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Abstract

Nowadays, the market for natural gas production and its use as a source of energy supply has been growing substantially in Brazil. However, the use of tools that assist the industry in the management of production can be essential for the strategic decision-making process. In this intuit, this work aims to evaluate the formulation of Holt Winter's additive and multiplicative time series to forecast Brazilian natural gas production. A comparison between the models and their forecast play a vital role for policymakers in the strategic plan, and the models estimated production values for the year 2018 based on the information contained in the interval between 2010 and 2017. Therefore, It was verified that the multiplicative method had a good performance so that we can conclude this formulation is ideal for such an application since all the predicted results by this model showed greater accuracy within the 95% confidence interval.

Keywords: Forecast Models; Holt-Winters; Natural gas; Time Series.

1. Introduction

The advent of the liberal policy spread in the 1970 decade happened simultaneously face of uncertainties caused by the oil shock, world security threats, and growing protectionist pressures. Likewise, the pre-existing concepts on the operational and financial efficiency of the state-owned companies were questioned, as well as the pressures arising from the search for maturation and the diversification of energy sources in the countries. This emergency led the introduction and increase of consumption of other energy sources, which is an attempt to contract the energy instability caused by dependence on oil and fossil fuels (JUNIOR, ALMEIDA, et al., 2007).

The reduction and demand for the use of petroleum products have led to an increase in the consumption of natural gas in locations appropriate for its prospection and commercialization. However, the progress of the natural gas industry did not take place on a global scale due to the intention through the best relation of risk versus the expected return, parallel to the high cost of implementation, which resulted with rigid and long-term contracts. According to Cavalini (2017) in the natural gas industry, the entire construction of the infrastructure for the operation is carried out in order to achieve a particular performance goal. The need for a continuous supply determines the understanding of the variation by the seasonality of the demand, as well as the continuity of the supply in case of an increase in consumption. One of the main characteristics of natural gas is the versatility; it can be used in electric power generation, as in combustion engines in the transportation industry, in the production of flames, heat, and steam. As a result, its application is possible in all sectors of the economy: industry, commerce, services, and residences (ANEEL, 2008).

The entire base of the Brazilian oil and gas market is handled with significant government involvement. Petrobras is the state-owned company responsible for controlling activities and investment decisions. Because of this, it is important to use forecasting techniques and methods, since they are tools that help industries and companies to solve problems. Among these solutions searches, we can highlight the evaluation of external factors that affect performance such as inflation; the price variation; planning the need for resources; planning changes in the workforce; the production area; management of inventories and in the development of complementary plans (PELLEGRINI and FOGLIATTO, 2001).

Traditional forecasting methods are based on studies of records and information obtained on certain parameters (DONATE, LI, *et al.*, 2013; TULARAM e SAEED, 2016). This method allows, through analysis, to understand the processes that were able to generate such information and, from that understanding, to predict their future values. Because of the low cost and optimum forecasting efficiency, the Computational Holt-Winters model has been widely used about the various time series models (ASSIS, RODRIGUES, and PROENÇA JÚNIOR, 2014; MOMIN, 2017).

This work aims at forecasting the Brazilian natural gas production for the year 2018. For this, the Brazilian national oil agency (ANP) data were collected from the equivalent monthly oil barrels (bps) produced from January 2010 to December 2017. The method of Holt-Winters additive and multiplicative seasonal exponential smoothing and the MAPE (Mean Absolute Percentage Error), the MAE (Mean Absolute Error) and the MSE (Mean Squared Error) were analyzed to verify the accuracy of the forecast. So, a comparison of the data obtained with the real values collected in 2018 was carried out, aiming to validate the forecasting capacity of the model for time series of Brazilian natural gas production.

2. Methodology

2.1 Time Series and The Methods of Forecasting

Time series is defined by a set of time-sequential data related to an event. Also, a given time variable can be replaced by other dependent variables within the same set. Therefore, the study of time series has the purpose of analyzing and modeling this type of dependence (ABDEL-AAL, 2008; BOX and JENKINS, 1976). The technique of forecasting time series, defined by the future demand, will be a projection of the past values, not being influenced by other variables (JERE, KASENSE, and CHILYABANYAMA, 2017) and consists of a simpler and more applied method for forecasting. Also, Moreira (2011) points out that, if the period covered is long enough, four behaviors or effects associated with a time series can be identified: the trend effect, the seasonal effect, the business cycles, and the random variations.

Forecasting techniques can be classified according to the type of elaboration of their speculative formulation and statistical basis. These techniques often include so-called spontaneous or intuitive methods, which simulate human behavior. Therefore, Box-Jenkins procedures, Bayesian methods, and neural networks. Usually, forecasting methods can be classified as qualitative or judgment based and quantitative or mathematical. We use a mathematical method based on time series since the mathematical model for the event under study has not yet been established. In fact, according to Makridakis (1998), quantitative methods must meet some existing conditions such as the availability of past information; the possibility of this information being quantified (numerical data); and the patterns of occurrence in the past that succeed each other in the future (continuity assumption). About the time-series methods, it is worth mentioning the exponential damping models, the method of Holt-Winters, moving averages, and Box-Jenkins (BOX and JENKINS, 1970) and neural networks. Considering the causal methods, we highlight the regression models, the simultaneous equation models, and different methods of parameter estimation and econometric models (BALLOU, 2001; JERE, KASENSE and CHILYABANYAMA, 2017).

2.2 Holt-Winters Model and Collect Data

The Holt-Winters method describes two distinct models that depend on the behavior of the initial series. This technique is based on the analysis of linear trend and seasonality component (PELLEGRINI and FOGLIATTO, 2000). The model considers three smoothing equations: one comprises the level, the tendency, and the other to the seasonality. When an increase in the seasonal amplitude is required, the series presents a difference between the highest and the lowest demand point in the cycles grows with time, and the multiplicative model becomes adequate. Thus, when the seasonal amplitude is constant, it means that the largest and smallest points in the cycles are independent of the temporal variation, and the model to be used is the additive (HOLT, 2004; WINTERS, 1960). In the evaluation presented by Morettin & Toloi (2006), to the detriment of low cost and for ease of understanding Holt-Winters model, there are difficulties in determining the constants of smoothing factor and impossibility to study the statistical properties, due to a lack of confidence interval becomes difficult. The results for the several types of models are presented in Table 1.

Table 1. Comparative equations for the multiplicative and additive Holt-Winters models.

	Additive Holt-Winters	**Multiplicative Holt-Winters**
Level	$\bar{L}_t = \alpha\left(Y_t - \hat{S}_{t-s}\right) + (1-\alpha)(\bar{L}_{t-1} + \hat{B}_{t-1})$	$\bar{L}_t = \alpha\frac{Y_t}{\hat{S}_{t-s}} + (1-\alpha)(\bar{L}_{t-1} + \hat{B}_{t-1})$
Trend	$\hat{B}_t = \beta(\bar{L}_t - \bar{L}_{t-1}) + (1-\beta)\hat{B}_{t-1}$	$\hat{B}_t = \beta(\bar{L}_t - \bar{L}_{t-1}) + (1-\beta)\hat{B}_{t-1}$
Seasonality	$\hat{S}_t = \gamma(Y_t - L_t) + (1-\gamma)\hat{S}_{t-s}$	$\hat{S}_t = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)\hat{S}_{t-s}$
Forecast	$F_{t+m} = \left(\bar{L}_t + \hat{B}_t m\right) + \hat{S}_{t-s+m}$	$F_{t+m} = \left(\bar{L}_t + \hat{B}_t m\right)\hat{S}_{t-s+m}$

In Table 1, $\hat{S}_t$ is the seasonality length, $\bar{L}_t$ is the series level, $\hat{B}_t$ is the trend, S_t is the seasonal component, F_{t+m} is the forecast for period m, Y_t is the observed value and α, β and γ are parameters exponentials of the level, trend, and seasonality respectively.

Even though based on the Makridakis model, Wheelwright and Hyndman (1998), the objective of this article is not directly concerning the related problem, but it is an analytical evaluation about the performance of the model used for each evaluated trait.

Table 2 presents the historical volume data as part of a BOE (Barrels of Oil Equivalent) of natural gas production between 2010 and 2017. This information is based on companies' annual reports submitted to the ANP official repository, refer to the product at a temperature of 20°C and a pressure of 1 atm. This full set of data collected corresponds to a total of 96 periods.

Table 2. BOE production between 2010 and 2017

Month	Year							
	2010	2011	2012	2013	2014	2015	2016	2017
Jan.	11.498.912	13.011.673	13.961.630	14.896.262	15.780.647	18.962.588	19.097.717	21.590.509
Feb.	10.736.536	11.142.546	12.327.927	13.576.204	14.766.589	16.914.418	17.948.670	18.915.591
Mar.	11.680.103	12.065.069	13.014.940	15.171.583	16.380.286	18.778.877	17.744.383	19.902.790
Apr.	11.634.058	11.886.393	12.412.695	14.196.847	15.746.916	17.929.785	18.201.374	19.495.531
May	12.194.224	13.092.248	13.433.047	14.699.846	16.601.715	18.289.762	19.600.761	20.577.310
Jun.	11.955.945	12.784.250	13.680.159	15.201.733	16.451.721	18.152.806	19.673.585	21.121.135
Jul.	12.252.244	13.133.946	13.939.230	15.415.581	17.257.811	18.721.362	21.047.102	22.585.455
Aug.	12.276.330	13.063.931	14.016.984	15.118.998	17.852.695	19.486.845	21.360.106	21.963.708
Sep.	12.148.245	12.402.815	13.634.773	14.851.216	16.901.427	18.503.232	20.988.405	21.666.913
Oct.	12.758.941	13.011.948	14.330.504	14.309.110	18.201.964	19.168.366	21.306.426	22.506.521
Nov.	12.587.745	12.898.266	13.934.461	15.025.976	17.426.646	17.901.095	21.117.073	21.553.586
Dec.	13.591.776	14.013.999	14.960.920	16.020.284	18.685.608	19.716.906	21.950.398	22.264.697

Source: ANP, 2019.

3. Results and Discussion

3.1 Preliminary data analysis

The non-stationary data behavior and the growth trend of Brazilian natural gas production over the years, due to the presence of seasonality, can be observed in Figures 1 and 2, respectively.

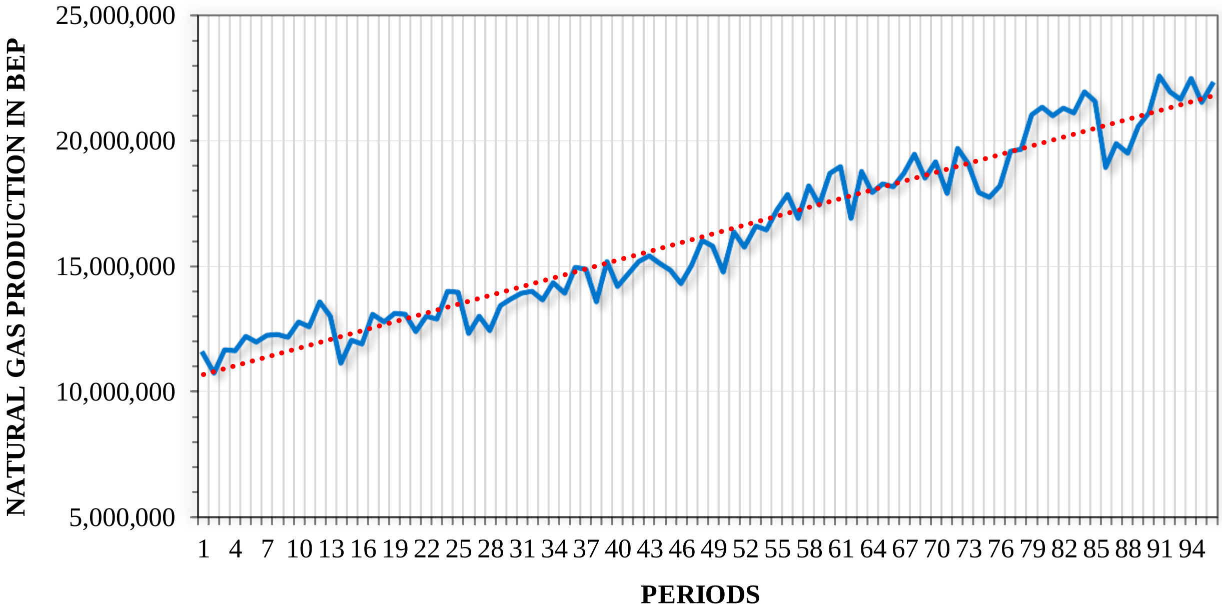

Figure 1. The growth trend in natural gas production between 2010 and 2017.
Source: Authors

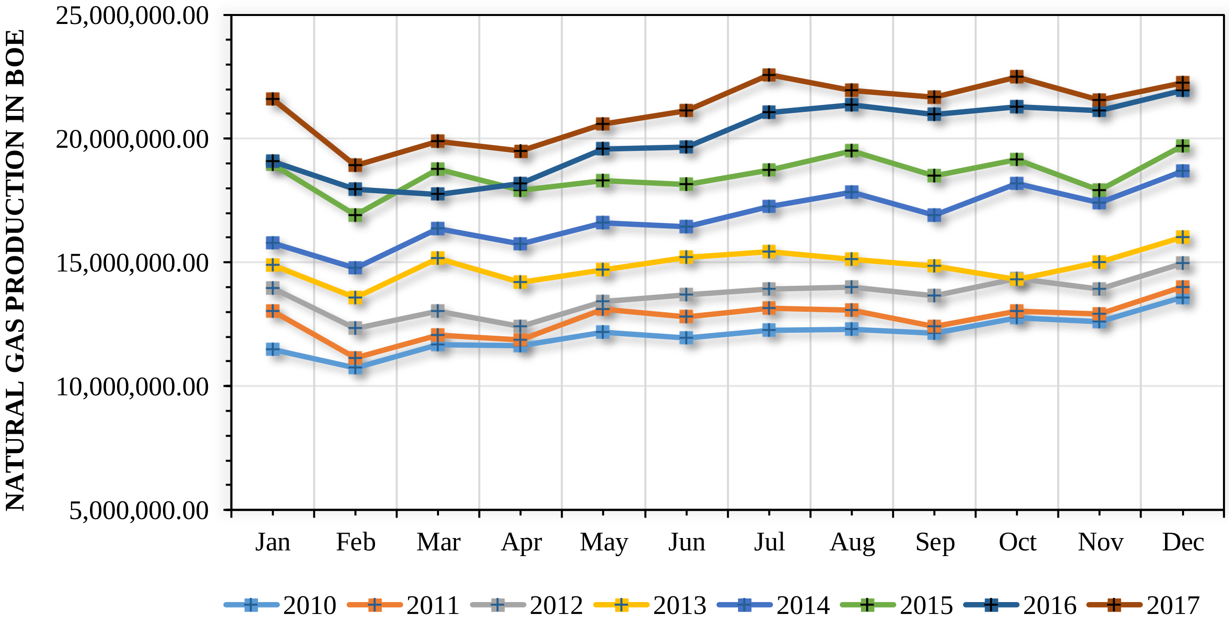

Figure 2. Evolution of natural gas production per year.
Source: Authors

The diagram in Figure 2 shows the most recent data available corresponding at a time interval related to the BOE production of natural gas. The monthly seasonality with the biggest drop in production from January to the beginning of February, and the period of greatest productivity from June to December. The average annual increase in production over the years is 7.6495%. It was also observed that the largest increment is found in 2014 with approximately 11.6653% and the lowest one is seen in the year 2011 with

4.7158%. The monthly average of production was 16,236,592 BOE, with a standard deviation of 3,358,694 BOE. The month of greatest production was July 2017, with 22,585,455 BOE and the lowest one was from February 2010 with 10,736,536 BOE.

3.2 Holt-Winters Method Analysis

The evaluation parameters (weights) α, β e γ has been obtained with values of 0.40; 0.18 and 0.16 for the level, trend, and seasonality, respectively. It should be noted that the lower weights produce a smoother line, and the larger ones a more accentuated line. Thus, using smaller weights for noisy data gives values that do not fluctuate along with noise.

Therefore, both additive and multiplicative methods presented low mean absolute percentage error (MAPE) and can be used for future predictions. Nevertheless, the model using the multiplicative method, although it did not present the best precision of measurements (MAPE, MAE, and MSE), obtained the best performance because, all the estimates, compared to the real data, remained within the confidence interval (CI) set at 95%, while some estimates of the additive model are not acceptable for predicting confidence within CI. This result is recurrent from the best fit to past data. It can be seen in Figure 3, which for multiplicative data, the magnitude of the seasonal pattern changes as the level of data often varies. However, for the additive data, the magnitude of the seasonal pattern remains constant with changes in the level of changes. Thus, the visual analysis of the patterns shows that the serial projection of the Brazilian natural gas production data, shown in Figure 1, presents greater adaptability with the seasonal pattern of the multiplicative model.

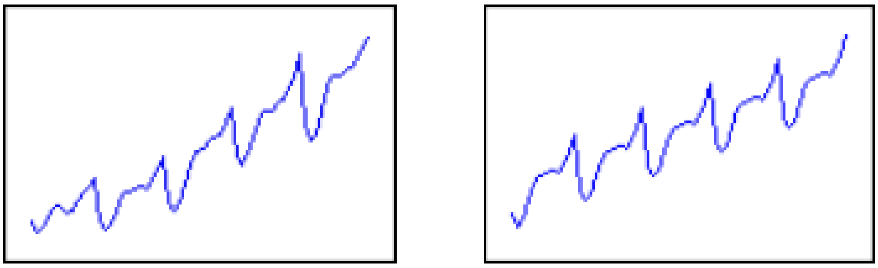

Figure 3. Seasonal pattern of the multiplicative and additive models
Source: MINITAB, 2017.

With this result, was opted for the multiplicative model for estimation of Brazilian natural gas production in 2018. Figures 4 and 5 present the predictions made through the methods cited in this text, as well as their accuracy.

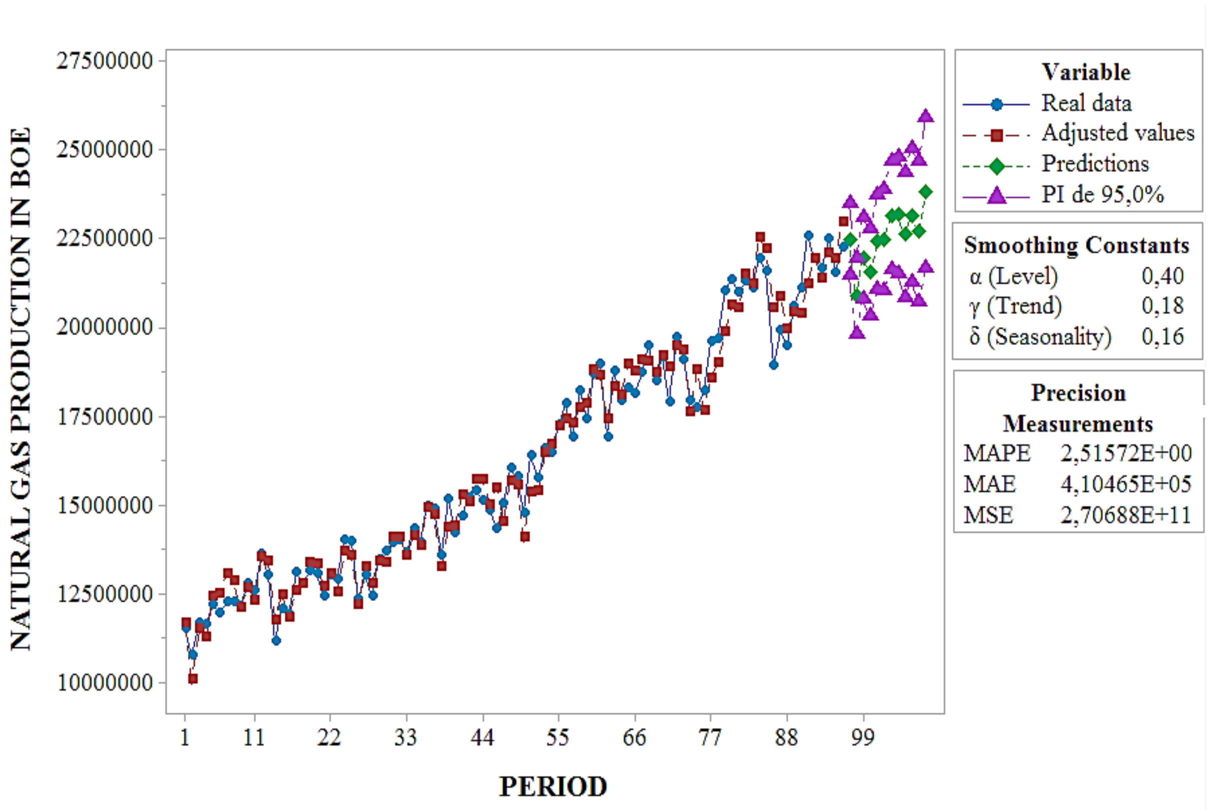

Figure 4. Graphical model of the additive Holt-Winters method
Source: Authors

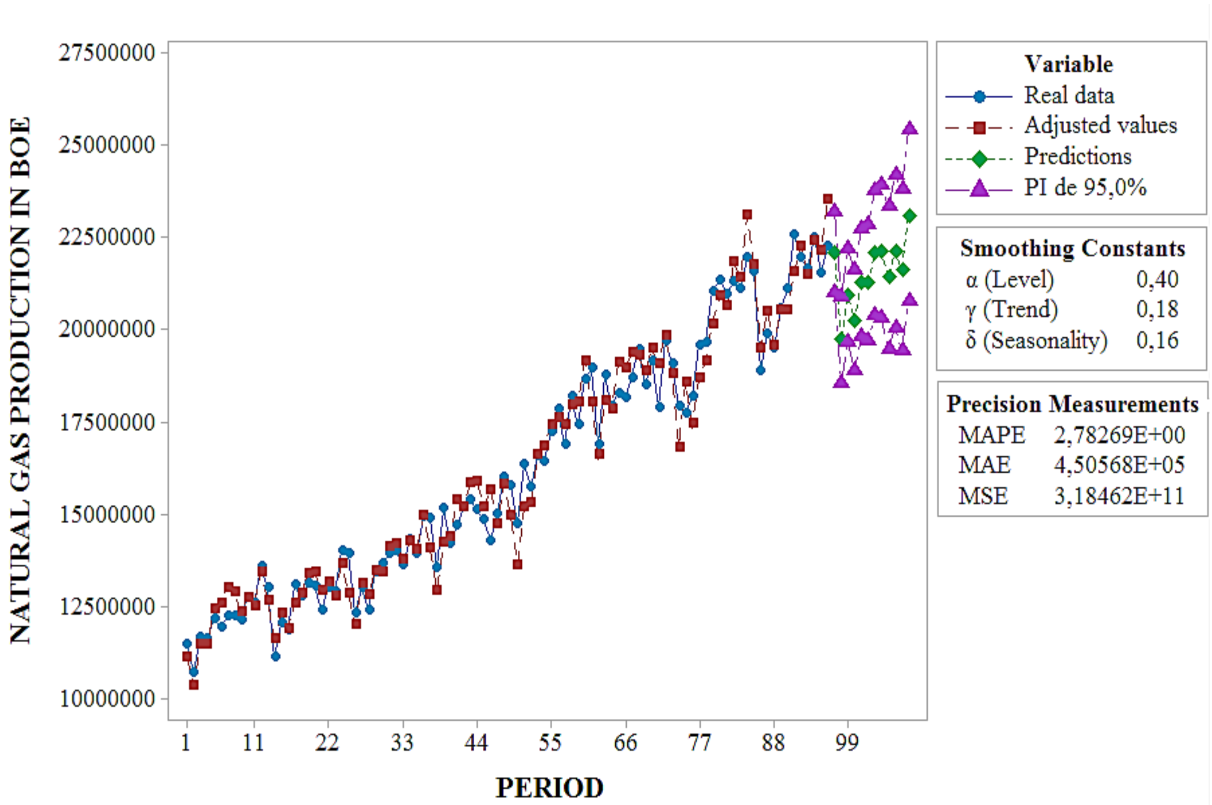

Figure 5. Graphical model of the multiplicative Holt-Winters method
Source: Authors

Figure 6 shows the trends and forecasts of both models for the year 2018. In this image, it can be observed that in August and October, the actual data could not be monitored closely by forecasts. However, an analysis of the predicted values presented in Tables 3 and 4 is necessary to admit that the results of the forecasts remained within the established confidence interval.

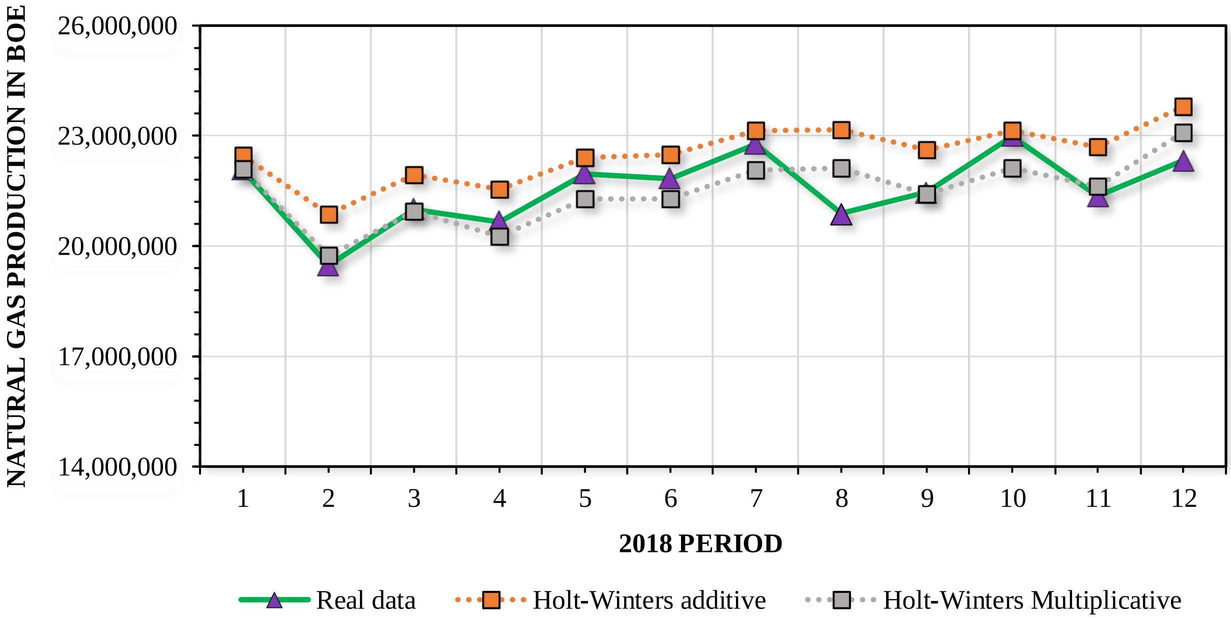

Figure 6. Predictions of the multiplicative and additive models of Holt-Winters

Source: Authors

Thus, the forecast and the confidence interval (CI), stipulated at a level of 95%, were carried out by January to December of 2018, according to the models. In 2018 was verified the comparison with the actual data collected with the generated CI of both prediction models. Tables 3 and 4 show the forecast data, Cis and the comparison for a given period, using the additive and the multiplicative method, respecti vely.

Table 3. Comparison of the results forecast with the real data using the additive method

Month	Lower limit 5%	Forecast	Upper limit 95%	Real data	Within a range?
Jan.	21.466.373	22.471.994	23.4776.15	22.077.612	Yes
Feb.	19.796.959	20.867.524	21.9380.90	19.478.594	No
Mar.	20.782.886	21.930.450	23.0780.13	21.007.735	Yes
Apr.	20.307.906	21.542.269	22.7766.32	20.667.439	Yes
May	21.087.542	22.416.586	23.745.629	21.973.987	Yes
Jun.	21.044.532	22.474.574	23.904.616	21.841.718	Yes
Jul.	21.615.400	23.151.512	24.687.623	22.774.707	Yes
Aug.	21.523.087	23.169.360	24.815.632	20.888.959	No
Sep.	20.850.289	22.610.046	24.369.803	21.457.046	Yes

Oct.	21.274.731	23.150.692	25.026.654	22.984.338	Yes
Nov.	20.701.771	22.696.183	24.690.594	21.352.470	Yes
Dec.	21.683.820	23.798.549	25.913.277	22.325.801	Yes

The results in Table 3 show that not all real production data remained within the 95% confidence interval for the additive model. The presented results can indicate that it was not able to predict the real results of February and August satisfactorily so that for both months the lower limit of 5% was above the values declared by the ANP.

Table 4. Comparison of the results forecast with the real data by using the multiplicative method

Month	Lower limit 5%	Forecast	Upper limit 95%	Real data	Within a range?
Jan.	20.993.029	22.096.901	23.200.773	22.077.612	Yes
Feb.	18.554.927	19.730.089	20.905.250	19.478.594	Yes
Mar.	19.672.282	20.931.965	22.191.648	21.007.735	Yes
Apr.	18.900.771	20.255.733	21.610.696	20.667.439	Yes
May	19.832.082	21.290.976	22.749.870	21.973.987	Yes
Jun.	19.718.024	21.287.784	22.857.543	21.841.718	Yes
Jul.	20.391.775	22.077.967	23.764.160	22.774.707	Yes
Aug.	20.310.259	22.117.375	23.924.491	20.888.959	Yes
Sep.	19.485.459	21.417.147	23.348.835	21.457.046	Yes
Oct.	20.067.182	22.126.429	24.185.675	22.984.338	Yes
Nov.	19.437.212	21.626.481	23.815.750	21.352.470	Yes
Dec.	20.772.130	23.093.471	25.414.813	22.325.801	Yes

Finally, it was observed that the real production data declared by the ANP, for the year 2018, are within the 95% confidence interval. Therefore, the applied model presented a good forecast capacity, generating reliable future data.

4. Final Considerations

Due to the importance of forecast and validation of the results of the analysis, in this work, some guidelines were considered, both in the collection of information and in the interpretation of the results, such as the data records in chronological order. The amount of data sufficient to assess trends or patterns; the collection of data at appropriate time intervals and the seasonal behavior of the series. Through the exponential smoothing method of additive and multiplicative Holt-Winters, in 2018 were evaluated the Brazilian natural gas production forecasts. With this, we have validated and compared the predicted values with the real data declared by the ANP. It was verified that both methods, additive and multiplicative, were well adapted to the behavior of the series and could be used in future production estimates. Even though the multiplicative model was considered more satisfactory since it was better adjusted to the seasonal pattern in large data sets. Thence, we can report that the study carried out is significant for the country's economy and energy industry, and consequently contributes as a model, whose purpose is to understand the behavior of production in barrels of oil equivalent (BOE) of natural gas. Moreover, this study allows, in the case of forecasting future demand, the sectors of industry and the economy to avoid unnecessary expenses, improving their decision making, inventory conditions, planning, control, and organization.

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