Original Research

A Multi-product, Multi-period and Multi-hub Routing and Scheduling Model for Offshore Logistics

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Abstract
Logistics in the upstream oil industry is a critical task as rigs need consistent support for ongoing production. In this paper, a multi-period, multi-product and multi-hub routing and scheduling model is presented for offshore logistics problems. As rigs can be served in specific time intervals, time window constraints are considered in the proposed model. Despite classic VRP models, vessels are not forced to return hubs at the end of duty days. Also, a vessel may leave and return to hubs several times during the planning horizon. Moreover, the model determines which vessels are applied on each day. In other words, a vessel may be applied on some days and be inactive on other days of the planning horizon. To develop a compromise model, the fueling issue is considered in the model. As a rig can be supplied by different vessels in real-world cases, the proposed model is split delivery. Based on these challenges and contributions, this research deploys an integrated optimization of routing and scheduling of vessels for offshore logistics. This paper deals with a combinatorial optimization model which is NP-hard. Hence, the Genetic Algorithm is applied as the solution approach. The average gap between objective functions of GAMS and the GA is only 1.18 percent while saving CPU time in GA is much more than GAMS (about 78.16 percent on average). The results confirm the applicability and efficiency of the GA.

Keywords- Routing; Scheduling; Mathematical model; Offshore logistics; Genetic Algorithm

INTRODUCTION

Nowadays, one of the most challenging issues in designing an efficient offshore logistics network is continuous growth in demand. Regarding the demand and other important factors, different strategies have been adopted by shipment companies. One of the common strategies is the used of large vessels [1]. Large vessels assist hubs with economies of scale, savings in fuel consumption, emission reduction, and lower transportation cost per unit [2]. Logistics in the upstream oil industry is a critical task as rigs need consistent support for ongoing production. The main part of the total cost in gas and oil industries is related to upstream operations. Moreover, logistics cost is among the main parts of the upstream oil industries' cost. Offshore facilities, i.e. rigs, need continuous and on-time support from the hubs. This is done by different types of vessels as well as other vehicles like helicopters. It is clear that a disruption in supporting rigs can impose a large amount of cost on rigs. So, exact planning is crucial for offshore logistics. As oil rigs need a lot of equipment and manpower that must be provided at the required time, offshore logistics is an important and complex problem. Delay in timely delivery of equipment to rigs can impose very high costs [2]. The cost of late delivery to the rigs is more than the transportation cost and renting a ship [3]. Therefore, it is necessary to carry out offshore logistics planning using optimization models in such a way that the equipment delivery to the rigs is not delayed and the costs are minimized.

In this paper, a new mathematical model is developed for multi-period, multi-product and multi-hub offshore logistics problems. A large number of issues that are common in real-world cases have been considered in this model. The offshore logistics network considered in this paper includes some hubs that supply the requested demands of rigs using several vessels. Rigs request different goods in different periods. As a rig may be served by more than a vessel and in specific time intervals, the model is split delivery type including time window constraints. However, the proposed model is significantly distinguished from classic VRP models. In the proposed model, vessels are not forced to return hubs at the end of duty days. Also, a vessel may leave a hub and return several days later. Moreover, as the problem is formulated in a multi-period horizon, routing constraints are much more complicated than classic routing problems. In this paper, a new Mixed Integer Programming model is presented to formulate a real-world offshore logistics problem. The proposed model includes routing, scheduling, supply and fuel constraints. As the problem is considered in a multi-period horizon and a vessel is not necessarily return hub at the end of the operation day, routing constraints are completely different from what is common in classic VRP models. This is the main contribution of the model. To solve such a complicated and NP-hard model, the Genetic Algorithm is applied. The conceptual model of the research is shown in Figure 1.

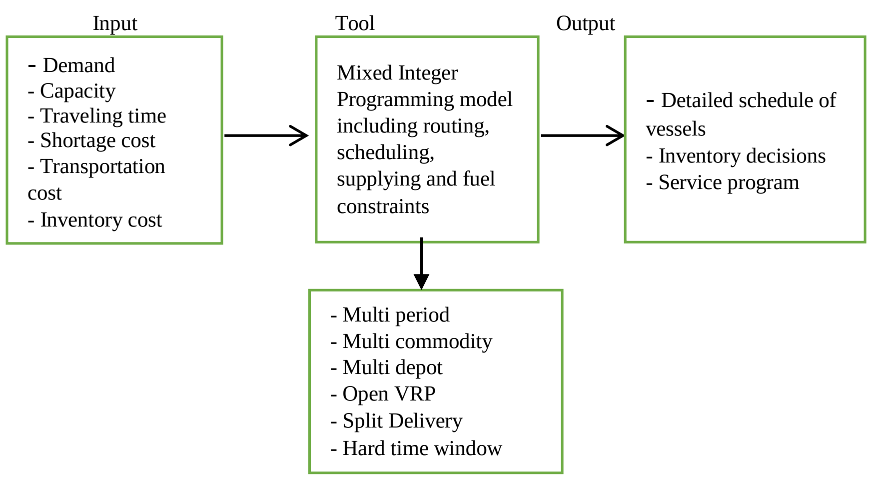

FIGURE 1
THE CONCEPTUAL MODEL

The rest of the paper is organized as follows: In the next section, recent literature is briefly reviewed. Then, the framework of the proposed problem and mathematical model is explained in detail. Then, the solution approach and computational results are discussed. Finally, concluding remarks are presented.

LITERATURE REVIREW

In this section, recent studies on liner ships and offshore logistics are reviewed. Some of the related researches include the aforementioned decisions have been conducted to date [3]. Giovannini and Psaraftis [4] discussed 1service frequency to maximize the total profit. Huang et al. [5] presented a mechanism to reposition empty containers. Ozcan et al. [6] designed ship schedules while addressing the cargo allocation problem and considering transshipment operations and transit times. Zhang et al. [7] studied shipment scheduling for a two-way tidal channel, whose depth was impacted by tides. Alehashemi et al., [8] proposed a novel three-phase algorithm to find the optimal fleet of vessels and a schedule of the routes. Amiri et al., [9] considered a hub location and ship routing problem for a real-world case. They formulated the model with VRP with time window constraints. In another research, Amiri et al., [10] generated a Lagrangian decomposition solution for a two-echelon node-based location-routing of an offshore logistics network design problem. Most notably, Borthen et al., [11] minimized the total cost of sailing costs and the changes from the baseline solution. A traditional genetic metaheuristic was used to find a tradeoff between two solutions. Abbasi-Pooya and Husseinzadeh Kashan [12] proposed models for offshore crew transportation by helicopters. Leggate et al. [13] developed crew scheduling (as well as rescheduling) problems in offshore logistics. Astoures et al. [14] discussed providing fuel requested by rigs. They formulated the model as a ship routing problem with time window constraints. Cuesta et al. [15] formulated a single hub ship routing problem considering regular and express voyages. If the demand for a rig exceeds ship capacity, an express voyage is scheduled.

Silva et al. [16] formulated an MILP model for an offshore logistics to balance fleet utilization and fuel cost. They used a number of data sets as benchmarks to justify the proposed model and solution approach. Bittencourt et al. [17] proposed an integrated simulation and optimization approach for offshore logistics and applied it in a Brazilian case. Based on benchmarks, they showed that their approach outperformed previous models in decreasing the number of applied vessels. Kondratenko et al. [18] formulated a model for an offshore logistics to supply drilling equipment to the rigs considering accidental events. They used the Artificial Bee Colony algorithm as the solution approach and justified it using some real case studies. Kisialiou et al. [19] formulated vessel scheduling under weather uncertainty for a Norwegian offshore oil and gas case. The model found the optimum composition of fleet among different types of vessels. Nafstad et al. [20] formulated personnel transportation from rigs to shore by helicopters. They considered the problem as a VRP with pickup and delivery with heterogeneous fleet. The main contribution of this paper is that vessels are not necessarily return hubs at the end of the operation day. This causes routing constraints to be more complex and different from what is common in classic VRP models. Moreover, the proposed model integrates routing, scheduling, supply and fuel constraints.

PROBLEM STATEMENT AND MATHEMATICAL MODEL

In this section, the problem and mathematical model are described in detail. To formulate the model in such a way that covers real-world conditions, four sets of constraints have been formulated: routing, scheduling, supplying and fueling constraints. Here, the specifications of each section are described:

To formulate the routing section, set N is defined to show all nodes of the network, including hubs (H) and rigs (D). So, $N = H \cup D$. We also use i, i' and j as indices of nodes. Clearly, i-j is considered as an arc in this graph. A fleet of vessels, which are indexed by v ($v \in V$), are applied to serve rigs by supplying different types of products ($p \in P$). The hub from which vessel v starts its trip is called H_v. As this is a multi-period problem, index t is introduced to show individual days of planning horizon ($t \in T$). Regarding the problem being formulated in a multi-period horizon, routing constraints are much more complicated than classic routing problems. For instance, if a vessel ends its trip on day t at rig i, it should resume the trip on day $t+1$ from i. To formulate routing constraints, index r is defined to indicate the trip number. To illustrate, suppose that a vessel starts its duty from hub i to rig i' and continues it by covering arcs i'-j and j-j' (i,i',j and j' are nodes of the network). In this case, r equals one for arc i-i', equals two for arc i'-j and equals three for j-j'.

Three binary variables are defined for the routing section of the model. X_{ijvrt} equals one if vessel v covers arc i-j at the r^{th} trip on day t. Also, Z_{vrt} equals one if vessel v ends its duty on day t in the r^{th} trip. In other words, if the last trip of vessel v on day t is related to its r^{th} movement, Z_{vrt} equals one. As a vessel is not necessarily applied on all days of the planning horizon, α_{vt} is defined to show whether vessel v is applied on day t.

In the scheduling section of the model, some new parameters and variables should be defined. Parameter Tra_{ij} shows the required time for covering arc i-j (traveling time from node i to j). To formulate time window constraints, (un)loading time is shown by UL_i and (a_i, b_i) is time window to serve node i. Positive variable Y_{ivrt} shows arriving time of vessel v (after r^{th} trip) to node i on day t.

In the supplying section of the model, some issues such as demand and capacity are considered. As each rig requires a certain type of goods (items), P_i means the set of required goods for rig i. Also, Dem_{pit} is the demand of rig i for good p on day t. Capacity of vessels and weight of goods are shown by Cap_v and W_p, respectively. Moreover, IC_{pi}

and SC_{pi} are inventory and shortage cost of good p for rig i, respectively. Four decision variables are defined for this section. Q_{pivrt} is the amount of good p delivered to rig i by vessel v after its r^{th} trip on day t. L_{pivrt} is the remaining amount of good p on vessel v when it reaches i after its r^{th} trip on day t. Finally, the shortage of good p for rig i on day t is shown by Sh_{pit}.

At the end, the parameters and variables of the fueling section of the model are described. Required fuel for covering arc *i-j*, fuel capacity of vessel *v* and required time for fueling is shown by $Fuel_{ij}$, FC_v and FT_v, respectively. Also, TC_{ij} is the cost of covering arc *i-j* (fuel cost). U_{ivrt} is a binary variable indicating whether vessel *v* is going to fuel at node *i* before starting r^{th} trip on day *t*. Also, G_{ivrt} is the remaining fuel of vessel *v* when it leaves node *i* after its r^{th} trip on day *t*. Below, the mathematical formulation is presented. To simplify the description, model constraints are divided into four sections: routing, scheduling, supplying and fueling constraints. The proposed model is based on the following assumptions:

- The model is considered for a multi-period and multi-product problem.
- The problem is a pickup and delivery VRP with time window.
- A vessel is not necessarily return hubs at the end of duty day and can end its duty to a rig.
- If a vessel is not going to be used on day *t*, it should return a hub at the end of *t*-1.
- Shortage is allowed and can be compensated in the following time periods.
- Fueling is done in hubs, not rigs.
- Vessels are heterogeneous.

At first, sets and indices, parameters and variables are presented as follows:

Sets and indices:

H	Set of all hubs
D	Set of all rigs
N	Set of all nodes, including hubs and rigs ($N = H \cup D$)
i, i', j	Index of node
V	Set of all vessels
v	Index of vessel
H_v	The hub of vessel *v* at the beginning of the planning horizon
P	Set of all products (goods)
p	Index of product
P_i	Set of all products required by rig *i*
T	Set of all time periods (days)
$t, t',, t''$	Index of time periods (day)
R	Set of all trip rounds
r, r'	Index of trip round

Parameters

TC_{ij}	Travelling cost from *i* to *j*
Tra_{ij}	Travelling time from *i* to *j*
$Fuel_{ij}$	Required fuel to travel from *i* to *j*
SC_{pi}	Shortage cost of product *p* for rig *i*
IC_{pi}	Cost of holding one unit of product *p* in rig *i* in a time period
Dem_{pit}	Demand of rig *i* from product *p* on day *t*
W_p	Weight of one unit of product *p*
UL_i	Unloading time of the demand of rig *i*
FT_v	Required time for fueling vessel *v*
FC_v	Fuel capacity of vessel *v*
Cap_v	Capacity of vessel *v*
(a_i, b_i)	Time window for rig *i*
M	Big number

Variables

X_{ijvrt} Binary variable indicating whether vessel *v* covers arch *i*-*j* in its *r*th travel on day *t*
Sh_{pit} Unfulfilled demand of rig *i* from product *p* on day *t*
Inv_{pit} Inventory of rig *i* from product *p* at the end of day *t*
α_{vt} Binary variable indicating whether vessel *v* is applied on day *t*
Z_{vrt} Binary variable indicating whether vessel *v* ends its mission on day *t* at its *r*th travel
Y_{ivrt} Arriving time of vessel *v* to node *i* on day *t* (after *r*th trip)
U_{ivrt} Binary variable indicating whether vessel *v* is going to fuel at node *i* before starting its *r*th trip on day *t*
Q_{pivrt} The amount of product *p* delivered to rig *i* by vessel *v* after its *r*th trip on day *t*
L_{pivrt} The remaining amount of product *p* on vessel *v* when it reaches *i* after its *r*th trip on day *t*
G_{ivrt} The remaining fuel of vessel *v* when it leaves node *i* after its *r*th trip on day *t*

I. Objective function

The objective function of the model is cost minimization and is written as follows:

$$Min \sum_{i\in N}\sum_{\substack{j\in N:\\ j\neq i}}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T} TC_{ij}X_{ijvrt} + \sum_{i\in D}\sum_{p\in P_i}\sum_{t\in T} SC_{pi}Sh_{pit} + \sum_{i\in D}\sum_{p\in P_i}\sum_{t\in T} IC_{pi}Inv_{pit} \tag{1}$$

The first term of the objective function (1) is to minimize transportation (fuel) costs. The second and the third terms show shortage and inventory costs, respectively.

II. Routing constraints

The routing section of the model significantly differs from classic VRP models. As the problem is multi-period type, vessels are not forced to return hubs at the end of each duty day. A vessel may end its duty on day *t* to a rig and resume its duty on the next day from that rig. Moreover, a vessel may be inactive on day *t*. If so, it should return a hub at the end of *t*-1. In other words, a vessel cannot spend its off day in a rig. Below, a set of routing constraints is presented:

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

$$\alpha_{vt} - \sum_{t'=1}^{t-1}\alpha_{vt'} \leq \sum_{\substack{j\in N:\\ j\neq i}} X_{ijvrt} \quad \forall v\in V, i=H_v, r=1, t\in T \tag{3}$$

$$\sum_{\substack{i\in N:\\ i\neq j}} X_{ijvrt} - Z_{vrt} \leq \sum_{\substack{i\in N:\\ i\neq j}} X_{jiv(r+1)t} \quad \forall j\in N, v\in V, r\in R, t\in T \tag{4}$$

$$\sum_{i\in N}\sum_{\substack{j\in N:\\ j\neq i}} X_{ijvrt} = \sum_{i\in N}\sum_{\substack{j\in N:\\ j\neq i}} X_{ijv(r+1)t} + Z_{vrt} \quad \forall v\in V, r\in R, t\in T \tag{5}$$

$$\sum_{i\in N}\sum_{\substack{j\in N:\\ j\neq i}} X_{ijvrt} \leq 1 \quad \forall v\in V, r\in R, t\in T \tag{6}$$

$$\alpha_{vt} - \alpha_{v(t+1)} \leq \sum_{i\in N}\sum_{\substack{j\in H:\\ j\neq i}} X_{ijvrt} + M(1-Z_{vrt}) \quad \forall v\in V, r\in R, t\in T \tag{7}$$

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

Equation (2) indicates that if a vessel is going to be applied on day *t*, it should perform its first trip on that day. In other words, a vessel cannot be applied without initiating its trip. Constraint (3) ensures that a vessel starts its first trip of the planning period from the related hub. Constraint (4) shows that if a vessel covers an arc while it is not on its last trip on that day, it should perform at least one other trip. Constraint (5) shows that if a vessel covers an arc and does not cover any arc afterward, it is assumed as its last trip on that day. Constraint (6) ensures that a vessel cannot cover more than one arc during a single trip. Relation (7) shows that if a vessel is not going to be applied on day *t*, it should return a hub at the end of *t*-1. Note that *M* is a big number. Constraint (8) ensures the trip continuity of a vessel on consecutive days. If a vessel ends its duty on day *t* at rig *i*, it should resume its duty on *t*+1 form *i*.

III. Scheduling constraints

Set of scheduling constraints are as follows:

$$Y_{jvrt} \geq Y_{iv(r-1)t} + UL_i + Tra_{ij} + FT_v U_{ivrt} - M\left(1 - X_{ijvrt}\right)$$
$$\forall i, j \in N: i \neq j, v \in V, r \in R, t \in T \quad (9)$$

$$Y_{ivrt} \leq 1440 \qquad i \in N, v \in V, r \in R, t \in T \quad (10)$$

$$Y_{jvrt} \geq a_j - M(1 - \sum_{\substack{i\in N:\\ i\neq j}} X_{ijvrt}) \quad \forall j \in D, v \in V, r \in R, t \in T \quad (11)$$

$$Y_{jvrt} \leq b_j + M(1 - \sum_{\substack{i\in N:\\ i\neq j}} X_{ijvrt}) \quad \forall j \in D, v \in V, r \in R, t \in T \quad (12)$$

$$Y_{ivrt} \leq M * \sum_{\substack{j\in N:\\ j\neq i}} X_{jivrt} \qquad \forall i \in N, v \in V, r \in R, t \in T \quad (13)$$

Constraint (9) shows that a vessel arrives at *j* after arriving *i*, unloading its demand, fueling (if needed) and spending travelling time from *i* to *j*. Also, Constraint (9) can be treated as a sub-tour elimination constraint. Relation (10) ensures that arriving time of a vessel to a node cannot exceed 24 hours. Relations (11) and (12) dictate time windows obligation. Constraint (13) shows the rational relation between decision variables. If Y_{ivrt} takes a value, $\sum_{\substack{j\in N:\\ j\neq i}} X_{jivrt}$ will be equal to one.

IV. Supplying constraints

The main supply constraints include rigs' demand, capacity of vessels and balance of goods in two consecutive nodes visited by a vessel.

$$\sum_{v\in V}\sum_{r\in R} Q_{pivrt} + Inv_{pi(t-1)} + Sh_{pit} = Dem_{pit} + Sh_{pi(t-1)} + Inv_{pit} \qquad \forall i \in D, p \in P_i, t \in T \quad (14)$$

$$\sum_{p\in P} W_p L_{pivrt} \leq Cap_v \qquad \forall i \in D, v \in V, r \in R, t \in T \quad (15)$$

$$L_{pjvrt} \leq L_{piv(r-1)t} - Q_{piv(r-1)t} + M(1 - X_{ijvrt}) \qquad \forall i \in D, j \in N: i \neq j, p \in P, v \in V, r \in R: r > 1, t \in T \quad (16)$$

$$L_{pjvrt} \leq L_{pivr'(t-1)} - Q_{pivr'(t-1)} + M(3 - \sum_{\substack{i' \in N: \\ i' \neq i}} X_{i'ivr'(t-1)} - Z_{vr'(t-1)} - X_{ijvrt})$$
$$\forall i \in D, j \in N: i \neq j, p \in P, v \in V, r = 1, r' \in R, t \in T \quad (17)$$
$$Q_{pivrt} \leq L_{pivrt} \quad \forall i \in N, p \in P, v \in V, r \in R, t \in T \quad (18)$$
$$\sum_{p \in P} Q_{pivrt} + \sum_{p \in P} L_{pivrt} \leq M * \sum_{\substack{j \in N: \\ j \neq i}} X_{jivrt} \quad \forall i \in N, v \in V, r \in R, t \in T \quad (19)$$

Equation (14) is demand constraint. According to this constraint, if the required demand of a rig is not met, the shortage is considered. Relation (15) is capacity constraint of vessels. Relation (16) indicates the balance of goods in two consecutive nodes visited by a single vessel in a day. Similarly, Constraint (17) indicates the balance of goods in two consecutive nodes visited by a single vessel in two consecutive days. In other words, it shows the balance of goods between the last rig visited on day t and the first rig visited on day *t*+1. Relation (18) ensures that amount of delivery does not exceed the available goods in the vessel. Finally, Relation (19) shows that if a rig is served, it should be visited. Similar to (13), if $\sum_{p \in P} Q_{pivrt}$ or $\sum_{p \in P} L_{pivrt}$ take a value, $\sum_{\substack{j \in N: \\ j \neq i}} X_{jivrt}$ will be equal to one.

V. Fuel constraint

To develop a compromise model, fueling issue is considered in the model. A vessel can fuel only in hubs. Fueling constraints are as follows:

$$G_{ivrt} \geq Fuel_{ij} - M(1 - X_{ijvrt}) \quad \forall i, j \in N: i \neq j, v \in V, r \in R, t \in T \quad (20)$$
$$G_{jvrt} \leq G_{iv(r-1)t} - Fuel_{ij} + M\left(1 - X_{ijv(r-1)t}\right) + MU_{jvrt} \quad \forall i, j \in N: i \neq j, v \in V, r > 1, t \in T \quad (21)$$
$$G_{jvrt} \leq FC_v + M\left(1 - X_{ijv(r-1)t}\right) + M\left(1 - U_{jvrt}\right) \quad \forall i, j \in N: i \neq j, v \in V, r > 1, t \in T \quad (22)$$
$$G_{jvrt} \leq G_{ivr'(t'-1)} - Fuel_{ij} + M(2 - X_{ijvr'(t'-1)} - Z_{vr'(t'-1)}) + MU_{jvrt} + M \sum_{t''=t'}^{t-1} \alpha_{vt''}$$
$$\forall i, j \in N: i \neq j, v \in V, r = 1, r' \in R, t, t' \in T: t' \leq t \quad (23)$$
$$G_{jvrt} \leq FC_v + M(2 - X_{ijvr'(t'-1)} - Z_{vr'(t'-1)}) + M(1 - U_{jvrt}) + M \sum_{t''=t'}^{t-1} \alpha_{vt''}$$
$$\forall i, j \in N: i \neq j, v \in V, r = 1, r' \in R, t, t' \in T: t' \leq t \quad (24)$$
$$G_{ivrt} \leq FC_v \quad \forall i \in N, v \in V, r \in R, t \in T \quad (25)$$
$$\sum_{i \in D} \sum_{v \in V} \sum_{r \in R} \sum_{t \in T} U_{ivrt} = 0 \quad (26)$$
$$G_{ivrt} \leq M \sum_{\substack{j \in N: \\ j \neq i}} X_{ijvrt} \quad \forall i \in N, v \in V, r \in R, t \in T \quad (27)$$

Constraint (20) ensures that a vessel has sufficient fuel for covering arc *i*-*j*. Relations (21) and (22) show the amount of fuel in a vessel in two consecutive nodes (*i* and *j*) covered in a single day. Constraint (21) is valid if the vessel does not take fuel in *i* while (22) is valid if the vessel takes fuel in *i* before traveling to *j*. Similarly, Relations (23) and (24) show the amount of fuel in two consecutive nodes (*i* and *j*) covered on two consecutive days (*i* is the last node visited by the vessel on day *t* and *j* is the first one visited on *t*+1). Constraint (25) indicates the fuel capacity of vessels. Relation (26) ensures that a vessel cannot take fuel in rigs. Finally, Constraint (27) is interpreted like (13) and (19).

SOLUTION APPROACH AND COMPUTATIONAL RESULTS

The literature approved that the routing and scheduling of ship models are classified as NP-hard problems. 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 motivates several researchers to propose novel metaheuristics. This study applies GA to provide a comparison with the exact solver based on the solution time and quality. GA is a traditional metaheuristic that has been used in many optimization models, especially the optimization of offshore logistics. Each solution is called a chromosome. This algorithm includes three important parts including selection, crossover and mutation: The selection process aims to evaluate the population to select the parents for the crossover and mutation operators.

In the crossover process, P_n is the probability of performing the crossover operator. Arbitrarily, a random number r is determined in the interval [0,1]. If $r \geq P_n$, the chromosome would be considered as the parent. The last section of GA is the mutation operator. Note that P_m is the probability of mutation. A multi-point jump operation is used accordingly. For each chromosome, a random number r is defined in interval [0,1]. If $r \geq P_m$, this chromosome would have this chance to select as the parents. Finally, the GA is terminated up to a maximum number of K iterations. For each iteration, the aforementioned processes are done. In this paper, 25 test problems are generated on different scales. Problems dimensions are reported in Table 1, where H, D, V, T and P show the number of hubs, rigs, vessels, planning horizon days and products, respectively. Some of these test problems can be solved using GAMS in a reasonable time. However, some of the large scale ones remain unsolved due to the NP-hardness of the problem. To validate GA as a proper solution approach for this problem, the results of GA are compared with GAMS. The results shown in Table 2 declare that using GA saves 78.16 percent in CPU time in turn of only 1.18 percent gap in objective function value (on average). Figure 2 shows the comparison of final solutions reached by GAMS and GA while Figure 3 shows the saving in CPU time. All these results confirm the validation of GA as a proper solution approach for this problem.

TABLE 1
PROBLEM DIMENSIONS

Problem Number	H	D	V	T	P
1	1	3	2	3	2
2	1	5	2	5	3
3	2	6	2	5	3
4	2	8	3	7	3
5	3	9	3	7	4
6	3	11	3	7	5
7	3	12	3	8	5
8	4	14	4	10	7
9	4	15	4	11	8
10	4	16	4	12	8
11	5	17	4	12	10
12	5	19	5	12	10
13	5	20	5	15	12
14	6	20	5	17	15
15	6	22	5	17	20
16	6	24	6	19	25
17	7	24	6	19	30
18	7	25	6	20	35
19	7	25	7	20	40
20	7	26	7	20	45
21	8	28	7	22	45
22	8	28	8	22	50
23	8	28	8	25	55
24	8	30	8	25	60
25	8	30	8	25	65

TABLE 2
COMPUTATIONAL RESULTS

		GA		GAMS		Comparison
Problem number	Total cost (Dollars)	CPU time (Seconds)	Total cost (Dollars)	CPU time (Seconds)	Gap in the objective function (%)	Improvement in CPU time (%)
1	225,622	10	225,622	12	0.00	16.67
2	366,666	28	366,666	48	0.00	41.67
3	402,094	33	402,002	160	0.02	79.38
4	455,079	105	453,072	556	0.44	81.12
5	487,120	170	477,110	1326	2.10	87.18
6	513,232	350	510,221	2408	0.59	85.47
7	566,397	445	556,385	3058	1.80	85.45
8	569,889	507	559,876	4965	1.79	89.79
9	581,713	709	571,699	7005	1.75	89.88
10	608,584	890	600,570	12075	1.33	92.63
11	615,566	905	605,551	15522	1.65	94.17
12	636,472	952	619,957	17590	2.66	94.59
13	651,444	970	-	-	-	-
14	683,941	1075	-	-	-	-
15	731,517	1200	-	-	-	-
16	755,878	1234	-	-	-	-
17	801,223	1537	-	-	-	-
18	846,255	1790	-	-	-	-
19	878,517	2087	-	-	-	-
20	891,152	2560	-	-	-	-
21	941,000	2745	-	-	-	-
22	963,533	3046	-	-	-	-
23	971,534	3468	-	-	-	-
24	1,005,220	3944	-	-	-	-
25	1,120,344	4005	-	-	-	-

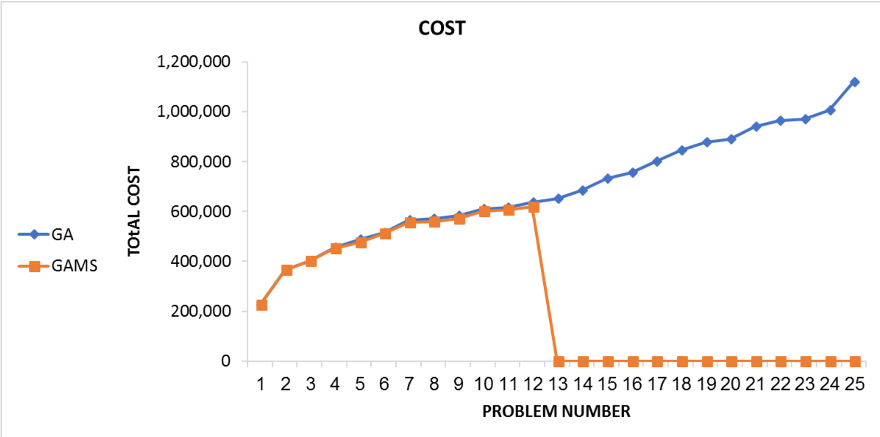

FIGURE 2
THE COMPARISON OF OBJECTIVE FUNCTION VALUES IN GAMS AND GA

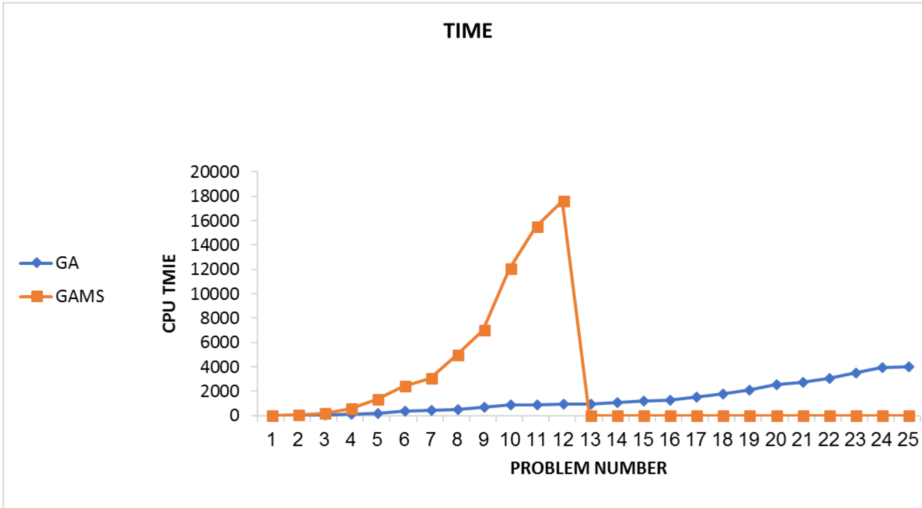

FIGURE 3
COMPARISON OF CPU TIME IN GAMS AND GA

For more analysis, the last test problem has been considered and sensitivity analysis has been performed on the number of vessels. The results indicate that adding two vessels lead to sharp decrease in total cost. It means that by increasing the number of vessels from 8 to 10, a 17 percent decrease is caused in the total cost. According to Figure 4, although adding vessels to 11 and 12 also leads to cost reduction (from 929,878 dollars to , the amount of decrease may not be preferable. In fact, if the vessel cost is more than 10,083 dollars (difference of the objective functions with 10 and 11 vessels), the best number of vessels will be 10.

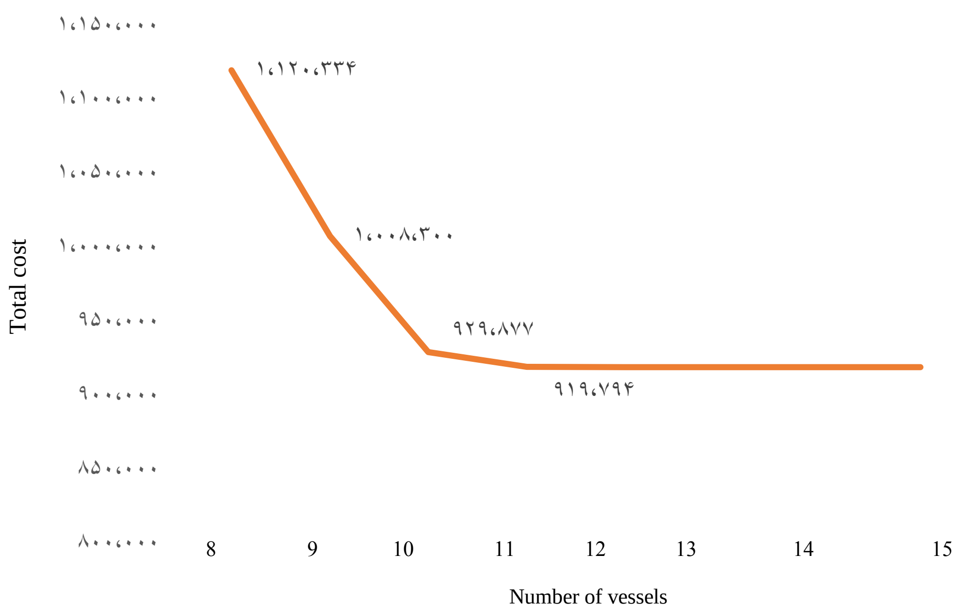

FIGURE 4
SENSITIVITY ANALYSIS ON THE NUMBER OF VESSELS

CONCLUSION

Providing goods and equipment at the right time is a critical issue in offshore logistics as delay cost is considerable in these systems. In this paper, a novel mathematical model has been developed for offshore logistics. The model is a multi-period, multi-product and multi-hub routing and scheduling problem. In the presented model, routing, scheduling, supplying and fueling constraints have been considered. The presented model includes several real-world constraints and is distinguished from classic VRP models in two aspects. Despite classic VRP models, vessels are not forced to return hubs at the end of each day. Moreover, it may leave and return to hubs several times during the planning horizon. These make routing constraints much more complicated than classic routing ones. Also, these cause solution process significantly. Due to the NP-hardness of the problem, the Genetic Algorithm has been applied as a solution approach. To validate the solution approach, 25 test problems were developed in different scales and solved by GAMS and the GA. The results indicate the average gap between the objective functions of GAMS and GA is only 1.18 percent. Moreover, saving CPU time in the GA is 78.16 percent more than GAMS. The sensitivity analysis result indicates that the optimum number of vessels in 10 if hiring cost of vessels to be less than 10,083 dollars. As future research studies, two areas can be suggested: Since fuel is one of the requirements of rigs and there is usually a significant amount of fuel in each rig, ships can refuel in the rig in addition to the hub. Moreover, weather condition is one of the most important and influential issues in the vessels' schedule, which has not been discussed in this paper. Researchers can add weather considerations to the model presented in this paper.

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