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Linear Regression and ARIMA Models for Electricity Demand Forecasting in West Africa

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

This article focuses on the predictive study of electricity demand in West African countries based on the multivariate linear regression model and the ARIMA model. The objective of the study is first to establish for each country a linear regression model and ARIMA model, then to compare the two (2) models based on the MAD, RMSE and MAPE coefficients, and finally to deduce of this comparison the best valid model to establish the electricity demand prediction of the country. We have come to the conclusion that the ARIMA model is more adequate for predicting the electricity demand of most of West African countries with the exception of Gambia, Ghana, Guinea, Liberia and Nigeria where the multivariate linear regression model performs better.

Keywords: ARIMA; demand; electricity; linear regression; model; prediction.

1. INTRODUCTION

In West Africa, more than 58% of the population (175 million people) do not have access to electricity despite the enormous resources of fossil fuels and renewable energies available. This situation make that the region lost 2% of its annual economic growth [1].

In order to achieve energy self-sufficiency before 2030, as recommended by the seventh Sustainable Development Goal (i.e. Guarantee access for all to reliable, sustainable and modern

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energy services , to a affordable cost), the West African energy system must be able to resolve the problem of financial insecurity and lack of investment in the energy sector, develop infrastructure for the production and transmission of electricity, resolve the problem of poor governance of energy companies and also resolve the problem of energy insecurity in the region [2].

The problem of energy insecurity is explained on the one hand by the dependence on oil imports for most West African countries and the inability of West African countries (like most developing countries) to be able to make better management of the global energy system of their countries [1,3].

The management of the energy system is intimately linked to planning. And to do better planning, you have to be able to predict future energy demands. In order to make our contribution in the planning of the West African energy system, in this article we propose linear regression and ARIMA models capable of predicting the electricity demand with the lowest margin of error.

2. LITERATURE REVIEW

Kim et al. [4] used linear regression model to predict the electricity consumption in a university building in the United States based on the occupancy rate and the environmental parameters (solar irradiation received by the building, the ambient temperature, etc.) of the building.

Tso et al. [5] also used a multivariable linear regression model to predict electricity consumption by sector in the city of Hong Kong in China.

Hong et al. [6] during the Gefcom 2012 competition, presented a very simple linear regression model to predict the electrical charge as a function of temperature, temporal variables (hour, day, month) and some interactions.

Ramanathan et al [7] developed a linear regression model for short-term electricity demand prediction and peak power prediction. Their model is based on previous data of electricity consumption and environmental parameters. With this model, they were able to establish a forecast between 4 p.m. and 40 p.m.

Vicenzo et al. [8] based on Italy's historical data of electricity consumption, GDP, GDP per inhabitant and population from 1970 to 2007, developed several multivariate linear regression models for the prediction in a first step of the electricity consumption in the domestic and non-domestic sector. In this study Vicenzo et al found that their model has better performance compared to the national (Italian) forecasting model which is a complex econometric model.

Aranda et al. [9] developed multivariate regression models for forecasting electricity consumption in the Spanish banking sector. Based on experimental data from 55 banks, they were able to develop three (3) multivariate regression models to predict respectively electricity consumption for the entire Spanish banking sector, electricity consumption for branches with little climatic impacts conditions in winter and those with major climatic impacts in winter.

Adeoye et al. [10] based on historical data from 1990 to 2015 (from the International Energy Agency and the US Energy Information Administration) of electricity consumption for the non-residential sector, GDP (from the Bank World) and the population (from the United Nations) of the ECOWAS countries, have established two (2) explanatory linear regression models of the annual electricity demand of the non-residential sector for all of these countries.

Ruch et al. [11], developed a simple linear regression model for the prediction of electricity consumption in a building taking into account only the temperature of the latter.

Tanveer et al. [12] used a nonlinear autoregressive model (NARM) to forecast medium and long-term electricity demand for energy management systems in utilities. Based on data from ISO-New England, the researchers established three models (including the nonlinear autoregressive model) for predicting electrical load before comparing their performance.

Jui-Sheng et al. [13] proposed models based on the use of time series. Indeed, they proposed categories of models, namely simple models (Moving average, ARIMA, linear regression, etc.), sets of models (combine several simple models) and hybrid models (which in addition to combining two (2) or several simple ones, use an optimization algorithm). The data used to establish their different models was collected on a smart grid system of a residence based in Xindian, Taiwan.

Nafil et al. [14] in their work on the prediction of Moroccan energy consumption, established three prediction models namely an exponential smoothing model, a temporal causality model and an ARIMA model. They used data from 1981 to 2016 to develop and validate their models. They used their models to predict energy consumption from 2017 to 2020. The results of evaluating the performance of the models nevertheless showed that the temporal causality model was much more interesting.

Prado et al. [15] used US energy consumption data from January 1973 to June 2016 to build long-term prediction models of US energy consumption. To develop and validate their models, they separated their data into two (2) parts. From January 1973 to July 2006 for model development and from July 2006 to January 2016 for model validation. In their work, they established two (2) categories of models, namely simple models and hybrid models. The AR model, the MA model, the ARMA model, the genetic algorithms, the artificial neural networks, the fuzzy interference systems (FIS) etc. are the simple models that they have developed and their hybrid models come from the combination of simple models. Thus, they developed ARMA-ANN, ARMA-FIS etc. models. To assess and compare the relevance of their different models, their results were evaluated based on the MSE and MAPE coefficients.

Wang et al. [16] developed three prediction models based on time series to forecast energy demand in China and India. These are indeed ARIMA models, ARIMA-MGM (Rolling metabolic gray model) and NMGM (non-linear metabolic gray model) being respectively linear, hybrid-linear and non-linear time series techniques.

Kaytez [17] in his work used a hybridization of the ARIMA model and the support vector machine (SVM) model to establish a net electricity demand forecasting model in Turkey. He compared his model with three other models of multiple linear regression and ARIMA model that he himself developed as part of his work and also compared his model with official predictions and other similar studies. He used, six categories of data from different sources and ranging from 1970 to 2017. The data was then separated into three parts (85% data for training his model, 11% for model validation and 4% for the evaluation of its model). He finally used his model to predict Turkey's net electricity consumption from 2017 to 2022.

Vu et al. [18] have in their study, developed an autoregressive model integrating a data adjustment algorithm to make the short-term prediction of the electricity demand. By testing their model on data from New South Wales (Australia), they found that their model has a lower error term than the artificial neural network model, the AR model, the ARMA model, the PARMA model and the naive model. In terms of performance, even though their model turns out to have the same performance as an ARMA model, the researchers believe that their model is preferable considering that it does not need to include many sub-models to follow the variation of the load in different seasonality.

In [19] Die et al realized a hybrid ARIMA and SVM (Support Vector Machine) model. The ARIMA model is used to simulate and forecast daily electrical power demands and the SVM model to correct the imperfections of the ARIMA model. The model was then applied to data from Heilongjiang Electricity Company in China with a MAPE of 3.85% and RMSE of 35.72.

3. MATERIALS AND METHODS

3.1 Multivariate Regression

Linear regression is a mathematical method making it possible to model a physical phenomenon by establishing a linear function to predict this physical phenomenon. It is a model which generally consists in explaining an endogenous variable from a series of variables called explanatory variables. The function itself (endogenous variable) is called “regression model” and other independent variables (explanatory variables) of the function are called “regressors” [20].

A regression model contains a number of parameters called "regression coefficients", which are chosen to minimize the deviation between the actual values and the values predicted by the model [20].

The method of least squares is often used to estimate linear regression models. There are generally two types of linear regression models: the simple regression model and the multivariate regression model.

A simple linear regression model uses a single explanatory variable. It can be written in the following form:

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (1)$$

y represents the explained variable, x the explanatory variable, (β_0, β_1) the model parameters and ε the error.

The multivariate linear regression model on the other hand uses two (2) or more explanatory variables. Its scalar form is given by the following equation:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \varepsilon_i \quad (2)$$

In equation (2) yi is the endogenous variable and the xi, k the explanatory variables.

In the case of electricity demand prediction, it is the variable y that is electricity demand.

3.2 The Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARMA) model results from the combination of the Autoregressive (AR(p)) model and the Moving Average (MA(q)) model. It is generally expressed as follows [21]:

$$\tilde{Z}_t = \varphi_1 \check{Z}_{t-1} + \varphi_2 \check{Z}_{t-2} + \cdots + \varphi_p \check{Z}_{t-p} + a_t + \vartheta_1 a_{t-1} + \vartheta_2 a_{t-2} + \cdots + \vartheta_q a_{t-q} \quad (3)$$

It can also be rewritten as follows:

$$\varphi(B)\check{Z}_t = \vartheta(B)a_t \quad (4)$$

In this last equation, B represents a lag operator.

The ARMA model has the particularity of combining the advantages of the AR model and the MA model. It depends not only on previous system inputs but also on previous system outputs [20]. It also allows time series to be represented with fewer parameters than an AR model.

In general, the ARMA model is only applicable to stationary series. But for series with a trend, that is to say non-stationary series, the ARMA process is not able to model them. To be able to do this, an integrating process must be integrated into the ARMA model and this makes it possible to obtain the Autoregressive Integrated Moving Average (ARIMA) model [21,20].

In the ARIMA model, p represents the number of autoregressive parameters, q represents the moving average parameter and d the number of passes to be performed [21]. The ARIMA model can be written as follows:

$$\varphi(B)\Delta_d \check{Z}_t = \vartheta(B)a_t \quad (5)$$

3.3 Assessing the Model's Prediction Accuracy

The evaluation of the relevance of a linear regression model or any other statistical or computational forecasting model is linked to a certain number of parameters or coefficients including the coefficient of determination of the MAD, the MAPE and the RMSE.

3.3.1 The mean absolute deviation (MAD)

The mean absolute deviation (Mean absolute deviation (MAD)) makes it possible to evaluate in absolute value, the average of the difference between the predicted value and the measured value. Being the absolute value of the average error (difference between predicted value and measured value), it only considers the dimension of the error without taking into account its polarity (unlike the error) [22]. It is given by the following equation:

$$MAD = {(\sum|Predicted\ value - Measured\ value|)}/{n} = {(\sum|Error|)}/{n} \quad (6)$$

3.3.2 Mean squared error (MSE)

The MSE (Mean Square Error) represents the average of the squared errors. Its use makes it possible to eliminate the problem of the difference in polarity as at the level of the MAD [22]. The disadvantage resulting from its use is that its square function penalizes large errors. It is given by the following relationship:

$$MSE = {\sum(Predicted\ value - Measured\ value)^2}/{n} \quad (7)$$

3.3.3 Mean absolute percent error (MAPE)

The MAPE (Mean Absolute Percent Error) makes it possible to calculate the average of the absolute errors and then to express the percentage of this value as a percentage of the real values expressed. The advantage of MAPE is that the percentage error from the actual value is reflected. However, the use of MAPE is not suitable for data whose real value is zero or close to zero as we can observe in the following equation [22]:

$$\mathrm{MAPE} = \left({}^{100}/_{n}\right) \sum_{t=1}^{n} \left\lfloor {}^{(A_t - F_t)}/_{A_t} \right\rfloor \qquad (8)$$

With n the number of observed values, A_t the current value and F_t the predicted value.

It should be noted that the MAPE values are between -200% and +200%.

3.4 Application of the Linear Regression and ARIMA Models to the Electricity Demand in West African Countries

A country's demand for electricity is closely linked to a certain number of variables which are of a macroeconomic and technological nature. For example, the International Atomic Energy Agency in its Model for the Analysis of Energy Demand (MAED) offers a demand forecasting model for the different types of energy (electricity, fossil fuels, etc.). which takes into account:

- Socio-economic variables that characterize and describe the economic and social development of the country;
- Technological variables related to the performance of the energy transfer process of the type of energy considered in the country.

Thus, as part of our present study, specifically related only to the prediction of electricity demand, we will consider for all fifteen (15) West African States:

- Two (2) macroeconomic variables: Gross Domestic Product (GDP) and population;
- A technological variable: the annual electricity demand.

3.4.1 Data

To establish our model, the data used was obtained from the open-source databases of international organizations such as the World Bank and United State Energy Information Administration (US EIA).

- Electrical energy demand data: Electrical energy demand data for all of the fifteen (15) West African countries (Benin, Burkina Faso, Cape Verde, Ivory Coast, Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo) come from the US EIA database. This is the annual electricity consumption from 1980 until 2018 and the losses on the electricity networks during the same period. All of these data can be consulted in [23];
- Demographic change data: The demographic change data that we used in this work comes from the World Bank's Open Source database. All of these data are available at [24] and show the evolution of the population of the various West African countries from 1980 to 2018 (i.e. the same period as that of the energy consumption values);
- GDP data: The Gross Domestic Product data that we used in this work come from the World Bank's Open Source database. All of these data are available at [25] and show the evolution of the GDP of West African countries from 1980 to 2018 (i.e. the same period as that of the values of energy consumption and demographic evolution).

3.4.2 Prediction algorithm for linear regression

To be able to set up these different models, we used the historical data of the West African countries mentioned above, namely electricity consumption, GDP and population. So we go chronologically:

- Define the model equation. This equation is a multivariate linear regression equation whose explanatory variables are GDP and population. The explained variable being the annual electricity consumption;
- Separate the data, having a train set and a test set;
- Develop the regression model based on the train set;
- Use the model to predict test set data.
- Evaluate model performance with MAD, RMSE and MAPE coefficients;
- If the results of the model are satisfactory then the model is valid. Otherwise, it is

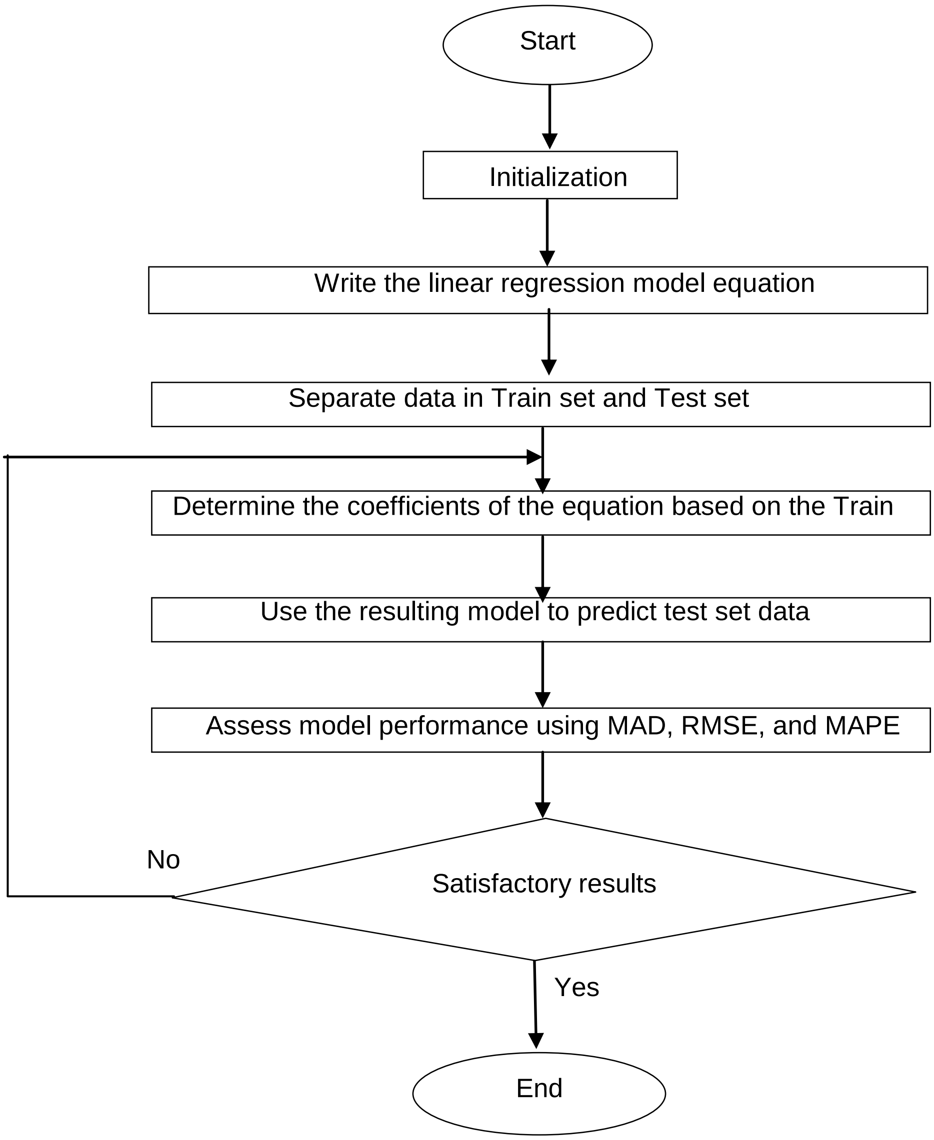

Fig. 1. Algorithm of linear regression model

necessary to redo the determination of the coefficients of the regression equation.

Fig. 1 illustrates the linear regression modeling methodology

3.4.3 Prediction algorithm for the ARIMA model

For our ARIMA model, we used only the annual electricity consumption to make the prediction. The annual electricity consumption being a time series, for each ARIMA model we will successively:

- Check whether the time series (historical electricity consumption data) is stationary, by performing a trend and seasonality test;
- Estimate model parameters;
- Test the significance of the parameters, the whiteness of the residues and normality;
- Separate data into train set and test set;
- Train the model on the train set;
- Use the model to predict test set data;
- Evaluate model performance with MAD, RMSE and MAPE coefficients;
- If the results of the model are satisfactory then the model is valid. Otherwise, it is necessary to redo an estimation of the parameters of the model.

The following graph illustrates this methodology of modeling by the ARIMA model.

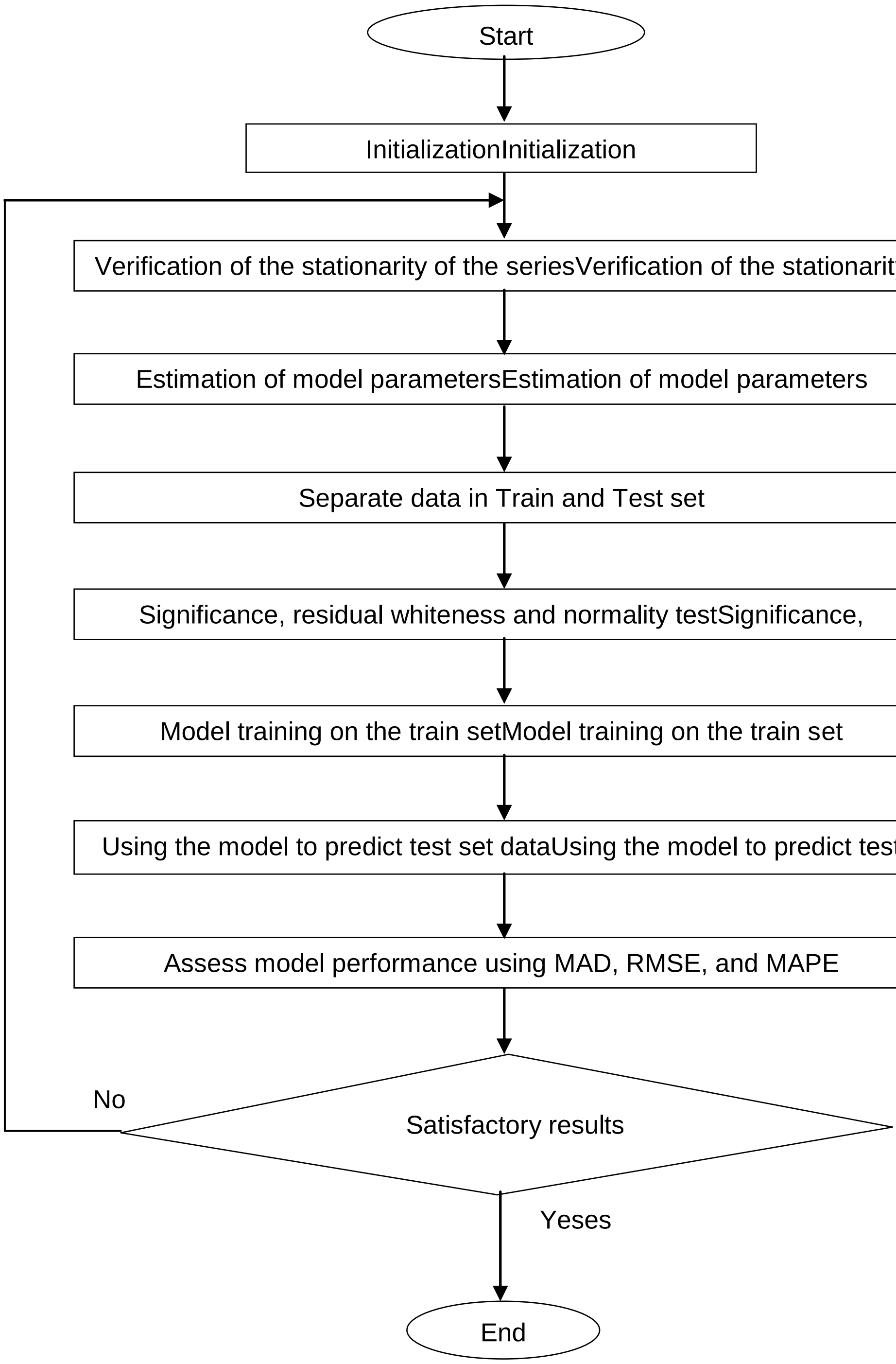

Fig. 2. Modeling algorithm based on the ARIMA model

4. RESULTS AND DISCUSSION

By applying these algorithms to the data of the annual electricity consumption we obtain the linear regression and ARIMA models with their efficiencies evaluated with the MAD, the MAPE and the RMSE. These algorithms have been implemented in the Python programming language especially in Scikit-learn library.

In Table 1, E represents the annual electricity consumption in Terawatt hours, POP the population in thousands of people and GDP the Gross Domestic Product in billions of US dollars.

If we make a comparison of the two (2) models established for each country, we deduce that for:

- Benin, Burkina Faso, Cape Verde, Ivory Coast: an ARIMA model (0, 2, 1) is more suitable for forecasting electricity demand because it presents the best performance compared to the models of linear regression;
- The Gambia: a linear regression model based on population and GDP is more appropriate. With the model given by the following equation:

$$E=0.18432216POP-0.00430332GDP-0.10431705 \quad (9)$$

Table 1. Multivariate regression models for electricity demand prediction in West Africa

Country	Multivariate Regression Model	MAD	MAPE	RMSE
Benin	E=0.04542877POP+0.07135319GDP-0.12686735	0.13	9.86	0.14
Burkina Faso	E=0.05955882POP+0.04099685GDP-0.42264437	0.31	19.55	0.33
Cape Verde	E=0.55734255POP+0.12724713GDP-0.17738849	0.092	20.93	0.094
Ivory Coast	E=0.14556033POP+0.11556113GDP-0.55597784	0.66	8.25	0.74
Gambia	E=0.18432216POP-0.00430332PIB-0.10431705	0.007	2.53	0.008
Ghana	E=0.30220902POP+0.05364103GDP+0.15498704	1.1	10.14	1.17
Guinea	E= 0.17747518POP-0.0812997GDP-0.40871548	1	49.55	1.12
Guinea Bissau	E=0.09356441POP-0.07134323PIB-0.04855777	0.008	19.6	0.01
Liberia	E=0.03241799POP+0.02392334GDP+0.08210438	0.043	11.99	0.05
Mali	E=-0.00474329POP+0.13687904GDP-0.03984079	0.78	27.89	0.85
Niger	E=0.01713791POP+ 0.06657688GDP+0.01559852	0.27	18.66	0.32
Nigeria	E=0.1944412POP+0.00039546GDP-6.71294107	2.5	7.77	2.52
Senegal	E=0.1292051POP+0.07364414GDP-0.66449418	0.75	21.1	0.76
Sierra Leone	E=-0.06076161POP+0.04789949GDP+0.37640422	0.09	38.53	0.1
Togo	E=0.16517109POP-0.00869743GDP-0.1750358	0.36	23.94	0.42

Table 2. ARIMA models for electricity demand prediction in West Africa

Country	ARIMA	MAD	MAPE	RMSE
Benin	(0,2,1)	0.043	3.29	0.05
Burkina Faso	(0,2,1)	0.116	6.95	0.14
Cape Verde	(0,2,1)	0.024	5.55	0.027
Ivory Coast	(0,2,1)	0.42	5.29	0.44
Gambia	(0,2,1)	0.045	15.24	0.05
Ghana	(0,1,1)	1.9	17.68	2.06
Guinea	(0,1,1)	1.17	55.64	1.32
Guinea-Bissau	(1,0,0)	0.005	13.35	0.006
Liberia	(0,1,0)	0.11	30.19	0.13
Mali	(1,2,4)	0.45	17.35	0.47
Niger	(2,2,1)	0.14	9,12	0.21
Nigeria	(1,1,0)	2.7	8.34	2.76
Senegal	(0,2,2)	0.28	7.78	0.29
Sierra Leone	(1,0,0)	0.054	24.47	0.06
Togo	(0,1,2)	0.372	24.86	0.44

- Ghana: a linear regression model based on population and GDP is more appropriate. With the model given by the following equation:

$$E=0.30220902POP+0.05364103GDP+0.15498704 \quad (10)$$

- Guinea: a linear regression model based on population and GDP is more appropriate. With the model given by the following equation:

$$E= 0.17747518POP-0.0812997GDP-0.40871548 \quad (11)$$

- Guinea Bissau: an ARIMA model (1,0,0) or quite simply an Autoregressive model with a coefficient p equal to 1 is more suitable for forecasting electricity demand;

- Liberia: a linear regression model based on population and GDP is more appropriate. With the model given by the following equation:

$$E=0.03241799POP+0.02392334GDP+0.08210438 \quad (12)$$

- Mali and Niger: respectively an ARIMA (1, 2, 4) and ARIMA (2,2,1) model are more suitable for forecasting electricity demand;

- Nigeria: a linear regression model based on population and GDP is more appropriate. With the model given by the following equation:

$$E=0.1944412POP+0.00039546GDP-6.71294107 \quad (13)$$

- Senegal, Sierra Leone and Togo: respectively an ARIMA (0, 2, 2), ARIMA (1, 0, 0) and ARIMA (0, 1, 2) model are more suitable for forecasting demand for electricity.

5. CONCLUSION

Predicting a country's electricity demand enables better management of the global energy system. And for West African countries, we were interested in establishing two models capable of making this prediction of electricity demand. We therefore established for each of the West African countries, a linear regression model and an ARIMA model and then we compared the two models.

For some states in the region, it is more interesting to use the linear regression model while for others, it is the ARIMA model. These models will therefore be used to predict the future electricity demand of these countries and could also be used to predict the electricity demand of other countries in sub-Saharan Africa.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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