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UNIVARIATE MODELLING AND FORECASTING OF ENERGY DEMAND

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ABSTRACT
A thorough assessment of energy sources and long-term energy demand predictions are crucial to the development of sustainable energy planning and policy for any country. However, these are uncommon practices in Nigeria, thereby resulting in shortage of energy supplies required by the economy and its growing population. In this study, energy demand in the commercial and public services, industrial, and residential sectors of the Nigerian economy is examined using Autoregressive Conditional Heteroskedasticity, Markov Switching, and Unobserved Component models. The results of the comparative study show that Markov Switching model performs better than Autoregressive Conditional Heteroskedasticity and Unobserved Component Model for energy demand forecasting. The outcomes further suggest that the energy demand in Nigeria will grow at an average annual rate of less than 2% from 2018 to 2050 in all the three sectors investigated. In view of these findings, the Nigerian Government should have made effort to collaborate with relevant stakeholders, aiming at harnessing the abundant energy resources needed to meet the future energy consumption with a guarantee of energy security and sustainability in the country.

INTRODUCTION
The demand for energy utilisation is increasing globally due to its importance in human activities, entrepreneurial and economic development. Energy is needed virtually in every sector of the economy and it can be obtained from fossil and non-fossil fuel sources. The fossil energy sources are obtained from fuel formed million of years ago through a natural process that convert dead organisms into carbon rich substances under extreme heat and pressure in the earth crust. The fossil fuel which includes crude oil, natural gas and coal constitute a threat to the environment because of the emission of carbon dioxide gases released during their combustions. There is a finite amount of fossil fuel on earth and they are irreplaceable. Non-fossil energy sources cover alternative and renewable energy sources. They are all sources of energy not extracted from fossil fuels which are referred to as clean energy. Wind energy, solar energy, hydropower, nuclear energy and bio-fuels are examples of non-fossil fuel; they are renewable energy sources and pollution-free. Presently, there are intense advocacy for nations to increase the use of non-fossil energy sources to address the effect of greenhouse gas emission and other environmental concerns such as global warming, climate change, resource sustainability (Rapu et al. 2015; Ozturk & Ozturk, 2018).
Nigeria is the most populous country in Africa with more than 200 million people. It is endowed with both fossil and non-fossil energy sources in large and commercial quantities. It is the third largest producer of bio-energy in the world. In Nigeria, non-renewable energy sources, especially oil and gas, have played a dominant role in meeting the energy requirements of the nation. Due to its large oil and gas reserves, Nigeria has political relevance and recognition among key stakeholders in the world energy sector, investors, and international development partners. It is also the major source of revenue or earning for the government. The country relies on oil revenue significantly when compared to non-oil revenue; which implies that more than 95% of the energy consumption in Nigeria are renewable while the non-renewable energy sources account for less than 5%. The Nigerian economy thus has been dependent on fossil fuel, liquefied gas, and petroleum products for domestic, commercial, and industrial activities (Akuru & Okoro, 2011; Sunny, 2014).

In spite of the abundant oil and gas reserves, there is a huge energy deficit in terms of its consumption demands as a result of low capacity utilisation of the refineries, and inadequate number of generation stations coupled with lack of adequate information to plan for future and long-term energy demand. The country depends on importation of refined petroleum products to address the unmet demand in the local production of refined products. This has impacted negatively on the economic growth of the country thereby leading to closed down of enterprises and industries, causing rising index of unemployment and insecurity in the country. In order to address the increasing demand for energy consumption in Nigeria, there is a need to pay more attention to energy demand planning for both fossil and non-fossil fuel energy sources to drive its economic development and attract more direct foreign investment into the country (Rapu et al., 2015).

Energy demand forecasting is important for both energy suppliers and consumers. It is useful for investment planning and energy sustainability. It serves as the bedrock of daily operations, market planning and risk management in the energy sector (Albayrak, 2010). Thus, a robust and effective forecasting technique is critical to make reliable energy demand prediction (Pao, 2007). A common approach for modelling energy demand is to use artificial intelligence and machine learning techniques. These techniques are easy to use to model complex nonlinear input-output relationship through supervised learning without prior knowledge of the underlying mathematical expressions or theoretical assumptions. They seem to have lower computation time, noise immunity, tolerance for faults, uncertainties and disturbances, parallel processing abilities and very slow degradation. However, the use of these techniques does not go without several concerns such as difficulty on how to determine the best optimum network topology and training parameters. They lack specific rules for determining their structures, and in most instances, the appropriate network structure is proposed through designer's experience, and trial and error approaches. This reduces the trust in using machine learning techniques. In addition, when these techniques are used to solve a problem, they do not offer convincing explanation, and adequate insight into the input-output relationship and the relative significance of various inputs on the output (Abdel-Aal, 2008). Thus, there is a need to search for alternative methods to model energy demand.

Univariate time series analysis has been considered in the literature to model and forecast energy demand. It is based on the past values of the time series. It requires historical data of the variable of interest to forecast its future trends of behaviour (Pao, 2009). It ignores important exogenous factors such as climatic, demographic, and socio-economic parameters. These exogenous factors may not be readily available or required permission to obtain. By using univariate analysis, the data dimensionality or number of variables involved in the case study being considered and modeled is reduced. This will eventually lead to reduction in computation time and improve forecasting accuracy (Abdel-Aal, 2008).

Studies on energy demand based on univariate modeling have been undertaking previously by scholars. For instance, Ediger and Akar (2006) used Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) methods to estimate the future primary energy demand of Turkey from 2005 to 2020. The study found that ARIMA prediction of the total primary energy demand appears to be more reliable than SARIMA forecasting technique. Sen, Roy and Pal (2016) studied and predicted energy consumption and GHG emission for a pig iron manufacturing organization in India using univariate modeling techniques. Rehman, Cai, Fazal, Walasai and Mirjat (2017) used ARIMA, Holt-Winter and Long-range Energy Alternate Planning (LEAP) models to forecast energy demand in terms of electricity, natural gas, oil, coal and liquefied gas in Pakistan. The demand forecast estimates of each of these methods were compared using annual energy demand data. The results of this study suggest that ARIMA is more appropriate for energy demand forecasting for Pakistan compared to Holt-Winter model and LEAP models.

Li and Li (2017) used Grey Model-Autoregressive Integrated Moving Average (GM-ARIMA) to predict the future energy demand of Shandong province in China. The prediction results show that the energy demand will grow at an average annual rate of 3.9%. Ozturk and Ozturk (2018) used coal, oil, natural gas, renewable and total energy consumption data from 1970 to 2015 to forecast energy consumption of Turkey for the next twenty-five (25) years, using ARIMA model. Ma and Wand (2019) used ARIMA model, nonlinear grey model (NGM) and nonlinear grey model–autoregressive integrated moving average (NGM-ARIMA) model to predict South Africa's energy consumption. The accuracy predicted by the NGM-ARIMA model is the highest. Jahanshashi, Jahanianfard, Mostafaie and Kamali (2019) examined the most functional and accurate ARIMA model to predict residential energy consumption for countries which belong to the Euro area. Thus, univariate modeling of energy demand is attracting more research studies recently to determine best techniques for such predictions.

Furthermore, ARIMA models have been given a lot of attention in the literature. The study is however considering other univariate modeling techniques that have not been widely examined in the literature. This would offer unique contribution to the development of energy demand forecasting especially for African countries that is either missing or inadequate. Autoregressive Conditional Heteroskedasticity (ARCH) model, Unobserved Component Model (UCM) and Markov Switching (MS) model techniques are used to model energy demand for the residential, industrial, and commercial and public sectors in Nigeria based on historical time-series data. Their performances are compared to determine the most appropriate model to forecast energy demand. Furthermore, the models were used to forecast energy consumption from 2018 to 2050.

It is expected that the findings of this study will provide useful insight and in-depth knowledge to policy makers, scholars and other professionals on the best approaches and strategies to adopt and plan energy consumption in Nigeria and perhaps to other developing countries. Energy demand forecasting is urgently needed to prepare effective energy planning and policy for the country and indirectly will support reliable and sustainable energy supplies for the three critical sectors of the economy. The study will also encourage provision of sustainable, reliable, affordable, and sufficient energy demand and supply system needed for national development. The article is organized as follows. Section twopresents the three models and performance evaluation index to measure and compare their performances. The results of the comparative analysis of univariate models in forecasting total energy consumption in Nigeria are presented and discussed in section three . Finally, concluding remarks are presented in section four.

MATERIALS AND METHODS

Autoregressive conditional heteroskedasticity model

Autoregressive conditional heteroskedasticity (ARCH) model was developed to capture the time-varying volatility patterns often observed in time series data. ARCH model assumes variance of the current error term to be a function of the actual sizes of the previous time periods' error term, that is, the variance is related to the squares of the previous error terms. The ARCH process allows conditional variance to change over time as a function of past errors leaving the unconditional variance constant as against the conventional time series models assuming constant variance (Bollerslev, 1986).

A process y_t is said to be an $ARCH(q)$ process if it is stationary and it satisfies, for all t and some strictly positive-valued process, σ_t, the equations

$$y_t = \sigma_t Z_t \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 \quad (2)$$

Where $\alpha_0 > 0$, $\alpha_i > 0$, $i = 1,\ldots,q$ and X_t is the error term in a time series, Z_t is $N(0,1)$.

This can be rewritten as

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + V_t \quad (3)$$

Where

$$V_t = \alpha_t^2 \left(Z_t^2 - 1\right)$$

Markov Switching model

Markov switching model have parameters that vary over states. The states are unobserved and follow a Markov process. The time of transition from one state to another and the duration between changes in state is random. Consider the following m-state Markov Switching model

$$y_t = \beta_{s_t}^{'} x_t + \sigma_{s_t} \varepsilon_t,\ \varepsilon_t \sim iid(0,1) \quad (5)$$

Where $\beta_{s_t} - \beta'_{s_t}, \beta_{s_t} - \beta'_{s_t}, B - \left(\beta'_1, \beta'_2, \ldots, \beta'_m\right)'$ is an $m \times k$ matrix, β_i is a $k \times 1$ parameter vector, x_t is a $k \times 1$ vector of exogenous regressors, $\sigma_{s_t} = \sigma' s_t$ $\sigma = (\sigma_1, \sigma_2, \ldots, \sigma_m)'$ are $m \times 1$ vectors of error standard deviations, and $s_t = (s_{1t}, s_{2t}, \ldots, s_{mt})'$ is an $m \times 1$ vector of binary state indicators, such that $s_{it} = 1$ and $s_{jt} = 0$ $j \neq i$ if the process is in state i at time t.

The state variable applies the values 1, 2,..., m, and these values represent each of m different states or regimes. The transition mechanism is a Markov process which specifies

$$\Pr(\alpha_t = i \mid \alpha_{t-1} = j) \text{ for } i, j = 1, \ldots, m \tag{6}$$

Given probabilities of being in each of the regimes at times $t-1$ the corresponding probabilities in the next time period are

$$\Pr(\alpha_t = i \mid Y_{t-1}) = \sum_{j=1}^{m} \Pr(\alpha_t = i \mid \alpha_{t-1} = j),\ \Pr(\alpha_{t-1} = j \mid Y_{t-1}),\ i = 1, 2, \ldots, m \tag{7}$$

and the conditional PDF of y_t is a mixture of distributions given by

$$p(y_t \mid Y_{t-1}) = \sum_{j=1}^{m} p(y_t \mid \alpha_t = j) \Pr(\alpha_t = j \mid Y_{t-1}) \tag{8}$$

Where $p(y_t|\alpha_t = j)$ is the distribution of y_t in regime j.

As regards updating

$$\Pr(\alpha_t = i \mid Y_T) = \frac{p(y_t \mid \alpha_t = i) \cdot Pr(\alpha_t = i \mid Y_{t-1})}{p(y_t \mid Y_{t-1})} \qquad i = 1, 2, \ldots, m \tag{9}$$

Given initial conditions for the probability that α_t is equal to each of its m values at time zero, the filter can be to produce the probability of being in a given regime at the end of the sample. Predictions of future observations can then be made, if **M** denotes the transition matrix with ijth element equal to $\Pr(\alpha_t = i \mid \alpha_{t-1} = j)$ and $\mathbf{p}_{t|t-k}$ is the $m \times 1$ vector with ith element $\Pr(\alpha_t = i \mid Y_{t-k}), k = 0, 1, 2, \ldots,$ then

$$p_{T+l|T} = M^{l}_{p_{T|T}},\ l = 1, 2, \ldots \tag{10}$$

and so

$$p(y_{T+l} \mid Y_T) = \sum_{j=1}^{m} p(y_{T+l} \mid \alpha_{T+l} = j) \Pr(\alpha_{T+l} = j \mid Y_T) \tag{11}$$

The likelihood function can be constructed from the one-step predictive distributions. The unknown parameters are made of the transition probabilities in the matrix **M** and the parameters in the measurement equation distributions,

$$p(y_t \mid \alpha_t = j), j = 1, \ldots, m \tag{12}$$

The above state space form may be extended by allowing the distribution of y_t to be conditional on past observations as well as the current state. It may also depend on past regimes, so the current state becomes a vector containing the state variables in previous time periods. The state vector at time t is $\alpha_t = (s_t, s_{t-1}, \ldots, s_{t-p})'$ where s_t is the state variable at time t (Hamilton, 1989).

Unobserved Component Model

This is also called Random Walk model. It is made up of a stochastic component, μ_t and a random irregular term. Suppose that the current level of a series of observations is to be estimated and this would serve as the basis for forecasting the future observations, then it is more desirable to put more weight on the recent observations. This is the estimate of the current level of the series is taken to be (Zeitz & Pen, 2008):

$$m_T = \sum_{j=0}^{T-1} w_j y_{T-j} \tag{13}$$

Where $w_j^{'}s$ represent a set of weights that sum to unity.

This estimate is then taken to be the forecast of future observations, that is the forecast function is

$$\hat{y}_{T+l|T} = m_T + b_T l, \qquad l = 1, 2, \ldots \qquad (14)$$

Where b_t is the slope of the forecast function.

An updating scheme to obtain m_T and b_T in which past observations are discounted by means of two smoothing constants, λ_0 and λ_1 in the range $0 < \lambda_0, \lambda_1 < 1$ Let m_{t-1} and b_{t-1} stand for the estimates of the level and slope at time $t-1$. The one-step-ahead forecast is then

$$\hat{y}_{t|t-1} = m_{t-1} + b_{t-1} \qquad (15)$$

A univariate structural time series model can be expressed as

$$y_t = \mu_t + \sum_i \sum_j \alpha_{ij} x_{i,t-j} + \varepsilon_t \text{ for } t = 1, \ldots, T \qquad (16)$$

Where y_t is the dependent variable, $x_{i,t-j}$ regressor variable i subject to time lag j, α_{ij}, a coefficient associated with variable $x_{i,t-j}$ and ε_t a zero mean constant variance error term. The term μ_t is a time-dependent intercept, which differentiates the model from a simple regression model.

The local level model consists of a random walk plus noise, can be expressed as

$$y_t = \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2), \qquad t = 1, \ldots, T \qquad (17)$$

$$\mu_t = \mu_{t-1} + \eta_t, \qquad \eta_t \sim NID(0, \sigma_\eta^2), \qquad (18)$$

Where the irregular and level disturbances, ε_t and η_t, respectively, are mutually independent and the notation, $NID(0, \sigma_\eta^2)$, denotes normally and independently distributed with mean zero and variance σ^2. When σ_η^2 is zero, the level is constant. The signal-noise ratio, $q = \sigma_\eta^2 / \sigma_\varepsilon^2$, plays the key role in determining how observations should be weighed for prediction and signal extraction. The higher is q, the more past observations are discounted in forecasting the future (Harvey, 2006).

The intercept term in (18) is specified to follow a random walk process with drift as

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta \sim NID(0, \sigma_\eta^2) \qquad (19)$$

$$\beta_t = \rho \beta_{t-1} + \xi_t \qquad \xi \sim NID(0, \sigma_\xi^2) \qquad (20)$$

In the context of (19) and (20), μ_t can be interpreted as the level of a stochastic trend and the drift parameter β_t as its slope. Both level and slope are assumed to follow random walks, with their respective white noise disturbances η_t and ζ_t independent of each other and of ε_t. This general trend model can be tested down to simpler form, such as a level only model, which would be expressed as

$$\mu_t = \mu_{t-1} + \eta_t \quad \eta \sim NID(0, \sigma_\eta^2) \qquad \eta \sim NID(0, \sigma_\eta^2) \qquad (21)$$

The stochastic trend incorporated by μ_t can be made more flexible or less flexible depending on the complexity of the unobserved trend direction in the dependent variable. The essence of the stochastic trend is to capture those trend movements that are not explainable by the regressor variables, which make up the observed component parts of the model. All unobserved components can in principle be stochastic or deterministic. If they are stochastic, they are allowed to change over time. If they are deterministic, they have a fixed impact.
As regards forecasting, the forecast function for prediction is

$$\tilde{y}_{T+1|T} = m_T + b_T l \qquad l = 1, 2, \ldots \qquad (22)$$

Performance Evaluation
The performance of each model used in the study was assessed using the root mean square error (RMSE). The RMSE mathematical expression is stated as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{n}} \quad (23)$$

Where P_i and A_i are ith predicted and actual values, and n is the number of predictions.

The RMSE is a measure of accuracy of the fitted models. For all measures, smaller values generally show a better fitting model (Edgar & Akar, 2006).

RESULTS AND DISCUSSION

Data Collection and Analysis

Nigerian energy consumption data measured as tonnes of oil equivalent (toe) were obtained from International Energy Agency (IEA) website. The data distributions for this study are from 1990 to 2017. The energy consumption data covered three sectors: Commercial and public service (CP); industrial (ID); and residential (RS). Table 1 presents the descriptive statistics of the energy demand showing measures of central tendency and dispersion. It can be shown from the skewness and kurtosis values that the data distribution is normal.

Table 1: Descriptive statistics of the energy consumption data in Ktoe

Variable	**Mean**	**Min**	**Max**	**Std. Dev.**	**Skewness**	**Kurtosis**
CP	2022.6	1272	3561	706.8	1.12	2.75
ID	5160.3	2126	10150	2578.8	0.41	1.97
RS	73641.5	50923	102830	15816.4	0.29	1.87

Diagnostic Tests

Augumented Dickey-Fuller (ADF) test was used in this study to check the stationarity or presence of unit roots in the dataset. The null hypothesis that there is a unit root for the series was rejected. The results of the ADF test in Table 2 show that the data set is stationary.

Table 2: Augumented Dickey-Fuller test of the energy demand dataset

Variable	Dickey fuller test statistics	Critical Value			Value of p
		1%	5%	10%	
CP	-1.398	-4.362	-3.592	-3.235	0.8615
ID	-1.901	-4.362	-3.592	-3.235	0.6543
RS	-0.108	-4.362	-3.592	-3.235	0.9930

Results of Model Performance

The Autoregressive Conditional Heteroskedasticity (ARCH), Unobserved Component (UCM) and Markov Switching (MS) models were fitted into the energy demand data from 1990 to 2017 using the STATA 15 software. The RMSE values of the three models for commercial and public services, industrial and residential energy demands in Nigeria are presented in Table 3.

The values show the goodness of fit for each model. The model with smallest value is regarded as the best among the three. The results showed that ARCH model is most suitable model for fitting the energy demand in the commercial and public services sector. Similarly, ARCH model is also found as the most suitable model for fitting energy demand in the industrial sector while MS model gives the best model fit for the energy demand in the residential sector.

Table 3: Root Mean Square Error

Sectors	ARCH	MS	UCM
Commercial and Public services	316.10*	463.39	317.61
Industrial	921.11*	954.29	921.29
Residential	753.61	559.38*	2019.81

The plots in Figures 1-3 show the realization of energy demand from 1990 to 2017 using the three models. For the period between 1990 and 2017, the average annual growth rate of energy demand for commercial and public services, industrial and residential sectors are 2.84 %, 5.61% 2.64%, respectively.

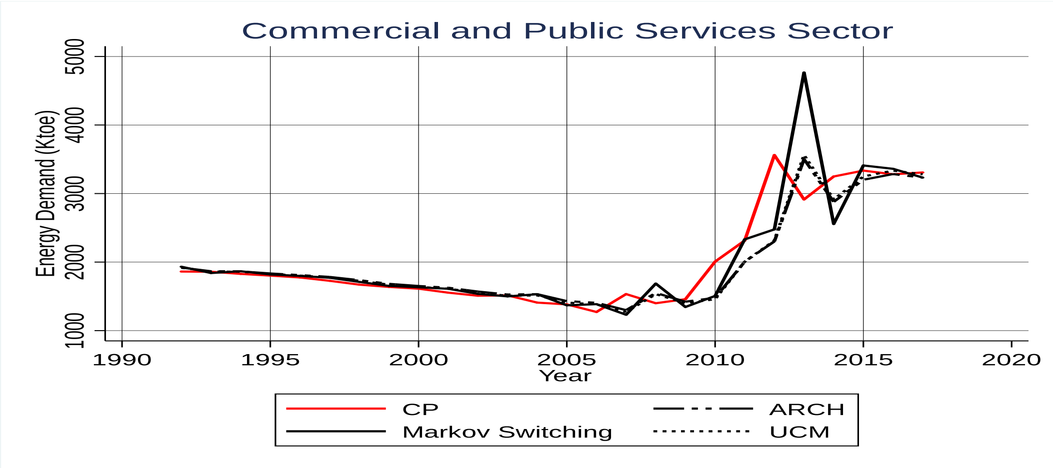

Figure 1: Modelling of energy demand in the Nigerian commercial and public services sector

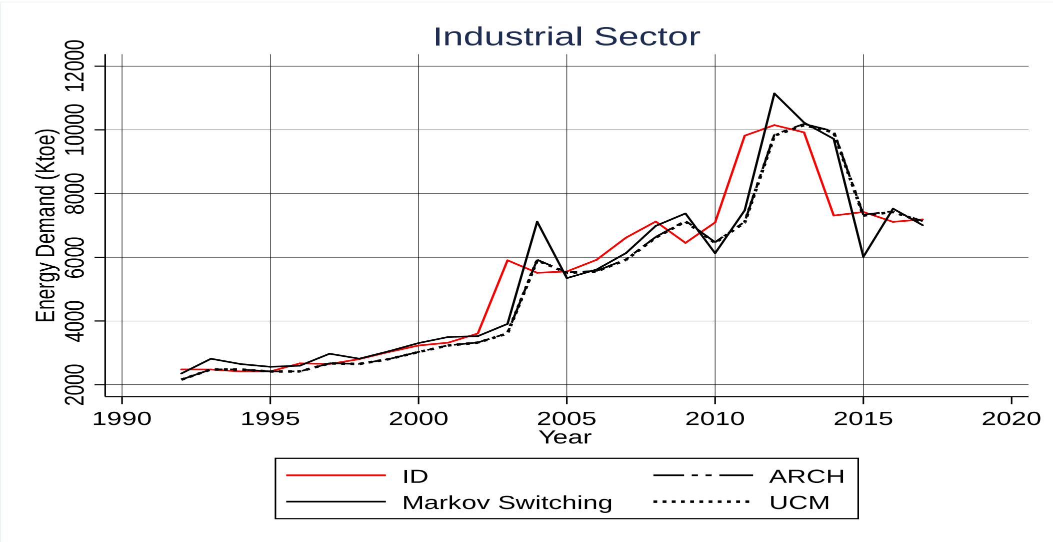

Figure 2: Modelling of energy demand in the Nigerian industrial sector

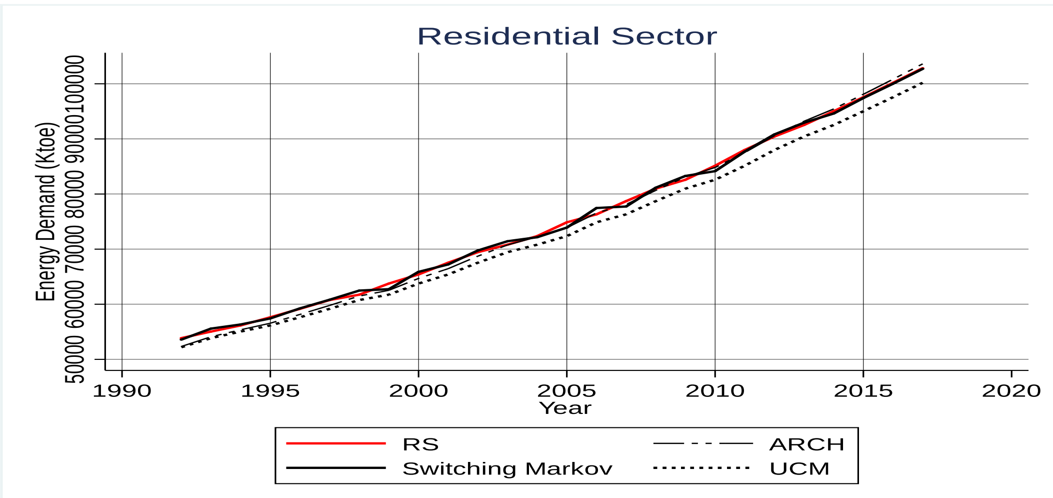

Figure 3: Modelling of the energy demand in the Nigerian residential sector

FORECASTING RESULTS

In order to compare the future trends of energy demands by the three sectors, the three models were used to forecast energy demand from 2018 to 2050. The forecast values for each sector from 2018 to 2030 are shown in Table 4. The average annual rate of change for the commercial and public services sector, using ARCH, MS and UCM are -0.96%, 0.01% and 0%, respectively. For the industrial sector, using ARCH, MS and UCM, the average annual growth rate of energy demand was estimated as 0.33%, 0.53% and 0%, respectively. The average annual rate of percentage for the residential sector using ARCH, MS and UCM, the average annual rate of change was estimated as 5.11%, 1.69% and 0%, respectively.

The forecast of UCM is indicating that there would not be any variation in the annual rate of change in energy demand in Nigeria. ARCH model shows average annual rates of change in energy demand from less than -0.1% to 6% for all the three sectors. MS model is indicating that there would be continuous increase in the annual rate of change in energy demand for all the three sectors at less than 2%.

In Liu (2015), it was suggested that energy demand would increase but at a lower rate. The study opined that the annual growth rate for enegy demand is expected to grow at 1.2% on yearly basis. On the strength of this, MS model is found to be most realiable and satisfactory model among the three models to forecast the long term enegry demand for Nigeria. By 2050, Markov switching model predicted that the energy demand for the commercial and public services, industrial, and residential sectors in Nigeria would be 3307.90 Ktoe, 8287.64 Ktoe, and179723.5 Ktoe, respectively. Figures 4, 5 and 6 show the plots of the three models to forecast energy demand or future trend of energy consumption.

Table 4 Forecasted values for the three sectors from 2018 to 2030

Year	**Commercial and Public Service(Ktoe)**			**Industrial Sector(Ktoe)**			**Residential SectorKtoe)**		
	ARCH	**MS**	**UCM**	**ARCH**	**MS**	**UCM**	**ARCH**	**MS**	**UCM**
2018	3185.79	3210.87	3281	7157.60	7006.20	7112	107288.4	105216.9	100184
2019	3140.86	3201.51	3281	7180.56	7054.29	7112	111210.8	107694.7	100184
2020	3097.61	3199.36	3281	7203.63	7123.86	7112	115402.7	110155.4	100184
2021	3055.98	3201.09	3281	7226.79	7200.87	7112	119882.7	112601	100184
2022	3015.92	3204.86	3281	7250.07	7278.45	7112	124670.5	115032.7	100184
2023	2977.36	3209.66	3281	7273.45	7353.43	7112	129787.3	117451.5	100184
2024	2940.25	3214.92	3281	7296.93	7424.51	7112	135255.7	119858.3	100184
2025	2904.53	3220.32	3281	7320.53	7491.29	7112	141099.9	122253.9	100184
2026	2870.15	3225.69	3281	7344.23	7553.79	7112	147345.6	124638.9	100184
2027	2837.06	3230.95	3281	7368.04	7612.22	7112	154020.5	127014	100184
2028	2805.22	3236.05	3281	7391.95	7666.85	7112	161154.1	129379.8	100184
2029	2774.57	3240.97	3281	7415.98	7717.95	7112	168777.9	131736.8	100184
2030	2745.07	3245.70	3281	7440.11	7765.77	7112	176925.5	134085.4	100184
2031	2716.68	3250.24	3281	7464.35	7810.55	7112	185633	136426	100184
2032	2689.36	3254.60	3281	7488.71	7852.52	7112	194938.8	138759.1	100184
2033	2663.06	3258.77	3281	7513.17	7891.86	7112	204884	141085	100184
2034	2637.74	3262.77	3281	7537.75	7928.76	7112	215512.7	143403.9	100184
2035	2613.38	3266.59	3281	7562.44	7963.36	7112	226871.6	145716.1	100184
2036	2589.94	3270.26	3281	7587.24	7995.83	7112	239011.1	148022	100184
2037	2567.37	3273.77	3281	7612.15	8026.30	7112	251984.8	150321.6	100184
2038	2545.65	3277.13	3281	7637.18	8054.89	7112	265849.9	152615.3	100184
2029	2524.74	3280.35	3281	7662.32	8081.72	7112	280667.8	154903.2	100184
2040	2504.63	3283.43	3281	7687.57	8106.91	7112	296503.9	157185.4	100184
2041	2485.26	3286.39	3281	7712.94	8130.54	7112	313428.2	159462.1	100184
2042	2466.62	3289.21	3281	7738.43	8152.73	7112	331515.4	161733.5	100184
2043	2448.69	3291.92	3281	7764.03	8173.56	7112	350845.4	163999.6	100184
2044	2431.42	3294.51	3281	7789.74	8193.11	7112	371503.8	166260.5	100184
2045	2414.81	3296.99	3281	7815.58	8211.46	7112	393581.6	168516.5	100184
2046	2398.81	3299.36	3281	7841.53	8228.68	7112	417176.5	170767.5	100184
2047	2383.42	3301.64	3281	7867.60	8244.85	7112	442392.7	173013.6	100184
2048	2368.61	3303.82	3281	7893.79	8260.03	7112	469341.7	175255	100184
2049	2354.35	3305.90	3281	7920.09	8274.27	7112	498142.4	177491.6	100184
2050	2340.63	**3307.90**	3281	7946.52	**8287.64**	7112	528922.1	**179723.5**	100184
% change	-0.96%	0.01%	0%	0.33%	0.53%	0%	5.11%	1.69%	0%

DISCUSSIONS

Energy is the backbone of sustainable economic growth and development. It results to improved wellbeing of citizens, promotes industrialization, creates employment, and increases productivity of any country. Nigeria is endowed with ample renewable and non-renewable energy sources. Nevertheless, the country is highly energy deficient due to political crises and unrest, pipeline vandalisation, decreased investment and fluctuation in prices. From IEA data, it showed that average annual growth rate of energy demand for commercial and public services, industrial and residential sector is estimated as 3.7% from 1992 to 2017, respectively.

The Nigerian population that was growing at the rate of 3.6% per annum has been identified as one of the key drivers of energy demand. As population increases over time, the need for better standards of living drives increases in energy consumption. The demand for energy in Nigeria is expected to increase due to high demographic growth, increase in foreign direct investment, gradual improvement in public services, increase in mobility, expansion of economy and uncertainties. For Nigeria to meet the increasing energy demand, there is a need to pay more attention to the available renewable energy sources and shift attention from fossil fuel resources that are being depleted due to extraction and consumption.

Renewable energy is sustainable and could address the environmental pollution arising from greenhouse gas emissions. This would involve identification and development of economically viable and sound energy sources to meet the deficit in the energy gap in different parts of the countries. For instance, the northern part of the country could be suitable for producing solar, wind and hydro energy while the southern part could be good location for investment in the biomass and wind energy production.

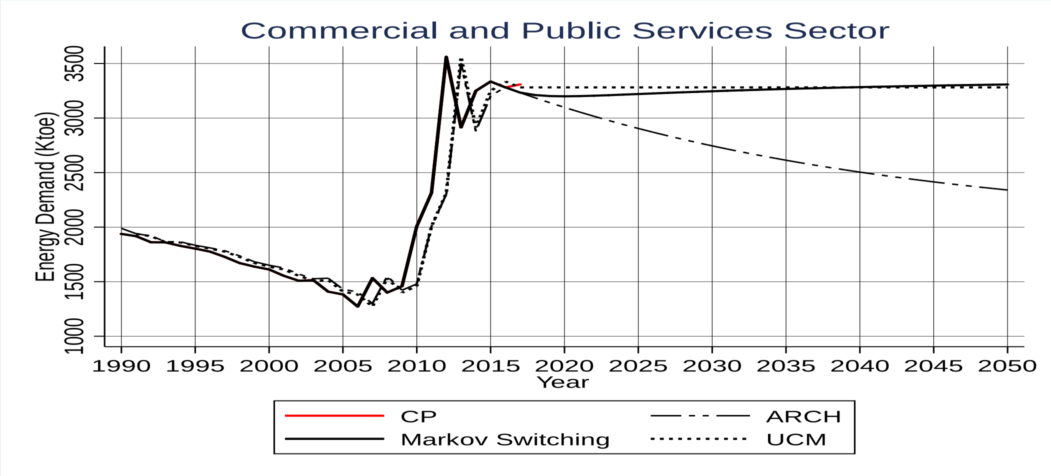

Figure 4 Comparison of ARCH, MS and UCM forecasting of energy demand in the commercial and public services sector

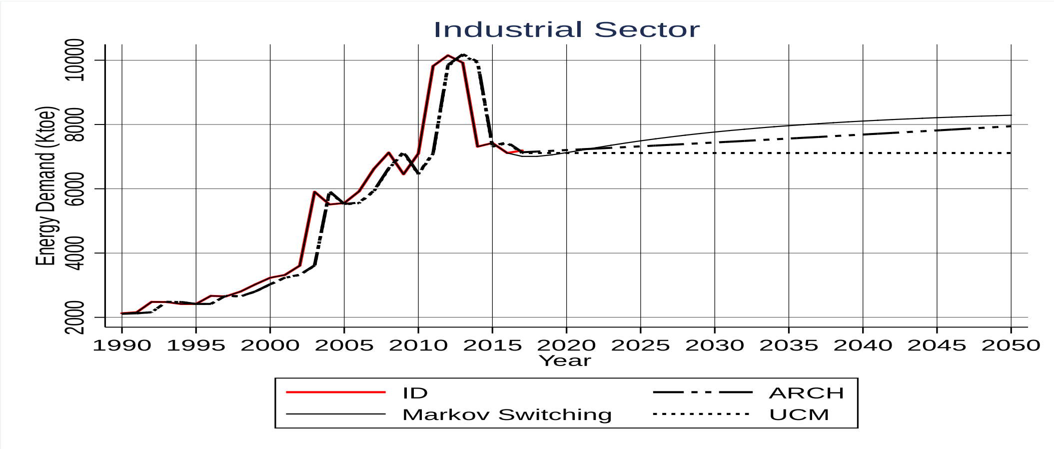

Figure 5 Comparison of ARCH, MS and UCM forecasting of energy demand in the industrial sector

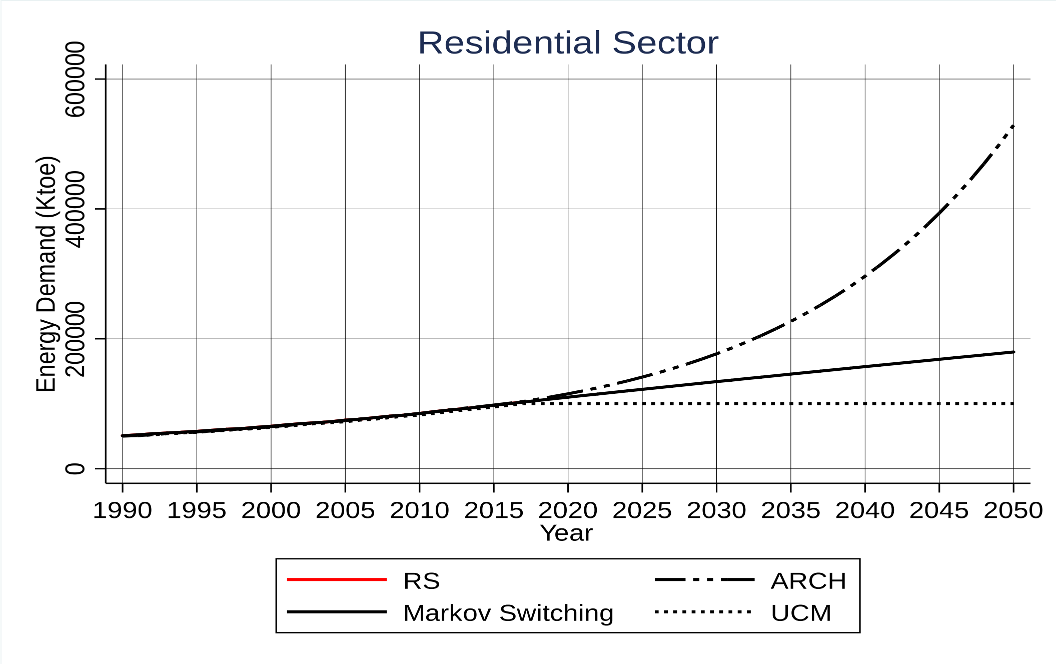

Figure 6 Comparison of ARCH, MS and UCM forecasting of energy demand in the residential sector

CONCLUSION

Energy demand forecasting is an essential tool to address the long term energy plans and policies of a country. Nigeria has a growing population, abundant natural resources and good prospect for industrialisation. This requires adequate energy supplies for the economy. Studies in the energy demand forecasting are still at an evolving stage or lacking in Nigeria and in most of the third world countries (Sunny, 2014). Although, there are various time series forecasting models in the literature with specific limitations concerning data and other modeling parameters. The modeling results shows that MS model to forecast the energy demand is found to be most satisfactory predicting an average annual growth rate of less than 2% for all the three sectors. By 2050, the estimated energy demands for the commercial and public services, industrial and residential sectors would be 3307.90 Ktoe,8287.64 Ktoe, and179723.5 Ktoe respectively.

Based on the findings of this study, it is highly important that policy-makers in Nigeria should undertake conscious initiative and develop long-term plan and policies that will ensure adequate energy supplies in the future to meet the increasing demand. The energy policy should take into consideration the promotion of energy security, stable energy supply, improved energy efficiency, economic competitiveness, energy diversification, energy market deregulation, environmental protection, and energy literacy. It is also important to develop new strategies to optimally exploit abundant renewable energy sources with a priority to meet the forecasted energy demand.

Nigerian Government is advised to support all the relevant stakeholders in the efforts to create a roadmap that would promote energy sustainability and efficiency. Nigeria needs to develop clear regulatory and competitive policies that will position the country as a competitive, low cost and highly reliable energy producer to the global market. Energy sector entails long term investment, adequate funding, and high-tech processes. In order to attract investors to the sector, there should be conducive and stable economic, political, and social environment to operate. This might require the energy sector to be totally deregulated and government involvement in the sector should be limited to policy formulation and regulations. Government should encourage investors to establish green energy institutions, wind power and solar photovoltaics (PV) industries, light emitting diode (LED) energy, information communication technology (ICT), bio-fuels industry that will engage in the electric vehicles technical knowhow, hydrogen energy and fuel cells in order to reduce fossil fuel energy consumption, greenhouse gases emission and increase renewable energy utilisation in the country. This research work could be extended in future by examining the performance of other data-based modeling techniques to forecast energy demand for more African countries.

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