuristics

To do the comparison among the employed metaheuristics, nine test studies are benchmarked from the literature(Dulebenets et al., 2019). These tests are selected from small to large scale instances. As the model of our work is novel and differs from previous works, no comparison between our results and previous studies is done. Accordingly, we compare our metaheuristics with each other and the results of the exact solver.

As the metaheuristics are naturally random, we run each algorithm for 10 times and the best, the worst, the average and the standard deviation of solutions among runs are reported. An average of the computational time of the algorithms is noted. To check the validation of the results, an exact solver implemented by GAMS software is used (DICOPT solution which is used for non-linear models, in a computer with 1.7GB CPU and 6.0GB RAM). Table 2 provides all the results. It should be noted that the exact solver is not able to find a solution for the large-scale instances after one hour. But, all the metaheuristics can solve the problem in a few minutes. Based on this criterion, a companion is provided in Fig. 5 to show the behavior of the algorithms. The gap of the algorithms' solutions to validate the results of the metaheuristics, is shown in Fig. 6. To show the accuracy and robustness of the metaheuristics, some statistical tests by an interval plot are performed as depicted in Fig. 7.

Generally, the behavior of the algorithms in the criterion of the solution time (Fig. 5) is very close. Both hybrid algorithm and KA has a neck and neck competition. However, the KA is slightly better than all the metaheuristics. Fig. 6 confirms that the behavior of the algorithms in the criterion of the gap is also the same. Without a doubt, the proposed H-RDKGA outperforms other algorithms and its solution is very close to the global solution based on the results.

Finally, the robustness and the accuracy of the algorithms, statistically have been approved in Fig. 7. This report indicates that based on the average of the standard deviation of the results and the gaps of the algorithm in the interval plot, the proposed hybrid algorithm, i.e., H-RDKAGA is highly better than other algorithms and outperforms the best. After this algorithm, there is a little difference between the KA and the RDA. But, the RDA is better. The last algorithm is the GA as the weakest performance in this comparison.

Table (2): Comparison of algorithms (EX=exact solver; B=best, W=worst, A=average, SD=standard deviation, CPU=computational time based on the second)

Algorithm		**Test problems**								
		P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
EX	A	24283	28641	84180	119046	218907	476036	-	-	-
	CPU	18	64	201	836	1872	3315	3600	3600	3600
GA	B	24283	28641	84180	119046	221470	476124	694902	952906	120094
	W	27925	32937	98482	139038	257709	572564	812835	1118365	138304
	A	24283	28641	85637	120903	224095	497882	706813	972491	120265
	SD	4205	4960	15740	22090	40414	101164	129847	180812	20929
	CPU	22	17	22	32	42	65	79	96	102
KA	B	24283	28641	84180	119046	219968	480789	701712	962243	121270
	W	24525	28927	85021	123807	228766	504828	736797	1010355	127333
	A	24428	28812	84684	121902	225246	495212	722763	991110	124907
	SD	194	230	677	3834	7085	19358	28254	38745	4882
	CPU	18	15	20	28	38	58	72	88	92
RDA	B	24283	28641	84180	119046	219850	476362	687953	943376	118893
	W	24524	28926	85021	122617	226445	490652	708591	971677	122459
	A	24451	28840	84768	121545	224466	486365	702399	963186	121389
	SD	160	190	560	2382	4399	9532	13767	18879	2378
	CPU	24	18	26	33	43	66	78	95	106
H-RDKGA	B	24283	28641	84180	119046	218907	476101	681004	933847	117692
	W	24283	29213	85863	121426	223285	485623	694624	952523	120045
	A	24283	28927	85021	120236	221096	480862	687814	943185	118868
	SD	0	286	841	1190	2189	4761	6810	9338	1176
	CPU	22	16	20	26	40	62	72	90	94

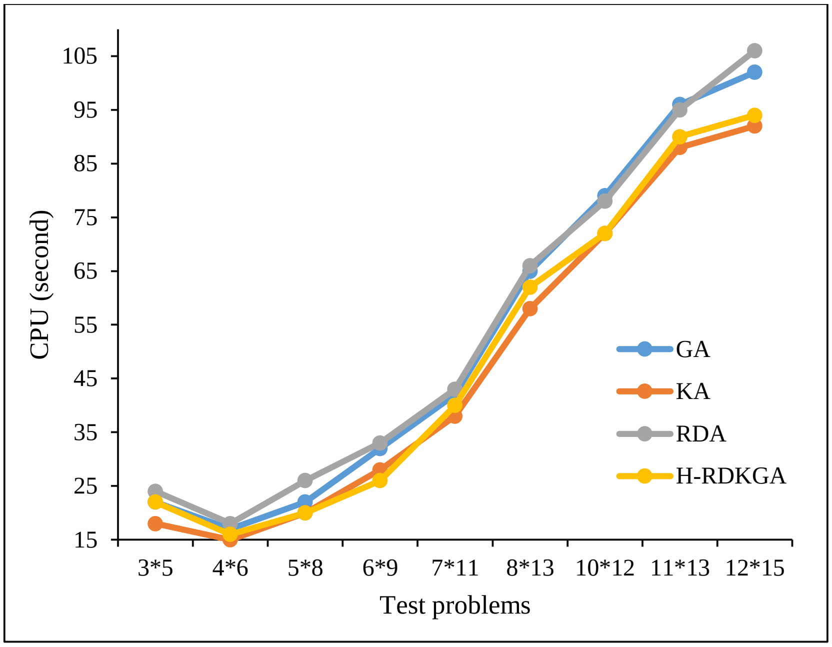

Fig. 5. Algorithms' behavior based on the computational time

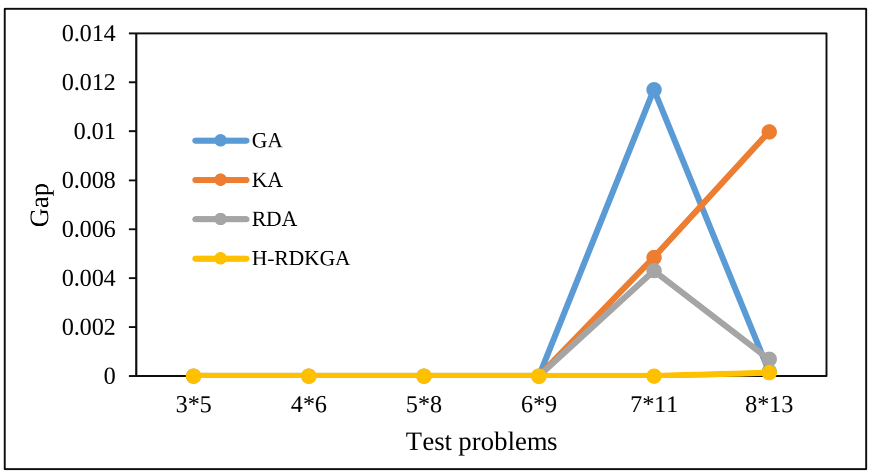

Fig. 6. Gap behavior of the metaheuristics

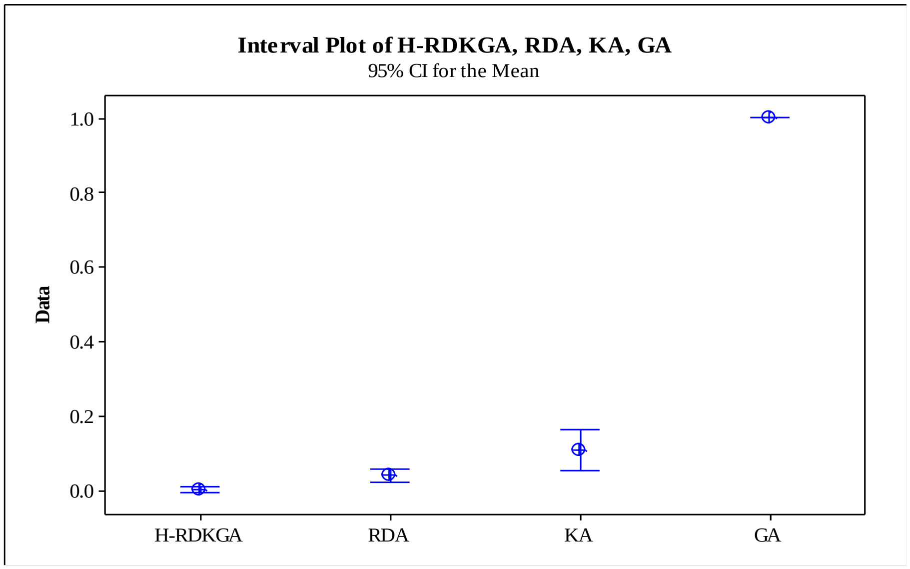

Fig. 7. Interval plots depicted by the metaheuristics' standard deviation

4.3. Sensitivity analysis

Here, to assess the proposed integrated optimization model, Fig. 8 illustrates the sensitivity of the average ship sailing speed, the average ship carrying capacity, the average handling productivity at ports, and the average frequency of service to the average freight rate.

It can be noticed that the average ship sailing speed was increased with the average freight rate. Therefore, the solution approach directed the ships to sail faster along the routes with higher average freight rates. This increase can be justified by the fact that the container demand in the integrated optimization model is proportional to the ship sailing speed. When the ship sailing speed was increased, the container demand was also increased for the routes with higher average freight rates. Hence, more revenue was generated from such routes, and the total turnaround profit was generally higher. Furthermore, the average carrying capacity was increased with the average freight rate. Therefore, the solution approach allocated larger ships to the routes with higher average freight rates. This increase can be explicated by the fact that when the average freight rate was higher, the container demand increased due to increasing ship sailing speed, and the solution approach aimed to load the additional container demand to the ships with higher carrying capacity (so that a higher profit could be achieved). Hence, it can be concluded that shipping lines would be able to generate more profit from the deployment of mega-ships at the routes with higher freight rates, which is in accordance with practice.

A longer duration between subsequent port visits was required to prevent an increase in the total cost of ship operating and the total cost of ship chartering for each route, as more frequent service of ports would necessitate the deployment of more ships (i.e., shipping line's own ships and/or chartered ships) that may further reduce the total turnaround profit to be generated by the shipping line.

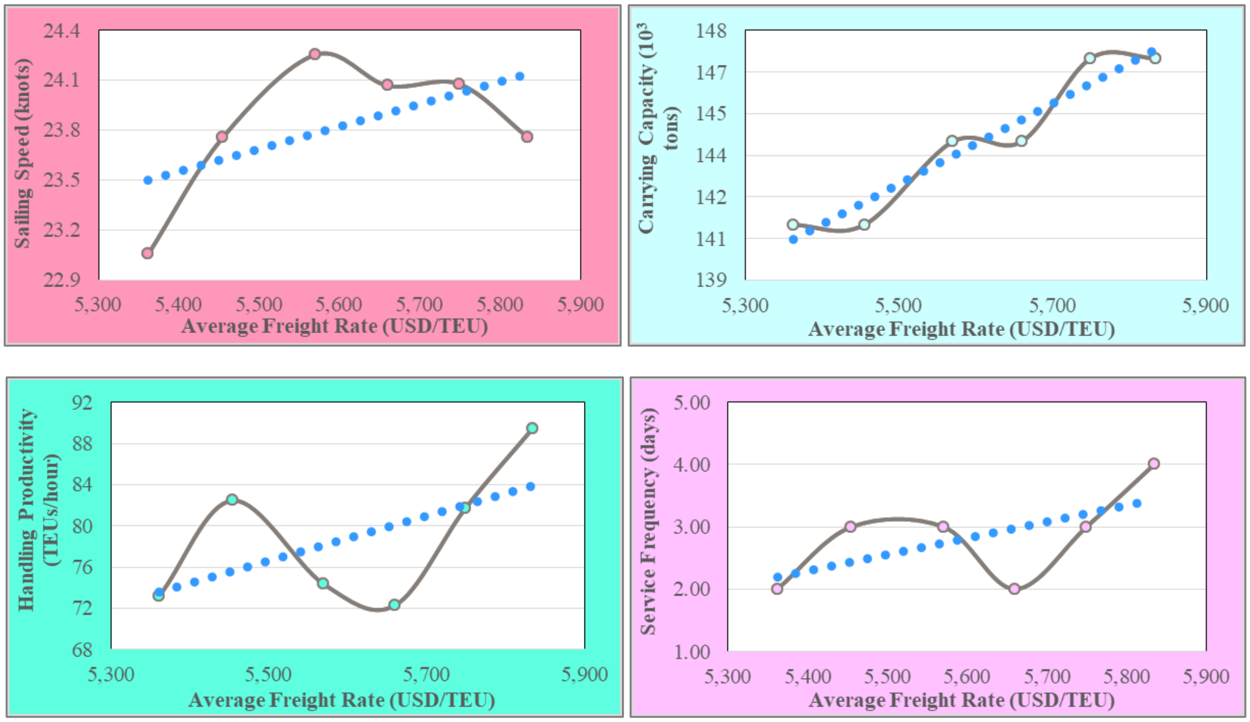

Fig. 8 Sensitivity of the average ship sailing speed, the average ship carrying capacity, the average handling productivity at ports, and the average frequency of service to the average freight rate.

5. Conclusion

In this paper, concerning to recent changes in the offshore logistics and liner ships planning, a novel optimization model is proposed with regards to the magnitude of maritime transportation in the offshore logistics. One of the common strategies is the deployment of large ships. The current practice in the liner shipping industry is to deploy a combination of ships of different types with different carrying capacities, especially at the routes with a significant demand. However, heterogeneous fleets of ships have been investigated by a very few studies addressing the tactical-level decisions in liner shipping of offshore logistics. In this regard, an integrated optimization model is developed. This paper deals with a multi-period multi-product model as a NP-hard problem with high computational time. So, we investigate the problem, in small, medium and large dimensions which fall in two sets of numerical examples, then for small sizes, the exact solver is used to obtain the best solution. One of the main innovations of this study is to propose a novel hybrid metaheuristic based on the advantages of Genetic Algorithm (GA), Keshtel Algorithm (KA) and Red Deer Algorithm (RDA) as a recent developed algorithm. We also obtain the main algorithms to show the high-performance of the proposed hybridized algorithm. With the use of the proposed hybrid metaheuristic, we did some sensitivity analyses to study different types of ships as the main contribution of the proposed model. Finally, the result confirm the applicability and efficiency of the proposed hybrid algorithm and the developed model in this context.

For future studies, there are many insightful recommendations. Extending the proposed problem by adding more sustainability factors such as the green emissions, suppliers' risk and satisfaction levels. More broadly, employing new metaheuristics such as the social engineering optimizer [36] is another good continuation of this study. At last but not least, the development and application of the proposed hybrid approach in other optimization problems such as healthcare routing and scheduling [37] is highly recommended.

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