

Modeling for evaluation critical offloading on oil platforms

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Abstract The growing oil production in Brazilian waters makes the logistic management of offloadings from the platforms increasingly important. The platform offloading schedule must be carried out in advance, avoiding production stoppage due to lack of available storage space. An interruption in oil production, however small, causes a direct revenue loss for the producing company. Offloadings performed very close to the platform TOP represent an imminent risk of production loss and are called critical offloadings. This work aims to carry out a statistical study with historical data from 2016 to 2019 to create a multivariate model for forecasting critical offloadings in a large Brazilian oil company. The dynamic regression model was used to evaluate how the variables present in the offloading scheduling process are related to the monthly percentage of critical offloadings. From the developed model, it was identified that the variables of monthly production, average stock, weather forecast, average batch and monthly exports impact the percentage of critical offloadings. A sensitivity analysis was carried out, from which it was possible to conclude that the company's inventory management is the fundamental factor for the reduction of critical offloadings and, consequently, the reduction of the chances of production loss.

Keywords: Offloading; modeling; dynamic regression; oil logistics; offloading schedule.

1 Introduction

Currently, oil production is responsible for a large part of the world economy and Brazil is the tenth largest oil world producer, responsible for approximately 3% world production in 2018 [1].

In recent years, investments in oil exploration and production have grown substantially in Brazil. Thus, the number of production systems gradually increases, as shown in Figure 1, with production data from 2009 to 2018 [2].

In addition, in Brazil, 4% of oil is produced on land and 96% is produced on the high seas (offshore) [2]. Flotation, Production, Storage and Offloading Units (FPSOs) are very popular in the oil and gas industry [3] and are used to process and temporarily store the oil and gas that comes from the production platforms or directly from oil wells at the deep-sea. Also known as oil platforms, it is the most used type in the Brazilian oil industry. Each one has its own characteristics, such as storage capacity, daily production rate and minimum stock in order to maintain unit stability.

The increase in offshore activities results in greater complexity in the logistics necessary for production flow and in support services for production continuity. Thus, companies are always looking for optimization alternatives to reduce operating costs and improve logistics management. In this paper, an oil production company in Brazil that has a large number of oil production platforms will be studied.

This paper aims to analyze how variables present in the day-to-day of the logistics team of this company influences platforms offloading demand meeting. For this, a study based on historical time series will be carried out and, using the dynamic regression method, a model of critical offloadings prediction defined

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for the next months will be elaborated. In addition, a sensitivity analysis will be performed assessing how these variables impact the logistics service level and company's strategic decisions.

Fig. 1. Oil production in Brazil over the last few years [2].

2 Critical Offloadings

As extraction of oil occurs, platform stock increases making necessary to drain production to the ships in a process called offloading. Offloading must be done before all the tanks in the platform are completely filled (TOP) to avoid oil production losses. Figure 2 represents a platform TOP. As shown, from the seventh day onwards, production is stopped because platform maximum storage capacity was reached. In this simulation, the offloading must occur until the sixth day to avoid oil production loss.



Fig. 2. TOP platform representation. Data Source: Own elaboration.

The TOP of any platform is very undesirable, once production loss has a direct impact on the company's revenue. Considering 2018 oil average price of \$ 71.31 / barrel [2] and a platform production of 150,000 barrels/day, each day of production stopped represents an estimated loss of \$10,696,500.00. This value justifies improvement on the offloading logistics management and meeting platform offloadings demand.

To prevent platform's TOP, logistics team program ship's arrival up to 48 hours before the platform reaches its maximum stock. See the example in Figure 2, the ship should be scheduled to arrive before fifth day. When ship arrives less than 48 hours before TOP, this offloading is defined as critical.



On a daily basis, unexpected events occur impacting on offloading logistics, resulting in critical offloading. Scheduled or emergency ships maintenance are often necessary, delaying their arrival in the platforms. Other times, bad weather prevent ships to mooring on platforms or discharge at terminals, delaying the offloadings. There are also anticipated TOP's, due to increase production events or platform tanks restrictions, that generate critical offloading.

Critical offloading percentage relation to total amount offloading done can be understood as offloading logistics service level. The lower this value, the lower is the chance of platform TOP occurring and consequently occurring production and financial loss.

Currently, offloadings with less than 48 and with less than 24 hours for TOP are measured, the latter being more critical, since it increases production loss chances.

3 Dynamic regression

In a discrete time series, data are collected at equal intervals of time [4]. In addition, a time series special characteristic is that adjacent observations are dependent and analysis must consider the order that they were collected. Time series analysis is based on this dependency. For discrete time series, the most used periodization's are daily, monthly or annually.

Methods for obtaining prevision models can be classified into univariate, which depend only on values of a single time series, and multivariate, when variable prediction depends on the values of one or more time series, denominated exploratory or independent variables.

The multivariable time series methods of analysis study the dynamics of the relationships between various time series and develop statistical models that better describe these interrelations [4].

One of the objectives of this paper is to analyse how day-to-day variables of platform's offloading programmer affects the amount of critical offloadings. The model type that allows this analysis is obtained through multivariate prevision methods, which enable the correlation analysis between dependent and independent variables.

Dynamic regression method, originally proposed by D. Cochrane and G. H. Orcutt in 1949, can be used to model relationship between a dependent variable and one or more independent variables. In this model, there is a combination between the dynamics of time series and explanatory variables effect, so dependent variable can be represented by its time-lagged values and current or lagged values of the causal variables [5]. Models can also use intervention variables, or dummy variables, to consider atypical situations, such as monthly demand abrupt variations for some product or any intervention performed for a period in the series studied.

The analyst usually has a good notion about the model form to be adjusted, but there may be uncertainty regarding the model structure [6]. The analyst may not know if all variables are necessary. Thus, this modeling type involves a large number of candidate variables to be used and analyst's objective is to adjust the regression model with the best set of variables. Generally, methods to select the set of variables to be used are step-by-step type. Variables are incorporated or removed at each step. In the bottom-up process, model starts without any dependent variables and sequentially inserts one variable at a time. Process continues until there are no more variables qualified to enter the equation.

For dynamic regression, in addition to independent variables, it is necessary to evaluate inclusion of the lags of these variables and the dependent variable.

Model verification must consider the consistence with prior knowledge and with data properties [7]. Therefore, even after assessing equation terms significance, it is still necessary to verify if the estimated coefficients are coherent and this assessment depends on the analyst's data knowledge.

4 Modeling

In this section, the variables used to model dynamic regression and the software used for the model will be presented.



4.1 Dependent variables

As the objective of this study was to predict offloading logistics service level for the coming months, a thorough research of all offloadings realized from January 2016 to December 2019 was carried out. In this period, the offloadings average was approximately 100 per month. Subsequently, the offloadings researched were defined as critical or not critical. From that, it was possible to calculate percentage of critical offloadings with less than 48 hours for TOP and with less than 24 hours for TOP. The graphs below show these data.



Fig. 3. Critical offloadings under 48 hours for TOP. Data Source: Own elaboration.



Fig. 4. Critical offloadings under 24 hours for TOP. Data Source: Own elaboration.

As can be seen, the two curves do not follow the same trend and must be analyzed separately. In a first analysis, it is not possible to identify a seasonality, but there is an upward trend at the end of analyzed period.

4.2 Independent variables

From the knowledge of offloadings programmers, all independent variables that could be made available to compose the model were identified.



The first independent variable identified was the number of ships. It considers all ships available in the company's fleet that month.

Then, was necessary to subtract the period that those ships were unavailable for offloadings, either by planned or emergency maintenance, thus discounting the hours in off-hire. This process resulted in the variable "number of ship hours" available in the month, measured in thousand hours.

Knowing which offloadings were performed each month, it was possible to count total number of platforms offloaded that month.

An important variable was the average monthly oil production, measured in thousands of cubic meters per day (m^3/d) . This variable counts the production of all platforms on which company is responsible for offloading operation logistics.

It was also important to analyze average monthly batch. This variable represents the average oil volume drained on offloadings in all platforms in the month, measured in thousand cubic meters (m³).

Another variable available was the average monthly refining. It includes the average volume oil processed per day at the company's refineries, measured in thousands of cubic meters per day (m³/d).

In addition to refining, another destination for crude oil is exports. Thus, the daily average of exports in the month, measured in thousands of cubic meters per day (m^3/d) , was used as a variable.

Monthly average oil stock was also available as an independent variable. It represents oil stock at all points operated by the company, including terminals, refineries, platforms and ships and is measured in thousands metric cubic (m³/d).

The inclusion of a dummy variable representing monthly weather forecast was also identified. A statistical research was performed with company's environmental monitoring area and was possible to identify which months of the year have the worst wind and wave height conditions, affecting the mooring of ships to platforms. Thus, the months of May, July, August and September were considered months with highest incidence of bad weather.

4.3 Software used

For modeling, an academic version of Forecast Pro for Windows 1.0.0.1 (FPW) was the software used [8]. With it, was possible to use the bottom-up technique, starting from a model with a dependent variable, explained only by a constant, and each round including a new variable. Based on hypothesis tests and p-value, the software indicates which variables are most suitable to integrate the model and which lags, both of dependent variable and independent variables, must be included. A hold-out of the last 3 months was used to evaluate out-of-sample model.

5 Results and discussions

5.1 Critical offloadings under 48 hours for TOP

The following model obtained the best result for predicting critical offloadings less than 48 hours for TOP:

 $aliv_{48_{t}} = -63,128174 + 0,006655est_{med_{t}} + 3,212322prev_{temp_{t}} + 0,134068prod_{t}$ (1)

Where:

 $aliv_48_t$ = percentage prevision of critical offloadings under 48 hours for TOP in the month t; est_med_t = average oil stock in the month t (x1000 m³/d);

 $prev_temp_t$ = dummy variable, in the months of May, July, August or September the value 1 must be used, in the other months use 0;

 $prod_t$ = Oil production in the month t (x1000 m³/d);



In the analysis of the coefficients, it can be noted that the bigger the oil production, the bigger the percentage of critical offloadings under 48 hours for TOP. This correlation is adequate, since larger production results in an early TOP date for platform, which creates need for the ships to arrive earlier.

Increase in the company's average oil stock also raises the percentage critical offloadings under 48 hours for TOP, as the ships cycle time increases, delaying their return to platforms.

Weather forecast dummy variable also has significant impact on prevision of critical offloadings under 48 hours for TOP, since months when bad weather is more severe, there are delays both in platforms offloadings and in ships unloading in terminals, making it difficult to attend the platforms offloading demand.

Model constant with a negative sign does not prevents from its use, since the other variables will never reach a value so low that critical offloading prevision becomes negative, which would be a failure in model use.

Lags, in both dependent variable and causal variables were not significant for inclusion in the model. There were also no other independent variables use indication.

Figure 5 bellow presents the curve with original data on percentage of critical offloadings under 48 hours for TOP plus trend curve of proposed model (red line). It can be seen that model presented an adequate fit for data presented and that the out-of-sample data were between minimum and maximum values predicted by the model.



Fig. 5. Original data on percentage of critical offloadings under 48 hours for TOP plus trend curve of proposed model (red line). Data Source: Own elaboration.

5.1.1 Sensitivity analysis for critical offloadings under 48 hours for TOP.

A sensitivity analysis was performed based on the model generated and it is shown in Figure 6. From this analysis, it was possible to conclude that a 5% increase both in oil production and monthly stock average results an increase of approximately 2% in critical offloadings with less than 48 hours for TOP, increasing probability of oil production loss.

This result is important for the logistics management. It allows balancing the two variables in order to avoid an increase in the critical offloadings. If an oil production increase is expected in the coming months, greater attention will be required to manage company's oil stocks, anticipating their reduction to maintain risk of critical offloadings at a lower level.

Of all variables available to compose the model, only average oil production, the average oil stock and weather forecast showed an influence on percentage of critical offloadings with less than 48 hours for the TOP. Knowing that weather forecast is not manageable and oil production is maximized, the company's average oil stock target must be strategically managed. Thus, oil stock management proves to be the main logistical planning tool for reducing critical offloadings, with consequent minimization of production losses.





Fig. 6. Sensitivity analysis for critical offloadings under 48 hours for TOP. Data Source: Own elaboration.

5.2 Critical offloadings under 24 hours for TOP

The following model obtained best result for predicting critical offloadings less than 24 hours for TOP:

$$aliv_{24_t} = 0.003364est_{med_t} - 0.042147exp_t - 0.143534lote_t$$
 (2)

Where:

 $aliv_24_t$ = percentage prevision of critical offloadings under 24 hours for TOP in the month t; est_med_t = average oil stock in the month t (x1000 m³/d); exp_t = average oil exports in the month t (x1000 m³/d); $lote_t$ = average batch in the month t (x1000 m³).

In the coefficient's analysis, it can be noted that the bigger the average oil stock, the bigger the percentage of critical offloadings under 24 hours for TOP, because the ships cycle time increases, causing delay in their return to platforms.

The amount of month oil exports reduces the percentage of critical offloadings with less than 24 hours, as it reduces company's stock oil as a whole, reducing ships cycle time and improving service to platforms.

The bigger the average batch, the smaller the percentage of critical offloadings under 24 hours for TOP because there is a better oil transport efficiency, providing ships cycle optimization.

Lags, in both dependent variable and causal variables were not significant for inclusion in the model. There was also an indication to use ships available hours as an independent variable. However, analysis of coefficient showed that relationship between the variables is reversed, that is, an increase in ships available hours meant an increase in percentage of critical offloadings, which is contrary to operational reality. Thus, this variable was discarded.

Figure 7 bellow presents the curve with original data on percentage of critical offloadings under 24 hours for TOP plus trend curve of proposed model (red line). Analysis of graph shows adequacy of the model for the data presented and that out-of-sample data were between minimum and maximum values predicted by the model.





Fig. 7. Original data on percentage of critical offloadings under 24 hours for TOP plus trend curve of proposed model (red line). Data Source: Own elaboration.

5.2.1 Sensitivity analysis for critical offloadings under 24 hours for TOP.

Prevision model for critical offloadings under 24 hours for TOP used average oil stock, average batch and daily exports average as causal variables. From it was possible to construct a sensitivity analysis to assess how each of these variables affects critical offloadings, that it is shown in Figure 8.



Fig. 8. Sensitivity analysis for critical offloadings under 24 hours for TOP. Data Source: Own elaboration.

From the sensitivity analysis, it can be seen that an increase of 10% in daily export average causes a small reduction, in the order of 0.3%, in the percentage of critical offloadings under 24 hours for TOP. Thus, this variable should not be treated as a priority in actions aimed to reduce critical offloadings.

A 5% increase in the average monthly oil stock means an increase around 1% in critical offloadings under 24 hours for TOP. Thus, oil stock policy is an important tool to manage critical offloadings being necessary to find a balanced average stock, in order to minimize production losses.

A 10% increase in average batch results in 1.3% reduction in critical offloadings under 24 hours for TOP. This is an important information for the offloadings scheduling, once programmer, observing physical restrictions of each platform, can define the batch size. Thus, programmer must always maximize the batch size, which increases the logistical optimization and reduces the lost production probability.

The model for prevision percentage of critical offloading under 24 hours to the TOP proved to be more suitable for operational decisions use in conjunction with strategic stock decisions.



For the company studied, this model can be used as a tool for critical offloading prevision for the coming months and also as a basis for the target of these variables, in order to find a balance between them and minimized percentage of critical offloadings under 24 hours for the TOP. In addition, it can be used to improve offloadings scheduling, minimizing production loss and generating financial gains.

6 Conclusions

Currently, studied company does not have any model for prevision of critical offloadings. Thus, the two models generated in this work can be used as a tool to increase logistical efficiency, making it possible to reduce loss production risk due to the lack of oil storage capacity on the platforms. Shutdown of a typical platform represents a financial loss of around 10 million dollars a day. Thus, a model that uses the company's own operational and strategic variables represents a gain for the offloadings programming process, generating a positive financial result.

Sensitivity analysis allows us to conclude that oil stock management is very important to maintaining percentage of critical offloadings under 48 hours for TOP at manageable levels. Thus, strategic decisions about average stock target is directly connected to the reduction of production loss probability and, consequent, company revenue maximization.

Increases in average batch size causes a significant reduction in critical offloadings under 24 hours for the TOP. As this variable is part of programmer's operational decisions, maximizing batch size should be a priority in day-by-day with the objective of critical offloadings reducing.

As with critical offloadings under 48 hours under the TOP, the average stock is very importance in critical offloadings under 24 hours under the TOP. Thus, this variable must be constantly monitored to avoid oil production losses. The fact of this variable is present in both models reinforces the importance of oil stock management in company strategic decisions.

The studied company can use the generated models to predict logistics service levels based on meeting the platforms offloading demand. With production projection data, average stock, exports and average batch size, in addition to the weather forecast, it is possible to predict critical offloadings percentage for the coming months.

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