Offshore Oil Rig Scheduling Simulation: a multi-perspective approach

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RESUMO

As companhias de Óleo e Gás tem um papel importante no desenvolvimento e na economia das nações. Altos investimentos são necessários para uma exploração e produção efetiva, segura e lucrativa. Os mais caros deles são os custos com sondas, principais recursos para perfuração e manutenção dos poços. Este artigo propõe uma Simulação de *Monte Carlo* para o Problema de Programação de Sondas em poços marítimos no médio prazo. Distribuições de probabilidades e método de *Bootstrap* foram usados para estimar a duração das atividades. Uma abordagem multi-perspectiva foi usada para avaliar os cenários. Os resultados sugerem que a simulação seja uma aproximação mais próxima do realizado que os planejamentos determinísticos, evidenciando a importância da abordagem estocástica em ambientes incertos. Ao fim do artigo trabalhos futuros são sugeridos.

PALAVRAS CHAVE. Programação de Sondas, Simulação de Monte Carlo, Óleo e Gás.

PO na Área de Petróleo e Gás, Simulação, Apoio à Decisão Multicritério.

ABSTRACT

The Oil & Gas companies have an important role in nation's development and the economy. High investments are necessary for an effective, safe and profitable E&P. The most expensive of them are the rigs costs, which are the main resource for drilling and maintenance wells. This paper proposes a Rig Scheduling Monte Carlo's Simulation for offshore wells in mid-term plan. Probability distribution and Bootstrap methods are used to estimate activities duration. A multi-perspective approach was used to evaluate schedules. Results indicate that the simulation is an approximation closer from the accomplished than the deterministic planning, evidencing the importance of stochastic approach in uncertainty environment. At the end of the paper, future researches are suggested.

KEYWORDS. Rig Scheduling, Monte-Carlo Simulation, Oil & Gas.

OR in Oil & Gas, Simulation, Multicriteria Decision Support.

1. Introduction

The Oil & Gas companies have an important role in the world, influencing significantly in development and economy of the nations, through the oil production. According to *BP Energy Outlook 2035*, oil and gas accounted for 56.6% of the global primary energy consumption and in 2035 will remain as world main fuels, supplying 55.1% of world's energy. However, petroleum is not only an energy source, but also the main raw material for industries, such as plastic, road construction and pharmaceutical (Devold, 2013). Due to the importance of the oil fields exploitation, researches are developed, aiming the efficiency in this process (EIA, 2016).

High investments are necessary for an effective, safe and profitable exploration. The most expensive of them are the rigs costs, which are the main resource for drilling and maintenance wells. A daily rig can vary between US$ 400,000 and US$ 600,000, and therefore they are scarce resources and must be scheduled in order to minimize costs (Osmundsen *et al.*, 2010). Nonetheless, scheduling rigs is a difficult task, not only as a result of the quantity and variety of activities, but also due to the uncertainties related to geological concepts (structure, reservoir seal and hydrocarbon charge), economic evaluations (costs, probability of finding and producing economically viable reservoirs, technology and oil price) and the development and production (infrastructure, production schedule, quality of oil and operational costs and reservoir characteristic) (Suslick *et al.*, 2009). All of these uncertainties add complexity to the problem and, consequently, increase the necessity of decision support techniques that assist in the planning and scheduling, minimizing risks and costs.

According to Reid *et al.* (2016), due to the complexity of the problem, the majority of Offshore Planning failed to meet the delivery, budgetary and performance expectations. They also failed in hitting production targets and those that achieved the results state longer deliveries times and higher budgets. There has been a vast number of researches aiming to help those companies in their decision making process. Most of the works focus on creating mathematical programming methods to optimize the net revenue or the oil production in the exploration phase (Tarhan *et al.*, 2009). Yet, there are few studies using simulation applied to the scheduling of tasks in the oil's exploration. Even less researches simulate or analyze the rigs scheduling, one of the most expensive and difficult task in Exploration and Production (E&P). None of the articles evaluate the schedules in the financial perspective, regarding only the time allocation without differentiate their costs.

Aiming to fill this gap, this paper proposes a Rig Scheduling Monte Carlo's Simulation for offshore wells in mid-term plan. The main objective of the simulation is to create several scenarios and from them analyze the budgetary curve. To deal with the uncertainties in the activities duration, different continuous distributions and the bootstrap method are estimated and statistically tested. The best-fitted distributions are used in the Monte Carlo's model. We designed indicators for qualitative and quantitative analysis of the scenarios. Due to the downturn in Oil & Gas prices and the increased focus on finding ways to optimize the process, a budget analyze is also presented.

The article is divided in 5 sections. First, we describe the framework of Oil & Gas Exploration, Oil Rigs and the Rig Scheduling Problem. After, the developed methodology to the research are presented. Then, we show the results and theirs analysis. Last, the final conclusions are made.

2. Problem description

In this section, we describe the framework of Oil & Gas Exploration, focusing in the field development, one of the most important phases at the Exploration & Production (E&P). First, the offshore E&P stages are briefly described. Follow, the process that includes the use of drilling rigs will be presented. Finally, we define and delve into the Rig Scheduling Problem and its critical steps.

2.1. Offshore Exploration & Production (E&P) of Oil & Gas

The Supply Chain of the Oil & Gas sector can be divided in upstream and downstream. The downstream part is responsible for the refine and distribution of oil and its products, while the upstream is accountable for the activities related to the E&P of the raw material (Devold, 2013).

The Offshore E&P can take many years and it’s a key part of the process to the company profitability. It can be separated in five main phases: (1) *Discovery* phase, which is the mapping and geological processes that identify possible oil fields; (2) *Evaluation* phase, when the possible presence of hydrocarbons is confirmed, or not, and evaluated through exploration wells drillers; (3) *Development* phase, responsible for important production activities and decisions, such as number of wells and if the well will be drilled or completed; (4) *Production* phase, accountable for the oil production, can extend through decades and has many different successive phases within itself to increase productivity, to correct oil flow loss and to solve mechanical failures; and (5) *Abandonment* phase, when the hydrocarbon production rate becomes economically invaluable and the reservoir is abandoned (Baker, 1996; IFP School, 2015; Pereira, 2005). The rigs are key resources to Exploration, used mainly in the *development* and *production* phases through the drilling and completion activities. Follow, we describe the different types of oil rigs and theirs purpose.

2.2. Oil Rigs

As pointed earlier, ones of the main resources used in the exploration of oil and gas are the rigs. These structures are used in critical activities like Evaluation, Drilling, Completion and Workover. They are high complexity and expensive ships used to explore well. There is a variety of oil rigs, each one with a purpose. The main offshore rigs are: fixed rigs (oil platform used until 300 meters water profundity); semisubmersibles rigs (floating platforms used up to 2,000 meters water profundity); jackup rigs (platform with elevating legs used until 150 meters) and drillships (floating platforms constructed in a vessel hull used up to 2,000 meter water profundity) (Petrobras, 2014; IHS Markit, 2016). Figure 1 illustrate the main types of rigs.

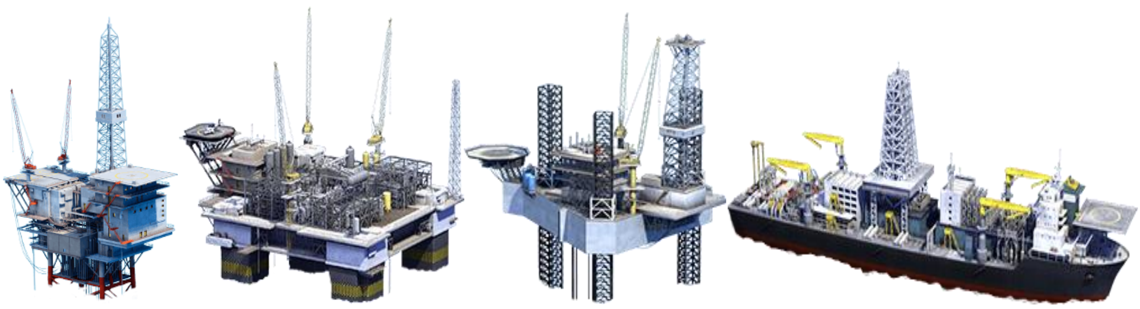

Figure 1 – Examples of oil rigs (from left to right: fixed rigs, semisubmersibles rig, jackup rigs and drillships) (Source: Petrobras, 2014).

As explained before, offshore rigs must perform a variety of complex tasks, regarding the scarcity of resource, extensive horizon plan and an environment full of uncertainties (Suslick *et al.*, 2009). Because of it, planning and scheduling of theirs tasks became key factor to success (Reid *et al.*, 2016). In the next section, we will describe the Rig Scheduling Problem.

2.3. Rig Scheduling Problem (*RSP*)

The Rig Scheduling Problem (*RSP*) can be defined as a set of wells, which have activities to be executed, and a set of resources available to perform these activities. Together, the set of wells, activities and resources provide a schedule. This schedule must take into account a complex list of operating and engineering constraints, the time window of activities, the rigs' availability and the predefined order to perform these activities. Therefore, a delay in one activity can affect in all scheduling and, consequently, more expenses that planned (Bassi *et al.*, 2012).

Many authors, such as Barnes *et al.* (1977), Pérez *et al.* (2016), Ribeiro *et al.* (2011) and Irgens *et al.* (2008), treat a simplification of the *RSP* known as Workover Rig Scheduling Problem (*WRSP*). Most of them address the subject using exact methods (Monemi *et al.*, 2015; Iyer *et al.*, 1998) or heuristics (Aloise *et al.*, 2006; Bassi *et. al.*, 2012; Ribeiro *et al.*, 2011; Ribeiro *et al.*, 2012). However, only few researchers analyze the quality of a solution through simulation and uncertainty models. Bassi *et al.* (2012) propose a simulation–optimization approach to the workover rigs, using a Greedy Randomized Adaptive Search Procedure (GRASP) heuristic and simulation to generate solutions and evaluate them. Atwal *et al.* (2016) create a two-phase simulation model for real-time decision making in the drilling operations, but the authors use exclusively temporal indicators.

3. Case Study: Methods and Approach

A high quality research comes from using the appropriate techniques and frameworks to a specific problem. In order to achieve our goals and good results in the simulation, frameworks and a consistently methodology were developed. In this section, we show a methodology that consists in five steps, illustrated in Figure 2.

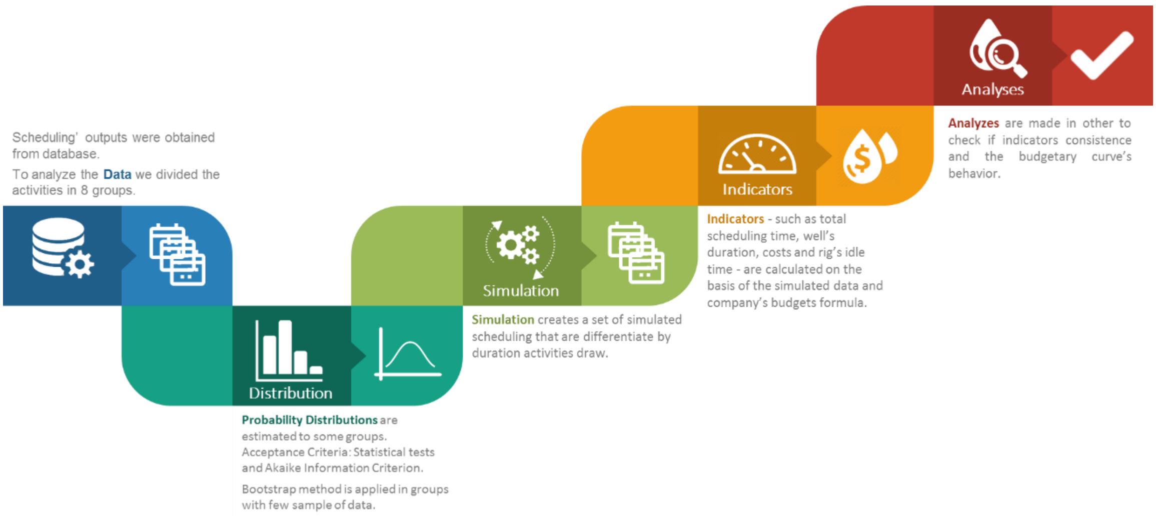

Figure 2 - Illustration of the methodology used in this Rig Scheduling Problem (Source: authors, 2016).

First, twenty-five scheduling outputs (planning and accomplished) were obtained from 2014 and 2015 databases. These outputs are historical rigs scheduling from an oil company that operates in Brazil, which represent drilled wells in offshore fields from 2016 to 2021. According to Bassi *et al.* (2012), for a profitable oil well drilling strategy it's important to consider the activities with an uncertain duration. After analyzing the database and observing the change in durations, we decided to consider this uncertainty in our simulations.

Follow, we divide data in sets, according to similar characteristics. The most of them are grouped by type of activities. Due to the large range of activities' duration variation and to better estimate the distributions, we assume an estimator as a variation between real duration and planned duration of the same activity. Equation 1 refers to this estimator p that measures the percent variation of done duration relates to the expected duration.

$$p = \frac{real\ duration}{planned\ duration} \qquad (1)$$

Equation 1 – Parameter to be estimated (Source: authors).

After calculating this parameter for all activities in database, we execute statistical analysis through *R*® software. First, we remove the outliers from boxplot analysis. After, three statistical tests are applied in the sample of data: *Kolmogorov–Smirnov* test, *Anderson–Darling* test and *Cramér–von Mises* criterion (Gibbons *et al.*, 2011) that are used to check the goodness-of-fit of a probability distribution, accepting a p-value greater than 1%. For groups of activities that have few sample of data, Bootstraps were used. Bootstrap is a computationally intensive statistical technique that allows the evaluation of the variability of estimators based on a unique sample first developed by Efron (1979). This technique is indicated for cases with small sample (Cyrino *et al.*, 2013). Table 1 shows the groups of activities, the estimation methods and their parameters. The rest of activities that are not grouped are simulated deterministically.

Group of Activities	Estimation Methods	Shape Parameter	Scale Parameter
Drilling	*Weibull*	3.42	1.00
Completion	*Weibull*	2.87	0.95
Workover	*Weibull*	2.29	0.97
Appraisal	*Weibull*	2.64	1.09
Support	*Bootstrap*	25 used observations	
Equipment Installation	*Bootstrap*	14 used observations	
DMA/DMM/MDP	*Bootstrap*	26 used observations	
Others	*Bootstrap*	20 used observations	

Table 1 – Group of Activities and estimated distributions/parameters (Source: authors, 2016).

The third step consists in simulating 15 runs, each one with 5,000 iterations, thus generating 75,000 scenarios. These scenarios are based on scheduling manually programmed. We assume some hypothesis such as: (1) inexistence of overlapped activities in the schedule; (2) the scheduled activities have precedence relation between well's activities and activities that share the same rig; (3) activities can be postponed, but cannot be anticipated; (4) the simulator does not regard time window for activities, so there is no needed to check schedule's feasibility. For emphasizing, this model do not propose an optimized scheduling and much less news activities allocations. It only rearranges the manually scheduling without changing allocation in rigs. The solutions are adapted, according to the new duration draw and following predefined premises. Figure 3 illustrates the framework of simulation process.

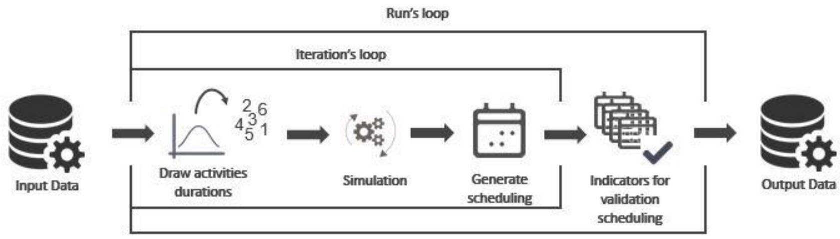

Figure 3 –Simulation Process Framework (Source: authors).

As shown in Figure 3, the process with data import and is mainly composed by the run's loop and the iteration's loop. The loops are responsible to generate scenarios. Iteration's loop starts with activities duration draw step, follow by simulation, which is responsible to allocate and adjust the initial date of activities in scheduling. At each iteration a simulated scheduling is generated and indicators are created for validation analysis. At the end of the iteration's loop, the information of all scheduling is consolidated, creating indicators for validation analyses. At the end of run's loop, all scenarios are performed and the indicators are exported for further analysis.

To measure the consistency of our simulated scheduling and the minimum of iterations required to reliable results, we analyze the Monte Carlo's Convergence chart to validate: (1) Total scheduling time; (2) Idle time of scheduling, and; (3) Scheduling budget. Figure 4 shows that the total of simulated scenarios are sufficiently to obtain stable simulations. Analyzing these charts, we note that near to 2,000 iterations all of the 15 runs are already converged in less than 6 hours. So, we conclude that for all of them the number of simulated scenarios (2,000x15) are sufficient to obtain a stable simulation.

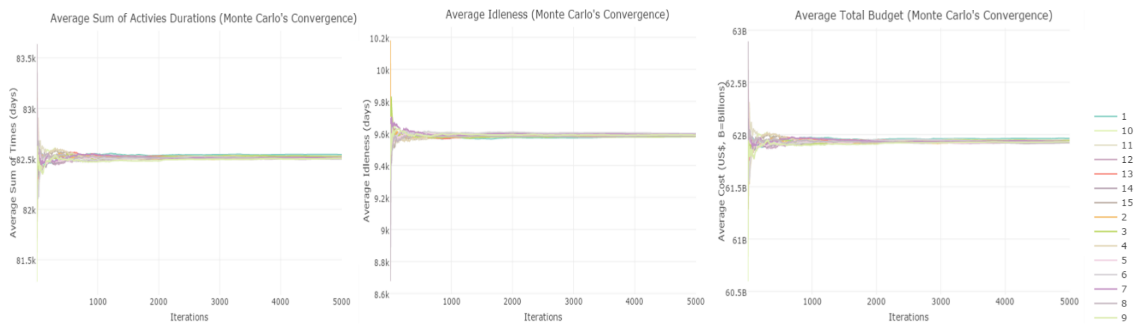

Figure 4 - Monte Carlo's Convergence Chart, mean for 3 indicators - Total Time, Idleness and Budget (Source: authors, 2016).

After performing all scenarios, indicators are generated. They state important information about rigs' operation. The total time corresponds to the sum of all activities' duration of scheduling, *i.e.* the total utilization time of the rigs, and the idle time refers to the time between two allocations that the rig is not operating in an activity, and not taking into account the rig's contract. These two influence directly the budget of company which is composed by rigs costs, calculated as the product of the average daily rate of rig by total utilization time; materials costs relates to wells' building and idleness cost, calculated as a percent of daily rate of rig payed for the idleness time.

From these indicators, the fifth step consists in checking the adherence between simulations and accomplished scheduling of 2016, identifying standards and trends in a set of data. Additionally, we take risk analysis measures, aiming to improve decision-making analyses as showed in the next section.

4. Results

In this section, we present the results and analyses of indicators. First, we compare the results given by the simulation model with the original scheduling, which are obtained from the database of Oil Company and then we estimate the budget distribution from simulated scenarios and analyze the risk of original solution. The simulation was implemented in *Python* programming language and using *Anaconda Accelerate Model* with *Spyder* cross-platform *IDE*. An interface in *Access®* was used for input and output data. *R®* and *Tableau®* softwares provided graphical visualization of instances and results. The computational experiments were performed in a computer with *Intel® Core™ i5-6200U CPU 2.30 GHz* with an *8.00 GB RAM* memory. The simulation model performed in 48,675 seconds, executing 15 Monte Carlo's runs, each one with 5,000 iterations – an average of 0.6490 seconds per iteration. For each simulation, the model return the scheduling generated and theirs indicators. Figure 5 illustrates a simplified simulated scheduling (without restricted data). Analyzing this figure, we states that model respects the premises and does not allow overlapped activities, neither delayed activities. Some activities are postponed to respect the precedence relations between well's activities and activities that share the same rig.

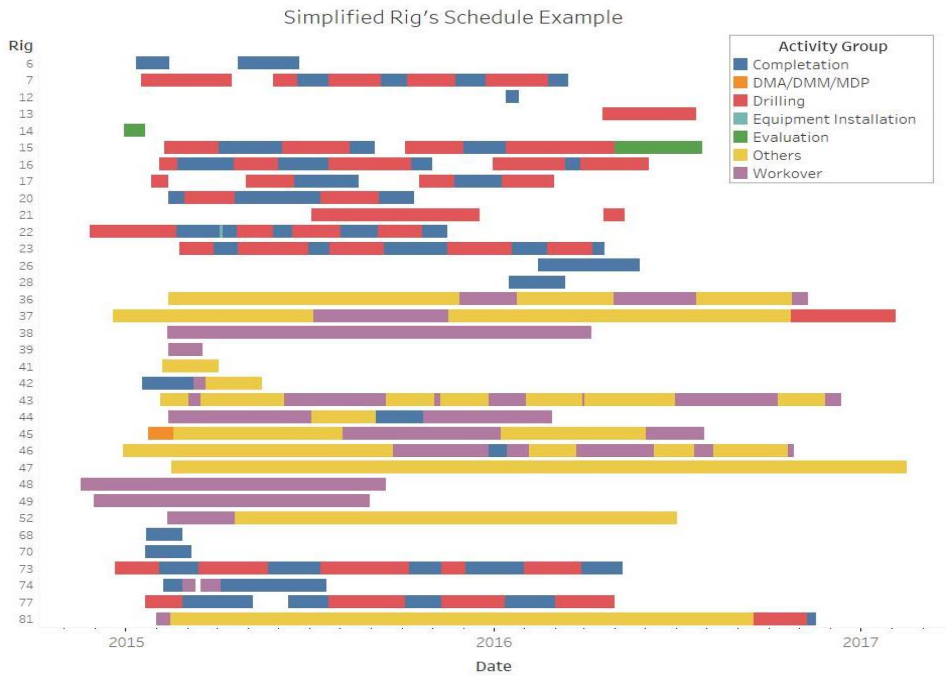

Figure 5 – Simplified Simulated Schedule Example (Source: authors).

In order to validate models results, a comparison between the out-of-sample data and the simulated schedule was performed over 2016`s year. Due to the often redesigned of the wells and projects according to company's guidelines and needs, there is no obligation that activities will remain with the same identification. So, we've used 2016 averages to compare the simulation with the accomplished scheduling, as shown in Figure 6.

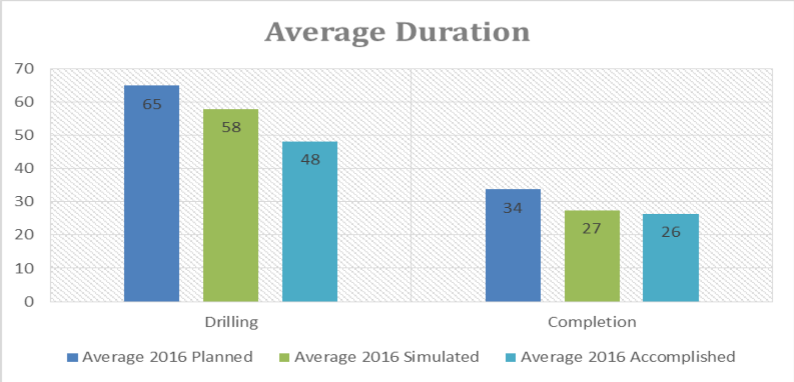

Figure 6 – Comparison between average durations between simulated, planned and accomplished in 2016 (Source: authors).

Inspecting the simulated and planned durations of drilling and completion in Figure 6, the chart presents a trend to reduce durations of activities groups, *i.e*. drilling and completion are expected to have accomplished scheduling with reduced durations. This behavior is observed in all activities that are estimated by probability distribution as Appraisal and Workover. We note that the durations have reduced around twenty-five percent accomplished scheduling. After average analyses, we conclude that the total time is adherent with the reality, because the others groups of activities are either deterministic or bootstrap and not varying in large scale. Follow this analyses, it's possible to observe that due to the duration's declines, the spaces between allocations become larger. It occurs due to the premise assumed that it is impossible to anticipate an activity, only postponed it. So, the idle time tends to increase, but not represent the reality, wherein planners are able to anticipate activities.

Indicator	Mean (μ)	Standard Deviation (σ)
Total Scheduling Time	82,511 days	713 days
Idle Time Scheduling	9,588 days	321 days
Total Rigs Budgets	US$ 61,934,667,401.00	US$ 672,998,550.00

Table 2 – Simulation model indicators – mean and standard deviations (Source: authors).

We remark that the deviation for original data refers to probability distributions trends in varying the total of activities duration, enhancing the importance of regarding the stochastic approach in problems with many uncertainties. These scenarios are also relevant to provide better analysis than a deterministic approach and from them to improve risk analysis.

Regarding the importance of costs, due to the high investments in offshore operating, we also analyze the budgetary curve generate from simulations. To estimate the curve, we use rigs' costs available at Kaiser *et al.* (2013) and IHS Markit (2016). Figure 7 represents the average of budget per year and maximum and minimum observed costs. We note an increase in cost operations between 2018 and 2020 and is related with the scheduled activities, whose majority is planned along this period, as shown in Figure 5. As expected, the contraction in activities durations results in a cutback in 2020 year, when rig's majority end their operation. However, the precedence rules imply in higher expenses in the schedule tail, from 2021 to 2024.

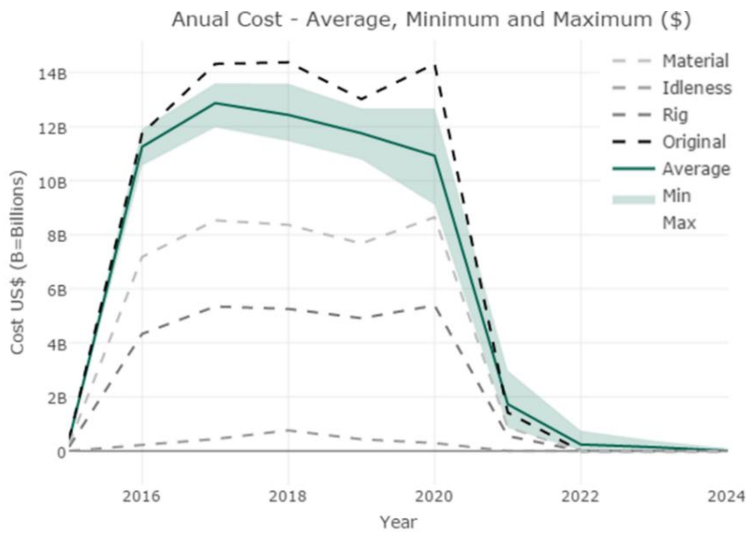

Figure 7 – Chart with the minimum, maximum and average annual simulated budget (2015-2028) (Source: authors).

In the studied company, the Rig Scheduling is still done using a manual approach considering only deterministic parameters. It's important to include the uncertainty in some analyses. The proposed model can generate thousands of realistic scenarios and theirs indicators in few minutes, allowing a support fast-decision making and improving risk analysis. In the next section, we state the final considerations and suggest futures researches.

5. Conclusions

The Oil & Gas sector plays an important role in nation's development and economy. However, petroleum supply chain is merged in an environment full with uncertainties and complex operations. To achieve success companies are required to make high investments in effective, safe and profitable exploration. Rigs become important as they are highly expensive and a main resource for drilling and maintenance activities. Instruments to support the decision making in Rig Scheduling have a great potential to reduce companies cost and improve their profitability. We made a literature review and identified a gap in the literature of Rig Scheduling, where most of the researches are made to find solutions through exact or heuristics methods, but few papers try to analyze an already existing scheduling and none paper was found trying to evaluate it in a multi- perspective approach. Aiming to fill this gap, this paper proposes a Monte Carlo's Rig Scheduling simulation for offshore wells during 8-year operation. The activities duration was draw based on estimate probability distribution and bootstrap method.

The simulation model was implemented in *Python* programming language and using *Anaconda Accelerate Model* with *Spyder* cross-platform *IDE*. Others software such as *Access*, *R*®, *Tableau*® and *Excel*® were used to treat the input and output data. The program was able to do an average of 0.6490 seconds per iterations and around 5 hours to generate reliable indicators. For each scenario generated, the simulator calculates three indicators (total scheduling time, idle time in scheduling and scheduling budget) and at the end of the process indicates the values registered, their average and their standard deviation. As expected, the results averages were diverging from the original scheduling plan, deviated at least 15.68% from the originals results. This can be explained by the quantity of uncertainties in the Scheduling Process and the complexity involved, where a delay in one activity generates delays in many other activities, due to the extensive precedence lists. The budget was also analyzed year-a-year. The simulation showed a high concentration of projects and activities between 2018 and 2020 that impacted in higher costs and operational times in those years, assisting the decision maker to prepare, in advance, resources (financial, labor and equipment) and availability with the use of the multi-perspective approach. The positioning of simulated schedules between the original solution and accomplished enhance the importance of the use of simulation tool and explain why the stochastic approach is so important in the Rig Scheduling.

Further research is still need to improve results quality, which depends strongly on the quality of the data used to estimate the distributions. To better improve it, data extraction methods must be used with advanced estimation methods. Besides, the results analysis can be enhanced using the indicators distributions provided by the model to analyze a solution risk using techniques such as Value-at-Risk (*VaR*), Conditional Value-at-Risk (*CVaR*), Decision Trees, etc. We hope this paper helps to improve the research of Simulation applied to Rig Scheduling Problem and others areas.

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6. References

Aloise, D. J., Aloise, D., Rocha, C. T. M., Ribeiro, C. C., Filho, J. C. R. and Moura, L. S. S. (2006), Scheduling Workover Rigs for Onshore Oil Production. *Discrete Applied Mathematics*, 154 (5), 695-702.

Atwal, H. S., and Knight, S. J. (2016), Enabling Efficient Drilling Operations Through Customized Data Driven Decision-Making. *Society of Petroleum Engineers*.

Baker, R. (1996), A Primer of Oilwell Drilling: a Basic Text of Oil and Gas Drilling, *Petroleum Extension Service,* 184.

Bassi, H. V., Filho, V. J. M. F., Bahiense, L. (2012), Planning and Scheduling a Fleet of Rigs Using Simulation-Optimization. *Computers & Industrial Engineering*, 63 (4), 1074-1088.

Barnes, J. W., Brennan, J. J. and Knapp, R. M. (1977), Scheduling a Backlog of Oil Well Workovers. *Journal of Petroleum Technology*, 29 (12), 1651–1653.

BP, British Petroleum (2014), *BP Energy Outlook 2035*. Available in: http://www.bp.com/en/global/corporate/about-bp/energy-economics/energy-outlook.html

Cyrino, F. L., Ferreira, P. G. C. F, and Souza, R. C. S. (2014), A Parsimonious Bootstrap Method to Model Natural Inflow Energy Series. *Mathematical Problems in Engineering*.

Devold, H. (2013), *Oil and gas production handbook: an introduction to oil and gas production*. Lulu.com.

Efron, B. (1979), Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics, 7* (1), 1-26.

EIA, U.S. Energy Information Administration (2016). Trends in U.S. Oil and Natural Gas Upstream Costs. U.S. *Department of Energy*. Available in: https://www.eia.gov/analysis/studies/drilling/pdf/upstream.pdf

Gibbons, J. D., Chakraborti, S. (2011). Nonparametric Statistical Inference. CRC Press. United States of America.

IFP SCHOOL, The Graduate School for Energy and Transportation Professions, (2015). *What are the Main Steps of an Oil or Gas Field Development Project?.* Available at: http://www.ifp-school.com/upload/docs/application/pdf/2015-2/3_main_steps_oil_gas_field_development.pdf

IHS Markit (2016), *Petrodata Offshore Rig Day Rate Trends*. Available at: https://www.ihs.com/products/oil-gas-drilling-rigs-offshore-day-rates.html

Irgens, M., Guzman, R. P., Stamatopoulos, J. G. and Jackson, K. (2008), Optimization for Operational Decision Support: The Rig Management Case. *SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA.

Iyer, R. R., Grossmann, I. E., Vasantharajan, S. and Cullick, A. S. (1998), Optimal Planning and Scheduling of Offshore Oil Field Infrastructure Investment and Operations. *Industrial & Engineering Chemistry Research,* 37 (4), 1380-1397

Kaiser, M. J., Snyder, B. (2013), The Five Offshore Drilling Rig Markets. *Marine Police*, 39, 201-214.

Massey Jr, F. J. (1951), The Kolmogorov-Smirnov Test for Goodness of Fit. *Journal of the American statistical Association*, 46 (253), 68-78.

Monemi, R. N., Danach, K., Khalil, W., Gelareh, S., Lima Jr, F. C. and Aloise, D. J. (2015), Solution Methods for Scheduling of Heterogeneous Parallel Machines Applied to the Workover Rig Problem. *Expert Systems with Applications*, 42 (9), 4493-4505.

Osmundsen, P., Roll, K. H., and Tveterås, R. (2010), Exploration Drilling Productivity at the Norwegian Shelf. *Journal of Petroleum Science and Engineering*, 73, 122-128.

Pereira, R. A. (2005), *Scheduling of development activities of oil wells: GRASP*, Thesis (Master of Science in Computer Science) – Instituto de Computação, Universidade Estadual de Campinas, Campinas, São Paulo, Brazil.

Pérez, M., Oliveira, F. and Hamacher, S. (2016), A New Mathematical Model for the Workover Rig Scheduling Problem. *Pesquisa Operacional,* 36 (2), 241-257.

Petrobras (2014), *Comparativo Entre Os Diferentes Tipos De Plataformas*. Available at: http://www.petrobras.com.br/infograficos/tipos-de-platformas/desktop/index.html

Reid, D., Yost, T., Russell, I. and Cheung, T. O. (2016), Avoiding the Money Pit: The Industrialization of Delivering Complex Drilling Facilities. *Society of Petroleum Engineers*.

Ribeiro, G. M., Laporte, G. and Mauri, G. R. (2012), A Comparison of Three Metaheuristics for the Workover Rig Routing Problem. *European Journal of Operational Research,* 220 (1), 28-36.

Ribeiro, G. M.; Mauri, G. R. and Lorena, L. A. N. (2011), A Simple and Robust Simulated Annealing Algorithm for Scheduling Workover Rigs on Onshore Oil Fields. *Computers & Industrial Engineering*, 60 (4), 519-526.

Suslick, S. B.; Schiozer, D. J. and Rodriguez M. R. (2009), Uncertainty and risk analysis in petroleum exploration and production. *Terræ*, 6 (1), 30-41.

Tarhan, B., Grossmann, I. E. and Goel, V. (2009), Stochastic Programming Approach for the Planning of Offshore Oil or Gas Field Infrastructure Under Decision-dependent Uncertainty. *Ind. Eng. Chem. Res*., 48 (6), 3078–3097.