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STATISTICAL EVALUATION OF SURFACE WIND METHOD FOR ELECTRIFICATION IN KEBBI STATE, NIGERIA

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ABSTRACT

Africa and Nigeria in particular is blessed with abundant and constant supplies of fine, clean and sustainable mean for rural and urban electricity generation (renewable energy). Renewable energy such as solar, Hydro, Geothermal, Biomass and surface wind etc., has been found very useful in power generation to many sub-Saharan African countries with attendant significant sustainability and reliability. This study was aimed at evaluating and assessing the potentiality of surface wind in Kebbi state for possible power generation thereby mitigating the challenge of energy crisis and demands for rapidly growing population. The suitable model used for the data analysis was ARIMA (1,1,2), and statistics were checked and stationarity of the data were observed and test using Kwiatkowski Phillips, Schmidt and Shin (KPSS) test. The study area from the analysis of surface wind at **0.01%, 0.05% & 0.1%** level of significances depicts well for reliability and sustainability for electricity generation in the state. The study found that surface wind due to its abundance in significant amount throughout the year all over the state with highest recorded values obtained in 2009, 2010 and 2011, if well-harnesses and utilizes it could serve as a good prospect for power generation in Kebbi state and its environs.

Keywords: ARIMA model, Evaluation, Renewable energy, Statistics & Surface wind.

INTRODUCTION

The energy resultant from fundamentally everlasting sources called "Renewable energy". These sources are naturally reinstated, limitless, and speedily refilled. The need to lessen the rate of greenhouse gas emissions as a means of addressing climate change has made the acceptance of renewable energy more substantial. Technological invention is a decisive aspect of renewable energy expansion as the world incessantly hunt for "carbon-free" (Uyigue *et al.*, 2007). Abdulkarim *et al.*, (2017), analyzed wind speed for electrical power generation in some selected sites in northern Nigeria to determine the accurate frequency distribution that fits wind speed data. The frequency distributions used include Weibull, Rayleigh and Gamma distribution functions. The performances of the probability distributions are based on the error evaluations between the predicted and the theoretical wind power densities of the site. The Results show that Weibull distribution modelled the wind speed better compared to other distribution functions. Also, the results have shown that Jos, Kano and Minna fall in class 4 and therefore suitable for both off grid and grid connected modes. In addition, the effects of c and k parameters on the probability distribution functions have been presented. Ahmed and Mohammed (2015)., Analyzed the renewable energy potential of particular sites, the wind-energy potential of Penjwen region, Iraq has been investigated and find out that the Weibull distribution was found to fit the wind-speed data. Similarly, Statistical analysis of wind-speed data for Malaysia using lognormal and Weibull distributions are given. Zaharim *et al.*, (2009), employed Weibull distribution is proposed to fit the wind speed energy potentials of Tehran.

Ali (2003), find out that, the Weibull is not suitable, and it was found that Burr, lognormal and gamma distributions performed better than Weibull, Rayleigh or Freshet distributions in Pakistan.

In all, it is substantial to partake statistics about accessibility of local wind power in order to make use of wind power for producing electricity and to define the expanse of energy to be produced. Likewise, the understanding of the wind physiognomies is of countless importance in the exploitation of wind energy resources for a site. Based on this, the northern part of Nigeria has been recognized as a region having great potential for wind energy utilization for power generation because of the prevailing wind situation of the place (Emmanuel *et al.*, 2021).

MATERIALS AND METHOD

The data used for this study was obtained at Yelwa-Yauri weather station in Kebbi state for a periods of ten years (10) spanning from 2009-2018. For the purpose of this study, the basic procedure adopts in achieving this objective is ARIMA model. Time domain is usually parametric in nature and is based on direct modelling of the lagged relationships between a series and its past history, possibly to forecast its future values. The models for time series that are required to achieve optimal prediction and possible control are stochastic models. These models are used to calculate the probability of future values falling between upper and lower units specified.

Box-Jenkins Model Identification

The identification stage is the most important and also the most difficult: it consists to determine the adequate model from ARIMA family models. The most general Box-Jenkins model includes difference operators, autoregressive terms, moving average terms, seasonal difference operators, seasonal autoregressive terms, and seasonal moving average terms. This phase is founded on the study of autocorrelation and partial auto-correlation. The first step in developing a Box-Jenkins model is to determine if the series is stationary and if there is any significant seasonality that needs to be modelled.

Stationarity in Box-Jenkins Models

The Box-Jenkins model assumes that the time series is *stationary* if the mean, variance and autocorrelation structure are constant. Stationarity can be assessed from a run sequence plot. The run sequence plot should show constant location and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay. Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationarity.

Time Series Models

White Noise Process: Newbold and Granger (1974) in their book on time series said a time series { X_t } is called a white noise process denoted by $\in_t$, if the following conditions are satisfied:

I. $E\{\in_t\} = 0$ (i.e. Zero mean)

II. $Var\{\in^2_t\} = \sigma^2 < \infty$ (i.e. constant variance)

III. Cov { $\in_1$, $\in_2$ } = 0 if $t_1 \neq t_2$ i.e. not serially correlated in this case we write $\in_t \sqcup WN(O,\sigma^2)$.

Autoregressive Process (AR): The auto regressive process uses weighted time lagged (previous) values to generate new current values for the time series. A time series { X_t } is an AR (p) process if it has the following representation.

$$Xn = m^i + e_n + \sum_{k=1}^{p} \phi_k X_{n-k}$$

$$= m^i + e_n + \phi_1 X_{n-1} + \phi_2 X_{n-2} + ... + \phi_p X_{n-p}$$

For $n \geq 0,$ where { e_n } $n \geq 0,$ is a series of independent identically distributed (iid) random variables, and m^i is some constant.

Moving Average Process (MA): The moving average technique is often used for linear fitting. A moving average process of order q denoted by (MA)q is a stationary time series process { X_t } by box and Jenkins (1976), if it has representation of the form

$$X_n = m + e_n + \theta_1 e_{n-1} + \theta_2 e_{n-2} + ... + \theta_q e_{n-q}$$

$$= m + e_n + \sum_{k=1}^{q} \theta_k e_{n-k}$$

ARMA (p,q) Process: According to Phadke and Kedem (1978), an ARMA(p,q) process is defined from the combination of the p^{th} order autoregressive and q^{th} order moving average process. A time series { X_n } is an ARMA (p,q) process if it has a representative form of

$$X_n - \sum_{k-1}^{p} \phi_k X_{n-k} = m^i + e_n + \sum_{j=1}^{q} \theta_j e_{n-j}\ ,\ n \geq 0$$

Where { X_n } $n \geq 1,$ m^i is some constant, and the ϕ_k and θ_j are defined as for AR and MA models respectively and e_n is a series of unknown random errors (white noise) which are assumed to follow the normal probability distribution. An ARMA process is stationary if the AR component of the series is stationary and invertible if the MA component is invertible.

ARIMA (p.d,q.) Process: This process was developed to help remove trends and uncover hidden patterns in non-stationary data because; ARMA process can only model stationary data. Although the theory behind ARIMA time series model was developed much earlier, the systematic procedure for applying the technique was documented in the landmark book by box and Jenkins (1970). Since the ARIMA forecasting and box and Jenkins forecasting usually refer to the same set of techniques.
Knowing that stationary time series is integrated of the order d and if by differencing the terms it becomes an ARIMA (p,d,q) process, then the difference process can have an ARIMA (p,d,q) representation. In this case the time series $\{X_t\}$ can be expressed as

$$\phi(L)\Delta^d X_t = \theta(L)e_t$$

Where $\Delta^d = (1-L)^d$

Statistical Test in Time Series
KPSS TEST: - Kwiatkowski, Phillips, Schmidt and shin (1992) proposed a test of the null hypothesis that an observable series is trend stationary (stationary around a deterministic trend). The integration properties of a series y_t may also be investigated by testing the null hypothesis that the series is stationary against a unit root. Assuming no linear trend term, the data generating process is given as:-

$y_t = x_t + z_t$ Where x_t a random is walk, $x_t = x_{t-1} + v_t, v_t \sim iid(0, \sigma_v^2)$ and is a stationary process. Kwiatkowski (1992) proposed the following test statistic

$$\text{KPSS} = \frac{1}{T^2}\sum_{t=1}^{r}\frac{S_t^2}{\sigma_\infty^2},$$

Where $S_t = \sum_{j=1}^{t} w_j$, With $w_j = y_t - \bar{y}$ and σ_∞^2 an estimator of the long run variance of

$$z_t, \sigma_\infty^2 = \lim_{T\to\infty} T^{-1}\operatorname{var}\left(\sum_{t=1}^{T} Z_t\right).$$

The null hypothesis of the test is $H_0 : \sigma_v^2 = o$ against the alternative hypothesis $H_1 : \sigma_v^2 \neq 0$. Reject the null hypothesis if the test statistic is greater than the asymptotic critical values.

Results and Discussion

Table 1.1: Descriptive Statistics (Surface wind)

Mean	Median	Std Deviation	Skewness	Kurtosis
65.667	59.5000	16.484	0.865	2.583

DISCUSSION

The data plots of the series or observations and displayed as ordinates against equally spaced time intervals as abscissa, which is used to evaluate the pattern and behaviour in the data over time. The summary statistics shown in Table 1.1 indicate the positive mean for surface wind. The positive standard deviation shows the dispersion from the mean and high level of variability of the series, this result also show positive asymmetry with the distribution are approximately normal. A visual inspection of the plot shows a fluctuating trend, which indicates a continuous non-stationarity in the series data figures 1.0 and 1.1.

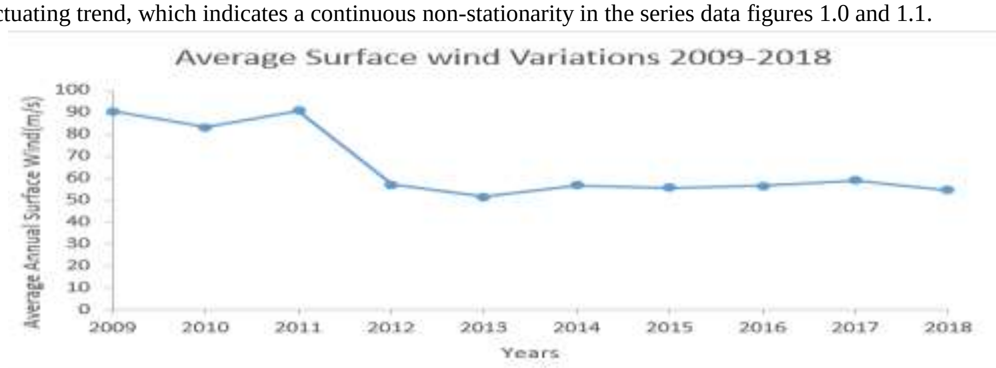

Figure 1.0 Time plot of the Average Surface Wind Variations in the study area.

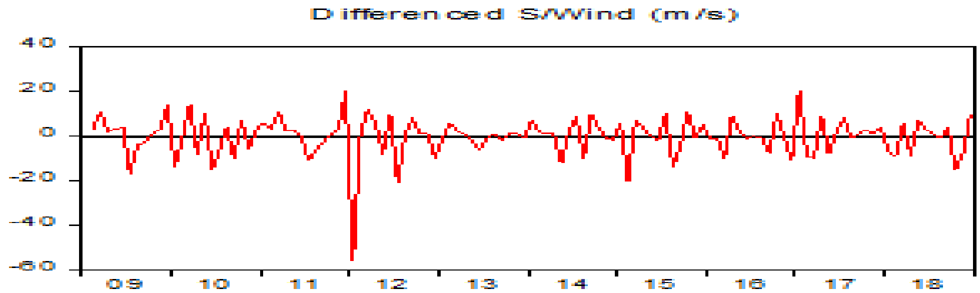

Figure 1.1 The Differenced Characterization of Surface wind in the study area.

Table 1.2: *Results of the KPSS Test*

	Number of lag	1%	5%	10%	Test statistics
S/wind	4	0.242	0.163	0.147	0.0228950***
	5	0.239	0.362	0.224	0.0181220***

Note: *** Denote rejection of null hypothesis at 1%, 5% & 10% level of significance

Table 1.3: *Results of ARIMA model identification for Surface Wind*

	Models	AIC	Log likelihood
S/wind	ARIMA (1, 1, 0)	960.55	-408.22
	ARIMA (1, 1,1)	979.82	-407.23
	ARIMA(1,1, 2) *	716.57*	-244.20*

Note: * Denote the model with minimum information criteria

Table 1.4: *Estimation Summary for the ARIMA (1,2,2) Model*

S/wind	$AR_1 : \hat{\phi}_1$	1.2721	0.0675
	$MA_1 : \hat{\theta}_1$	-0.1022	0.2160
	$MA_2 : \hat{\theta}_2$	-2.9724	0.0675

The ARIMA (1, 1, 2) Model for the surface wind series is:

$$Y_t = 1.2721 Y_{t-1} - 0.1022 \varepsilon_{t-1} - 2.9722 \varepsilon_{t-2}$$

CONCLUSION

The study has been carried out with aim of evaluating and harnessing the potential of surface wind in Kebbi state, using ten years' data (2009-2018) obtained at Yelwa-Yauri weather station of daily mean wind speed recorded. Due to the abundance of surface wind in the study area throughout the year with 2009, 2010 and 2011 shows a great potential of surface wind for electrification and as a better alternative to argument favourably in energy demands. Therefore, it has become necessary to alternatively adopt the use of surface wind sources that is suitable and available in the study area. Wind energy becomes more and more attractive as one of the renewable energy resources. The study area from the analysis of surface wind at **0.01%, 0.05% & 0.1%** level of significances depicts well for reliability and sustainability for electricity generation.

REFERENCES

Aas, K. and Dimakos, X. K. (2004). Statistical Modelling of Financial Time Series. *Applied Research and Development.* 1-37.

Abdulkarim A., Abdelkader, S.M & Morrow, D. J (2017). "Statistical Analyses of Wind and Solar Energy Resources for the Development of Hybrid Microgrid," *in 2nd International Congress on Energy Efficiency and Energy Related Materi*als (ENEFM2014). Switzerland: Springer International Publishing, pp. 9-14, 2015.

Ahmed S. S and Mohammed, H. O (2015)"A statistical analysis of wind power density based on the Weibull and Raleigh models of Penjwen region Sulaimani-Iraq," JJMIE, vol. 6, no. 2, pp. 135-140, 2012.

Ali, N. C (2003) "A statistical analysis of wind power density based on the Weibull and Rayleigh models at the southern region of Turkey," Renewable Energy, vol. 29, pp. 593–604, 2003.

Anderson O.D (1979). Time series Analysis and Forecasting: The Box-Jenkins Approach. But Tamworth, London; Boston.

Box, G. E. P. and Jenkins, G. M (1976). Time series analysis forecasting and control. Fourth Edition (Willey series incorporated).

Dickey D. A. and W. A. Fuller, (1979). Distributions of the estimators for autoregressive time series with a unit root. J. *Am. Stat. Assoc*., 74: 427-431.

Emmanuel. P. Agbo, Collins. O. Edet, Thomas O. Magu, Armstrong. O. Njok, Chris.M. Ekpo, Hitler Louis, (2021). Solar energy: A panacea for the electricity generation crisis in Nigeria: Heliyon 7 (2021) e07016. www.cell.com/heliyon.

Kwiatkowski, D., Peter, C. B., Schmidt, P. and Shin.Y.(1992). Testing the null hypothesis of stationarity against the alternative of the unit root. *Journal of econometrics,* 54,159-176

Ljung, G. M. and Box, G. E. P. (1978). "On a Measure of a Lack of Fit in Time Series Models," *Biometrika*, 65, 297-303.

Newbold, P and Gringer, P. (1974). The exact likelihood function for a mixed auto-regressive moving average process, *Biometrika,* 71, 197-202.

Ozoegwu, C. G, Mgbemene, C. A & Ozor, P. A. (2017). The status of solar energy integration and policy in Nigeria, Renew. Sustain. Energy Rev. 70, Pp: 457–471.

Phadke, M. S., Kedem, G. (1978). Computation of exact likelihood function of multivariate moving average models, *Biometrika*, 65, 511-519

Uyigue, E. M. Agbo, A. Edeubara (2007). Promoting renewable energy and efficiency in Nigeria, in: The Report of a One-Day Conference Which Held at the University of Calabar.

Zaharim, A., Razali A. M, Abidin, R. Z and Sopian, K (2009) "Fitting of statistical distributions to wind speed data in Malaysia," *European Journal of Scientific Research,* vol. 26, no. 1, 2009.