NONLINEAR DYNAMICAL CHARACTERIZATION OF WIND SPEED AND WIND POWER IN KANO, JIGAWA AND KATSINA STATES OF NIGERIA.

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ABSTRACT
Accurate forecasting of wind speed and wind power potential as wind based generation remains the fastest growing source of renewable energy. However this cannot be achieved except if the dynamics of the wind speed is known so as to accurately select the most appropriate models to forecast and harness the vast wind potential. The focus of this research is nonlinear dynamical characterization of wind speed and wind power for the period of thirty eight years (38) in three (3) states; Kano (11°59'47''N, 8°31'0''E), Jigawa (11°45'22''N,9°20'20''E) and Katsina (12°59'26''N, 7°36'06''E) in Northwestern Nigeria. The data were subjected to various components of nonlinear analyses using the MATLAB software which included; Phase Portrait, Power Spectral analysis and Poincaré Map. The results from the Phase Portraits shows a spongy bird's nest-like structure in all the sampled locations which are made up of distinct curves indicating chaotic behavior, nonlinearity and nonstationarity in the time series. The Power Spectral Analysis shows that there are no regular sharp dominant peaks which implies an irregular nature of the time series and also indicated low predictability. The existence of the higher harmonics in the power spectra plots indicates that the processes underlying the time series are nonlinear and have a broadband noise with continuum of frequencies observed which peaks at f_o = 39 cycles/day for all the three locations. The Poincaré map affirmed the characterization which showed distinct points scattered in phase space and are more concentrated in the origin (attractor) indicating chaos in the time series data. This research can help in adapting the best strategy to harness wind energy in the northern part of Nigeria. From this research, it was observed that Katsina has the highest wind potential in terms of wind energy harnessing. Kano has the highest chaotic behaviour and jigawa has the least.
Keywords: Poincaré map, Wind speed, Wind power, Phase portrait and Power spectrum analysis.

INTRODUCTION

Wind based electricity generation has become the fastest growing renewable source of energy in both developed and developing countries for example wind energy is widely used to produce electricity in countries like Spain, USA, China and India among many others. 93GW of new wind power capacity was installed in 2020, driven by China and the US. China's wind industry is now competing successfully with its coal industry without any support and it is estimated that between 10.7GW and 15.1GW of new offshore wind capacity will come in 2021. In Africa Egypt's wind generated power capacity is expected to reach 7GW by 2022 (Global wind energy council, 2021). This is because of high energy consumption, cost of fossil fuels high pollution and the need to reduce the environmental impacts of the conventional methods of generating electricity such as burning of coal, oil and gas. Wind energy by nature is free, abundant and clean renewable resource of energy which emits no air pollutant or green house effect (Amjady, Keyima and Zareipour, 2011).

Wind energy could be highly fluctuations because of the earth's natural atmospheric variability despite its significant environmental benefits. These natural fluctuations can put at risk the power system reliability which may in turns requires more backup than the conventional form of electricity generation in a form of reserves and regulation services. Since the wind energy production depends on the wind speed of the designed station, it is now necessary to predict the energy generated by the wind in order to benefit from a large scale of wind energy in electrical grid (Foley et al, 2012). In order to forecast the wind speed potential and utilize the resource for power production, two major questions should be answered. These are; what is the dynamics of the wind speed and wind power and how these time series can be predicted for harnessing. Therefore, there is need for characterizing the nature and predictability of the recorded time series in order to find the proper model structure and as well the model inputs to claim their validity. Based on these background the research has characterizes the nature of the fluctuations of the recorded data as nonlinear chaotic systems.

In recent times, advances in computing have recorded breakthrough in the detailed exploitation of some complex phenomena in nature, one of the most relevant accomplishments is the unraveling of the structure and nature of disorder or chaos in the atmosphere. This is the basis of a new science called 'chaos theory' (Gleick, 1990) and (Strogatz, 2000) described chaos as a periodic long-term behavior in a deterministic system that exhibits sensitive dependence on initial conditions. According to him, and a periodic long-term behavior implies the trajectories of these systems, they do not settle down to fixed points, periodic orbits, or quasi-periodic orbits as the radius of the orbit tends to infinity, a deterministic system on the other hand has no random or noisy inputs or parameters involved in the development of its future states. Chaotic systems have been reported in many disciplines such as physics, economics, finance, electronics, meteorology and hydrodynamics. The concept of chaos theory reveals that if the behaviour of a system in terms of its past and present behaviour is known, then it is possible to make predictions of the systems future behaviour on a long term basis. Chaos theory involves the reconstruction of time series data in the phase space which can be characterized by studying the dynamics of the movement of the phase space points (Abarnabel et al, 1992). For the purpose of this research an attempt have been made to study the chaotic behaviour of these time series of wind speed and wind power, data from three states (Kano, Katsina and Jigawa) in the Northwestern Nigeria have been utilized.

Table 1: Some Dynamical Systems and the Structure of their Power Spectrum, Phase Portraits and Poincaré Maps.

Solution of Dynamical System	Fixed	Periodic	Quasi Periodic	Chaotic
Power spectrum	-	Single dominant peak	Dominant peak and other sub-peaks	Broad band noise with continuum of frequencies; may peak at $f_o = 0$
Phase portrait	Point	Closed	Torus	Distinct Shapes
Poincaré Maps	-	Curve Point	Closed Curve	Space filling or Ergodic points

Source: Ozer *et al.* (2017)

METHODS

Method of data collection: The material used is daily secondary data for wind speed in m/s downloaded from satellite maps of the Modern Era Retrospective Reanalysis (MERRA2) of the National Aeronautical and Space Administration (NASA) for Kano, Katsina and Jigawa in Northwestern Nigeria from January 1982 to December 2020. The wind power (kW) time series was generated from the expression (RWE, 2019).

$$P = \frac{1}{2}\rho A V^3 C_p \quad (1)$$

Where; $\rho = 1.23 kg/m^3$ density of the air. $A = \pi r^2$ is the swept area by the blade. r is the length of the blade. V is the wind speed.

The swept area of the model turbine was calculated from the length of the turbine blades using the equation for the area of a circle while the height of the model turbine is 50 m above the ground. Thus, the wind speed was converted to the value at that height using the expression (Abbes and Belhaj, 2014)

$$\frac{v2}{v1} = \left(\frac{h2}{h1}\right)^a \quad (2)$$

v_1 and v_2 are the wind speed at the desired heights h_1 and h_2 respectively while a is the friction coefficient, for neutral and stable conditions α is taken as 0.1423 (i.e. 1/7). h_1 is set at 2 m while h_2 is set at 30 m, v_1 is the wind speed from the data measure at 2 m while v_2 is the desired values evaluated using equation (2).

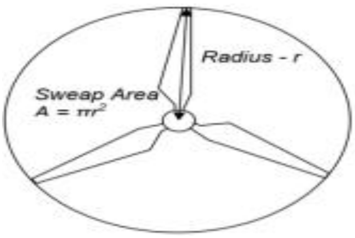

Figure 1: Illustration of the Swept area of a model Wind Turbine

CONSTRUCTION WORK

Tools and Software for analysis: The tools required for this research includes: A personal computer of window10 with 4 GHz RAM, Intel Pentium (i-series) processor and MATLAB software (R2015b) installed in the computer.

Qualitative Analysis of Wind Speed and Wind power time series

These were done by plotting the Phase portraits, Power spectrum, Poincaré map, Recurrence plots using MATLAB software. The classifications of different dynamical systems were highlighted in Table 1.

RESULTS AND DISCUSSION

Qualitative Tools of Nonlinear Characterization: The qualitative tools of nonlinear characterization that were used in this research include; phase portraits, Poincaré maps and power spectral analysis.

Phase portraits: This is a two-dimensional or three-dimensional projection of the phase space. For a discrete time series (e.g. weather time series) a plot of $x_{n+\tau}$ against x_n points in phase space gives a phase portrait while for a continuous system such as a driven pendulum, an angular velocity versus position graph gives us a phase portrait (Ozer and Akin, 2005). The phase portraits of chaotic systems and other systems where characterized according to Table 1. The phase portraits of wind speed and wind power for the three states showed a spongy bird's nest-like structures. These are made up of distinct curves indicating chaotic/stochastic (random) behavior in the time series (Ozer *et al*.., 2005).

Figures 2a-4b show phase portraits of the meteorological variables plotted; The phase portraits of Kano (figure 2a and 2b) shows that the attractor dynamics of wind speed have more concentration at the centre while that of wind power (figure 2b) showed the concentration at the origin. The phase portraits of katsina (figure 3a and 3b) also showed concentration at the centre for wind speed (figure 3a and wind power (figure (3b) showed attractor concentration at the origin. Jigawa phase portraits (figure 4a and 4b) showed more distinct points in wind power (figure 4b than wind speed (figure 4a) Hence one can infer the plausibility of deterministic chaos in the weather data recorded across the location sampled in this study. Phase portraits are a display of trajectories of the data points in phase space which usually gives us a pictorial view of the attractor dynamics of the system.

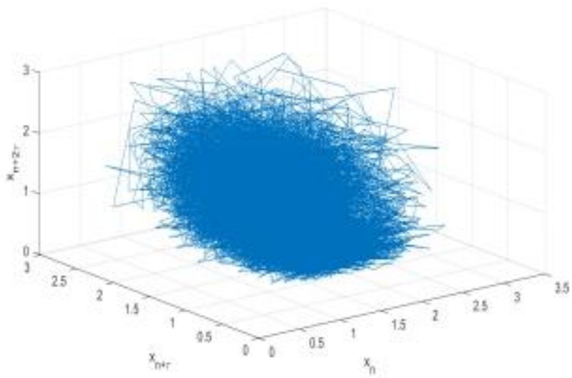

Figure 2a: phase portrait of wind speed

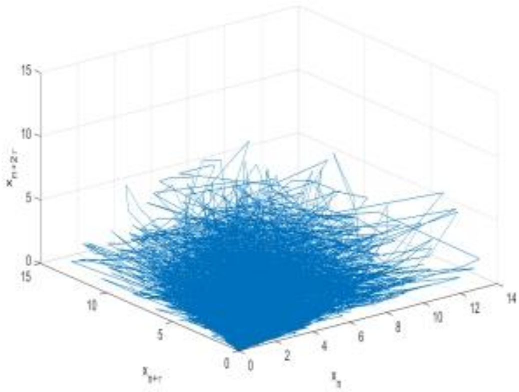

Figure 2b: phase portrait of wind power for Kano

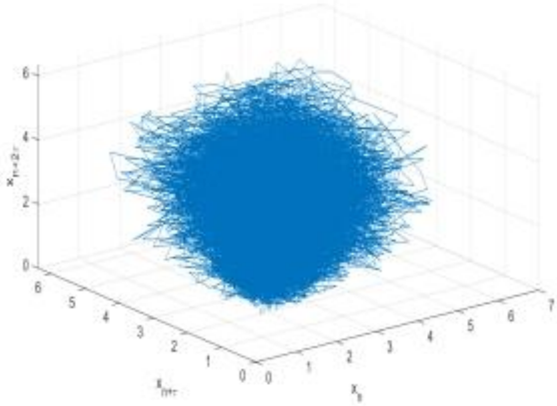

Figure 3a: Phase portraits of wind speed

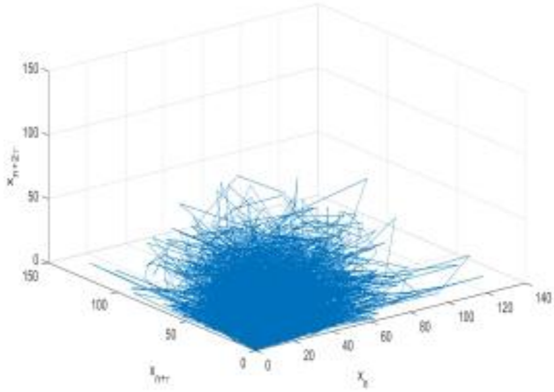

Figure 3b:Phase portraits of wind power for Katsina

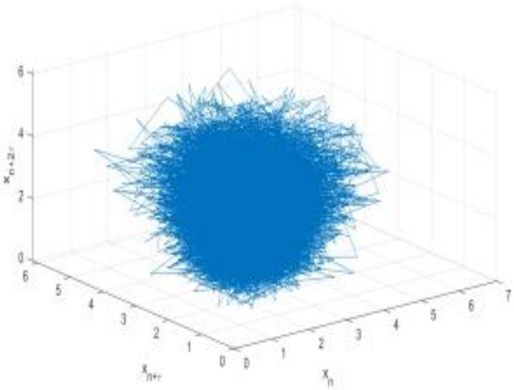

Figure 4a: Phase portraits of wind speed

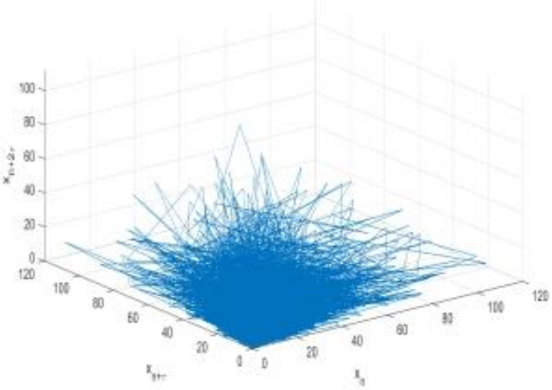

Figure 4b: Phase portraits of wind power for Jigawa

Power spectrum analysis: This is an analysis that is used in characterizing a time series which portrays how a signal's power is distributed by the frequency domain. In this characterization, the Fast Fourier transform (fft) is applied in order to convert the time domain series data to the frequency domain where the power spectral density are obtained from the expression (Shannon, 1948).

$$power/Hz = abs\{fft[x(t)]\}^2 \qquad (3)$$

A power spectrum graph is usually a graph of the power/Hz against the frequencies; the frequencies are used as the inverse of the time values in the time series. The mean period of a time series is estimated from the power spectrum as the reciprocal of the dominant peak frequency of the power spectrum graph (Telgarsky, 2013). Power spectrum analysis is a way to characterize the attractors of a system and is used to qualitatively have a difference in quasi-periodic or chaotic behavior from periodic structure and also to identify different periods embedded in a chaotic signal (Ozer *et al*., 2005). The computed power spectral density (PSD) of wind speed and wind power provides information on the character of fluctuations in the time series data. The (PSD) describes how the power of a time series is distributed with frequency. The graph was plotted based on fast Fourier transform estimation method for PSD.

From the results in Figures 5a-7b it is observed that there are no regular sharp dominant peaks, which implies that a periodic or irregular nature of the time series data in the sampled states. Kano exhibits much higher harmonics in wind speed (figure 5a) than in wind power (figure 5b) and the spectrum plots tends to decrease with time domain indicating the chaotic nature of the time series data. Katsina exhibits higher harmonics in wind power (figure 6b) due to the fact that Katsina has the highest wind potential among the three locations sampled in the research. Also, in Jigawa there no regular sharp peaks indicating the irregular nature of the time series data in which wind speed (figure 7a) have much more higher harmonics than that of wind power (figure 7b). This irregularity also implies low predictability of these time series. In terms of the frequency content of the plots, the broadband noise with continuum of frequencies observed which peaks at f_o = 39 cycles/day (a point where peak frequencies is not equal to zero).

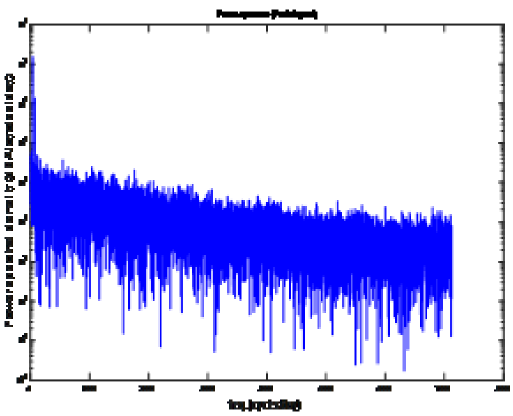

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Figure 5a: Power spectrum analysis of wind speed

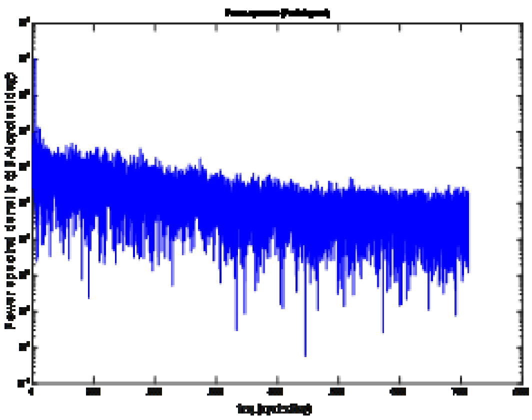

Figure 5b: Power spectrum analysis of wind power for Kano

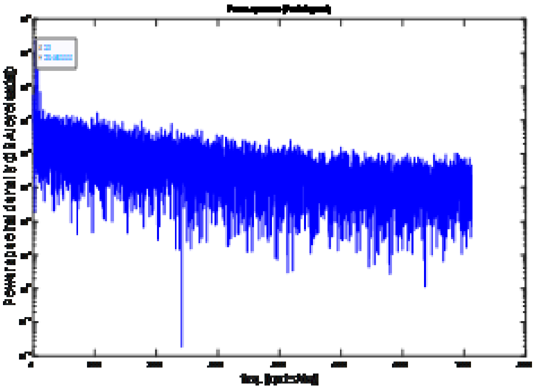

Figure 6a: Power spectrum of wind speed

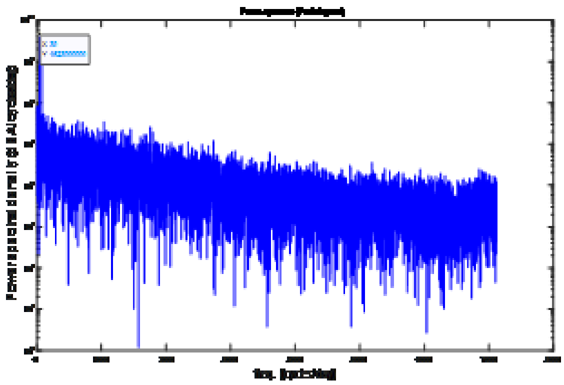

Figure 6b: Power spectrum of wind power for Katsina

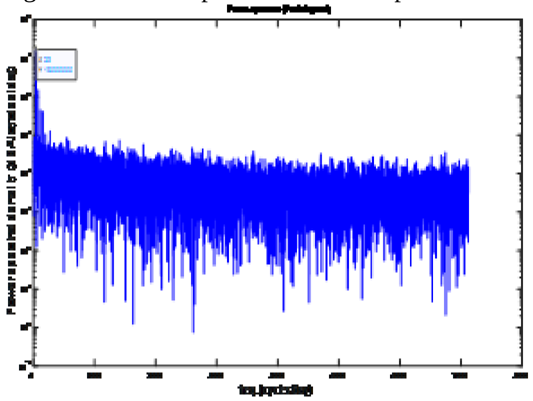

Figure 7a: Power spectrum of wind speed

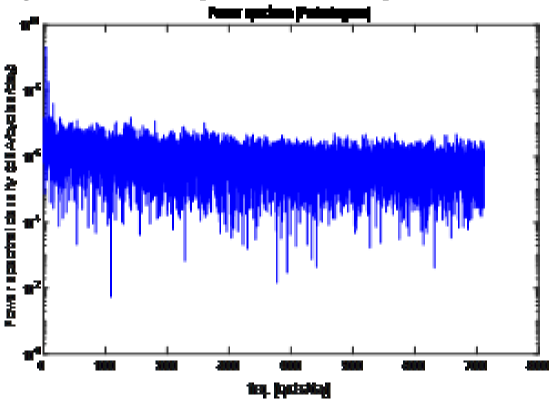

Figure 7a: Power spectrum of wind power for Jigawa

Figure 5a and 5b showed the power spectral analysis of wind speed and wind power. Figure 5a shows the existence of many higher harmonics than that of wind power which means that the wind speed dynamics exhibits more chaotic behaviour than the wind power.

Poincaré maps: Poincaré section or map is a classical and convenient technique for visualizing in details the dynamics of a system. It replaces the flow of an $(n+1)^{th}$ order continuous-time system with an n^{th} order discrete-time system (Velickov, 2006). It is the first recurrence map in a nonlinear dynamical systems named after Henri Poincaré and it is the intersection of a periodic orbit in the phase space of a continuous dynamical system with a certain lower-dimensional subspace called the Poincaré section which is transverse to the flow of the system. More precisely, one considers a periodic orbit with initial conditions within a section of the space, which leaves that section afterwards and observes the point at which this orbit first returns to the section. Figure 8 shows a Poincaré surface constructed across a set of trajectories in 3-dimensional phase space.

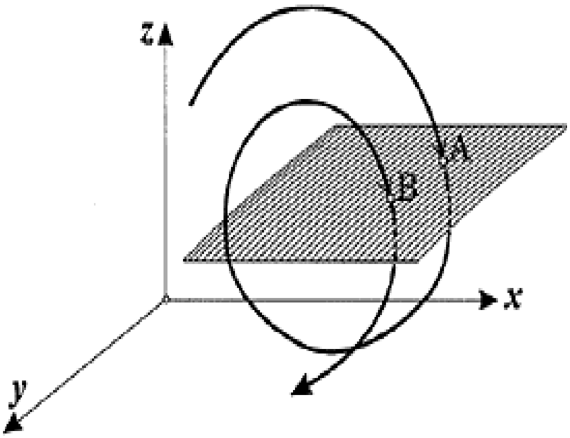

Figure 8: Poincaré map in 3-Dimensions. The Successive Intersection Points A, B,… of the Continuous Trajectory with the Surface of Sections , Define Iterates of a Two-Dimensional Map in this Case (Velickov, 2006).

The Poincaré maps represent a slice through the phase portrait of the time series data. It affirms the characterization of the data by giving us the inner dynamics of the attractor via the first return map of the dynamical variable as the trajectory traverses the Poincaré surface. The wind speed (Figure 9a) plot shows concentration towards the centre and not scattered as that of wind power (Figure 9b) shows concentration from the origin in the wind power plot and distant scattered points in the centre. Figure 10a shows the plot of wind speed does not show any concentration in the phase space the points are scattered evenly and Figure 10b shows the plots of Jigawa which also showed a distinct points scattered in phase space which are more concentrated in the origin than Kano. Figure 11a shows the plot of wind speed that is concentrated at the origin also Figure 11b shows concentration the origin and scattered towards the centre. This scattering indicated that the trajectories of the system do not settle to a fixed point.

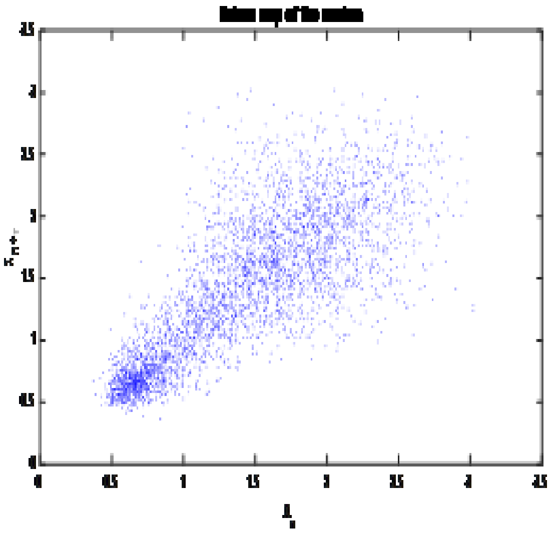

Figure 9a: Poincaré map of wind speed

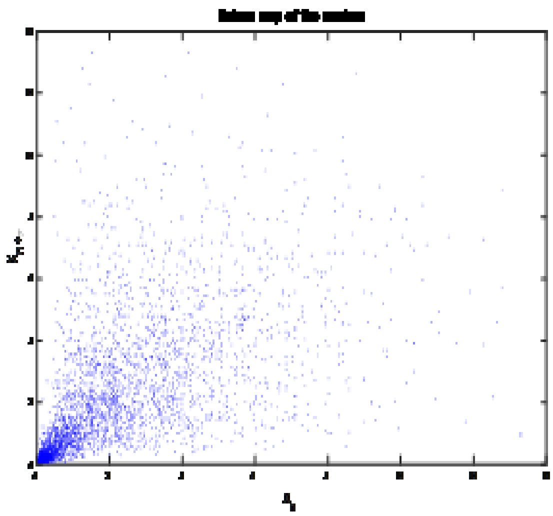

Figure 9b: Poincaré map wind power for Kano

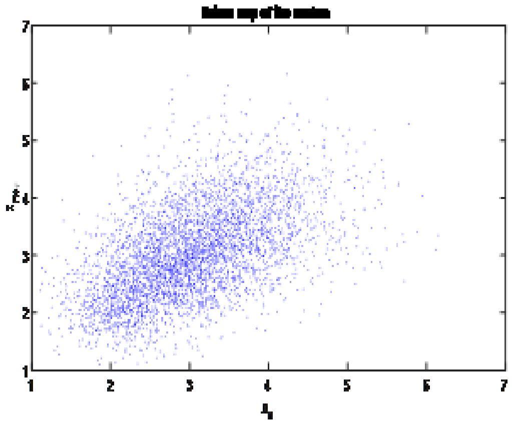

Figure 10a: Poincaré map of wind speed

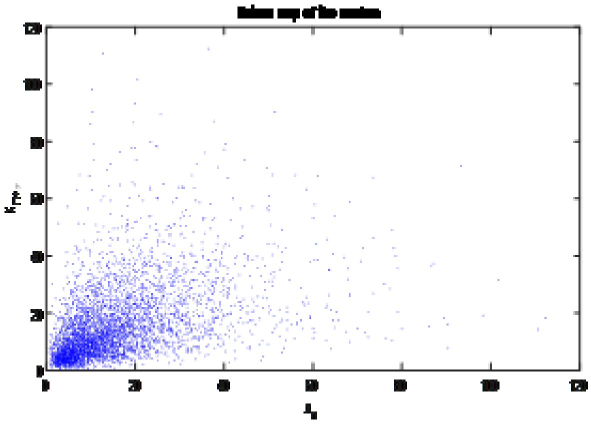

Figure 10b: Poincaré map of wind power for Jigawa

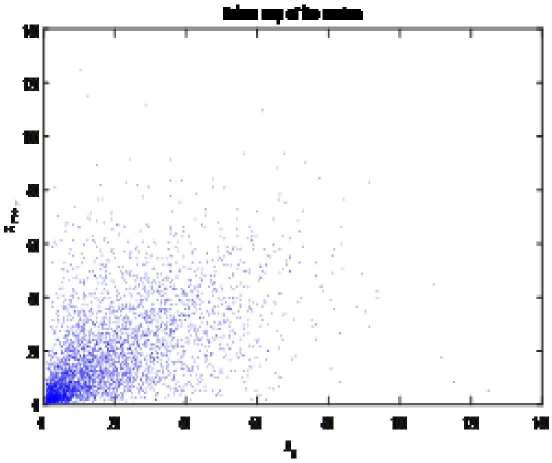

Figure 11a: Poincaré map of wind speed
Katsina

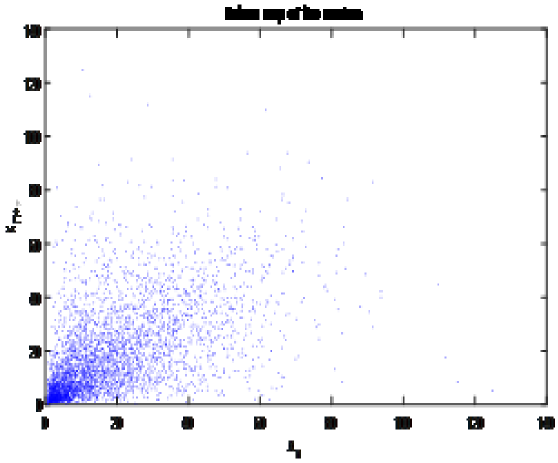

Figure 11b: Poincaré map wind power for

CONCLUSION

The research used the tools of nonlinear dynamical analysis on wind speed (m/s) and wind power (kW) time series collected across the three locations in the Northwestern Nigeria in order to determine the extent to characterize the data of wind speed and wind power over the last three decades. Qualitative tools of nonlinear analysis such as phase portraits, power spectrum and Poincaré maps were successfully constructed. The results from the Phase Portraits showed a spongy bird's nest-like structure in all the sampled locations which are made up of distinct curves indicating chaotic behavior, nonlinearity and nonstationarity in the time series. The Power Spectral Analysis shows that there are no regular sharp dominant peaks which implies an irregular nature of the time series and also indicated low predictability. The Poincaré map affirmed the characterization which showed distinct points scattered in phase space and are more concentrated in the origin (attractor) indicating chaos in the data. The time series data of all the three locations showed that the data is chaotic, nonstationarity and nonlinear. Wind is a very important renewable energy resource which has vast potentials in the Northern part of Nigeria and if properly harnessed could help solve Nigeria's energy crisis by providing up-to-date meteorological data and greenhouse emissions data for the selected locations could be obtained and correlated to different models so as to explain quantitatively the effect of climate change on the chaotic/stochastic trends in the weather conditions across Nigeria.

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