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A Discrete-Event Simulation Approach for Platform Support Vessels Operations under Stochastic Effects

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Abstract

The essence of logistics operations is complex by nature. Upstream logistics is constantly challenged to maintain and even increase profitability at oil exploration and production (E&P) system, where production costs are impressive. Since there are high risks involved, the research field around E&P systems is benefic to assure system performance. This paper addressed a simulation model for fleet design optimization in E&P logistics. The model regards deck cargo transportation between port and offshore unit, realized by platform support vessels. The simulation was developed in software of discrete-event environment for process flow analysis. This system was parameterized under the influence of stochastic parameters as demand, weather conditions and charter prices, by the application of probability distribution functions. The results present an effective tool for fleet design estimation, with total cost and operation data appended.

1. Introduction

Offshore logistics, or upstream logistics, consist of logistic support activities at offshore exploration and production (E&P) system. These activities address supply, service and labor management aspects. At supply activity, logistic connect several elements in a flow of supplies (supply chain).

This flow is affected by several stochastic (uncertain) factors, resulting in a complex environment. Weather conditions, vessels off-hire rates, vessel waiting time and unforeseen incidents are examples of stochastic factors. Furthermore, the production cost is impressive, considering the high added value in oil and gas industry.

Thus, the logistics main challenge is to handle a network full of risks and uncertainties due to high costs involved in E&P system processes and high stochastic parameters influence.

1.1. Bibliographic review

Upstream logistics main purpose is to reduce operational costs and to ensure high quality performance even under risky and uncertain situations. One of the pioneers on upstream logistics simulation modeling was Aas et. al. (2007). They developed a simplified routing problem for only one supply vessel regarding storage requirement problems. They used mixed integer linear programming model and they were willing to prove that it was possible to perform simultaneously both pickup and delivery system. Slightly similar to Aas study, Nishi et. al. (2011) addressed ship scheduling problems by a column generation approach. The main objective was to provide an algorithm to assist crude oil transportation, regarding both of inbound and outbound transportation simultaneously. Kaiser (2010) modeled a logistic network in Gulf of Mexico as linear time-invariant deterministic system. As he intended to provide a methodological framework for upstream logistic services, the simulation quantified the number of offshore supply vessel and crew boat departures by activities. He claimed that his paper is the first integrated modeling study on service vessel trips in the Gulf of Mexico. Maisiuk & Gribkovskaia (2014) addressed a supply vessel planning problem, regarding the effect of weather conditions over support vessels weekly schedules.

They considered the possibility to hire a vessel from the spot market and also the stochastic factor of future spot vessels rate. Their model was validated and tested on real data from North Sea.

There are also several studies focused on Brazilian scenario, specifically Brazilian southeast coast.

Da Silva (2017) presented a simulation-based model focused mainly on defining the supply vessel fleet size to perform a suitable level of service, with minimum cost. The master thesis considers specifically deck cargo transported from Port of Macaé to offshore units in Campos basin. The methodology applied was discrete-event simulation.

Leite (2012) developed a study at Campos basin, Rio de Janeiro, based on Petrobras data. His master thesis analyzes deck cargo transportation empirically, investigate the effect of different service polices and propose new ones in order to optimize the system. This study also aimed to increase academic knowledge about maritime support.

Upstream logistic academic field is quite unexplored, however, it is possible to notice the evolution of academic research subjects: from one single support vessel in a linear programming model to fleet design considering stochastic factors. Besides, these studies addressed specific characteristics of each geographic location, since each specific parameter (as environment, management policies, available vessels) heavily affect the simulation result. Therefore, modeling similar systems for distinct parameters admits a wide range of research to be explored in this field.

1.2. Objectives

The main objective of this study is to develop a simulation-based model of a platform support system, regarding the offshore transportation (supply vessels), considering stochastic effects of weather condition over the system. The output of this simulation is fleet composition, offshore operation data and costs involved.

1.3. Methodology

Law & Kelton (1991) classified simulation models (simplified description of a system or process in order to enable calculations and predictions) along three different dimensions:

- Static and Dynamic Model;
- Deterministic and Stochastic Simulation;
- Continuous and Discrete Simulation.

Each dimension polarity reflects the characteristics of the system and objectives of the model. The model may be static or dynamic, depending on how it considers time influence. For static model, time is not a determinant element i.e. a static model represents a system in a particular instant of time. Meanwhile, a dynamic model represents a system as it evolves over time. In this case, the elements are all functions of time and are constantly changing. A simulation will be denominated deterministic if there is no probabilistic element in its model. In this model, the output is determined once the inputs quantities and relationships in the model have been specified. On the other hand, stochastic simulation is modelled having at least some random input components. Stochastic model output is random and represents an estimate of the true characteristics of the model. The difference between continuous and discrete simulation is in how time is considered. Continuous time has advantages over discrete time when the elements of the system may be aggregated. On the other hand, discrete time is better considering that, between two main events of each element over separate points in time (steps), nothing relevant occurs.

Considering the constant change of state in the transportation scenario and the presence of stochastic factors (as weather conditions) the model of the present study is dynamic and stochastic. Since there are main events that can be described as steps (e.g. a vessel departure, a request sending), the simulation is discretised in events.

2. Scenario description

2.1. Upstream logistics flow

Upstream logistics supply chain uses a pull strategy. Sarbjit (2017) has defined pull strategy as when the “customer needs” pulls material through the supply chain. This strategy allows a better waste control and less negative effects due to demand fluctuation. In E&P system, the offshore unit (as the final customer) pulls every material flow in upstream logistics supply chain. Figure 1 simplifies the upstream logistics supply chain.

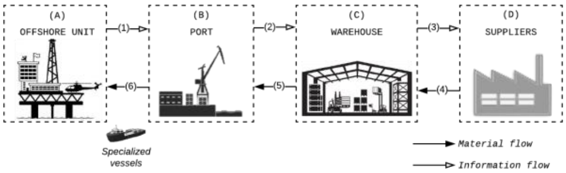

Figure 1 - Upstream logistics flow

When offshore units (OU) demand any material, it sends a request (1) to the port. This information is processed and a solution is considered. The port sends the solution as an information to the warehouse (2). Warehouses usually keep a minimum stock to attend OU needs in time, considering the high costs for production stop.
Material flow begins as the warehouse sends the requested material to the port (3). Then, this material is transported from the port to OU by specialized vessels (platform support vessels).
The warehouse establishes a demand for minimum stock according to a demand-basis related to OU. Therefore, suppliers provide every good (2') as an answer to warehouses demand (1').
Regarding transportation, movements (1) and (2) might be realized by trucks, trains, ships, tubes and even airplanes, depending on cargo characteristics. While transport service at (3) is realized mainly through a multi-task vessel: platform supply vessels (PSV).

2.2. Material

Regarding the material flow, in the offshore units routine of demand, they consist of equipment, instrumentation and general goods, food and drinking water, chemical, waste and garbage, risers and pipes, industrial water, diesel, fluids (brine and drilling mud), dry bulk (cement, barite and bentonite) (Table 1).

Table 1 – Cargo caracteristics in upstream logistcs

Type	Load	Back load	Deck		Tank
			Unitized	*Non-unitized*	
General Cargo	X	X	X	X	
Food and drinking water	X		X		
Pipes	X	X	X	X	
Risers	X	X		X	
Chemical	X	X	X		
Insdustrial water	X	X			X
Diesel	X				X
Fluids	X	X			X
Dry bulk	X				X
Waste and garbage	X	X	X		

2.3. Transportation

Platform support vessel (PSV) is the main element in charge of transportation between land and OU. Those vessels possess deck space for containers and large elements transportation and compartments for dry and liquid bulk. Furthermore, PSV are especially design for operations at the sea. They are more robust, being able to face bad weather conditions (above the 5 Beaufort scale).
Around the world, PSV are actually used as a multi-task vessel, maximizing transport capacity of the vessels. However, in Brazil, supply vessels operate with only one cargo type at time.
The most common sizes for PSV in Brazil are, according to Leite (2012), PSV 1500, PSV 3000 and PSV 4500. Their average dimensions are presented in Table 2.

Table 2 – PSV 1500, 3000 and 4500 dimensions

Vessel Type	Deck area (m^2)	Useful deck area (m^2)	Length (m)	Width (m)
PSV 1500	394	295	62	15
PSV 3000	575	431	70	16
PSV 4500	880	660	87	18

PSV diesel consumption is an important factor on the PSV total cost. Table 3 presents diesel consumption, in service, in stand by and at the port.

Table 3 – Marine diesel oil consumption per PSV

Vessel	Consumption (ton/day)		
	in service	*in stand by*	*at the port*
PSV 1500	11.4	4.3	1.1
PSV 3000	13.3	4.3	1.3
PSV 4500	16.7	5.7	1.3

2.4. Offshore units

At E&P system, offshore units (OU) refer to drilling and production units, which have several different characteristics in terms of the deck area, diesel and bulk storage capacity limit, water maker, operating water depth, well depth, unit size, people on board, age, maintenance program, fixed or mobile, etc. Because of these characteristics, each OU have a unique demand pattern.
Due to oil wells physical conditions, it is usual to see OU grouped on a specific region in order to better seize its potential. This grouping is known as clusters.

2.5. Operation conditions

Platform support vessels operations (as navigation, loading and unloading on unsheltered area) are interrupted whenever the cargo and/or crew safety is threatened. This usually happens under specific weather and sea conditions (metocean conditions), as rain, wind speed and wave height. An operation disruption leads to expressive opportunity costs (from economy, cost incurred by not choosing or fulfilling a given process). Whereas a misfortune would result in labor disputes or contract clause for loss of cargo, i.e. more extra costs. As these factors are slightly unpredictable and any unforeseen, Brazilian support operations request complex planning.

3. Model description

Figure 2 summarize the dynamics of the model. When the simulation starts, at each scheduled day, platform support vessels (PSV) will be mobilized according to offshore units demand. The system verifies how many PSV and which ones are suitable for the required task. PSV usually will load general cargo at the port and then sail to the cluster. Arising at the first offshore unit, a question will be done: "Which is the weather condition at this time?". If the answer is "bad weather", then the vessel will wait until it is considered good. Once this requirement is fulfilled, PSV continue its load/unload activities until every OU is attended. A new load/unload activity only star under this primary condition. Then, the PSV sail to the port to unload any backload received in the operation. The considerations and details of this dynamic are addressed in next sections.

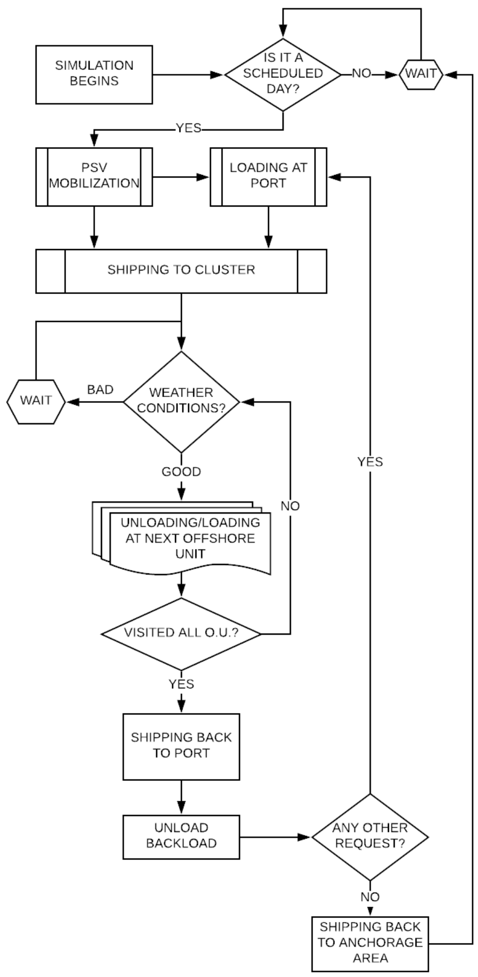

Figure 2 – Model process flowchart

3.1. Elements

a. Port

Regarding port characteristics, the development of this model considered the following assumptions.

- The port has an infinite number of berths, with no dimension or equipment restrictions;
- The port has unlimited area for loaded and unloaded cargo;
- There is only one port.

b. Cluster

For simplification purpose, this model considers only production units type FPSO (Floating Production Storage & Offloading). According to Petrobras Annual Report 2008, it was observed that each cluster contained either three or four floating production units. Then, the quantity of offshore units was set to four. In order to establish the distance between these units, a probability density function (Log-logistic) was applied to a dataset composed by 71 platforms pairs. The mode for this

statistical distribution was 6.37 kilometers (distances b to h, in
Figure 3). Also, regarding data from Petrobras Annual Report, the average distance from coast to Brazilian clusters is over 250 kilometers. Therefore, this distance considered in the model was set to 300 km (distance a, in
Figure 3).

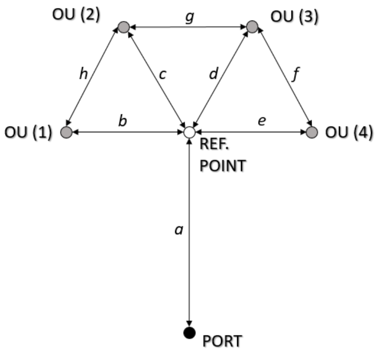

Figure 3 – Distances between elements in the model. Distances between offshore units (OU) are equal, as well as their distances from the reference point.

c. Platform support vessel

In the model, three types of platform support vessels will be available to answer OU requests: PSV 1500, PSV 3000 and PSV 4500. Their dimensions are presented in Table 2 and their diesel consumption is presented in Table 3.

3.2. Cargo demand and schedule

PSV operate according to a schedule to meet production units demand. The schedule is defined based on a weekly-based demand.

This model regard only deck cargo transportation. Demanded deck cargo can be measured by its occupied area, by its tonnage or by lifts (number of crane movements required). Each option is applied depending on the situation. Area measurement is used when deck occupation is under analysis. Tonnage is used to assist the payment of the port operators and for enabling comparisons with other types of cargo. The number of crane movements is used as a measurement to calculate the operation time of the vessels at the port.

As this study addresses PSV performance while it is transporting deck cargo, demand will be measured by occupied area on deck and the database used will be one provided by Leite (2012). This data is illustrated in Figure 4 and contains weekly demand numbers for production units in Campos Basin (between April 2011 and March 2012).

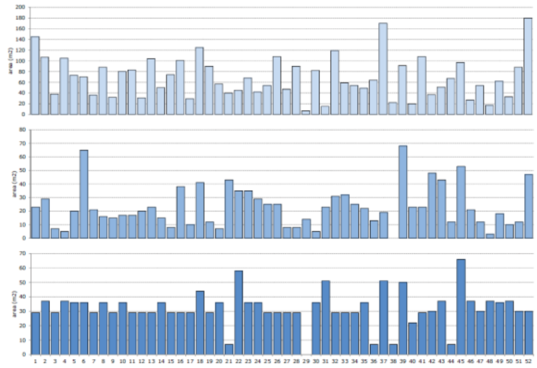

Figure 4 – Average weekly demand of production units (m² occupied) per week in Campos Basin between April 2011 and March 2012. From top to bottom, the bar chart represents general cargo, chemicals and food and drinking water.

Statistical demand distributions were defined according to gamma distribution. Gamma distribution advantage is to be highly versatile, being applicable in many areas, including industrial engineering to represent delivery times. Statistical demand distributions are defined by equation 1.

$$f(x) = \frac{(x-\gamma)^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \cdot exp\left(-\frac{x-\gamma}{\beta}\right) \qquad (1)$$

Considering that PSV will attend to the offshore unit twice per week, Table 4 contains the applied parameters for gamma function.

Table 4 – Parameters applied in Statistical demand distributions for loading and back loading operations

Demand	α	β	γ
Load	6.1662	10.008	0
Backload	7.2059	9.2576	0

3.3. Operation time

In order to represent offshore operation time in the simulation, it is needed to consider the time of loading and unloading at both port and offshore unit.

Regarding loading and unloading at the port, a database of 415 operations was used under a truncated normal distribution, following the probability density function below.

$$f(x) = exp\left(-\frac{1}{2} \cdot \left(\frac{x-\mu}{\sigma}\right)^2\right) \cdot \frac{1}{\sigma\sqrt{2\pi}} \qquad (2)$$

Truncated aspect in this distribution allows negative values neglection. The values of parameters μ and σ used in equation 2 are in Table 5.

Table 5 – Parameters applied in normal distribution for loading and unloading operation times at the port

Parameter	Value
μ	0,62102
σ	0,34329

Regarding back loading and unloading at the platform, a database of 335 operations was submitted gamma distribution. Equation 1 represents its probability density function. Parameters values are shown in Table 6.

Table 6 - Parameters applied in gamma distribution for loading and unloading operation times at the offshore unit

Parameter	Value
α	1.3218
β	0.7851
γ	0

Both databases considered PSV 1500, PSV 3000 and PSV 4500 operations.

3.4. Weather conditions

Weather conditions representation was based in National Buoy Program database (PNBOIA), a public data source. The chosen buoy location was in Santos (SP) region (Latitude -25.27°, Longitude -44.93°). The data was collected on each hour, from April 2011 and June 2017. Database contain average and maximum wind speed for 10 meters high from the sea surface, significant wave height, maximum wave height, peak period and wave and wind directions. However, the records contained flaws and discontinuities, foiling a suitable wave mapping of the region.

A consistent wave model was obtained from a simulation, which was developed for a 15 years model, with weather recording from hour to hour. The software used (Wave Watch III) was capable of emulating the physical process of wave growth, propagation and dissipation in two dimensions, from the sum of the energy transfer from wind fields to the waves through a wind-wave interaction, with the dissipation of the wave and nonlinear interactions between waves.

The created database allowed few considerations. The average wave height occurrence is 1.94 meters. About 60% of wave height occurrences are below 2 meters and only 6% is above 3 meters.

According to the regulatory standard NR 18, item 14, Handling and Transport of Materials and People, paragraph 18.14.24.6.2, any crane operation must be suspended when wind speed is over 42 kilometers per hour. (SIT Ordinance No. 114, of January 17, 2005). In order to relate the wave height database with wind speed limitation, it is necessary to resort to Beaufort scale. According to this scale (Table 7), for 42 kilometers per hour wind speed, wave height limit would be between 2.4 and 4 meters. Thus, for this study, the stop criterion for load lifting operations is wave height over 3.5 meters.

Table 7 – Section of Beaufort scale highlighting the limit classification for PSV operations

Beaufort number	Wind name	Wind speed (kph)	Wave height (m)
5	fresh breeze	29 – 38	1.2 – 2.4
6	**strong breeze**	**39 – 49**	**2.4 – 4**
7	moderate gale	50 – 61	4 – 6

Therefore, the next step is to set this parameter under a probabilistic distribution.

The database created with Wave Watch III allowed the estimation of discrete probability distributions of good and bad weather successive intervals. Then, an annual period was divided in quarters (seasons), in order to obtain a greater precision and verify the frequency of wave height in each quarter (seasonality). The quarters are defined as Q1, Q2, Q3 and Q4. Q1 is composed by January, February and March. Q2 is composed by April, May and June. Q3 is composed by July, August and September. Finally, Q4 is composed by October, November and December.

A Bernoulli distribution was applied in order to define the probability of bad weather (p) in each quarter.

Table 8 – Bernoulli distribution for bad weather probability

Quarter	p
Q1	0.13115
Q2	0.39655
Q3	0.39623
Q4	0.30769

Table 8 shows that there is a greater probability of bad weather in the second quarter (Q2), while the lowest probability occurs in the first quarter (Q1).

Then, Anderson-Darling test was applied for several continuous distributions to verify the most suitable one. Gamma distribution was chosen (equation 1). The parameters used are in Table 9. This distribution was used to model meteorological conditions for the main discrete event simulation.

Table 9 – Gamma distributions for good and bad weather.

Weather	Quarter	α	β	γ
Good	T1	8.7481	69.856	0
Good	T2	1.5557	192.55	0
Good	T3	1.4249	174.82	0
Good	T4	2.174	185.68	0
Bad	T1	2.8862	4.6342	0
Bad	T2	2.1501	8.8165	0
Bad	T3	1.5621	9.4124	0
Bad	T4	1.4604	8.0456	0

The influence of sea conditions on support vessels activities was considered through the variation of travel time throughout the year. The navigation time between the units i and j is calculated by the equation 2.

$$t_{ij} = \frac{d_{ij}}{V_s} * f_c \qquad (2)$$

Where d_{ij} is the travelled distance, V_s is the supplier speed and f_c is a correction factor which adjusts travel duration according to the sea conditions. For f_c estimative, the annual variation of the average cycle (regarding Petrobras suppliers operation in Imbetiba Port) was considered. Figure 5 presents the correction factor for each month, which was considered constant during each month.

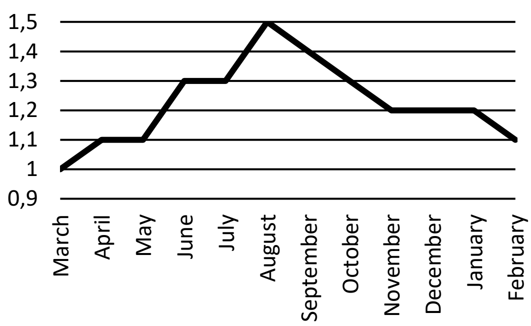

Figure 5 – Correction factor for shipping time

In contrast with PSV operation time delineation (which is determined by the probabilistic dynamic), Figure 5 assisted a relatively simple shipping time delineation. This simplification allowed a clearer modelling and also a lighter simulation run, satisfactory for a first approach.

3.5. Costs

The cost considered in this study is composed by two elements: charter contract and voyage costs. Time charter is the most usual contract for platform support vessels in which a vessel is rented through the payment of a charter fee (named hire). Besides that, the voyage cost is on the contractor responsibility. Voyage cost consists in fuel consumption and port costs.

Charter rates series were collected in Clarksonsnet (available in www.clarksons.com) for PSV 4000 in the North Sea market, between June 2008 and August 2016.

Mean-reversion method (MRM) is a collection of processes which provide a suitable approximation to parameters stochastic characteristics (Termos. 2008). As charter cost fluctuation is inherently stochastic, MRM was the method chosen to represent charter cost probability distribution along the project life cycle.

The chosen mean-reversion model was Dixit & Pindyck geometric model. Equation 3 was applied on geometric model discretization.

$$P_t = e^{(q_1 \cdot q_2 + (lnP_{t-1}) \cdot q_4 + q_5)} \qquad (3)$$

Where the elements q_1, q_2, q_4 and q_5 , as well as constant q_3, are defined on equations below.

$$q_1 = \left(ln\,\overline{P} - \frac{\sigma^2}{2*\eta*A}\right) \qquad (4)$$

$$q_2 = \left(1 - e^{-\eta A \Delta t}\right) \qquad (5)$$

$$q_3 = q_1 \cdot q_2 \qquad (6)$$

$$q_4 = e^{-\eta A \Delta t} \qquad (7)$$

$$q_5 = \sigma \cdot \sqrt{\frac{1-e^{-2\eta A \Delta t}}{2\eta A}} \qquad (8)$$

From time charter database, standard deviation and variance were calculated. Then, the constant values were found. The results are in Table 10.

Table 10 – Constants values of Dixit & Pindyck MRM for time charter prices

Constant	Value
q_1	3.114626
q_2	0.1037362
q_3	0.3230995
q_4	0.8962638
q_5	0.1061013

From this, random series were created, ruled by the time series of time charter prices.

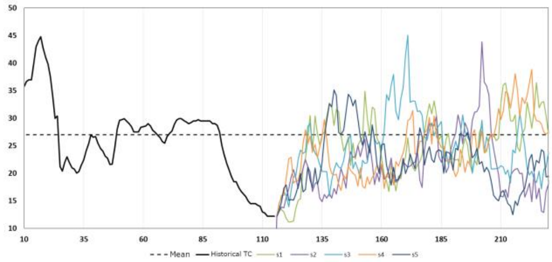

Figure 6 – Time Charter values behavior for PSV 4000

Figure 6 presents time charter historical values (continuous black line) and other five random forecasting series (gray lines). The mean is represented by the dashed line.

A correction factor was used to find PSV 1500, 3000 and 4500 respective values from MRM. This factor was appraised using average difference of PSV characteristics. Time Charter correction factor is presented in Table 11.

Table 11 – Correction factor for PSV adaptation.

PSV	Correction factor
1500	0.65
3000	0.82
4500	1.00

Diesel cost also was estimated by a Dixit & Pindyck mean regression model. Bunker Index website provided a suitable database for marine diesel oil (MDO) during March 2009 and July 2017. The constants values are presented in Table 12.

Table 12 - Constants values of Dixit & Pindyck MRM for MDO prices

Constant	Value
q_1	6.621451
q_2	0.000634
q_3	0.004198
q_4	0.999366
q_5	0.009112

Therefore, a random series ruled by MDO prices time series was generated.

4. Results and discussion

The obtained results considered a 30 years discrete-event simulation model for wave height limit of 3.5 meters. As the model is essentially stochastic, this experiment also considered one hundred iterations in order to observe results convergence (Figure 7 illustrates this convergence).

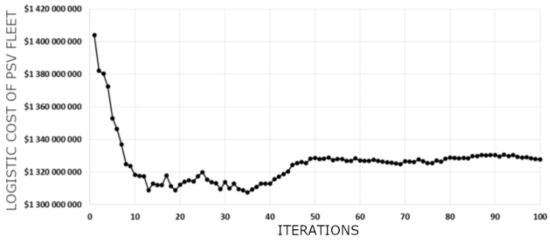

Figure 7 – Cost convergence

Therefore, the results shown from now on will regard to an average of one hundred preliminary results.

4.1. Fleet Composition

This simulation model was developed as a self-adjusting fleet system, i.e. platform support vessels fleet varies according to stochastic fluctuations of cargo demand. The simulation always prioritizes smaller PSVs. Figure 8 presents the average number of PSVs that operate each year. At the first year, mainly PSV 1500 operated. Until the fourth year, the number of PSV 3000 and 4500 started to grow. After this period, the fleet composition remained in balance, being composed by approximately 2 PSV 1500, 3 PSV 3000 and 1 PSV 4500.

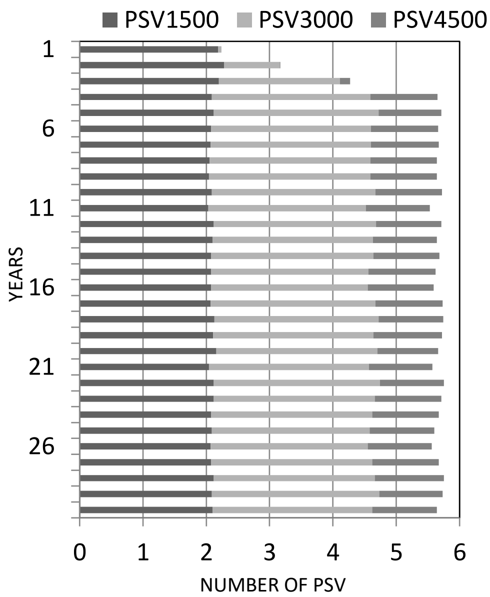

Figure 8 – Average number of chartered PSVs.

On early years, the most frequent vessel was PSV 1500. It is related to the initial conditions of the system. From the beginning, there was the installation of one offshore unit per year. This means that in four years demand grown four times and the fleet had to be adapted. That is the reason its composition changed in a small period of time, comparing to the rest of the simulation years.

The inclusion of larger vessels on the fleet contributes to fleet stabilization, once they are able to better answer demand peaks.

4.2. Operations

Figure 9 shows the average quantity of operations realized by each PSV class. Along 30 years, PSV 1500 are responsible for, at least, 40% of every operation, with especial regard to early years (when they are the absolute majority in the fleet). After the fourth year, PSV 3000 executed about 50% of the total operations while PSV 4500 did not surpassed 10% of the total. The percentages are represented in Figure 10.

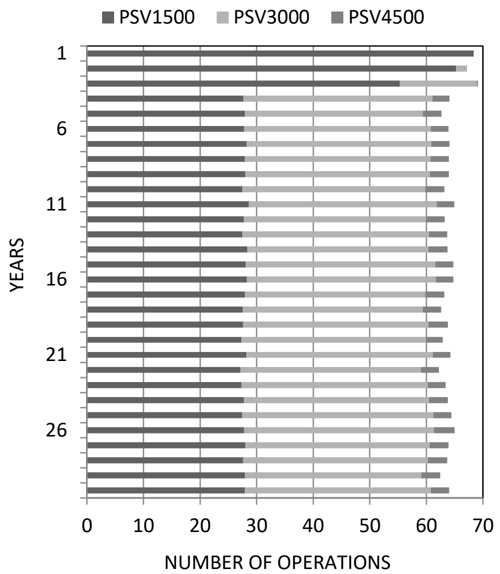

Figure 9 – Average number of operations for each PSV class

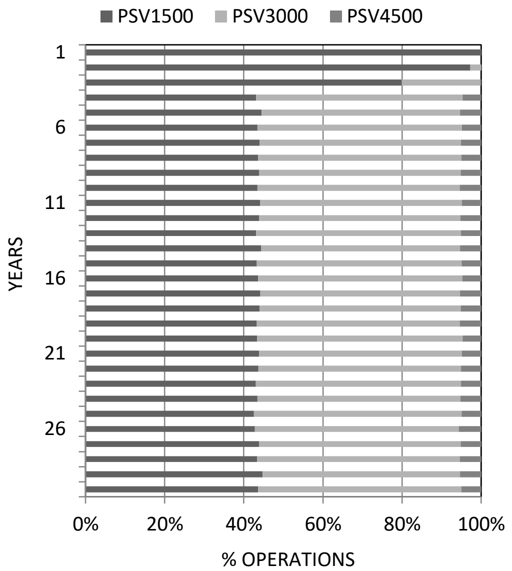

Figure 10 – Percentage of operations per PSV class

4.3. Logistics cost

At Figure 11, the annual total cost is represented per year and per PSV class. Despite PSV 1500 be on 40% of the operations, it causes about 30% of total cost, while PSV 3000 and 4500 cause about 45% and 25%. It is interesting to remember that the minimum cost at early years is related to offshore units progressive installation mentioned before.

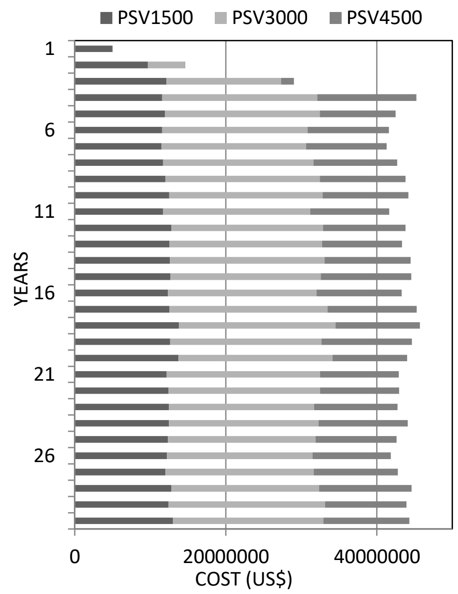

Figure 11 – Annual mean of logistics costs

5. Conclusion

This study addressed the modelling of a complex system in upstream logistic, considering stochastic parameters. The methodology was based on the observed concept and characteristics of the system and followed by a structured mathematical model, implemented and validated by computational means. The model presented a good convergence for 100 iterations and also suitable results, providing good output information. Most relevant behaviour in the result charts were recognized and justified. In other words, Simulation proved to be a useful tool in upstream logistic management, considering an extremely risky and uncertain scenario, with massive costs involved as E&P system.

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