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Analysis of Energy Consumption in Colombia Using the Holt Method

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ABSTRACT

Energy production is constantly facing major challenges today, because despite initiatives to promote the insertion of renewable energy, electricity consumption has shown considerable growth in recent years. In order to use an instrument that facilitates forecasts and predictive processes for the design of strategic plans associated with energy management, the application of the Holt Method is proposed using data on electricity demand in Colombia, GDP per capita and industrial value added, making an analysis of the last 10 years, based on figures from the World Bank. The final results predict that energy consumption for the period 2018-2020 will be between 66,231 GWk and 66,885 GWk.

Keywords: Energy Consumption, Holt Method, Energy Efficiency, Colombia
JEL Classifications: D24, Q43, M31

1. INTRODUCTION

In Colombia, natural phenomena have been the subject of study since approximately 1950. It was in that year when one of the first periods of extreme drought and high temperatures occurred in more than 55 municipalities with temperatures above 40°C (Salcedo et al., 2016). In addition to the above, the time of affectation was almost 2 years, which resulted in great economic losses, both for agriculture and for commerce, industry and other productive activities (Contreras, 2016).

As if that weren't enough, along with the increase in inflation, the country faced another series of problems, since it did not have the strategic plans necessary to ensure energy production, so it was necessary to resort to plans such as rationalization, which meant suspending energy for hours and even days in some regions of the country, which clearly resulted in a negative impact both at the family and business level (Martínez et al., 2017).

Towards 2015-2016 this phenomenon repeated itself and it was common to find throughout the country, large areas affected by high temperatures; a large number of animals and crops were lost due to lack of appropriate water inputs which added to the lack of electricity service as a direct effect of the natural phenomenon known as El Niño (Tovio and Alfaro, 2016).

The control and management bodies in the energy production part as a result of these drastic changes have been notably hit, because despite having monitoring and projection tools for electricity production, they have sometimes observed scenarios of uncertainty because the calculations have not been adjusted to reality, which has caused even more losses and impacts at the residential, industrial, commercial and agricultural levels (Sant'Ana et al., 2017).

Therefore, in recent times, the need to achieve more competitive environments, especially for the productive sectors, has led to the implementation of various alternatives to reach diagnoses closer to reality (Stephanidis, 2018), which allow the design of appropriate and timely strategies to address environmental phenomena and promote more stable production programs in each of the regions of Colombia (Mojica et al., 2015). Thus, in search of mathematical options, the Holt Method or exponential smoothing is proposed as a prediction or prognostic technique.

Combined with other procedures, this model has served as the basis for research that makes projections based on historical data to give greater precision on forecasts (Ghalehkhondabi et al., 2017). Among the great variety of studies that can evidence such application, is the one developed by Barassi and Yuqian (2017) who perform an analysis of six of the univariate and multivariate models most used in the estimation of electricity demand in the United Kingdom, considering Holt-Winter as part of the most used. Likewise, other researches such as Tratar and Strmčnik (2016) have used the comparison of estimation methods such as multiple regression with Holt, considering in their results that the latter provides better adjustments to the predicted values of the variables in both the short and long term.

2. METHOD

The double exponential smoothing method developed by Charles Holt in 1957 was used, it is widely used to make forecasts based on demand or production data (Jalil et al., 2013). The model is configured based on three main equations, the estimate of the current level (a), the estimate of the trend (b) and the forecast of the period p in the future (c), mathematically expressed as follows (Hyndman and Athanasopoulos, 2018):

$$\text{a) } L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$\text{b) } T_t = \beta\left(L_t - L_{t-1}\right) + (1-\beta)T_{t-1}$$

$$\text{c) } \hat{Y}_{t+p} = L_t + pT_t$$

where:
L_t = New smoothed value
α = Smoothing constant for the level, must meet $0 < \alpha < 1$
Y_t = Real value of the series in period t (actual value)
β = Smoothing constant for trend estimation, must meet $0 < \alpha < 1$
T_t = Trend Estimate
p = Period to be predicted
$\hat{Y}_{t+p}$ = Forecast for period p (estimated values).

The reliability of the forecast performed is done through the Measurement of Forecast Error (MSE) which results from the average of the model errors (Delgadillo-Ruiz et al., 2016). This parameter is used to verify its reliability based on the minimization of this indicator, the so-called attenuation constants α and β, that is, the purpose is to find a level in these two variables so that the minimum is achieved in the MSE (Villada et al., 2014). This is achieved with the use of the Microsoft Excel solver complement, applying the following restrictions (Lesaca et al., 2014):

a) $0 < \alpha < 1$
b) $0 < \beta < 1$

Established the parameters that were used for the calculation of the forecast, the variables considered for the estimate were identified, such as energy consumption, per capita GDP per purchasing power parity (PPP) at current international prices and the value added of industry as a percentage of GDP, considering that these are related to the behaviour of energy demand, according to studies carried out by Farhani and Ozturk (2015) and Hu et al. (2015). The data used for the projection were taken from the Operation Report of the National Interconnected System (SIN) and the World Bank platform (2017), corresponding to the period 2007-2017; Table 1 shows the extracted data.

At the procedural level it is important to explain that the first step necessary to develop the Holt method was to organize the historical data of the period of interest, indicated in Table 1. Then, in the next phase, the expressions of each component of the formula were presented in Excel in order to obtain the results of the forecast.

3. RESULTS

This section shows the estimates made for the variables energy consumption, GDP per capita PPP and industrial value added, indicating the contrast between actual and projected values, arguing about the reliability of the method. In this sense, the first step consisted of formulating Holt's Forecast Model with the support of the spreadsheet, structuring the formulas described at the beginning of the section (a, b and c) and using the data from Table 1. The procedure for constructing the model is shown in Table 2 below.

The table shows the data for the period 2007-2017 and the forecasts made for 2018, 2019 and 2020 according to the Holt method. Column Yt indicates the estimate of the current level (a) or current values; column Lt shows the estimate of the trend (b); and column Y't shows the forecast of the period p in the future (c) or predicted value. Configured the cells with the method formulas, the data that gave way to the estimates were entered. Subsequently, the model was optimized by minimizing the average error (MSE) using the complement solver in Excel (Ünal et al., 2015). Table 3 gives these results.

Once the model error (MSE) has been minimized, it is possible to show a comparative graph between real values (Y_t) and predicted values (pT_t) in order to observe the future behaviour of the expected energy production, see Figure 1 below.

As detailed in the graph, the Holt Model adjusts very closely to actual values, since the forecast line (Y't) is positioned similarly to historical data. This method confirms that it is one of the most reliable to predict electricity consumption (Jalil et al., 2013; Haiges et al., 2017) considering the short and long term.

Table 1: Variables projected by the holt method

Year	Y	X_1	X_2
	Annual energy demand in Colombia (GWh)	GDB per capita, PPP (US$ at current international prices)	Industry, value added (% of GDP)
2007	52,853	9710,9176	30,63
2008	53,870	10132,2657	32,42
2009	54,679	10260,2267	31,71
2010	56,148	10680,003	32,02
2011	57,155	11496,4777	34,27
2012	59,370	12058,3438	34,57
2013	60,890	12725,0437	34,16
2014	63,571	13395,5162	32,71
2015	66,174	13827,6728	30,54
2016	66,318	14165,4512	29,72
2017	66,893	14552,0086	29,25

Source: SIN (2017) and World Bank (2017)

Table 2: Holt's model for forecasting energy consumption in Colombia

Year	t	Yt	Lt (a)	Tt (b)	Y't (c)	Error
2007	1	52,853	52,9	-		
2008	2	53,870	53,8	0,9	52,853	1,0
2009	3	54,679	54,7	0,9	54,679	0,0
2010	4	56,148	56,1	1,4	55,592	0,6
2011	5	57,155	57,2	1,1	57,503	0,3
2012	6	59,370	59,3	2,1	58,290	1,1
2013	7	60,890	60,9	1,7	61,329	0,4
2014	8	63,571	63,5	2,5	62,610	1,0
2015	9	66,174	66,2	2,7	66,011	0,2
2016	10	66,318	66,6	0,4	68,842	2,5
2017	11	66,893	66,9	0,3	66,995	0,1
2018	12		Forecast		67,231	
2019	13				67,558	
2020	14				67,885	

Source: own calculations based on historical data, 2018

Table 3: Parameters that minimize the MSE in the model

α	0,898
ß	1,000
p	1,000
MSE	0,719

Source: own calculations with solver in Microsoft Excel, 2018

When the electricity consumption variable was estimated, the analysis of the behaviour of GDP per capita PPP at current international prices began, given that researches such as those by Farhani and Ozturk (2015) indicate that there is a causal relationship between real GDP and energy consumption, indicating that economic growth in the regions is sometimes at the expense of environmental deterioration as a result of the extraction of energy from non-renewable sources. In this sense, the results shown in Table 4 were obtained.

As in the procedure carried out for the electricity consumption variable, Tables 4 and 5 show, on the one hand, the projection of the GDP per capita PPP for the period 2018-2020, showing a positive trend if the principle of ceteris paribus is compiled and additionally the error (MSE) of 165.059, which adjusts the forecast to the real data as shown in Figure 2.

Finally, the value added of industry as a percentage of GDP was studied as a predictor of energy consumption using the same

Table 4: Holt model for forecasting GDP per capita PPP at current international prices

Year	t	Yt	Lt (a)	Tt (b)	Y't (c)	Error
2007	1	9.710,9	9.710,9	-		
2008	2	10.132,3	10.005,5	294,6	9.711	421,3
2009	3	10.260,2	10.272,2	266,7	10.300	39,8
2010	4	10.680,0	10.637,6	365,3	10.539	141,1
2011	5	11.496,5	11.347,9	710,4	11.003	493,6
2012	6	12.058,3	12.058,3	710,4	12.058	0,0
2013	7	12.725,0	12.738,2	679,8	12.769	43,7
2014	8	13.395,5	13.402,3	664,1	13.418	22,5
2015	9	13.827,7	13.899,5	497,2	14.066	238,7
2016	10	14.165,5	14.235,0	335,5	14.397	231,3
2017	11	14.552,0	14.557,6	322,6	14.571	18,6
2018	12		Forecast		14.880	
2019	13				15.203	
2020	14				15.525	

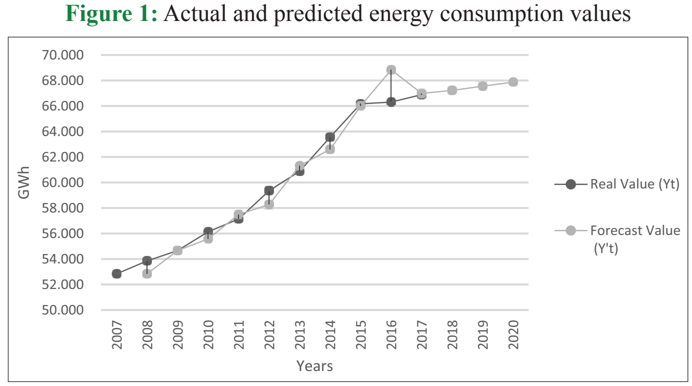
Source: Own calculations based on historical data, 2018

Table 5: Parameters that minimize the MSE in the model

α	0,699
ß	1,000
p	1,000
MSE	165,059

Source: Own calculations with solver in Microsoft Excel, 2018

Figure 1: Actual and predicted energy consumption values



Source: own elaboration, 2018

method, since the evidence shown by Hu et al. (2015) points to the existence of a strong relationship between these two variables, demonstrating that a 1% increase in value added in the industrial sector impacts energy consumption by 1.103%. Tables 6 and 7 below present the findings of the procedure.

According to the Holt model, stability in industrial value added is expected for the period 2018-2020, given that after 2012 there will be a decrease in this indicator, going from 34.57 to 29.25 in 2017. Since solver gave a ß = 0 to minimize MSE, the value of the estimate of the trend (column Tt) takes the zero value equally, keeping the forecast stable as a function of this slope. In order to visualize this trend, Figure 3 shows these data.

Table 6: Holt model for forecasting industrial value added as a percentage of GDP

Year	t	Yt	Lt (a)	Tt (b)	Y't (c)	Error
2007	1	30,63	30,6	-		
2008	2	32,42	32,4	-	30,63	1,8
2009	3	31,71	31,7	-	32,42	0,7
2010	4	32,02	32,0	-	31,71	0,3
2011	5	34,27	34,3	-	32,02	2,3
2012	6	34,57	34,6	-	34,27	0,3
2013	7	34,16	34,2	-	34,57	0,4
2014	8	32,71	32,7	-	34,16	1,4
2015	9	30,54	30,5	-	32,71	2,2
2016	10	29,72	29,7	-	30,54	0,8
2017	11	29,25	29,2	-	29,72	0,5
2018	12		Forecast		29,25	
2019	13				29,25	
2020	14				29,25	

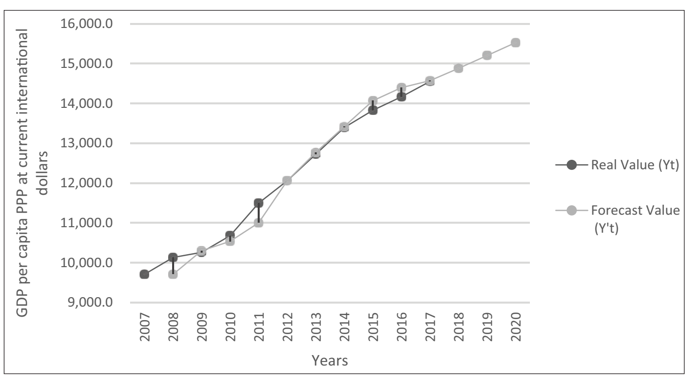
Source: own calculations based on historical data, 2018

Table 7: Parameters that minimize the MSE in the model

α	1,000
ß	-
p	1,000
MSE	1,069

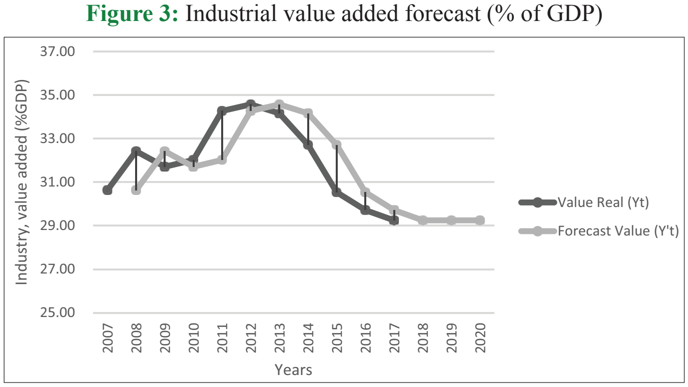
Source: Own calculations with solver in Microsoft Excel, 2018

Figure 2: Forecast GDP per capita PPP



Source: Own elaboration, 2018

Figure 3: Industrial value added forecast (% of GDP)



Source: Own elaboration, 2018

Based on reported data, electricity consumption for the period 2018-2020 would be between 67,231 and 67,885 GWk, if GDP per capita remains between 14,880 and 15,525, at the same time that the industrial value added stabilizes around 29,25.

4. CONCLUSIONS

Energy production in Colombia has been analyzed from different fronts. It is considered a vital component to achieve high levels of productivity and competitiveness in the local and global environment. Therefore, to have a tool that allows predicting the production required in such sense is considered a valuable technique to promote actions that generate tranquility to the parties of interest and allow to visualize possible alterations associated among other aspects to environmental factors. Thus, the Holt Method facilitated observing a constant trend in energy consumption for the years 2018, 2019 and 2020, noting that the prediction is very close to the official values, therefore, this model could be applied at a smaller, medium and large scale for future analysis processes.

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