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EVALUATION OF RISK AND EFFICIENCY IMPACTS ON OFFSHORE DIESEL LOGISTICS OF DIFFERENT OPERATIONAL PROCESSES THROUGH DISCRETE-EVENT SIMULATION

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ABSTRACT

Since the Oil and Gas industry crisis in late 2014, oil companies are increasing their focus on optimizing operations and reducing cost on upstream logistics. However, this effort must be followed by the concern of maintaining satisfactory logistics service to guarantee the continuity of the maritime units operations. The objective of this paper is to propose a different supply strategy that reduces the risk of diesel shortages in maritime units at Campos Basin, Brazil. The impacts of the new strategy on service level and cost are also taken into account. A discrete-event stochastic simulation model has been developed to consider the uncertainty components involved at the upstream logistics processes. Results show that the supply strategy designed enables the reduction of the risk of diesel unavailability, decreases the demand's lead time and requires fewer supply vessels.

1 INTRODUCTION

The Exploration and Production (E&P) operations of the petroleum industry take place onshore or offshore and comprise a broad range of activities, such as geophysical surveying, exploratory drilling, field development, structure installation, production, and abandonment. These operations demand constant support from the so-called upstream logistics, which requires a large variety of specialized vessels, helicopters, ports, airports, warehouses, trucks and several other resources.

Historically, upstream logistics has never been the main concern of companies, since it is not the core business of the Oil and Gas sector. In addition, the logistics cost is significantly less than those arising in other E&P activities. However, since the 2014 crisis, the efforts on reducing the upstream logistics costs turned out to be a concern of the oil companies. Thus, the industry has been searching for tradeoffs between cost, service level, and risk management.

The maritime units demand a large amount of different products, commonly named cargo. There are three main classes of cargo: deck or general cargo, dry bulk and liquid bulk. Containers, pipes, and well equipment such as Christmas trees are typical deck cargo items. Cement, barites and bentonites are examples of dry bulks used by drilling rigs during well construction. Diesel, brine and drilling fluid are examples of liquid bulks also demanded by rigs. Every product has its importance to the maritime units and the shortage of any of them can generate extra costs and retard operations. For instance, diesel is crucial for power generation and for preventing hydrates formation inside the production lines.

The volume of diesel required varies from one maritime unit to another and strongly depends on the type of operation the unit will perform. Moreover, each maritime unit has its own demand pattern and diesel tanks setting, with a required minimum level of diesel stored. Maintaining the diesel stock above this level is mandatory to avoid discontinuities and interruptions of the operation. Therefore, the logistics system must be prepared to meet diesel demand satisfactorily.

Maritime transportation represents upstream logistics' main cost. Hence, most of the published works in this area concentrate efforts in optimizing operations involving vessels. The main type of vessel utilized is the Platform Supply Vessel (PSV), designed to serve as a multipurpose resource, capable of transporting simultaneously all classes of cargo demanded by the maritime units simultaneously, where general cargo is transported on the deck and bulk products are located in tanks and silos under the deck.

Nevertheless, oil companies such as PETROBRAS made a decision to operate under a specialized strategy that separate fleets by group of products. From this decision, the company might use tailor-made vessels with larger capacity to transport a specific product. The scope of this paper concerns diesel logistics, which uses specialized vessels known as Diesel PSV (DPSV). These vessels had their diesel capacity increased and bulk capacity reduced, keeping space and deadweight restrictions respected.

In this context, the objective of the present work is to study a different logistics strategy that minimizes the risk of diesel shortages at PETROBRAS maritime units located at Campos Basin. The proposed strategy should also evaluate the impacts on service level and cost.

This article employs a simulation-based approach to cope with intrinsic stochastic elements of the upstream logistics process and to guarantee a robust solution. The scope of this work is limited to maritime transportation from the supply base and diesel terminals to offshore installations.

Usual fleet sizing methods available in the literature explicitly give absolute fleet numbers. However, this paper does not mention absolute fleet numbers, as this is PETROBRAS classified information with respect to costs. Instead, references to fleet sizes appear a function of the historical fleet size (n).

The structure of the remaining sections of this article is as follows. Section 2 provides the literature review in upstream logistics and simulation approaches. Section 3 shows a definition of the problem statement. Section 4 contains the conceptual model and general assumptions, data gathering and treatment, techniques used to verify and validate the model, and the experiments performed. Section 5 presents results in terms of fleet occupation, service level and risk of diesel unavailability. Conclusions appear in Section 6.

2 LITERATURE REVIEW

A few years ago, the literature on offshore logistics was making its first steps. Nowadays, this subject has gained importance and the number of publications addressing problems in this area has been constantly increasing (Silva et al 2017). Most approaches center their solution methods solely on mathematical programming, although operational uncertainties often require simulation techniques. This section briefly reviews some works whose root problem involve supply vessels.

Aas (2008) wrote a paper on the role of supply vessels in upstream logistics. Moreover, Aas et al. (2007) developed a deterministic model applied to vessel routing whose objective was to study the impact of client cargo capacity on the logistics system. Leite (2012) analyzed consumption of general cargo at offshore installations to design a method applied for reduction of lead-time and vessel fleet. Halvorsen-weare et al. (2012) presented a voyage planning method organized in two phases: firstly, they list all possible voyages and, secondly, they find a solution to the problem by considering minimal cost and fleet. Their algorithm solves one voyage at a time, without dealing with variability on the parameters involved. Shyshou et al. (2012) created a heuristic search approach to the problem of planning of supply vessels. This problem consists of estimating fleet composition regarding the deadweight tonnage of each vessel, as well as scheduling the vessels. Seixas et al. (2016) tackled the problem of deck cargo allocation with a heuristic approach that attempts to optimize deck utilization of supply vessels. Silva et al. (2015) focused on dimensioning of supply vessel fleets, berths and maritime transport policies aiming to cope with transportation of cargos related to hydrogen sulfide removal systems designed for production units at Brazilian Pre-Salt fields. Sopot and Gribkovskaia (2014) presented a study of supply vessel routing with deliveries and pickups of multiple commodities, in which a voyage occurrence depends on the availability of a vessel capable of transporting all demand concerning both pickups (backloads) and deliveries (loads). Each visit to a maritime unit must fully attend the demand. Alehashemi and Hajiyakhchali (2018) studied the problem of servicing drilling rigs aiming to optimize fleet and vessels routes. Cruz (2019) studied berth allocation together with the fleet-sizing problem, using a heuristic solution. Cuesta et al. (2017) presented a study on the Vessel Routing Problem with Selective Pickups and Deliveries (VRPSPD) and regarded it as a multi-vessel problem.

So far, a common theme in these papers is the tendency of focusing the study only on the deterministic aspect. However, uncertain elements indeed complicate supply vessel operations (Maisiuk and Gribkovskaia 2014). Therefore, it is relevant to study approaches that take into account stochastic components.

Pantuso et al. (2014) published a literature review on the problem of fleet estimation and composition. They state that existing methods to supply vessel fleet estimation and routing are in general not applicable to maritime transport, given that this area is highly uncertain and integrates a production chain whose financial resources are huge. According to the authors, most of the papers treat the problem deterministically. From a selection of thirty-seven papers, ten treat uncertainties superficially. From these, only three employ simulation. Additionally, they found that an important portion of the papers that consider stochastic elements propose deterministic methods of resolution. As a conclusion, the authors claim that future research should increase the focus on more sophisticated methods to deal suitably with uncertainty.

Other authors have also highlighted the need for different approaches to manage uncertainty. Maisiuk and Gribkovskaia (2014) argued that the stochasticity of meteorological conditions causes relevant impact to the vessel navigation and operation. Therefore, they propose a discrete-event simulation (DES) model to evaluate the size of the supply vessel fleet. According to Cigolini et al. (2014), although Excel sheets and integer programming algorithms frequently appear as methods for decision support in supply chain projects related to oil and gas area, such techniques ignore important dynamic factors. Rahman et al. (2019) have developed a model to study risk in marine logistics operations in remote areas with harsh weather conditions. They proposed fault trees to identify failure models.

Some studies discuss logistics operations to service wind farms. Although the clients are very different from a rig or an oil production asset, wind farms logistics face similar problems regarding routing and uncertainties due to weather conditions. Sperstad (2017) et al. studied fleet sizing and its robustness for operation and maintenance of offshore wind farms. They have compared an analytic method with an optimization and four simulation methods, which return "somewhat different results for the same input data". Beinkem et al. (2017) used a discrete-event and agent-based simulation to study the installation of offshore wind farms, concluding that weather conditions contribute significantly with installation times, while sharing resources has a saving potential. Stalhane et al. (2019) studied fleet sizing with a stochastic programming approach.

In another study, Shyshou et al. (2010) employed stochastic dynamic simulation, specifically discrete-event simulation, to assess the fleet size of Anchor Handling Tug Supply (AHTS) vessels. Operators commonly use such vessels to move maritime units (for instance, drilling rigs) among locations and to aid anchoring procedures. Besides uncertainty factors that emerge from the usually disconnected plan between activities of rigs/installations and supply vessels, there also are changing environmental conditions. All these aspects together make the problem of managing vessels even more complex and challenging. The authors therefore support DES as the suitable method to analyze problems with intrinsic uncertainty.

Concerning the problem of diesel supply to offshore operations, the literature is even scarcer. Diuana et al. (2016) contributed to reduce this gap, using DES to compare two logistic policies concerning diesel orders generation of a Brazilian oil company. Silva et al. (2017) also used DES to study how concurrency with other services affects diesel logistics. The present work is another step in the direction of studying diesel offshore logistics, since none of the references studied how changing the recharging location affects the logistics operations.

A major solution approach present in many of the articles mentioned is modeling the real system as a DES with stochastic parameters. According to Fishman (2001), simulation is the process of designing a computer model of a real system and conducting experiments with this model, in order to figure it out through "What – If" questions and evaluate feasible strategies for their operation. For Freitas Filho (2008), modeling by events means conceptualizing a system of interest through the identification of instantaneous occurrences, which are unconditional and depend solely on time. Occurrences such those receive the name "events", and they change the values of the model state variables at discrete quantities. Regardless of simulation is not primarily intended to optimize a system in a realm of mathematical programming, DES is indeed a proper technique to cope with stochastic outcomes linked to the risk issue addressed in the present article. Examples of stochastic data that matter for this work are vessel speed, downtime and demand fluctuations. Moreover, DES allows one to grasp the dynamic behavior of the maritime transportation system studied. Consequently, it is possible to observe concurrency for resources, infrastructure and inter-dependencies among stochastic variables over time. Deciding for DES, hence, makes the analysis of the present problem richer.

3 PROBLEM STATEMENT

Multipurpose or specialized vessels can deliver diesel. The DPSVs stay in different locations along the basin, fully charged, waiting for an installation request. The maritime units consume diesel to perform several operations. When the diesel quantity is below the refueling level, logistics planners place a new delivery order and the logistics team schedules an appropriate DPSV to fulfill such orders. When the operation is completed, the vessel checks if its remaining stock is sufficient to attend another order. Case positive, the DPSV continues at the basin, waiting for the next order. Otherwise, the vessel navigates to a recharging spot. Furthermore, DPSVs need to go to the supply base periodically to change crew. Periods of scheduled docking and downtime occurrences also take place.

During the last decades, the available diesel infrastructure at Campos Basin supply bases had serious limitations regarding storage capacity. Besides, there was no possibility to receive tankers to reload the port tanks, which obliged PETROBRAS to find another solution for the diesel supply to the maritime units. The company has overcame such adverse situation by utilizing tankers as diesel hubs. After refueling at diesel terminals, the tanker navigates to the basin and moors at buoys, staying in location until it has diesel to provide to other vessels. The diesel transfer in an offshore context is a difficult procedure due to changing weather conditions, which impose hard constraints to operate at higher flows rates and with more than one vessel simultaneously. On the order hand, having a hub close to the demand might reduce the navigation time, which reduces diesel shortage risk. Once the tanker runs out of diesel, it navigates back to the terminal for reloading to another supply cycle.

Another facility where DPSVs can receive diesel is the supply base, which provides suitable infrastructure at an area practically free of weather uncertainty. DPSV must come to the shore when diesel is needed, leading to longer navigation times. In that case, the supply base receives diesel from a tanker, previously loaded at a terminal. Tanker cycles between supply base and terminal follow a pre-defined schedule.

4 METHOD

4.1 Conceptual Model and Assumptions

The simulation model presented in this work mimics the main components of the upstream logistic system such as supply base, waiting area where vessels await before accessing the port, maritime units, mooring buoys and diesel terminals. The simulator also contains several modeling artifices such as virtual locations to facilitate codification of specific real system behavior such as vessel downtime, docking, and a centralized control location. The latter is mainly important, given that it helped to manage the diesel fleet, preventing the necessity of somehow representing an unknown large number of decentralized control gates to cope with fleet location. The resources represented at the model are DPSVs and tankers.

Other important aspects of the real system also represented in the model are geographic coordinates and diesel infrastructure of the maritime units. Other aspects also embraced by the model are docking schedule, navigations speed variations, storage capacity of the DPSV, supply base characteristics, uncertainty on environmental conditions and on diesel daily consumption rate of each installation. Figure 1 shows the model graphic representation.

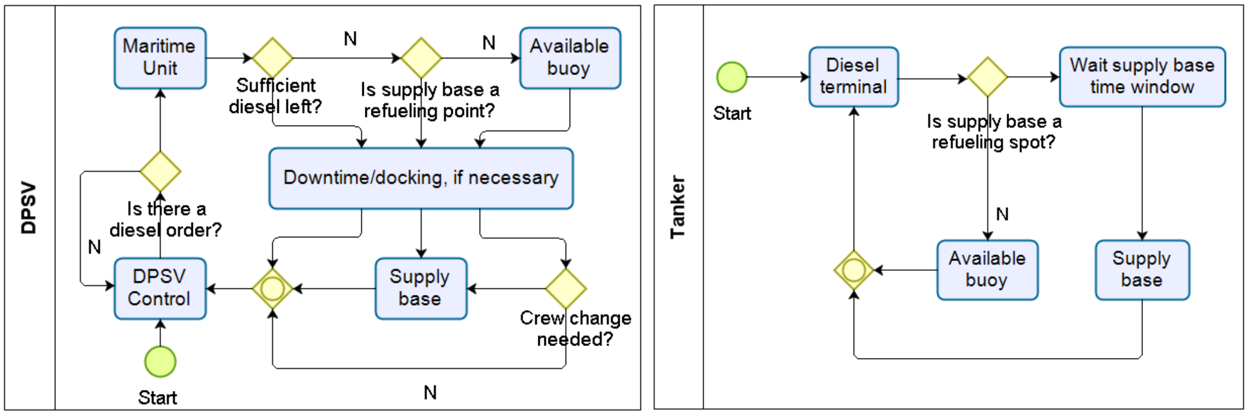

Figure 1: Conceptual model for DPSV and tanker operations.

4.2 Data Gathering and Treatment

Discrete-event simulation is a technique proper for handling with uncertainty. By using in the model stochastic parameters as probabilistic distributions, it is possible to obtain robust results in decision-making, since uncertainty turns better represented. In this way, the present simulation model encompasses many real system variables represented as fitted statistical distributions. In order to estimate these distributions, Kolmogorov-Smirnoff tests were the statistical measures used at significance level of 5%. The software used to generate the probabilistic distributions was Stat::Fit®. When more than one distribution was available, the one with the biggest p-value was the option chosen.

4.2.1 Resources

The main resources represented in the model are DPSVs and tankers. The DPSV fleet offers a storage capacity that may vary between 783 and 2680m³. Crew change must occur every 28 days. DPSV stochastic attributes are navigation speed, which has a different distribution depending on the distance traveled, downtimes and docking events. Table 1 shows the sample, statistics, chosen distribution, parameters and p-values for the stochastics attributes, concerning DPSVs.

Different from the DPSV fleet, the tanker fleet is homogeneous in terms of diesel storage capacity. Thus, the volume 18.000m³ was a value considered for all vessels. Real flow rate values depend on the volume transferred (they are positive correlated), therefore is a natural choice to divide historical flow rate data into three categories: below 700m³; between 700m³ and 2000m³ and above 2000m³.

Data concerning tankers navigation, downtime, docking and terminal operations times were not available by the time of the model development. However, tanker dates of arrival at and depart from basin were known. As a modeling artifice, a distribution referring to the time between departure from the basin and arrival of the next trip represents the tanker cycle time. Hence, once the tanker needs to navigate to the terminal to reload, the model samples a cycle value from that distribution and the tanker stays unavailable during the time sampled. Such as for the DPSVs, Table 2 shows the sample, statistics, chosen distribution, parameters and p-values for the stochastics attributes, concerning tankers.

Table 1: DPSV parameters.

Parameters	Detail	Sample	Mean	Standard Deviation	Maximum	Distribution	Distribution Parameters	P-value
Navigation Speed (km/h)	Below 18 km	32	11.38	4.27	21.33	Johnson SB	- Minimum: 2 - λ:17.6 - γ: -0.124 - δ: 0.788	0.997
	Above 18 km	121	15.18	2.79	19.02	Weibull	- Minimum: 5 - α: 4.4 - β:11.5	0.805
Downtime	Duration (days)	591	2.41	4.12	31	Lognormal	- Minimum: 0 - μ: -0.0215 - σ: 1.38	0.147
	Occurrence (%)	60	3.79%	After offshore operations, the probability to occur a downtime follows the mean value				
Docking	Duration (days)	46	13.39	9.33	47.3	Weibull	- Minimum: 0 - α: 1.5 - β: 14.9	0.826
	Occurrence	DPSVs dock once every two years						

Table 2: Tanker parameters.

Parameters	Detail	Sample	Mean	Standard Deviation	Maximum	Distribution	Distribution Parameters	P-value
Flow rate (m^3/h)	V < 700m³	16	66.59	28.51	154.28	Weibull	Minimum: 34 - μ: 3.05 - σ: 52.5	0.857
	700 < V < 2000m³	195	91.11	16.72	135.68	Weibull	Minimum: 44 - μ: 3.05 - σ: 52.5	0.637
	V > 2000m³	99	100.9	21.62	236.38	LogLogistic	Minimum: 47 - μ: 4.85 - σ: 51.6	0.291
Duration (days)	Time between a departure and an arrival of the next trip at the basin	36	13.32	6.12	28.03	LogLogistic	- Minimum: 2 - μ: 2.9 - σ: 10	0.959

4.2.2 Maritime Units and Supply Base

The attributes of the maritime units were divided according to three classes: individual for each unit; common to a group off units; and common to all units. The individual attributes are location, diesel consumption rate, storage capacity, refueling level and minimum level. An example of attributes common to a group attribute is the unavailability to operate due to weather conditions. Finally, the diesel flow rate was consider common to all units. Besides the location, all other attributes are represented by probabilistic distributions. These parameters were not detailed in this work because the model considers 90 maritime units.

The supply base represented at the simulation model was the Açu Port, located at the north of State of Rio de Janeiro. Its diesel storage capacity was considered 18,000m³. The flow rate distributions were estimated as a Triangular distribution T(500, 600, 700) for the operation of reloading the supply base tanks and Uniform U(100,120) for refueling DPSVs.

4.3 Codification and Verification

ProModel® was the software used to develop simulation model. It provides an environment for modelling and simulation of discrete-event systems. The model designed is flexible for application in every offshore logistics system involving supply base berth operations, PSV maritime transport fleets and installations demanding diesel. The entire model has about 13300 lines of code. The reason of choosing ProModel® was the availability of licenses at PETROBRAS and the authors' previous experience with it.

Additionally, during the model codification, some verification techniques seemed reasonable for use. Verification is an important part in the development of a simulation model, which aims to reduce implementation and logic errors. There are different verification techniques such as use of deterministic model, robustness test, variation of the input data, simulation simplify cases, verification routines and graphic animation. All these techniques were rigorously applied during the verification process.

4.4 Validation

The validation process started with the definition of an adequate number of replications (n). Among all the stochastics variables presented at the model, the Vessel Fleet Utilization (VFU) for DPSVs was chosen to defined n, once the supply vessels are expensive resources and the highest utilization levels are desired for them. The average value of VFU is automatically calculated by the simulation software through the formula

$$VFU = \frac{\sum_{i=1}^{N} t_i}{NT},$$

where N is the fleet size, t_i is the time interval that vessel i was in use and T is the total simulation time. Then, the mean μ and standard deviation σ values obtained from replications were $\mu = 75.23\%$ and $\sigma = 3.49\%$.The semi-confidence interval h formula is

$$h = t_{n-1,\alpha/2}\frac{\sigma}{\sqrt{n}},$$

where σ is the standard deviation of the data sample, n is the number of replications (sample size), α is the desired confidence level and $t_{n-1,\alpha/2}$ is the critical value of *Student-t* distribution. To define n, the following criteria were adopted:

- Given a 95% confidence level, half of the confidence interval should be less or equal to 1% of μ.
- Given a 99% confidence level, half of the confidence interval should be less or equal to 2% of μ.

Table 3 shows the resulting semi-confidence interval h for 95% and 99% confidence levels, according to the number of replications.

Table 3: Semi-confidence interval (h) for different numbers of replications.

Confidence Level	α	Number of replications (n)							
		45	46	47	48	49	50	51	52
95%	0.05	1.050	1.034	1.023	1.012	1.002	0.992	0.982	0.973
99%	0.01	1.399	1.384	1.369	1.350	1.336	1.322	1.310	1.292

We observe that both criteria were met when the replication number is 50 or bigger: the semi confidence interval h is less than 1% of the mean given 95% of confidence level. Being more rigorous, given a 99% confidence level, h is less than 1.5%. Thus, 50 replications are enough to the validation process.

Table 4: Validation results.

Parameter	Description	Operational value (OV)	Simulated value (SV)	% Error: (SV-OV)/OV
Offshore operation (days)	Time interval while a vessel is operating at an installation. For the current analysis, a vessel operates at an installation when the loading diesel operation is undergoing at that installation.	0.28	0.30	-6.5
Waiting before offshore operation (days)	Time interval while a vessel waits to start operation at installation. This interval is due to two main reasons: environmental conditions for safe operation or some other installation issue avoiding supplies transfer.	0.52	0.49	-5.0
Diesel per visit (m^3)	Average volume of diesel delivered per visit to the installation.	372	365	-1.8
Total diesel per year (m^3) – Data about diesel per year are classified.	Total volume of diesel delivered to the installation per year.	-	-	-2.2
Downtime (%)	Average percentage of supply vessel fleet that is in downtime state. Usually a vessel enters a short downtime due to corrective maintenance.	3.79	3.70	-2.4
Docking (%)	Average percentage of the fleet that is docked. Usually, vessels enter a dock due to preventive maintenance policies. Docking periods tend to be greater than downtime ones.	1.77	1.88	-6.3

After the definition of the number of replications, some key performance indicators (KPIs) were selected for the validation process. Each replication of the validation experiment considers six months of warm up and one year of simulation. The obtained results were compared to real operational KPIs to verify the model's ability to reproduce real-world performance, allowing its application in alternative scenarios. Table 4 presents the selected KPIs with their description, operational value, simulate value and the error. It can be noticed that 50% of the KPIs presented the absolute error inferior to 2.5% and none fell above 6.5%. The results confirm that the model represents satisfactorily the real operation and can serve as a decision support tool to evaluate new operational strategies.

4.5 Experiments

The data used in the model refers to a period of time where the DPSV were loaded by tankers at the basin. In that time, Imbetiba port, located at Macaé city was the main supply base of Campos Basin. This supply base presents some limitations in terms of diesel infrastructure such as tanks with low storage capacities and the challenge of receiving tankers to fill its diesel stock. The solution was to provide diesel at an offshore environment. The operation with tankers that moor at buoys to load the offshore vessels was an appropriate solution for those circumstances. Later on, PETROBRAS has started to operate at Açu Port. This supply base was a green field project and it has more appropriated infrastructure than the other ports close to Campos Basin. In terms of diesel capacity, the port offers to PETROBRAS a storage capacity of approximately 18.000 m^3. It is also possible to moor PETROBRAS tankers to load the supply base with diesel.

The operation in a supply base with adequate diesel infrastructure has permitted the study of new strategies for cost reduction, increasing the service level and, most importantly, reducing the risk of not suppling some products at the right time, thus avoiding great losses for E&P operations.

This work chose the diesel to develop its analysis. Two scenarios were defined according to the DPSVs refueling points. Both scenarios descriptions and graphic representations (Figure 2) are shown below.

Scenario 1 (S1): DPSV refueling point is the tanker moored at the buoys, which functions as a diesel hub. In this case, DPSV must navigate to the supply base to change crew every 28 days. Since the tanker has diesel available, it stays at the basin loading DPSVs. Once the tanker runs out of diesel, it navigates to the terminal to reload and start another cycle.

Scenario 2 (S2): DPSV comes to the supply base in order to refuel its tanks from diesel. In this case, the crew change occurs while the vessel is at the supply base. The diesel tanks are load by the tankers that visit the supply base following a defined schedule.

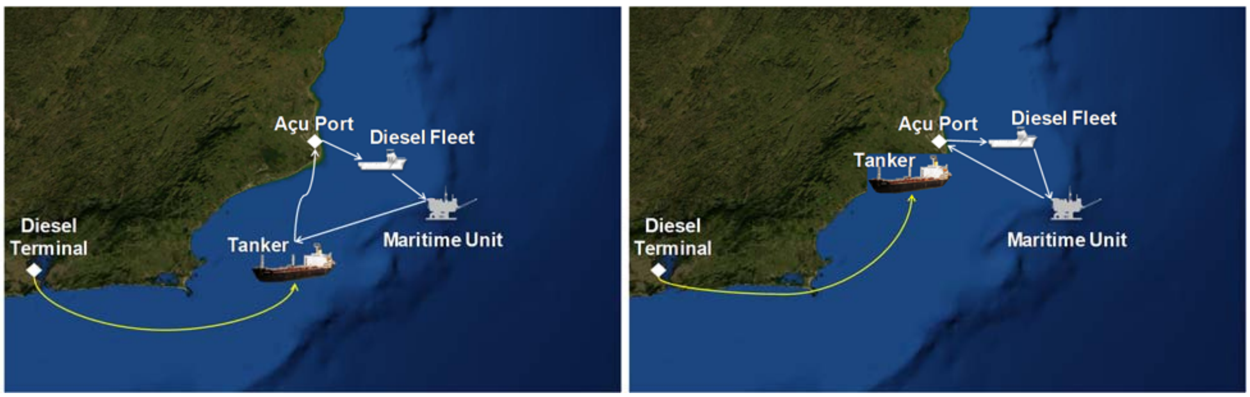

Figure 2: Scenarios.

5 RESULTS

The KPIs chosen to compare the results of each scenario can be divided into three categories: Fleet, Service Level and Risk. The first round of experiments were performed considering the historical fleet size (n) for both scenarios. Since the number of vessels under contract is a sensible parameter to oil companies, this paper does not contain this information. From now on, we will refer to the scenario with the associated fleet of the experiments as function of n. Thus, in the first round, the scenarios are S1(n) and S2(n)

The results show that for the same fleet size, S2(n) permits a 10% decrease in the fleet occupation. In terms of Service Level KPIs, a small decrease in diesel delivered per visit occurs. However, there is a significant reduction of the diesel lead-time (mean and percentile 90), from 1.07 and 1.21 days to 0.49 and 0.59 days, respectively. Finally, concerning risks KPIs, there were enormous improvements: In S1(n) the number of occurrences when the diesel stock was below the minimum level was 71. Additionally, the number of stock outs events was 33. In both cases, the results refer to 50 replications with the duration of one year. Nevertheless, in S2(n) there were not any occurrences of low diesel quantities or stock outs.

Despite the fact that using a diesel hub reduces the distance between the supply and the offer, this solution presents undesirable inefficiencies. The first of them is the non-productive time of vessels' loading operation, because usually the tanker can just operate with one offshore vessel at a time and the reduce flow rate in comparison with the port operation. The second one is the necessity to stop the operations caused by rough weather conditions. Another issue is the longer tankers' cycles due to long times moored at the buoys. At last, larger uncertainties at the process resulting in periods of unavailability of tankers at the basin, affecting the diesel offer to the maritime units. For instance, the results show that, on average, the DPSVs waits 0.84 days to operate with the tanker.

Afterwards, a second round of experiments were performed seeking the equalization of the fleet occupation in both scenarios. The same occupation rate was found when the fleet size of Scenario 2 was set to n-2 vessels [S2(n-2)]. The fleet reduction in this scenario relies on a small increase of diesel delivery per visit and the lead-times, in comparison with a fleet of n vessels [S2(n)]. It is observed that there is one occurrence of diesel level below the minimum required. Additionally, the number of stock outs was kept to zero. However, S2(n-2) presents more interesting KPIs when compared to S1(n), despite the same fleet occupation.

The tremendous advantage presented by the S2 at the two first rounds of experiment led to a third round, where the fleet size was decreased until the risks KPI were close to the S1(n). The results show that the equivalency between both scenarios is reached when Scenario 2 fleet is placed between n-5 and n-6 vessels. Because of the necessity of fleet size being an integer number, the equivalent scenario, in terms of risk KPIs, is S2(n-5). Even with a fleet occupation of 97%, the risk KPIs were more interesting than S1(n). For instance, occurrences of stock below the minimum level were 23 and number of stock outs were 9, for 50 replications. The high fleet occupation shows that this scenario is close to an inflection point. This perception is confirmed with S2(n-6) results. In this experiment the fleet occupation raise to 100% and the risk KPIs suffer a significant increase, as it is presented at Figures 3 and 4. In addition, the proposed strategy presents none occurrence of stock outs even with a reduction of 4 vessels [S2(n-4)]. Table 5 shows the results of the 3 rounds of experiments.

Table 5: Results.

Category	KPI	S1(n)	S2(n)	S2(n-1)	S2(n-2)	S2(n-3)	S2(n-4)	S2(n-5)	S2(n-6)
Fleet	Fleet Occupation	75%	65%	70%	75%	80%	88%	97%	100%
Service Level	Diesel deliver per visit (m^3)	372	338	339	342	346	357	389	508
	Lead-time – Mean (days)	1.07	0.49	0.51	0.56	0.65	0.90	1.99	6.43
	Lead-time – P90 (days)	1.21	0.59	0.60	0.64	0.74	0.99	2.13	6.65
Risk	Occurrences of stock below the minimum level	71	0	2	1	1	9	23	329
	Occurrences stock outs	33	0	0	0	0	0	9	84

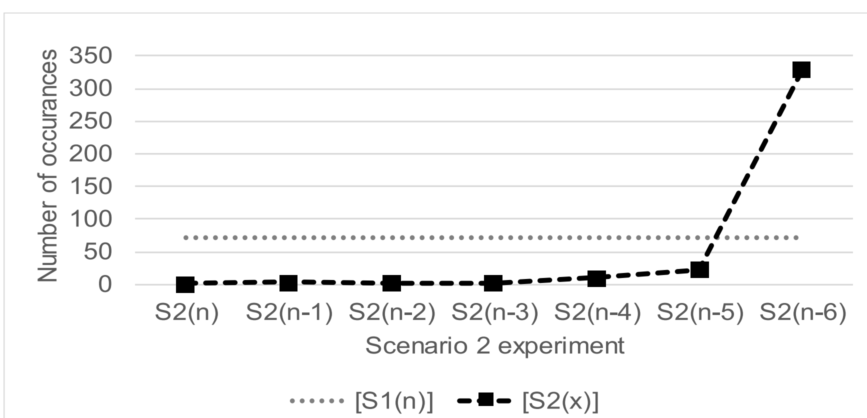

Figure 3: Occurrences of stock below minimum level.

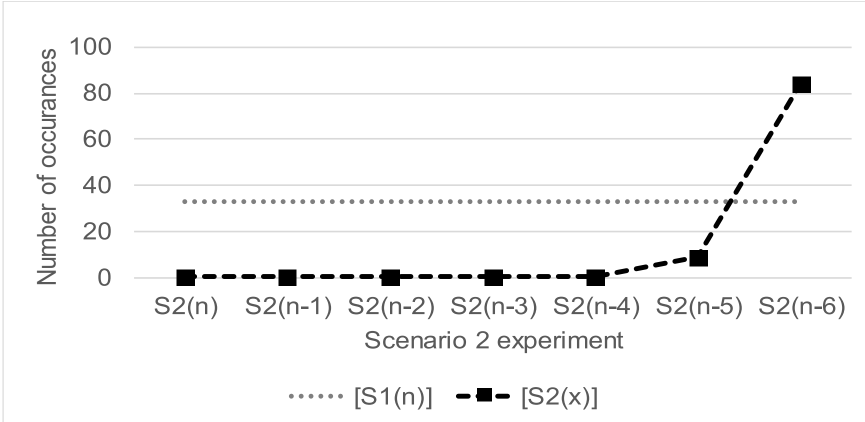

Figure 4: Occurrences of stock outs.

6 CONCLUSIONS

In this work, different strategies of diesel supply were compared to evaluate the impacts in terms of risk of diesel unavailability, service level and cost. The analyses took place for Campos Basin, where there is a high concentration of maritime units close to each other. Historically, the utilization of a diesel hub was adopted because of the absence of an appropriate infrastructure onshore. Even though common sense shows that a hub close to the demand should improve the operation, the possibility of using a new supply base with high capacity of diesel storage has led to the study of the scenario where the PSVs are loaded at the supply base. None of the articles found in the literature review studied how changing the refueling location affects logistics operations.

A simulation approach was chosen because of the presence of innumerous stochastic components in upstream logistic processes. A discrete-event simulator of the maritime system was developed involving DPSVs, maritime units, tankers and mooring buoys. The diesel terminal and the supply base, with its tanks and berth, were also represented in the model. The experiments followed three phases for each of the scenarios: 1) The same fleet; 2) The same fleet occupation; 3) The same risk management KPIs values. In all steps, the scenario where the DPSVs receive diesel at the supply base offers considerable advantages in terms of risk and cost reduction and increase at the service level. The work reached its objectives, once improving all these aspects simultaneously can be considered one of the main challenges of upstream logistics. Future research can be developed considering other products and multipurpose PSVs.

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