Analyzing and Forecasting Electricity Consumption in Energy-intensive Industries in Rwanda

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ABSTRACT

Accurate forecast in electricity consumption (EC) is of great importance for appropriate policy measures to be undertaken to avoid significant over or underproduction of electricity compared to the demand. This paper employs multiple regression (MLR) and autoregressive integrated moving average (ARIMA) for the econometric analysis. MLR has been used to investigate the impact of the potential economic factors that influence the consumption of electricity in energy-intensive industries while ARIMA is used for the electricity consumption forecasting from 2000 to 2026. ADF test has been applied to test for the unit-roots, the results show that all variables include a unit root on their levels but all series become stationary as a result of taking their first difference. Johansen technique and the Residuals based approach to testing for long-run relationships among variables has been used. The outcomes show that the variables are co-integrated. GDP per capita is statistically significant at a 1% level and EC decreases with higher GDP per capita. The results also show that EC increases with population, while Gross Capital Formation and Industry Value Added have less influence on EC. The ARIMA (1,1,1) was found to be the best model to forecast EC and the conclusion is provided.

Keywords: Co-integration, Electricity Consumption, Forecasting, Industry Sector, Stationarity
JEL Classifications: C22, C52, E17

1. INTRODUCTION

Electricity consumption forecasting is an active research topic with significant practical implications for almost any industry or organization (Gordillo-Orquera et al., 2018). This is not surprising, as the accurate prediction of energy consumption and requirements has a positive impact on operational budgets of organizations (Soliman and Al-Kandari, 2010). Electrical load or demand forecasting is the prediction and projection of peak load demand levels and over all energy consumption patterns that supports an electric utility future system and business operation (Julio, 2000). It provides a projection of electric peak load, customer connections and energy demand within an area covering a period into the future to provide a good lead-time for planning so that the utility company can arrange for the needed investments and additions of equipment in a timely and efficient manner(Okoye and Madueme, 2016).

Depending on the time horizons of the planning strategies, the energy demand and peak load forecasting can be divided into following three categories namely: Short-term load forecasting with a period ranging from 1 h to 1 week. Medium term load forecasting with a period ranging from 1 week to 1 year. Long-term load forecasting with a period, which is longer than a year. Countries may vary the definition of the time horizons, to meet their specific energy demand requirements. The long term is used by electric utility companies to predict the future needs for power supply and delivery system expansion such as generation units, transmission and distribution system, as well as equipment purchase and staff hiring (Anwar et al., 2018).

Over the last decade, Rwanda has shown a large increase in electricity generation. National figures seem to suggest that the country will reach an installed capacity of 570 MW by 2026 from

230MW in 2019. To achieve this objective, the government has involved private companies in the generation sector under long term 'take or pay' contracts through power purchase agreements (PPAs). To meet the economic growth vision of the country a significant increase in generation capacity is needed. With the rapid growth and target in installed power generation capacity, accurate forecast in electricity consumption is important for appropriate policy measures to be undertaken to avoid significant over or under production of electricity compared to the demand.

Rwanda Utility Regulatory Authority (RURA) (Rwanda Utilities Regulatory Authority, 2017), report that Energy Utility Corporation Limited (EUCL)- Rwanda Energy Group (REG) divide on-grid electricity customers in two categories for metering purposes. The first is postpaid metered category, which is mainly composed of industries, telecom towers as well as water treatments plants classes. The second is prepaid metered customers' category, which covers mainly residential and non-residential customer classes. The total number of customers on prepaid metering system is 955,108 while the postpaid metered customers amount to 2,589, giving a total connected customer number of 957,697 by June 2019 (Rwanda Electricity Group, 2019).

While the postpaid entered on grid electricity customers represent only 0.3% of the total number of electricity consumers, they consumed 60% of all sold electricity during the second quarter of 2019. This follows the same trend in the previous years. In terms of energy consumption, the postpaid metered customers energy demand was 106,920,380 kWh of electricity during the second quarter of 2019, while prepaid customers consumed 70,247,648 kWh in the same period (Rwanda Electricity Group, 2019).

This study focuses on electricity intensive industries as big consumers of electricity, since they consume at least 60% of the energy produced and sold by the power utility in Rwanda. The study therefore carries out analysis of their energy consumption trend over the past 20 years and forecast their consumption for 6 years based on time series annual data. Forecasting electrical peak load and energy consumption in electricity intensive industries can help policy makers, in power generation planning to develop medium to long term plans and mechanisms necessary to balance electricity supply and demand at all times.

A number of studies have been done in an effort to model and forecast electricity demand in the Electricity Supply Industry but such empirical study is yet to be conducted in Rwanda. The results from this study will no doubt contribute to Rwanda's energy demand-side management, as well as policy and investment decisions in energy infrastructure, especially with regard to power generation options to meet the projected electricity demand.

According to Kaytez et al. (2015) overestimation of electricity consumption would lead to excess and idle capacity which means wasted financial resources, whereas underestimation would cause potential supply shortages and hence energy outages. Therefore, accurate and reliable modelling and forecasting of electricity demand in Rwanda is very important. Currently, the installed electricity generation capacity is 230 MW and with the

ongoing projects in power generation in Rwanda, the installed capacity is expected to increase to 570 MW by 2026. Although, the number of customers with access to electricity from the main grid continue to increase, the electrical load consumption does not follow the same path to meet the rapid growth in electricity generation, hence the need for accurate and robust energy demand forecasting.

This study seeks to assess electricity consumption trends in the Industrial customer categories in Rwanda, over the period from 2000 to 2019. It will develop a consistent and robust electricity demand-forecasting model for energy intensive customer category in Rwanda. This model will be used to project electricity demand for the industrial customer categories in Rwanda for the period 2020 – 2026. This research will also identify the main variables, which have significant impact on the electricity demand by the energy intensive industry in Rwanda.

2. LITERATURE REVIEW OF ENERGY FORECASTING METHODS

Operating an electricity supply system to provide a secured supply of electricity to consumers is one of the most demanding tasks facing practitioners today. On the demand side, it involves forecasting consumers' demand for electricity, and on the supply side, it involves scheduling electricity generating plant such that sufficient capacity is available, including adequate reserve margins, to meet the demands placed on the system. Failure to carry out these tasks accurately and efficiently will result in a failure of generation supply or this could result in the power utility's inability to keep plant in operational readiness to meet peak demand.

For electrical distribution and generation industry, load forecasting is very important. It has many applications including energy purchasing, generation, transmission, load switching, contract evaluation, and infrastructure development. Electricity as a product has different characteristics compared to material products since it cannot be stored in bulk, which means that it should be generated as soon as it is demanded (Reddy, 2017; Almeshaiei and Soltan, 2011), hence the reason why investment in generation, has to take into account the current and the future demand for electricity. It is therefore of great importance for the electric power producers to estimate in advance the future load on their systems using robust methods to define quantitatively future loads.

While numerous forecasting methods and models were developed to compute an accurate load forecasting, finding an appropriate forecasting model for a specific electricity network is not an easy task, and none of them can be generalized for all demand patterns (Zhanga and Wanga, 2017; Kuster et al., 2017; Hammad et al., 2020). The choice of a model, method and techniques to use for electricity forecasting is generally based on available data and forecasting period (short, medium and long-term). The nature of the data whether linear or non-linear, play a great role in choice of the model. The methods used for energy forecasting are described below.

2.1. Econometric Models

Mahmoud et al. (2020), point out that models can be divided into two types, the multi-factor/cross-sectional forecasting method, which focuses on the search of the causal relationships between different influencing factors and forecasting values. The other type uses the time series forecasting method, which depends more on the historical series (Hammad et al., 2020). According to Mahmoud et al. (2020), because time series models are easy, quick and objective, they are the widely used and be sub-divided as follows: statistical models, machine learning models, and hybrid models. Saravanan et al. (2012), has also indicated that that long-term forecasting methods can be classified into two categories: conventional approaches and technique based on artificial intelligence. They additionally note that, traditionally regression models have been the most popular in load forecasting and used to model the relationship between the load and external factors.

A hybrid ARIMA–ANN model for the prediction of time series data, was proposed by Zhang (2003). This hybrid model was shown to outperform individual ARIMA and ANN models in the case of one-step-ahead prediction. Another linear autoregressive integrated moving average (ARIMA) and nonlinear artificial neural network (ANN) models have been explored by Narendra (2014) to devise a new hybrid ARIMA–ANN model for the prediction of time series data. They point out that many of the hybrid ARIMA–ANN models which exist in the literature apply an ARIMA model to given time series data, consider the error between the original and the ARIMA-predicted data as a nonlinear component, and model it using an ANN in different ways.

A numerous number of studies used different techniques to forecast long, medium and short-term electricity consumption based on historical consumption and economic factors that are relevant to affect electricity demand. Ghanbari et al. (2009), employ artificial neural networks (ANN) and regression (Linear and Log-Linear) approaches for annual electricity load forecasting to present a model that is affected by two economical parameters, which are Real- GDP and Population. The nonlinear ANN and three types of linear models namely, multiple log-linear regression (LNREG), response surface regression (RSREG), and regression with ARMA errors model (ARMAX), were proposed by Pao (2006) and noted that the forecasting performance of ANN is higher than the other linear models. By adopting the linear and nonlinear ANN methods, surprisingly, they find that economic indicators, GDP and CPI, have less effect on Taiwan's electricity consumption than country population (POP) and National Income (NI).

Feilat et al. (2017), present a neural network (NN) based approach for long-term load forecasting (LTLF) of the Jordanian power system from 2015 to 2029. They examined two types of feed forward neural networks (FFNN), namely, the back-propagation and the radial basis function neural networks; (BPNN) and (RBFNN), respectively. The simulation results show that both neural networks show quite good performance over a long forecasting period. They also found that peak load is related to the GDP and population. Saravanan et al. (2012) used multiple linear regression (MLR) and ANNs to predict the long-term electricity consumption in India using CO_2 emissions, population,

Per capita GDP, gross national income (GNI), gross domestic saving, consumer price index (CPI), industrial production index (IPI), Imports, Wholesale price, Exports and Per capita power consumption as economic factors. The results showed that the use of ANNs led to more accurate results than linear models.

Kumaran and Ravi (2014) proposed a model, which comprises two regression models, the former one predicts the population (POP) and per capita GDP for a given future year and the later one estimates the sector wise energy demand by considering the output of the former as input. In this study, they agreed with most of the literature (Ghanbari et al., 2009; Saravan et al., 2012) that among economic factors, the population growth as well the continuous improvement in the public revenue and living standards, represented through per capita GDP are linked with the total energy consumption of any country. Therefore, their proposed model can help the policy makers to develop robust energy demand models to serve as the basis for making the necessary investments in new generation plants and transmission systems, to meet the future demands and offer reliable service to current and future.

For modeling and forecasting future electricity consumption some of the literature proposed univariate Box-Jenkins time-series analyses, which are Autoregressive Moving Average (ARIMA models) (Box and Jenkins, 1970). Univariate Box-Jenkins time-series analyses (ARIMA models), were used for modeling and forecasting future energy production and consumption in Asturias (Gonzales et al., 1999). Thabani (2019) used annual time series data on electricity demand in Zimbabwe from 1971 to 2014 to model and forecast the demand for electricity using the Box-Jenkins ARIMA framework. He found that demand for electricity in Zimbabwe reached its annual peak in 1976, and since then, electricity consumption declined until 2019. The ARIMA (1, 1, 6) model proves that in the next 10 years (2015–2025), demand for electricity in Zimbabwe will continue to fall.

Mahmoud et al. (2020), point out that regression analysis based models and artificial neural networks (ANN) are more appropriate, preferred and most utilized in electricity predictions, while the statistical models like the Box-Jenkins models' family in particular, are not widely used anymore as was the case in the past, but their use still cannot be neglected or overlooked. Although, ARMA, ARIMA, ARM\AX, and ARIMAX are the most often used classical time series methods Tahreem et al. (2018), concluded that electricity demand forecasting techniques based on soft computing methods are gaining major advantages for their effective use. They add that there is also a clear move towards hybrid methods, which combine two or more of these techniques. Hybrid models, which combine the strengths of ARIMA and ANN models, are better than the individual types of models, as they are capable of exploiting the advantages of both types of models simultaneously (Babu and Reddy, 2014; Barak and Sadegh, 2016).

2.2. Trend Method

This method falls under the category of the non-causal models of demand forecasting that do not explain, how the values of the variable being projected are determined. This approach expresses the variable to be predicted purely as a function of

time, rather than by relating it to other economic, demographic, policy and technological variables. This function of time is obtained as the function that best explains the available data, and is observed to be most suitable for short-term projections. The trend method has the advantage of its simplicity and ease of use. However, this method is important as it provides a preliminary estimate of the forecasted value of the variable. It may well serve as a useful method for crosschecking the robustness of results from other prediction methods, particularly for short-term forecasts.

2.3. End-use Method
The end-use approach attempts to capture the impact of energy usage patterns of various devices and systems. It directly estimates energy consumption by using extensive information on end use and end users, such as appliances, the customer use, their age, sizes of houses, and so on (Anwar et al., 2018). The end-use method is based on the premise that energy is required for the service that it delivers and not as a final good.

This method takes into account improvements in efficiency of energy use, utilization rates, inter-fuel substitution etc., in a sector as these are captured in the power required by an appliance. These models are based on the principle that electricity demand is derived from customer's demand for light, cooling, heating, refrigeration, etc. Thus, the end-use models explain energy demand as a function of the number of appliances used and in the market.

2.4. Time Series Method
A time series is defined to be an ordered set of data values of a certain variable. Time series models are, essentially, econometric models where the only explanatory variables used are lagged values of the variable to be explained and predicted. The intuition underlying time-series processes is that the future behavior of variables is related to its past values, both actual and predicted, with some adaptation/adjustment built-in to take care of how past realizations deviated from those expected. It has been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARM\AX (autoregressive moving average with exogenous variables), and ARIMAX (auto regressive integrated moving average with exogenous variables) most often used classical time series methods (Anwar et al., 2018).

The essential prerequisite for a time series forecasting technique is the need to have data for the last 20-30 time - periods. The difference between econometric models based on time series data and time series models lies in the explanatory variables used. It is worthwhile to highlight that in an econometric model, the explanatory variables (such as incomes, prices, population etc.) are used as causal factors while in the case of time series models only lagged (or previous) values of the same variable are used in the prediction.

In general, the most valuable applications of time series come from developing short-term forecasts, for example monthly models

of demand for 3 years or less. Econometric models are usually preferred for long-term forecasts. Another advantage of time series models is their structural simplicity. They do not require collection of data on multiple variables. Observations on the variable under study are sufficient. A disadvantage of these models, however, is that they do not describe a cause-and-effect relationship. Thus, a time series does not provide insights into why changes occurred in the variable.

2.5. Hybrid Approaches
According to Hesham and Nazeeruddin (2002), after surveying different approaches, they observe a clear trend toward new, stochastic, and dynamic forecasting techniques. They also mention that, despite a lot of research in the 2000s, effort was focused on fuzzy logic, expert systems and particularly neural networks. There was a clear move towards hybrid methods, which combines one or more of the above approaches and techniques.

For instance, it is common to use a combination of econometric and time series models to achieve greater precision in the forecasts. This has the advantage of establishing causal relationships as in an econometric model along with the dependency relationship. Various functional forms such as linear, quadratic, log-linear, translog, etc. are used to capture the possible trends that may be evident in the data.

3. METHODOLOGY

The objective of this study is to analyze and forecast electricity consumption in the industrial sector in Rwanda from 2000 to 2026. As shown in the literature review, the level of electricity consumption is generally influenced by different economic factors such as industrial efficiency, gross capital formation, total population as well as the Gross Domestic Product (GDP) per capita as independent variables.

The model uses a Cobb-Douglas function in which electricity consumption in the energy intensive industries in Rwanda depends on national gross domestic product (GDP) per capita, industrialization represented through gross capital formation (GF), industrial efficiency represented through industry value added (IV) and total population of Rwanda (POP).

$$EC = f (GDPC, GF, IV, POP) \qquad (1)$$

The function (1) can be expressed as follows:

$$EC_t = e^{\alpha 0} \times (GDPC_t)^{\alpha 1} \times (GF_t)^{\alpha 2} \times (IV_t)^{\alpha 3} \times (POP_t)^{\alpha 4} \times e^{\varepsilon t} \qquad (2)$$

The coefficients (alphas) in equations (2) and (3) measure the relative importance of each factor in explaining the underlying behavior of electricity consumption. To be able to interpret these coefficients as elasticities, we transform the equation above by taking the natural logs of both sides of Equation (2). Thus, Eq. (2) becomes;

$$Log\ EC_t = \alpha_0 + \alpha_1 Log\ GDPC_t + \alpha_2 LogGF_t + \alpha_3 Log\ IV_t$$
$$+ \alpha_4 Log\ POP_t + \varepsilon_t \qquad (3)$$

Where:

EC_t is the electricity consumption for period t in kWh, in the industrial sector

α_0 is the intercept term;

$\alpha_1, \alpha_2, \alpha_3$ and α_4 are the estimated coefficients of the explanatory variables;

ε_t is the noise stochastic disturbance term.

The relevance of the factors in Rwandan context and data availability within the sample period are the main factors that informed the choice of explanatory variables. The empirical specification is based on the modified one by Adom et al. (2012) and that of Zuresh and Peter (2007) by including Population and Gross Capital Formation (GF) for measuring industrialization.

3.1. Brief Explanations of the Variables

3.1.1. GDP per capita

Per capita gross domestic product (GDP) as a metric that breaks down a country's economic output per person, and is calculated by dividing the GDP of a country by its total population. GDP per Capita thus measures the continuous improvement in the public revenue and living standards of the population. The data used for the modelling are in constant 2010 U.S. dollars. Based on economic theory, the increase in GDP per capita is expected to increase the purchasing power of a population and the population demand for industrial products. To satisfy the demand, this can be achieved by using more efficient technologies to keep the level of electricity consumption unaffected or to achieve significant reduction in electricity consumption as first scenario. The second scenario is to increase the number of machines and equipment and this approach could lead to the consumption of more electricity, by the industrial company. In the first scenario, the increase in GDP per capita could have a negative effect on the electricity consumption but in the second scenario, the increase in GDP per capita could increase the electricity consumption in industrial sector. Therefore, in the long run, the expected sign of α_1 for GDP per Capita can be negative or positive depending on industry strategies adopted to increase industrial production.

3.1.2. Gross capital formation

Gross capital formation (GF), also called "investment," is the acquisition of assets including purchases of second-hand assets, as well as the production of such assets by industrial producers for their own use. The relevant assets relate to assets that are intended for use in the production of other goods and services for a period of more than a year. Economic structure and productivity are important determinants of energy demand, at the macro level, each of them influences energy intensity (Medlock, 2009). The decision to invest in capital stock, the type of capital stock, and the rate of utilization have a great impact on energy demand. As more energy efficient capital is deployed, the energy requirement for a given level of output declines, requiring less energy. This implies that it is possible for industrial sector growth to increase without an increase in energy demand.

Dan (2002) finds that there has been a gradual decline in energy consumption in China since 1978 despite increasing growth and attributed this to energy efficiency. After the oil price shocks in 1973/74 and 1979/80, average productivity in energy use has increased due partly to the replacement of energy-inefficient capital with efficient ones (Berndt, 1990). This implies that the increase in gross capital can reduce the consumption of energy if the investment is made in energy efficient capital. Consequently, GF is expecting to reduce the electricity consumption of the sector if the investment is made in energy efficient capital replacing the energy inefficient ones. It is however possible to experience an increase in electricity consumption if the country is on starting phase of industrial development. In the latter case, the accumulated capital stock is not replacing the existing ones but it is new that is going to start to consume energy. Thus, α_2 could be either negative or positive depending on whether energy efficient or inefficient capital stock was acquired or deployed.

3.1.3. Industry value added

According to World Development Indicators 2019, Industry Value Added equals the difference between an industry's gross output and the cost of its intermediate inputs including energy, raw materials, semi-finished goods, and services that are purchased from all sources. Manufacturing is one of the pillars of development; this is based on transformation of raw materials in consumable goods and using complex technical transformation processes. Some of the sources of that, is technological advancement and fixed capital accumulation. This transformation leads to higher value added and greater economic welfare.

Industry efficiency through technological advancement and the structural changes in economy are the main drivers of a country's industrial value added growth. The use of scale economies, the information and communication technology (ICT) revolution of recent decades has been the principal source of productivity growth for firms (Commission, 2016). For this study the measure of industry efficiency follows the study of Zuresh and Peter (2007) and Adom et al. (2012). In their model, the industry value added is used to capture the industrial efficiency and value addition effect.

Therefore, a decline in electricity consumption can be explained by a growth in industrial efficiency through technological progress represented by Industry value (IV). Thus, a negative correlation is expected between EC and IV and the sign of the coefficient, α_3, is expected to be negative.

3.1.4. Total population

The population of a country is a demographic variable, which if combined with its purchasing power, will influence the consumption level of any country. This implies that, the increase in the population of a country is assumed to increase the demand of industrial production. Therefore, the industrial sector to satisfy the increased demand, need to produce more and consume more electricity.

3.2. Testing the Robustness of the Model

3.2.1. Test for multicollinearity

The size of variance of model estimators is practically important. A larger variance means a less precise estimator, and this translates into larger confidence intervals and less accurate hypotheses tests (Wooldridge, 2015). For given X_j independent variables,

R_j^2 (R-squared) is the proportion of the total variation in X_j that can be explained by the other independent variables appearing in the model. This implies that Multicollinearity occurs when independent variables in a regression model are correlated with each other. This correlation is a problem because the main goal of regression analysis is to isolate the relationship between each independent variable and the dependent variable, However, when independent variables are correlated, it indicates that changes in one variable are likely to be associated with those in another variable. This can reduce the robustness of the estimate coefficients, and weaken the statistical power of the regression model. According to Wooldridge (2015), Variance inflation Factor (VIF) can be used to test for multicollinearity.

$$VIF_j = 1/(1 - R_j^2) \tag{4}$$

The equation (4) shows that VIF_j is a function of R_j^2, this means that as the correlation between independent variables becomes high, VIF also becomes high. The objective is to have smaller VIF. The value 10 is chosen, below or above which to conclude that multicollinearity is a "problem" for estimating coefficients (Wooldridge, 2015).

3.2.2. Test and correct for serial correlation
Consequences of the error terms being serially correlated include inefficient estimation of the regression coefficients, resulting in under estimation of the error variance (mean square error), under estimation of the variance of the regression coefficients, and inaccurate confidence intervals. The Durbin-Watson test is used to test the presence of serial correlation.

$$DW = \frac{\sum_{t=2}^{n} \left(\hat{u}_t - \hat{u}_{t-1} \right)^2}{\sum_{t=1}^{n} \hat{u}_t^2} \tag{5}$$

Where $\hat{u}_t$ are estimated residuals.

Following Wooldridge, 2015, we use the first differencing of data to eliminate the serial correlation.

3.2.3. Stationarity/unity root test
Suppose that each of the variables in the model is represented by Y_t

$$Y_t = \phi Y_{t-1} + \varepsilon_t \tag{6}$$

Where ε_t is an error term, which is a random walk.
When $\phi = 1$, the variable Y_t is not stationary because Y_t is still influenced by Y_{t-1}
When $\phi = 0$, the variable Y_t is stationary because $Y_t = \varepsilon_t$

We use Augmented Dicky Fuller Test (ADF) for Unity root test.

To use a time series for prediction, it has to be independently identically distributed (iid). This means that there is no auto-correlation of errors. This is based on the following classical assumptions:
- $E(\varepsilon_t) = 0$
- $Var(\varepsilon_t) = \sigma^2$
- $Cov(\varepsilon_t, \varepsilon_{t-1}) = 0$

3.2.4. Co-integration test
The starting point of the model is to provide evidence about the effect of each independent variable on electricity consumption for industrial sector in Rwanda. The basic idea is to apply the multivariate co-integration test to check the long run relationship between the electricity consumption for industrial sector and each of the independent variables. Though co-integration is a statistical characteristic, and whether it exists among economic variables of interest is a question that has significant implications for understanding the behavior of those variables. It simply implies that, there is a linear combination of nonstationary variables, which is stationary. Evidence of co-integration means that a stationary long-run relationship among jointly endogenous random variables is present.

The distribution theory supporting the Dickey-Fuller test assumes that the error in the regression is identical and independently distributed. Hence, autocorrelation and heteroscedasticity should not be present in the estimated residuals. Once the variables are co-integrated the model can be used for forecasting electricity consumption in industrial sector and identify the variables that influence the consumption of electricity in the long run.

As regard to co-integration test among the variables, two broad approaches have been frequently applied. The Engel and Granger method, which is based on assessing whether single-equation estimates of the equilibrium errors, appear to be stationary (Engle and Granger, 1987). The second approach due to Johansen and Juselius (1990), is a version of analyzing multivariate co-integrated system based on the Vector Auto-regression (VAR) approach. To carry out the Johansen test, we should first formulate the VAR system and two statistic tests of the Johansen-Juselius method, the trace and maximum eigenvalue tests enable us to determine the presence and the number of co-integrating vectors.

3.3. Auto Regressive Integrated Moving Average (ARIMA) Model
This study will use Auto Regressive Integrated Moving Average Model for forecasting electricity consumption in the industrial sector in Rwanda. Assuming X_t is the current electricity consumption, and X_{t-1} to X_{t-p} refers to electricity consumption in previous periods, μ_t is the current error term and $\mu_{t-1\ to}\ \mu_{t-q}$ the error terms in previous periods, then:

- The moving average (MA) model can be written as:

$$X_t = \alpha_0\, \mu_t + \alpha_1\, \mu_{t-1} + \ldots + \alpha_q\, \mu_{t-q} \tag{7}$$

This means that the current consumption of electricity depends on current and previous error terms or disturbances where μ_t is a purely random process with mean zero and variance σ^2.

- The autoregressive (AR) model

$$X_t = \beta_1\, X_{t-1} + \ldots + \beta_p\, X_{t-p} + \mu_t \tag{8}$$

This means that the current consumption of electricity depends on the level of electricity consumption in previous periods.

- The autoregressive moving average (ARMA) model
  As put forward by Box and Jenkins (1970), an ARMA (p, q) process is simply a combination of equations (7) and (8) or AR (p) and MA (q) processes. Thus, an ARMA (p, q) process can be specified as follows:

$$X_t = \beta_1 X_{t-1} + \ldots + \beta_p X_{t-p} + \mu_t + \alpha_1 \mu_{t-1} + \ldots + \alpha_q \mu_{t-q} \quad (9)$$

- The autoregressive integrated moving average (ARIMA) model
  Making prediction in time series using univariate approach is best done by employing the ARIMA models (Alnaa et al., 2011). A stochastic process X_t is referred to as an Autoregressive Integrated Moving Average (ARIMA) [p, d, q] process if it is integrated of order "d" [I (d)] and the "d" times differenced process has an ARMA (p, q) representation. If the sequence $\Delta^d X_t$ satisfies an ARMA (p, q) process; then the sequence of X_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d X_t = \sum_{i=1}^{p} \beta_i \Delta^d X_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \quad (10)$$

The generalized ARIMA model is frequently used in empirical work because most variables, especially financial and economic variables are non-stationary.

3.4. Data

The data sets used in this paper are the historical data of the Rwanda's industrial electricity consumption in Kilowatt Hours (kWh) for the years 2000 to 2019 (Table 1). The datasets were obtained from the Rwanda Energy Group. Gross Domestic Product per capita (GDPC), Gross Capital Formation (GF), Industry Value Added (IV) and Population (POP) as economic data, were obtained from the World Bank's World Development Indicators (WDI) 2019.

4. FINDINGS

The regressions and forecasting, including all robustness tests were done using Eviews 7 software.

4.1. Unit Root/Stationarity Test

To start the co-integration analysis among the variables, the univariate properties of the data were first investigated. The underlying variables could be co-integrated only if each of them is stationary and integrated with the same order. The findings of stationarity test for all variables of the model are given in the following tables (Tables 2-6).

The Augmented Dickey-Fuller test is used for stationarity and shows that all variables include a unit root on their levels. While all variables include unit root as of their levels, all series become stationary as a result of taking their first difference to correct their serial correlation. This indicates that there are all integrated with order one, denoted as I (1). This implies that the variables could be co-integrated as each of them is stationary and integrated with the same order. This is because, if the time series do not follow the same order of integration, the estimated model can suggest no meaningful relationship among them.

4.2. Co-integration Tests

This study used the Johansen technique approach to test for long run relationship among variable through co-integration tests.

The results in Table 7 show that EC, GDPC, GF, IV and POP series are co-integrated and have a long run relationship, as the probabilities are less than 5%. This implies that the model can be used for forecasting.

4.3. Estimating Representative Equation

Regression results are presented in Table 8.

Representative equation

$$LN\ (EC) = -82.64 - 1.75*LN\ (GDPC) + 0.03*LN(GF) - 0.15*LN(IV) + 7*LN(POP)$$

4.4. Test of the Model Accuracy

To test the accuracy of the model, the residuals based approach is used. This approach consists of stationarity test of residuals from the estimated model. This implies that if the residuals are stationary at level, the model is accurate because the residuals of the model are not correlated over time (Table 9). Additionally, this involves also that the variables of the model are co-integrated and have a long run relationship. Thus implies that the model can be used for forecasting.

5. RESULTS AND DISCUSSION

- Model estimation results show that R-squared statistic is 0.985. Since R-squared of the regression is the proportion of the variation in the dependent variable that is predicted by the independent variables, this implies that GDPC, GF, POP and IV as explanatory variables in the model account for about 98.5 % of the variation in the dependent variable EC. Thus, the explanatory power of the model is high and appears to suggest that the included variables are good predictors of EC. F-statistic being significant implies that the overall goodness of fit of the model is satisfactory since Prob (F-statistic) is zero
- Meanwhile, considering the statistical significance of the coefficients, which could be judged from the Standard Error,

Table 1: Variable name, measurement, expected sign (based on underlying theory) and data source

Variable	Measurement	Expected sign	Data source
Electricity consumption in Industrial sector (EC)	kWh	-	Rwanda Energy Group (REG)
Gross Domestic Product per capita (GDPC)	US$	Positive or Negative	World Development Indicators (WDI)
Gross Capital Formation (GF)	US$	Positive or Negative	WDI
Industry Value Added (IV)	%	Negative	WDI
Population (POP)	-	Positive	WDI

Table 2: Stationarity test for electricity consumption variable

Null Hypothesis: D (LNEC) has a unit root		
Exogenous: Constant, Linear Trend		
Lag Length: 0 (Automatic - based on SIC, maxlag=4)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	–4.139765	0.0222

Table 3: Stationarity test for GDP per capita (GDPC) variable

Null Hypothesis: D (LNGDPC) has a unit root		
Exogenous: Constant		
Lag Length: 0 (Automatic - based on SIC, maxlag=4)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	–5.253754	0.0006

Table 4: Stationarity test for gross capital formation variable

Null Hypothesis: D (LNGF) has a unit root		
Exogenous: Constant		
Lag Length: 0 (Automatic - based on SIC, maxlag=4)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	–3.155956	0.0401

Table 5: Stationarity test for industry value added (IV) variable

Null Hypothesis: D (LNIV) has a unit root		
Exogenous: Constant		
Lag Length: 0 (Automatic - based on SIC, maxlag=4)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	–4.227023	0.0047

Table 6: Stationarity test for total population variable

Null Hypothesis: D (LNPOP) has a unit root		
Exogenous: Constant		
Lag Length: 1 (Automatic - based on SIC, maxlag=4)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	–12.33640	0.0000

Table 7: Johansen system co-integration test

Sample (adjusted): 2002–2019				
Included observations: 18 after adjustments				
Trend assumption: Linear deterministic trend				
Series: LNEC LNGDPC LNGF LNIV LNPOP				
Lags interval (in first differences): 1–1				
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.994272	201.0492	69.81889	0.0000
At most 1 *	0.969995	108.1255	47.85613	0.0000
At most 2 *	0.788507	45.01059	29.79707	0.0004
At most 3 *	0.582809	17.04646	15.49471	0.0290
At most 4	0.070226	1.310641	3.841466	0.2523

Trace test indicates 4 cointegrating eqn (s) at the 0.05 level. *Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) P-values

T-Statistic and the probability value of each coefficient, the results show that GDP per capita and population are statistically significant and therefore have great impact on electricity consumption of industrial sector. However, Gross capital formation and industry value added, have less impact as both variables are not statistically significant. However, Gross fixed capital has a positive impact and Industry value added has a negative impact on industry electricity consumption

- Gross domestic product per capita (GDPC) is statistically significant as its probability value is 0.0106. In other words, there is a 99% probability of being correct that GDPC variable is having effect on electricity consumption in the industrial sector of Rwanda. Unlike in most of the literature, GDPC has a negative effect on electricity consumption in the industrial sector (dependent variable). Based on the regression results, if GDPC increases by 1%, the electricity consumption in the industrial sector reduces by 1.75%. This can be attributed to the use of more modern and efficient technologies, and hence reduction in energy consumption. This was the same case in China after the oil price shocks in 1973/74 and 1979/80 (Berndt, 1990)

- The variable population (POP) is statistically significant as the probability value of its coefficient is zero. This means that there is a 100% probability of being correct that Population is having effect on electricity consumption in the industrial sector of Rwanda. The results show that if Population increases by 1%, the electricity consumption is expected to increases by 7%. This can be attributed to the fact that the increase in population means more people will purchase goods produced by the industrial sector, and hence increase in the electricity consumption as the industrial companies seek to meet the demands of the population

- The variable gross capital formation (GF) is not statistically significant as its probability value is 0.9. It means that there is 10% probability that GF influences industry electricity consumption. The estimated model shows that if GF increases by 1%, the EC increases by 0.03%. It is clear that this effect of change in GF to EC is negligible compared to the other variables. This can be attributed to the type of capital stock, which is being accumulated in Rwanda. It is likely more energy efficient capital through ICT and modern technology have been deployed, which reduces energy requirement for a given level of output

- Like GF, industry value added (IV) is not statistically significant. Its probability value is 0.35, which means that there is 35% of probability that IV influences industry electricity consumption. It is shown that if IV increases by 1%, the EC reduces by 0.15%. The negative sign that was expected is consistent with some of the literature (Berndt, 1990). This can be attributed to the growth in industrial efficiency through technological progress.

6. CHOICE OF THE FORECASTING MODEL

After checking each ACF, PACF plot and simulations, the search for the optimal model to be used is shown in the table X. The

Table 8: Regression results

Dependent Variable: LNEC				
Method: Least squares				
Sample: 2000 2019				
Included observations: 20				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−82.64103	11.66550	−7.084226	0.0000
LNGDPC	−1.757125	0.647253	−2.714744	0.0160
LNGF	0.031627	0.269643	0.117290	0.9082
LNIV	−0.147142	0.153799	−0.956717	0.3539
LNPOP	7.138558	0.878567	8.125229	0.0000
R-squared	0.985066	Mean dependent var		18.92573
Adjusted R-squared	0.981084	S.D. dependent var		0.452499
S.E. of regression	0.062235	Akaike info criterion		−2.503477
Sum squared resid	0.058098	Schwarz criterion		−2.254544
Log likelihood	30.03477	Hannan-Quinn criter.		−2.454883
F-statistic	247.3567	Durbin-Watson stat		1.516143
Prob (F-statistic)	0.000000			

Table 9: Stationarity test for residuals

Null Hypothesis: RESIDUALS has a unit root			
Exogenous: Constant			
Lag Length: 1 (Automatic - based on SIC, maxlag=4)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		−3.829471	0.0106
Test critical values:	1% level	−3.857386	
	5% level	−3.040391	
	10% level	−2.660551	

*MacKinnon (1996) one-sided P-values

Table 10: Simulations results

Model	AIC	SIC	RMSE	Theil inequality coefficient (U)
ARIMA (1,1,1)	34.76981	34.91893	6714	0.016
ARIMA (0,1,2)	38.76331	38.86288	8992	0.230
ARIMA (0,1,5)	38.99238	39.09196	8375	0.199
ARIMA (2,1,1)	37.26163	37.41002	32,300	0.948
ARIMA (2,1,2)	35.15098	35.29937	5824	0.123
ARIMA (2,1,3)	35.35191	35.50031	8249	0.201
ARIMA (2,1,4)	35.87350	36.02190	19,900	0.335
ARIMA (3,1,1)	37.91999	38.06702	15,000	0.488
ARIMA (3,1,2)	38.15872	38.30576	16,200	0.544
ARIMA (3,1,3)	35.48037	35.62741	3,139	0,073
ARIMA (3,1,4)	36.37713	36.52417	11,600	0.216
ARIMA (4,1,1)	37.63717	37.78203	6,669	0.134
ARIMA (4,1,3)	38.55401	38.69887	6,618	0.139
ARIMA (4,1,4)	38.32752	38.47238	6,527	0.1362

candidate model is selected based on the lowest Akaike Information criterion (AIC) value and is considered as the most appropriate model to be used in forecasting. Moreover, additional various forecasting validation tools and statistical metrics such as Schwarz information criterion (SIC), Root Mean Squared Error (RMSE) and Theil inequality coefficient (U) were considered in selecting the appropriate model for forecasting electric consumption. The results show that ARIMA (1, 1, 1) is the most appropriate model to be used for forecasting because the ARIMA (1, 1, 1) has the lowest AIC, SIC and U value as shown in Table 10.

The lower are AIC, RMSE, bias proportion and U, the better is the forecasting model. This means that actual Electricity consumption and the forecasted EC are moving together. If "U" is equal to zero, it means that there is a perfect fit and there is no error. If "U" equal 1 means that, the predictive power of the model is worst (Figure 1). Therefore, the "U" value, which is between 0 and 1, can be used to determine the best model. The best model is the one that has a "U" value that is closer to zero. The Figure 2, shows that this model has the bias proportion or systematic error, which is the gap between mean actual "EC" and forecasted "EC" is around 8% and it is considered to be very low.

EC line represents the actual values and ECF11 line represents the forecasted values. The way both lines are moving together further proves the accuracy of the forecast model. The Table 11,

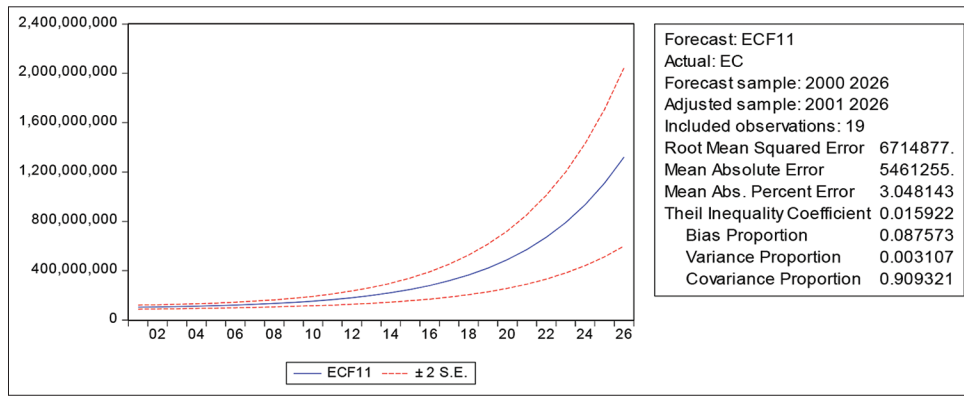**Figure 1:** Forecasting estimation and evaluation

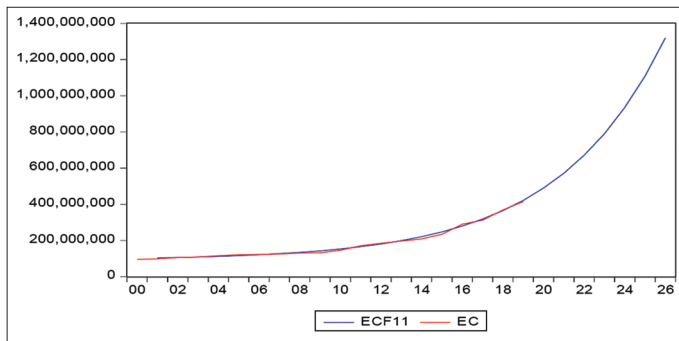**Figure 2:** Forecast graph from ARIMA (1, 1, 1)

Table 11: Forecasted values of electric consumption for industrial Sector in Rwanda

Year	Forecasts in kWh
2020	489,476,216
2021	571,653,518
2022	670,850,741
2023	790,592,919
2024	935,135,163
2025	1,109,613,869
2026	1,320,229,243

shows an increasing trend in projected values of electricity consumption (kWh) for industrial use from 2020 to 2026, which is evident. An expected electric consumption of 489,476,216 kWh is expected by the end of 2020 and 1,320,229,243 kWh by the end 2026. The specific forecasted values of electric consumption for industrial use in Rwanda for years 2020 to 2026 are shown in Table 11.

7. CONCLUSION AND POLICY IMPLICATIONS

This study uses hybrid model to forecast industrial electricity consumption in Rwanda and investigates the long run relationship between economic variables and industrial electricity consumption. ADF test have been applied to test for the unit roots of the variables, the results showed that all variables are integrated with order one, denoted I (1). This means that the variables could be co-integrated, as each of them is stationary and integrated with the same order. If the time series do not follow the same order of integration, the estimated model can suggest no meaningful relationship among them.

We used the Johansen technique and the Residuals based approach to test for long run relationship among industrial electricity consumption, economic growth, industrialization, industrial efficiency and population through co-integration tests. The outcomes showed that the variables are co-integrated with four co-integrating equations, which means that there is a long run relationship between the variables. The regression model estimation showed that Electricity Consumption in the industrial sector decreases with higher GDP per capita but increases with country population, while Gross Capital Formation and Industry Value Added are not statistically significant and hence have less influence on industrial electricity consumption.

Even if the predicted values of industrial electricity consumption showed an increasing trend for the forecast period (2020 to 2026), the electricity demand trend is still low compared to the expected electricity production of the same period. Therefore, policy makers should take into consideration the electricity consumption trend as well as other technological and economic factors influencing the electricity demand at the level of planning.

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