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Investigating the Impact of Electric Power Production on Economic Growth in the Sub-Saharan African (SSA) Countries.

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ABSTRACT

The main objective of the study was to investigate the impact of the selected three (3) sources of electricity production namely electricity production from hydroelectric sources (% of total), electricity production from natural gas sources (% of total) and electricity production from oil, gas and coal sources (% of total) on economic growth in Sub-Saharan African. This is to help cope with the increasing electricity demand and to overcome the distribution shortage of electricity and advise policy makers based on the findings. Annual time series data from the world development indicator (WDI) ranges from 1993 to 2022 on forty-one (41) Sub-Saharan African countries were obtained and treated in this study as a panel data analysis. Majority of the empirical work done relied on the electricity consumption by using traditional or classical models but this study explored on machine learning models which makes it unique from other works. The study used XGBoost model and multilayer perceptron model. The multilayer perceptron model was discovered as the best model. Out of it variable importance analysis, it was revealed that electricity production through natural gas is the major source which contribute significantly to economic growth within the Sub-Saharan African. Policy makers needs to invest towards modern economy electricity generation such as natural gas source, solar among others to generate electricity.

1. INTRODUCTION

Sources of power generation continues to be a major challenge in Sub-Saharan African despised many reforms in the energy sector around the globe. In the past decades, Sub-Saharan African countries have experienced an improvement with their economic growth. Due to the persistent increase in population within the Sub-Saharan African, it has increased electricity demand which has resulted in distribution shortage. This is a major issue that does not attract investment hence affecting economic growth in the long run. Most of the work done concentrated on electricity consumption level. This study investigated the impact of the three main source of electricity production on economic growth in Sub-Saharan African and advised policy makers on the need to channel more resources to that area. Ogundipe (2013) in the study investigated the impact of electricity consumption and economic growth in Nigeria. The study revealed that there is a significant impact of electricity consumption on the Nigerian economy. Similarly, another study examines the causal relationship between CO_2 emissions, economic growth, financial development, and energy consumption for South Africa between 1971 and 2012. Based on the results, it was added that policy-makers should formulate concrete plans to boost investment in the electricity sector to ensure reliability of supply to consumers (Bah and Azam, 2017).

Smagulova et al. (2024) in the study investigated the impact of electricity production on economic growth in Kazakhstan. The study revealed that the main source of electricity generation mainly comes from thermal power plants

using coal. The study advised to increase funding for the development of nuclear power plants, new renewable energy facilities, and cutting-edge power plants. Alhassan (2017) in the study model the impact of electricity generation and economic growth in Ghana using Autoregressive Distributed Lag Model (ARDL) bounds testing of cointegration and Granger causality. It was revealed that the electricity generation affects economic growth in the long run. Yoo and Kim (2006) in the study investigated the relationship between electricity generation and economic growth in Indonesia. The study used time-series techniques for the period of 1971 to 2002. The study revealed that countries investing towards modern economy electricity generation, and consumption grows in all sectors.

Based on the 2019 United Nations (UN) population report, Africa will account for over half of global population growth between now and 2050. With that, the population of Sub-Saharan Africa is estimated to double by 2050. Over the years, the region's population is anticipated to increase, while other regions are anticipated to have a decline rate. The majority of empirical research concluded that population growth has a negative effect on economic growth. This put a major threat on the power supply which needs to be addressed well. The source of electricity production is highly dominated by the hydroelectric sources in Sub-Saharan Africa.

This study investigated how the three main selected electricity source namely electricity production from hydroelectric sources (% of total), electricity production from natural gas sources (% of total) and electricity production from oil, gas and coal sources (% of total) contribute to economic growth in Africa.

2.0 METHODOLOGY

2.1 Data Source and Variables in the Study.

This study sourced annual time series data from the world development indicator (WDI) ranges from 1993 to 2022 on forty-one (41) Sub-Saharan African countries treated in this study as a panel data analysis. Three (3) source of electricity production namely electricity production from hydroelectric sources (% of total), electricity production from natural gas sources (% of total) and electricity production from oil, gas and coal sources (% of total) were used to model their impact on economic growth in Sub-Saharan African.

The countries that were used are Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Comoros, Dem. Republic of Congo, Republic of Congo, Cote d'Ivoire, Equatorial Guinea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Uganda, Zambia and Zimbabwe. The number of countries and variables are selected based on the data availability.

2.2 Dependent variable

Gross Domestic Product (GDP): GDP is the total income earned through the production of goods and services in an economic territory during an accounting period (WDI, 2022).

2.3 Independent variable

1. Electricity production from hydroelectric sources (% of total). The share of electricity production from hydroelectric sources of total electricity production. Sources of electricity refer to the inputs used to generate electricity. Hydropower refers to electricity produced by hydroelectric power plants.

2. Electricity production from natural gas sources (% of total). The share of electricity production from natural gas sources of total electricity production. Gas refers to natural gas but excludes natural gas liquids.

3. Electricity production from oil, gas and coal sources (% of total).

2.4 Neural Network

Neural networks (NNs) are very useful for assessing complex non-linear relationship. Haykin (1998) confirmed that the basic principles that underline the function of the human brain serve as the foundation for artificial neural networks. It has been proven in many studies that feed-forward neural networks can approximate any continuous function of many real variables arbitrarily well (Hornik, 1991). Neural networks have been shown to forecast well and have a good ability to approximate complex nonlinear functions. However, because they do not allow for descriptions of the relationships in the data, they are frequently criticized as being unintelligible or a "black box".

It was revealed in the study that neural networks are able to model data that is insufficient (Aiken, 1996). Missing data is a major issue with other methods. Despite the lack of some of the necessary components for the analyses, neural networks can provide an accurate model with a level of acceptable error tolerance information. Zhang et al. (1998) for modeling and predicting chronological data sets, the most widely used model is an artificial neural network. It uses activation functions.

2.4.1 Activation functions (AF)

ANN uses AF in achieving the output. Some activation functions

2.Sigmoid (Logistic AF)

It is often used for models which we intend to forecast the probability as

output. Mathematically is represented as

$$\phi(z) = \frac{1}{1+e^{-z}} \quad (1)$$

where ;

$$z = \sum_{i=1}^{n} w_i x + b_i$$

X_i are the input signals

w_i are weights associated to the input signa

b_i are the biases

2.ReLU (Rectified Linear Unit) activation function.

The ReLU is the most used activation function. It is used in almost all convolution neural networks in hidden layers only. The ReLU is half rectified (from bottom). It avoids vanishing gradient problem.

2.4.2 Cross-validation

The cross-validation (CV) scheme comprises of selection on the overall architecture of the neural network including the total number of layers (L), neurons (M), the learning rate (ρ) of SGD, the batch size, dropout rate, the hidden parameters, and a choice on the activation functions. The activation function can be hyperbolic tangent activation function for the hidden layers and a linear function for the output layer. The selection between deep or shallow learning is completely data-driven, as it is selected from the CV scheme (Chronopoulos et al., 2023).

2.4.3 Multi-layer perceptron regression model (MLP).

A single perceptron (LP) has certain limitations in terms of input-desired output mapping capability. This limitation occurs since it only contains a single neuron per adaptable synaptic weights and bias (Josepha and Ojuhb, 2020). Multi-layer Perceptron (MLP) is fully connected feed forward networks. With this type of neural network, the training is usually performed by error back-propagation or a related procedure. With MLP there is one or more hidden layers between the input and output layers. It is able to learn non-linear problems.

2.4.4 Extreme gradient boosting regression model

This is an ensemble model that is base on boosting. It consists of a sequential series of models, each model trying to improve the errors of the previous one. It can be used for both regression and classification tasks. This study focused on the regression part. In boosting, an initial model is fit to the prepared panel data. Then a second model is built on the results of the first one, trying to improve the inaccurate results of the first one, and so on until a series of additive models is built, which together are the ensemble model. The individual models are generally know as weak learners, which means that they are simple models with low predictive skill. The algorithm of the XGBoost basically have the form,

Set a Fixed value as the model's starting point.

$$F_0(x) = \arg\min_y \sum_{i=1}^{n} (Y, \overset{:}{y}) , \qquad (2)$$

where Y is a value as observed, and $\overset{:}{y}$ is a value as predicted. $F_0(x)$ is the average of the observed.

2.5 Model Evaluation Techniques

The study used the following model evaluation techniques in accessing the performance accuracy of the models.

2.5.1 R-squared (R^2)

R-squared (R^2) or coefficient of determination is a statistical measure that determine or provide information about the goodness of fit of a model. For instance when R^2 computed is 1, it means that all the variations in the dependent variables is accounted for by the predictors, when it is 0 it implies that non of the variation in the dependent variable is accounted for by any of the independent variables and when is 0.60 means that 60% of the variation in the dependent variable is accounted for by the predictors.

2.5.2 Mean squared error (MSE)

This gives the average squared difference between the expected and actual values of the target variable. Mathematically is represented as:

$$MAE = \frac{\sum_{t=1}^{n} (Y_t - X_t)}{n} , \qquad (3)$$

Where Y_t is the predicted value, n is the number of observations the training dataset and X_t is the true value.

2.5.3 Root mean squared error (RMSE)

It is the mean squared discrepancy between the values predicted by the model and the actual outcome values that were observed. Mathematically is represented as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \bar{Y}_t)^2}{n}}, \quad (4)$$

Where Y_t is the predicted value, n is the number of observations in the training dataset and $\bar{Y}_t$ is the mean.

2.5.4 Mean absolute percentage error (MAPE)

This measures the error. It is the mean absolute discrepancy between actual and anticipated results. MAPE is less sensitive to outliers as compared to RMSE. Mathematically is;

$$MAPE = \frac{\sum_{t=1}^{n}\left(\frac{Y_t - \ddot{Y}_t}{Y_t}\right)}{n} \times 100, \quad (5)$$

Where Y_t is the fitted value and $\ddot{Y}_t$ is the mean.

2.6 Variable Importance Analysis

Variable importance is a technique that measures the contribution of each feature to the end outcome prediction based on the Gini impurity (Kuhn et al., 2013). This is very crucial in most analysis because it gives enough evidence for researchers to know which variables is more significant and how they contributes to the dependent variables.

Under the XGBoost variable importance, the gain column represent the improvement in accuracy which is brought by a variable to the branches it is on. It basically measures the relative contribution of each independent feaures towards the dependent feature used in a study.

Frequency is simpler way of measuring the gain. The idea behind is that, its counts the number of times a feature is used in all generated trees.

3.0 RESULTS AND DISCUSSIONS

The study used the median approach in filling the missing values in the data since median is not affected by outliers hence gives accurate results for this data than the mean.

3.1 Descriptive statistics

Table 1 and Table 2 presents the descriptive statistics such as means, standard deviation, minimums and maximums for all the variables in the data. Forty-one (41) Sub-Saharan African countries were considered. The normality of the variable distribution is evaluated using the skewness and kurtosis measurements.

From Table 1 and Table 2, the average GDP growth is 4.248 % with a standard deviation of 7.9576. GDP growth is positively skewed(skewness value of 6.970) and leptokurtic in nature(kurtosis value of 121.00). The minimum value of GDP is -50.2481% recorded by Rwanda in 1994 whilst the maximum GDP is 149.973% recorded by Equatorial Guinea in 1997.

From Table 1 and Table 2, electricity produced through hydroelectric source average is 51.5875% with a standard deviation of 34.5535. It is negatively skewed (skewness value of -0.124) and platykurtic in nature (kurtosis value of -1.270). The minimum value is 0 and the maximum value is 100% which were recorded by more than three countries.

From Table 1 and Table 2, electricity production from oil, gas and coal sources (OGC) average is 45.354% with a standard deviation of 34.0896. It is positively skewed (skewness value of 0.172) and platykurtic in nature (kurtosis value of -1.270). It minimum value is 0 and a maximum value of 100% recorded by more than three countries.

From Table 1 and Table 2, electricity production from natural gas averaged 9.197%. It is positively skewed (skewness value of 2.340)

and leptokurtic in nature (kurtosis value of 4.27). The minimum value is 0 and a maximum value of 94.1624% which was recorded by Equatorial Guinea in 2011.

Table 1: Descriptive statistics

Variable	Observation	Mean	Std. Dev.	Kurtosis	Skewness
GDP Growth:					
Overall	1230	4.248	7.9576	121.0000	6.9700
Between	41		2.4488		
Within	30		7.5807		
Hydroelectric sources:					
Overall	1230	51.5875	34.5535	-1.2700	-0.1240
Between	41		30.7013		
Within	30		16.5413		
OGC:					
Overall	1230	45.354	34.0896	-1.2700	0.1720
Between	41		28.4954		
Within	30		19.2166		
Natural gas source:					
Overall	1230	9.197	20.7239	4.2700	2.3400
Between	41		17.2856		
Within	30		11.7361		

Table 2: Descriptive statistics (continued)

Variable	Minimum			Maximum		
	value	country	year	value	country	year
GDP Growth	-50.2481	Rwanda	1994	149.973	Equatorial Guinea	1997
Hydroelectric sources	0			100		
OGC	0			100		
Natural gas source	0			94.1624	Equatorial Guinea	2011

3.2 Scatter Plot, to ascertain the relationship between the variables.

This visual representations depict the relationship between two of the variables. From Figure 1, it is clear that the scatter plot of the variables does not show any sign of linear relationship between the variables. Non of the independent variables used in this studies have a linear relationship with the dependent variable (unemployment rate).

Based on the non linearity evidence from the result, this study used the "reg:gamma" which is the gamma loss function as the objective in fitting the XGBoost model. In reality this kind of objective is preferred in modeling continuous dependent variables with a non-linear relationship. The gamma loss function is more robust to outliers than the mean squared error when conducting a study of this nature.

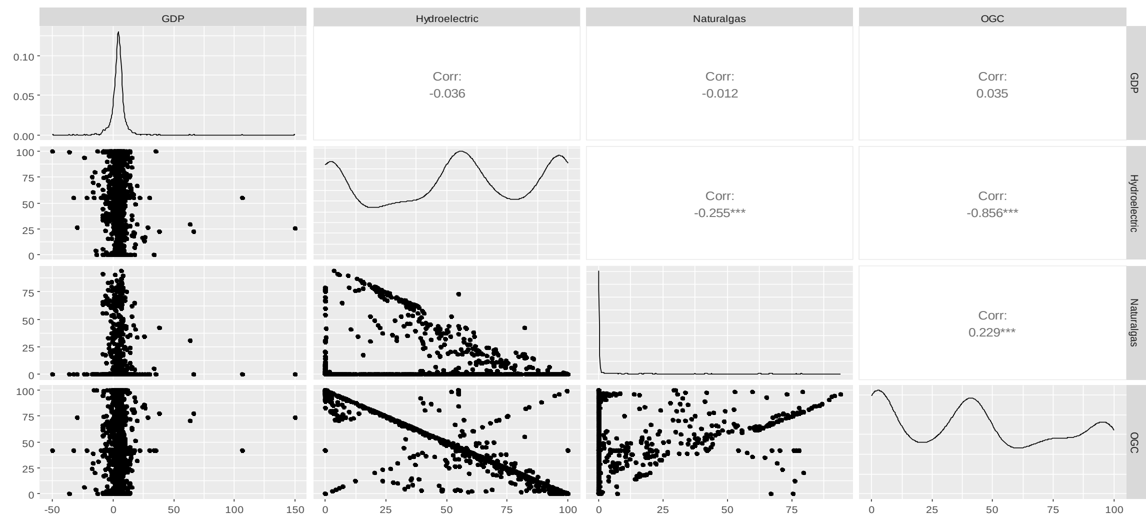

Figure 1: Preliminary analysis plot

3.3 MultiLayer Perceptron (MLP) Results.

3.3.1 Parameter selection and algorithm flow for the MultiLayer perceptron (MLP) algorithm.

The main package used is the RSNNS. In the implementation stage, first an excel file containing the raw panel data was first read via the read-xlsx method. The various features and labels were then standardized using the MinMaxScaler. After that, the data set was then split into train set and test set using the train-test-split method for subsequent model training and evaluation which were 70% for train and 30% for test. A multilayer perceptron model containing fully connected and MLP layers was constructed and trained using the training set. During training, the parameters for the initialization function was set to be "c(-0.3, 0.3)" which was varied, the learning function used was "Std-Backpropagation", the activation function of the output units was set to linear.

3.3.2 MultiLayer perceptron (MLP) results.

Table 3 shows the results of some parameter value of the multilayer perceptron model that was tried with their respective iteration plot which followed the table. From the Table 3, at the high epochs 200, 400 and 700 the test MSE were 1.9169, 1.9039 and 1.9159 respectively. AT the same epochs, the test set MAPE were 2.0731, 2.0466 and 1.8053 respectively. From this result, it can been seen that both MSE and MAPE values keep on reducing as the number of epochs keep increasing which is a sign that the model is likely to perform well on the unseen data. But from Figure 4, Figure 5 and Figure 6 which represent the iteration error plot for epoch 200, 400 and 700 respectively, it can be seen that there is a high possibility of the issue of overfitting and underfitting.

From Table 3, epoch 150 yield the best result with no sign of overfitting which was confirmed by it iteration error plot in Figure 3. It has a positive train set correlation of 0.0651 and a weak negative test set correlation of -0.0518. It has a train and test sets MSE of 5.6341×10^{-5} and 0.001101 whilst it has a train and test set MAPE of 2.0885 and 1.9648 respectively.

Table 3: MLP parameter values checked

Parameters	100 Epoch	**150 Epoch**	200 Epoch	400 Epoch	700 Epoch
Hidden-dim	(5, 2)	(5, 2)	(5, 2)	(5, 3)	(8, 4)
Int. Func. Param.	(-0.3 ,0.3)	(-0.5 ,0.5)	(-0.3 ,0.3)	(-0.3 ,0.3)	(-0.5, 0.5)
Learning rate	0.01	0.05	0.01	0.02	0.05
Train Set Cor.	0.0656	0.0651	0.0421	0.0458	0.0671
Test Set Cor.	-0.0474	-0.0518	0.0286	0.0279	-0.0401
Train MSE	8.9437×10^{-5}	5.6341×10^{-5}	5.4315×10^{-5}	1.5200×10^{-5}	1.5886×10^{-6}
Test MSE	0.0011	0.001101	0.0012	0.0012	0.0010
Train MAPE	2.1736	2.0885	1.9169	1.9039	1.9159
Test MAPE	2.0484	1.9648	2.0731	2.0466	1.8053

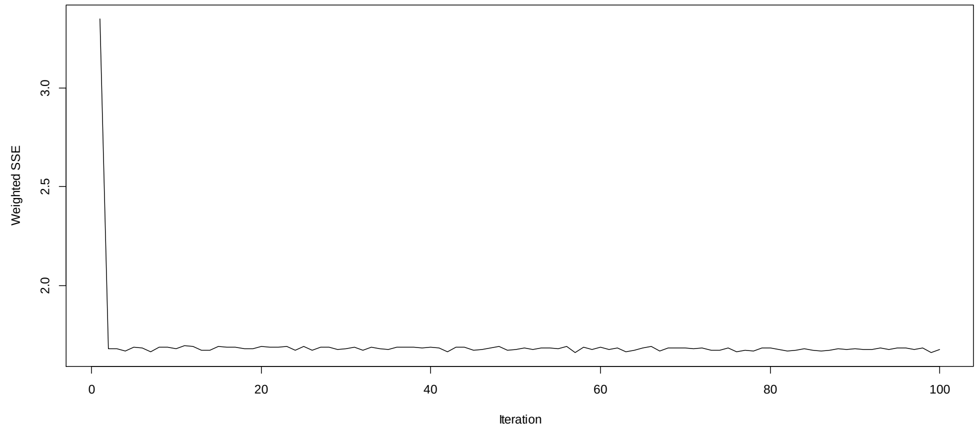

Figure 2: Iteration error (100epoch, (5, 2))

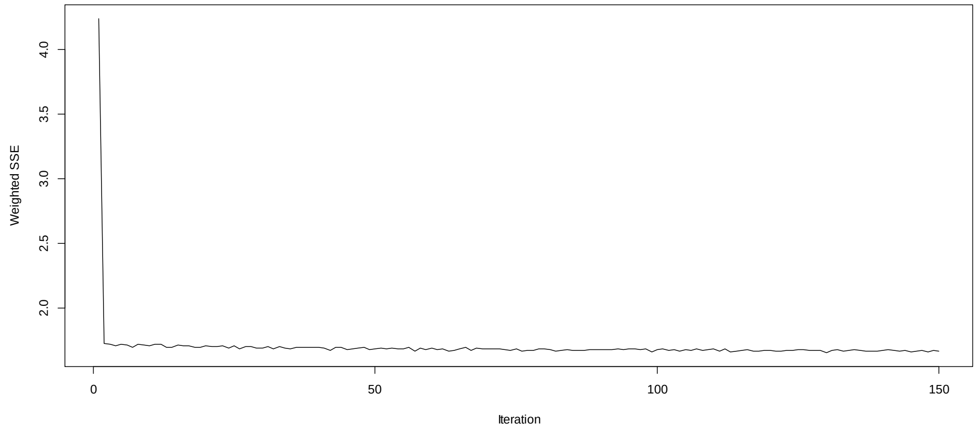

Figure 3: Iteration error (150epoch, (5, 2))

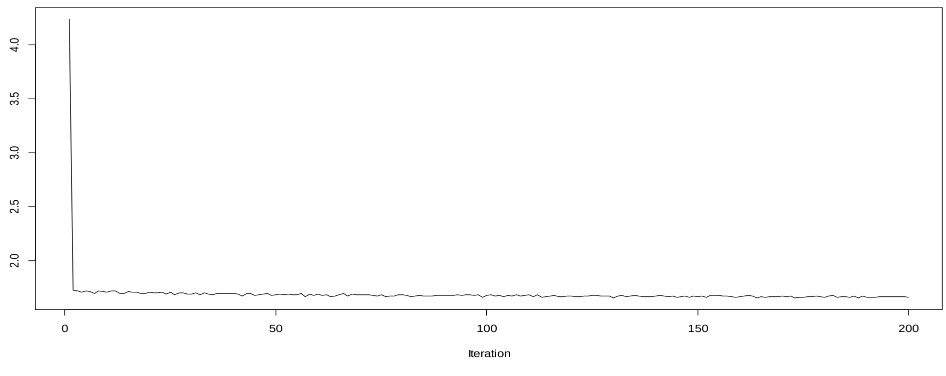

Figure 4: Iteration error (200epoch, (5, 2))

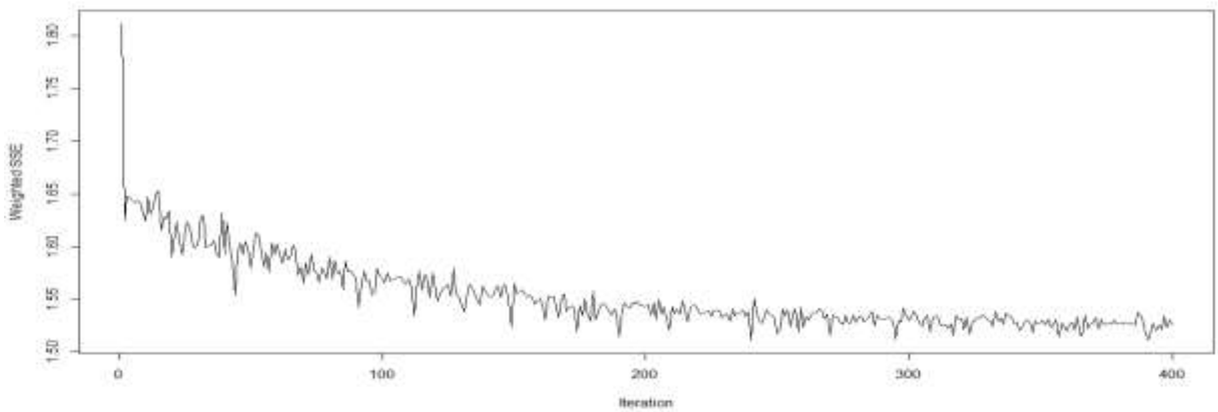

Figure 5: Iteration error (400epoch, (5, 3))

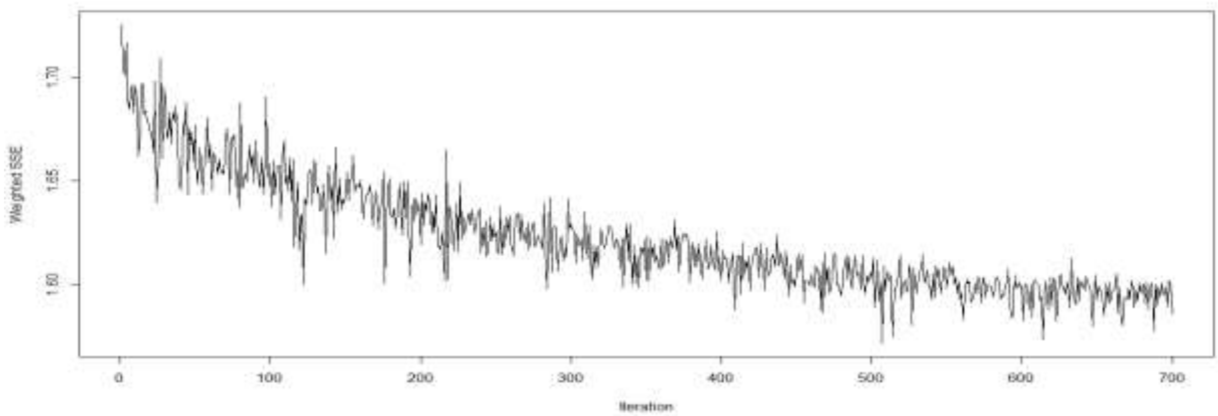

Figure 6: Iteration error (700epoch, (8, 4))

3.3.3 Multilayer perceptron model variable importance.

Figure 7 represent the variable importance of the multilayer perceptron model. The results revealed that electricity production from natural gas source contribute more to GDP than the other two sources. For instance, in Ghana companies such as KEDA ceramics company among others rely on the natural gas produced to generate electricity for their production. This serve as a great a source of revenue to the country. This is followed by electricity production from oil, gas and coal sources and lastly electricity production from hydroelectric source.

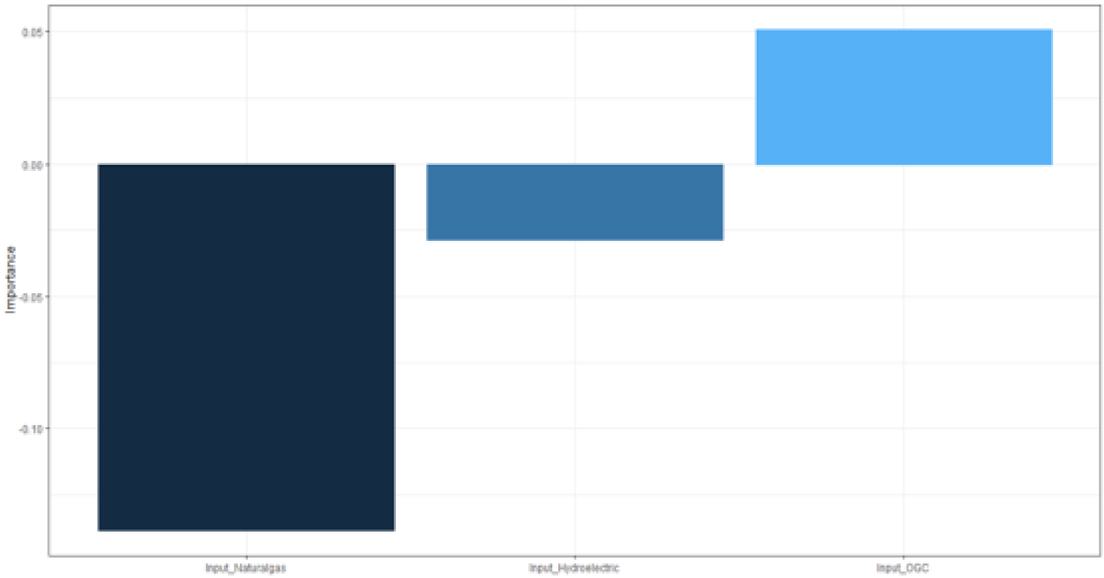

Figure 7: Multilayer perceptron variable importance plot

3. 4 XGBoost Results

3.4.1 Parameter selection and algorithm flow for the XGBoost model.

The implementation of an XGBoost model involves little techniques. First an excel file containing the raw panel data was first read via the read-xlsx method. The various variables and labels were then standardized using the MinMaxScaler. After that, the data set was then split into train set (70%) and test set (30%) using the train-test-split method for subsequent model training and evaluation. An XGBoost regressor was then initialized, setting the objective to "reg:gamma" and trained using the training set. Other rounds were tried but 200 yield the best results.

3.4.2 XGBoost variable importance Analysis

From Table 4, electricity production from hydroelectric source contributes greatly to economic growth than the other two sources. It has a gain value of 0.64976 which approximately represent 65% contribution towards economic growth out of the total. The reason could be that since is the main dominating source of electricity production where many people use. The second contributing source is electricity production from oil, gas and coal sources which has a gain value of 0.22728 that is approximately 23 % contribution towards economic growth out of the total. The last source is through natural gas. It has a gain value of 0.12296 which is approximately 12 %. The variable importance is further confirmed in Figure 8.

Table 4: XGBoost variable importance

Variables	Gain	Frequency
Hydroelectric sources	0.64976	0.48083
OGC	0.22728	0.33604
Natural gas source	0.12296	0.18313

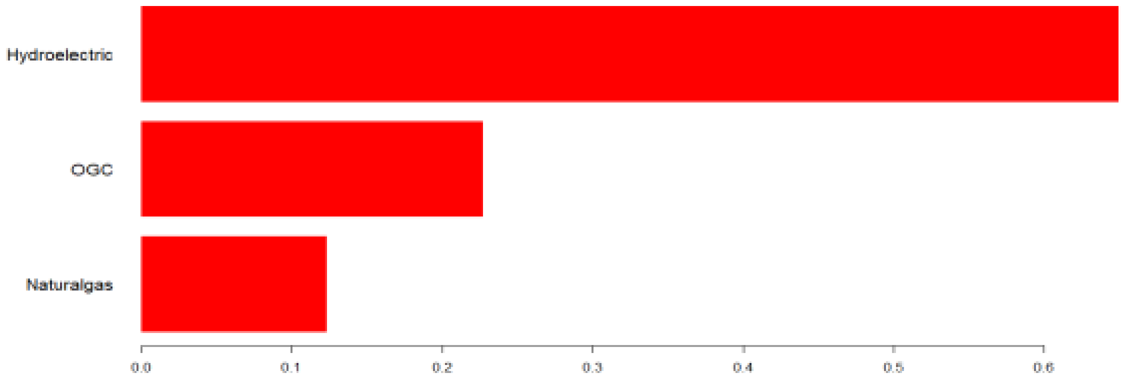

Figure 8: XGBoost variable importance plot

3.5 Comparing of Models Performances.

From Table 5, the multilayer perceptron model is the best model since it has more of the measure accuracy. It has a weak positive correlation of 0.06508 for the train set while the test set has a weak negative correlation of -0.05178. It has a test set MSE and train set MSE of 0.00110 and 5.6341×10^{-5} respectively. These MSE values are less as compared to that of the XGBoost model. It has a test and train set MAPE of 1.96481 and 2.08849 respectively. On the other hand, the XGBoost model has a strong positive correlation for train set of 0.86175 and a weak positive correlation for the test set of 0.13485. The train and test set MSE are 0.00047 and 0.00118 respectively whilst the train and test set MAPE are 0.57167 and 2.01123.

Table 5: Cross-validation accuracy results for the utilized models

Model	Tr-Cor	Test-Cor	Tr-MSE	Test-MSE	Tr-MAPE	Test-MAPE
MLP	0.06508	-0.05178	**5.63411×10^{-5}**	**0.00110**	2.08849	**1.96481**
XGBoost	**0.86175**	**0.13485**	0.00047	0.00118	**0.57167**	2.01123

Tr means train and Cor means correlation

4.0 Discussion of results

From the variable importance of the best model (multilayer perceptron model), the major source of electricity production that contributes more to economic growth in Sub-Saharan Africa is through natural gas sources. This result contradict the work of (Azam et al., 2021). The study used panel fully modified ordinary least squares, panel heterogonous Dumitrescu and Hurlin causality assessment to analyze the estimation of long-run elasticity. The result revealed that the long run elasticity and causality test proved that natural gas does not contribute to economic growth. The discovery of natural gas in large quantity among most Sub-Saharan African countries have increased within the past few decades. This might confirms it impact to economic growth within the continent.

The second most contributing factor is electricity production from oil, gas and coal sources. This significantly influence economic growth. This has attract a lot of investment within most Sub-Saharan African countries. For instance, Nigeria is noted to be one of the leading Sub-Saharan African countries that produce oil in large quantity. Most high profile companies relies on the oil to generate their electricity for their activities which in the long run affect economic growth.

The last contributing source is electricity through hydroelectric sources. The reason could be that though the hydroelectric source is the leading electricity production within Sub-Saharan African but it regulations continue to be a major problem. For instance, around the year 2024 in Ghana, the electricity company of Ghana (ECG) complained about high electricity debt on the part of their consumers therefor making it difficult for them to maintain the Akosombo dam as the main source of producing hydroelectric power within the country. This has been on of the major causes of power shortage in Ghana. This same issue is common among Sub-Saharan African countries such as Benin, Malawi, Mozambique, Namibia, Niger among others. Revenue generated from this source keep on declining each year therefor affecting economic growth.

5.0 Conclusions

The aim of the study was to investigate the impact of the three selected sources of electricity production namely hydroelectric source, natural gas source and oil, gas and coal sources on economic growth in Sub-Saharan African. Data on forty-one (41) Sub-Saharan African countries were selected.

The models used in the study are XGBoost model and multilayer perceptron model.

Under the XGBoost model result, hydroelectric source was discovered as the major source that contribute to economic growth which was followed by electricity production from oil, gas and coal sources. The last source is electricity production from natural gas.

The multilayer perceptron model variable importance analysis revealed that electricity production through natural gas source is the major source that contribute greatly to economic growth in Sub-Saharan African. This is followed by electricity production from oil, gas and coal sources. The last contributing source is through hydroelectric source.

The multilayer perceptron model was discovered as the best model that is able to capture the dynamics within the data.

6.0 Recommendations

The following recommendations are made;

1. The findings of this study revealed that electricity production through natural gas source contribute greatly to economic growth based on the best model. Hence, the study recommend that policy makers such as president of countries which have discovered natural gas in large quantity needs to invest in that source to attract more investment.

2. The study recommend that policy makers such as the president of the various countries needs to modernized the structures such as medium of paying electricity bills pertaining to consumers of the hydroelectric source since it continues to be the major production of electricity within the Sub-Saharan African. This will enable them to generate more revenue to develop the economy.

3. Lastly, this study recommend that feature study should be channel to investigate on electricity regulations that will help to reduce electricity shortage in Sub-Saharan African.

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