



The Behavior of the Annual Electricity Demand and the Role of Economic Growth in Colombia

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ABSTRACT

The electricity demand forecast allows countries to establish long-term plans and objectives for identifying gaps, selecting strategies, and designing the electric power system's architecture. Traditional models use GDP as the primary variable to forecast the electricity demand. The work presents an analysis of the relationship between electricity demand and economic growth, using regression methods with one or more variables. The GDP and sectoral GDP data was provided by Banco de la República de Colombia. The results validate the traditional model and offer alternative models that can relate the economy's different sectors with the electricity demand.

Keywords: Energy Forecasting, Electricity Demand, Macroeconomics Indicator, Backward, Forward, and Stepwise Methods

JEL Classifications: Q41, Q43, Q47

1. INTRODUCTION

Population and economic expansion demand energy such as electricity and fuels (Ferguson et al., 2000; Nepal and Paija, 2019); maintaining energy security requires strategic planning of energy systems (Gironès et al., 2015; Madrigal et al., 2018). In electrical energy, the generation, transmission, and distribution sectors require the continuous development of electrical power systems (Lumbreras and Ramos, 2016).

The generation sector plans are oriented to the expansion and diversification of generation parks, mainly integrating renewable generation systems (Lumbreras and Ramos, 2016; Oree et al., 2017). The transmission and distribution systems' objective is to expand coverage, flexibility in operation, implement new technologies, and increase the transfer capacity (Moradijoz et al.,

2018; Niharika and Mukherjee., 2016). These plans are designed and updated according to the demand for electricity. Long-term models are used to estimate the behavior (Ghalekhondabi et al., 2017; Ivan Silva et al., 2018; Paez et al., 2017).

Long-term models use macroeconomic variables such as GDP, population, or some energy price (Alfalah et al., 2020; Günay, 2016; Li and Jones, 2020; Paez et al., 2017; Rafati et al., 2016). The GDP is the variable of preference for annual forecasting models. The implementation of (Ley 1715, 2014) in the Colombian electricity sector generated an increase in renewable energy and self-generation projects. It influenced the updating of the electric infrastructure growth plans to support entry and avoid future problems (Andrade-Becerra et al., 2019; Carlini et al., 2019).

The research presents an analysis of the relationship between electricity demand and economic growth, using global and sectoral

GDP data provided by the Banco de la República de Colombia. The results obtained will evaluate new alternatives in the forecasting models, which may not be affected by exogenous conditions and technological changes.

2. METHODOLOGY

To prove the normality of electrical energy demand data, it used the Shapiro-Wilks test (Hanusz et al., 2016); the null hypothesis is the normality of the data, and the alternative is the non-normality of the data.

To forecast the electricity demand are designed five (5) models. The two first ones are linear regression PIB the GDP, while the last three use sectoral GDP and the Backward, Forward, and Stepwise methods (Derksen and Keselman, 1992; Yuan and Lin, 2006; Zabrodin et al., 2020). For the estimation of the models was used the R software (R Foundation for Statistical Computing, 2016), the Akaike information criterion (AIC) is used to select the best model (Maaouane et al., 2021; Sahraei et al., 2021). The AIC value increases according to the number of regressive variables used in the model, impacting its complexity.

3. RESULTS

Figure 1 presents the yearly Electricity Demand (ED) behavior in GWh, the ED growth, and the GDP growth from 2006 to 2020. The data comes from XM (XM, 2021) and the Banco de la República (BRC, 2021), entities in charge of the electricity market and state finances.

The percentage behavior of the ED and GDP has similar growth and decrease behavior due to the different problems and successes that the Colombian economy has achieved; among them the COVID-19 pandemic, which had substantial repercussions on economic issues closure of the countries in 2020.

Table 1 presents the ED normality test. The result indicates that the p-value is 0.4816; therefore, the null hypothesis of normality of the data is accepted and allows us to perform linear regressions.

3.1. GDP Model

Figure 2 presents the ED percentage growth and the GDP percentage growth, and Table 2 presents the regression model.

The regression results present the P-value below 0.05, which guarantees the coefficient’s relevance and constant model. The model is expressed as:

$$ED(\%) = 0.457572 * GDP(\%) + 0.010588 \quad (1)$$

The model indicates that the GDP’s growth can forecast the ED’s growth. It can be an essential point for the expansion plans of generating parks and ensuring energy security and the correct operation of power systems.

Figure 3 presents the behavior of ED in GWh and GDP in billions of COP (10E9 COP), Table 3 presents the regression model.

Model 02 presents an R² equal to 0.9753, a lower dispersion than model 01 with an R² equal to 0.611. The regression results present the P-value below 0.05, which guarantees the coefficient’s relevance and constant model. The model is expressed as

$$ED = 0.061381 * GPD - 16617.125380 \quad (2)$$

Table 1: Shapiro-Wilks normality test results

Variable	n	Media	D.E.	W*	P-value
ED	16	60548.125	7359.273	0.94949	0.4816

Table 2: Results of the regression model using percentual growth of GDP

Model 01	Estimate	Std. Error	t value	P-value
(Intercept)	0.010588	0.004432	2.389184	0.032741
% GDP	0.457572	0.101267	4.518489	0.000577

Table 3: Results of the regression model using GDP

Model 02	Estimate	Std. Error	t value	P-value
(Intercept)	16617.125380	1893.224396	8.777156	0.000000
GPD	0.061381	0.002612	23.500133	0.000000

Figure 1: The behavior of the yearly Electricity Demand and GDP in Colombia

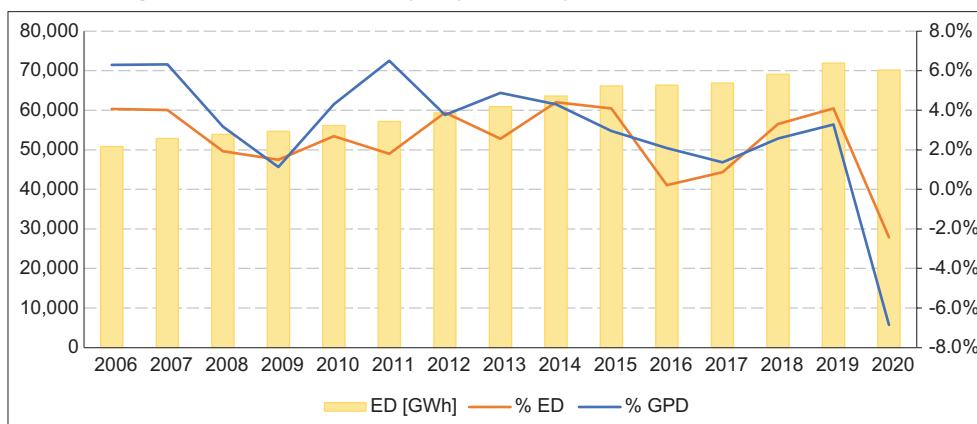


Figure 2: The behavior of the percentage growth of the ED and GDP

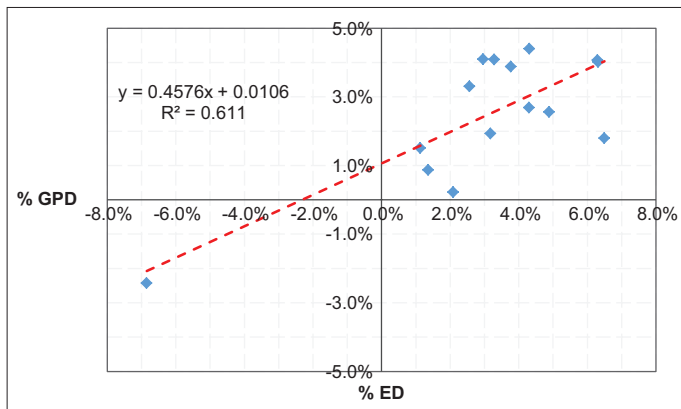
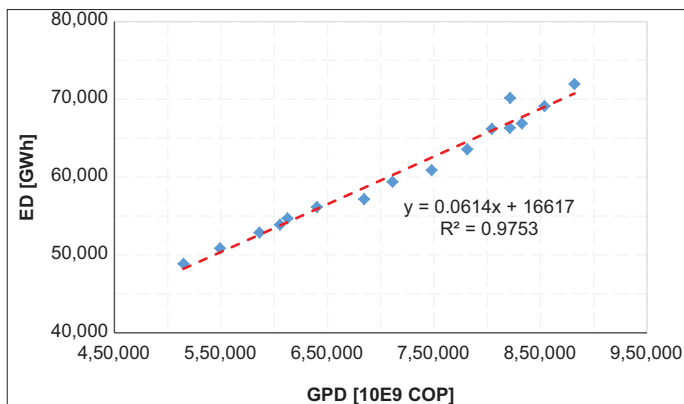


Figure 3: The behavior of ED and GDP



3.2. Sectoral GDP Model

The Banco de la República de Colombia defines the contributions to total GDP according to different economic sectors (BRC, 2021); Table 4 presents each of the sectors’ descriptions.

The R software selects the best model, applying the backward, forward, and stepwise methods and the Akaike information criterion (AIC) to the 12 variables. Table 5 presents the backward model; from the 12 variables available, the backward method estimated that the model must use the variables X1, X2, X5, X10, and X11.

The variables and the intercept present a P-value lower than 0.05; therefore, they are relevant in the model. The model is expressed as:

$$ED = 32640 - 0.56570 * X_1 - 0.2001 * X_2 + 0.1024 * X_5 + 0.3917 * X_{10} + 0.3684 * X_{11} \tag{3}$$

Table 6 presents the forward model; from the 12 variables available, the forward method estimated that the model must use the variables X6 and X8.

The variables and the intercept present a P-value lower than 0.05; therefore, they are considered relevant in the model. The model is expressed as:

Table 4: Sectors of the economy according to the Banco de la República de Colombia

Variable	Economy sector description
X1	Agriculture, livestock, hunting, forestry, and fishing.
X2	Mining and quarrying.
X3	Manufacturing industries.
X4	Public services.
X5	Building.
X6	Wholesale and Retail; Transportation and storage; Accommodation and food services.
X7	Information and communications.
X8	financial and insurance activities.
X9	Real estate activities.
X10	Professional, scientific, and technical activities; Administrative and support service activities.
X11	Public administration and defense; Education; Human and social health care activities.
X12	Artistic, entertainment, and recreation activities, and other service activities.

Table 5: Results of the regression model backward

Model 03	Estimate	Std. error	t value	P-value
(Intercept)	32640	4223	7.72900	0.00002
X1	-0.5657	0.21280	-2.65900	0.02395
X2	-0.2001	0.06142	-3.25800	0.00860
X5	0.1024	0.02955	3.46500	0.00607
X10	0.3917	0.10260	3.81600	0.00339
X11	0.3684	0.06973	5.28300	0.00036

Table 6: Results of the regression model forward

Model 04	Estimate	Std. error	t value	P-value
(Intercept)	33190	1340	24.77800	0.00000
X8	0.65400	0.04684	13.96300	0.00000
X6	0.07180	0.02115	3.39500	0.00479

$$ED = 33190 + 0.07180 * X_6 + 0.65400 * X_8 \tag{4}$$

Table 7 presents the forward model; from the 12 variables available, the stepwise method estimated that the model must use the variables X6 and X8. Model 05 is the same as model 04, obtained with the forward method.

Like model 04, the variables and the intercept present a P-value lower than 0.05; therefore, they are considered relevant in the model. The model is expressed as:

$$ED = 33190 + 0.07180 * X_6 + 0.65400 * X_8 \tag{5}$$

Table 8 presents a summary of the results obtained by the five (5) models obtained. The second row indicates the number of elements that make up the model. The third row presents the R2 value, and the last row presents the AIC criterion. All the models had acceptance of the regressive variables and the constant.

According to the AIC criterion, model 01 has the lowest value. The AIC can be positive or negative; regardless of the values, it must always select the lowest one (Kery and Royle, 2016; Narisetty, 2019). Its R² value is the lowest among the models, which indicates that it has a low correlation.

Figure 4: Evaluation of the equations obtained from models 02, 03, 04, and 05



Table 7: Results of the regression model stepwise

Model 05	Estimate	Std. error	t value	P-value
(Intercept)	33190	1340	24.77800	0.00000
X8	0.65400	0.04684	13.96300	0.00000
X6	0.07180	0.02115	3.39500	0.00479

Table 8: Results of the regression model stepwise

Model	01	02	03	04	05
Variables	2	2	6	3	3
R ²	0.611	0.9753	0.998	0.9957	0.9957
AIC	-130.27	228.69	196.3	202.84	202.84

Models 02, 03, 04, and 05 obtained an R² value above 0.97. Being model 02 obtained the highest AIC despite being made up of a variable and constant; this high correlation coefficient allows the models to explain the data’s variation better. Excluding model 01, model 03 gets the best AIC and R², despite having six (6) elements in its model, five (5) variables, and the constant. Figure 4 presents the graphic behavior of models 02, 03, 04, and 05.

According to Figure 4, model 02 presents a more significant mismatch in the demand forecast, mainly in 2020, while the other models present a better fit according to demand’s natural behavior. Model 03 has the best performance for the years 2019 and 2020. This result allows us to accept the modeling of the demand for electricity through the sectoral GDP, which can avoid exogenous variables such as the economic decline in 2020 caused by the COVID-19.

4. CONCLUSIONS

The research presented regression models for electricity demand forecast based on the economy’s total GDP and sectors, defined by the Banco de la República de Colombia. The results have the expected behavior of the demand for electricity, which allowed obtaining the forecasting models. Model 02 used only the GDP variable; its results indicate a strong relationship between the national electricity demand and GDP. According to Figure 4, the adjustment is lost in 2020 when isolation and quarantine measures were imposed.

The multivariate models obtained with the backward, forward, and stepwise methods were selected using the AIC criterion; the backward model is expressed with five (5) elements. The forward and stepwise models obtained the same results, being expressed by three (3) elements. These models expand the relationship between the energy markets and the economic markets; the results of the multivariable models indicate a lower error and more significant adjustment than the GDP model. The adjustment of the year 2020 was better compared to model 02.

Future research will propose to monitor and update these models to validate the forecasting capacity. Other countries can implement this methodology to evaluate alternatives for forecasting demand.

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