WIND POWER FORECASTING USING AUTOREGRESSIVE MOVING AVERAGE(ARMA)

BELLO TUKUR BUHARI

SPS/11/MEE/00030

(B. Eng. Electrical)

A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, BAYERO UNIVERSITY, KANO,

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR AWARD OF THE DEGREE OF

MASTER OF ENGINEERING (ELECTRICAL)

November, 2015

DECLARATION

I declare that this project report entitled "*Wind Power Forecasting Using Statistical Model: Auto-Regressive Moving Average (ARMA)*", is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature________________ `

Date______________

Bello Tukur Buhari

SPS/11/MEE/00030

CERTIFICATION

This is to certify that the dissertation titled "Wind power forecasting using Autoregressive Moving Average (ARMA)" by Bello Tukur Buhari (SPS/11/MEE/00030), were carried out under my supervision.

Supervisor: Sign: __________________

Name: **PROF. BENJAMIN AKUSO GONOH**

Date: _________________

Head of Department: Sign: __________________

Name: **DR. SABO IBRAHIM BIRNIN KUDU**

Date: __________________

APPROVAL

This is to certify that this research project has been read carefully and approved as meeting the requirements for the award of master of Engineering (Electrical). Department of Electrical Engineering, Faculty of Engineering, Bayero university kano.

External Examiner: Sign: ___________________
Name: **PROF. JIMOH BOYI**
Date: ___________________

Internal Examiner: Sign: ___________________
Name: **DR. ABDULKARIM MAYERE**
Date: ___________________

Supervisor: Sign: ___________________
Name: **PROF. BENJAMIN AKUSO GONOH**
Date: __________________

Head of Department: Sign: ___________________
Name: **DR. SABO IBRAHIM BIRNIN KUDU**
Date: ___________________

SPS Representatives

Date: ___________________

ACKNOWLEDGEMENTS

I am particularly grateful to ALLAH (S.W.T.) for giving me the courage, strength and ability to successfully undertake and complete this report work.

I would like to express my gratitude to my project supervisor, Prof. B.A Gonoh for his moral support, making useful corrections, comments, suggestions to improve the quality of this project and took the pains in reading the entire thesis scripts.

I would like to thanks, Dr. Muhammed Buhari, Dr. Hassan Bashir and Dr. Abdulkarim Mayere for continuous support, patience, motivation, enthusiasm towards the success of this project report.

I am indebted to express my thanks to my friends Eng. Lukman Aminu Yusuf, Harrison Oyibo Idakwo, Eng. Fatima Dalhatu Sani and Issaku Ibrahim, my colleagues, entire staffs of Electrical Engineering Department.

DEDICATION

I would like to dedicate this achievement to my Late father Alhaji Tukur Buhari, and my Mom Hajiya Maryam Abubakar. my brothers my sisters for their encouragement and blessing, support and caring.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND UNITS

N/S	Symbols	Definition	Units
1	E	Kinetic Energy	J
2	ρ	Density	kg/m3
3	m	Mass	Kg
4	A	Swept Area	m^2
5	v	Wind Speed	m/s
6	C_p	Power Coefficient	-
7	P	Power	W
8	$\boldsymbol{R}$	Radius	M
9	$\frac{dm}{dt}$	Mass flow rate	kg/s
10	$\boldsymbol{x}$	distance	M
11	$\frac{dE}{dt}$	Energy Flow Rate	J/s
12	$\boldsymbol{t}$	time	S

LIST OF ABBREVIATIONS

ARMA - Auto-Regressive Moving Average

ARMAX - Auto-Regressive Moving Average with Exogenous

ARIMA - Auto-Regressive Integrated Moving Average

f-ARIMA - fractional Auto-Regressive Integrated Moving Average

s-ARIMA - seasonal Auto-Regressive Integrated Moving Average

kW - kilowatts

MW - Megawatts

AR - Auto-Regressive

ARX - Auto-Regressive with Exogenous

MA - Moving Average

AIC - Akaike Information Criterion

ANN - Artificial Neural Network

RMSE - Root Mean Square Error

KS - Kolmogorov Smirnor

FL30 - Fuhrlander 30

SAM - System Advisor Model

WECS - Wind Energy Conversion scheme

LOLFS - Loss of load frequencies

KF - Kalman Filter

MAE - Mean Absolute Error

NWP - Numeric Weather Prediction

SSM/I - Special Sensor Microwave/ Image

NIMET - Nigerian Meteorological Agency

WTG - Wind Turbine Generator

Std - Standard deviation

ABSTRACT

The uncertainty, uncontrollability and fluctuating nature of wind posed difficulty in deployment of wind power generation. In view this, when wind power is deployed to account for higher proportion of total electricity generation of the system, power generation plan needs to be arranged in accordance to the variation of wind power output. One way to address this problem is by forecasting the wind power. In this research work, 6hours wind power forecasting into the future is considered using MATLAB/Simulink. ARMA model was used as a forecasting model for wind power, and AR model used as a bench mark for comparison. ARMA(4,3) was selected due to its numerous advantages such as best fit to estimated data of 41.99%, low mean square error (MSE) of 7.957, low final prediction error of 7.962 and lesser number of coefficients. similarly, AR(4) whose best fit to estimated data of 40.19, mean square error of 8.457and final prediction error of 8.46 was considered as the best AR model. the performance of the two models were carried out based on the results obtained and ARMA modeling technique was found to be more suitable for representing wind speed behaviour necessary for carrying out reliability assessments involving wind turbine generator outputs. No assumptions or previously estimated factors are introduced into the model. Therefore, ARMA could be a valuable forecasting tools for wind turbine generator outputs of kano.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

Wind power forecast has been defined as an estimate of the expected production of one or more wind turbines (referred to as a wind farm) in the near future. Production is referred to the available power for wind farm considered (with units kW or MW depending on the wind farm nominal capacity)[1]. Wind power has gained a great importance in the electrical sector over the past years. The wind is nowadays a source of energy economically viable to explore in terms of electrical energy production, and thus competitive with other sources. It is also environmentally safe, since the corresponding process of energy production does not emit any pollutant gases. Wind power production, is subject to availability of wind. which can be controlled within the margin of the possible production. The extraction of energy from the wind should be maximized for economic and environmental reasons. It was reported that the use of wind energy allows saving between 0.5 and 1 tons of greenhouse effect gas (GHG) per MWh [1], that would be emitted to the atmosphere if natural gas or coal were used instead. This is a great contribution to the achievement of the Kyoto Protocol goal, the GHG emissions is reduced by 5% of the 1990 levels over the five-year period 2008–2012. Regarding the economic benefits, in 2012, the wind power sector had a turnover of 60 billion Euros N14.4 Trillion, and employed 670,000 people worldwide. In 2014, the global capacity is expected to reach 400GW. By the end of the year 2020, at least 1,000GW can be expected globally[2],[3]. The growing importance of wind power raises the issue of understanding its behaviour and its impact in the electrical sector. In comparison to the cost of the energy produced with a conventional coal or natural gas power plant, the cost of producing wind energy is still slightly higher. This cost is strongly related to the amount of wind energy produced: since the utilization of the wind is free, the more wind energy is produced the smaller is its cost per MWh [4]. There is need to carefully schedule the electrical energy production; with the expected load and the available power plants, this leads to what is called wind power prediction. Regardless of all the advantages listed above, wind power has some related problems too. One of this, is the uncertainty associated with it, which is a common problem for other renewable energy sources. This is critical since, in a power system, the total amount of electricity that is provided at each instant has to match a varying load from the electricity consumer. To achieve this in a cost effective way, the power plants must be scheduled in advance according to increasing marginal operating costs. The variable production pattern of wind power changes the scheduling of the other production plants. This is cost-wise inefficient. And sometimes is technically unfeasible. These reasons justify that the electrical system cannot be totally or even mostly dependent on renewable energy plants. This maintains the electrical balance between the supply and the load. Therefore, conventional power plants are required to be active, no matter the reliability of the renewable energy sector. Nevertheless, an accurate forecast of the renewable energies contribution is mandatory to minimize the uncertainty factors. Wind power is the most important renewable energy utilized today, the wind power forecasting problem is of extreme importance[5],[6].

1.2 MOTIVATION AND SIGNIFICANCE OF THE RESEARCH

What motivates this research work is the fact that:

1- The utilization of wind is free, this means that it is cheap.

2- The more the wind energy produced, the less is its costs per MWh.

3- Wind power is environmentally safe, since wind energy production does not emit any pollutant gases.

The significance of this study is that, it will boost the economy of the country if properly implemented.

1.3 AIM AND OBJECTIVES

The aim of this dissertation is to develop a wind power forecasting model of Kano using autoregressive moving average(ARMA) modelling technique: These would be achieved using the following set of objectives.

1- Data collection.

2- Development of ARMA model.

3- Development of AR model.

4- To carried out short time forecast in

5-To compare the performance of both models.

1.4 METHODOLOGY

In this research, a statistical model is used in forecasting the wind power. The specific application of Autoregressive moving average (ARMA) to wind power forecasting will be adopted.

The three steps involved in ARMA statistical methods are:

1. Model definition: selection of the *(p,q)* order of the ARMA model, denoted as model structure.

2. Model training: estimation of the model parameters through a least squares minimization process.

3. Prediction of the forthcoming value: estimation of the forthcoming value of the time series.

If the estimation of more than one forthcoming value is required, one estimation at a time is performed, and the estimated values are used to perform the next.

Software tools. The simulations performed make use of Matlab software for implementing the ARMA model[7],[8]. Thus, it is possible to select the best between several predetermined models, although it is necessary to estimate the parameters of all these before the evaluation functions are employed.

1.5 SCOPE OF THE WORK

This work will addresses the issue of forecasting wind power using statistical model, the Autoregressive Moving Average. The basic theory and the respective application of this model to perform wind power prediction, the ability and capability when compared with Autoregressive(AR) model is presented.

1.6 THESIS ORGANISATION

The rest of the dissertation is organized in chapters as follows. Chapter two reviews some previous research and literatures related to this research. Chapter three provides the design procedure to be followed in order to achieve the aim of the research. Chapter four gives a detailed discussion of the results obtained from simulation and discusses the outcomes of the research work. Conclusion on the achievements and recommendations for further future works, are presented in chapter five.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

Overviewed of previous works carried out on power forecasting using statistical models were presented in this chapter. Special attention is given to power forecasting based on Autoregressive moving average(ARMA).

2.2 PREVIOUS WORKS

Several works have been done on wind power prediction, by different researchers using different methods, in order to come up with better technique for wind power forecasting.

Pedro and Rui castro, addresses the issue of forecasting wind power using two statistical models: the Autoregressive Moving Average and Artificial Neural Networks. The basic theory and the respective application of these models in wind power prediction were presented. They compared the forecasting ability with three different case studies. They showed that ARMA models achieved slightly better forecast than the ANN models, but with higher computational time [4]. Lingling Li et.al. used ARMA (q, p) model of time series to forecast wind speed and atmospheric pressure through Radial Basis Function (RBF) neural network, based on this to forecast the wind power [9]. R. Billinton et.al. presented two different time-series models generated using different available wind data. Wind data from Canada and Sask Power were used to evaluate these models. No assumptions or previously estimated factors are included in the models. In order to check the adequacy of the proposed models, the F-criterion and Q-test were used (These are other alternative options for confirming the validity of a model on the sample data) and the statistical characteristics of the simulated wind speeds were compared with those obtained from the actual wind speeds. The model satisfies the basic statistical tests (i.e. F-test and Q-test) and preserves the high-order auto-correlation, seasonal property and diurnal distributions of the actual wind speed [10]. Ding M et.al. in their studies, a wind speed forecasting model based on time series analysis were used. In order to check the effectiveness of the model, Akaike information criterion (AIC) function was used. According to the AIC value of the models ARMA(5,4) was employed to calculate the 1-month average wind speed and the 1h averaged wind speed, and the results were compared with the actual wind speed [11]. Lalarukh k, Yasmin ZJ. developed ARMA model for short and long-term, based on the wind speed data of 2-years. Considering auto-correlation, non-Gaussian distribution and diurnal non-stationarity. The conclusion was that forecast values of variance and wind speed with a confidence interval of 95% can be acceptable both for short and long-term prediction [12]. Torres JL et.al. used ARMA model to predict hourly averaged wind speed and compared it with the persistence model. In their study, the transformation and standardization of the time series was proved very important to form the appropriate model. If the root mean square errors (RMSE) is not to surpass the 1.5m/s limits, the method proposed in the article is only applicable to short-term prediction. They also concluded that the ARMA model outperformed the persistence model. In forecasting horizon of 1h, the persistence had less errors than ARMA model, while for forecasting 10h in advance, the error of the ARMA model are between 12% and 20%, smaller than that of the persistence model [13]. Erasmo C, Wilfrido R. Forecasted the wind speed of south coast of Oaxaca, both ARIMA model and ANN model were used and compared to each other. The final results indicated that the seasonal ARIMA model presented a better sensitivity to the prediction of wind speed. However, when the number of training vectors was increased for the ANN model, its performance improved [14]. Michael Milligan et.al. developed several statistical forecasting models that can be useful for hour-ahead markets that have a similar tariff. Although longer-term forecasting relies on numerical weather models, the statistical models used here focused on the short-term forecasts that can be useful in the hour-ahead markets. The purpose of their paper was not to develop forecasting models that can compete with commercially available models. Instead, they investigate the extent to which time-series analysis can improve on simplistic persistence forecasts. This thesis applied a class of models known as autoregressive moving average (ARMA) model to both wind speed and wind power output. The ARMA approach was selected because it is a powerful, well-known time-series technique and has been used by the California Independent System Operator in some of its forecasting work. Results were presented for operating wind farms in Iowa and Minnesota, and indicated that a significant improvement over persistence models can be achieved [15]. Joseph Aidan, presented wind speed distribution of Kano which can be assumed Weibull or normally distributed with 5% significance level (95% confidence level). The Kolmogorov-Smirnov (KS) and Anderson-Darling goodness-of-fit tests on this speed distribution of Kano are both accepted. Therefore, this distribution could be used to determine a better accuracy of wind power potentials in Kano. With a FL30 turbine, close to 50% of its installed capacity and for almost 50% of the time it may be operated in a year can be extracted. While other turbines like Vestas47 and NW100/19 were not found be suitable for wind power generation in Kano, because they lacks the wind to offer this capacity generation for 50% of its operation time is almost not available at the hub height of 55 or 42m respectively [16]. Rui Huang et al. uses ARMA model and the persistence model to predict the future solar generation. In the forecasting procedures, the historical solar radiation data originates within the area under consideration. System Advisor Model (SAM) was applied to obtain the historical solar generation data, by inputting the data from Solar system. In order to validate the solar forecasting models, simulations in the System Identification Toolbox, Matlab platform were performed. The forecasting results with error analysis indicated that, the ARMA model excels at short and medium term solar forecasting, whereas the persistence model performs well only under very short duration [17]. Billinton R et al. simulated wind velocities using a wind speed time series model including auto regressive and moving average parameters (ARMA), with variations obtained by using white noise was considered [18]. Billinton R, Karki R. used similar technique in [18] to generate hourly weather data from the monthly mean values for the simulation of PV power generation output [19].

The advantages of this ARMA modelling technique includes:

1) eliminating the need for extensive measured data.
2) .eliminating the need for handling large data measurements.
3) reducing computational efforts in handling large data, etc.

R. Billinton and H. Dange. compared several wind speed modelling techniques using the wind speed data from two different locations in Canada (Bonavista and Swift current sites). The techniques compared include: hourly observed data, hourly mean observed wind speed, ARMA time series, moving average (MA) time series, normal distribution and Markov chain models. It was concluded that, when more years of data are utilized the variations of the reliability indices become insignificant. The closer the observed mean wind speed obtained is to the WECS rated output, the lesser the amount of years of the wind speed to be simulated using ARMA. This will eventually produce indices similar to that using actual observed data [20]. They also reported the following five critical observations:

1. Reliability indices can be highly dependent on the wind regimes, particularly when a small number of years is used.

2. Neglecting the auto-correlation of the wind speed from hour to hour can lead to having higher wind speed variations and higher LOLFs.

3. Also, larger variations between chronological wind speeds results into higher loss of load frequencies (LOLFs).

4. Analytical techniques (multi-state techniques) tend to post pessimistic indices no matter which method is used.

5. The level of correlation between load and wind power indicate a good check to establish the validity of the reliability indices.

Robin Axelsson, examines the Swedish electricity market and the effects from the deregulation of it. The fact that the deregulation has given rise to highly volatile prices has created a strong need for more sophisticated models to yield better electricity price forecasts. The ARMA model was examine and evaluated as forecasting models for electricity prices, the effect of outdoor temperatures on electricity consumption and electricity prices was also examined. Hourly and daily temperature data were then used as exogenous input to ARMAX models, which was also evaluated for use as forecasting models. Both ARMA model and ARMAX model provide good fits during shorter time–periods. Using temperature data has turned out to provide a significant improvement to the models. However, they all fail to properly capture the extreme behaviour with price spikes that occur during the winter seasons.

They are not suitable for long run prediction without further sophistications e.g. by using time-varying parameters such as time–varying volatilities and mean values. The conclusions are, there is need for improved forecasting methods. ARMA and ARMAX models have proven to be good prediction tools in some circumstances [21]. Atsushi Yona et al. reported that, in recent years, there has been introduction of alternative energy sources such as wind energy. However, wind speed is not constant and wind power output is proportional to the cube of the wind speed. In order to control the power output for wind power generators as accurately as possible, a method of wind speed estimation is required. The techniques considered are, the Auto Regressive model (AR), Kalman Filter (KF) and Neural Network (NN) to forecast wind power, for the purpose of comparing the forecasting abilities of these models. It was concluded that, the calculated results of mean absolute error (MAE) with AR model, KF and NN are similar. But the forecast result of the power output of AR, KF and NN differs [22]. Kavasseri R. G, and Seetharaman K. used the fractional Autoregressive Integrated Moving Average model (f-ARIMA) model to predict the day-ahead wind speeds. Comparing the result with the persistence model, the authors indicated that significant improvements were realized by using f-ARIMA model as compared to persistence model [23]. In a similar case, Cadenas E, and Rivera W. used Artificial Neural Network (ANN) and seasonal-ARIMA (s-ARIMA) based models for the prediction of wind speed. The authors concluded that seasonal ARIMA models provide a better approach for predicting the wind speed and respond well to the structural changes in the wind regime [24]. Ergin Erdem et al. developed mixed ARMA model that incorporates the wind direction into short term wind speed and wind power output forecasts. For this purpose, existing association between the wind speed and wind direction were examined using a clustering approach. Using *k*-means algorithm, wind directions are classified based on the accompanying wind speeds. Using an ARMA model for forecasting the wind direction, those values are associated with the formed clusters by using dummy variables. The dummy variables are employed in the mixed ARMA model. The analysis indicated that, incorporating wind direction provides slightly but consistently better estimates for the wind speed for short term forecasts. Improvements in forecasting accuracy for the wind power output are also realized by employing mixed-ARMA model [25]. Daiana Geninasca, investigated the effects of wind power feed-in as an exogenous variable on the forecasting accuracy of electricity prices. For this purpose, ARMA(X) and ARMA(X)-GARCH models have been implemented on deseasonalised electricity prices during summer and winter time, for the 24h/day and for the three periods of the day, i.e. off-peak I, peak, and off-peak II hours. The empirical results reveal three important patterns:

1- The wind power feed-in is related to the stochastic part of the electricity prices.
2- During the summer time, both ARMAX and ARMA(X)-GARCH models outperform ARMA and ARMA-GARCH models (in particular during the off-peak I hours). During the winter time the wind power feed-in partly worsens the model performance (e.g. during peak hours).
3- The wind power feed-in has different impacts on the forecasting accuracy over the three periods of the day.

The second part of the analysis captured the complexity of the relationship among wind power feed-ins, electricity log price returns, fuel and CO_2 log price returns. The analysis confirmed that there is a statistical evidence of an influence of wind power feed-ins on electricity prices. The wind power feed-in has a rather poor linkage with the remaining variables, but some conclusions are still possible. The most important being a longer-term linkage between wind power feed-in and CO_2 allowance prices [26].

2.3 THEORETICAL BACKGROUD OF WIND PARAMETERS

2.3.1 WIND POWER

Wind power is the kinetic energy of wind, harnessed and redirected to perform a task mechanically or to generate electrical power. Wind power is very consistent from year to year but has significant variation over shorter time scales. It is therefore used in conjunction with other sources to give a reliable supply [27].

2.3.1.1 MATHEMATICAL MODEL OF WIND POWER

Under constant acceleration, the kinetic energy of an object having mass m and velocity v is equal to the work done W in displacing that object from rest to a distance s under a force F, i.e.

$$E = W = Fs \quad \text{-----------------------------------}(2.1)$$

According to Newton's Law, we have:

$$F = ma \quad \text{---------------------------------------} (2.2)$$

Hence,

$$E = mas \quad \text{---------------------------------------} (2.3)$$

Using the third equation of motion:

$$v^2 = u^2 + 2as \quad \text{-------------------------------------} (2.4)$$

we get:

$$a = \frac{(v^2 - u^2)}{2s} \quad \text{-------------------------------------} (2.5)$$

Since the initial velocity of the object is zero, i.e. $u = 0$, we get:

$$a = \frac{v^2}{2s} \quad \text{-------------------------------------- (2.6)}$$

Substituting it in equation (3), we get that the kinetic energy of a mass in motions is:

$$E = \frac{1}{2}mv^2 \quad \text{-------------------------------------- (2.7)}$$

The power in the wind is given by the rate of change of energy:

$$P = \frac{dE}{dt} = \frac{1}{2}v^2\frac{dm}{dt} \quad \text{--------------------------------------(2.8)}$$

As mass flow rate is given by:

$$\frac{dm}{dt} = \rho A\frac{dX}{dt} \quad \text{-- (2.9)}$$

and the rate of change of distance is given by:

$$\frac{dX}{dt} = v \quad \text{--------------------------------------- (2.10)}$$

we get:

$$\frac{dm}{dt} = \rho Av \quad \text{------------------------------------- (2.11)}$$

Hence, from equation (8), the power can be defined as:

$$P = \frac{1}{2}\rho Av^3 \quad \text{-------------------------------- (2.12)}$$

A German physicist Albert Betz concluded in 1919 that, no wind turbine can convert more than 16/27 (59.3%) of the kinetic energy of the wind into mechanical energy turning a rotor. To this day, this is known as the **Betz Limit** or **Betz' Law.** The theoretical maximum **power efficiency** of *any* design of wind turbine is 0.59 (i.e. no more than 59% of the energy carried by the wind can be extracted by a wind turbine) [28]. This is called the "power coefficient" and is defined as:

$$C_{P\,max} = 0.59 \quad \text{-------------------------------- (2.13)}$$

Also, wind turbines cannot operate at this maximum limit. The C_P value is unique to each turbine type and is a function of wind speed that the turbine is operating at. Once we incorporate various engineering requirements of a wind turbine - strength and durability in particular - the real world limit is well below the *Betz Limit* with values of 0.35-0.45 common even in the best designed wind turbines. By the time we take into account the other factors in a complete wind turbine system. e.g. the gearbox, bearings, generator and so on , only 10-30% of the power of the wind is ever actually converted into usable electricity. Hence, the power coefficient needs to be factored in equation (2.12) and the extractable power from the wind is given by:

$$P_{avail} = \frac{1}{2}\rho A v^3 c_p \quad \text{---------------------------- (2.14)}$$

The swept area of the turbine can be calculated from the length of the turbine blades using the equation for the area of a circle:

$$A = \pi r^2 \quad \text{-- (2.15)}$$

where the radius is equal to the blade length as shown in the figure 2.1[28]:

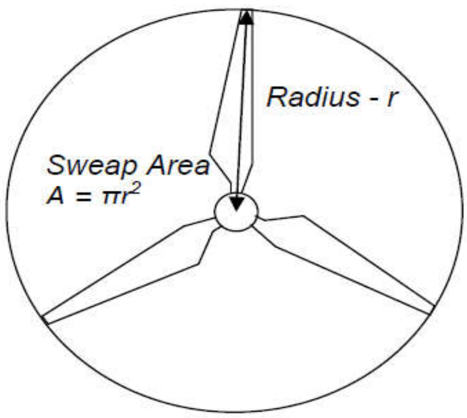

Fig. 2.1: Turbine blades length

2.3.2 WIND TURBINE POWER OUTPUT VARIATION WITH WIND SPEED

Fig.2.2, shows a sketch a how the power output from a wind turbine varies with wind speed.

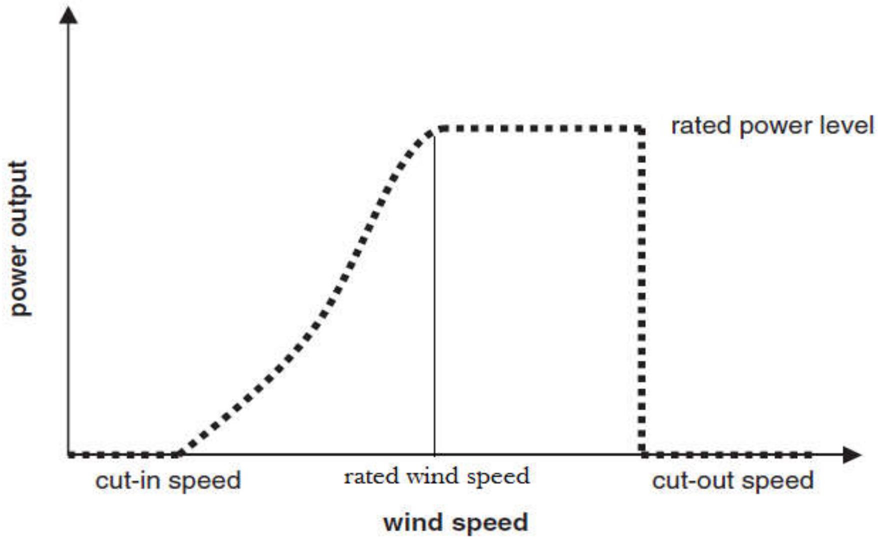

Figure 2.2: Wind turbine power curve

a. Cut-in speed

From fig.2.2, at very low wind speeds, there is insufficient torque exerted by the wind on the turbine blades to make them rotate. However, as the speed increases, the wind turbine will begin to rotate and generate electrical power. The speed at which the turbine first starts to rotate and generate power is called the ***cut-in speed*** .

b. Rated output power and rated output wind speed

From fig.2.2, as the wind speed rises above the cut-in speed, the level of electrical output power rises rapidly as shown. The power output reaches the limit that the electrical generator is capable of. This limit to the generator output is called the rated power output and the wind speed at which it is reached is called the rated output wind speed. At higher wind speeds, the design of the turbine is arranged to limit the power to this maximum level and there is no further rise in the output power. How this is done varies from design to design but typically with large turbines, it is done by adjusting the blade angles so as to keep the power at a constant level.

c. Cut-out speed

As the speed increases above the rated output wind speed, the forces on the turbine structure continue to rise and, at some point, there is a risk of damage to the rotor. As a result, a braking system is employed to bring the rotor to a standstill. This is called the cut-out [29].

2.4 WIND SPEED

Wind speed or wind flow velocity, is a fundamental atmospheric rate. Wind speed is caused by air moving from high pressure to low pressure. Wind speed is now commonly measured with an anemometer but can also be classified using the Beaufort scale which is based on people's observation of specifically defined wind effects [30].

2.4.1 ANEMOMETER

An anemometer is a device for measuring the force or speed of the wind. This instrument has been around since at least 1450. There are many different types of anemometers, each with unique characteristics. The types are cup anemometer, hot wire, wind mill, pressure tube, ultrasonic and laser doppler etc [31].

In this research work, the data collected from the Nigerian Meteorological Agency (NIMET), Kano was recorded using cup anemometer and it was placed at the height of 6.1m above the tower .

2.4.1.1 CUP ANEMOMETER

The cup or rotational anemometer is one of the oldest types of anemometers. The cups are placed onto a vertical axis, and when the wind presses against them, this causes the cups to rotate around. The faster the cups rotate, the faster the wind speed. Cup anemometers usually have digital readouts. Researchers, educational institutions and meteorologists worldwide use this type of anemometer for research and commercial activities [31].

Fig. 2.3 cup anemometer[31]

2.4.2 THE BEAUFORT WIND FORCE SCALE

Table 2.1 shows a wind chart, created by Admiral Beaufort. Beaufort arranged the numbers 0 to 12 to indicate the strength of the wind from calm (force 0) to hurricane (force 12). Here's a scale adapted to land [32] .

Table 2.1 beaufort wind force scale.

Beaufort Force	Description	When You See or Feel This Effect	Wind (mph)	Wind (km/h)
0	Calm	Smoke goes straight up	less than 1	less than 2
1	Light air	Wind direction is shown by smoke drift but not by wind vane	1-3	2-5
2	Light breeze	Wind is felt on the face; leaves rustle; wind vanes move	4-7	6-11
3	Gentle breeze	Leaves and small twigs move steadily; wind extends small flags straight out	8-12	12-19
4	Moderate breeze	Wind raises dust and loose paper; small branches move	13-18	20-29
5	Fresh breeze	Small trees sway; waves form on lakes	19-24	30-39
6	Strong breeze	Large branches move; wires whistle; umbrellas are difficult to use	25-31	40-50
7	Moderate gale	Whole trees are in motion; walking against the wind is difficult	32-38	51-61
8	Fresh gale	Twigs break from trees; walking against the wind is very difficult	39-46	62-74
9	Strong gale	Buildings suffer minimal damage; roof shingles are removed	47-54	75-87
10	Whole gale	Trees are uprooted	55-63	88-101
11	Violent storm	Widespread damage	64-72	102-116
12	Hurricane	Widespread destruction	73+	117+

2.5 TIME SERIES

A time series is a sequence of data points, typically consisting of successive measurements made over a time interval. Examples of time series are ocean tides, counts of sunspots. Time series are very frequently plotted via line charts. Time series are used in statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, astronomy, communications engineering, and largely in any domain of applied science and engineering which involves temporal measurements [33].

2.5.1 OVERVIEW OF WIND POWER FORECASTING METHODS

Most common wind forecasting techniques developed and reported in literature use one of the following methods illustrated in the below chart:

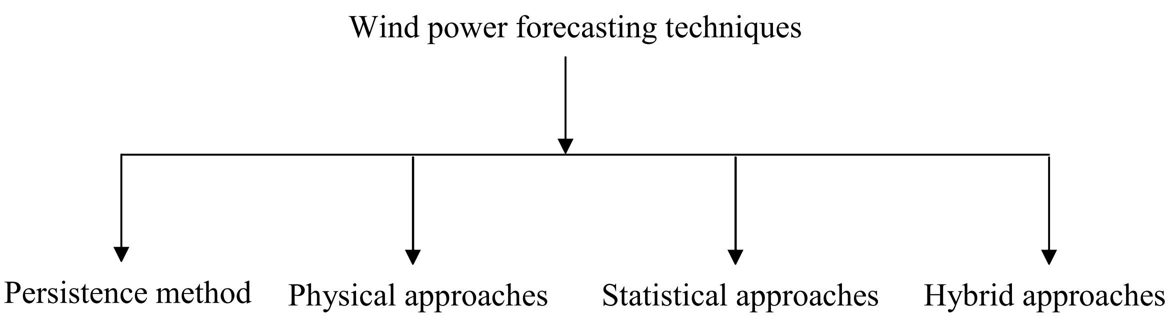

Fig.2.3: Wind power forecasting techniques chart

1) Persistence Method

This method is also known as 'Naïve Predictor'. It is assumed that the wind speed at time 't+Δt' will be the same as it was at time 't'. Unbelievably, it is more accurate than most of the physical and statistical methods for very-short to short term forecasts. Industry still uses it for very-short term forecasts [34],[35]. Hence, any forecast method that is developed should, first, be tested against classical benchmark of persistence method to check how much it can improve over this technique [36].

2) Physical Approach

Physical systems use parameterizations based on a detailed physical description of the atmosphere. Usually, wind speed given by the weather service on a coarse grid is transformed to the onsite conditions at the location of the wind farm [37]. *Numeric Weather Prediction (NWP):* This method is a physical approach to wind forecasting. NWP models operate by solving complex mathematical models that use weather data like temperature, pressure, surface roughness and obstacles. NWPs are rendered on supercomputers as they need lots of computations. Customarily, NWPs are run 1 or 2 times a day due to the difficulty to gain information in short-time and the associated high costs. This limits its usefulness to medium to long-term forecasts (> 6 h ahead). NWP give most accurate predictions when weather conditions are stable [35],[38].

3) Statistical Approach

The statistical approach is based on training with measurement data and uses difference between the predicted and the actual wind speeds in immediate past to tune model parameters [35], [37]. It is easy to model, inexpensive, and provides timely predictions. It is not based on any predefined mathematical model and rather it is based on patterns. Errors are minimized if patterns are met with historical ones. Sub-classification of this approach is: *Time-series based models*, and *neural network (NN) based methods*. Auto-Regressive Moving Average (ARMA) models are the most popular type in the time-series based approach to predict future values of wind speed or power. Several variations are auto regressive integrated moving average (ARIMA), *seasonal*- and *fractional*-ARIMA, ARMA with exogenous input (ARMAX or ARX). Other time-series models are grey predictors, linear predictions, exponential smoothing, etc.

4) Hybrid Approach

In general, combination of different approaches such as mixing physical and statistical approaches etc, is referred to as a hybrid approach. For example, radioactive transfer and NN techniques are combined with Special Sensor Microwave/Imager (SSM/I) to get ocean surface wind speeds and direction in [39]. Results show that combination of NN would substantially enhance the impact of these data in NWPs as compared to SSM/I.

For this research work, time-series based approach i.e Auto-Regressive Moving Average (ARMA) models is used to predict 6hrs future wind power.

2.5.2 AUTOREGRESSIVE MOVING AVERAGE MODEL

The Autoregressive Moving Average (ARMA) model is a useful and powerful tool to describe the dynamics of an individual time series. This model allows one to estimate the forthcoming value of an individual time series as a linear combination of values already observed. The computation of the coefficients of this linear combination, which are the parameters of the model, is based on the time series itself, so that each value of the series is explained by the linear combination of some of its prior values, in the best possible way. This computation corresponds to the training step of the model, and the estimation of the forthcoming value corresponds to the prediction step. A mixed *p*th-order autoregressive process and *q*th-order moving average process, ARMA (p,q), is formally given by [6]:

$$Y_t = C + \sum_{i=1}^{p} \; {}_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i} \quad \text{-------------------------} \; (2.16)$$

In equation (16) $\{Y_t\}$ is the time series to be described, C is an internal constant value of the process, $(\; {}_1, \; {}_2, \ldots, \; {}_p)$ are the AR process parameters, $(\theta_1, \theta_2, \ldots, \theta_q)$ are the MA process parameters and $\{\varepsilon_t\}$ is a white noise process. A sequence $\{\varepsilon_t\}$ is called a white noise sequence, if each ε_t is a random variable with mean zero and covariance σ^2 and, for every t,τ≥0 with t≠τ, ε_t and ε_τ are uncorrelated. Formally,

$$E(\varepsilon_t)=0, \quad E(\varepsilon_t^2)=\sigma^2, \quad E(\varepsilon_t\varepsilon_\tau)=0 \quad \text{------------------------------} \ (2.17)$$

This process includes a component computed from the known information up to the instant t 1, which is the autoregressive process, and another component that represents the uncertainty of the mean of $\{Y_t\}$, which is the moving average process. To estimate the parameters of the ARMA models, a least squares minimization is often employed. This mathematical procedure tries to find the best-fitting curve to a set of values of a time series by minimizing the sum of the squares of the residuals – the differences between the values of the time series and the same values reproduced by the model.

2.6 TIME HORIZON

Time horizon is the range of time ahead for forecasting into the future. Classification of the wind forecasting methods based on time scale is vague. It is classified into very-short term, short term, medium term and long term forecasting [40]

1-Very-short term: few seconds to 30min ahead. Its implications are in electricity market clearing.

2-Short-term: 30min to 6hours ahead. Its implications are in Economic load dispatch planning.

3-Medium-term: 6hour to 1day ahead. Its implications are in Generator online/offline decisions.

4-Long-term: More than 1day ahead. Its implications are for unit commitment decisions and reserve requirement decisions.

The above time horizons are strictly limited and some relaxation is possible based on the application of forecasting model. Different governing bodies, countries will have different standards and protocols. So, there is strict limit on the range of each horizon. There is no universal forecasting model for all time horizons mentioned above because there exists no model which can be applicable to all time horizons, as each model either it is statistical or neural networks or any other has its own restrictions and implications for each time horizon. The restrictions can be accuracy, complexity, cost, time for processing, number of input variables, training the data. All the above features cannot be set right for all the time horizons with feasibility and in practical perspective. For this work, short term forecasting is considered for 6 hours forecast.

2.7 SUMMARY

A lot of research work on wind power forecasting using ARMA model and using different models have been reviewed. ARMA model was found to outperform other models when exogenous input where not consider to the wind speed such as temperature, atmospheric pressure, relative humidity, solar radiation, wind direction etc. ARMA modelling technique was adopted in my evaluations because of the advantages mentioned as well as it been a widely accepted method found in the literature. The data obtained from Nigerian Meteorological Agency(NIMET), Kano wind speed data will be used as a case study.

CHAPTER THREE

MODELLING PROCEDURE

3.1 INTRODUCTION

This chapter presents the processes involved in modelling and simulation of historical wind speed data in order to translate the measured wind speed into power generation based on AR and ARMA using MATLAB. The processes are: Data sourcing, Data acquisition, Wind speed data pre-processing, Creation of iddata object for wind speed, partitioning the iddata into estimation and validation sets, modelling the wind speed using Auto-Regressive (AR) modelling technique, modelling the wind speed using Auto-Regressive Moving Average (ARMA) modelling technique, chosen AR and ARMA model parameter for analysis and validation, forecasting future wind speeds from both AR and ARMA models, wind turbine generator output modelling.

3.2 WIND SPEED DATA ACQUISITION

The wind speed data was obtained from the Nigerian Meteorological Agency (NIMET), Kano. The data are recorded continuously over every 30 minutes intervals to obtain the wind attributes using anemometer which is placed at the height of 10m, the height of the station is 475.8m above sea level. The period with which the data is considered is between January 1, 2005 to December 30, 2009. (5 years).

The available wind speed data contains 80,000 measurements sampled at 30 minutes intervals. The flow chart shown in figure 3.1, illustrate the entire process involved in the formulation of the forecasting model for wind power plant.

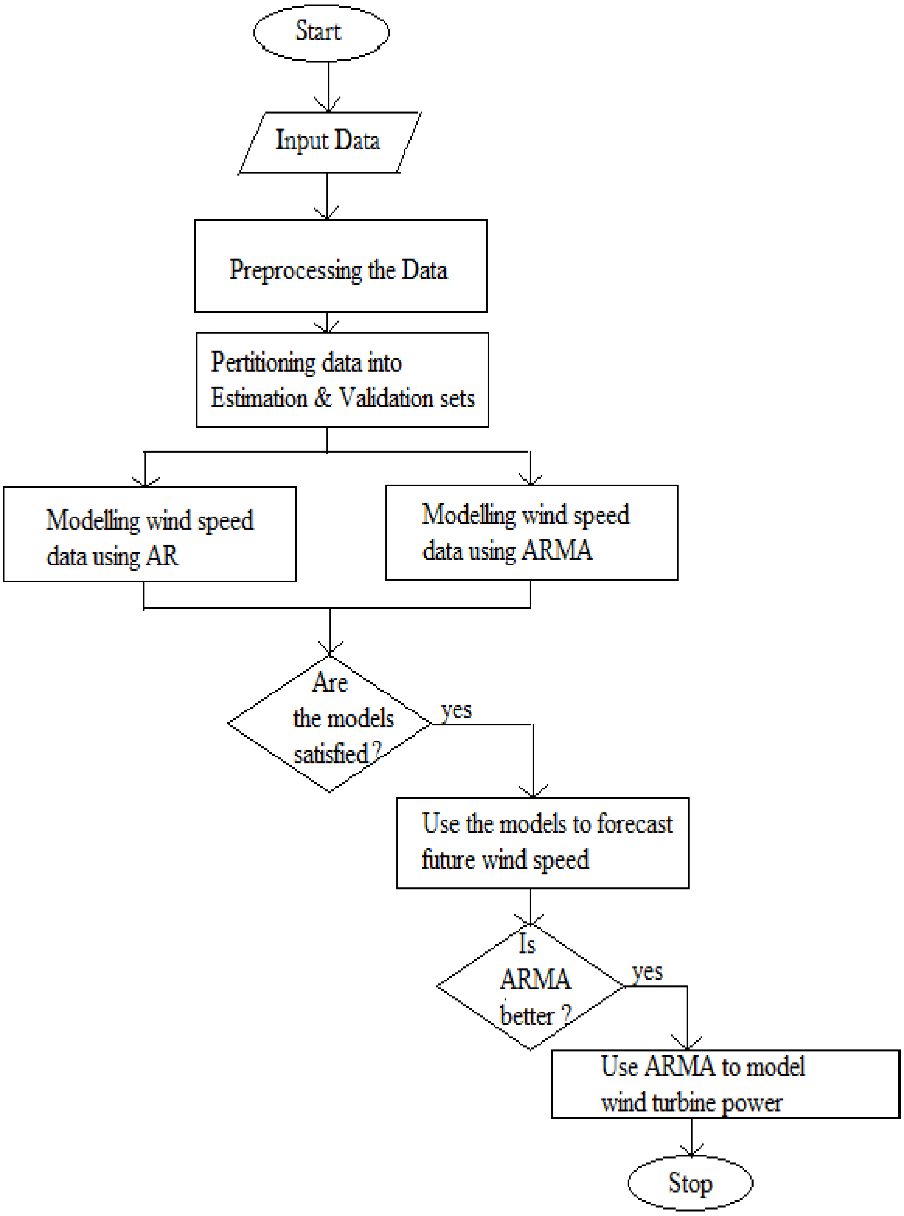

Fig. 3.1 Flow chart for wind power forecasting

The wind speed data was loaded into the MATLAB workspace, to have a snapshot of its nature for observation (see fig. 3.2), a one week wind speed profile was plotted.

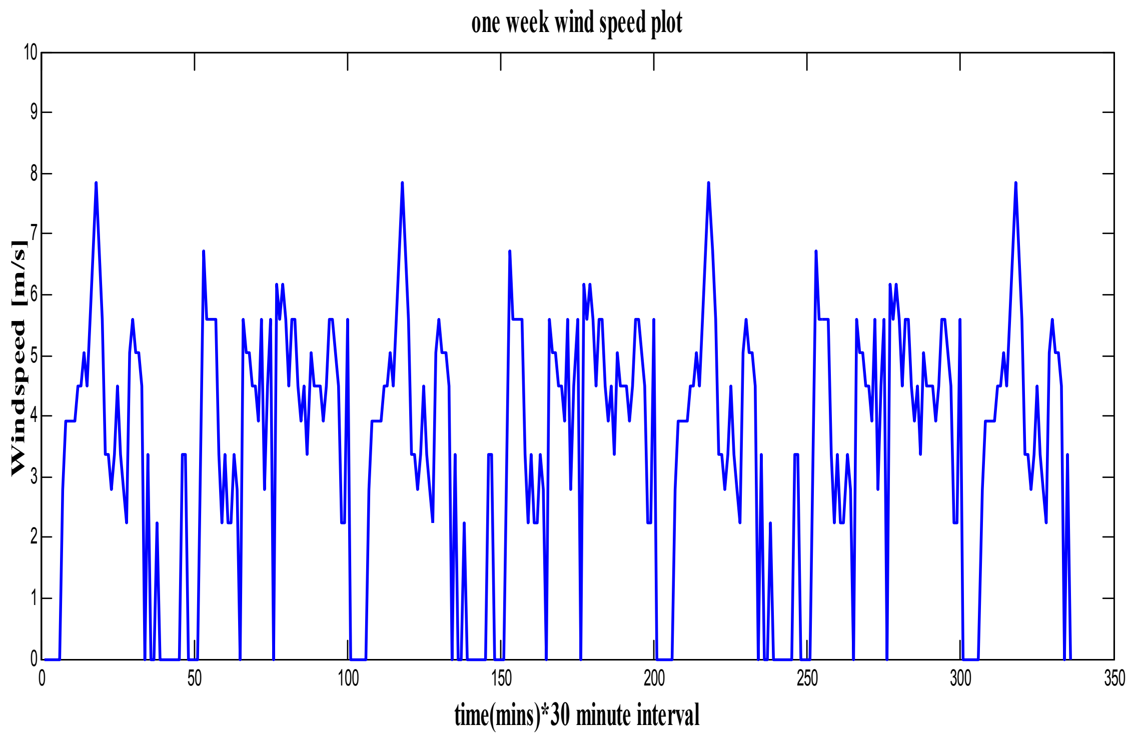

Fig.3.2: Shows the plot of the dataset for one week (7 days)

3.3 PREPROCESSING THE WIND SPEED DATA

In order to reconstruct missing input and output data, the data was preprocessed using misdata command.

Syntax:

Data = misdata(Data) .... (3.1)

Description:

Data is time-domain input-output data in the iddata object format. Missing data samples (both in inputs and in outputs) are entered as NaNs.

Data is an iddata object where the missing data has been replaced by reasonable estimates.

kanoWindspeed = misdata(kanoWindspeed) .... (3.2)

In order to eliminate outliers, the data was preprocessed using z-score.

Syntax:

Z = zscore(X) .... (3.3)

[Z,mu,sigma] = zscore(X) .... (3.4)

Description:

Z = zscore(X) returns a centered, scaled version of X, the same size as X. For vector input x, output is the vector of z-scores

z = (x–mean(x))./std(x) .... (3.5)

For matrix input X, z-scores are computed using the mean and standard deviation along each column of X. For higher-dimensional arrays, z-scores are computed using the mean and standard deviation along the first non-singleton dimension.

The columns of Z have mean zero and standard deviation one (unless a column of X is constant, in which case that column of Z is constant at 0). z-scores are used to put data on the same scale before further analysis. Also returns mean(X) in mu and std(X) in sigma. A negative z-score means that the original score was below the mean, as the sample size becomes large, approximately half the z-score should be negative and half of the z-score should be positive.

3.4 DECLARING THE WIND SPEED DATA AS IDDATA OBJECT TO MATLAB PROGRAM

This declaration of data is necessary for activating the AR and ARMA tools in MATLAB system identification toolbox. For better book keeping, the data is updated by adding iddata profile parameters. Having removed the outliers using z-score, for estimation and cross validation purposes, the data is partitioned (split it into two halves).

3.5 PARTITIONING THE IDDATA INTO ESTIMATION AND VALIDATION SETS

In this section the stored data was divided into two halves in order to compute the model Auto-regressive (AR) and AR with moving average (ARMA) models. These techniques was used to model the characteristics of the wind speed and also to simulate the output performance of a wind turbine generator. The next section, considered which of the two models (AR and ARMA) best capture the dynamic behaviour of the wind speed using the validated data.

3.6 MODELLING THE WIND SPEED USING AR AND ARMA

To achieved the models of wind speed using AR and ARMA the following steps were followed.

The first step was the identification of the model, this involved specifying the appropriate structure and order of the model, this was done by an automated iterative procedure with the help of MATLAB using a goodness of fit statistic to select the best model.

The second step was to estimate the coefficient and parameters for both AR and ARMA models, this was achieved by writing MATLAB scripts (appendix A), that were ran in order to obtained the parameters of the models.

The final step was to check the models for the best fit, this is done to ensure that the chosen model is the simplest possible model with fewest parameters and best or adequate described the data.

Following the steps illustrated above, several models of both AR and ARMA were obtained and presented in Table 4.1 and 4.2. From these table AR(4) and ARMA(4,3) were chosen to be the best models for the wind speed.

3.7 FOCASTING FUTURE WIND SPEEDS FROM BOTH AR AND ARMA MODELS

In order to further confirm the validity of the developed AR and ARMA models, a forecast of 6 hours ahead was made. From the result obtained, ARMA (4,3) and AR (4) gives 27.4% and 25.87% level of accuracy.

3.8 WIND TURBINE GENERATOR OUTPUT MODELLING

The simulated wind speed was retrended (i.e. de-normalised) for modelling the output of the wind turbine. The generator specifications used are; [42]

$P\_r = 2$; $V\_ci = 1.44$; $V\_co = 8.0$; $V\_r = 3.6$;

Where,

- power unit is in kW and wind speed in m/sec.

- P_r is the rated power of the wind turbine generator (WTG).

- V_ci is the cut in speed of the WTG.

- V_co is the cut out speed of the WTG.

- V_r is the rated output speed of the WTG.

The plots for wind turbine generator output and that of non-linear of WTG output curve would be presented and discussed in chapter four.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter considered the discussion of the results and plots obtained in chapter three.

4.2 ONE WEEK WIND SPEED CHARACTERISTIC

There is a trend that can be seen from fig.3.2, the graph is fluctuating rapidly with trend of decreasing and then increasing. The wind speed is swiftly changing with respect to time; it is due to the dynamic nature of wind. There is high volatility in fig.3.1, following a certain trend and this trend can be due to seasonality effect. The mean of the data set is 3.7345(m/s). The plot has time intervals on the horizontal and wind speed on the vertical axis, the minimum wind speed is zero and it can speed up to about 8m/s. This output characteristics further confirms the intermittent nature of the wind speed.

4.3 IDDATA PROFILE

```
This is the iddata profile
                Domain: 'Time'
                  Name: ''
            OutputData: {[80000x1 double]}
            OutputName: {'kanoWindspeed model'}
            OutputUnit: {'m/s'}
             InputData: {[80000x0 double]}
             InputName: {}
             InputUnit: {}
                Period: {[0x1 double]}
           InterSample: {0x1 cell}
                    Ts: {[1]}
                Tstart: {[]}
      SamplingInstants: {[80000x0 double]}
              TimeUnit: 'seconds'
        ExperimentName: {'Exp1'}
                 Notes: {}
```

```
UserData: []
```

The displayed information is the data profile of the system identification object as indexed by MATLAB. It presents the output data size stored (i.e line 4 OutputData: {[80000x1 double]}). This means that 80000 units of data in double precision numbering format is to be used for the next processes. The remaining information include other profiling information for record purposes.

4.4 SIMULATION FOR AUTO-REGRESSIVE MODEL

Table 4.1shows the simulated results for AR models, the fit to estimation data, final prediction error, mean square error and the model equations are presented for choosing the best among the models.

Discrete-time AR model:

$$A(z)y(t) = e(t) \qquad (4.1)$$

Table 4.1 Different AR models

S/N	ORDER	AR MODEL	FED (%)	FPE	MSE	EQUATION
1	1	AR(1)	23.22	0.5564	0.5563	$A(Z) = 1 - 0.6486\, Z^{-1}$
2	2	AR(2)	24.48	0.5382	0.5382	$A(Z) = 1 - 0.5314Z^{-1} - 0.1807Z^{-2}$
3	3	AR(3)	24.77	0,5341	0.534	$A(Z) = 1 - 0.5154Z^{-1} - 0.1337Z^{-2}$ $-0.08839Z^{-3}$
4	4	AR(4)	25.87	0.5187	0.5185	$A(Z) = 1 - 0.5304Z^{-1} - 0.1565Z^{-2}$ $-0.1761Z^{-3} - 0.1702Z^{-4}$
5	5	AR(5)	25.95	0.5177	0.5174	$A(Z) = 1 - 0.5381Z^{-1} - 0.1485Z^{-2}$ $-0.169Z^{-3} - 0.1941Z^{-4}$ $-0.04518Z^{-5}$
6	9	AR(9)	26.1	0.5158	0.5153	$A(Z) = 1 - 0.5371Z^{-1} - 0.1533Z^{-2}$ $-0.1587Z^{-3} - 0.1904Z^{-4}$ $-0.03524Z^{-5} - 0.0535Z^{-6}$ $-0.03325Z^{-7} - 0.008377Z^{-8}$ $-0.03741Z^{-9}$
7	18	AR(18)	29.92	0.4642	0.4634	$A(Z) = 1 - 0.5806Z^{-1} - 0.1144Z^{-2}$ $-0.1424Z^{-3} + 0.1882Z^{-4}$ $-0.06431Z^{-5} - 0.002779Z^{-6}$ $-0.04506Z^{-7} + 0.06767Z^{-8}$ $-0.0007312Z^{-9} + 0.1294Z^{-10}$ $-0.2817Z^{-11} + 0.2169Z^{-12}$ $-0.04176Z^{-13} - 0.0383Z^{-14}$ $-0.04883Z^{-15} + 0.1043Z^{-16}$ $-0.06265Z^{-17} + 0.1153Z^{-18}$

The properties described in the following provide the details of AR(4) which is the best choice based on a good compromise of fit to the estimation data of 25.87%, It has a low mean squared error (MSE) of consecutive data measures of 0.518 and a low final prediction error (FPE) of 0.5187 and in order to handle less number coefficient for practical reason. From the displayed properties the important points to note are that; a, b, c and d are the orders of the chosen AR model. Also, integrate Noise (i.e. line 6) means that no outliers were used in the parameter estimation, further confirming the success of the step in Appendix (i.e. Zscore). The Noise Variance (i.e line 10) means that the simulated output wind speed using this AR(4) function

would weakly vary from the actual data when compared. This confirms the suitability of this AR(4) model for simulating the wind speed characteristic.

```
These are the properties of AR(4)
                 a: [1 -0.5304 -0.1565 -0.1761 0.1702]
                 b: {1x0 cell}
                 c: 1
                 d: 1
                 f: {1x0 cell}
          Variable: 'z^-1'
           ioDelay: [1x0 double]
    IntegrateNoise: 0
         Structure: [1x1 pmodel.polynomial]
     NoiseVariance: 0.5186
            Report: [1x1 idresults.polyest]
        InputDelay: [0x1 double]
       OutputDelay: 0
                Ts: 1
```

```
      TimeUnit: 'seconds'
     InputName: {0x1 cell}
     InputUnit: {0x1 cell}
    InputGroup: [1x1 struct]
    OutputName: {'kanoWindspeed model'}
    OutputUnit: {''}
   OutputGroup: [1x1 struct]
          Name: ''
         Notes: {}
      UserData: []
```

The AR(4) model created based on the properties above can be represented by equation (19).

$$Y_t = 0.5304Y_{t-1} + 0.1565Y_{t-2} + 0.1761Y_{t-3} - 0.1702Y_{t-4} \text{ ---------------------- } (4.2)$$

4.5 SIMULATION FOR ARMA MODEL

Table 4.2, shows the simulated results for ARMA models, the fit to estimation data (FED), final prediction error (FPE), mean square error and the model equations are presented for choosing the best among the models.

Discrete-time ARMA model:

$$A(z)y(t) = C(z)e(t) \text{ .... } (4.3)$$

Table 4.2 Different ARMA models

S/N	ORDER	ARMA MODEL	FED (%)	FPE	MSE	EQUATION
1	(1,1)	ARMA(1,1)	24.55	0.5373	0.5372	$A(Z)=1-0.7999Z^{-1}$ $C(Z)=1-0.2672Z^{-1}$
2	(1,2)	ARMA(1,2)	24.65	0.5358	0.5357	$A(Z)=1-0.7707Z^{-1}$ $C(Z)=1-0.2627Z^{-1}+0.07488Z^{-2}$
3	(1,3)	ARMA(1,3)	25.41	0.5251	0.525	$A(Z)=1-0.5449Z^{-1}$ $C(Z)=1+0.00884Z^{-1}+0.1419Z^{-2}$ $+0.2139Z^{-3}$
4	(1,4)	ARMA(1,4)	25.9	0.5182	0.518	$A(Z)=1-0.7912Z^{-1}$ $C(Z)=1-0.2452Z^{-1}+0.0162Z^{-2}$ $+0.1324Z^{-3}-0.1738Z^{-4}$
5	(1,5)	ARMA(1,5)	26	0.516	0.5167	$A(Z)=1-0.7318Z^{-1}$ $C(Z)=1-0.1958Z^{-1}+0.04896Z^{-2}$ $+0.171Z^{-3}-0.1615Z^{-4}$ $+0.06537Z^{-5}$
6	(2,1)	ARMA(2,1)	24.58	0.5368	0.5367	$A(z)=1-0.695Z^{-1}-0.0772Z^{-2}$ $C(Z)=1-0.1728Z^{-1}$
7	(2,2)	ARMA(2,2)	24.98	0.5312	0.531	$A(Z)=1-1.797Z^{-1}+0.8138Z^{-2}$ $C(Z)=1-1.279Z^{-1}+0.3097Z^{-2}$
8	(2,3)	ARMA(2,3)	26.31	0.5126	0.5124	$A(Z)=1+0.0890Z^{-1}-0.5799Z^{-2}$ $C(Z)=1+0.6365Z^{-1}-0.0896Z^{-2}$ $+0.1995Z^{-3}$
9	(2,4)	ARMA(2,4)	26.36	0.512	0.5117	$A(Z)=1+0.1825Z^{-1}-0.5614Z^{-2}$ $C(Z)=1+0.741Z^{-1}-0.0211Z^{-2}$ $+0.2515Z^{-3}+0.06954Z^{-4}$

10	(2,5)	ARMA(2,5)	25.56	0.5092	0.5089	$A(Z)=1+0.1089Z^{-1}-0.6826Z^{-2}$ $C(Z)=1+0.6655Z^{-1}-0.1806Z^{-2}$ $+0.1674Z^{-3}-0.0477Z^{-4}$ $-0.107Z^{-5}$
11	(3,1)	ARMA(3,1)	26.01	0.5168	0.5166	$A(Z)=1+0.3969Z^{-1}-0.6292Z^{-2}$ $-0.2368Z^{-3}$ $C(Z)=1+0.9536Z^{-1}$
12	(3,2)	ARMA(3,2)	28.87	0.4775	0.4773	$A(Z)=1+0.5822Z^{-1}+0.1176Z^{-2}$ $-0.6896Z^{-3}$ $C(Z)=1+1.295Z^{-1}+0.9982Z^{-2}$
13	(3,3)	ARMA(3,3)	29.67	0.467	0.4668	$A(Z)=1+0.4781Z^{-1}-0.0138Z^{-2}$ $-0.7905Z^{-3}$ $C(Z)=1+1.1Z^{-1}+0.7362Z^{-2}$ $-0.2011Z^{-3}$
14	(3,4)	ARMA(3,4)	29.87	0.4643	0.464	$A(Z)=1+0.5231Z^{-1}+0.045Z^{-2}$ $-0.7425Z^{-3}$ $C(Z)=1+1.129Z^{-1}+0.8673Z^{-2}$ $-0.04508Z^{-3}+0.101Z^{-4}$
15	(3,5)	ARMA(3,5)	26.56	0.5092	0.5089	$A(Z)=1+0.1639Z^{-1}-0.6743Z^{-2}$ $-0.0335Z^{-3}$ $C(Z)=1+0.7196Z^{-1}-0.142Z^{-2}$ $+0.1638Z^{-3}-0.0355Z^{-4}$ $-0.1038Z^{-5}$
16	(4,1)	ARMA(4,1)	25.93	0.5179	0.5177	$A(Z)=1-0.3545Z^{-1}-0.2474Z^{-2}$ $-0.2003Z^{-3}+0.1559Z^{-4}$ $C(Z)=1+0.1815Z^{-1}$
17	(4,2)	ARMA(4,2)	29.79	0.4653	0.461	$A(Z)=1+0.6991Z^{-1}+0.1Z^{-2}$ $-0.7823Z^{-3}+0.1671Z^{-4}$ $C(Z)=1+1.305Z^{-1}+0.9983Z^{-2}$
18	(4,3)	ARMA(4,3)	27.24	0.4998	0.4995	$A(Z)=1-0.477Z^{-1}-0.4006Z^{-2}$ $-0.7509Z^{-3}+0.6746Z^{-4}$ $C(Z)=1+0.1572Z^{-1}-0.2379Z^{-2}$ $-0.8251Z^{-3}$

19	(4,4)	ARMA(4,4)	30.05	0.462	0.4617	$A(Z)=1-0.5165Z^{-1}-0.4733Z^{-2}$ $+0.756Z^{-3}+0.8008Z^{-4}$ $C(Z)=1+0.0937Z^{-1}-0.3358Z^{-2}$ $-0.8913Z^{-3}+0.2423Z^{-4}$
20	(4,5)	ARMA(4,5)	30.14	0.4608	0.4605	$A(z)=1-0.4837Z^{-1}-0.4638Z^{-2}$ $-0.7643Z^{-3}+0.7656Z^{-4}$ $C(Z)=1+0.1174Z^{-1}-0.2634Z^{-2}$ $-0.8751Z^{-3}-0.2001Z^{-4}$ $-0.0714Z^{-5}$
21	(5,1)	ARMA(5,1)	25.95	0.5176	0.5174	$A(Z)=1-0.6838Z^{-1}+0.0712Z^{-2}$ $-0.1461Z^{-3}+0.2203Z^{-4}$ $+0.0710Z^{-5}$ $C(Z)=1-0.1459Z^{-1}$
22	(5,2)	ARMA(5,2)	29.82	0.465	0.4648	$A(Z)=1+0.6966Z^{-1}+0.0784Z^{-2}$ $-0.7798Z^{-3}-0.15Z^{-4}$ $+0.0279Z^{-5}$ $C(Z)=1+1.307Z^{-1}+0.9983Z^{-2}$
23	(5,3)	ARMA(5,3)	30.13	0.4609	0.4606	$A(Z)=1-0.2553Z^{-1}-0.5882Z^{-2}$ $-0.8747Z^{-3}+0.5958Z^{-4}$ $+0.189Z^{-5}$ $C(Z)=1+0.3458Z^{-1}-0.2549Z^{-2}$ $-9582Z^{-3}$
24	(5,4)	ARMA(5,4)	30.86	0.4514	0.4511	$A(Z)=1+0.2078Z^{-1}+0.9122Z^{-2}$ $-0.3389Z^{-3}+0.3601Z^{-4}$ $-0.6237Z^{-5}$ $C(Z)=1+0.7907Z^{-1}+1.609Z^{-2}$ $+0.789Z^{-3}+0.9972Z^{-4}$
25	(5,5)	ARMA(5,5)	30.87	0.4512	0.4509	$A(Z)=1+2.111Z^{-1}+1.482Z^{-2}$ $-0.4164Z^{-3}-1.232Z^{-4}$ $-0.513Z^{-5}$ $C(Z)=1+2.751Z^{-1}+3.317Z^{-2}$ $+1.969Z^{-3}+0.384Z^{-4}$ $+0.0355Z^{-5}$

From the result obtained it was observed that the fit to estimation data varies in proportion with the number of coefficients as illustrated in table 4.2. However, the disparity in the fitness tends to remain constant with little or no disparity as the number of coefficients increases. Therefore, for practical evaluation a model with appropriable fitness and lesser co-efficient is considered. The following IDDATA properties provides the details of ARMA(4,3) (Number 18 on the Table 4.2) which had a better performance fit based on a good compromise of fit to the estimation data, It has a low mean squared error (MSE) of consecutive data measures and a low final prediction error (FPE) as well. From the displayed properties the important points to note are that; a, b, c and d are the orders of the chosen ARMA model. Also, integrate Noise (i.e. line 6) means that no outliers were used in the parameter estimation.

```
These are the properties of ARMA(4,3)
              a: [1 -0.4770 -0.4006 -0.7509 0.6746]
              b: {1x0 cell}
              c: [1 0.1572 -0.2379 -0.8251]
              d: 1
              f: {1x0 cell}
       Variable: 'z^-1'
        ioDelay: [1x0 double]
 IntegrateNoise: 0
      Structure: [1x1 pmodel.polynomial]
  NoiseVariance: 0.4996
         Report: [1x1 idresults.polyest]
     InputDelay: [0x1 double]
    OutputDelay: 0
             Ts: 1
       TimeUnit: 'seconds'
      InputName: {0x1 cell}
      InputUnit: {0x1 cell}
     InputGroup: [1x1 struct]
     OutputName: {'kanoWindspeed model'}
     OutputUnit: {''}
    OutputGroup: [1x1 struct]
           Name: ''
          Notes: {}
       UserData: []
```

The ARMA(4,3) model created based on the properties above can be represented by equation (4.4).

$$\begin{aligned} Y_t &= 0.4770Y_{t-1} + 0.4006Y_{t-2} + 0.7509Y_{t-3} - 0.6746Y_{t-4} \\ &+ \alpha_t + 0.1572\alpha_{t-1} - 0.2379\alpha_{t-2} - 0.8251\alpha_{t-3} \end{aligned} \quad \text{------------------} \quad (4.4)$$

4.6 COMPARISON OF CHOSEN AR AND ARMA MODELS FOR VALIDATION

Since both models (ARMA and AR) have been developed, there is need to validate the models using 95% confidence interval, the plots for both models is illustrated in fig.4.1 and fig.4.2.

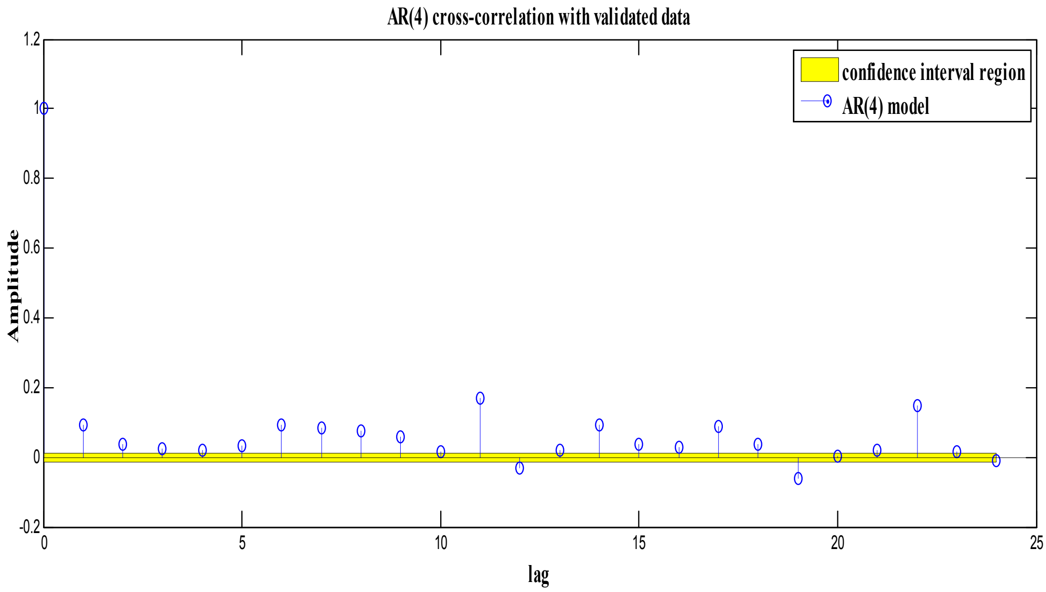

Fig 4.1: AR cross-correlation with validated data

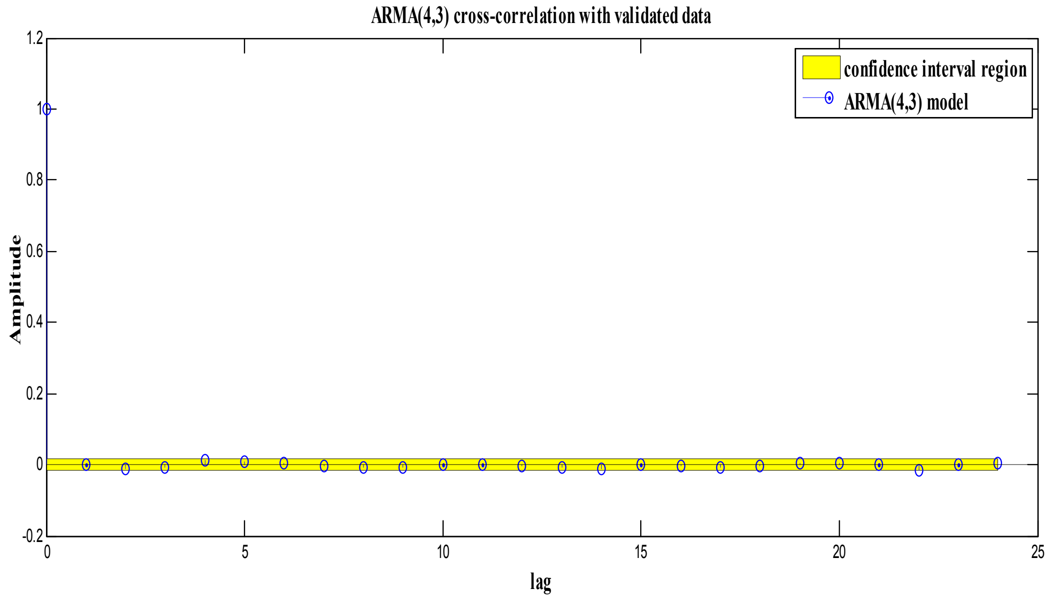

Fig 4.2: ARMA(4,3) cross-correlation with validated data

From fig.4.1, 87.5.3% of the outputs residuals are outside the confidence interval region coloured yellow. While in fig.4.2 only 8.3% of the output residuals are outside the confidence interval region coloured yellow, indicating that the essential dynamics of the wind speed have been captured by the model. Also ARMA(4,3) has demonstrated to a better model when the two correlation plots were compared.

4.7 PERFORMANCE COMPARISON BETWEEN ARMA AND AR IN FORECASTING ABILITY

After developing both ARMA and AR models, there is need to forecast wind speed using these models. Figure 4.3 shows the forecasting performances of both models. from the figure, it can be seen that ARMA(4,3) outperformed AR(4) in the short time forecast. .

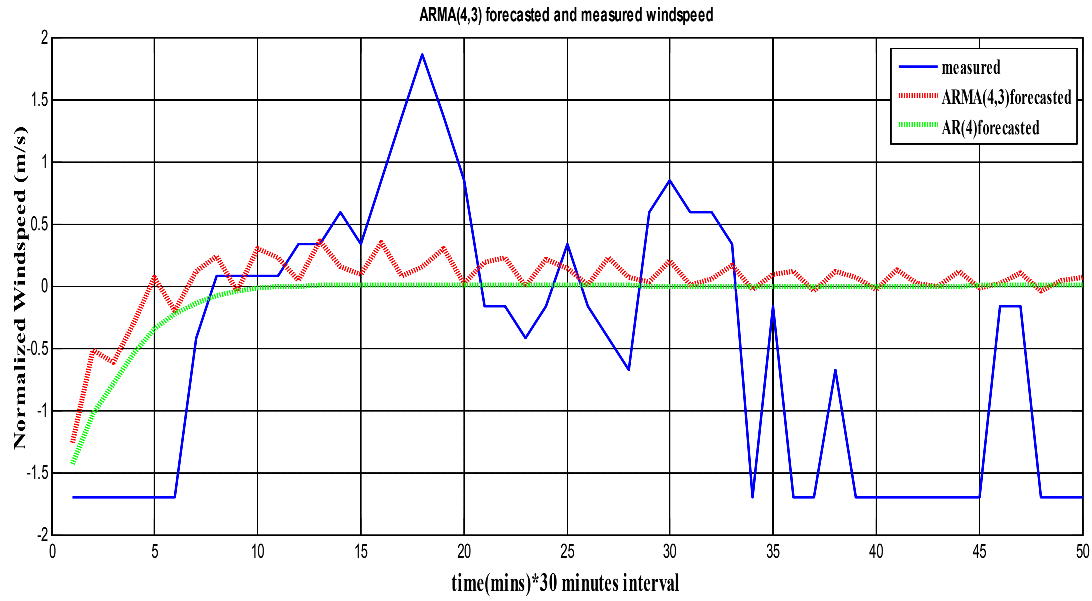

Fig 4.3: ARMA(4,3) and AR(4) forecasted wind speed

In the case of AR(4), the forecasting trend tends to show no any oscillation. therefore AR(4) cannot serve as a good guide for wind speed forecast in the near future. Hence, ARMA(4,3) can be considered to be the better approximate model for the wind speed forecasting model for short term. Also it shows that both the models failed at a longer periods forecast into the future, so an advanced models would be required if a more accurate forecast of longer periods into the future is required.

4.8 COMPARISON BETWEEN SIMULATED ARMA(4,3) AND ACTUAL DATA PLOTS

The developed simulated ARMA(4,3) is compared with the actual wind speed plot in order to observe the behaviour of the model.

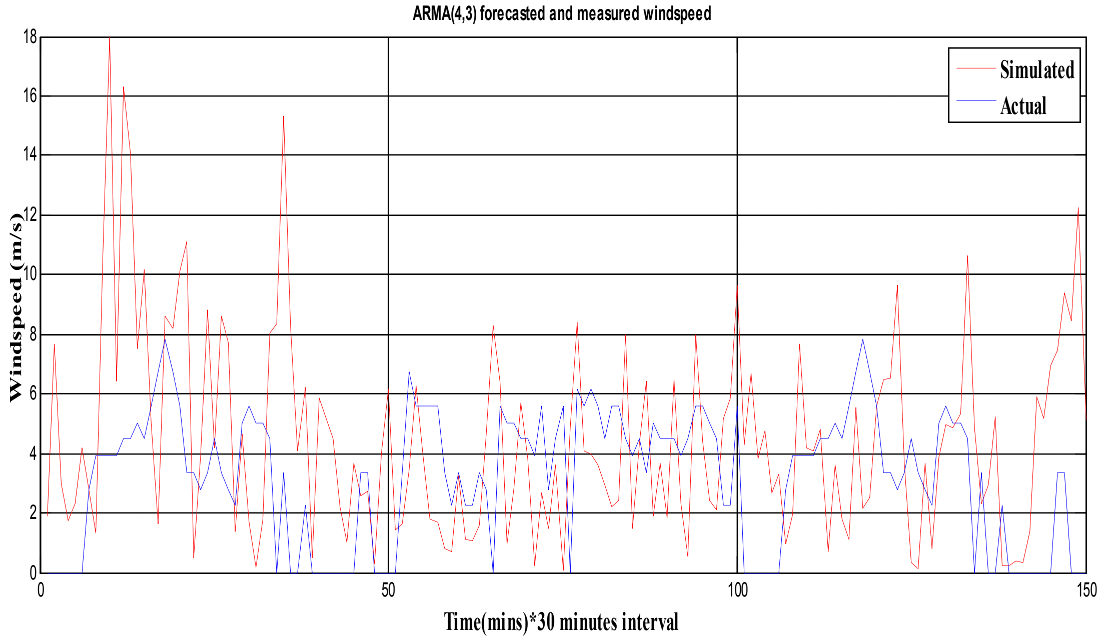

Fig 4.4: Simulated ARMA(4,3) and actual wind speed plots

From fig. 4.4, the result obtained showed that the simulated ARMA (4,3) follows the actual wind data, this is a good indication that the model behave well. when more training data is considered, the model is expected to be more accurate.

The validity of the developed ARMA (4,3) model is examined using an 6hours forecast. The developed parameter model in equation (4.4) was simulated to forecast future wind speeds and the performance are displayed in Fig 4.5, this figure present plots of normalized wind speeds on the vertical axes against time intervals on their horizontal axes in order to evaluate forecast performance within a statistical 95% confidence interval. The observed wind speeds are from the actual data while the 6hours-ahead forecast are from simulated value using the equations (4.4)(i.e developed ARMA (4,3) model).

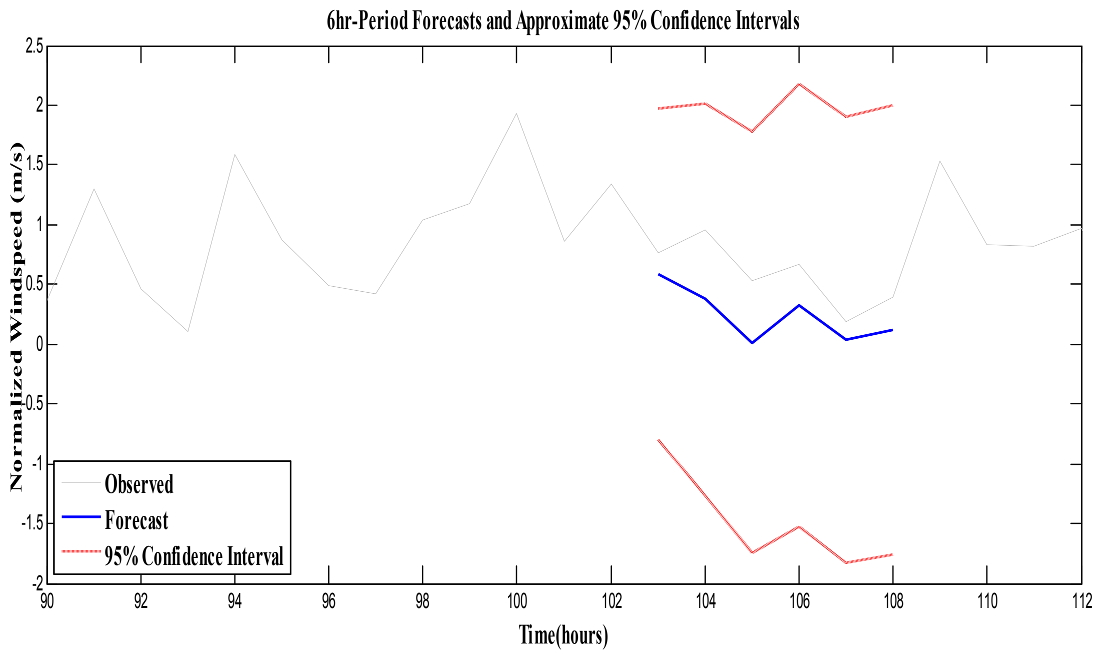

Fig 4.5 6hrs-period Forecasts and Approximate of 95% Confidence Intervals

From the plots in Figure 4.5, the forecasted wind speeds using ARMA model, it can be remarked that the ARMA model distinguishes by capturing the variability behaviour of the wind speed and can provide a good estimate of the wind speed especially in the shorter term periods. These forecasts can be utilised in estimating WTG power outputs for planning assessments.

Finally, the plot in Figure (4.6) presents the non-linear power output characteristics of a 2KW rated WTG simulated using the created ARMA model. It has rated , cut in and cut-out speeds of 3.6m/sec, 1.44m/sec and 8.0m/sec respectively. The wind turbine generator (WTG) specification was choosing based on the topographical location of Kano and recorded average wind speed of 3.735m/sec. This non-linear characteristic represents the three features of a typical Wind turbine generator(WTG) output performance in relation to the designed rated, cut-in and cut-out speeds. The linear part of the curve represents the performance of the turbine output power up to 3.6m/sec (i.e. cut-in speed characteristics output) while the flat top of the plot ranging between 3.6m/sec to 8.0m/sec represents the rated output characteristics of the turbine (i.e. WTG supplying the rated 2kW output). From 8.0m/sec and above the WTG is cut-out from the network i.e. does not supply any output power as the wind speed is deemed unsafe for normal designed operation of this WTG unit.

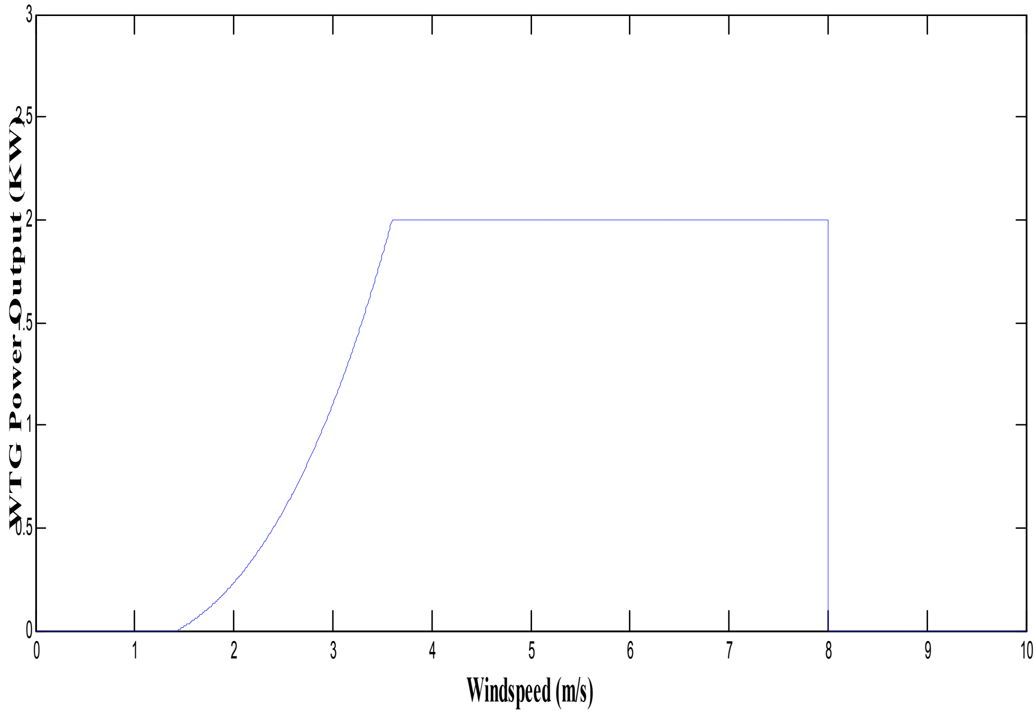

Fig 4.14 Wind turbine power output as a function of wind speed

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 INTRODUCTION

This chapter presents the conclusion based on the result obtained, as well as some recommendation for further research.

5.2 CONCLUSION

From the research carried out, the data used was collected successfully from Nigerian Meteorological Agency (NIMET), Kano using direct approach. From the data ARMA model was developed by writing a MATLAB scripts, similarly AR model was also developed in the same view as ARMA model. A short time forecast (6 hours) was carried out using both AR and ARMA model.

Table 5.1 Performance comparison between ARMA (4,3) and AR (4)

MODELS	FED (%)	FPE	MSE
ARMA (4,3)	27.24	0.4998	0.4995
AR (4)	25.87	0.5187	0.518

From the result, in table 5.1 it was obtained that ARMA model performs much better than AR model, in that fit to the estimation data, final prediction error and mean square error. Therefore, ARMA model could be a valuable forecasting tools for wind power forecasting of Kano.

5.3 CONTRIBUTION

Autoregressive moving average (ARMA) model, was developed for wind power forecasting of Kano and its performance was validated by comparing it with Autoregressive (AR) model developed.

5.4 RECOMMENDATION

1- Only wind speed is taken as input but in actual and practically other variables effecting wind speed should also be taken as exogenous input to the wind speed such as temperature, atmospheric pressure, relative humidity, solar radiation, wind direction etc. For further research.

2- Seasonality effects should also be taken into consideration.

3- Availability of actual wind speed data in sufficient detail yield better outputs .

REFERENCES

[1] R. Doherty and M. O'Malley. wind power forecasting,

http://en.wikipedia.org/wiki/wind-power-forecasting. 24th may, 2015. at 10:30am.

[2] World wind Energy Association (2011), world wind Energy Report 2010 Germany.

[3] G. sanger Stefan, jean-Daniel Pitteloud. World wind Energy Association, Annual report, Bonn/Germany (2012).

[4] R. castro Pedro , International journal of sustainable Energy Development(IJSED), Volume 1, issues 1/2 march/June 2012.

[5] R. Huang, Tiana Huang, Rajit Gadh and Na Li. Generation Prediction using the ARMA model in a Laboratory-level micro grid, smart Grid Energy Research Centre,

University of California, Los Angeles, USA.

[6] J. Hamilton, Time series Analysis, Princeton University press. (1994),

[7] H. Tong, Professor Hirotugu Akaike, 1927-2009. Journal of the Royal Statistical Society, Series A173: 451-454.(2010)

[8] A.E Raftery.. Bayesian Model Selection In Social Research. In Vol. 25 of Sociological Methodology, ed. PV. Marsden, 111-163 Oxford: Blackwell. (1995)

[9] L. Lingling, Minghui Wang, Fenfen Zhu, and Chengshan Wang, Wind power forecasting based on Time series and Neural networks. Proceedings of the Second

Symposium International Computer Science and Computational Technology (ISCSCT '09) Huangshan, P. R. China, 26-28,Dec. 2009, pp. 293-297.

[10] R. Billinton, Hua Chen and R. Ghajar, Time-series models for reliability evaluation of power systems including wind energy. Microelectron. Reliab., Vol. 36, No. 9, pp.1253 -1261, 1996.

[11] M. Ding, Zhang L-j, Wu Y-c. Wind speed forecast model for wind farms based on time series analysis. Electric power Automation Equipment 2005; 25(8): 32-4 in chinese.

[12] k. Lalarukh, Yasmin ZJ. Time series models to simulate and forecast hourly averaged wind speed in quetta, pakistan. Solar Energy 1997; 61(1): 23-32.

[13] J.L Torres, Garcı´a A, De Blas M, De Francisco A. Forecast of hourly average wind speed with ARMA models in Navarre. Solar Energy 2005;79(1):65–77.

[14] C. Erasmo, Wilfrido R. Wind speed forecasting in the South Coast of Oaxaca, Mexico. Renewable Energy 2007;32(12):2116–28.

[15] M. Michael (Consultant), Marc Schwartz ,Yih-Huei Wan. Statistical wind power forecasting models: Results for U.S wind farms. conference paper presented at wind power 2003 Austin, Texas. May 18- 21,2003.

[16] A. Joseph, An Assessment of Wind Availability for Turbine Power Generation in Kano, Nigeria. IOSR Journal of Applied Physics (IOSR-JAP) e-ISSN: 2278-

4861.Volume 6, Issue 5 Ver. II(Sep.-Oct. 2014), PP 30-36, www.iosrjournals.org.

[17] H. Rui, Tiana Huang, Rajit Gadh and Na Li. solar Generation using the ARMA model in a laboratory-level micro grid, 2012 IEEE third national conference on smart grid communication(smartgridcomm), pp 528-588, 5-8 November 2012. 11/11/2014.

[18] R. Billinton, Chen H, Ghajar R. A sequential simulation technique for adequacy evaluation of generating systems including wind energy. IEEE Trans Energy Convers 1996;11/4:728–34.

[19] R. Billinton, Karki R. Reliability/cost implications of utilizing photovoltaics in small isolated power systems. Reliab Eng Syst Safety 2003;79/1:11–6.

[20] R. Billinton and H. Dange, "Incorporating Wind Power in Generating Capacity Reliability Evaluation Using Different Models," *Power Systems, IEEE Transactions on,* vol. 26, pp. 2509-2517, 2011.

[21] A. Robin. Stochastic modelling of electricity prices using ARMA and ARMAX models, a thesis for the degree of master of science in engineering physics, department of mathematical sciences division of mathematical statistics chalmers university of technology gothenburg, sweden 2012. www. publications.lib.chalmers.se/records/fulltext/157066.pdf (4/12/2014).

[22] Y. Atsushi et al. Very Short-Term Generating Power Forecasting for Wind

Power Generators Based on Time Series Analysis. (www. file.scirp.org/Html/7-6401236_32183.htm (4/12/2014).

[23] R. G Kavasseri and Seetharaman, K. “Day-ahead wind speed forecasting using f-ARIMA models,” Renewable Energy, 34(5), 1388-1393.11/12/2014.(2009).

[24] E. Cadenas and Rivera W. “Wind speed forecasting in the south coast of Oaxaca, Mexico,” Renewable Energy, 32(12), 2116-2128. 11/12/2014. (2007).

[25] E. Ergin, Jing Shi, Yidong Peng. Short-term forecasting of wind speed and power a clustering approach, proceedings of the 2014 industrial and systems engineering research conference, Department of Industrial and Manufacturing Engineering North Dakota State University Fargo, ND 58108, USA (11/12/2014).

[26] G. Daiana. Wind Power Feed-In Effects on prices. university of st.galle (hsg) master’s thesis, master of arts in banking and finance.

[27] H. Matthew, what is wind power http://whatis.techtarget.com/definition/wind-power 19/4/15. posted by Margaret Rouse.

[28] Wind Turbine Power Calculations RWE npower renewables Mechanical and Electrical Engineering Power Industry The royal academy of engineering, http://www.raeng.org.uk/publications/other/23-wind-turbine.

[29] www.wind-power-program.com/turbine_characteristics.htm 21/4/15.

[30] C.Michael Hogan. 2010. Abiotic factor. Encyclopedia of Earth. eds Emily Monosson and C. Cleveland. National Council for Science and the Environment. Washington DC, http://en.wikipedia.org/wiki/Wind_speed

[31] E. Michael Carpenter, http://www.ehow.com/info_8526081_different-types-anemometers.html 17/4/2015,1:42am.

[32] B. Admiral, How to measure wind speed. http://www.almanac.com/beaufort-wind force-scale 17/4/2015.

[33] D. Zissis, Xidias, Elias; Lekkas, Dimitrios. "Real-time vessel behavior prediction" Evolving Systems:1–12 http://en.wikipedia.org/wiki/Time_series 17/4/2015.(2015).

[34] Y-K Wu, and J-S Hong, "A literature review of wind forecasting technology in the world," IEEE Power Tech 2007, Lausanne , pp. 504-509, 1-5 July 2007.

[35] C. W. Potter, and M. Negnevitsky, "Very short-term wind forecasting for Tasmanian power generation," IEEE Trans. Power Syst., vol. 21, no. 2, pp. 965-972, May 2006.

[36] M. Milligan, M. Schwartz, and Y. Wan, "Statistical wind power forecasting models: Results for U.S. wind farms," in Proc. Wind power, Austin, TX, May 1-21, 2003, NREL/CP-500-33 956 Rep.

[37] M. Lange, and U. Focken, "New developments in wind energy forecasting," IEEE Power and Energy Society General Meeting 2008 - Conversion and Delivery of Electrical Energy in the 21st Century, pp. 1-8, 20-24 July 2008.

[38] B. Candy, S. J. English, and S. J. Keogh, "A Comparison of the impact of

QuikScat and WindSat wind vector products on met office analyses and forecasts," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no.6, pp. 1632-1640, June 2009.

[39] P. S. Chang, and L. Li, "Ocean surface wind speed and direction retrievals from the SSM/I," IEEE Trans. Geosci. Remote Sens., vol. 36, no. 6, pp. 1866-1871, Nov 1998.

[40] S.S Soman, Zareipour. H., Malik, O., Mandal, P., "A review of wind power and Wind speed forecasting methods with different time horizons," North American Power Symposium (NAPS), 2010, vol., no., pp.1-8, 26-28 Sept. 2010.

[41] I. Boris and David Hoaglin. 'Volume 16: How to detect and handle outliers', The ASQC Basic References in Quality Control: statistical Techniques, Edwards F. Mykytka, Editor (1993). http://www.itl.nist.gov/div898/handbook/eda/section4/eda43.htm#Iglewicz

[42] H. Xiaoqing et al, 'Four-Dimensional Wind speed model for adequacy assessment of power systems with wind farms', IEEE Transactions on Power Systems, 2013) .

APPENDIX A

MATLAB CODES

```
close all
close all force
clear all, clc


%______________________________________________________________________

_


load myWindspeed;


WindVel = kanoWindspeed;

figure(1);plot(kanoWindspeed(1:336));title('one week wind speed
plot');axis([0 350 0 30]); xlabel('30-mins time
intervals');ylabel('Windspeed [knots]');
%______________________________________________________________________

_                              kanoWindspeed=iddata(kanoWindspeed,[],1)

kanoWindspeed=misdata(kanoWindspeed);


[Z,mu,sigma]= zscore(kanoWindspeed.OutputData);


kanoWindspeed.OutputName='kanoWindspeed model';
kanoWindspeed.OutputUnit='knots';

disp('This is the iddata profile'); disp(get(kanoWindspeed));
%______________________________________________________________________
_

kanoWindspeedEst=kanoWindspeed.OutputData(1:40000);%estimation data
kanoWindspeedVal=kanoWindspeed.OutputData(40001:80000);%validation
data

%______________________________________________________________________
_
 m1=arx(kanoWindspeedEst,1);
m_pem1=pem(kanoWindspeedEst,m1,'tol',1e-5,'maxiter',50);
figure(21), compare(kanoWindspeedVal,m_pem1);
m_pem1
```

```
m2=arx(kanoWindspeedEst,2);
m_pem2=pem(kanoWindspeedEst,m2,'tol',1e-5,'maxiter',50);
figure(22), compare(kanoWindspeedVal,m_pem2);
m_pem2

m3=arx(kanoWindspeedEst,3);
m_pem3=pem(kanoWindspeedEst,m3,'tol',1e-5,'maxiter',50);
figure(23), compare(kanoWindspeedVal,m_pem3)
m_pem3

m4=arx(kanoWindspeedEst,4);
m_pem4=pem(kanoWindspeedEst,m4,'tol',1e-5,'maxiter',50);
figure(24), (compare(kanoWindspeedVal,m_pem4));
m_pem4

m5=arx(kanoWindspeedEst,5);
m_pem5=pem(kanoWindspeedEst,m5,'tol',1e-5,'maxiter',50);
figure(25), compare(kanoWindspeedVal,m_pem5);
m_pem5

m9=arx(kanoWindspeedEst,9);
m_pem9=pem(kanoWindspeedEst,m9,'tol',1e-5,'maxiter',50);
figure(29), compare(kanoWindspeedVal,m_pem9);
m_pem9

m18=arx(kanoWindspeedEst,18);
m_pem18=pem(kanoWindspeedEst,m18,'tol',1e-5,'maxiter',50);
figure(218), compare(kanoWindspeedVal,m_pem18);
m_pem18

disp('These are the properties of AR(4)');disp(get(m_pem4))
%_____________________________________________________________________
_

 m11=armax(kanoWindspeedEst,[1,1]);
m_pem11=pem(kanoWindspeedEst,m11,'tol',1e-5,'maxiter',50);
figure(311), compare(kanoWindspeedVal,m_pem11);
m_pem11

m12=armax(kanoWindspeedEst,[1,2]);
m_pem12=pem(kanoWindspeedEst,m12,'tol',1e-5,'maxiter',50);
figure(312), compare(kanoWindspeedVal,m_pem12);
m_pem12
m13=armax(kanoWindspeedEst,[1,3]);
m_pem13=pem(kanoWindspeedEst,m13,'tol',1e-5,'maxiter',50);
figure(313), compare(kanoWindspeedVal,m_pem13);
m_pem13
m14=armax(kanoWindspeedEst,[1,4]);
m_pem14=pem(kanoWindspeedEst,m14,'tol',1e-5,'maxiter',50);
figure(314), compare(kanoWindspeedVal,m_pem14);
m_pem14
m15=armax(kanoWindspeedEst,[1,5]);
m_pem15=pem(kanoWindspeedEst,m15,'tol',1e-5,'maxiter',50);
figure(315), compare(kanoWindspeedVal,m_pem15);
m_pem15

m21=armax(kanoWindspeedEst,[2,1]);
m_pem21=pem(kanoWindspeedEst,m21,'tol',1e-5,'maxiter',50);
```

```
figure(321), compare(kanoWindspeedVal,m_pem21);
m_pem21

m22=armax(kanoWindspeedEst,[2,2]);
m_pem22=pem(kanoWindspeedEst,m22,'tol',1e-5,'maxiter',50);
figure(322), compare(kanoWindspeedVal,m_pem22);
m_pem22

m23=armax(kanoWindspeedEst,[2,3]);
m_pem23=pem(kanoWindspeedEst,m23,'tol',1e-5,'maxiter',50);
figure(323), compare(kanoWindspeedVal,m_pem23);
m_pem23

m24=armax(kanoWindspeedEst,[2,4]);
m_pem24=pem(kanoWindspeedEst,m24,'tol',1e-5,'maxiter',50);
figure(324), compare(kanoWindspeedVal,m_pem24);
m_pem24

m25=armax(kanoWindspeedEst,[2,5]);
m_pem25=pem(kanoWindspeedEst,m25,'tol',1e-5,'maxiter',50);
figure(325), compare(kanoWindspeedVal,m_pem25);
m_pem25

m31=armax(kanoWindspeedEst,[3,1]);
m_pem31=pem(kanoWindspeedEst,m31,'tol',1e-5,'maxiter',50);
figure(331), compare(kanoWindspeedVal,m_pem31);
m_pem31

m32=armax(kanoWindspeedEst,[3,2]);
m_pem32=pem(kanoWindspeedEst,m32,'tol',1e-5,'maxiter',50);
figure(332), compare(kanoWindspeedVal,m_pem32);
m_pem32

m33=armax(kanoWindspeedEst,[3,3]);
m_pem33=pem(kanoWindspeedEst,m33,'tol',1e-5,'maxiter',50);
figure(333), compare(kanoWindspeedVal,m_pem33);
m_pem33

m34=armax(kanoWindspeedEst,[3,4]);
m_pem34=pem(kanoWindspeedEst,m34,'tol',1e-5,'maxiter',50);
figure(334), compare(kanoWindspeedVal,m_pem34);
m_pem34

m35=armax(kanoWindspeedEst,[3,5]);
m_pem35=pem(kanoWindspeedEst,m35,'tol',1e-5,'maxiter',50);
figure(335), compare(kanoWindspeedVal,m_pem35);
m_pem35

m41=armax(kanoWindspeedEst,[4,1]);
m_pem41=pem(kanoWindspeedEst,m41,'tol',1e-5,'maxiter',50);
figure(341), compare(kanoWindspeedVal,m_pem41);
m_pem41

m42=armax(kanoWindspeedEst,[4,2]);
m_pem42=pem(kanoWindspeedEst,m42,'tol',1e-5,'maxiter',50);
figure(342), compare(kanoWindspeedVal,m_pem42);
m_pem42

m43=armax(kanoWindspeedEst,[4,3]);
```

```
m_pem43=pem(kanoWindspeedEst,m43,'tol',1e-5,'maxiter',50);
figure(343), compare(kanoWindspeedVal,m_pem43);
m_pem43

m44=armax(kanoWindspeedEst,[4,4]);
m_pem44=pem(kanoWindspeedEst,m44,'tol',1e-5,'maxiter',50);
figure(344), compare(kanoWindspeedVal,m_pem44);
m45=armax(kanoWindspeedEst,[4,5]);
m_pem45=pem(kanoWindspeedEst,m45,'tol',1e-5,'maxiter',50);
figure(345), compare(kanoWindspeedVal,m_pem45);
m_pem45

m51=armax(kanoWindspeedEst,[5,1]);
m_pem51=pem(kanoWindspeedEst,m51,'tol',1e-5,'maxiter',50);
figure(351), compare(kanoWindspeedVal,m_pem51);
m_pem51
m52=armax(kanoWindspeedEst,[5,2]);
m_pem52=pem(kanoWindspeedEst,m52,'tol',1e-5,'maxiter',50);
figure(352), compare(kanoWindspeedVal,m_pem52);
m_pem52

m53=armax(kanoWindspeedEst,[5,3]);
m_pem53=pem(kanoWindspeedEst,m53,'tol',1e-5,'maxiter',50);
figure(353), compare(kanoWindspeedVal,m_pem53);
m_pem53;
m54=armax(kanoWindspeedEst,[5,4]);
m_pem54=pem(kanoWindspeedEst,m54,'tol',1e-5,'maxiter',50);
figure(354), compare(kanoWindspeedVal,m_pem54);
m_pem54

m55=armax(kanoWindspeedEst,[5,5]);
m_pem55=pem(kanoWindspeedEst,m55,'tol',1e-5,'maxiter',50);
figure(355), compare(kanoWindspeedVal,m_pem55);
m_pem55


disp('These are the properties of ARMA(4,3)');disp(get(m_pem43))
%___________________________________________________________________
_

 figure(41), compare(kanoWindspeedVal,m_pem43,m_pem4,'r-')

u=iddata([],idinput([21000,1],'rbs'));
SimWind=sim(m_pem43,u);
figure(42), plot(SimWind(1:4320),kanoWindspeedEst(1:4320),'r-
');legend('Simulated','Observed')

figure('Name','AR cross-correlation function plots',...
    'NumberTitle','off')
set(gcf,'color',[1 1 1]);
resid(m_pem4,kanoWindspeedVal,'corr')
ttl = 'AR cross-correlation with validated data';
title(ttl,'FontWeight','bold');

figure('Name','ARMA cross-correlation function plots 1',...
    'NumberTitle','off')
set(gcf,'color',[1 1 1]);
resid(m_pem43,kanoWindspeedVal,'corr')
ttl = 'ARMA cross-correlation with validated data';
```

```
title(ttl,'FontWeight','bold');

figure('Name','ARMA cross-correlation function plots 2',...
    'NumberTitle','off')
set(gcf,'color',[1 1 1]);
resid(m_pem43,SimWind,'corr')
ttl = 'ARMA cross-correlation with Simulated Windspeed';
title(ttl,'FontWeight','bold');
```

%____

_

```
 past_data=kanoWindspeed.OutputData(1:12);
K=12;
 yfar=forecast(m_pem4,past_data,K);
figure(51), plot(yfar)
ttl=('AR(4) forecasted windspeed');legend('AR(4) forecast')
title(ttl,'FontWeight','bold');set(gcf,'color',[1 1 1]);
xlabel('30-mins time intervals')
ylabel('Windspeed (knots)')
t=kanoWindspeed.samplingInstants;
t1=t(1:12);
t2=t(12:23);
figure(52), plot(t1,past_data,t2,yfar,'r:')
ttl=('AR(4) forecasted and measured windspeed');
title(ttl,'FontWeight','bold');
legend('measured','forecasted')
set(gcf,'color',[1 1 1]);
xlabel('30-mins time intervals')
ylabel('Windspeed (knots)')

yfarma=forecast(m_pem43,past_data,K);
figure(53), plot(yfarma)
ttl=('ARMA(4,3) forecasted windspeed');legend('ARMA(4,3) forecast')
title(ttl,'FontWeight','bold');
set(gcf,'color',[1 1 1]);
xlabel('30-mins time intervals')
ylabel('Windspeed (knots)')

t=kanoWindspeed.samplingInstants;
t1=t(1:12);
t2=t(12:23);
figure(54), plot(t1,past_data,t2,yfarma,'r:')
ttl=('ARMA(4,3) forecasted and measured windspeed');
title(ttl,'FontWeight','bold');
legend('measured','forecasted')
set(gcf,'color',[1 1 1]);
xlabel('30-mins time intervals')
ylabel('Windspeed (knots)')
```

%____

_

```
 SW=SimWind.OutputData*sigma+mu;
SW = SW + abs(min(SW));

P_r=2.0; V_ci=2.57; V_co=14.29; V_r=6.423;

[r c]=size(SW);

 P_wtg=ones(21000,1);
```

```
check1 = 0; check2 = 0; check3 = 0; check4 = 0;check5=0;
for i=1:r
    if SW(i) >= 0 && SW(i) < V_ci
       check1 = check1 +1;
        P_wtg(i)=0;

    elseif SW(i) >= V_ci && SW(i) < V_r
        check2 = check2 +1;
        P_wtg(i)= ((SW(i)^3 - V_ci^3)/(V_r^3 - V_ci^3))*P_r;
    elseif SW(i) >= V_r && SW(i) <= V_co
        check3 = check3 +1;
        P_wtg(i)=P_r;
    else
        check4 = check4 +1;
        P_wtg(i)=0;
    end
end


  figure('Name','WTG output behaviour',...
  'NumberTitle','off');
  set(gcf,'color',[1 1 1]);
  stem((P_wtg(1:80)),'r')
  ttl=('WTG power output characteristic');
  title(ttl,'FontWeight','bold');
  grid on
  xlabel('30-mins time intervals');
  ylabel('WTG Power Output (KW)');
 [sorted_SW, idxSort_SW] = sort(SW);
 sorted_P_wtg  = P_wtg(idxSort_SW);
   figure('Name','WTG output behaviour',...
 'NumberTitle','off');
 set(gcf,'color',[1 1 1]);
 plot(sorted_SW,sorted_P_wtg);
 ttl=('WTG power output characteristic');
 title(ttl,'FontWeight','bold');
 xlabel('Windspeed (knots)');
 ylabel('WTG Power Output (KW)');
 axis([0 16 0 3]);

 model = arima('Constant',0,'AR',{3.5599,-4.7050,2.7232,-
0.5781},'MA',{-2.9124,2.8435,-0.9303},'Variance',.1131);

rng('default')
Y1 = simulate(model,150);
Y=8*Y1;
Y_a = simulate(model,21000);
figure('Name','Viewing Sim and validated Windspeed plots',...
     'NumberTitle','off');
set(gcf,'Color',[1 1 1]);
plot((abs(Y)),'Color','r')
hold on
plot(kanoWindspeed(1:150))
xlim([0,150])
ttl=title('Simulated ARMA(4,3) Process');
title(ttl,'FontWeight','bold');
xlabel('minutes')
ylabel('Windspeed (knots)')
legend('Simulated','Actual')
```

%____
_

```
[YF, YMSE] = forecast(model,8,'Y0',Y1(1:150));
Y2=Y*5;
figure('Name','Forecast Using ARMA(4,3)',...
    'NumberTitle','off');
h1 = plot((abs(Y2)),'Color',[.7,.7,.7]);
hold on
h2 = plot(136:143,(abs(YF)),'b','LineWidth',2);
h3 = plot(136:143,(abs(YF)) + 2.96*sqrt(YMSE),'r:',...
        'LineWidth',2);
plot(136:143,(abs(YF)) - 2.96*sqrt(YMSE),'r:','LineWidth',2);
xlim([132,152])
xlabel('hours')
ylabel('Windspeed (knots)')
legend([h1 h2 h3],'Observed','Forecast',...
        '95% Confidence Interval','Location','SouthWest');
title(['8hr-Period Forecasts and Approximate 95% '...
            'Confidence Intervals'])
set(gcf,'Color',[1 1 1]);
hold off
```