IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2023, 13(4), 255-263.

EJ EconJournals

Sustainability Analysis of Electricity Generation in Colombia through the Projection of Energy Efficiency Indicators

Melissa Valencia-Duque, Juan Zapata-Mina*, Juan E. Tibaquirá, Juan Carlos Castillo

Energy Management Research Group - Genergética, Faculty of Mechanical Engineering, Universidad Tecnológica de Pereira, Colombia. *Email: juan.zapata1@utp.edu.co

Received: 26 February 2023 **Accepted:** 11 June 2023 **DOI:** https://doi.org/10.32479/ijeep.14206

ABSTRACT

The objective of this study is to determine whether current electric power generation practices in Colombia will cover future electricity demand in a sustainable manner. For this purpose, a projection of a current trend scenario was made using the Autoregressive Vectors model, and the results were compared with the projected electricity demand for the country to the year 2030. An analysis of generation efficiency as a technical indicator, of primary energy intensity as an economic indicator, and of carbon emission intensity as an environmental indicator was carried out. It was identified that starting in 2025, electricity generation will not be able to cover the country's electricity demand at its upper limit, and by 2030 demand will exceed generation in its medium scenario. Therefore, it is advisable to implement energy efficiency strategies that will either reduce end-user electricity demand or increase electricity generation by 2025. On the other hand, the country's electricity generation process tends to increase its η and reduce both its IEP and IEC by 2030, which indicates that the rate of improvement of electricity generation practices in Colombia, which is implicit in the historical data analyzed, will be sufficient to achieve sustainable generation in the future.

Keywords: Power Generation, Forecast Performance, Energy Efficiency, Sustainability Indicators
JEL Classifications: P18, Q47, Q43

1. INTRODUCTION

Increased global energy resource consumption reflects rapid economic and population growth, but also contributes to environmental pollution. According to the European Union, energy efficiency is key to countries' clean energy transitions, reducing energy losses in processes and, therefore, the polluting emissions associated with the consumption of fossil fuels, which contributes to countries' energy security. (Directiva 2012/27/UE Del Parlamento Europeo y Del Consejo, 2012; Nam and Jin, 2021). The success of initiatives to control and reduce pollution and increase energy efficiency is often supported by effective energy management, recognizing the relationship between technical, economic and environmental aspects.

Colombia, through its Nationally Determined Contribution (NDC), committed to emit a maximum of 169.4 Mt CO_2eq (Million Tons of CO_2 equivalent) by 2030, equivalent to a 51% reduction in emissions compared to the country's current baseline scenario (Gobierno de Colombia, 2020a). One of the sectors prioritized for action is the energy sector, specifically in the electricity generation process, which was responsible for emitting about 13.4 Mt CO_2eq by 2020 (Gobierno de Colombia, 2020b; UPME, 2020). The country has different primary energy sources such as water, coal, natural gas, petroleum derivatives, biomass, solar radiation and wind. These energy sources are processed in different electric power generating plants. By 2021, hydroelectric plants provided approximately 70.3% of the electricity generated in the country, favored by the climatological and geographical conditions of the national territory. Thermoelectric plants generated approximately 14.3% and still operate mainly with fossil fuels such as coal and natural gas. Self-generation and cogeneration plants accounted for 15% of generation in 2021, and currently operate with fossil and biomass sources. Finally, for the same year, solar and wind power plants had a share close to 0.4% of the country's electricity generation (XM, 2021).

Despite having an electricity generation based on renewable sources, which represent approximately 69% of the installed capacity in the country, the Colombian electricity system is unstable due to its dependence on hydraulic energy. Variable weather conditions, high prices of energy resources, decreasing oil reserves and electricity losses in transmission and distribution are some of the main problems of the country's low-energy security (Unidad de Planeación Minero Energética [UPME], 2015). Therefore, Colombia has developed policies to diversify its electric power generation processes. Such as the carbon tax in Law No. 1819 of 2016 (Ley 1819 de 29 de Dic de 2016, 2016), the promotion of the adoption of Non-Conventional Renewable Energy Sources (Ley 2099 10 Jul 2021, 2021) and the Program for the Rational and Efficient Use of Energy (Ministerio de Minas y Energía, 2010). These policies seek to reduce 51% of its emissions by 2030 according to the baseline scenario (Ley 2099 de 2021, 2021; Ley 1715 De 2014, 2014). In addition, by 2023, annual growth in national electricity demand is expected to be close to 3.4% (Ali, 2020). Hence, it is necessary to determine whether current electric power generation practices in Colombia will cover future electricity demand in a sustainable manner, from a technical, economic and environmental point of view. This would allow identifying the need to implement energy efficiency strategies.

Some studies on the sustainability of the energy sector have analyzed electricity generation through energy, economic and environmental indicators. (Ali, 2020), developed measurable sustainability indicators for coal-fired power generation. Through these, he integrated impacts on water and land use with GHG emissions and the Levelized Cost of Energy for generation (LCOE). Ali identified that most published studies on sustainability of coal-fired power generation have focused on GHG emissions and the related economic effect, neglecting the effect of conversion efficiencies of different power plants. E.L.L. (Rovere et al., 2010) presented a methodological proposal to analyze the sustainability of the electricity generation expansion, integrating technical, socioeconomic, environmental and technological indicators of the different alternatives for the expansion of the sector. However, they did not consider the distribution of each variable and its correlation, from a statistical point of view. (Mohammadi-Aylar et al., 2022) determined, out of eight study areas in Iran, those with the greatest potential for renewable energy power generation. They used the Analytical Hierarchical Process (AHP) method analyzing economic, environmental and energy criteria. This study did not consider the change of variables over time, which would allow for proper energy planning.

On the other hand, some authors describe the importance of sustainability indicators such as (Marrasso et al., 2019b) that claim that the electricity generation efficiency indicator allows to evaluate the contribution of each primary energy source, fossil and renewable, on the technical capacities of the system. (Bello and Ch'ng, 2022), claim that the primary energy intensity indicator (PEI) allows to identify the relationship between economic growth and sustainable energy consumption in all sectors and subsectors of a country. (Ang and Su, 2016), report that the carbon emissions intensity indicator (CEI) is used to identify the effectiveness of climate change mitigation strategies applied to an economic sector. However, the determination of sustainability indicators does not guarantee changes in the energy matrix of a country or sector, but allows analyzing the historical behavior and proposing energy efficiency strategies for sustainable growth.

From the literature review, it was identified that sustainability studies of the electricity sector have not yet considered the change of indicators over time, nor the correlation between variables. Therefore, in this study the variables associated with electricity generation in Colombia were projected using a statistical model based on their correlation, and under a BAU (Business As Usual) scenario, which was compared with the country's projected electricity demand to the year 2030. Additionally, the following energy efficiency indicators were analyzed for the projected electricity generation: generation efficiency, PEI and CEI (Dargahi and Khameneh, 2019; Dong et al., 2018). This study aims to reduce the knowledge gap between the information gathered on Colombian electricity generation and the analysis of correlated data series. This will allow identifying when the current operating conditions of the electricity generation process will be insufficient to cover the national electricity demand, foreseeing the implementation of energy efficiency strategies, which will also contribute to climate change mitigation and the reduction of the country's energy costs.

2. METHODOLOGY

To determine whether current electric power generation practices in Colombia will cover the country's future electricity demand in a sustainable manner, energy, economic and environmental indicators were analyzed, calculated based on the projection of the variables associated with national electricity generation up to 2030, considering a BAU scenario. To this end, first we began with the selection of the indicators to be used in this study, then we identified the models used in the projection of energy variables, characterized the variables needed to calculate the indicators and the quality of the historical data series. Finally, the data series of the selected variables were projected and the results were compared with the national electricity demand, which was forecasted by the Unidad de Planeación Minero Energética (UPME) for the year 2030. The indicators used in this study are presented below.

2.1. Sustainability Indicators

This study proposes the calculation of three energy efficiency indicators to analyze the sustainability of electricity generation in Colombia: electricity generation efficiency, PEI and CEI (Dargahi and Khameneh, 2019; Dong et al., 2018).

2.1.1. Efficiency in electricity generation

This technical-energy indicator shows how efficient an electricity generation process is in terms of the conversion of primary energy into electricity, by providing the percentage of energy output over the input energy or energy consumed by the process, Eq. (1) (Marrasso et al., 2019a).

$$\eta = \frac{\sum G}{\sum C} \tag{1}$$

where η is the electricity generation efficiency [%], $\sum G$ is of electricity generated [GWh], $\sum C$ is the sum of consumption of primary sources [GWh].

2.1.2. Primary energy intensity

Energy-economic indicator, refers to the primary energy consumed in power generation plants C_i per unit of GDP, which indicates the general relationship of primary energy consumption with economic development, as shown in Eq. (2) below (Al Garni et al., 2016; Lam et al., 2019).

$$PEI = \frac{\sum C}{GDP} \tag{2}$$

Where *PEI* is the Primary Energy Intensity of electricity generation [kWh/USD] and *GDP* is the Gross domestic product of the country at constant 2015 price [Billions of USD]. Constant-price GDP, also known as real GDP, is an inflation-adjusted measure that reflects the value of all goods and services produced by an economy in a given year. It takes into account adjustments for changes in inflation. This means that if inflation is positive, Real GDP will be lower than nominal GDP and vice versa. Without a GDP adjustment, positive inflation inflates GDP considerably in nominal terms.

2.1.3. Carbon emissions intensity

Initially, electricity generation emissions are calculated to determine the carbon footprint associated with carbon dioxide (CO_2), methane (CH_4), nitrous oxide (NO) and other pollutant emissions generated in the electricity generation process. To determine the equivalent CO_2 emissions, the primary energy sources with the potential to generate emissions must be identified (Marrasso et al., 2019a). In this case study, the main sources of pollutant emissions were identified as coal, natural gas, diesel, gasoline, oil, liquefied petroleum gas and sugarcane bagasse. Eq. (3) presents the calculation of CO_2 equivalent emissions.

$$ECO2 = \frac{\sum_j SC_j FE_j}{1000} \tag{3}$$

where ECO_2 is the CO_2 equivalent emissions from electricity generation associated with fuels [$MtCO_2$], SC_j is the consumption of each primary energy source *j* that generates pollutant emissions [GWh], FE_j is the emission factor of each primary energy source *j* that generates emissions [$ktCO_2eq$/GWh]. The emission factors associated with the polluting sources were present in Table 1.

Finally, *CEI* is the carbon emissions intensity of electricity generation for a period of time [gCO_2eq/USD], it is an energy efficiency indicator of an economic-environmental nature. Eq. (4), relates the ECO_2 of electricity generation to the economic development of the country as measured by GDP at constant 2015 price (Dong et al., 2018).

Table 1: Emission factor for each pollutant source (Nieves et al., 2019; Unidad de Planeación Minero Energética, 2016)

Source	Emission factor ($ktCO_2$/GWh)
Coal	0.3173
Naural gas	0.1997
Diesel	0.2669
Fuel oil	0.2815
Crude oil	0.2803
Liquefied gas	0.1710
Bagasse	0.4066

$$CEI = \frac{ECO2}{GDP} \tag{4}$$

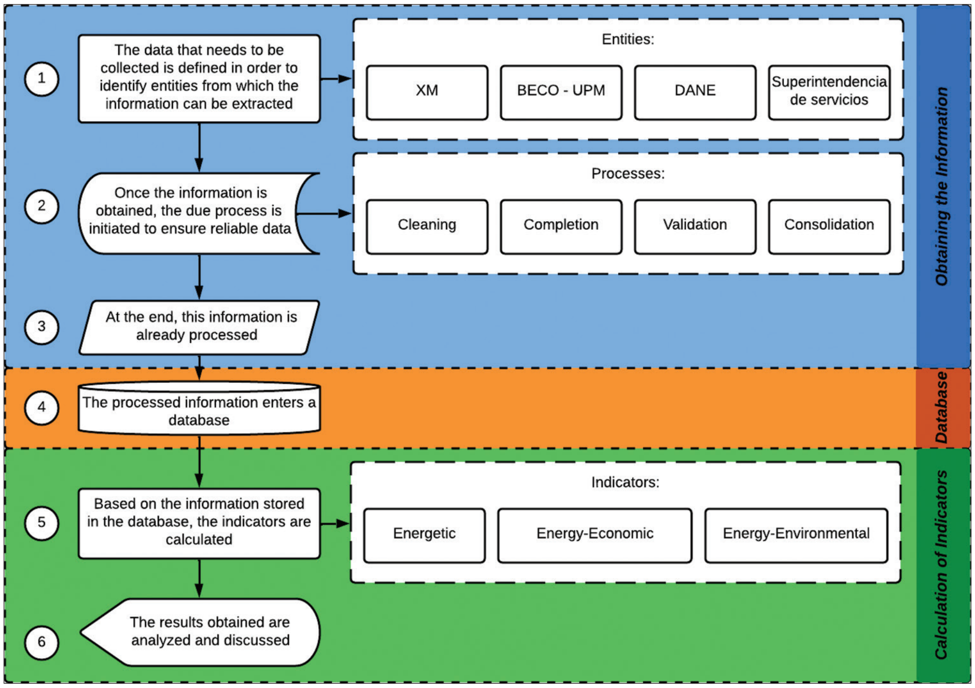
2.2. Forecasting Model

The purpose of this study is to apply a long-term projection model, i.e. annually, on the historical data series of the variables associated with national electricity generation. According to (Wei et al., 2019), the most widely used models for the forecasting of annual energy consumption at the national level, above those based on Artificial Intelligence (AI), are the conventional ones. In this study the authors compare different data series projection models, where they perform a statistical analysis of the Mean Absolute Percentage Error (MAPE) of these models. Conventional models based on time series (TS), regression models (RM) and based on Grey's theory (GM) are mostly used for the forecasting of annual energy consumption at the national level, since the information contained in the databases provides for it. For long-term forecasts, the TS have a standard deviation and a MAPE of <5% (Wei et al., 2019). STs are popular for electric power consumption prediction, while RMs are widely applied in statistical techniques. Although most AI-based models have a MAPE of <5%, unlike TS models they require a large amount of data (Mat Daut et al., 2017).

In order to define the forecasting methodology, it was first necessary to identify the quality of the information available in the country's databases, such as: The Colombian Energy Balance (BECO), the Information System of Technical Parameters of Elements of the Colombian Electric Sector (PARATEC), the Sinergox platform and the national accounts system; which belong to government entities and companies of the national electric sector. It was identified that the data series have an annual periodicity and can be collected from 2006 to 2020. For a series size of 15 data. Taking into account the indicators selected for this study, the following variables were collected: *G*, *C*, ECO_2 and *GDP* at constant 2015 price. Additionally, a data treatment process was carried out, which consisted of cleaning, completing, validating and consolidating the information in data series, as shown in the Figure 1.

The regression models that best fit the size and periodicity of the data series of this study are those based on ST. Considering the need to forecast different variables, during the literature review it was found that in some studies they generally forecast with multivariate linear regression models. However, these models are not affected by the correlation between variables. Among the TS models is the Vector Autoregressive (VAR)

Figure 1: Schematic diagram of data acquisition process and methodology



model, which allows relating different variables and observing their joint variation based on a correlation between them. (Lütkepohl, 2013). A specific feature of this model is that it includes lagged values of the variables used as regressors. This allows us to estimate not only the instantaneous effects but also the dynamic effects in the relationships up to *n* lags (Lütkepohl, 2013; Novales, 1993).

2.2.1. VAR model

VAR model requires the series to be stationary. A series is stationary if the overall level (mean) and the mean deviation of the level (variance) are constant throughout the series. The most common characteristics of time series are: trend; stationarity and variance that grows with the mean. Therefore, it is necessary to stabilize the series through data transformations that eliminate these usual characteristics, guaranteeing the stationarity of the series in mean and/or variance (Zivot and Wang, 2006). For this case, a logarithmic transformation of the data series was performed.

In this study we have a VAR model that explains the temporal behavior of 3 variables. Therefore, we have 3 lagged explanatory variables, plus a constant in each equation, for a total of 12 coefficients to be estimated, plus the 6 elements of the covariance matrix of the innovations (18 parameters in total). Eqs. (5) (6) y (7), represent the VAR model of the data series of interest for this study, modeled as endogenous variables. For a year *t* the natural logarithms of C, ECO_2 and G, are known as $y_1(t)$,$y_2(t)$ y $y_3(t)$, respectively. Understanding the dependence between variables, these are calculated as a function of their past values $y_{1(t-i)}$, $y_{2(t-i)}$ y $y_{3(t-i)}$, denoting a vector ($n\times 1$) of time-series variables; and of the model coefficients $a_{k\,i}^{j}$ as a matrix ($n\times n$), for $j,k\epsilon[1,3]$, where j refers to the variable of interest and k to the equation of each model. As a function of a vector of constants of order ($n\times 1$) known as c_k, and unobservable zero-mean white noise perturbations ($n\times 1$) named u_k. Where p is the optimal number of lags (Guefano et al., 2021a).

$$y_1(t)=c_1+\sum_{i=1}^{p}\left[a_{1i}^{1}\,y_{1(t-i)}+a_{1i}^{2}\,y_{2(t-i)}+a_{1i}^{3}\,y_{3(t-i)}\right]+u_1(t) \quad (5)$$

$$y_2(t)=c_2+\sum_{i=1}^{p}\left[a_{2i}^{1}\,y_{1(t-i)}+a_{2i}^{2}\,y_{2(t-i)}+a_{2i}^{3}\,y_{3(t-i)}\right]+u_2(t) \quad (6)$$

$$y_3(t)=c_3+\sum_{i=1}^{p}\left[a_{3i}^{1}\,y_{1(t-i)}+a_{3i}^{2}\,y_{2(t-i)}+a_{3i}^{3}\,y_{3(t-i)}\right]+u_3(t) \quad (7)$$

2.2.2. VAR model validation

VAR model must be statistically validated before making predictions. Table 2 presents some of the statistical tools used in this study to analyze the reliability and accuracy of the VAR model. To analyze the predictive capacity of the model, the Mean Absolute Error (MAE) was used by means of the Eq. (8), the Mean Absolute Percentage Error (MAPE) with the Eq. (9), and the Root Mean Square Error (RMSE) with the Eq. (10). Both MAE and RMSE provide information on model fidelity and straightness. The higher the RMSE relative to the MAE, the greater the variance of the prediction error. That is, the lower the RMSE and MAE, the better the predictive ability of the model (Guefano et al., 2021b). A MAPE of <10% indicates excellent predictive ability, between 10% and 20% indicates good prediction, and >50% indicates poor prediction (Eidestedt et al., 2012).

$$MAE=\frac{\sum_{i=1}^{N}\left|\widehat{y_l}-y_i\right|}{N} \quad (8)$$

$$MAPE=\frac{1}{N}\sum_{i=1}^{N}\frac{\left|\widehat{y_l}-y_i\right|}{y_i}\Delta 100 \quad (9)$$

Table 2: Statistical tools used for the vector autoregressive model validation (Athanasopoulos et al., 2010; Greene, 2002; Zivot and Wang, 2006)

Statistical tool	Description	Validation criteria
Lag length criteria	Using information criteria such as the AIC, SC and HQ, the optimal number of lags P that best fit the model to the data is determined	La cantidad P es aquella con las puntuaciones más bajas de los criterios
Vector autoregression estimations	R^2 y R^2 are the normal and adjusted coefficients of determination of the model, respectively. They indicate the proportion of the variance of each variable explained by the model, reflecting its fit to the data	About 1
	RSS. Deviation of the predicted empirical values from the actual values	<5%
Stability condition	The unit root test verifies the stationarity of the model when no root is outside the unit circle. Null hypothesis: There is a unit root	Root modulus, <1
Normality test	Analyzes that the disturbances have a normal distribution, with zero mean and constant variance; from the Jarque-Bera test. Null hypothesis: The residuals are multivariate normal	P about 1

AIC: Akaike, SC: Schwarz, HQ: Hannan-Quinn, RSS: Residual sum of square

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{N}\left(\widehat{y_l} - y_i\right)^2}{N}} \tag{10}$$

where N represents the number of predictions, $\widehat{y_l}$ y y_i indicate the predicted value and the actual value.

3. RESULTS

This section presents the statistical results of the VAR model validation, the results of the interest variables forecast, the analysis of the comparison between the national electricity demand and the forecasted electricity generation, and finally, the results of the calculation of the indicators.

3.1. R VAR Model Results

It is worth mentioning that all estimates were made using EViews software. Table 3 presents the results of the lag length criteria. Where the symbol "*" indicates the lag order selected for the Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ) criteria. The table shows that the values with the lowest scores for the three criteria are presented at P = 3. Therefore, 3 lags were used to model the data series of interest using the VAR model. However, some iterations were carried out, extending the analysis up to a maximum of 8 lags, observing an increase in the scores of the information criteria analyzed after lag number 3.

Table 4 presents the results of the vector autoregression estimations of the VAR model, for each variable and in general. The values of the coefficients of determination (R^2 y R^2 ajustado) are close to 1, indicating a good fit of the model to the data. According to the RSS, y_3 y y_2 are the variables that best and worst fit the model, respectively. Compared to the studies on forecasting variables associated with the electricity sector, which have been analyzed in this work, the average R^2 is similar or similar to what is found in the state of the art (Lin et al., 2020; Mulaosmanovic and Ali, 2017; Zabaloy and Viego, 2022).

In the stability condition test, the roots of the characteristic polynomial had values between 0.19 and 0.99, so they are within the unit circle (Figure 2). This indicates that the time series are stationary and that the VAR model satisfies the stability condition.

Table 3: Lag length criteria

P	AIC	SC	HQ
0	−5.6117	−5.1869	−5.6163
1	−8.9001	−8.0504	−8.9091
2	−8.5536	−7.2791	−8.5672
3	−11.0271*	−9.3277*	−11.0452*

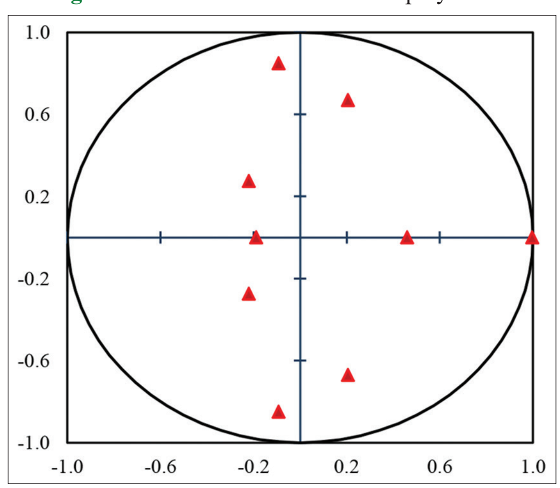
*Indicates the lag order selected, AIC: Akaike, SC: Schwarz, HQ: Hannan-Quinn

Table 4: Vector autoregression estimations

Parameters	y_1	y_2	y_3
R^2	0.9766	0.9667	0.9949
R^2 adjusted	0.8907	0.8445	0.9764
RSS	0.0063	0.0278	0.0008

RSS: Residual sum of squares

Figure 2: Roots of the characteristic polynomial



The results of the normality test are presented in Table 5, where P-value is close to 1 for all components. This indicates that the residuals are uncorrelated and approximately normally distributed with zero mean and constant standard deviation.

The above results show that the VAR model is statistically valid and fits the historical data of the variables. Therefore, we proceeded to forecast the series by analyzing the predictive capacity of the model as showed in Table 6. The RMSE and MAE values were close to zero, indicating a good predictive ability of the model. The MAPE was <10% for all variables, indicating excellent

Table 5: Normality test results

Component	Jarque-Bera	df	P
1	0.0224	2	0.9889
2	0.0346	2	0.9829
3	0.8257	2	0.6618
Joint	0.8826	6	0.9897

Table 6: Model predictive ability results

Variable	RMSE (−)	MAE (−)	MAPE (%)
y_1	0.0370	0.0267	0.2274
y_2	0.1004	0.0775	0.8030
y_3	0.0097	0.0077	0.0693

MAE: Mean absolute error, MAPE: Mean absolute percentage error, RMSE: Root mean square error

predictive ability. Finally, *C*, ECO_2, and *G* were forecasted under a BAU scenario, which considers only the historical trend of the data series. Figure 3 the adjustment and forecast of the variables using the VAR methodology.

The model results indicate a significant growth in G. However, for the C and ECO_2, despite increasing their value for the year 2030, the increase is not significant compared to the year 2020. Peaks of ECO_2 are higher in the years 2024 and 2028 compared to the 2020 value. It is also observed how the forecasting model replicates the trend of the variables over time.

3.2. Sustainability Análisis

Figure 4 shows the comparison between the electricity generation (GE) forecasted by the VAR model up to 2030, and the electricity demand of the National Interconnected System (SIN) projected to the same year under the Medium scenario (Unidad de Planeación Minero Energética [UPME], 2021). This projection of the SIN's electricity demand was made by the country based on quarterly historical series of the system operator (XM) of the SIN's electricity demand up to the last available quarter. It includes the incorporation of special consumers and the forecast of electricity demand from electric vehicles (Unidad de Planeación Minero Energética [UPME], 2020). This comparison makes it possible to determine whether the current conditions of electricity generation in Colombia will cover future electricity demand.

On the other hand, it can be observed that for the year 2030 the electricity demand of the SIN will be 96,615 GWh, with a high limit of 109,728 GWh and a low limit of 83,747 GWh. According to the results of the forecast of the variables of interest using the VAR model for a BAU scenario, for the year 2030 an electricity generation of 96,339 GWh is expected, with an upper limit of 100,691 GWh and a lower limit of 91,987 GWh. Therefore, for this same year, the forecasted electricity generation will not be enough to cover the SIN's electricity demand. By 2025, the upper limit of electricity generation will fall short of the upper limit of demand. Both limits were determined for a 95% confidence interval. This implies that, if the SIN's electricity demand reaches its maximum value as of 2025, the country's current power plants will not be able to supply the country with electricity, requiring the government to resort to actions that may quickly guarantee energy security. There is a clear need to implement energy efficiency strategies that reduce the SIN's electricity demand or increase electricity generation as of 2025.

Figure 3: (a-c) Results forecasting variables by means of VAR model

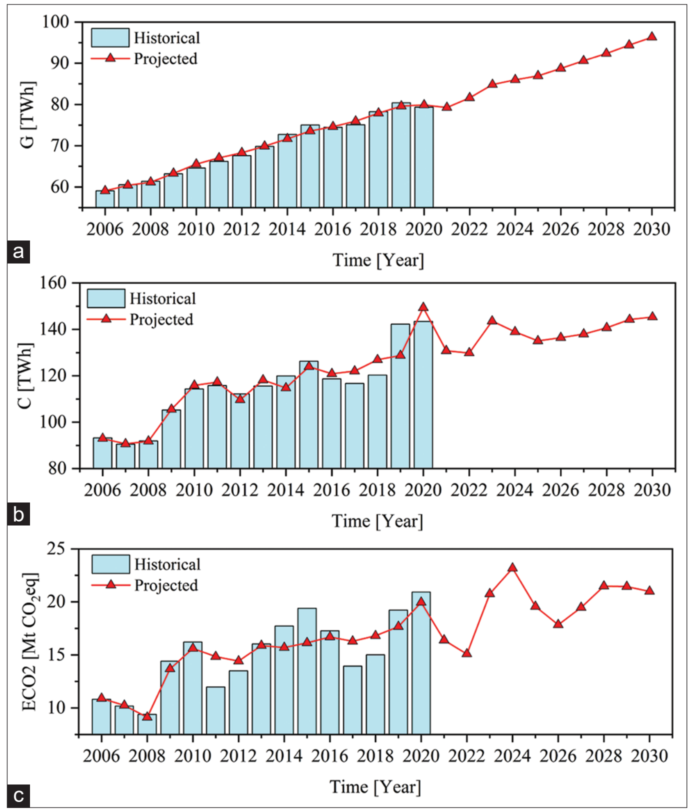
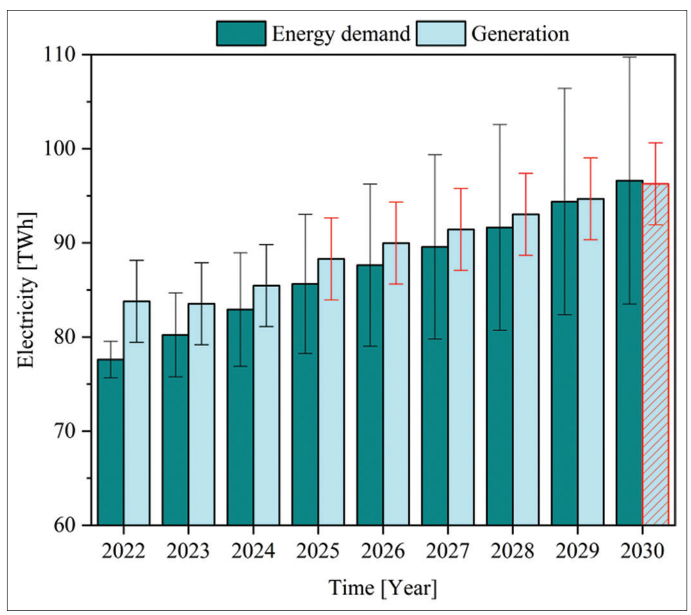


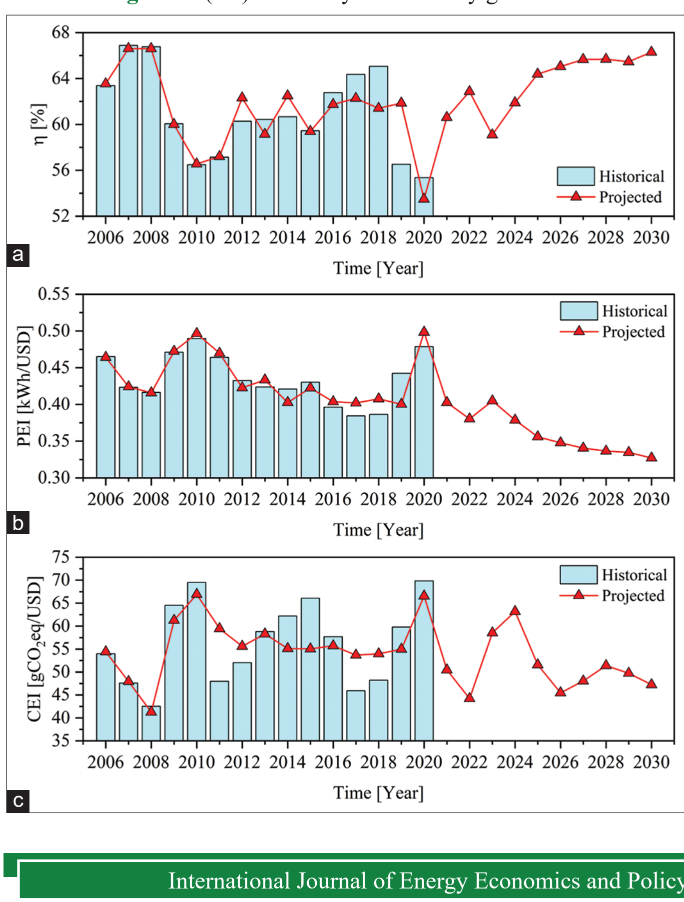
Figure 4: Comparison of SIN electricity demand with VAR electricity generation



In addition, in order to identify whether this demand coverage will be sustainable, an analysis of the selected indicators will be carried out, which will make it possible to identify the possible years in which it is necessary to reinforce actions. The calculation of the indicators was made both with the values of the historical series of the variables involved, and with the values of the series forecasted using the VAR model to the year 2030, specifically *C*, ECO_2, and *G*. In both cases, the same GDP of the country was used at a constant 2015 price, forecasted to the year 2030 by the Departamento Administrativo Nacional de Estadística (DANE).

According to the results presented in Figure 5a, the efficiency in electricity generation (η) as a technical indicator, tends to increase by 2030, compared to 2020. Regarding its historical behavior, it is observed that between 2008 and 2010 there was a reduction of close to 10% in the efficiency of the country's power plants; this could be due to the increase in the use of thermal and auto and cogeneration plants, which have lower efficiency than hydroelectric plants. During the years 2009 to 2011, the environmental phenomenon El Niño-Southern Oscillation (ENSO) occurred, which generated a period of prolonged drought producing a decrease in river flow and therefore in the useful volume of water to produce electricity through hydroelectric plants (Restrepo-Trujillo et al., 2020). Between 2018 and 2020, another drop-in system energy efficiency is observed, which could have been related to the economic constraints arising from the Covid-19 pandemic in early 2020 in the country's main economic sectors. As expected in Figure 5b, if efficiency increases, the PEI decreases by reducing the consumption of primary sources to generate more electricity. The PEI tends to reduce its value by 19% by 2030, with respect to 2020. In other words, by 2030, less energy is expected to be consumed for each monetary unit produced, compared to 2020. Likewise, in Figure 5c the carbon emissions intensity (*CEI*) is reduced with a relative percentage variation of 7% between 2020 and 2030. This is evidence of the reduction in the consumption of fossil fuels as primary sources in the country's power plants,

Figure 5: (a-c) Efficiency in electricity generation



which have a higher emission factor than renewable sources. In other words, by the year 2030 it is expected to emit less pollutant emissions for each monetary unit produced, compared to 2020.

4. CONCLUSION

In this article, a sustainability analysis of the projection of electricity generation in Colombia under a Business as usual (BAU) scenario was carried out through the following energy efficiency indicators: efficiency in electricity generation (η), primary energy intensity (*PEI*) and carbon emissions intensity (*CEI*). The electricity generation forecasted using the Vector Autoregressive Regression and Estimation (VAR) model was compared with the country's forecasted electricity demand for the year 2030. The above, to determine whether the current operating conditions of the country's electricity generation process, as shown by the historical behavior of the variables, would be sufficient to cover the national electricity demand. This allowed identifying the need to implement energy efficiency strategies with positive results for the year 2025. Year in which the electric generation curve approaches the upper limit of the electric demand.

Different statistical tools were used to validate the VAR model. According to the vector autoregression estimations, the normal and adjusted coefficients of determination (R^2) of the model were close to 1 and the Residual Sum of Squares (RSS) was <5%. The root modulus were less than one, so the model complies with the stability condition and verifies the stationarity of the model. The probability value (P-value) of the normality test presented values close to one, affirming the null hypothesis, which indicates that the disturbances have a normal distribution, with zero mean and constant variance. This indicates a good fit of the model to the historical data series and enables the model to generate the forecasts.

In terms of predictive capacity, the mean absolute percentage error (MAPE) was between 0.8% and 0.07%, i.e. <5%. The mean absolute error (MAE) presented values between 0.02 and 0.008; as well as the Root Mean Square Error (RMSE) with values between 0.1 and 0.01, both very close to zero. This indicates that the model has a good predictive capacity and the results are valid.

According to the projections made using VAR model, with the current operating practices represented under a BAU scenario, by 2030 electricity generation will not be able to cover the national electricity demand in its medium scenario, which implies the need to apply energy efficiency strategies in the short term.

Compared to 2020 by 2030 the Efficiency in electricity generation η tends to increase and both the Primary Energy Intensity (*PEI*) and the Carbon Emissions Intensity (*CEI*) tend to reduce their value by 23% and 7%, respectively.

5. ACKNOWLEDGEMENTS

The authors would like to thank Ministerio de Ciencias Tecnología e Innovación for financing the project "Strategy for the management and use of energy efficiency indicators in the processes of generation, distribution and final use of energy in Colombia", associated with the "Program for the efficient integration of electric energy from non-conventional renewable sources to favor the country's economic growth - INTEGRA2023" with code 111085271060 and contract 80740-774-2020.

REFERENCES

Al Garni, H., Kassem, A., Awasthi, A., Komljenovic, D., Al-Haddad, K. (2016), A multicriteria decision making approach for evaluating renewable power generation sources in Saudi Arabia. Sustainable Energy Technologies and Assessments, 16, 137-150.

Ali, B. (2020), Development of sustainability indicators for the assessment of coal-based power generation pathways. Water-Energy Nexus, 3, 198-208.

Ang, B.W., Su, B. (2016), Carbon emission intensity in electricity production: A global analysis. Energy Policy, 94, 56-63.

Athanasopoulos, G., de Carvalho Guillény, O.T., Issler, J.V. (2010), Model Selection, Estimation and Forecasting in VAR Models with Short-run and Long-run Restrictions. Working Paper Series. Vol. 205. Available from: https://www.bcb.gov.br/pec/wps/ingl/wps205.pdf

Bello, M.O., Ch'ng, K.S. (2022), Convergence in energy intensity of GDP: Evidence from West African countries. Energy, 254, 124217.

Dargahi, H., Khameneh, K.B. (2019), Energy intensity determinants in an energy-exporting developing economy: Case of Iran. Energy, 168, 1031-1044.

Directiva 2012/27/UE del parlamento Europeo y del Consejo. (2012), Pub. L. No. DIRECTIVA 2012/27/UE, Diario Oficial de la Unión Europea 1. Available from: https://eur-lex.europa.eu/lexuriserv/lexuriserv.do?uri=oj: l:2012:315:0001:0056:es: pdf

Dong, F., Yu, B., Hadachin, T., Dai, Y., Wang, Y., Zhang, S., Long, R. (2018), Drivers of carbon emission intensity change in China. Resources, Conservation and Recycling, 129, 187-201.

Eidestedt, R., Ekberg, S., Lyhagen, J. (2012), Evaluating Forecast Accuracy for Error Correction Constraints and Intercept Correction [Uppsala University]. Available from: https://www.diva-portal.org/smash/get/diva2:605334/fulltext01.pdf

Gobierno de Colombia. (2020a), Actualización de la Contribución Determinada a Nivel Nacional de Colombia (NDC). p.112. Available from: https://www4.unfccc.int/sites/ndcstaging/publisheddocuments/colombia first/ndc actualizada de colombia.pdf

Gobierno de Colombia. (2020b), Actualización de la Contribución Determinada a Nivel Nacional de Colombia (NDC). United Nations Framework Convention on Climate Change. p112. Available from: https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/Colombia First/NDC actualizada de Colombia.pdf

Greene, W.H. (2002), Econometric Analysis. 5th ed. New Jersey: Prentice Hall. Avilable from: https://spu.fem.uniag.sk/cvicenia/ksov/obtulovic/Manaž.štatistika a ekonometria/EconometricsGREENE.pdf

Guefano, S., Tamba, J.G., Azong, T.E.W., Monkam, L. (2021a), Forecast of electricity consumption in the Cameroonian residential sector by Grey and vector autoregressive models. Energy, 214, 118791.

Guefano, S., Tamba, J.G., Azong, T.E.W., Monkam, L. (2021b), Forecast of electricity consumption in the Cameroonian residential sector by Grey and vector autoregressive models. Energy, 214, 118791.

Lam, K.L., Kenway, S.J., Lane, J.L., Islam, K.M.N., de Berc, R.B. (2019), Energy intensity and embodied energy flow in Australia: An input-output analysis. Journal of Cleaner Production, 226, 357-368.

Ley 1715 13 Mayo 2014, Pub. L. No. Ley 1715 de 2014 (2014). Available from: https://www.funcionpublica.gov.co/eva/gestornormativo/norma.php?i=57353

Ley 1819 de 29 de Dic de 2016. (2016), Pub. L. No. Ley No. 1819 de 2019, 1. Available from: https://es.presidencia.gov.co/normativa/normativa/ley1819del29dediciembrede2016.pdf

Ley 2099 10 Jul 2021. (2021), Pub. L. No. Ley 2099 de 2021. Available from: https://www.funcionpublica.gov.co/eva/gestornormativo/norma.php?i=166326

Lin, J., Liu, X., He, G. (2020), Regional electricity demand and economic transition in China. Utilities Policy, 64, 101047.

Lütkepohl, H. (2013), Vector autoregressive models. In: Hashimzade, N., Thornton, M.A., editors. Handbook of Research Methods and Applications in Empirical Macroeconomics. United Kingdom: Edward Elgar Publishing. p139164.

Marrasso, E., Roselli, C., Sasso, M. (2019a), Electric efficiency indicators and carbon dioxide emission factors for power generation by fossil and renewable energy sources on hourly basis. Energy Conversion and Management, 196, 1369-1384.

Marrasso, E., Roselli, C., Sasso, M. (2019b), Electric efficiency indicators and carbon dioxide emission factors for power generation by fossil and renewable energy sources on hourly basis. Energy Conversion and Management, 196, 1369-1384.

Mat Daut, M.A., Hassan, M.Y., Abdullah, H., Rahman, H.A., Abdullah, M.P., Hussin, F. (2017), Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review. Renewable and Sustainable Energy Reviews, 70, 1108-1118.

Ministerio de Minas y Energía. (2010), Programa de Uso Racional y Eficiente de Energía y Fuentes No Convencionales - PROURE Plan de Acción al 2015 con Visión al 2025. Available from: https://www.minminas.gov.co/documents/10180/558752/informe_final_consultoria_plan_de_accion_proure.pdf/e8cdf796-d7b1-4bb1-90b9-e756c7f48347

Mohammadi-Aylar, S.O., Almassi, M., Bakhoda, H. (2022), Economic, environmental and energy analysis of the utilization of renewable energy based on Analytic Hierarchy Process: A case study. International Journal of Low-Carbon Technologies, 17, 430-435.

Mulaosmanovic, M., Ali, E. (2017), Short-Term Electricity Price Forecasting on the Nord Pool Market. School of Business, Society and Engineering. Sweden: Mälardalen University.

Nam, E., Jin, T. (2021), Mitigating carbon emissions by energy transition, energy efficiency, and electrification: Difference between regulation indicators and empirical data. Journal of Cleaner Production, 300, 126962.

Nieves, J.A., Aristizábal, A.J., Dyner, I., Báez, O., Ospina, D.H. (2019), Energy demand and greenhouse gas emissions analysis in Colombia: A LEAP model application. Energy, 169, 380-397.

Novales, A. (1993), Econometría Segunda Edición (I. Capella (ed.). 2nd ed. United States: McGraw-Hill. Available from: https://econometriai.files.wordpress.com/2011/04/econometrc2a1a-2c2a6-ed-2000-alfonso-novales-mcgraw-hill.pdf

Restrepo-Trujillo, J., Moreno-Chuquen, R., Jimenez-Garcia, F.N. (2020), Strategies of Expansion for Electric power systems based on hydroelectric plants in the context of climate change: Case of analysis of Colombia. International Journal of Energy Economics and Policy, 10(6), 66-74.

Rovere, E.L.L., Soares, J.B., Oliveira, L.B., Lauria, T. (2010), Sustainable expansion of electricity sector: Sustainability indicators as an instrument to support decision making. Renewable and Sustainable Energy Reviews, 14(1), 422-429.

Unidad de Planeación Minero Energética (UPME). (2015), Plan Energético Nacional Colombia: Ideario Energético 2050. Colombia: Ministerio de Minas y Energía. p184.

Unidad de Planeación Minero Energética (UPME). (2020), Metodología Para Proyecciones de Demanda de Energía Eléctrica y Gas Natural.

Available from: https://www1.upme.gov.co/demandayeficiencia/documents/metodologia_pde.pdf

Unidad de Planeación Minero Energética (UPME). (2021), Proyección Demanda Energía Eléctrica y Gas Natural 2021-2035. Available from: https://www1.upme.gov.co/demandayeficiencia/paginas/proyecciones-de-demanda.aspx

Unidad de Planeación Minero Energética. (2016), Consultoría Técnica Para el Fortalecimiento y Mejora de la Base de Datos de Factores de Emisión de los Combustibles Colombianos - FECOC. Colombia: Unidad de Planeación Minero Energética.

UPME. (2020), BECO Consulta. Demanda y Eficiencia Energética. Colombia: UPME.

Wei, N., Li, C., Peng, X., Zeng, F., Lu, X. (2019), Conventional models and artificial intelligence-based models for energy consumption forecasting: A review. Journal of Petroleum Science and Engineering, 181, 106187.

XM. (2021), Capacidad Efectiva por Tipo de Generación. PARATEC-XM. Available from: https://paratec.xm.com.co/paratec/SitePages/generacion.aspx?q=capacidad

Zabaloy, M.F., Viego, V. (2022), Household electricity demand in Latin America and the Caribbean: A meta-analysis of price elasticity. Utilities Policy, 75, 101334.

Zivot, E., Wang, J. (2006), Modeling financial time series with S-PLUS®. In: Modeling Financial Time Series with S-PLUS®. Berlin: Springer.