Original Article

A simulation-based multi-objective optimization study of the fleet sizing problem in the offshore industry

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Abstract Oil companies usually hire a number of offshore supply vessels (OSVs) under long-term contracts for offshore supply logistics. If the number of long-term chartered vessels is not sufficient to satisfy platform demands, one or more OSVs would be required under short-term contracts. In this article two policies for OSV routing to installations are compared: routing based on a fixed schedule, currently used in Iranian offshore oil company and routing based on platform demands. A discrete-event simulation model is developed and simulation-based optimization is used to find near-optimal fleet size and composition that minimize expected total cost subject to a minimum desired expected platform service level. Changing the platform service level constraint allows results to be obtained for multiple best compromise solutions along a performance trade-off curve. For each routing policy, an optimal trade-off curve is obtained using simulation-based optimization. Performance evaluation of routing policies is compared at different service levels. Experimental results indicate that the routing based on platform demands dominates the routing based on a fixed schedule under near-optimal decision variable settings.

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Introduction

Oil and gas production from oil fields located in the sea, is known as offshore oil industry. About 35 per cent of world oil production is produced in offshore resources (Offshore Outlook, 2012). The offshore activity is extensive and getting more complex, so optimization of production processes has become an issue of great concern for oil companies. Because of the large investments involved in the offshore oil industry, even small operational improvements could result in substantial cost reductions and savings.

There are two different types of logistics in this market: upstream and downstream. Upstream logistics is the operation of providing the required equipment and materials to the production and drilling units, while downstream logistics focuses on the shipment of oil and gas to consumers (Kaiser, 2010).

The production of offshore oil and gas cannot be accomplished uninterruptedly unless installations are supplied seamlessly. It is generally understood that the supply of offshore drilling and production units is such a challenging logistics task.

The supply operation requires a fleet of different vessels. The main type of vessel playing a critical role in upstream logistics is the offshore supply vessel (OSV). Their design is suitable for transportation of on-deck containers and a variety of wet and dry bulk cargoes to and from offshore installations (Aas *et al*, 2009).

High level of operational coordination is necessary to keep the supply service costs at a reasonable level. This goal is achieved by planning and optimizing vessel schedules and routes, fleet size and composition, and good estimation of offshore platform demands (Aneichyk, 2009).

Determining an appropriate number of OSVs for long-term hiring, known as the *fleet sizing problem*, is among the most difficult questions to answer. The number of required vessels for the appropriate supply of installations is greatly influenced by OSVs routing, weather conditions and demand variation.

Generally speaking, maritime transport is subject to many stochastic elements and using analytical modeling to deal with the problems of this context will lead to large models which are extremely complex to solve. On the other hand, simulation models are powerful tools to consider uncertain elements, but it is difficult to optimize them. As analytical modeling has often shortcomings when it comes to handling stochastic elements, while simulation usually has to omit routing and scheduling aspects, combining these two methods seems to be the appropriate approach. In this article a simulation-based optimization approach is used to determine OSV fleet size and composition, subject to a desired platform service level constraint in for Iranian offshore oil company (IOOC).

Two different routing policies are also considered here; the first one, which is currently used by IOOC, is routing based on fixed schedule; the second one is routing based on platform demands.

Routing policies play an important role in the performance of supply operations of offshore oil platforms. Therefore, it is very important to select the most appropriate policy. This requires evaluation of alternative routing policies, so as to identify effective policies that satisfy offshore platform service requirements as expediently as possible. To make a fair comparison, the performance of routing policies is compared under conditions where the decision variables for each routing policy are optimally set by using simulation-based optimization, to determine settings that will minimize total cost subject to a desired service level constraint. Furthermore, by varying the desired service level constraint value, multiple best compromise solutions can be obtained to form an optimal trade-off curve for each routing policy. Thereafter, these curves can be compared with determine if one routing policy dominates the other.

The remainder of this article is organized as follows. The section ‘Literature review’ presents a relevant literature review. In the section ‘Problem description’, the problem description is given, whereas input modeling is presented in the section ‘Input modeling’. Simulation model development, verification and validation are described in the section ‘Simulation model’. Experimental settings of the simulation model are given in the section ‘Experimental settings’ and experimental results and a discussion of the observed performance follows in the section ‘Results and discussion’. Finally, some conclusions are drawn in the section ‘Conclusions’.

Literature Review

The problem we study is highly affected by uncertain elements. However, uncertainties are often neglected in the literature. Pantuso *et al* (2014), Christiansen *et al* (2013) and Christiansen *et al* (2007) are some of the recent reviews on ship routing and scheduling, revealing that most problems are solved employing analytical models. Although, the majority of papers discussed in literature are solved in deterministic setting, there are a few papers using simulation to capture the stochastic nature of the problems studied. The literature review here focuses on research papers solely discussed in maritime transport applications, and they consider uncertainty in their study. References outside the maritime domain including locomotive fleet sizing and airline crew scheduling are not considered here.

Andrews *et al* (1996) have provided a simulation model of crude oil lightering in Delaware Bay. Crude oil destined for Philadelphia area refineries is transferred to tankers in Big Stone anchorage in Delaware Bay. Weather conditions and amount of crude are random elements which affect service times. The model is used to evaluate the effect of various policies on service level.

Darzentas and Spyrou (1996) have developed a simulation model of ferry traffic in the Aegean Island. Most important uncertain factors are demand variance and weather conditions. Weather conditions are measured by the speed of the wind which might slow down vessels.

A discrete event simulation model of New York city’s refuse marine transport system is developed by Richetta and Larson (1997). Waste trucks bring their cargoes to transfer stations. Then, refuse is sent in barges to Kills Landfill in Staten Island. Uncertainty source in the simulation is the inflow rate of refuse, depending on season and site. The model is used to determine best barge and tug fleet size.

Imai and Rivera (2001) have used simulation modeling for fleet size planning of refrigerated containers. The model is used to find the most appropriate composition of owned and leased containers. Fleet size and composition are determined under five different demand patterns.

Fagerholt and Rygh (2002) used simulation modeling to design a system for fresh water transportation from Turkey to Jordan. Fresh water is to be sent to a tank terminal in Israel, and it finally goes to Jordan through pipeline. The process of transferring water to Israel is done by ship. The purpose of this study is to determine the number of required ships and the capacity of tank farm and pipeline. Main performance measures are waiting times of the vessels, maximum storage use, number of pipeline flow stops and total amount of delivered water.

Vis *et al* (2005) developed an integer linear programming model to determine the truck fleet size. Then, a discrete-event simulation model is used to validate the results of the analytical model. Crane cycle times and travel time of vehicles are considered to be stochastic. Results reveal that there is a considerable agreement between analytical and simulation models.

Shyshou *et al* (2010) used simulation to model the movement of offshore mobile platforms, known as anchor handling operations. Two sets of stochastic elements are considered in the model: weather conditions and short-term hire rates. The annual cost of short-term hired vessels is the main performance measure affected by the number of vessels on long-term hire and future short-term hiring rates.

Fagerholt *et al* (2010) proposed a decision support methodology for strategic planning in tramp and industrial shipping, where a Monte Carlo simulation framework is built around an optimizations-based decision support system for short-term routing and scheduling. Their methodology was tested on a real case, where the shipping company has almost 100 per cent contract coverage, that is, almost all cargoes carried come from long- term contracts.

However, the interest in methods for achieving robustness in fleet size, routes and schedules has increased in the last years. Alvarez *et al* (2011) proposed a mixed integer programming model of the multi-period fleet sizing and deployment problem. They extended the basic model into a robust optimization model to deal with uncertainty in future prices and demand. More recently, Halvorsen-Weare *et al* (2013) studied a real-life liquefied natural gas ship routing and scheduling problem to find out routes and schedules for the fleet that are more robust with respect to uncertainty, such as in sailing times, because of changing weather conditions and daily production rates. They evaluate the resulting solutions using a simulation model with a recourse optimization procedure. In another study, Cigolini *et al* (2013) present a simulation-based metamodel to support logistics providers in sizing transshipment systems. Their suggested approach has been used in two case studies and it helped service providers design transshipment systems for various environments, whenever the experience from previous projects is helpless.

We now proceed to some applications on simulation modeling of vessel traffic on waterways for scenario and policy analyzes. Among them, Golkar *et al* (1998) developed a simulation model for the Panama Canal as a tool for scenario and policy analyzes. Cortés *et al* (2007) simulated both the freight traffic and terminal logistics for the port of Seville, Spain, using Arena software, focusing on port utilization and dredging in order to accommodate bigger vessels. Köse *et al* (2003) presented a model of the Strait of Istanbul and tested the effect of arrival intensity on waiting times. More recently, Almaz and Altiok (2012) developed a simulation model of the vessel traffic in Delaware River to study the impact of deepening on navigational efficiency in the River. There are of course many more studies in literature on maritime traffic which are beyond the scope of our own study.

It is clear from this brief review that there is a need to develop a more robust solution approach to compare the performance of different routing policies, fleet size and composition in maritime vehicle routing problems with pickups and deliveries applications. The contribution of our paper is to design and develop a discrete-event simulation model to determine OSV fleet size and composition under two routing policies in IOOC and then, make a fair comparison between performances of routing policies. To the best of our knowledge, the application we consider is original and the problem has not been previously studied. In addition, a simulation-based optimization approach has not been applied to offshore oil logistic systems before. To evaluate the performance of each routing policy, we employ a simulation-based optimization approach to identify non-dominated solutions that constitute the trade-off curve between total cost and service level.

Problem Description

The focus area of this article is on the supply operations of offshore oil and gas installations. Offshore supply vessels are widely used to deliver periodic supplies of food and equipment from an onshore base to offshore installations.

Kharg district

Offshore operations of IOOC in the Persian Gulf are mostly performed in four offshore operation regions: Bahregan, Kharg, Siri and Lavan districts.

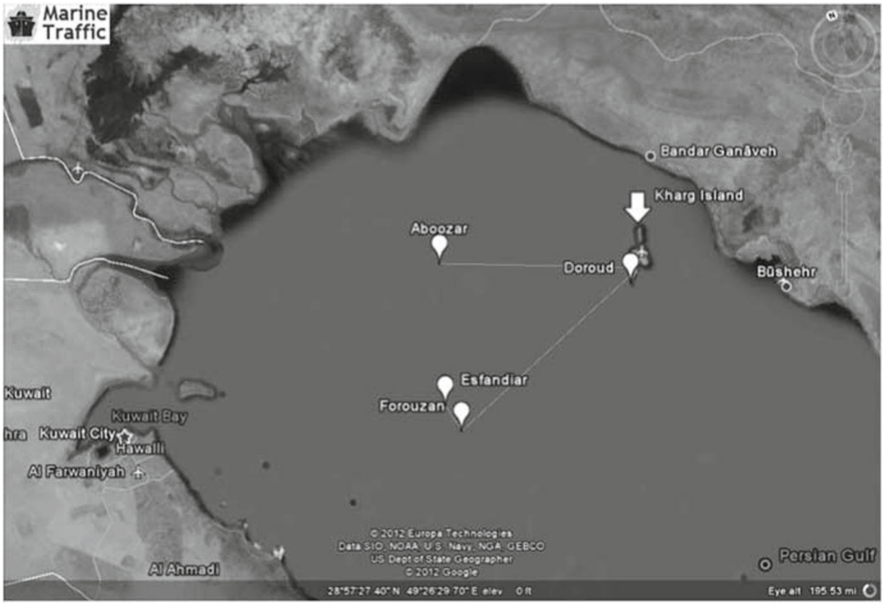

Figure 1: Kharg district map.

These operations are performed by different kinds of offshore installation units, like drilling and exploration units in production platforms. In this article we focus on Kharg district.

Kharg Island, a 35 square km coral island, is located at 57 km off the north west of Bushehr Seaport and 28 km from Genaveh Port. The oil production activities began by the ex-Iran Pan American Oil Company in 1959. Kharg district includes four major oil production fields: Doroud, Forouzan, Esfandiar and Aboozar. Figure 1 shows the four oil production installations, along with a single onshore base in Kharg district.

Each offshore installation faces two types of demand: pickup demand and delivery demand. Pickup demand includes empty containers, waste and rented equipment which must be returned to the supply base. Delivery demand includes containers, equipment, food, water and fuel is necessary to the installation to continue production.

Offshore supply vessels

Offshore supply vessels, usually known as OSVs, are 65–350 ft in length. These vessels are mainly used to transport food and equipment to offshore oil and gas installations, and bring waste and empty containers to an onshore base (Aneichyk, 2009). OSVs are capable of transporting two different types of cargoes: deck cargo and bulk cargo. Items like pipes, pumps and other equipment in containers are placed on deck and called deck cargo. Water and food supply, liquid chemicals and other cargoes, stored in tanks under the deck, are called bulk cargoes. OSVs are sometimes used to extinguish fires and cleanup of oil spills. Useful information on the role of supply vessels in offshore logistics can be found in Aas *et al* (2009).

Routing policy

Routing policy determines the sequence of jobs and offshore installations that each of OSV should follow. The routes might have different shapes under different policies. Routing policies have an effect on the number of OSVs used to supply the installations.

We have examined two different routing policies. The first one (named here RP1), which is currently used by IOOC, is based on a fixed schedule. Under this policy each vessel has a predetermined schedule regardless of the platforms demand pattern. For example, vessel number 1 starts its journey to platforms each Saturday and goes to platforms 1 and 2. If there are some pickup and delivery demand on these platforms, which is usually the case, the ship satisfies them and goes back to the supply base on Tuesday.

The second policy (named here RP2) is a demand based routing policy. In RP2, all routing and planning are based on the pattern of platform demands. Under this policy, assignment of vessels to platform demands is done on the basis of some general rules. These are;

1. Assign platform request to smallest possible vessel
2. Assign platform request to a long-term vessel (if a long-term vessel is available)
3. If it is possible, assign more than one platform request to a vessel.

Input Modeling

This section describes the basic model assumptions and general data considerations. We also describe the modeling of major inputs: weekly OSVs moving plan, high-sea and low-sea period durations, and specification of daily hire rates for OSVs.

Weekly vessel plan

Owing to uncertainty in offshore supply operations, it is not reasonable to build annual or even monthly plans for OSV departures and returns. Usually OSV plans are prepared for periods of 1 week. The following items are mentioned in a weekly plan:

- vessel departure time from onshore base
- vessel itinerary (order of platforms that a given vessel will visit)
- vessel arrival and departure time at each platform
- duration of loading and unloading operations at each platform.

Offshore supply operations are highly weather dependent. It is rather obvious, therefore, that vessel plans are different in spring and summer, and autumn and winter (Aneichyk, 2009).

Operations duration

Loading and unloading operations vary with the number of containers or the amount of bulk cargo. Based on expert opinion, it has been determined that the duration of loading and unloading operations is Triangular (4, 6.5, 8) in hour.

Sailing times from onshore base to offshore platforms, and between offshore platforms, are determined based on vessel velocity and distance. Vessel speed is multiplied by a parameter (here called α) to take effect of weather conditions into account. The values for α under different weather conditions are shown in Table 1 (taken from IOOC technical documents). Significant wave height (SWH) is a measure used to quantify weather conditions in supply operations. It is defined as the average height (trough to crest) of the one-third of the largest waves (Shyshou *et al*, 2010).

Vessel rates and specifications

There are basically two types of hire contracts: long term and spot (short term). Spot rates are significantly higher than the long-term ones, and spot vessels are typically hired when there is a shortage of long-term ones. Spot rates are estimated based on simple moving average. For a given week, the spot rate is calculated as the average of short-term hire rates in the last 3 weeks.

Twenty different vessels are available to be hired in Kharg district. Main vessel specifications which are of interest to us here are velocity, capacity,

Table 1: Amount of α under different weather conditions

Weather Condition	α
Very Bad (SWH>2.5)	0.75
Bad (1.5<SWH<2.5)	0.90
Good (SWH<1.5)	1.00

Table 2: Ranges of values for main vessel specifications

Vessel	*Velocity (Knot)*	*Capacity (No. of containers)*	*Operational cost ($/kilometer)*	*Short-term and long-term hiring cost (1000$/day)*
V_i (i = 1, …, 20)	[10–15]	[70–100]	[75–95]	[6, 10] and [2–4]

operational cost, short-term and long-term hiring costs. These 20 vessels are different from each other at least in one of their characteristics. The ranges of values for main vessel specifications are given in Table 2. Long-term and short-term hire rates are provided by IOOC. Spot rates range from US$6000 to 10000, while long-term rates are between $2000 to 4000 .

Platform demand

To generate the amount of pickup and delivery demand for each platform we fit probability distributions to the historical data in Input Analyzer. Under RP1, each platform should be visited by vessels a certain number of times each week. The number of weekly visits to a platform is determined based on former experiences and knowledge of experts about each individual platform. Each platform might be visited 2, 3 or 4 times a week. Then the number of visits to a specified platform is a fixed value, determined by expert opinion. The distribution that best represents platform demand is the random normal distribution with mean of 60 and standard deviation of 12.

Under RP2 the main purpose is to determine OSV's scheduling and routing based on delivery and pickup demand received from platforms. The inter-arrival time between platform requests is then required, in addition to the amount of pickup or delivery demand. To have a fair comparison between RP1 and RP2 routing policies, the platform demand size and the inter-arrival time of demands under RP2 is taken the same as RP1.

Weather conditions modeling

The feasibility of cargo transfer operations between vessel and offshore installations is highly dependent on weather conditions. OSVs hired by IOOC in the Persian Gulf are allowed to do the cargo transfer operations only when the short wave height (SWH) is less than 1.75 m.

Times when the SWH is greater than 1.75 m are called high-sea periods; when SWH is below that threshold are called low-sea periods. Before a vessel sets sail, it is necessary to ensure that the predicted low-sea period is longer than the duration of the transfer operation. When a vessel arrives at an offshore installation in high-sea period, it has to wait until weather conditions improve. This waiting time for a low-sea time window is called wait-on-weather. In this study, the Shyshou *et al* (2010) approach is used to model weather conditions (Aneichyk, 2009).

Probability distributions of low-sea and high-sea periods are determined by historical data. The Arena® Input Analyzer is used to fit the best distribution to low-sea and high-sea periods (Kelton *et al*, 2007). The results for different months of the year and periods are shown in Table 3.

Simulation Model

In this article we develop a discrete-event simulation model (Law, 2007) for the evaluation of alternative supply fleet size configurations. The characteristics of offshore supply operations including pickup and delivery demand for each platform, high-sea and low-sea period modeling, delays happening at the onshore supply base, platforms extra demands and spot-vessels for platform extra demands, are considered in the model.

Model implementation

A top-level flowchart for the simulation model is depicted in Figure 2. As it was described in the section 'Routing policy', we have implemented two different routing policies. Simulation model logic for both policies is the same, except that under RP1 platform requests are not considered in decision making. In other words, under RP1, vessel departure to installations is scheduled based on a fixed predetermined timing. Then in Figure 2 if RP1 is taken, there is no connection between the 'platform request generation' box and the 'decision making' box.

Table 3: High-sea and low-sea period duration

Month	*Low-Sea Duration*	*High-Sea Duration*
January	WEIB(62, 0.538)	2+EXPO(44.9)
February	WEIB(87, 0.74)	2+EXPO(43.2)
March	WEIB(75.4, 0.621)	1+WEIB(29.6, 1.17)
April	WEIB(141, 0.593)	2+WEIB(23..2, 1.06)
May	WEIB(269, 0.854)	2+EXPO(25.8)
June	2.280e+003 * BETA(0.52, 1.20)	1+EXPO(20.1)
July	EXPO(480)	3+62 * BETA(0.653, 2.52)
August	8+WEIB(431, 0.812)	1+WEIB(16, 0.984)
September	EXPO(190)	4+WEIB(20.6, 1.15)
October	WEIB(73.1, 0.61)	1+WEIB(26, 1.36)
November	WEIB(84.2, 0.709)	1+WEIB(27.8, 1.03)
December	EXPO(63.9)	1+GAMM(20.18, 1.40)

Conceptual model

Conceptual modeling is defined by Mylopoulos as the activity of formally describing some aspects of the physical and social world around us for the purposes of understanding and communication (Roussopoulos and Karagiannis, 2009). Under RP1, there is a fixed schedule for each vessel. When a request for service (delivery or pickup) arrives from a platform, experts try to assign that request to the next long-term vessel about to leave the onshore base. This predetermined timing is affected by uncertainty inherent in offshore operations. Therefore, there might be urgent platform requests, while there is no long-term vessel available to satisfy them. It is then required to hire one or more short-term vessels.

Under RP2, there is no predetermined schedule for vessel departures, and the departure schedules are determined based on platform requests. Using RP2 thus leads to a decrease in the number of unnecessary departures to installations. A conceptual model for offshore supply operations is depicted in Figure 3.

Vessels go through their assigned routes after assigning the platform requests. Weather forecast is checked by vessels before they leave the onshore base. If weather conditions at platform are suitable for loading/unloading operations at the time of vessel arrival, the vessel will leave the onshore base. Otherwise, the vessel will wait until its arrival time at the platform falls in low-sea period. Even if weather conditions are in high-sea period when the vessel arrives at the platform, it will have to wait until the condition is suitable for loading/unloading operations. Finally, the vessel either moves to the next planned platform or returns to the onshore base.

Model verification and validation

When a model is verified, it means that model behavior is correct. It is important to have a tool for model verification. In this study, animation is used as such a tool.

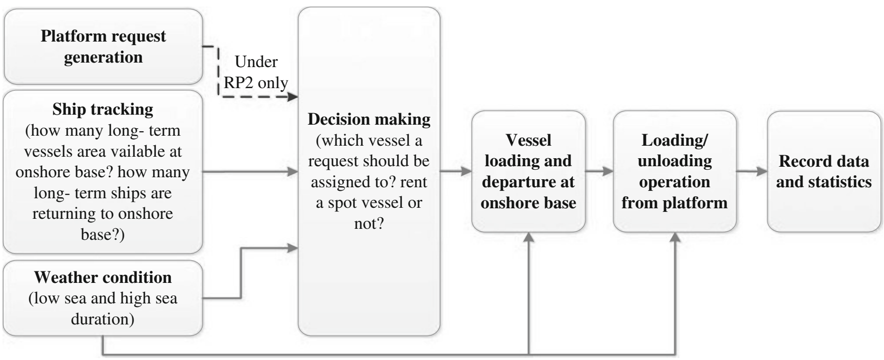

Figure 2: Top-level flowchart for simulation model.

The animation of the model shows that when an installation makes a demand, a vessel waits for loading operations and then starts from onshore base in Kharg, to satisfy the demand. It also shows that when weather conditions are not good, the vessel behavior is correct. The animation was watched for several times in the presence of IOOC experts and it was agreed that the simulation model was verified.

Model validation is defined by Sargent (2005) as 'substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model'. It is often difficult to separate verification and validation, as these two processes are closely related, and often the same techniques are used for both.

Major state variables in our system are the number of vessels currently in use and the total number of spot-hire days. The number of vessels currently in use

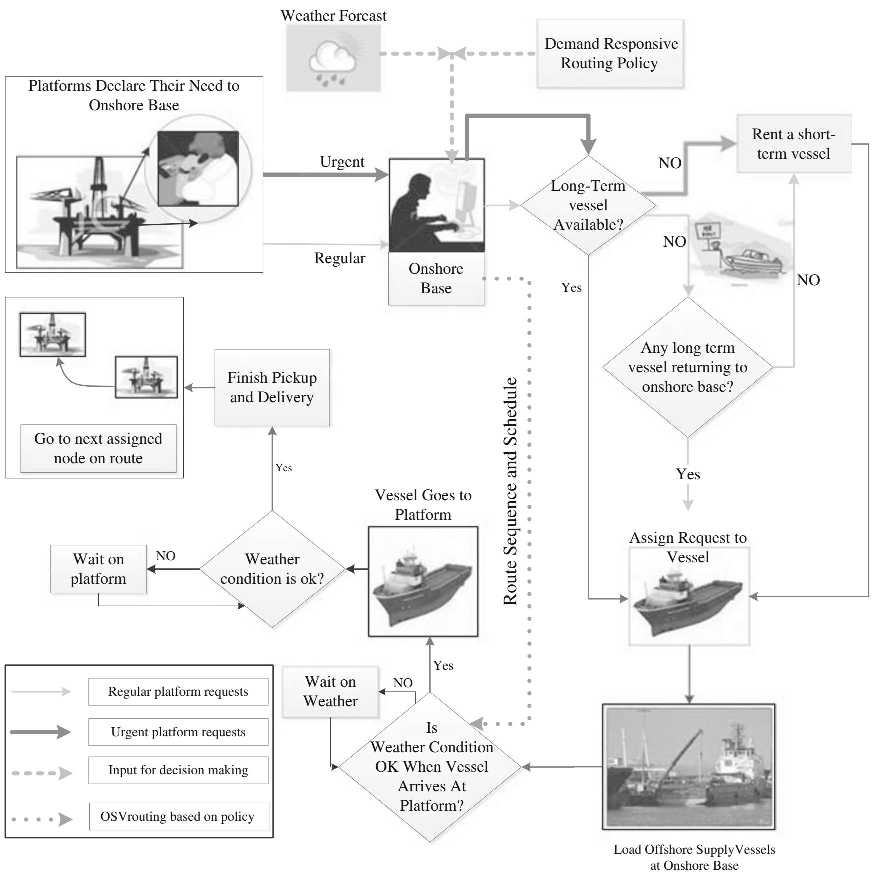

Figure 3: Conceptual model for offshore supply operations under demand responsive routing policy.

equals the sum of long-term and spot vessels. The number of long-term vessels under contract is a parameter which could simply be kept fixed and equal to its real value. Currently five long-term vessels are under contract in Kharg region. Therefore, if all model parameters including number of long-term vessels, are set according to their real values, the total number of spot-hire days will be the main measure to check model validity. We compare real data on *total number of spot-hire days* with simulation results using paired *t*-test. Real data and simulation results are shown in Figure 4.

The *t* – Student Statistic test determines whether the difference between the means of the two series of values (real data and simulation results) is statistically significant. A *t* test at the 0.05 level of significance is employed for the following hypothesis:

$$\begin{cases} H_0: & \mu_{Simulation} = \mu|_{Real} \\ H_1: & \mu_{Simulation} \neq \mu|_{Real} \end{cases}$$

The obtained confidence interval for the difference is $[-1.39832, 7.81548]$. The *t*-statistic is 1.441. The critical value is $t_{0.025,23} = 2.069$. Since $T < t_{0.025,23}$, the null hypothesis cannot be rejected; therefore, there is no significant difference on the total number of spot hire days between real data and simulation.

Experimental Settings

We have two performance measures: expected total cost (*TC*) and expected platform service level (*PSL*). *TC* is equal to the sum of operational costs, long-

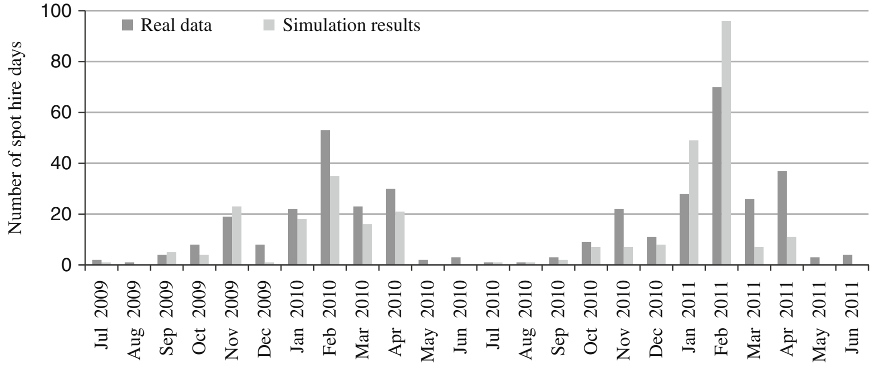

Figure 4: Real and simulation results for spot-hire days.

term hiring costs and short-term hiring costs, given by:

$$TC = \frac{1}{t_f - t_0} \sum_{i \in Vessels} \int_{t=t_0}^{t=t_f} (Operational\,Cost_i + Long\,Term\,Hiring\,Cost_i + Short\,Term\,Hiring\,Cost_i) \times v_i \qquad (1)$$

where i represents vessel number, v_i is a binary variable which is equal to 1 if vessel i is hired under long-term contract and 0 otherwise, and t_0 and t_f are simulation start and finish times, respectively.

If it takes too long to service a platform, drilling or production operations might face serious problems or even stop. Any disorder, which causes offshore operations to slow down or stop, would result in some extra costs. PSL_j is defined as the proportion of platform j orders filled on time, given by:

$$PSL_j = \frac{Number\,of\,platform\,j\,orders\,filled\,on\,time}{Total\,number\,of\,platform\,j\,orders} \qquad (2)$$

PSL is the weighted sum of PSL_j, given in equation (3), in which the weight of PSL_j shows the relative importance of the operations of platform j in comparison to other platforms. Weight values (W_j) in equation (3), empirically determined through discussion with IOOC experts, are given in Table 4.

$$PSL = \sum_{j \in platforms} W_j \times PSL_j \qquad (3)$$

There are two separate exerimental phases in this research. The purpose of the first phase is to determine the optimal values for decision variables, whereas service level is constrained at a certain level. The second phase is to set decision variables on their best values, found in the first phase, and then running the model with a large number of replications. Then the routing policies could be statistically compared. The optimal values for the decision variables (phase 1) were found using OptQuest® for Arena®. To find optimum values for a simulation model, we have to define the objective function, constraints, and decision variables (Grewal *et al*, 2010).

Table 4: Relative importance of operations at platforms

Platform number (j)	W_j
1	0.23
2	0.32
3	0.16
4	0.29

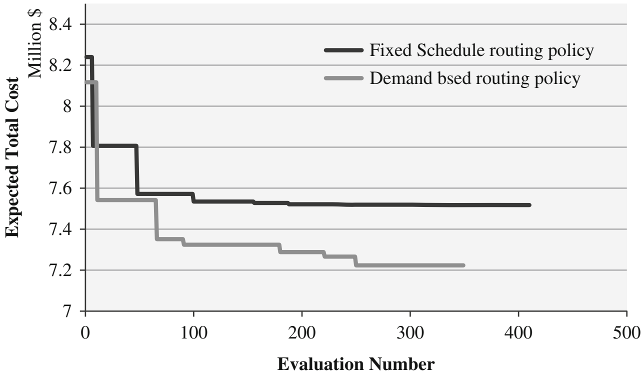

Figure 5: Expected total cost obtained from OptQuest at platform service level of 75 per cent.

Equation (4) shows the objective function, the decision variables and the constraints used in this simulation.

$$MinTC = \frac{1}{t_f - t_0} \sum_{i \in Vessels} \int_{t=t_0}^{t=t_f} (Operational\,Cost_i + Long\,Term\,Hiring\,Cost_i + Short\,Term\,Hiring\,Cost_i) \times v_i \quad (4)$$

$$\begin{aligned} &\text{Subject to :} \\ &PSL \geq DSL \\ &v_i \; are\; binary\; \text{var}iables \end{aligned} \quad (5)$$

where *PSL* is platform service level and *DSL* is the minimum desired service level. The objective function minimizes average TC subject to minimum desired service level. The *DSL* was changed from run to run in order to generate results for a performance trade-off curve.

OptQuest® for Arena® is used to find near optimal values for RP1 and RP2 over five given values of desired platform service level. These five values for *DSL* are 0.75, 0.80, 0.85, 0.90 and 0.95.

The observed platform service level *PSL*, was constrained to be greater than or equal to the *DSL*. Data provided by IOOC range from January 2008 to July 2011. Warm-up period is set to 18 months and the simulation run length is set to 24 months (from July 2009 to July 2011). In this phase, the number of replications is taken five.

Given the fact that 20 different vessels are available to be hired, we have 20 binary decision variables here ($v_1, v_2, v_3 \ldots v_{20}$) resulting in more than 1 million solution points.

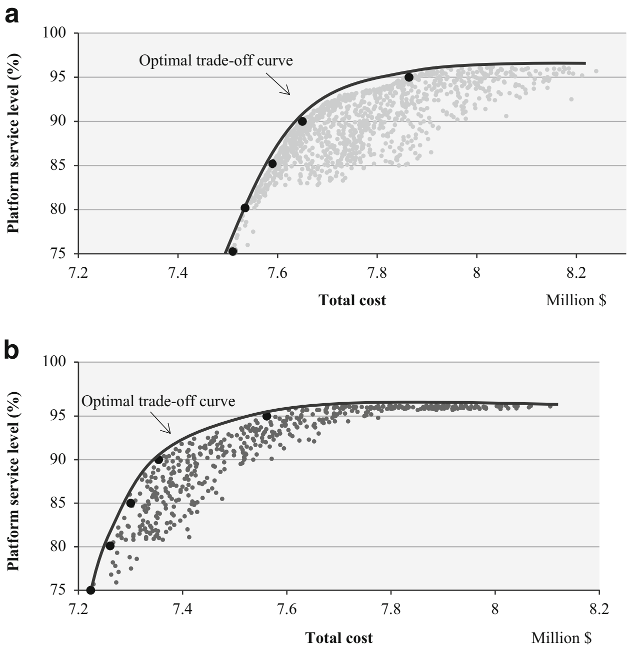

Figure 6: Optimal trade-off curve for (a) fixed schedule routing policy RP1, and (b) demand based routing policy RP2.

The second phase involved running each of the 10 combinations (five service levels × two strategies) for 50 replications, each using the optimal decision variable settings obtained in the first phase. As no optimization was required in the second phase, these runs were made using only Arena®.

Results and Discussion

In this section, experimental results for the first phase (optimal decision variable settings) are presented. Then, the results of the second phase (running simulation model with optimal variable settings), with statistical performance analysis of RP1 and RP2, are presented.

Figure 5 illustrates the search progress of both routing policies RP1 and RP2 are obtained by OptQuest at the desired service level of 75 per cent. Both algorithms stop after 100 consecutive configurations for which there is no improvement in the expected total cost. RP2 starts from the initial solution of about $130 000 lower expected total cost than RP1, and at the end of simulation run RP2 found the best obtained solution with the expected total cost of $7530.105,

Table 5: Best solutions obtained for fixed schedule and demand based routing policy.

Platform service level (%)	*Routing policy*					
	Fixed schedule (RP1)			*Demand based (RP2)*		
	Total cost ($)	*Fleet size*	*Fleet composition*	*Total cost ($)*	*Fleet size*	*Fleet composition*
75	7 517 422±55 432	3	V_1, V_2, V_7	7 223 493±74 322	3	V_1, V_2, V_{17}
80	7 534 659±63 929	4	V_1, V_2, V_7, V_9	7 260 933±59 214	3	V_1, V_2, V_9
85	7 598 246±98 543	4	V_1, V_2, V_7, V_9	7 309 266±83 272	4	V_1, V_2, V_7, V_9
90	7 649 000±105 673	5	$V_1, V_2, V_7, V_{12}, V_{17}$	7 353 917±77 109	4	V_1, V_2, V_7, V_9
95	7 863 300±5 6431	6	$V_1, V_2, V_7, V_9, V_{12}, V_{17}$	7 561 624±94 200	5	$V_1, V_2, V_7, V_9, V_{12}$

while RP1 found the best obtained solution with the expected total cost of $7 232 500. It is important to note that in simulation-based optimization problems we do not typically know the optimal solutions and we just attempt to find the best possible solution(s) within an acceptable number of solution evaluations, or an acceptable period of search time. So, in this study, instead of using the term 'optimal solution', we use the term 'near-optimal solution' or 'best found solution'.

All feasible solutions produced by OptQuest® in all experiments under RP1 and RP2 routing policies are shown in Figure 6. For any given PSL, the point which has the minimum amount of total cost represents the best solution. Different combinations of optimal values for decision variables result in optimal trade-off curve, which represents the highest achieved platform service level with lowest total cost. If a decision variable is set on a non-optimal value, the total cost of achieving platform service level exceeds from optimal trade-off curve and another curve lower than the optimal one would be obtained.

Table 5 shows the best OptQuest® results at different values for platform service level under each routing policy. As mentioned earlier, the problem here is to decide how many vessels should be hired under long-term contract (fleet size) and which vessels lead to less hiring and operational costs (fleet composition). Clearly, at any given service level the near-optimal fleet sizes and compositions are different for the two policies, indicating that comparative analysis, under the condition where fleet size and composition is the same, would not be a fair comparison. Figure 7 presents the best solutions found for both RP1 and RP2 in a two-dimensional plot to better understand the superiority of RP2 over RP1.

To get better estimations of total cost, the simulation model is run for 50 replications with the settings shown in Table 5. Figure 8 shows the average

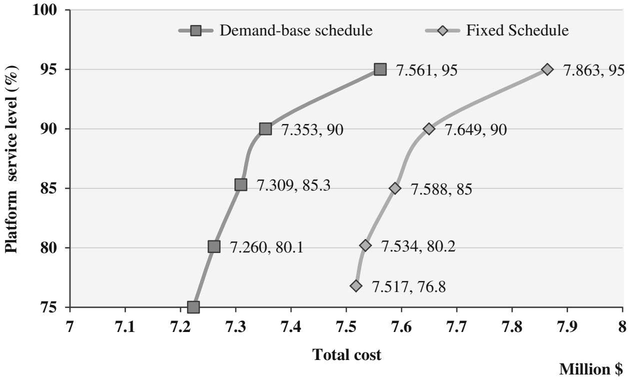

Figure 7: Trade-off curves for both policies at different platform service levels.

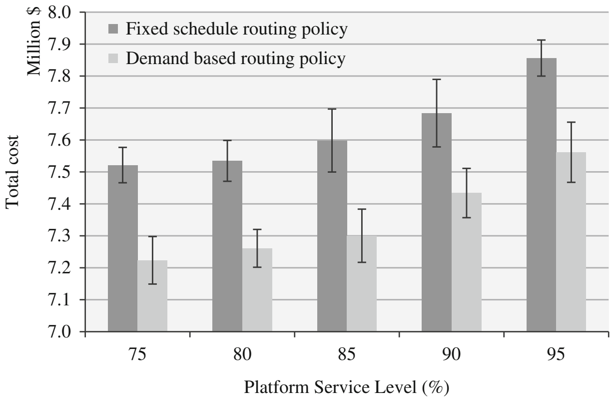

Figure 8: Total cost under optimal decision variable settings after 50 replications.

total cost of all replications for a given platform service level. It can be clearly seen from Figure 8 that the difference between total cost under RP1 and RP2 policies are statistically significant.

Table 6 provides additional measures on the performance of each routing policy at different service levels. The half width for each measure, at the significance level of 0.05, is given in parenthesis. The half width values for cost measures are less than 1.5 per cent of their corresponding mean values, implying that the mean estimates are relatively precise.

Table 6 shows the decomposition of total cost into long-term hiring costs, short-term hiring costs and operational costs. It is observed that long-term hiring

Table 6: Decomposition of total cost, platform waiting time and platform service level under optimal parameters setting and 50 replication

Routing policy	*Platform service level (PSL)*	*Total cost ($)*	*Long term hiring cost ($)*	*Short term hiring cost ($)*	*Operational costs ($)*	*Average waiting time of platform j* (Hour)				*Individual platform service level (PSL_j)*			
						1	*2*	*3*	*4*	*1*	*2*	*3*	*4*
Fixed schedule routing policy	75	7 530 105	4 894 568	1 204 817	1 430 720	13.6	20.21	24.9	19.3	75.5	72.4	71	80.1
		(55, 432)	(39, 458)	(27, 241)	(21, 058)	(0.7)	(0.6)	(0.1)	(0.6)	(1.9)	(1.0)	(0.9)	(2.0)
	80	7 539 580	4 297 561	1 432 520	1 809 499	12.9	15.6	12.8	13.6	82.5	74	80.1	85
		(63, 929)	(22, 798)	(23, 223)	(36, 974)	(0.8)	(1)	(0.9)	(0.7)	(2.9)	(1.0)	(3.0)	(2.9)
	85	7 600 932	4 297 561	1 596 196	1 707 176	11.2	9.9	12.4	10.5	83	85.8	80	89
		(98, 543)	(27, 194)	(36, 807)	(25, 896)	(0.7)	(0.1)	(0.9)	(0.6)	(1.0)	(3.0)	(1.9)	(3.0)
	90	7 689 251	4 844 228	1 691 635	1 153 388	7.3	8.7	9.6	10.1	89.1	93.4	92.1	86.7
		(105 673)	(27 922)	(28 877)	(29 845)	(0.9)	(0.8)	(0.8)	(1)	(1.0)	(2.0)	(3.1)	(3.2)
	95	7 863 000	5 268 210	1 887 120	707 670	5.4	8.6	7.4	6.4	95.3	93.2	98.5	95.6
		(56, 431)	(24, 844)	(20, 688)	(34, 602)	(1)	(0.6)	(0.3)	(0.5)	(1.1)	(3.3)	(2.8)	(2.9)
Demand based schedule routing policy	75	7 232 500	3 760 900	1 157 200	2 314 400	12.6	19.2	22.9	17.3	73.8	76.8	75	75
		(74, 322)	(25, 361)	(37, 514)	(23, 979)	(0.4)	(0.1)	(1)	(0.4)	(3.2)	(2.1)	(2.9)	(3.0)
	80	7 272 830	4 145 513	1 381 838	1 745 479	10.9	14.6	10.8	11.6	80.1	83.4	85.6	73.7
		(59, 214)	(39, 995)	(20, 693)	(20, 796)	(0.5)	(1)	(0.6)	(0.3)	(3.1)	(2.1)	(1.0)	(2.9)
	85	7 389 266	4 297 561	1 699 531	1 182 283	9.2	8.9	11.4	9.5	85.9	85.1	87	84
		(83, 272)	(27, 780)	(21, 172)	(30, 277)	(0.5)	(0.6)	(0.5)	(0.6)	(1.2)	(3.2)	(0.9)	(3.1)
	90	7 419 037	4 297 561	1 563 807	1 557 669	5.3	7.7	8.6	8.1	86.3	90.2	90.9	93
		(77, 109)	(31, 912)	(39, 775)	(38, 160)	(0.2)	(0.3)	(0.6)	(0.4)	(1.1)	(3.2)	(2.1)	(1.0)
	95	7 439 821	4 507 452	1 636 761	1 505 500	3.4	6.6	6.4	4.4	95.1	98	92.6	93.3
		(94, 200)	(31, 439)	(24, 139)	(29, 804)	(0.4)	(0.8)	(0.7)	(0.7)	(2.1)	(1.2)	(2.0)	(0.9)

costs under RP1 are higher than RP2, but short-term hiring costs are higher under the demand-based routing policy. Under RP1, decision maker decides to hire more vessels under long-term contracts. Having a larger fleet for the long-term means more fixed capital expenses and less short-term hiring expenses. Such a large fleet is able to satisfy many platform demands and consequently the number of required short-term vessels is less. Average waiting time of a platform is here defined as the average time duration for the assignment of a vessel to orders received from that platform. Table 6 shows that waiting time for each platform increases as minimum platform service level decreases; RP1 has a longer waiting time for each platform at any given service level.

Conclusions

This research has focused on the performance evaluation of fixed schedule routing policy and demand based routing policy using an optimal trade-off curve approach. A discrete-event simulation model is developed and simulation-based optimization is used to find near-optimal fleet size and composition that minimize expected total cost subject to a minimum desired expected platform service level. The strength of this approach is that objective comparisons can be made under optimal decision variable settings at each service level. This resulted in a more robust conclusion that demand based routing policy is better with respect to total cost and a given service level. One limitation of this study was the long run time needed for OptQuest® to find near-optimal fleet size and composition.

The simulation results showed that the demand based routing policy dominates the fixed schedule routing policy. Waiting time for each platform increases as minimum platform service level decreases and demand based routing policy has a longer waiting time for each platform at any given service level.

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References

Aas, B., Halskau, Sr. Ø. and Wallace, S.W. (2009) The role of supply vessels in offshore logistics. *Maritime Economics & Logistics* 11(3): 302–325.

Almaz, O.A. and Altiok, T. (2012) Simulation modeling of the vessel traffic in Delaware river: Impact of deepening on port performance. *Simulation Modelling Practice and Theory* 22(1): 146–165.

Alvarez, J.F., Tsilingiris, P., Engebrethsen, E.S. and Kakalis, N.M.P. (2011) Robust fleet sizing and deployment for industrial and independent bulk ocean shipping companies. *INFOR* 49(2): 93–107.

Andrews, S., Murphy, F.H., Wang, X.P. and Welch, S. (1996) Modeling crude oil lightering in Delaware Bay. *Interfaces* 26(6): 68–78.

Aneichyk, T. (2009) Simulation model for strategical fleet sizing and operational planning in offshore supply vessels operations. Master Thesis, Molde University College, Molde, Norway, http://hdl.handle.net/11250/153446.

Christiansen, M., Fagerholt, K., Nygreen, B. and Ronen, D. (2007) Maritime transportation. In: C. Barnhart and G. Laporte (eds.) *Handbooks in Operations Research and Management Science: Transportation*. Vol. 14, Amsterdam, The Netherlands: North-Holland, pp. 189–284.

Christiansen, M., Fagerholt, K., Nygreen, B. and Ronen, D. (2013) Ship routing and scheduling in the new millennium. *European Journal of Operational Research* 228(3): 467–483.

Cigolini, R., Pero, M., Rossi, T. and Sianesi, A. (2013) Using simulation to optimize transshipment systems: Applications in field. *Maritime Economics & Logistics* 15(3): 332–348.

Cortés, P., Muñuzuri, J., Ibáñez, J.N. and Guadix, J. (2007) Simulation of freight traffic in the Seville inland port. *Simulation Modelling Practice and Theory* 15(3): 256–271.

Darzentas, J. and Spyrou, T. (1996) Ferry traffic in the Aegean Islands: A simulation study. *Journal of the Operational Research Society* 47(2): 203–216.

Fagerholt, K., Christiansen, M., Hvattum, L.M., Johnsen, T.A.V. and Vabø, T.J. (2010) A decision support methodology for strategic planning in maritime transportation. *Omega* 38(6): 465–474.

Fagerholt, K. and Rygh, B. (2002) Design of a sea-borne system for fresh water transport – A simulation study. *Belgian Journal of Operations Research, Statistics and Computer Science* 40(3–4): 137–146.

Golkar, J., Shekhar, A. and Buddhavarapu, S. (1998) *Panama Canal Simulation Model*. Proceedings of the 30th conference on Winter Simulation, Los Alamitos, CA: IEEE Computer Society Press, pp. 1229-1238.

Grewal, C.S., Rogers, P. and Enns, S.T. (2010) Performance evaluation of inventory replenishment strategies in a capacitated supply chain under optimal parameter settings. *Int. J. Value Chain Management* 4(3): 195–212.

Halvorsen-Weare, E.E., Fagerholt, K. and Rönnqvis, M. (2013) Vessel routing and scheduling under uncertainty in the liquefied natural gas business. *Computers & Industrial Engineering* 64(1): 290–301.

Imai, A. and Rivera, F. (2001) Strategic fleet size planning for maritime refrigerated containers. *Maritime Policy and Management* 28(4): 361–374.

Kaiser, M.J. (2010) An integrated systems framework for service vessel forecasting in the Gulf of Mexico. *Energy* 35(7): 2777–2795.

Kelton, W.D., Sadowski, R.P. and Sturrock, D.T. (2007) *Simulation with Arena*. 4th edn. New York: McGrawHill.

Köse, E., Basar, E., Demirci, E., Güneroglu, A. and Erkebay, S. (2003) Simulation of marine traffic in Istanbul strait. *Simulation Modelling Practice and Theory* 11(7–8): 597–608.

Law, A.M. (2007) *Simulation Modeling and Analysis*, 4th edn. Boston, MA: McGraw-Hill.

Offshore Outlook. (2012) Oil, gas & marine business analysis & intelligence, "www.infield.com/articles/offshore-outlook-2012.pdf".

Pantuso, G., Fagerholt, K. and Hvattum, L.M. (2014) A survey on maritime fleet size and mix problems. *European Journal of Operational Research* 235(2): 341–349.

Richetta, O. and Larson, R.C. (1997) Modeling the increased complexity of New York City's refuse marine transport system. *Transportation Science* 31(3): 272–293.

Roussopoulos, N. and Karagiannis, D. (2009) Conceptual modeling: Past, present and the continuum of the future. In: A. Borgida, V. Chaudhri, P. Giorgini and E. Yu (eds.) *Conceptual Modeling: Foundations and Applications, Lecture Notes in Computer Science*. Berlin; Heidelberg, Germany: Springer, pp. 139–152.

Sargent, R.G. (2005) *Verification and Validation of Simulation Models*. Proceedings of the 37th conference on Winter simulation, Baltimore, MD: IEEE Computer Society Press, pp. 130–143.
Shyshou, A., Gribkovskaia, I. and Barceló, J. (2010) A simulation study of the fleet sizing problem arising in offshore anchor handling operations. *European Journal of Operational Research* 203(1): 230–240.
Vis, I.F.A., de Koster, R.M.B.M. and Savelsbergh, M.W.P. (2005) Minimum vehicle fleet size under time-window constraints at a container terminal. *Transportation Science* 39(2): 249–260.

