RIO OIL & GAS 2016 EXPO AND CONFERENCE
24-27 de outubro de 2016
Riocentro | Rio de Janeiro - Brasil
Promoção: ibp

IBP1521_16

UPSTREAM SUPPLY CHAIN SIMULATION OF OFFSHORE PLATFORMS USING DES AND AIS DATA

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Abstract

Considering that the price of crude oil is actually coming back to the lower levels existing before 2000's, cost reductions is becoming a critical factor for offshore industry. Therefore, improving the offshore upstream supply chain efficiency is becoming a major challenge for the O&G companies. In this paper, we present a discrete-event simulation model that may evaluates alternative fleet size configurations taking into consideration uncertainty in weather conditions and unexpected delays. Innovation states in the use of automatic identification system (AIS) data as model input. A time depend historical database of 6 months for 90 platform supply vessels has been analyzed. Based on these data, a methodology has been developed to detect the most probable navigational behavior of the vessels (sailing, waiting at sea, loading/unloading at port, loading/unloading at platform, moored, etc.). Later, it is shown that straightforward statistical distributions can be used to characterize speed, loading and unloading times at port terminals, loading and unloading time at offshore platforms as well as mooring time. A discrete-event simulation (DES) model representing the Campos Brazilian basin that includes one port, 23 PSVs and 38 offshore production platforms has been used as a validation case. The preliminary results show a good accordance between the simulation outputs and real data. We suggest that this novel approach can be adopted as a tool to examine the efficiency of existing PSV fleets as well as to identify the effect of different operational and management strategies in offshore logistics activities such as adjusting the routes of vessels, deciding the fleet size, determining the composition of PSV fleets, optimizing the scheduling of platform clusters.

1. Introduction

1.1. Contextualization

Offshore Oil and Gas (O&G) industry is one of the most important industries in the world with a direct impact on the worldwide economies. It has become a remarkable source of energy over the past years due to swift increase in global energy needs. According to annual world energy statistics, it is stated that in 2012 approximately 57% of total energy consumed in the world has been produced from oil and natural gas, IEA (2014). On the other hand, renewable energy is requesting from the society, but it is not possible to supply the global energy demand purely based on renewable energy today or in the relative near future. Thus, O&G will continue to play the major role in the world's energy production in order to meet this increasing demand. Some studies predict that the usage of oil will be doubled in 2025, Kloff et al (2004). Over the last decades, the O&G industries has expanded consistently from land operations to offshore to serve this purpose, Sandrea et al (2007). New type of vessels and drilling technologies have been developing with this intention to be able to reach deeper waters and further points for offshore exploration and production activities.

The O&G industry has one of the most complex and advanced supply chains around the world. It is vertically integrated, covering activities from exploration to transformation in refineries and product distribution with a large logistic network. The whole supply chain is divided into upstream, midstream and downstream. The upstream activities include exploration and production of crude oil. The midstream segment consists of refining, infrastructure and modes used to transport crude oil by pipelines, tankers or railways. The downstream involves processes following refining as transportation, marketing and distribution of petroleum products.

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Considering that the price of crude oil is actually coming back to the lower levels existing before 2000's, cost reductions is becoming a critical factor for offshore industry. Therefore, improving the upstream supply chain efficiency is becoming a major challenge for the O&G companies.

In the upstream logistic, Platform Supply Vessels (PSVs) provide production platforms and drill ships with required supplies on periodic basis. However, the operation of PSVs are affected by weather conditions and unexpected delays for loading and unloading. The duration of service operations at installations and sailing time increases when weather conditions deteriorate. In compliance with guidelines for safe offshore operations, PSVs are not allowed to perform service in production platforms when wave height and wind speed exceed certain thresholds. Because of the bad weather and unexpected delays, duration of a voyage scheduled for a vessel may be longer than planned, so that this vessel cannot return to the base in time to start its next planned voyage. This results in an upset of the complete logistic planning.

The dependence of PSVs on weather conditions and unexpected delays of loading and unloading at terminal make the fleet sizing problem highly stochastic.

1.2. Gap

Offshore logistic have been studying since 2000's in scientific literature. There are some researches about offshore logistics with different approaches, objectives, methods and proposals such as efficiency of supply vessel fleet, role of supply vessels in offshore logistics, planning of supply vessel's operations. However, there are only few studies considering effects of weather conditions on the performance of the system.

1.3. State of the Art

Darzentas and Spyrou (1996) have developed a simulation of ferry traffic in the Aegean Island. The simulation model is a decision aiding tool for transport system design and regional development. Main uncertainty factors are demand variance and weather conditions. In this study, weather conditions are described by the strength of the wind, and may cause the delays in departure from the port or slower speed of the vessel, while in the present study the weather is described by the past performance of the vessels through AIS data and may cause the delays in loading/unloading operations. Also the model of Darzentas and Spyrou (1996) is used for strategic planning and does not mention any operational planning apart from routing, which is not of interest in this study.

Shyshou et al. (2008) proposed a simulation model for offshore anchor handling operations related to movement of offshore mobile units. The operations are performed by anchor handling tug supply (AHTS) vessels, which can be hired either on the long-term basis or from the spot market. The stochastic elements are weather conditions and spot-hire rates. The requirements on the weather conditions are similar to the methodology developed in this paper. However, the authors are using metocean data to assess theses distributions.

The work developed by Aneichyk (2009) covers the designing of a simulation model for offshore supply process with the aim of creating a tool to plan the operations and fleet size. Some uncertainty factors affecting the process are taken into account such as weather conditions, varying demand and delays. A discrete-event simulation (DES) model is developed in order to model those uncertainties with a stochastic approach. Results obtained show that simulation may be seen as an important tool to develop new strategies under varying conditions and improve the efficiency of the process dramatically. The authors stated that simulation has a promising future in offshore logistics field and the usage will increase in near future.

To the best of our knowledge, the novel approach to use AIS data as DES input is original and the problem has not been previously studied in that way.

1.4. Purpose

Similarly to the studies mentioned previously, this paper investigate the upstream offshore supply chain logistic using a discrete-event simulation (DES) modeling in order to consider the stochastic phenomena due to weather conditions. However, this work differs from other studies by the way to consider uncertainties and stochastic variables.

The authors of similar works are usually modelling the effect of weather on offshore vehicles using joint probabilities of wave height and wind speed at sea. Then, considering the maximum limits on sea state for each vehicle, they are able to check if a vehicle can be operated at certain time of the simulation. In that way, they can assess off hire of the vehicle due to bad weather conditions. The main drawback of this methodology is that these meteocean data are private and generally extremely expensive to measure. Moreover, they are generally specific to one region. This fact motivates the authors to develop another strategy using past operational database on automatic identification system (AIS) to feed-up the DES model.

The outline of this paper is as follows. The method and the modelling are explained in Section 2, then, the results and a discussion of the case study are presented in Section 3. Lastly, recommendations and conclusions are provided in Section 4.

2. Methodology

Since 2002 new ships and later all larger sea-going vessels (>300 GT) and all passenger vessels are required to carry an automatic identification system (AIS) onboard. Through dedicated public very high frequencies (VHFs), AIS information is broadcasted between vessels, from vessels to shore, or vice-versa. In simple terms, AIS is a technology to make ships “visible” to each other. As an aid to collision avoidance, it records the information of ship behavior, including the effects of human action and ship maneuverability. This information can be displayed on the monitor of other ships or in a vessel traffic service center (VTS). That information includes ship positions, ship course, ship speed, ship type, time stamp, together with a unique identification number maritime mobile service identity (MMSI). AIS is always in operation when ships are underway or at anchor. Because the data are transmitted at frequent intervals of approximately 3–10s, it is possible for researchers to use historical AIS data to study the characteristics of vessel traffic to further improve safety and efficiency. Here, historical data analysis is used to lay the basis for a realistic simulation of PSVs logistic.

The reliability of the AIS data need to be carefully analyzed, Harati-Mokhtari et al (2007). However, based on our experience only a very small proportion of signals shows ambiguous positions, for example, onshore. This is not a problem since the ambiguous positions, speed or course can be eliminated in the statistical analysis. Missing several signals for a single ship track is another kind of problem for data analysis. However, it has been shown that this proportion is really small.

In order to be able to extract valuable operating information of the vessels (mean value and statistical distribution), a series of treatments of the data has been performed as presented in Figure 1. The following subsection describe the several stages of the process step by step.

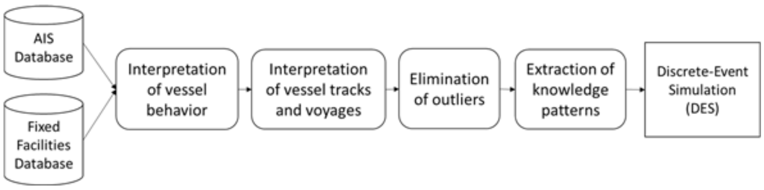


Figure 1. Workflow of the methodology

2.1. Interpretation of the Vessel Behavior

One of the main purpose of the developed methodology is to attribute a vessel behavior for each recorded AIS point. This include “loading/unloading at port”, “mooring”, “sailing”, “waiting/idle at sea” and “loading/unloading at platform”. In order to perform this task, a database of fixed facilities such as mooring areas, port areas and platform areas has been defined with the position of the center of each area as well as its related diameter. Therefore, it is possible to check if an AIS record is inside or outside a certain zone.

One important point of this task is to understand the data and the inconsistencies that can occur. Since the data comes from global positioning system (GPS), errors in the positioning and velocity may happen. In order to avoid local inconsistencies of the vessel behavior, the algorithm has been designed to check the most likely vessel behavior from the seven closely AIS records. In that way, local inconsistencies are avoided.

Using the distance travelled between two successive AIS records it is possible to assess the average speed of the vessel in this period. This average speed has been confronted to the instant speed provided by the AIS system in order to detect outliers.

Finally, algorithm makes the decision for each AIS record by combining the data about the velocity of vessel and the zone where it is located, see Figure 2. A velocity threshold of 1.25 knots has been chosen to determine if a vessel is sailing or idle. Figure 3 (a) give an example of the results of the output of the algorithm around Macaé logistic terminal while Figure 3 (b) give an example of the output of the algorithm around a cluster of platforms.

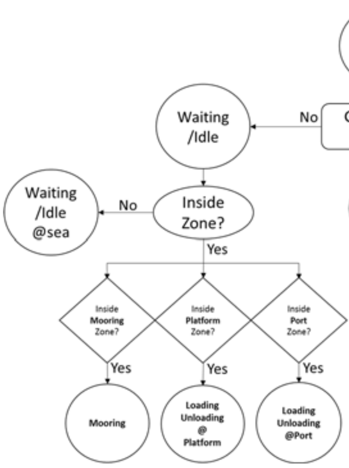
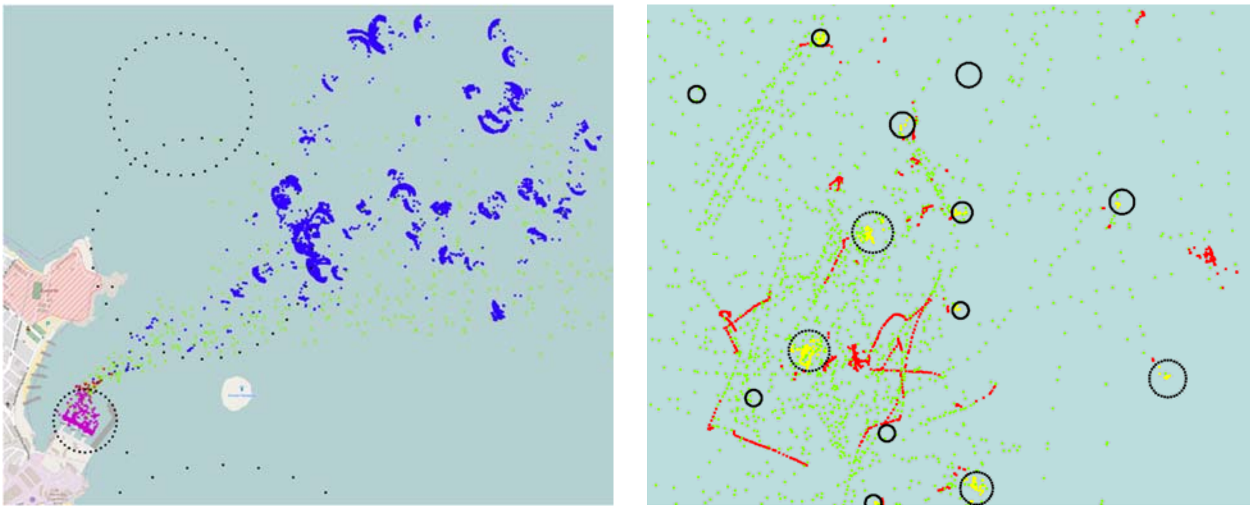


Figure 2. Workflow of the algorithm to define the vessel behavior



(a) Around Macaé logistic terminal

(b) Around a cluster of offshore platforms

Figure 3. Interpretation of behavior of one PSV using 6 month AIS data where purple means loading/unloading at port, blue means mooring, green means sailing, red means waiting/idle at sea, yellow means loading/unloading at platform and black point highlight the position of fixed facilities.

2.2. Interpretation of the Vessels Tracks and Voyages

In this study, a vessel track is identified by any change of the vessel behavior. For instance, a vessel moored, a vessel sailing from mooring area to the port and a vessel operated at the pear are three different vessel tracks. In addition, a voyage can be seen as a collection of tracks. As illustration, a typical voyage of a PSV start from the mooring zone of the port. The vessel sail until the port terminal where it is loaded. After completing this task, the PSV sails until the offshore field where the supply activities are performed to the platforms. Then, the PSV sail back to the mooring zone of the port waiting for a new cycle.

2.3. Elimination of the Outliers

After a normalization between 0 and 1, extreme outliers related to speed and time of operations were excluded using equation 1 and 2.

$$p < Q_1 - (3 \cdot IQR) \qquad \textbf{(1)}$$

$$p < Q_3 - (3 \cdot IQR) \qquad \textbf{(2)}$$

Where p data points,
Q1 the lower quartile,

Q3 the upper quartile,
IQR the distance between Q1 and Q3.

2.4. Gathering the Knowledge Patterns From the Data

After the previous treatments, the data are gathered by tracks in order to extract the knowledge of the database. Average speed as well as total time is calculated for each track. Similarly, number of records for each track is calculated.

2.5. The Discrete-Event Simulation

Simulation is a modelling tool widely used in operational research (OR), Burgess et al (1999). One of the most common approaches is discrete-event simulation (DES). It started and evolved with the advent of computers, Myron (1987) and Robinson (2005). DES represents individual entities that move through a series of queues and activities at discrete points in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation can directly jump in time from one event to the next. Since a DES does not have to simulate every time slice, it can typically run much faster than the corresponding continuous simulation.

Models are generally stochastic in nature. The issues on how to define probability distributions for activity duration through sample data in manufacturing field have been widely studied by Fente et al (2000), Maio et al (2000) and Robinson et al (2007). The most difficult aspect of duration assessment is gathering data of sufficient quality, quantity and variety, Robinson et al (2014). Moreover, the impact of the uncertainties in the duration of the activities characterizing the real world, due to factors such as weather conditions, has been little studied.

DES has been traditionally used in the manufacturing sector, Khedri et al (2015) and Yeong et al (2014), while recently it has been increasingly used in the service sector including applications to airports, call centers, fast food restaurants, banks, health care, and business processes.

Here, DES is used to investigate the upstream offshore supply chain logistic by PSVs. This work differs from other studies by the way to consider uncertainties and stochastic variables. In this context, AIS data are used to obtain sailing velocity, waiting and idle time at sea, loading and unloading time at platform, loading and unloading time at port and anchorage time for the supply vessels.

3. Case study

The case study presented in this paper focus on the Campos basin with latitude between 21° 49' 33.2414" S and 22° 40' 47.6969" S and longitude between 39° 42' 26.1104" W and 40° 43' 5.083" W.

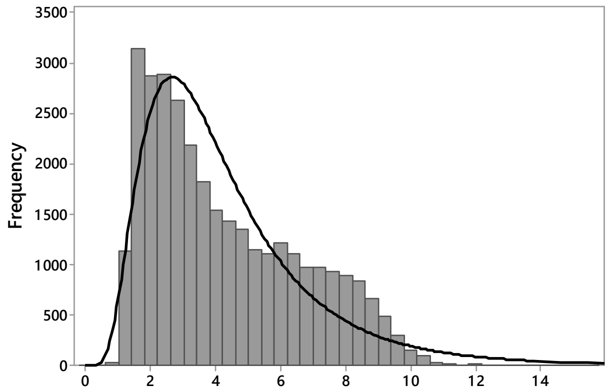
3.1 Extraction of the Statistical Distributions

Several years of AIS data are available in Campos/Santos basin, but in this paper the emphasis is put on a database of 6 months from 1 April 2014 to 1 October 2014. Dealing with the original AIS data, a time step of 10 minutes is taken. The author focused the study on the analysis of 90 platform supply vessels (PSVs) that are performing the supply of the platforms, FPSO's and drilling ships in this region. Finally, these data represents about 5 million of AIS records.

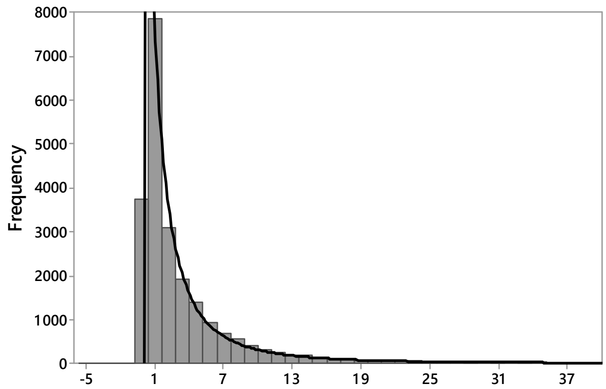
Applying the methodology described in the previous section the histograms presented in Figure 4 have been extracted for the 90 PSVs. Table 1 gives number of tracks, mean and standard deviations for each behavior of the PSVs while Table 2 present the probability density functions that best fits the histograms presented in Figure 4.

These data have been generated for any type of PSVs operated during the above-mentioned period. However, in a near future, it is planned to make the difference between various sizes of PSVs as well as to check the effect of weather seasonality on the statistical distributions. Similarly, the histogram related to the loading and unloading time at the logistic port corresponds to various terminals and the loading and unloading time at platform correspond to both production and drilling platforms.

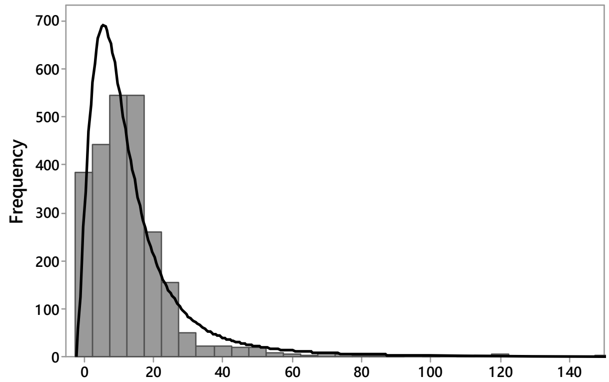
It is interesting to note that the sailing velocity histogram seems to be decomposable into two different components. A first component for the small velocities around 2 knots and a second component for the highest velocities between 6 to 10 knots. This behavior could be explained by the fact that these ships has more than one operational profiles, e.g. PSVs operating close to the platforms are using a small velocity while in transit to port velocity is higher.



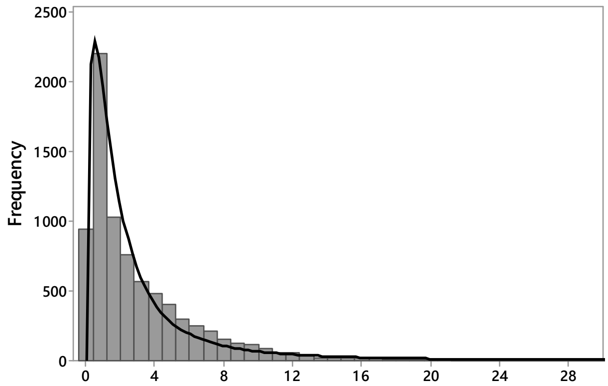
(a) Histogram of the sailing velocity in knots



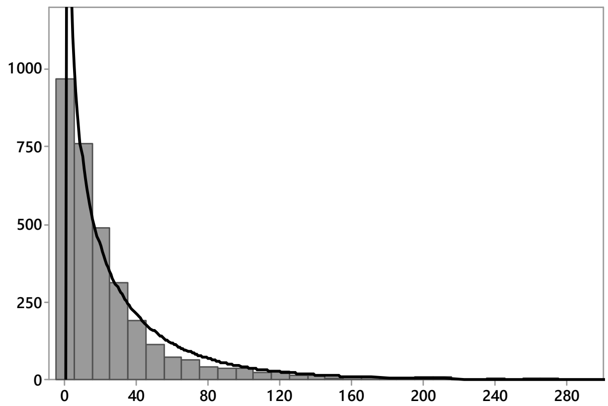
(b) Histogram of the waiting/idle time at sea in hours



(c) Histogram of loading/unloading time at port in hours



(d) Histogram of the loading/unloading time at platform in hours



(e) Histogram of the mooring time at port in hours

Figure 4. Histograms of the 6 months operation of 90 PSVs in Campos and Santos basin

Table 1. Extracted data from the AIS database

Behavior of the PSVs vessel	Unit	Number of Tracks	Number of Records	Number of tracks outliers	Mean	Standard Deviation
Sailing velocity	Knots	32 016 (43%)	1 638 680	39	4.34	2.31
Waiting/Idle time at sea	Hours	27 399 (36%)	973 299	0	3.75	7.76
Loading/Unloading time at port	Hours	3018 (4%)	441 414	5	16.09	33.53
Loading/Unloading time at platform	Hours	9064 (12%)	319 678	7	3.24	4.36
Mooring time	Hours	3798 (5%)	1 012 490	0	28.06	49.40

Table 2. Best fitting statistical distributions

Behavior of the PSVs vessel	Unit	Type	Parameters
Sailing velocity	Knots	Log Normal	Location = 1.34; Scale = 0.54; Threshold = -0.067
Waiting/Idle time at sea	Hours	Log Normal	Location = 0.44; Scale = 1.33; Threshold = -0,0012
Loading/Unloading time at port	Hours	Log Logistic	Location = 2.51; Scale = 0.46; Threshold = -2,072
Loading/Unloading time at platform	Hours	Log Logistic	Location = 0.54; Scale = 0.72; Threshold = 0,016
Mooring time	Hours	Gamma	Shape = 0.58; Scale = 47.68; Threshold = 0,016

3.2 The Discrete-Event Simulation

To illustrate the concept presented in this paper, a case study based on the Brazilian Campos basin has been developed using discrete-event simulation (DES). The aim of the model is to assess alternative fleet size configurations taking into consideration uncertainty in weather conditions and unexpected delays.

The configuration of the layout consist in one logistic port terminal (Macaé) containing 6 berths to load and unload the 23 PSVs considered in the simulation. Figure 5 presents the relative location of the 38 platforms organized in 19 clusters (group of platforms) as well as the port. The DES results are presented for 6 months of the operation of the PSV fleet.

Figure 5. Location of platforms and logistic port terminal (Macaé) considered in the DES. Color of the points represents the 19 clusters of the platforms

In the simulation, platforms are requiring supplies on a periodically base to the logistic port. That period has been defined as a constant in the simulation but differ with the type of the platform. Here the frequency has been chosen around twice a week, i.e., a platform require a visit of a PSV twice a week. Then, the requests are organized by priority of the load and platform clusters. Depending of the availability of a berth in the terminal a PSV available in the mooring area is called to be loaded in the port terminal. Finally, the PSV will sail to supply the platform cluster, deliver the load to each platform of the cluster, and then, sail back to the mooring area after the process. The process of PSV allocation and routing is repeated periodically until the end of the simulation.

The dimension, capacity and speed has been considered equal for all PSVs. Moreover, the route of the vessel has been considered straight lines. The statistical distribution of sailing velocity, waiting/idle time at sea, loading/unloading time at port and loading/unloading time at platform has been implemented in each relative process inside the DES while mooring time at port can be considered as the variable to be calibrated.

Figure 6 presents the overall traveled distance by all PSVs along 200 iterations for a period of six months. As the result is highly stochastic, testing the convergence of the output is required. Figure 7 presents the convergence of the overall travelled distance of all PSVs. It is observed that the accumulated mean value tends to converge roughly after 200 iterations, i.e. with a variation of less than 50km per iteration.

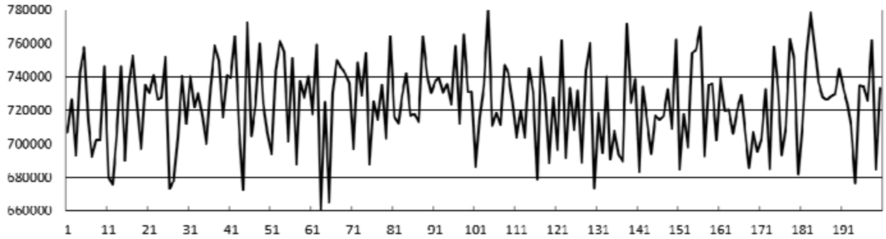


Figure 6. Simulated traveled distance of PSVs during 6 months of operation. Results of the first 200 iterations.

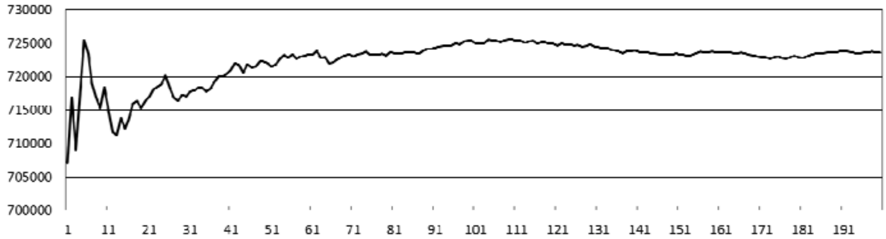
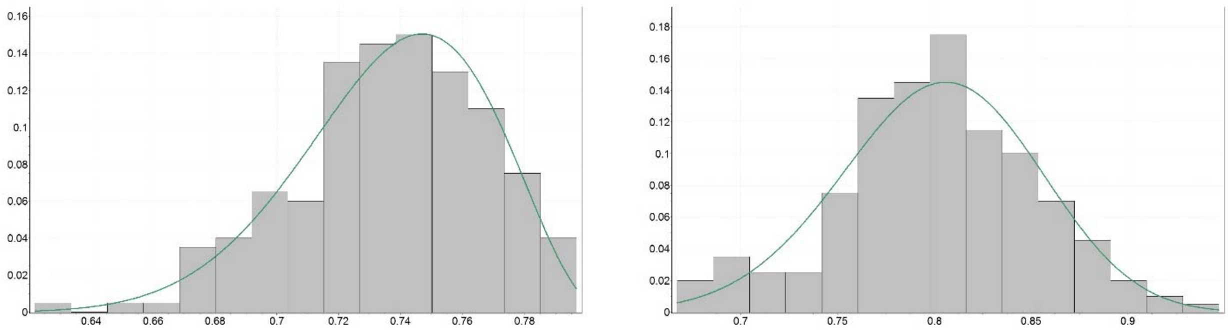


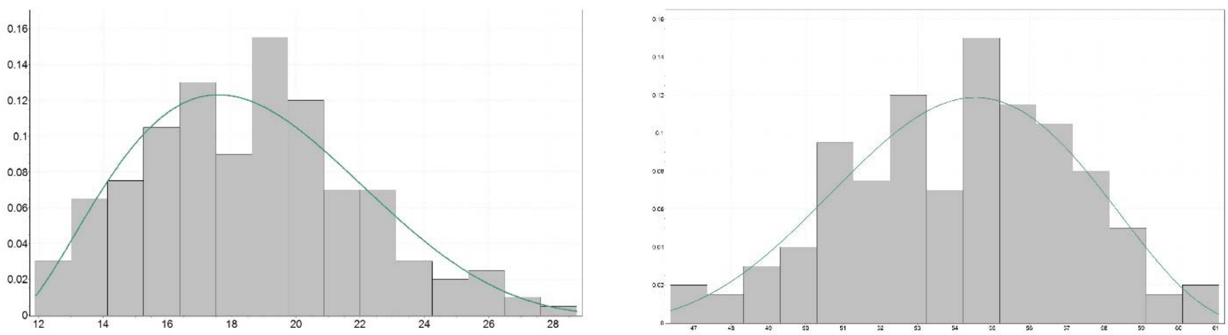
Figure 7. Convergence of the simulation after 200 iterations of the accumulated overall travelled distance measured in kilometers for 6 months of operation.

Any simulation required to be carefully validated. In this paper, the validation data were not presented for confidentiality reasons. However, following section shows typical preliminary results that can be obtained from the DES.



(a) Average utilization of the 23 PSVs in % (b) Average utilization of the 6 berths in %

Figure 8. Probability density function of the utilization of the resources considering 200 iterations and 6 months of operation



(a) Average mooring time per PSV in hours (b) Number of clusters supplied per PSV

Figure 9. Probability density function of typical outputs considering 200 iterations and 6 months of operation

Figure 8 shows respectively the probability density function of the average utilization of the 23 PSVs (mean 75%) and the average utilization of the 6 berths at the logistic terminal (mean 80%). These values indicates that for that configuration the logistic port is saturated. The average mooring time per PSV, Figure 9 (a), and the number of clusters visited per PSV, Figure 9 (b) are other typical results that can be generated. The mean value of the number of clusters supplied per PSV is around 55. That is cross checking the assumption on two visits of clusters per week for each PSV.

The actual DES model is limited to the study of the influence of the uncertainties due to weather downtimes and sea-going operation delays. However, in a near future, the model would be improved to included additional factor such as deck-load capacity, dry bulk capacity, load delivery delays, etc. Anyway, the presented methodology provide a novel approach to develop realistic simulation starting from AIS data. This represent the basic framework for fleet size decision making, scheduling optimization, cluster optimization, etc.

4. Conclusions and recommendations

This paper examines the upstream logistic of an offshore supply chain by using stochastic approach. A DES model that is able to evaluate the fleet size alternatives has been developed. The consideration of uncertainties due to weather conditions and unexpected delays has been considered trough the extraction of vessels patterns using automatic identification system data. A time depend historical database of 6 months for 90 PSVs has been analyzed. This represents about 5 million of AIS records. Vessels patterns (probability density functions) such speed, loading and unloading times at port terminals, loading and unloading time at offshore platforms as well as mooring time and waiting/idle time at sea has been extracted.

A DES model representing the Campos Brazilian basin that includes 1 logistic port, 23 PSVs and 38 offshore production platforms has been developed to demonstrate the feasibility of the methodology. The preliminary results show a good accordance between the simulation outputs and real data.

We suggest that this novel approach can be adopted as a tool to examine the efficiency of existing PSV fleets as well as to identify the effect of different operational and management strategies in offshore logistics activities such as adjusting the routes of vessels, deciding the fleet size, determining the composition of PSV fleets or optimizing the platform clusters.

As future work, we recommend the coupling of an optimization engine to the DES model in order to identify the optimal parameters of the upstream PSVs supply chain simulation. In parallel, it is planned to study the impact of seasonality of meteorological data on the performance of the system as well as the sensitivity to PSVs capacity (size). It is planned to perform similar work for other kind of vessels involved in the supply chain management such as for the shuttle tankers responsible for the crude oil off-loading, anchor handling tug supplies (AHTS), etc. Another issue that could be studied in the future is the optimization of platform clusters considering that drill ships are not fixed and operate for a certain time in each offshore field.

5. Acknowledgements

This research was partially supported by Grant 456288/2013-9 of the Brazilian National Research Council (CNPq).

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