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Research Article

Modelling and Forecasting of Some Energy Growth Indicator Variables in Ethiopia Via a Multivariate VAR Model

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Abstract

Energy is the heart of the most critical economic, environmental, and developmental issues. Ethiopia is aggressive working to produce electrical energy from hydroelectric sources. However, currently, the net energy imports and power losses also increase. Therefore, this study aims to investigate the relationship between energy growth indicators in Ethiopia by using a VAR time series model. A time series technique using annual data for the period 1971 to 2015 from the World Bank was utilized. VAR. (1) One model result lagged electricity production from hydroelectric sources is significantly explained by one period lagged values of itself. Furthermore, the result indicates that electric power consumption explained in a period. The forecast error variance decomposition result indicates that most of the variations in the series were explained by their shock in the first horizon. In the short-run, electricity production had a positive significant effect on consumption in Ethiopia. On the basis of these results, it is recommended that the government and manager work together to increase stable consumption opportunities but should reduce energy import and electric power losses.

Keywords

Energy Growth Indicator, Vector Autoregressive, Model Diagnosis, Forecasting

1. Introduction

Energy is at the heart of the most serious economic, environmental, and developmental issues facing the world today. Energy growth is an important economic development indicator, particularly the production of electricity, and managers manage strategic decisions in the electricity industry. There are numerous methods for the production of electricity (modern energy), which is the source of fast growth for electricity production are rarely studied [1]. Access to electricity in Sub-Sahara Africa (SSA) is subject to frequent outages due to insufficient generation capacities and/or poor transmission and distribution infrastructure [2]. However, economic development is dependent on energy consumption [3].

The efficiency of energy is a means of using energy more efficiently, through a change of behaviour, improved management, or the introduction of new technology [4]. In recent years, important international agencies and institutions of the power sector have been evaluating how Brazil has

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highlighted the potential energy use [5].

Conversely, the rate of energy consumption is an aspect that needs careful consideration in its analysis and standardization, and a key technological metric in assessing businesses is energy efficiency in operations [6].

There is often a need to develop internal production standards, differentiated by the object of expenditure and electricity losses.

Hydroelectric generation is the second largest generation in the world, providing 7% of domestic electricity production and much larger percentages in the western states. A lack of availability of modern energy and a lack of education are the main causes of this phenomenon; however, a gradual increase in awareness of the people demand for electrification in Ethiopia is increasing to approximately 20% per annum [7]. The study conducted on electric power loss is one of the critical challenges in confronting Ghana's electricity sector [8]. Electric power losses whose current figure exceeds the 5% threshold have become prevalent in Ghana, contributing to the increasing demand-supply gap in the power sector.

Ethiopian Electric Power Corporation, the sole electric power producer, is currently generating much less than 1000 MW of power. Specifically, there were 2895 GWh of electricity in the year 2005–2006 [9].

Energy consumption in Ethiopia has been the lowest compared to several developed countries [10]. Ethiopia faces chronic power problems, including insufficient generation capacity, low connectivity, and poor reliability of transmission and distribution, all of which constrain development [11].

The Ethiopian government aims to transition from a developing nation to a middle-income country by the year 2025 as part of its GTP I and II plans [12]. However, Electric power corporation access to electricity in Ethiopia is one of the lowest by any standard since it is one of the energy-deficient countries in the world with a net energy importer [13], due to the fact that energy usage per individual is significantly lower than that in many other nations globally. For instance, the overall energy consumption per person is noted to be 0. 40 tons of oil equivalent, a figure that is notably less than the average energy usage in Sub-Saharan Africa, estimated to be around 0. 80 tons of oil equivalent [14].

Numerous investigations have been carried out regarding the generation of electricity from hydropower, electricity usage, energy imports, losses in electric power transmission and distribution, as well as the interconnections of the United Kingdom, China, and South Africa with the Western and Tax regions through methods like spatial analysis, ordinary least squares, cointegration, and the VECM and ARDL models [15-18]. However, the finding emphasizes its determinants rather than examining its instability and does not see the relationship and trends of these indicators simultaneously.

As our knowledge is concerned, no previous studies have been conducted to assess the relationships between these energy growth indicators in Ethiopia. This study addressed the modelling and forecasting of energy growth indicator variables in Ethiopia.

Hypothesis Tests

Hypothesis 1: The energy growth indicator variables are stationary.

Hypothesis 2: The multivariate VAR model is able to show the relationships of the energy growth indicators.

Hypothesis 3: The significance tests will be statistically significant.

2. Methodology

2.1. Description of the Study Area

The study was administered in Ethiopia. Ethiopia is situated in the Alarm of Land of the Sahara (3 °-14 °N and 33 °-48 °) and is surrounded by Djibouti and Somalia to the orient, Eritrea to the northward, Kenya to the on west side when facing north, and Sudan and Cold Sudan to the west. The country has a extreme main level, changes in height from 4550 meters above ocean's surface to 110 meters beneath ocean's surface, and covers 1.1 heap square kilometers [19].

2.1.1. Data Source and Description

The data set for this study were based on secondary sources collected from the World Bank https://databank.worldbank.org/. World development indicators (WDIs) offer metrics for social advancement, energy growth, economic growth, societal infrastructure development, environmental protection, and the government.

2.1.2. Variables in the Study

Energy growth is characterized by its metrics, which include energy accessibility, energy sales abroad, electricity generation, energy effectiveness, and the significance of energy, among others. Nonetheless, depending on the data that can be obtained and the primary focus of the research, the dependent variables in this analysis consist of electricity generation from hydro sources (as a percentage of the total), per capita electricity usage (in kWh), net energy imports (as a percentage of total energy consumption), and losses in electricity transmission and distribution (as a percentage of total output). In this context, time and previous values of the dependent variables relate to the independent variables.

2.2. Methods of Data Analysis

Time Series Analysis

A time series is defined as a set of data views, usually measured at successive points in time within the same time interval. It can be divided into two main parts: univariate time series and multivariate time series.

Multivariate analysis builds upon univariate time series analysis and involves examining statistical models and analytical techniques that uncover the connections between various variables. Consequently, in multivariate time series analysis, vectors and matrices play a crucial role. According to [20], the main purpose for modelling and analysing vector time series jointly is to improve the understanding of the dynamic relationships between the series over time and to improve the accuracy of forecasts for individual series.

2.3. Stationarity and Testing of Stationarity

Stationarity is an essential feature underlying almost all time series models [21]. A time series X_t is said to be strictly stationary if and only if the joint distribution of $X_{t1}, \cdots, X_{tk}$ is same to that of $X_{t1+t}, \cdots, X_{tk+t}$ for all t, where k is an arbitrary positive integer and $t_1, t_2 \cdots, t_k$ is a collection of k positive integers; a weaker version of stationarity is often assumed. A time series X_t is weakly stationary if both the mean of X_t and the covariance between X_t and X_{t-k} are time invariant. More specifically, X_t is weakly stationary.

$$E\,(Xt) = \mu, constant\ for\ all\ value\ of\ t$$

$\mathrm{Cov}\,(X_t, X_{t-1}) = E[(X_t - \mu)(X_{t-1} - \mu)'] = \Gamma_j$ for all t and j= 0, 1, 2. However, for any t, j ≥ 1, cov $(X_{t,}X_{t-1})$ depends only on j, not on t

The most Popular Stationarity Tests

a. Time Series Graph

A graph initially displays the probable characteristics of the time series. For instance, if a time series line graph reveals an increasing trend, it suggests that the average of the data has been fluctuating [22].

Unit Root Test. In many studies, it remains unclear if the variables exhibit integration or trend stationarity. Preliminary tests for unit roots are frequently necessary to assess if the data series maintains stationarity or not [23].

Consider a simple AR (1) process

$$X_t = Y_t'\delta + \rho X_{t-1} + \varepsilon_t \tag{1}$$

where Y_t is an optional exogenous that can consist of a constant and trends, ρ and δ are the estimated parameters, and εt is assumed to be white noise. If $|\rho|$ =1, X_t is a nonstationary series, and the variance of X_t increases with time. For $|\rho|$< 1, Xt is a stationary series.

b. The augmented Dickey-Fuller (ADF)

ADF test is a popular and recognized method for detecting non-stationarity in a time series. This ADF test builds upon the basic Dickey-Fuller test and is performed by rearranging equation [1] once X_{t-1} is removed from both sides of the equation; subsequently, the resulting equation is derived:

$$X_t - X_{t-1} = (\rho - 1)X_{t-1} + Y_t'\delta + \varepsilon_t.$$

This can be written as:

$$\Delta X_t = \phi X_{t-1} + Y_t'\delta + \varepsilon_t$$

where $\phi = \rho - 1$. Therefore, the null and alternative hypotheses are as follows:

$$H_0\text{: the series is not stationary } (\phi = 0),$$
$$H_1\text{: the series is stationary} (\phi < 0)$$

c. The Phillips Perron (PP)

Test is an alternate (nonparametric) regulator method for serial correlation when testing for a unit root [24]. This method is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis $\rho = 1$ in $\Delta X_t = (\rho - 1)X_{t-1} + \epsilon_t$. where Δ is the first difference operator. Like the ADF test, the PP test addresses the issue that the process generating data for X_t might have a higher order of autocorrelation than is admitted in the test equation, making X_t endogenous and thus invalidating the Dickey-Fuller t test. Then, the PP test makes a nonparametric correction to the t test statistic.

2.4. Data Transformation Mechanism

We are aware of the issues that come with nonstationary time series. The important question is how to address this. In order to prevent misleading regression issues that could result from analyzing a nonstationary time series, we must convert nonstationary time series into stationary ones through the use of suitable transformation methods.

a. Logarithm

This transformation mechanism is often considered to stabilize the variability or variance of the series [25]. The standard deviation of the original series increases linearly with the mean [26].

b. Differencing

This technique is frequently used to transform a time series. From a nonstationary to stationary, each data X_t in a series is subtracted from its predecessor or its lagged values X_{t-1}. It is used to avoid trending in the series. The set of observations X_t that link to the initial time (t) when the quantity has taken is described as a series at level [27]. $\nabla X_t = X_t - X_{t-1}$ can also be written as follows by using the backshift operator $\nabla X_t = (1 - B)X_t$: *where* $BX_t = X_{t-1,} B^2X_t = X_{t-2,} \ldots, B^kX_t = X_{t-k}$, k=0, 1, 2, …

In general, the n^{th} order of differencing via backshift is defined as $\nabla^n X_t = (1 - B)^n X_t$

c. Square Root Transformation

The square root of each value is applied (technically, a special case of the power transform where all values are raised to a power of half). However, we cannot take the square root of a negative number; we need to add a constant to shift the minimum value of the distribution above 0, preferably 1.00 [28].

2.5. Vector Autoregressive (VAR) Model

To explore the relationships among energy expansion metrics in Ethiopia, this research utilized the vector autoregressive (VAR) model. These models consist of linear equations, featuring n equations and n variables, where each equation is defined by its own lag value along with the lagged values of the other variables [29]. This method is beneficial as it can clarify historical connections and causal interactions among several variables across time. Furthermore, the interpretation and forecasting of future data rely on the accurate formulation of the VAR model and the estimation of its parameters [30].

Let $X_t = (X_{1t}, X_{2t}, \ldots X_{nt})'$, denote an $(n\times 1)$ vector of a time series variable. The basic p lag vector autoregressive (VAR (p)) model has the form [31].

$$X_t = C + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \varepsilon_t,\ t= 1, 2. T, \quad (2)$$

where C represents an $(n\times 1)$ vector of constant and Φ_j an $(n\times n)$ matrix of autoregressive coefficients j=1, 2, … p, and $\varepsilon_t = (\varepsilon_1, \varepsilon_2, \ldots \varepsilon_n$ is an $(n\times 1)$ observable zero mean white noise vector process (serially uncorrelated) with a time-invariant covariance matrix $\sum$. $E(\varepsilon_t) = 0$ and $Cov(\varepsilon_t, \varepsilon_s) = E(\varepsilon_t \varepsilon_s^T) = \begin{cases} \Sigma, & \forall t = s \\ 0, & \forall t \neq s \end{cases}$ where the covariance matrix $\sum$ is an $(n \times n)$ symmetric positive definite matrix and is assumed to be non-singular if not otherwise stated.

Let C_i be the i^{th} element of a vector C and let Φ_{ij}^1 represent the i^{th} row and the j^{th} column element of the matrix Φ^1; then, the first row of the matrix system can be specified as

$$X_{1t} = C_1 + \Phi_{11}^{(1)} X_{1,t-1} + \Phi_{12}^{(1)} X_{2,t-1} + \cdots + \Phi_{1n}^{(1)} X_{n,t-1} + \Phi_{11}^{(2)} X_{1,t-2} + \Phi_{12}^{(2)} X_{2,t-2} + \cdots + \Phi_{1n}^{(2)} X_{n,t-2} + \cdots + \Phi_{11}^{(p)} X_{1,t-p} + \cdots + \Phi_{1n}^{)p)} X_{n,t-p} + \varepsilon_{1t}$$

$$\vdots \vdots \vdots$$

$$X_{4t} = C_4 + \Phi_{41}^{(1)} X_{1,t-1} + \Phi_{4}^{(1)} X_{2,t-1} + \cdots + \Phi_{4n}^{(1)} X_{n,t-1} + \Phi_{41}^{(2)} X_{1,t-2} + \Phi_{42}^{(2)} X_{2,t-2} + \cdots + \Phi_{4n}^{(2)} X_{n,t-2} + \cdots + \Phi_{41}^{(p)} X_{1,t-p} + \cdots + \Phi_{4n}^{(p)} X_{n,t-p} + \varepsilon_{4t}$$

The general form VAR(p) with the deterministic variable is given by

$$X_t = C + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + BY_t + \varepsilon_t$$

where Y_t represents an (nx1) vector of deterministic (other exogenous) variables and where B_{nxn} is a parameter matrix. Generally, the VAR(p) model equation for the study under the study variable has the following form:

$$\begin{bmatrix} EPH_t \\ EPC_t \\ EIM_t \\ EPTADL_t \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \end{bmatrix} + \begin{bmatrix} \Phi_{11}^{(1)} & \Phi_{12}^{(1)} & \Phi_{13}^{(1)} & \Phi_{14}^{(1)} \\ \Phi_{21}^{(1)} & \Phi_{22}^{(1)} & \Phi_{23}^{(1)} & \Phi_{24}^{(1)} \\ \Phi_{31}^{(1)} & \Phi_{32}^{(1)} & \Phi_{33}^{(1)} & \Phi_{34}^{(1)} \\ \Phi_{41}^{(1)} & \Phi_{42}^{(1)} & \Phi_{43}^{(1)} & \Phi_{44}^{(1)} \end{bmatrix} \begin{bmatrix} EPH_{t-1} \\ EPC_{t-1} \\ EIM_{t-1} \\ EPTADL_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \Phi_{11}^{(p)} & \Phi_{12}^{(p)} & \Phi_{13}^{(p)} & \Phi_{14}^{(p)} \\ \Phi_{21}^{(p)} & \Phi_{22}^{(p)} & \Phi_{23}^{(p)} & \Phi_{24}^{(p)} \\ \Phi_{31}^{(p)} & \Phi_{32}^{(p)} & \Phi_{33}^{(p)} & \Phi_{34}^{(p)} \\ \Phi_{41}^{(p)} & \Phi_{42}^{(p)} & \Phi_{43}^{(p)} & \Phi_{44}^{(p)} \end{bmatrix} \begin{bmatrix} EPH_{t-p} \\ EPC_{t-p} \\ EIM_{t-p} \\ EPTADL_{t-p} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \quad (3)$$

Where EPH represents the percentage of electricity generated from hydropower sources out of the total, EPC indicates the amount of electric energy consumed per person in kilowatt-hours, EIM denotes the proportion of energy imported, net, compared to total energy use, and EPTADL refers to the losses in electric power during the processes of transformation and distribution within Ethiopia. The VAR(p) is stable if the root of the determinant of $(I_n - \Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p) = 0$, lies outside the unit circle (has a modulus greater than one).

The mean-adjusted form of VAR(p) is

$$X_t - \mu = \Phi_1(X_{t-1} - \mu) + \Phi_2(X_{t-2} - \mu) + \cdots + \Phi_p(X_{t-p} - \mu) + \varepsilon_t$$

Order Specification for VAR Model

The general method is to fit VAR models with orders P 0,….Pmax, and selecting the value of p which minimizes some model selection criteria [32]. The three most common information criteria are considered to pick out an optimal lag order for the VAR that is fit. These are Akaike (AIC), Schwarz (SC, and Hannan Quin (HQ).

$$AIC(p) = \log\left|\hat{\Sigma}_p\right| + \tfrac{2}{T} pn^2,$$
$$SBIC\ (p) = \log\left|\hat{\Sigma}_P\right| + \tfrac{\log T}{T} pn^2$$
$$HQIC(p) = \log\left|\hat{\Sigma}_P\right| + \tfrac{2\log(\log T)}{T} pn^2$$

where $C_T = \frac{2}{T}, C_T = \frac{\log T}{T}, C_T = \frac{2\log T(\log(T)}{T}$, respectively. In each case, $\varphi(p, n) = pn^2$ is the number of VAR parameters in a model with order p, and n is the number of variables.

Parameter Estimation of the VAR Model

Consider n dimensional multivariate time series

$X_1, X_2, \ldots X_T$, where $X_t = (EPH_t, EPC_t, EIM_t, EPTADL_t)^T$ is known to be generated by a stationary $VAR(p)$ process of form in equation (3). Maximum likelihood estimation is considered asymptotic when employing the VAR process with a normal distribution as a different approach to the least square method [33]. The coefficients of a (p) model can be effectively calculated using least squares for each equation individually. Since it is presumed that the disturbances follow a normal distribution, the conditional density exhibits a multivariate normal distribution [34].

$$[X_t | X_t, X_{t-1}, \ldots, X_{T-P}] \sim \text{MVN}\ (\Phi X_t, \Sigma_\mu)$$

The estimate of VAR, which maximizes the log-likelihood, is called the estimator of the VAR (p) model coefficients and is determined by:

$$\hat{\Phi} = [\textstyle\sum_{t=1}^{T} X_t X_t'][\sum_{t=1}^{T} X_t X_t']^{-1} \tag{4}$$

The estimated values that maximize the log-likelihood function are the ML estimators of the VAR coefficients.

2.6. Model Diagnosis

A wide range of procedure exists for assessing the sufficiency of VAR. Assessments for residual autocorrelation, normal distribution, conditional variability, and stability can be utilized to evaluate the fitness of the estimated VAR model [34].

2.6.1. Test of Residual Autocorrelation

The two most common methods used to test the residual of autocorrelation are the Portmanteau LM test and the Breusch-Godfrey LM test.

2.6.2. Portmanteau Autocorrelation Test

Let $X_t = (X_{1t}, X_{2t}, \ldots, X_{nt})'$ be the n-dimensional vector of observable time series variables with r<k cointegration relations. The residual autocovariance is

$$\hat{\Sigma}_\varepsilon = \frac{1}{T} \textstyle\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j}$$

where

$$\hat{\varepsilon}_t = \nabla X_t - \Pi X_{t-1} - \textstyle\sum_{i=1}^{p-1} \Gamma_i \nabla X_{t-i} - BY_t$$

where $\hat{\varepsilon}_t$ is the estimated residual. The portmanteau test for residual autocorrelation checks the null hypothesis that all residual covariance is zero [35].

$$H_0: E(\varepsilon_t \varepsilon_{t-j}') = 0, H_1: E(\varepsilon_t \varepsilon_{t-j}') \neq 0, \text{at least one j}, j = 1, 2, \ldots h$$

It is tested against the alternative in which at least one covariance is nonzero.

2.6.3. Autocorrelation LM Test

The test developed by [36] the VAR model for the error u_t is given

$$\text{by } u_t = B_1 u_{t-1} + \cdots B_h u_{t-h} + \varepsilon_t$$

where υ_t is the white noise of the error term

For testing the autocorrelation in u_t, the following claims should be tested:

$$H_0: B_1 = B_2 = \cdots = B_h = 0, H_1: B_j \neq 0, \text{for at least one } j < h$$

where $B_1, B_2 \ldots, B_h$ represents the coefficient matrix.

2.6.4. Normality of the Residuals

Although several normality tests are available, especially in multivariate time series analysis [36], the Jaque Bera test examines the multivariate normality of residua s. It tests skewness (3^{rd} moment) and kurtosis (4^{th}moment) properties of residual $u_t = (u_{1t}, u_{2t}, \ldots, u_{nt})$ against those of a multivariate normal distribution of appropriate dimensions.

$$H_0: E(\hat{u}_{nt}^s)^3 = 0\ V_s\ H_1: E(\hat{u}_{nt}^s)^3 \neq 0 \text{ for skewness}$$
$$H_0: E(\hat{u}_{nt}^s)^4 = 3\ V_s\ H_1: E(\hat{u}_{nt}^s)^4 \neq 3 \text{ for kurtosis}$$

2.6.5. Testing for Stability

The stability system of the model can be tested from the inverse root characteristics polynomial or cumulative sum (CUSUM) square [37].

2.7. Measures of Forecasting Accuracy

Measuring the forecast accuracy of time series models is an important task.

If X_{jt} is the actual observation of the j^{th} variable at time t and F_{jt} is the forecast X_{jt} for the j^{th} variable at time t, then the error of the j^{th} variable at time t is defined as

$$\hat{\varepsilon}_{jt} = X_{jt} - F_{jt}$$

Typically, F_{jt} is calculated using data $X_{j1}, X_{j2}, \ldots, X_{jt-1}$. It is a one-step forecast because it forecasts one period forward of the last observations used in the calculation. Therefore, $\hat{\varepsilon}_{jt}$ is described as a one-step forecast error. If there are observations and forecasts for T periods, then there would be T error terms for each variable , and the following standard statistical measures can be defined as

$$\text{Mean error(ME)} = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{jt}$$

$$\text{Mean absolute error(MAE)} = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\varepsilon}_{jt}\right|$$

$$\text{Mean squared error(MSE)} = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{jt}^{2}$$

The mean error (ME) may be minimal since positive and negative errors often offset one another. The mean error solely indicates whether there is a consistent rise or fall in predictions, a phenomenon referred to as forecasting bias.

To make a comparison, the relative percentage error, which is defined below, is considered.

$$\mathrm{PE_t} = \left(\frac{\mathrm{X_{jt}} - \mathrm{F_{jt}}}{\mathrm{X_{jt}}}\right) \times 100\%$$

Then, two relative measures are commonly used:

Mean percentage error (MPE)= $\frac{1}{T}\sum_{t=1}^{T}\mathrm{PE_t}$

Mean percentage absolute error (MPAE)= $\frac{1}{T}\sum_{t=1}^{T}\left|\mathrm{PE_t}\right|$

However, ME and MPE are probably small because they tend to balance positive and negative PEs. Alternatively, Theil's U statistic can be used as a measure of forecasting accuracy. Theil's U can be estimated or calculated as

$$\mathrm{U} = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(\mathrm{X_{jt}} - \mathrm{F_{jt}})^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\mathrm{F_{jt}^2}}\sqrt{\frac{1}{n}\sum_{t=1}^{n}\mathrm{X_{jt}^2}}}$$

Like the MPAE statistics, high values suggest poor performance in the forecast. The scaling of U is such that it always lie between 0 and 1. If U = 0, $Xjt = Fjt$ for all forecasts, and there is a perfect fit. In contrast, if U = 1, the predictive performance is not good.

Forecasting

Suppose that we have a sample of observations on $\mathrm{Y_t}$ that ends in period T and that we wish to forecast their values in $\mathrm{T+1, T+2,}$ etc. For the period $\mathrm{T+1}$, our VAR is as follows:

$$X_{T+1/T} = C + \Phi_1 X + \cdots + \Phi_p X_{T-p+1}, T \geq p \tag{5}$$

The h-step-ahead forecasts can be obtained via the chain rule of forecasting:

$$\mathrm{Y_{T+h/T}} = \mathrm{C} + \Phi_1 \mathrm{Y_{T+h-1/T}} + \cdots + \Phi_p \mathrm{X_{T+h-p/T}}$$

where $\mathrm{X_{T+j}/T} = \mathrm{X_{T+j}}$ forj ≤ 0

3. Results and Discussion

3.1. Descriptive Statistics of the Study Variables

In this empirical analysis, four variables, namely, electricity production from hydroelectric sources (% of total), electric power consumption (KWh), energy import net (% of energy use), and electric power transmission and distribution losses (% of output) were used.

Table 1. *Summary Results of the Study Variable.*

Variables	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
EPH	84.21	99.69	51.06	14.75	-0.742	2.342	4.945	0.084
EPC	28.29	70.88	15.04	14.62	1.071	4.704	8.190	0.000
EPTADL	10.495	22.92	4.79	4.066	1.561	4.739	23.95	0.000
EIM	3.657	5.996	2.588	0.911	0.973	3.065	7.106	0.018

Table 2. *Summary Result of the SQRT-Transformed Variables.*

Variables	Mean	Maximum	Minimum	Std. Dev.	Probability
SQRTEPH	9.12547	9.9847	7.1459	0.84705	0.0530
SQRTEPC	5.07166	7.0344	3.8781	0.94617	0.0525
SQRTEPTADL	1.89954	4.7874	2.1891	0.57805	0.0874
SQRTEIM	3.24545	2.4486	1.6086	0.22842	0.0547

Table 1 illustrates that the generation of electricity through hydroelectric means rose from its lowest point of 51. 06 in 1971 to a peak value of 99. 69 by 2006 (as a percentage of the total). The usage of electric power grew from its lowest figure of 15. 04 in 1971 to its highest figure of 70. 88 in 2015. Likewise, the energy brought in from abroad increased from a minimum of 2. 58 in 1971 to a highest level of 5. 996 in 2015.

The Jarque Bera test is conducted to assess normality, revealing that the variables were not normally distributed on their own, except for EPH, which has a probability of 0. 084. In contrast, all of the transformed variables (SQRTEPH, SQRTEPC, SQRTEPTADL, and SQRTEIM), with probabilities of 0. 053, 0. 0525, 0. 0874, and 0. 0547 respectively, are considered normal, as indicated in Table 2.

The individual plots of the series against the research period are displayed in Figure 1. All of the data appear to be non-stationary based on the overall increasing trend in all of the series. However, since differencing is a technique for preventing trends in a series, all of the study variables appear stationary at first difference in Figure 2. To conclude that the series are patterned, it is important to note that graph inspections alone are insufficient.

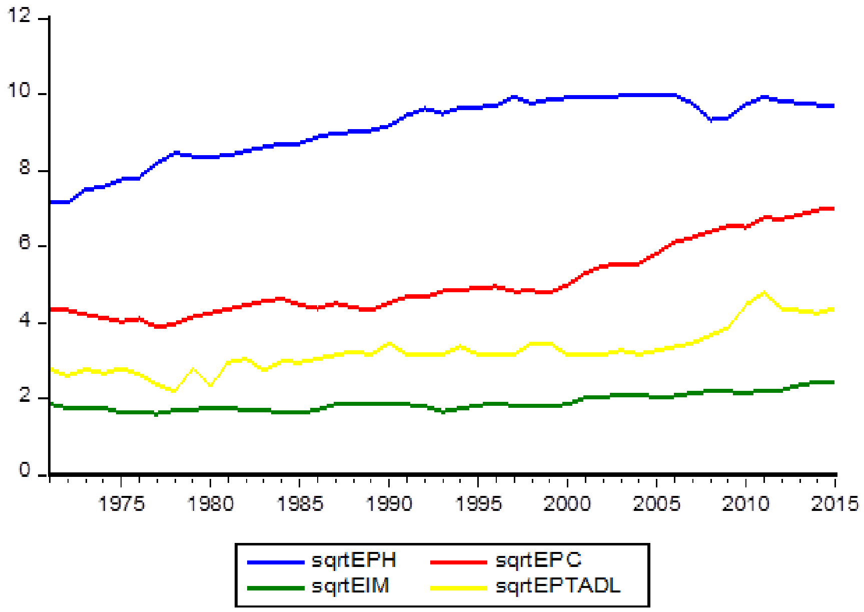

Figure 1. Time Plot of the Study Variables (at Level).

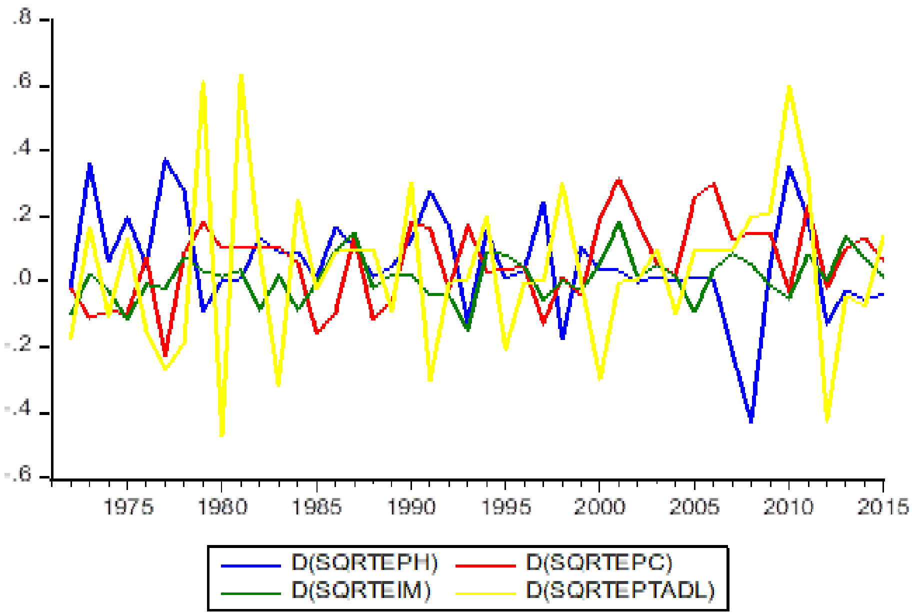

Figure 2. The Time Plot of the Study Variables at Their First Difference.

3.2. Stationarity Test

Time Series Unit Root Test (s)

Table 3 displays the results of the ADF and PP tests when the intercept for each series is considered at the level. According to the findings in Table 3, at this level, there is insufficient evidence to confidently reject the null hypothesis, which asserts that the series contains a unit root (is nonstationary) for all-time series, as the calculated test statistic is lower than the critical value for each series at the 5% significance level (α).

Once the presence of unit roots across all series has been established, the subsequent action is to apply differencing to achieve stationarity in the data. At this juncture, the orders of integration for the four nonstationary series examined in this research are identified. The order of integration indicates how many unit roots must be present in the series before reaching stationarity. The identical tests are then conducted on the initial differences. In Table 3, we can reject the null hypothesis (the test statistic exceeds the critical value for each series at the 5% significance level) for all series. All variables in their first differences exhibited stationarity.

Table 3. *Unit Root Test Results [At Levels and First Difference].*

	Level with intercept		With intercept at first difference	
	Test statistic		Test statistic	
	ADF	PP	ADF	PP
SQRTEPH	-2.9254	-4.6580	-5.4027	-5.3669
SQRTEPC	1.8814	1.6370	-4.9805	-4.9467
SQRTEIM	-0.4576	-1.1119	-5.9312	-6.1090
SQRTEPTADL	-0.8334	-0.8334	-8.5207	-8.5869
5% critical value	-2.9297		-2.9314	
Decision	Nonstationary		Stationary	

3.3. Vector Autoregressive (VAR) Model Specification

Vector auto regression (VAR) is a stochastic process model used to capture the linear interdependencies among multiple time series. The series (variable) has an equation explaining its evolution based on its own lagged values, the lagged values of the other variables, and an error term [33].

The rationale for using square-rooted data in time series regressions and macroeconomic forecasts is rooted in the normality assumption and aims to limit the detrimental effects of heteroscedasticity and skewness in the level data on the estimation and testing results.

3.3.1. Cross-Correlation Matrix

The cross correlation matrix illustrates how closely related various time series variables are to one another. A positive cross correlation signifies that when one variable's value rises, the associated variable tends to either rise or fall at the same time for those that are correlated [38]. The findings displayed in Table 4 indicate a strong positive cross correlation exists between SQRTEPH, SQRTEPC, SQRTEIM, and SQRTEPTADL up to the second-order predetermined (lagged) value during the sampled period.

Table 4. *The Correlation Matrix of the Study Variables.*

CCM at lag: 0	SQRTEPH	SQRTEPC	SQRTEIM	SQRTEPTADL
SQRTEPH	1.000	0.6638	0.5842	0.6411
SQRT EPC	0.6638	1.000	0.9371	0.8838
SQRTEIM	0.5842	0.9371	1.000	0.8220

CCM at lag: 0	SQRTEPH	SQRTEPC	SQRTEIM	SQRTEPTADL
SQRTEPTADL	0.6411	0.8838	0.8220	1.000
CCM at lag: 1				
SQRTEPH	1.000	0.6886	0.6380	0.6353
SQRTEPC	0.5704	1.000	0.8845	0.8373
SQRTEIM	0.4870	0.5842	1.000	0.7560
SQRTEPTADL	0.6353	0.8373	0.7560	1.000
	+	+	+	+
Simplified Matrix CCM at lag 2	+	+	+	+
	+	+	+	+
	+	+	+	+

3.3.2. Specification of VAR Order

The process of determining the specification of VAR models includes establishing the lag length that most appropriately fits the model, as any conclusions based on the model depend on the correct identification of the lag order. If the lag length applied in a model differs from the true lag length, the resulting estimates will lack consistency. In this study, the best lag order for the VAR model was determined using the Akaike information criterion (AIC), the Schwarz Bayesian information criterion (SBIC), and the Hannan-Quin information criterion (HQIC). For each of these criteria, the lag length that resulted in the smallest criterion value was selected as the optimal lag length for the model. As a result, it was determined that VAR (1) was the most appropriate choice for the dataset when compared to the other models listed in Table 5.

Table 5. *AR Lag Order Selection (Specification).*

Lag	AIC	SC	HQ
0	2.285627	2.452804	2.346503
1	-4.911670*	-4.075781*	-4.607286*
2	-4.541554	-3.036955	-3.993662
3	-4.286874	-2.113563	-3.495474
4	-4.622688	-1.780666	-3.587780

3.4. Estimation of Parameters for the VAR (1) Model

There are various methods for estimation, the most well-known being least squares estimation and maximum likelihood estimation. The main advantage of maximum likelihood estimation is that it is efficient asymptotically [31]. Fitting the VAR model with the trend is appropriate in some cases rather than differencing. When integrating order likelihood estimation [39], in this case, the researcher fits the VAR(1) model by using MLE. According to Equation (3), the exogenous variables (lagged series) are significantly affected by the respective endogenous variables at the 5% level of significance.

The result from Table 6 the SQRTEPH was significantly explained by its first lag. Specifically, for a 1% increase in one period, the lagged values of EPH led to an increase in the current production of electricity from the hydroelectric source b 0.930% in square root where other variables are constant. The constant value of 0.823 in the model indicated that the current EPH was increased by 0.823% while the other variables were kept constant. This increment comes from another activity that contributes to electricity production from hydroelectric sources (EPSs) positively but are not included in the model in the EPH in the short run during the study period.

In addition, the current value of electric power consumption (EPC) was explained by the one period lagged value of the production of electricity from a hydroelectric source (EPH) and its first lag.

Result from Table 6 1% increase in one period lagged value of itself and electric production from a hydroelectric source (EPH) leads to an increase in the current electric power consumption by 0.975% and 0.074% in their square root form respectively (other variables are kept constant).

The constant value of 0.750 in the model indicated that the current EPC is decreased by 0.750% while the other variables remain constant. Thus, EPH had a positive significant impact on electric power consumption in the short run. The adjusted R square value (0.9857) implied that 98.57% of the variation in electric power consumption was explained by those significant variables.

Similarly, the current value of Energy Import (EIM) was explained by the one-period lagged value of electric power consumption (EPC), in their square root form. The adjusted R square value (0.9224) implied that 92.24% of the variation in the future Energy Import is affected by those significant variables.

The current value of electric power transmission and distribution losses (EPTADL) is affected by the one-period lagged value of electric power consumption (EPC) and its first lag in the square root form. When electric power consumption increases, electric power losses also increase during transmission and distribution. The adjusted R square value (0.8547) implied that 85.47% of the variation in the future electric power losses during transmission and distribution were affected by those significant variables.

***Table 6.** Full Maximum Likelihood Estimation of the Study Variables in the VAR (1).*

*** Indicates the significance at 5%**

Standard errors in ( ) & Probability [ ]

	SQRTEPH	**SQRTEPC**	**SQRTEIM**	**SQRTEPTADL**
SQRTEPH (-1)	0.929860*	0.077436*	0.018927	0.019017
	(0.03475)	(0.02793)	(0.01620)	(0.05504)
	[0.0000]	[0.0032]	[0.2145]	[0.7136]
SQRTEPC (-1)	-0.045138	0.974974*	0.074446*	0.269810*
	(0.08198)	(0.06590)	(0.03822)	(0.12985)
	[0.5580]	[0.0000]	[0.0377]	[0.0273]
SQRTEIM (-1)	-0.152141	0.252888	0.691612*	-0.054423
	(0.27576)	(0.22166)	(0.12856)	(0.43679)
	[0.5576]	[0.2209]	[0.0000]	[0.8947]
SQRTEPTADL (-1)	0.120812	-0.076329	-0.002549	0.558851*
	(0.08010)	(0.06439)	(0.03734)	(0.12688)
	[0.1090]	[0.2062]	[0.9422]	[0.0000]
C	0.821872*	-0.750163*	0.056908	0.029990
	(0.33639)	(0.27040)	(0.15682)	(0.53284)
	[0.0090]	[0.0030]	[0.6990]	[0.9523]
TREND	0.052728*	0.015979	0.014521*	0.041325
	(0.01662)	(0.01480)	(0.00839)	(0.02885)
	[3.17164]	[0.2204]	[0.0433]	[0.1137]
R-squared	0.977640	0.987396	0.931398	0.871556
Adj. R-squared	0.974698	0.985738	0.922372	0.854655
Sum sq. resides	0.617547	0.489649	0.157352	1.859194
S. E. equation	0.127480	0.113514	0.064349	0.221193
F-statistic	332.2912	595.3995	103.1846	51.56966
Log-likelihood	31.42288	36.52835	61.50285	7.175732
Akaike AIC	-1.155586	-1.387652	-2.522857	-0.053442
Schwarz SC	-0.912287	-1.144354	-2.279558	0.189856
Mean dependent	9.170140	5.088195	1.900536	3.256170
S. D. dependent	0.801427	0.950517	0.230959	0.580191

3.5. VAR (1) Model Adequacy Checking

After model development, it is necessary to verify whether the fitted model is suitable. All the time it is after model validity examination that forecasting will be made. Diagnostic checking for the fitted model is a mandatory step before one can use it for structural analysis and forecasting in time series analysis. Whenever the test confirms the underlying assumptions of residuals, it is possible to go for further analysis and forecasting.

3.5.1. Test of Residual Autocorrelation

Table 7 presents the results of the Portmanteau Q statistic and Lagrange Multiplier (LM) test for the whole VAR model residual serial correlation and the test for the overall significance of the residual autocorrelations up to lag 2. Both tests imply that residuals do not suffer from autocorrelation problems up to lag 2, as all p values exceed the 5-level threshold.

Table 7. *Test of Residual Autocorrelation.*

Lag	Portmanteau Q statistic				Lagrange Multiplier	
	Q-Stat		Adj Q-Stat		LM-Stat	
	Value	Prob	Value	Prob	Value	Prob
1	9.8911	----	10.121	----	20.802	0.1862
2	18.842	0.9686	19.499	0.9594	10.560	0.8358

*The test is valid only for lags larger than the VAR lag order.

The tests in Table 7 above were used to test for the overall significance of the residual autocorrelations up to lag 2. Similarly, in Table 8, there was no heteroscedasticity individually and jointly in the case of the ARCH test at a 5% level of significance. Thus, the results confirmed that the residual terms were pure from white noise.

Table 8. *VAR Residual Heteroscedasticity Test (Levels and Squares).*

Dependent	DF.	Chi -sq	Prob.
res1*res1	14	16.337	0.2932
res2*res2	14	11.032	0.6835
res3*res3	14	9.908	0.7689
res4*res4	14	21.906	0.0806
res2*res1	14	11.872	0.6166
res3*res1	14	12.931	0.5319
res3*res2	14	9.021	0.8297
res4*res1	14	23.537	0.4224
res4*res2	14	13.022	0.5248
res4*res3	14	16.735	0.2706
Joint	140	151.0724	0.2468

3.5.2. Testing Normality

A multivariate form of the Jarque Bera test is utilized to evaluate the normality of the residuals. It assesses the third and fourth moments (skewness and kurtosis) against those of a normal distribution. The null hypothesis for the test suggests that the model's error exhibits skewness and kurtosis that align with a normal distribution, as illustrated in Table 9; beneath the graph, the normality of the VAR (1) model is demonstrated.

Table 9. *Test of Normality.*

Components	Skewness		Kurtosis		Jarque-Bera Statistic	
	Values	Prob	Values	Prob	Values	Prob
1	-0.2147	0.5609	3.8303	0.2609	1.6020	0.4489
2	-0.0301	0.9351	2.1825	0.2683	1.2319	0.5401
3	-0.5601	0.1293	3.1710	0.8169	2.3544	0.3081
4	0.3848	0.2974	2.8171	0.8044	1.1472	0.5635
Joint		0.4436		0.6261		0.6097

3.5.3. Stability Analysis of the VAR (1) Model

The stability conditions of the models estimated should be checked via the CUSUM square stability condition. Thus, since the fitted models lie at the 5% significance level, the estimates of the VAR models satisfy the CUSUM square stability condition. This graphical result is confirmed by the eigenvalue stability condition test in Figure 3.

In addition, the inverse roots of the characteristic polynomials have moduli of less than one and lie inside the unit circle, implying that at the chosen lag length of order, one is in Table 10. Therefore, the stability of the VAR model was well satisfied.

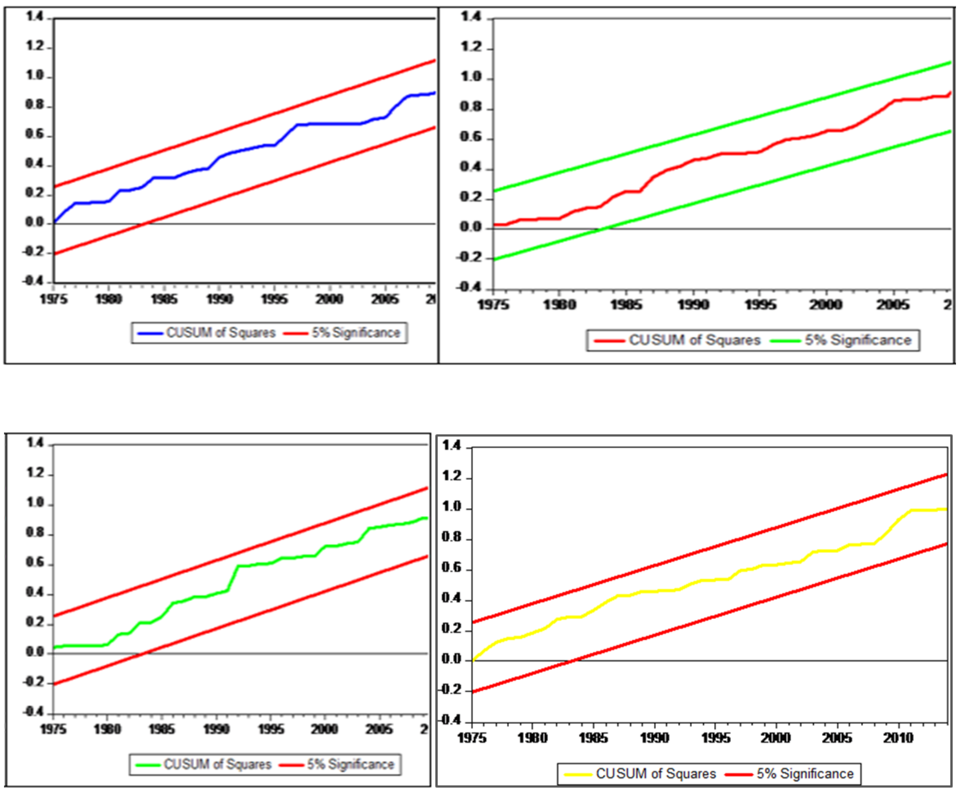

Figure 3. *Cusum Square Stability Test of EPH, EPC, EIM, and EPTADL, Respectively.*

Table 10*. Eigenvalue Stability of VAR (1).*

Roots of Characteristic Polynomial	
Lag specification: 1	
Root	Modulus
0.902342	0.902342
0.643761 - 0.035301i	0.644728
0.643761 + 0.035301i	0.644728
0.342912	0.342912
No root lies outside the unit circle.	
VAR satisfies the stability condition.	

3.6. The Measure of Forecasting Accuracy

The mean square error (MSE), root mean square error (RMSE), mean absolute error MAE) and Theil U statistic were used to assess the forecasting accuracy. The Theil U statistics are independent of the scale of the variables and are constructed to lie between zero and one, zero indicating a perfect fit. In evaluating the performance of the forecasting models, the lower RMSE, MAE, MAPE, and Theil U statistics implied better forecasting accuracy. Table 11 reports the forecasting accuracy statistics of the estimated model. The result indicates that all the estimated models were sufficient to describe the series. For each endogenous series (SQRTEPH, SQRTEPC, SQRTEIM, and SQRTEPTADL), the RMSE, MAE, and MAPE values were less than 5%, and the U statistics were close to zero, which indicated that the differences between the actual values.

Table 11*. Measure of Forecast Accuracy.*

Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
SQRTEIM	45	0.085145	0.069208	3.616999	0.022096
SQRTEPC	45	0.246638	0.182744	3.631070	0.023621
SQRTEPH	45	0.215515	0.192343	2.085818	0.011724
SQRTEPTADL	45	0.299837	0.240806	7.266775	0.045027

Forecasting

It is one of the fundamental goals of time series analysis in addition to fitting a time series model. The previous analysis results confirmed that the vector autoregressive model of order one VAR (1) was the paramount model to suitably describe the series of this study. In this section and forward, the forecasting accuracy of the fit VAR model was examined, and then the model was previously used from 2016 to 2025 for ten years before electricity production from the hydroelectric source, electric power consumption, energy importance and electric power transmission and distribution losses in Ethiopia.

Sample forecasting

The sample values for the series under study, using the vector autoregressive model results from Table 12, revealed annual values show an increasing trend in all series together in their square root form. Specifically, electric power consumption increased from 7.56% in 2016 to 8.129% in 2025; similarly, electricity production from hydroelectric sources (EPSs), energy import (EIM), and electric power transmission and distribution losses increased from 9.720% to 9.841%, 2.457842 KWh to 2.658 kWh, and 4.463% and 5, respectively.% in their square root form according to the sample forecast from the VAR(1) model.

Table 12*. Forecast Values from the VAR (1) Model.*

Year	SQRTEPH	SQRTEPC	SQRTEIM	SQRTEPTADL
2016	9.720443	7.156130	2.457842	4.462608
2017	9.738805	7.271464	2.472074	4.534098
2018	9.754827	7.382772	2.490030	4.602927

Year	SQRTEPH	SQRTEPC	SQRTEIM	SQRTEPTADL
2019	9.769446	7.491569	2.510632	4.670094
2020	9.783085	7.598851	2.533080	4.736123
2021	9.795948	7.705281	2.556808	4.801369
2022	9.808144	7.811297	2.581430	4.866101
2023	9.819739	7.917181	2.606684	4.930529
2024	9.830782	8.023116	2.632390	4.994811
2025	9.841314	8.129209	2.658428	5.059061

4. Conclusion

The major objective of the study was multivariate time series analysis to assess the relationship between the energy growth indicators from 1971 to 2015 in Ethiopia. All four series were nonstationary at the level but were stationary at the first difference and VAR(1) with the trend. The optimal lag length selection criteria for the vector autoregressive models were indicate VAR (1) was found to be appropriate and the optimality test (lag exclusion test) approved the selected lag order. The cointegration analysis via the Johansen procedure revealed evidence for the existence short-run (no-cointegration) relationship among energy growth indicators of Ethiopia in the sample period. From the VAR model, the researcher observed that electricity production from a hydroelectric source was significantly affected by one period lag in the short run. Additionally, electric power consumption was significantly affected by its one-period lagged value and lagged value of electricity production from hydroelectric sources. Similarly, energy imports, electric power transmission, and distribution losses were significantly affected by their own lagged value and lagged value of electricity power consumption. In model adequacy, residual autocorrelation, heteroscedasticity, normality, and stability are satisfying.

5. Recommendations

On the basis of the results obtained from this empirical finding, the following points are recommended.

The findings of this study revealed increasing electricity production in Ethiopia until 2025. Thus, this encourages to engage in consumption, whereas the government and policymakers look forward and work aggressively to strengthen production.

The government should implement education and awareness-raising campaigns to encourage the sustainable utilization of water resources for electricity production in the country.

The scope of the analysis in this study has been limited to the relationship among electricity production from hydroelectric sources, electric power consumption, energy import, electric power transmission and distribution losses. Thus, this study should come up with additional susceptive influential variables such as energy prices, access, and production of other renewable energy (wind, solar, geothermal.

6. Limitations

The data under this study are at the country level since the distribution is not well known at the regional and zonal levels.

7. Significance of the Study

Energy-focused policy choices carry extensive and enduring effects on the configuration of the current energy framework. To foster more sustainable and socially responsible methods of electricity generation in the future and to assist policymakers in formulating suitable policies, a precise forecast of changes in electricity production is essential. Consequently, this research can assist energy policymakers in strategizing and making informed choices concerning electricity while recognizing key influencing factors.

In addition, this paper provides a pathway for researchers and students to apply multivariate time series models in the energy sector and other variables. In addition to this supply, it would be for the government and producers who are interested in producing and/or distributing electricity.

Abbreviations

AIC	Akaike Information Criterion
AR	Auto-Regressive
EIM	Energy Import
EPC	Electricity Power Consumption
EP	Electricity Production
GTP	Growth and Transformation Plan

HQIC	Hannan-Quin Information Criterion
LM	Lagrange Multiplier
MA	Moving Average
PP	Phillips and Perron
SBIC	Schwarz-Bayesian Information Criterion
WDI	World Development Indicator

Conflicts of Interest

The authors declare no conflicts of interest.

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