INVESTIGATION AND PREDICTION OF WIND SPEED POTENTIALS IN KANO STATE FOR ELECTRIC POWER GENERATION USING ARTIFICIAL NEURAL NETWORK

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CERTIFICATION PAGE

This is to certify that the research work for this Dissertation and the preparation of this Dissertation by (Issaku Ibrahim SPS/11/MEE/00020), were carried out under my supervision. The report has been prepared and written in accordance with the requirements of Department of Electrical Engineering for the award of Masters of Engineering (M.Eng.) Degree in Electrical Engineering.

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DECLARATION PAGE

I, ISSAKU IBRAHIM, SPS/11/MEE/00020 hereby declare that this work is the product of my research efforts undertaken under the supervision of (Professor S.S. Adamu) and has not been presented anywhere and will not be presented elsewhere for the award of degree or certificate. All sources have been duly acknowledged.

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APPROVAL PAGE

This is to certify that this project report on Investigation and Prediction of Wind Speed potentials in Kano state for Electric Power Generation using Artificial Neural Network has been examined and approved by the undersigned persons on behalf of the Department of Electrical Engineering, Bayero University, Kano, as meeting one of the requirements for the award of M.Eng. (Electrical) Degree of Bayero University Kano.

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DEDICATION

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ABSTRACT

Meteorological condition has a great impact on the level of wind speed (energy) availability in the natural world. ANN been excellent in solving nonlinear and complex problems necessitated it usage in forecasting problems. This work develops a Neural Network based monthly average wind speed prediction for Kano state. The monthly averages of maximum temperature, minimum temperature and relative humidityfrom 1970 to 2014 was obtained from NIMET Kano. The Levenberg-Masquardt optimization technique is used as a back propagation algorithm for the Multilayer Feed Forward ANN model using MATLAB R2012b ANN toolbox. The 1970- 2006, 2008-2013 data was used for training (learning) while that of 2007 and 2014 was reserved for testing. The forecasted output from the best network obtained had a mean square error of $1.35e^{-11}$ which can be regarded as acceptable.

CHAPTER ONE
INTRODUCTION

1.0 BACKGROUND

One technology to generate electricity in a renewable way is to use wind turbine that convert the energy contained by wind into electricity. The main advantages of renewable power generation are the usage of an infinitely available primary source (such as wind, sunlight or biomass) and the less severe environmental consequences.

The failure of the Nigerian Government to the task of finding a long-term solution to the energy crisis through the adoption of the Renewable Energy Master Plan (REMP) with a target of increasing the5,000MW generation capacity to 16,000MW by the year 2015 through the exploration of renewable energy resources (lloje, 2002) has to be resuscitated. In order to realize this goal, the exploration of wind energy resources shouldbe one of the key elements of that master plan. Wind energy is among the potential alternatives as renewable clean energy. At present the share of wind energy in the national energy consumption has remained on the lower end with no commercial wind power plants connected to the national grid. Only a few number of stand-alone wind power plants have been installed in the country in the early 1960s, some northern states used wind power sources mainly to power water pumps such as at Goronyo in Katsina state, Kedada in Bauchi state and Gidan-Gada village in Sokoto state. There are issues to worry about regarding the future energy production in the world, having been established that the availability of electrical energy is a precondition for the functioning of modern societies. It is used to provide the energy needed for operating information and communication technology, transportation, lighting, food processing and storage as well as a great variety of industrial processes, all of which are characteristic of a modern society.

Research has indeed shown that there is a significant relation between economic growth and even societal development in general, measured by indicators such as illiteracy and life expectancy and electricity consumption**(**Reddy, 2002**)**.

1.1 STATEMENT OF THE PROBLEM

The power generated by electric wind turbines changes rapidly because of the continuous fluctuations (uncertainty) of wind speed. Therefore it becomes imperative to have the capability to perform its prediction for planning, sitting, sizing and diagnostic purposes.

1.2 SIGNIFICANCE OF THE PROJECT

An analysis of Nigeria's electricity supply problems and prospects found that the electricity demands far outstrip the supply, which is epileptic in nature. The epileptic electricity supply hinders the country's development, notwithstanding the availability and abundant of renewable energy resources in the country among the significant once being wind energy. Research and adoption of renewable energy potentials (wind) for most part of the country will improve electricity supply, enhance the overall economic development and the attainment of vision 202020 of the federal government and the renewal effort to actualized the realization of the Renewable Energy Master plan which has failed at the moment. Because of the variable nature of the wind resource, the ability to forecast wind speed some time ahead is always valuable. Such forecasts may be useful for assisting with the operational control of wind turbines or wind farms, and also useful for planning the deployment of other power stations on the network. (Balasingam, 2010)

Several methods have been proposed to provide wind speed prediction, among them are algebraic curve fitting, auto regressive integrated moving average (ARIMA) model, extrapolation using periodic curve fitting model, Fractional- ARIMA models and some advanced statistical methods like artificial intelligence, fuzzy logic, auto regressive moving average (ARMA) and some hybrid model.

The Artificial Neural Network being one of the advanced model is simpler to construct, requires shorter development time and reduction of prediction error (Bhaskar, Amit and Venkata, 2010)

1.3 AIM AND OBJECTIVES

The primary aim of this project work is to Investigate and Predict Wind Speed potentials in Kano state for Electric Power Generation using Artificial Neural Network. The model will further be analyzed for 45 years and prediction made on wind speed using Artificial Neural Network (ANN).

The objectives of the research include

1. Investigate the wind energy potential for Kano State by analyzing the wind speed data obtained and compare it to the global minimum wind speed limit for viable exploration of wind power in Kano
2. Modeling of wind turbine using Mathematical model
3. Developing a wind speed prediction model using Neural Network

1.4 METHODOLOGY

The monthly wind speed data for this study were sourced from Nigeria Meteorological Agency, Aminu Kano International Airport, Kano, for the period 1970-2014(45years). The data sought are the meteorological and geographical data of wind in Kano state.

In this research, the wind speeds data variation will be analyzed by evaluating the mean average wind speed and power density of Kano and compared it to the global minimum limit for viable exploration of wind power in Kano state. Prediction of wind speed will be made at the end of the analysis using Artificial Neural Network.

The methods to be adopted in carrying out this research include:

1. Mathematical modeling of wind turbine to establish the significance of wind speed in wind power generation using derivation from first principles.
2. Preprocessing of the predictor variable obtained by transforming the data into matlab format (matrix) and Normalizing the data between 0 and 1
3. Splitting of the data into learning set and test set
4. Design of the Network architecture using Multi – layer feed-forward back-propagation with the aid of Neural Network Toolbox from Matlab.
5. Training the Network using 70% of the data set randomly selected by Supervised Training Method
6. Validation of the network will be carried out with 15% of the data set randomly selected
7. Testing of the Model will be carried out with the remaining 15% of the data set

8. Evaluation of the network outputs and performance using unknown data to the network (2007 and 2014 data).

1.5 SCOPE AND LIMITATION OF THE RESEARCH

The research work is limited to Investigation and prediction of wind speed in Kano state. The data obtained will be analyzed to predict the optimal period of wind power harvesting using artificial neural network.

1.6 REPORT ORGANIZATION

The layout of this report is as follows: Chapter One is made up of introduction, Chapter Two contains literature review of wind power and an overview of Artificial Neural Network: Chapter Three presents the Modeling and Design of the neural network architecture and Chapter Four covers the result and analysis of simulated results from the model with the data obtained. Conclusions, Recommendations and contributions are presented in Chapter Five and appendix is presented after the list of consulted reference.

1.7 CONCLUSION

In order to meet the electricity demand of this country there is the urgent need for the exploration of renewable energy resources (wind energy in particular). Wind speed which is the major factor in determining the amount of energy in the wind has to be accurately forecasted to help in evaluating the economic viability as well as the sizing and sitting of wind turbine.

CHAPTER TWO
LITERATURE REVIEW

2.0 INTRODUCTION

This chapter presents an overview of wind energy, history of successful works carried out on the topic of wind speed prediction and the methods used in achieving accurate results. Also the basis of neural network, its training process and some associated algorithms for learning are explained.

2.1 HISTORY OF WIND ENERGY

The wind is a meteorological phenomenon that occurs when the air present in the atmosphere begins to move due to natural causes. This phenomenon usually takes place in the troposphere that is the part of the atmosphere next to the earth's surface.

Mainly the translation and rotation movements of the earth produce the movement of the air. These two movements cause differences in the solar radiation and therefore differences in the radiation absorption of the atmosphere.

The hotter air will expand taking in this way a higher volume and therefore decreasing its density. This fact will make this mass of air to move to higher places in the atmosphere letting some new cold air to take the place, which the hot air was occupying. This movement produces the wind. The wind has played a long and important role in the history of human civilization. The first known use of wind dates back to 5,000 years in Egypt, where boats used sails to travel from shore to shore. The first true windmill, a machine with vanes attached to an axis to produce circular motion, may have been built as early as 2000 B.C. in ancient Babylon. By the 10th century A.D., windmills with wind-catching surfaces as long as 16 feet and as high as 30 feet were grinding grain in the area now known as eastern Iran and Afghanistan (Ibrahim,2014).

The western world discovered the windmill much later. The earliest written references to working wind machines date from the 12th century. These too were used for milling grain. It was not until a few hundred years later that windmills were modified to pump water and reclaim much of Holland from the sea (Ibrahim, 2014).

The familiar multi-vane "farm windmill" of the American Midwest and West was invented in the United States during the later half of the l9th century. In 1889 there were 77 windmill factories in the United States, and by the turn of the century, windmills had become a major American export (Wind energy manual, 2013). Until the diesel engine came along, many transcontinental rail routes in the U.S. depended on large multi-vane windmills to pump water for steam locomotives.

Farm windmills are still being produced and used, though in reduced numbers, and show no sign of becoming obsolete. They are best suited for pumping ground water in small quantities to livestock water tanks (American wind energy association, 2008). Without the water supplied by the multi-vane windmill, beef production over large areas of the West would not be possible.

The use of wind as an energy source begins in ancient times. Vertical-axis windmills for grinding grain were reported in-Persia in the tenth century and in China in the thirteenth century (Eldrigde, 1980). At one time wind was a major source of energy for transportation (sailboats), grinding grain, and pumping water. Windmills, along with water mills, were the largest power source before the invention of the steam engine. Windmills numbering in the thousands, for grinding grain and pumping drainage water were common across Europe, and some windmills were even used for industrial purposes, such as sawing wood. As the Europeans set off colonizing the world, windmills were built across the world (Hon, 2004).

Except for sailing, the main long-term use of wind has been for pumping water. Besides the Dutch windmills, another famous example was the sailing blades for pumping water for irrigation on the island of Crete. One of the blades had a whistle on it to notify the operator to change the sail area when the wind was too high.

In the 1930s and 1940s, hundreds of thousands of electricity producing wind turbines were built in the U.S. They had two or three thin blades which rotated at high speeds to drive electrical generators. These wind turbines provided electricity to farms beyond the reach of power lines and were typically used to charge storage batteries, operate radio receivers and power a light bulb or two. By the early 1950s, however, the extension of the central power grid to nearly every American household, via the Rural Electrification Administration, eliminated the market for these machines. Wind turbine development lay nearly dormant for the period 1950-1970 (American wind energy association, 2008).

Major factors that have accelerated the development of wind power technology are as follows:

1. High-strength fiber composites for constructing large and low-cost blades
2. Falling prices of the power electronics associated with wind power systems
3. Variable-speed operation of electrical generators to capture maximum energy
4. Improved plant operation, pushing the availability up to 95% of rated speed (Ibrahim,2014)

5. Accumulated field experience (the learning-curve effect) improving the capacity factor up to 40%

Following the OPEC Oil Embargo of 1973, interest in wind energy resurfaced in response to climbing energy prices and questionable availability of conventional fuels. Federal and state tax incentives and aggressive government research programs triggered the development and use of many new wind turbine designs. Some experimental models were very large, with a blade diameter of 300 feet. A single machine was able to supply enough electricity for 700 homes, (Ojosu, 1990 andRagheb, 2007). A wide variety of small-scale models also became available for home, farm and remote uses.

2.2 GENERATION OF ELECTRICITY FOR UTILITIES

There were a number of attempts to design and construct large wind turbines for utility use. These designs centered on different concepts for capturing wind energy: airfoil-shaped blades with the axis of the rotor being horizontal or vertical, Savonius and Magnus effect. With a vertical axis there are no orientation problems of the rotor due to different wind direction. A rotating cylinder in an airstream will experience a force or thrust perpendicular to the wind, the Magnus effect. In 1926 Flettner build a horizontal-axis wind turbine with four blades, where each blade has a tapered cylinder driven by an electric motor. The cylinders (blades) were 5m long and 0.8m in diameter at the midpoint. The rotor was 20m in diameter on 33m tower, with a rated power of 30kw at wind speed of 10m/s (Ibrahim, 2014)

2.3 WIND ENERGY

Wind is a natural phenomenon related to the movement of air masses caused primarily by differential solar heating of the earth's surface. Seasonal variations in the energy received from the sun affect the strength and direction of the wind. The ease with which aero turbines transforms energy in moving air to rotary mechanical energy suggests the use of electrical devices to convert wind energy to electricity.

A study on the wind energy potentials for a number of Nigerian cities shows that the annual wind speed ranges from 2.32 m/s for Port Harcourt to 3.89m/s for Sokoto (Ojosu, 1990). The maximum extractable power per unit area, for the two cities was estimated at 4.51 and 21.97 watts per square meter of blade area, respectively (Ojosu, 1990).

Wind energy used to be relied upon in the 1950s and 1960s for provision of water in many locations of the northern part of Nigeria. However, this was largely abandoned when the development of petroleum products reached advanced stages. In recent years, there are a few modern water pumps in some parts of the country. There is also one wind electricity generator of 5kW capacity supplying electricity from wind energy at Sayya Gidan Gada in Sokoto State.

Hydraulic Equipment Development Institute, Kano had made attempts in the past to design and develop a wind turbine to be installed within its premises. However, the scarcity of permanent magnets that are known to easily generate electricity from wind is the major challenge that was faced.

Wind is a clean and plentiful source of energy. In reality, wind energy is a converted form of solar energy. As long as there is sunlight, there will be wind (Hirst, 2014).

Approximately 2% of the sun's energy reaching the earth is converted into wind energy (Golden, 1985). The sun's radiation heats different parts of the earth at different rates, most notably during the day and night, but also when different surfaces (for example water and land) absorb or reflect at different rates. This in turn causes portion of the atmosphere to warm differently, air rises, reducing the atmospheric pressure at the earth's surface and cooler air is drawn in to replace it. The result is wind. Air has mass, and when it is in motion, it contains the energy of that motion ("kinetic energy"). Some portion of that energy can be converted into other forms mechanical force or electricity that we can use to perform work. A wind energy system transforms the kinetic energy of the wind into mechanical or electrical energy that can be harnessed for practical use. Wind speed is the rate at which air flows past a point above the earth's surface.

2.4 REVIEW OF RELATED RESEARCH

A number of wind speed forecasting techniques are available in order to predict the uncertainty of the wind, which is key to estimating wind power generation availability for the grid. Several methods have been proposed to provide wind speed prediction. In the recent years there is a lot of research happening to predict wind speed with several mathematical methods and biologically inspired computing techniques to reduce the prediction error.

The benefit of clean wind energy also brings the challenge of predicting wind power for optimal management of electricity grids. As the wind energy penetration grows in present power systems it places increasing demand on generation system for meeting the load reliably, and also poses new challenges for managing transmission and distribution networks. Wind speed forecasting plays a key role to address these challenges in wind energy. Wind speed forecasting is already a part of weather forecasting for many decades where it is being used for ship navigation, Missile guidance, Air traffic control and Satellite launch (Sreeklakshmi and Kumar, 2008).

It is possible to provide wind speed forecasts that are better than traditional methods. Some of the latest models existing now are physics-based forecasting models, computational learning systems such as artificial neural networks (ANN), support vector machines (SVM), and particle swarm optimization (PSO). The modern era of computing technologies with more processing speed and computing power are helping the researchers to work on novel forecasting models like artificial neural network model, which was difficult and time consuming to model few years before.

Statistical models are easy to model and cheaper to develop compared to other models. Statistical methods generally use the previous history of wind data to forecast the present over the next few hours. They are good for short time periods. The disadvantage with this is that the prediction error increases as the prediction time increases (Wu and Hong, 2007). Algebraic curve fitting, Auto Regressive Integrated Moving Average (ARIMA) model, and extrapolation using periodic curve fitting models require less number of input parameters for wind speed prediction (Kulkari, 2008). Fractional-ARIMA models are used to forecast wind speeds for 24hour and 48hour time periods (Kavasseri and Seetharaman, 2009). An advanced statistical method including artificial intelligence and fuzzy logic techniques showed that it is suitable for 48 hours forecasting for an accurate estimation of a wind farm's output. The Auto Regressive Moving Average (ARMA) is a well-known time-series statistical model. This model has shown good forecasting results from 1 to 2 hours. But when the time horizon is increased the prediction error also gets increased (Milligan, 2004).Torres, Garcia, Blas and Francisco (2005) used the ARMA and persistence models to forecast hourly average wind speed up to 10hours in advance. This model proves that it is considerably better in forecast than persistent model when the transformation and standardization of the original series allow the use of ARMA model.

An Artificial Intelligence technique is to mimic the learning processes of the brain to discover the relations between the variables of a system. The traditional AI technique includes the steps like searching for a good material, finding ways that will fit into a confined space, finding items with similar characteristics, and drawing conclusions based upon understood reasoning methods such as deduction and induction. ANN and SVM are considered as Black-box models and are constructed from data that includes solution pattern in input and output form.

Artificial Neural Networks (ANN) have been a good selection to model and forecast time series. ANN models can represent a complex nonlinear relationship and extract the dependence between variables through the training and learning process. Unlike statistical methods, ANN models are simpler to construct and require shorter development time and these don’t require to explicitly defining mathematical expressions. In simple terms ANN models can be just designed by identifying correct inputs, set up the network structure and then model a training algorithm, which gives the best prediction results. Some of the existing ANN models are Radial Basis Functions topology, Adaptive Fuzzy-Neural networks, multi-layer perceptron, and recurrent network. A neural network simulation method is proposed by Lopez, Velo and Maseda (2008). At selected site this method provides a reliable estimate of annual average wind speed with an error of 3%. The neural network used in this method is a multilayer perceptron with one hidden layer of 15 neurons, trained by Bayesian regularization algorithm. Katsigiannis, Tsikalakis, Georgilakis and Hatziagyriou (2012) proposed ANN model that takes the advantage of the past performance of neuro-fuzzy model and gives more accurate wind forecasting values. This improved wind forecast and provides 85% confidence interval for the operators.

Wind speed prediction is also done by the Support Vector Machine (SVM) algorithm. The results from SVM compare favorably with the Multi-Layer Perception (MLP) model based on root mean square error between the actual and predicted data. The results of model proposed by Sreelakshmi and Kumar (2008) has shown that wind speed forecasting using SVM model takes less computational time when compared to ANN models using back propagation algorithms. It is also shown that this model followed expected pattern of wind speed variations.

Evolutionary algorithms (EA) have been used for optimization in particular in both genetic algorithms and other evolutionary programming techniques like Particle Swarm Optimization. The EA is a powerful optimization technique similar to the natural selection process in genetics. EA based techniques meet the global optimum solution with high probability. EA is natural parallel process that is very useful when other optimization methods fail in finding the optimal solution. The latest computational techniques like distributed parallel processing methods would help in reducing execution times and possible to do large amount of computation in order to obtain the global optimal solution.

Jursa (2012) compared PSO method along with other four methods of wind prediction. The results showed that there is an advantage to use group of different models for wind prediction. A hybrid approach of combining both neuro fuzzy and ANN model for wind forecasting is proposed where neurofuzzy output is used to the ANN structure to exploits the past performance of the neurofuzzy model and give more accurate wind prediction (Katsigiannis, Tsikalakis, Georgilakis and Hatziagyriou, 2012). Adaptive Neural Fuzzy Inference System (ANFIS) is a hybrid of two intelligent system models, which is a combination of both neural network and fuzzy inference system. This model initially trained as a neural network and then functions as a fuzzy expert system. Jursa, Lauge and Rohrig (2006) proposed a wind forecasting model based on the nearest neighbor search with an optimization of the input data selected by PSO algorithm and concluded in this work that prediction error can be reduced by using the nearest neighbor search in combination with the optimization of the input data.

More and Deo (2002) employs the technique of Neural Network to forecast wind speed daily, weekly and monthly. It employs the use of past data in an auto regressive manner using backpropagation and cascade correlation algorithm. A generally satisfactory forecast with lower deviation from actual observation. Comparison study of three artificial neural network model for wind speed forecasting was realized (Li and Shi, 2009). Adaptive linear element, backpropagation and radial basis function was evaluated using the same data set and realized that none of the network outperforms others universally in terms of all evaluation matrices (MAE, RMSE, MAPE).

Monthly mean daily air temperature, relative humidity and vapour pressure measured at 10m height were used to create ANN model for wind speed prediction. The network fared satisfactory with a MAPE of 12.32 and R value of 93.12% (Barati,Hossein and Zadeheli, 2013). (Kalogirou, Costas, Stelios and Christos, 2014) predicted mean monthly wind speed and confined the maximum percent difference for the validation set to 1.8% on an annual basis. (Li, 2001) evaluated the characteristic of wind turbine power generation so as to establish the relative importance for the network and realized that four input network was superior to the single parameter traditional model approach. The potential capability of artificial neural network for prediction and decision making was assessed and found to compare favorably with statistical model (Tim, Leorey, Marcus and William, 1994).

Numerical forecast of wind speed and direction was used as input to a three recurrent neural network model. The infinite impulse response multi-layer perceptron, the local activation feedback multilayer network and the diagonal recurrent neural network all having internal feedback paths. The recurrent model found to outperform among them (Thanasis, Theocharis, Alexiadis and Dokopoulos, 2006). (Liu and Gao, 2012) used historical data of wind speed and direction for the prediction of short term wind speed. Probalistic neural network was applied to classify and screen the raw data before the training. Curve fitting, Auto Regressive Integrated Moving Average Model (ARIMA), extrapolation with periodic function and ANN were employed to predict wind speed and found that out of the four methods, extrapolation using periodic curve fitting and ANN performs better to a reasonable degree of accuracy (Buhari, 2011).

2.5 OVERVIEW OF ARTIFICIAL NEURAL NETWORK(ANN)

ANN is also defined as a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and process data parallel. In most cases ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning process. ANN is non-linear statistical data modeling tools and can be used to model complex relationships between inputs and outputs, or to find patterns in data. One of the major advantages of ANN is its ability to be used as an arbitrary function approximation mechanism which learns from observed data. Moreover, using it is not so straightforward, and a relatively good understanding of the following theory is necessary.

1. Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning
2. Learning algorithm: There are numerous tradeoffs between learning algorithms. Almost all algorithms will work well with the correct type of parameters for training on a particular fixed dataset. However, selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.
3. Robustness: If the model, cost function, and learning algorithm are selected appropriately, the resulting ANN can be extremely robust.

2.6 MULTILAYERED PERCEPTRON TRAINING PROCESS

One of the widely used Artificial Neural Network model called the Multi-Layer Perceptron (MLP) Neural Network is shown in Figure 2.1. The MLP type of ANN consists of one input layer, one or more hidden layers, and one output layer. Each layer employs several neurons, and each neuron in a layer is connected to the neurons in the adjacent layer with different weights.

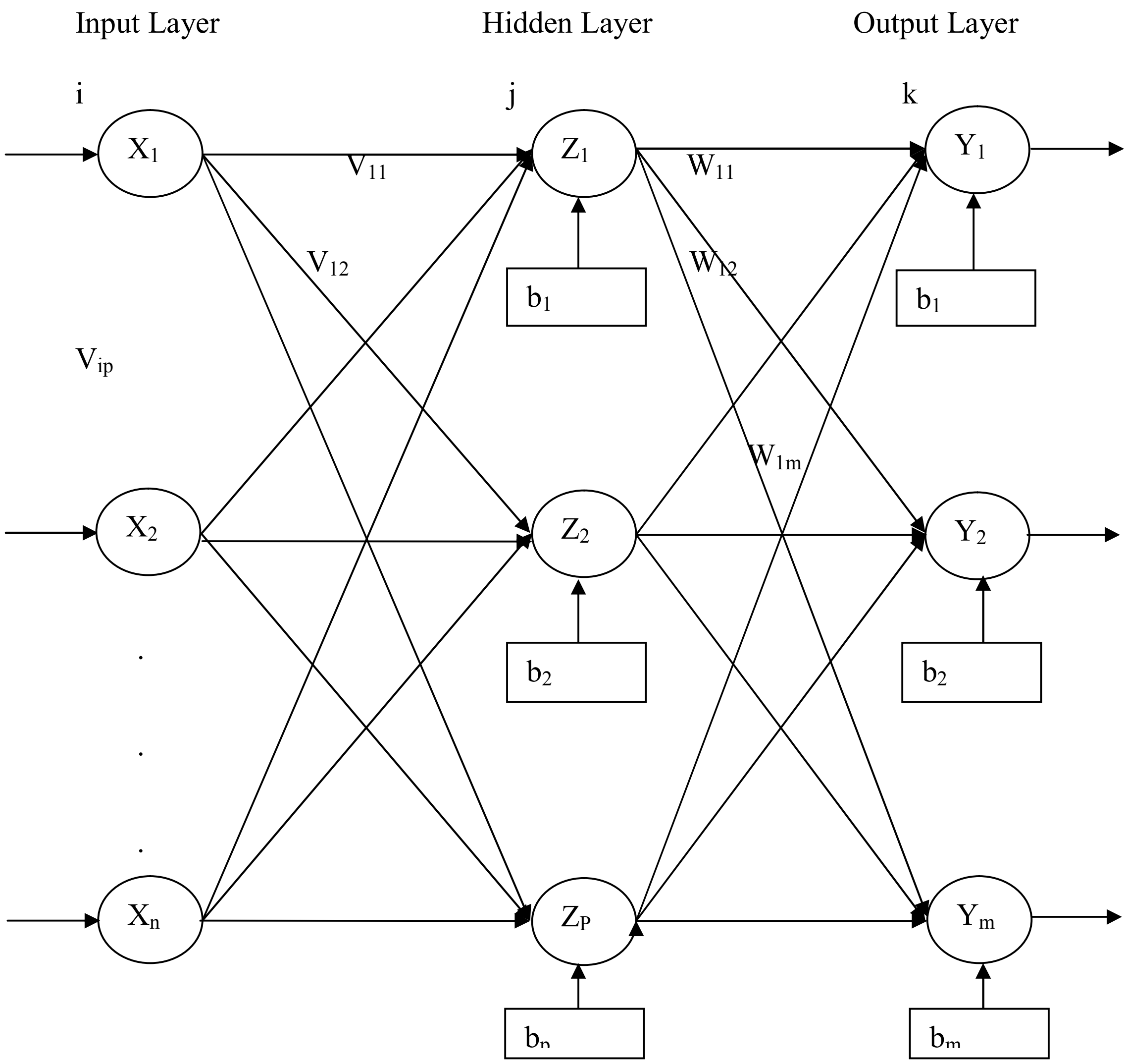

Figure 2.1 Architectural Graph of an MLP with One Hidden Layer

Signal flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signal from the neurons of the previous layer. The incoming signals (x_{ij}) are multiplied by the weight (V_{ij}) and summed up with the bias (b_j) contribution. The output of a neuron is determined by applying an activation function to the total input (net_j) as calculated by the equation (2.1)

$$net_j = \sum_{i=1}^{n} x_{ij} v_{ij} + b_j \quad (2.1)$$

Where, net_j: total input of the hidden layer neuron j

x_{ij}: input to the hidden layer neuron j from input layer

v_{ij}: Weight between the input layer neuron i and hidden layer neuron j

b_j: Bias of the hidden layer neuron j

n: number of neurons in the input layer

Activation functions for the hidden units are needed to introduce nonlinearity into the network. Without nonlinearity, hidden units would not make MLPs more powerful than just plain networks which do not have any hidden layer units, just input and output units. The sigmoid functions, such as logistics and hyperbolic tangent functions are the most commonly used activation functions in networks trained by back propagation (Fausett, 1994). The logistics function with the output amplitude lying inside the range [0.0 to 1.0] is calculated by equation (2.2)

$$z_j = f(net_j) = \frac{1}{1+e^{-net_j}} \tag{2.2}$$

The output amplitude of the hyperbolic tangent function lies inside the range [-1.0 to 1.0] and is calculated by equation (2.3)

$$z_j = f(net_j) = \tan \quad (net_j) \frac{1-e^{-2net_j}}{1+e^{-2net_j}} \tag{2.3}$$

The output of the activation function becomes the input to the layers downstream. The ultimate output of a NN model;y_k, is the output of the activation function at the output layer. The activation function for the output units is mostly chosen to be logistics, hyperbolic tangent or linear (identity) functions.

The identity function is calculated by equation (2.4)

$$z_j = f(net_j) = net_j \tag{2.4}$$

If the computed outputs do not match the known values, Neural Network model is in error. Then, a portion of this error is propagated backward through the network. This error is used to adjust the weight and bias of each neuron throughout the network so the next iteration error will be less for the same units. The procedure is applied continuously and repetitively for each set of inputs until there are no measurable errors, or the total error is smaller than a specified value.

At this point, the network remembers the patterns for which it was trained and is able to recognize similar patterns in new sets of data. Once the structure and training are completed, predictions from a new set of data may be done, using the already trained network. During the training process, the neural network develops the capability of recognizing different patterns and capturing relevant relationships in the training dataset.

Therefore, the underlying assumption in using the Neural Network model is that the relationships between the input and output variables in the training dataset, the testing dataset and prediction dataset are the same. The most commonly used learning algorithm is the standard Back Propagation and its variants such as resilient propagation and quick-prop (Koksal, 2008).

During training, an associated error is determined for each output layer neuron. Based on this error, the error information term is computed, which is then used to distribute the error of output layer neuron back to all neurons in the hidden layer by updating the weights between the hidden layer and output layer.

To develop a Neural Network model, the dataset is first divided into three sets, one to be used for the training of the network, and the others for testing and validation of its performance respectively. After deciding which activation function to use for the hidden and output layer units, the datasets are scaled down so that each value falls within the range for which the amplitude of the outputs of the chosen activation functions lies.

There are no established rule as to the number of hidden layers and the number of neurons for each hidden layer for a particular application. Network architecture is decided basically by trial and error; comparing the performance of the network with different number of neurons in the hidden layer(s). The weights and the biases are initialized with distributed random values before the training starts. The learning algorithms resulting in the best performance when compared to those of the other algorithms is chosen for the training of the network. The training is repeated until the Mean Square Error (MSE) for the entire training data is less than a specified value.

A smaller number of data that have never been shown to the network during the training (testing dataset) is used to test the prediction performance of the network after training is complete. The output of the network is compared with the actual value. Once the network weights and biases are initialized, the network is ready for training. The network can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. The training process requires a set of examples of proper network behavior (parameters), network inputs p' and target output t'. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function *net.performFcn.* The default performance function for feed forward network is mean square error (mse): the average squared error between the networks output and the target outputs t. There are several different training algorithms for feed forward networks. All these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. The gradient is determined using a technique called back propagation, which involves performing computations backward through the network. The back propagation computation is derived using the chain rule of calculus.

2.7 BACKPROPAGATION ALGORITHMS

The back propagation training algorithm is such that, the weights are moved in the direction of the negative gradient, as described below. More complex algorithms that increase the speed of convergence such as the Levenberg-Masquardt training algorithm (trainlm) are also available. However, there are many variations of the backpropagation algorithm. The simplest implementation of backpropagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. An iteration of this algorithm is described in equation 2.5.

$$x_{k+1} = x_k \quad \alpha_k g_k \tag{2.5}$$

Where x_ka vector of current weights and biases, g_k is the current gradient, and $\alpha_k$is the learning rate. There are two different ways in which this gradient descent algorithm can be implemented: incremental mode and batch mode. In incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In batch mode, all the inputs are applied to the network before the weights are updated.

The gradient descent algorithm is generally very slow because it requires small learning rates for stable learning. The momentum variation is usually faster than simple gradient descent, because it allows higher leaning rate while maintaining stability, but it is still too slow for many practical applications. These two methods are normally used only when incremental training is desired. Levenberg-Marquardt is normally used for training small and medium size networks, if enough memory is available (Demuth and Beale, 2014). If memory is a problem, then there are a variety of other fast algorithms available. For large networks you will probably want to use *trainscg*or*trainrp*.

Multilayered networks are capable of performing just about any linear or nonlinear computation, and can approximate any function arbitrarily well. Such networks overcome the problems associated with the perceptron and linear networks. However, while the network being trained might theoretically be capable of performing correctly, backpropagation and its variation might not always find a solution. Picking the learning rate for a nonlinear network is a challenge. As with linear networks, a learning rate that is too large leads to unstable learning. Conversely, a learning rate that is too small results in longer training times. Unlike linear networks, there is no easy way of picking a good learning rate for nonlinear multilayer networks. With the faster training algorithms, the default parameter values normally perform adequately (Demuth and Beale, 2014).

The error surface of a nonlinear network is more complex than the error surface of a linear network. The problem is that nonlinear transfer functions in multilayer networks introduce many local minima in the error surface. As gradient descent is performed on the error surface it is possible for the network solution to become trapped in one of these local minima. This can happen, depending on the initial starting conditions. Settling in a local minimum can be good or bad depending on how close is the local minima to the global minimum and how low an error is required. Although a multilayer back propagation network with enough neurons can implement just about any function, back propagation does not always find the correct weights for the optimum solution. Networks are also sensitive to the number of neurons in their hidden layers. Too few neurons can lead to under-fitting while too many neurons can contribute to over-fitting, in which all training points are well fitted, but the fitting curve oscillates widely between these points (Demuth and Beale, 2014).

Artificial neural network (ANN) has been used for many years in sectors and disciplines like medical sciences, defense industry, robotics, electronics, economy, forecasts etc. the main property of ANN that it can learn from examples (experience) is the key fact of preferring ANN in many nonlinear and complex problems.

From the beginning of 1990s, forecasting with ANN has become the commonly used tool. It is capable of identifying the complex interactions between dependent variables since it has nonlinear architectural structure (Buhari, 2011).

2. 8 CONCLUSION

Artificial Neural Network (ANN) has been shown to be a good tool to model and forecast time series, hence its application in forecasting wind speed of Kano state.

CHAPTER THREE
METHODOLOGY

3.0 INTRODUCTION

The methods to be adopted in realization of the aim and objectives of Investigation And Prediction Of Wind Speed Potentials In Kano State For Electric Power Generation Using Artificial Neural Network is highlighted.

3.1 MATHEMATICAL MODELING OF WIND TURBINE SYSTEM

With constant acceleration 'a', the kinetic energy 'E' 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.

$$E = W = Fs \qquad (3.1)$$

From Newton Second Law of motion

$$F = ma \qquad (3.2)$$

Therefore kinetic energy becomes

$E = mas$(3.3)

From kinematics of solid motion

$v^2 = u^2 + 2as$(3.4)

Where'u' is the initial velocity of the object. This implies that

$a = (v^2 \quad u^2)/2s$(3.5)

Taking the initial velocity to be zero, we obtained

$$a = v^2/2s \qquad (3.6)$$

From equation (3.3) it is obtained that

$$E = 1/2\, mv^2 \qquad (3.7)$$

However, considering wind (air in motion) as a fluid, both density and velocity can change and hence no constant mass. For this reason Manyonge, Ochieng, Onyango and Shichika (2012) formulated the kinetic energy law with a factor of $2/3$ instead of $1/2$. Assuming the density of air does not vary considerably even with variation in altitude or temperature, hence the kinetic energy(joules) is of mass m moving with velocity v_w(wind) can be obtained from equation (3.7) above. The power P in the wind is given by the rate of change of kinetic energy, thus

$$P = dE/dt = 1/2 \ dm/dt V_w^2 \quad (3.8)$$

Mass flow rate dm/dt is given by:

$$dm/dt = \rho A V_w \quad (3.9)$$

Where 'A' is the area through which the wind is flowing and ρ is the density of air.From this expression equation (3.8) becomes

$$P=1/2 \rho A V_w^3 \quad (3.10)$$

The actual mechanical power P_w extracted by the rotor blades in watts is the difference between the upstream and the downstream wind power (Manyonge et al, 2012)

3.2 DATA COLLECTION AND THEIR TYPE

The data required for this research were obtained from Nigerian Meteorological Agency, Mallam Aminu Kano International Airport. The data sought and received were Hourly Average Wind speed, Hourly average Minimum Temperature, Hourly Average maximum Temperature, daily average Relative Humidity measured at 09hours and 15hours, all spanning the period of 1970 to 2014. All the data were measured at a synoptic height of 10m.

3.3 DATA PREPROCESSING

Data preprocessing is a common step in many disciplines, including data mining, data warehousing, and optimization problems. As this section explains, data preprocessing also plays a very important role in neural networking. First, data normalization is examined. Data normalizing is the process of scaling data "to fall within a smaller range, such as -1.0 to 1.0, or 0.0 to 1.0 (Koksal, 2008). The central idea behind data normalization is to remove the dependence on measurement units, which is directly relevant to wind speed forecasting since predictor variables are measured using a wide variety of units (Degrees Celsius, meters per second, percentage etc.). Data normalization has direct implications to neural network performance. In fact, "normalizing the input values for each attribute measured in the training set will help speed up the learning phase (Koksal, 2008). Furthermore, it is important to normalize neural network training data in order to prevent weights from being overly adjusted due to the many possible large magnitudes of measured predictor variable values (Fausett, 1994).

3.4 DESIGN OF THE MODEL

This section gives the detail procedures for training the neural network in order to recognize the pattern existing from monthly average data of year 1970 to 2014 of Kano state.

The Mat lab ANN toolbox was used in designing the network architecture. The Multilayer Feed forward Network Architecture with two layers was adopted (the Hidden layer and the Output layer). The input consist of monthly averages of temperature(minimum and maximum) and relative humidity for year 1970 to 2006, 2008-2013(43years) altogether making 3 ×12month inputs rows by 43years columns. The test data consist of year 2007 and 2014 data of all the inputs(minimum temperature, maximum temperature and relative humidity) making 3×12month rows by 1 year column each. The target data will be a monthly average of wind speed forecast from January to December (1970-2006, 2008-2013) making 12 rows by 43columns. The transfer function used in the two layers is the Tan-sigmoid function for the hidden layers and the purelin function at the output layers. Figure 3.1 shows the network architecture

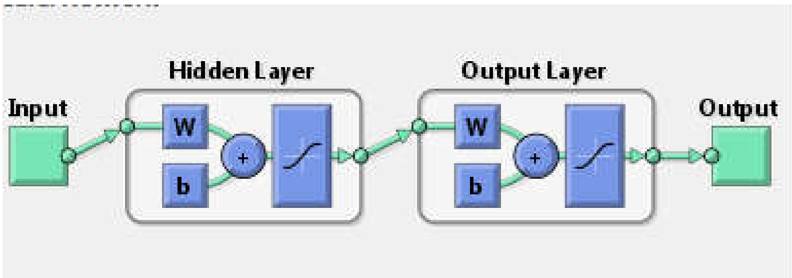

Figure 3.1 Generalized Two Layer Network Architecture (Matlab, R2012)

3.5 THE TRAINING PROCESS OF THE NETWORK

This involves entering correctly the input vectors, the target vector and several other training parameters as listed below. This include

i. Composition of the network architecture
ii. Defining the various inputs to the network
iii. Setting the target
iv. Choosing the required number of neurons in the hidden layer
v. Choosing the number of expected output layer
vi. Initializing of the weights and biases
vii. Setting of the training goal, number of epochs, learning rate, learning function, transfer function, performance function and training function

Figure 3.2 shows the neural network training tool window.

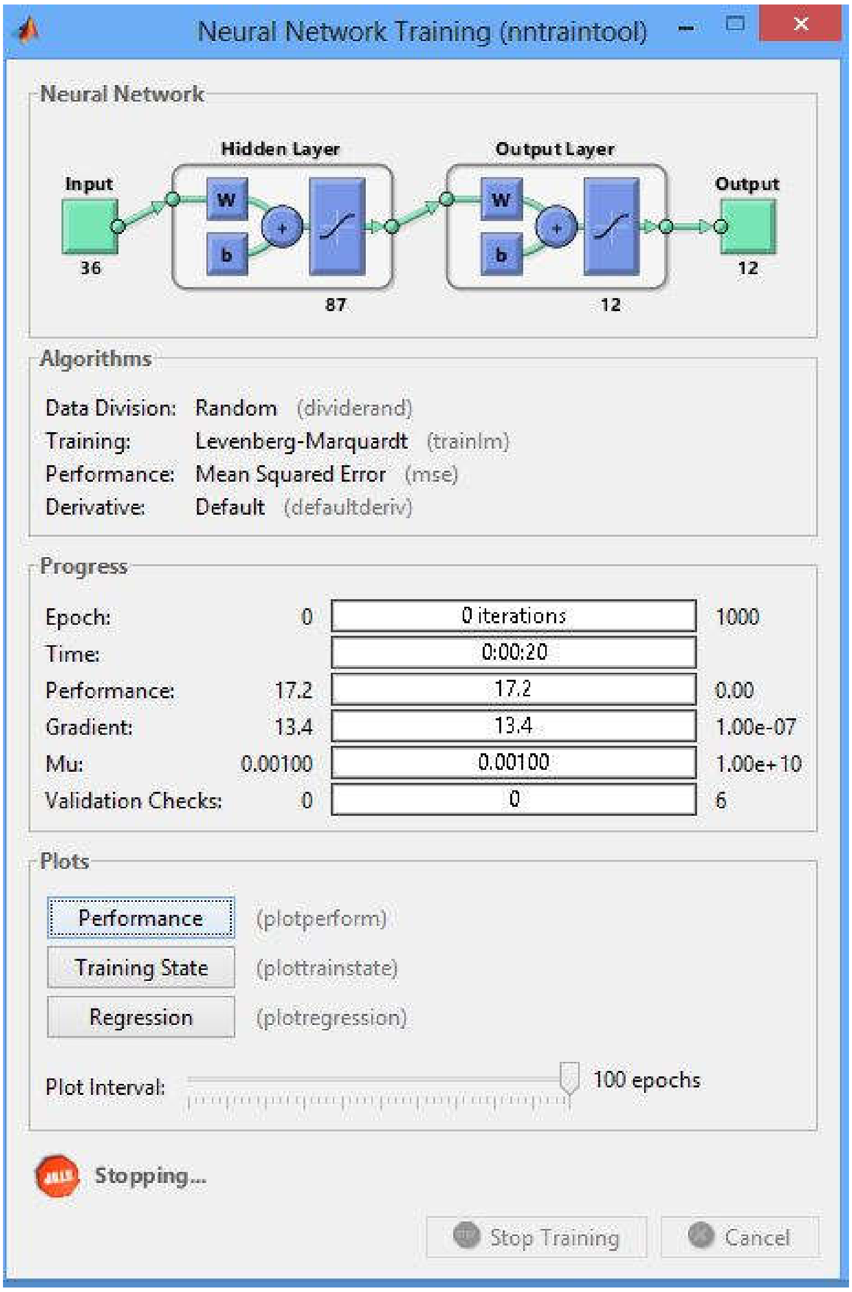

Figure 3.2: The ANN Matlab Training Tool Window

3.5.1 Realization of Training Parameter

I. The number of hidden layer of the network is crucial and linked to the generalization capability of the network. Problems that require more than two hidden layers are rarely encounter and for most practical problems, there is no strong theoretical reason to use more than one hidden layer (Muazu, Jimoh and Jibril, 2009), for this research, composition of the network architecture was achieved using one and two hidden layers in determining the number of hidden layer neurons that gives the best performance.

II. The input vector to be used are monthly average reading of year 1970-2006,2008-2013 of monthly averages of relative humidity,maximum temperature, minimum temperature since they have considerable effect on the wind speed. Altogether making up 36×43 matrices.

III. Setting up of the target data is much straight forward since the neural network is expected to compare its resulting output with the target data in order to learn accurately the complex relationship between the variables under consideration. In this project the monthly average winds speed reading from 1970-2006, 2008-2013 was used as the target data. 12 by 43 matrices were formed as the target data.

IV. Determining the appropriate number of hidden layer neuron to use is critical for effective learning and performance of the network. There is no systematic approach to determine the optimal number of neurons to utilize for a problem (Gaya, Bature, Zango, Madugu, Abubakar and Yusuf, 2008).Hence the trial and error approach was adopted until the best R-value performance was obtained and the number of neurons recorded as the optimal choice.

V. The choice of the number of output layer neurons is the same as the number of rows of the target data vector in this case 12month averages.

VI. Initializing of the weights and biases is also an important process because it helps in making the NN learn quicker and converge with the least possible error and the training error goal to be achieved faster. The weights and biases were initialized with the default values of 0.00

VII. In this research, 0 was set as the training goal in order to ensure zero tolerance to network computational errors. Tan-sigmoid transfer function was used in the hidden layer neurons while purelin function was used in the output layer in order to constrain the outputs values. The default steepest gradient descent method was used as the learning function while Levenberg-Marquardt learning was adopted as the training function. The maximum number of epochs was set to 1000 which was the default value, similarly the learning rate was left at the default value.Figure 3.3 shows the neural network training parameter window

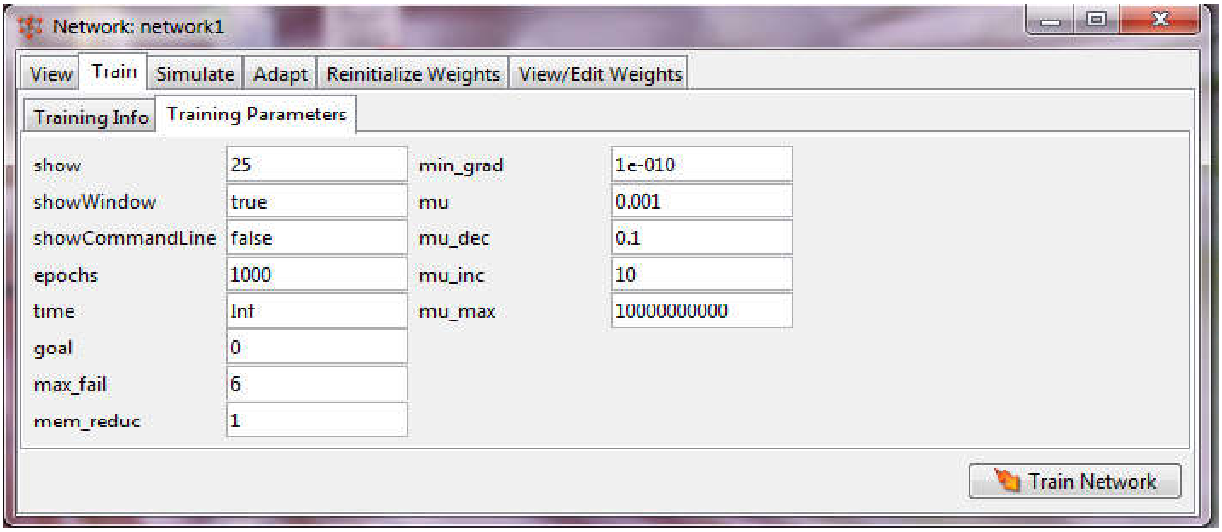

Fig 3.3: The Training Parameters Window

3.5.2 Matlab Operations carried out on the Training Data

The following steps were carried out on Matlab to realize the project

1. Transformation of data into matrix form
2. Normalization of the data between 0 and 1
3. Extraction of Input, Target and test data from the overall data
4. Simulation of the best result
5. Evaluation of the model

Transformation of data into matrix

$$r \quad = [43 \times 12]$$

$$tmax = [43 \times 12]$$

$$tmin = [43 \times 12]$$

$$wind = [43 \times 12]$$

Normalization of Data

The data transformed has to be normalized between 1 and 0 across each month. Its transpose was first obtained before dividing each monthly row by the maximum value, as indicated below. Only the inputs data was normalized excluding the Target data.

$$r \ ' = [43 \times 12]'$$

$$tmax' = [43 \times 12]'$$

$$tmin' = [43 \times 12]'$$

$$wind' = [43 \times 12]'$$

$$r \quad ' = [12 \times 43]$$

$$tmax' = [12 \times 43]$$

$$tmin' = [12 \times 43]$$

$$wind' = [12 \times 43]$$

$$nr \quad = \frac{[12 \times 43]}{max}$$

$$ntmax = \frac{[12 \times 43]}{max}$$

$$ntmin = \frac{[12 \times 43]}{max}$$

<u>Extraction of input and test data from the overall data</u>

$$X1 = ntmin(1{:}\,12{,}1{:}\,end \quad 1)$$

$$X2 = ntmax(1{:}\,12{,}1{:}\,end \quad 1)$$

$$X3 = nr \quad (1{:}\,12{,}1{:}\,end \quad 1)$$

$$t1 = ntmin(1{:}\,12, end)$$

$$t2 = ntmax(1{:}\,12, end)$$

$$t3 = nr \quad (1{:}\,12, end)$$

$$Input = [X1; X2; X3]$$

$$Test = [t1; t2; t3]$$

Simulation of the best result

$$y = sim(best\ network\ name, [Test])$$

Evaluation of the model

Plot (actual)

Hold on

Plot(y,'r')

3.6 CONCLUSION

It has been established that wind power production intimately depends on wind speed, which changes with weather condition and necessitated the accurate prediction of wind speed using Artificial Neural Network.

CHAPTER FOUR
RESULTS AND DISCUSSIONS

4.0 INTRODUCTION

This section explains the result obtained from the trained ANN model. This includes the regression analysis plots between the output and target vectors, the general network error performance and the training state. Discussions were also made of economic viability of establishing wind turbine in Kano state.

4.1 WIND ENERGY POTENTIAL OF KANO

Nigerian energy situation has worsened for the past decades and electricity generation both from fossil fuel and hydropower has degenerated largely due to decayed power generation infrastructure in spite of huge amount of investment in that sector. This has caused the closure of most industries while those that survive depend largely on power generating sets.

Physical features of Kano state in terms of elevation, latitude and longitude are 472.1m, $N12^0$ and $E08^0$ respectively (Adamu and Abdullahi, 2011). The useful way to evaluate the wind resource available at a potential site is the use of power density/specific power. It gives the measure of wind energy available in the wind stream of cross sectional area A (m^2), when the wind speed is V (m/s). The power density P (W/m^2) is given by (Adamu and Abdullahi, 2011)

$$P_w = 1/2 \rho V^3 \quad (4.1)$$

Where ρ is the standard air density (Kg/m^3) and V is the mean wind speed (m/s)

The wind speed regime of Kano was analyzed for their wind energy potential at heights of between 30m-80m (being the standard and available wind turbine hub-height globally at the moment operates at those heights).

The wind speed data obtained was measured at a synaptic height of 10m, hence there is the need to extrapolate it at those standard heights by making use of Logarithm Power Law (Iowa Wind Energy Center, 2006) given below

$$V_h = V_{10}(\ /10)^{\propto} \qquad (4.2)$$

Where $\propto$ is the roughness factor for the terrain under consideration. Similarly the roughness factor recommended by Iowa wind Energy Center (2006) for the region where Kano belongs is between 0.20 and 0.30. For this analysis a conservative value of 0.25 has been adopted. The table below gives the extrapolated wind speed (mean yearly) from 2000-2014.

Table 4.1 Values of Extrapolated Mean Annual Wind Speed of Kano at some Heights

Year	**Yearly AVG(V_{10})**	**V_{30}(m/s)**	**V_{40}(m/s)**	**V_{50}(m/s)**	**V_{60}(m/s)**	**V_{70}(m/s)**	**V_{80}(m/s)**
2000	4.733083	6.229088	6.693591	7.07761	7.407676	7.698722	7.960066
2001	5.122867	6.742072	7.244828	7.660472	8.01772	8.332735	8.6156
2002	4.647417	6.116344	6.57244	6.949509	7.2736	7.559379	7.815992
2003	4.12485	5.428608	5.833419	6.168089	6.455739	6.709384	6.937143
2004	4.17625	5.496254	5.906109	6.24495	6.536184	6.79299	7.023587
2005	3.9835	5.242581	5.63352	5.956722	6.234514	6.479468	6.699422
2006	4.403267	5.795025	6.227159	6.584419	6.891485	7.16225	7.405382
2007	4.544617	5.981052	6.427059	6.795787	7.112709	7.392167	7.643104
2008	5.4998	7.238144	7.777892	8.224119	8.607652	8.945846	9.249524
2009	4.454667	5.862671	6.29985	6.66128	6.97193	7.245856	7.491826
2010	4.7031	6.189628	6.651188	7.032775	7.360749	7.649952	7.90964
2011	4.887283	6.432027	6.911662	7.308193	7.649012	7.949541	8.219398
2012	5.354167	7.04648	7.571935	8.006347	8.379724	8.708962	9.004599
2013	4.390417	5.778113	6.208987	6.565204	6.871373	7.141349	7.383771
2014	5.491233	7.226869	7.765777	8.211309	8.594245	8.931911	9.235117

From the result obtained in the table above, it is seen that even at the lowest hub height of 10m, the wind speed of Kano is more than the cut-in speed of most wind turbines (3m/s). Also from Iowa wind Energy Center (2006), for economic viability, wind turbine site should experience not less than 5.4m/s of average wind speed. From table 4.1 at standard hub-height of 30m-80m Kano wind regime seems to be far above the recommended value from the height of 40m and above hence is economically viable in wind power generation.

As earlier stated, the useful way to evaluate the wind resources available at a site is the use of its power density. Table 2 gives the annual average power density from 2000 to 2014 of Kano state at those standard hub heights of 30m to 80m. Using equation (4.1) and taking standard air density to be 1.225kg/m^3, the annual average power densities is presented in table 2 below.

Table 4.2 Mean Annual Power Densities of Kano at Various Hub Heights

Year	**P_{30} (W/m^2)**	**P_{40} (W/m^2)**	**P_{50} (W/m^2)**	**P_{60} (W/m^2)**	**P_{70} (W/m^2)**	**P_{80} (W/m^2)**
2000	148.040	183.689	217.153	248.973	279.487	308.927
2001	187.709	232.911	275.342	315.688	354.380	391.708
2002	140.146	173.895	205.574	235.697	264.585	292.455
2003	97.988	121.584	143.734	164.795	184.992	204.479
2004	101.697	126.186	149.174	171.033	191.995	212.218
2005	88.255	109.508	129.458	148.427	166.619	184.170
2006	119.199	147.903	174.847	200.468	225.037	248.742
2007	131.051	162.608	192.232	220.400	247.412	273.474
2008	232.267	288.199	340.702	390.625	438.501	484.690
2009	123.422	153.143	181.042	207.570	233.010	257.555
2010	145.244	180.220	213.052	244.271	274.209	303.093
2011	162.986	202.234	239.076	274.108	307.703	340.115
2012	214.300	265.905	314.347	360.409	404.581	447.197
2013	118.158	146.612	173.321	198.718	223.073	246.570
2014	231.183	286.854	339.112	388.803	436.455	482.429

From the result above, it is evident that at any given standard height, Kano showsvery reasonable potential for wind farms, appreciable potentials for wind energy application and can be concluded that the specific power for Kano state is sufficient for establishment of off-grid wind turbines for electricity generation, for water pumping application and also a good potential for a grid-connected wind farms.(American wind Energy Association, 1998).

4.2 DISCUSSION OF NEURAL NETWORK TRAINING RESULTS

After the successful completion of the training, the following plots were made:

i. The regression plot
ii. The performance function Versus epochs plot
iii. The training state plot
iv. The Forecast and Actual Data comparison plot

Also included is the optimized network training tool.

The default division of the input data was adopted, thus, 70% was used as the training set, and while 15% each was used for testing and validation of the network output results. The Weight and bias values were obtained during the network training from the training data set. The ability of the network to generalize is periodically tested by the validation data set while the evaluation of the generalized error (i.e. MeanSquare Error in this case) is done by the test data.

Table A.3.1 to A.3.4 under Appendix presents the monthly average data of minimum temperature, maximum temperature, relative humidity and wind speed for Kano from year 1970 to 2014. Tables A.3.5 to A.3.8 show the Normalized Monthly Averages of the data while A.3.9, A.3.10 and A.3.11 are the Input, Target and Test vectors to the network respectively, all attached in the Appendix.

The optimized network input weights, layer weights, hidden neuron bias(s) and output neuron bias(s) are shown in tables A.4.1 to A.4.4 attached in the appendix. Lastly Tables A.4.5 and A.4.6 present comparison of simulated output to the target and Actual Output and Target of 2007 and 2014 respectively.

I. The regression plots: It consist of four regression analysis plots; the plot of the computed network output of the training data set versus the target, the second is the plot of validation data output versus target while the third and last plot is that of test data output versus the target and the overall network output data against the target respectively. All these plots present the correlation between the output data and the target data. It gives the idea of the accuracy of the trained network with desired target. They show how well the network has learned the complex relationship of the input data. Figure 4.1 presents the regression plots.

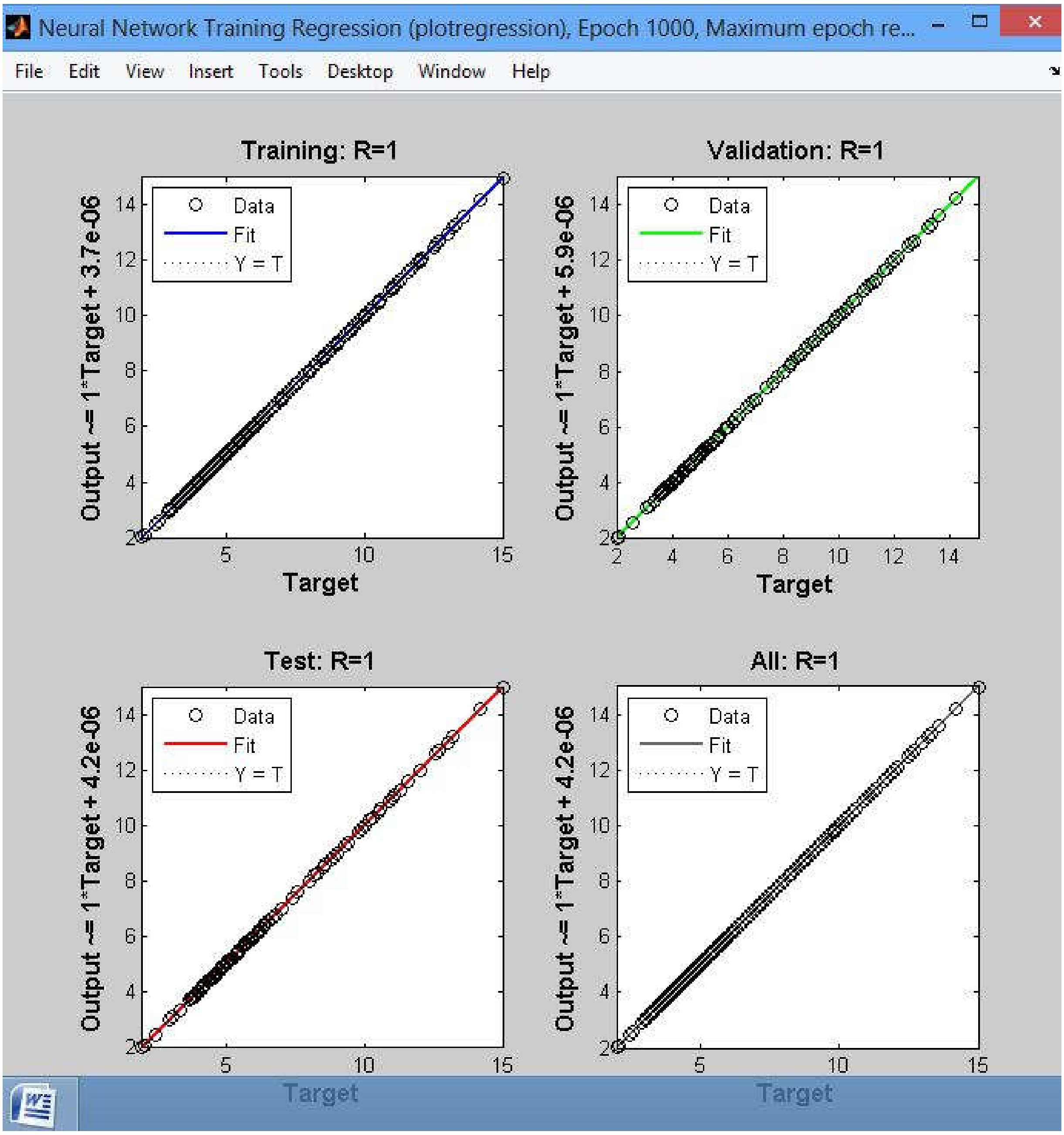

Figure 4.1: The Regression Plots

II. The performance function (MSE) versus number of epochs plot: This plot describes the plot of the mean squared error against the number of training epochs. It also shows the learning trend and computational error improvement as the number of iterations increases. It can be deduced that as the number of iteration increased (training epoch) so did the network errors reduces up to a best value of $1.35e^{-11}$ at 1000 Epochs. This shows that the trained neural network forecast error is expected to be at about $1.35e^{-11}$ of any input figures. This is quite negligible and the network can be said to have successfully learned the complex and nonlinear relationship that was presented by the input data. Figure 4.2 shows the training performance plot.

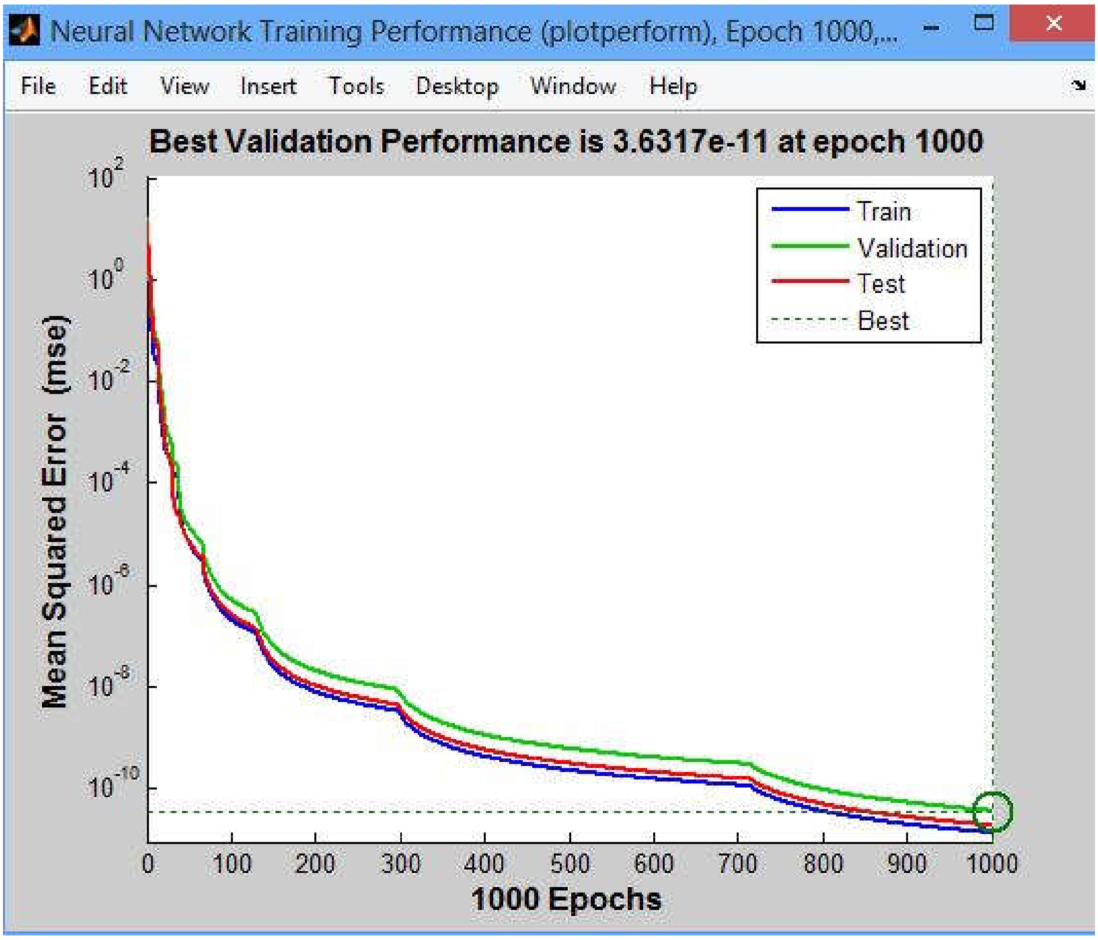

Figure 4.2: The Training Performance Plot

III. The training state plot: It consists of three different plots. The first plot being the learning function versus number of epochs. This shows the trend of the gradient values as the number of computational iterations increases. This is necessary in monitoring the manner in which the training progresses. The next plot is that of the learning rate at which the computed network error reduces during the progress of the training. The last plot is that of the validation checks carried out automatically any time a sudden change is observed in the network gradient computation is carried out.Figure 4.3 shows the training state plot

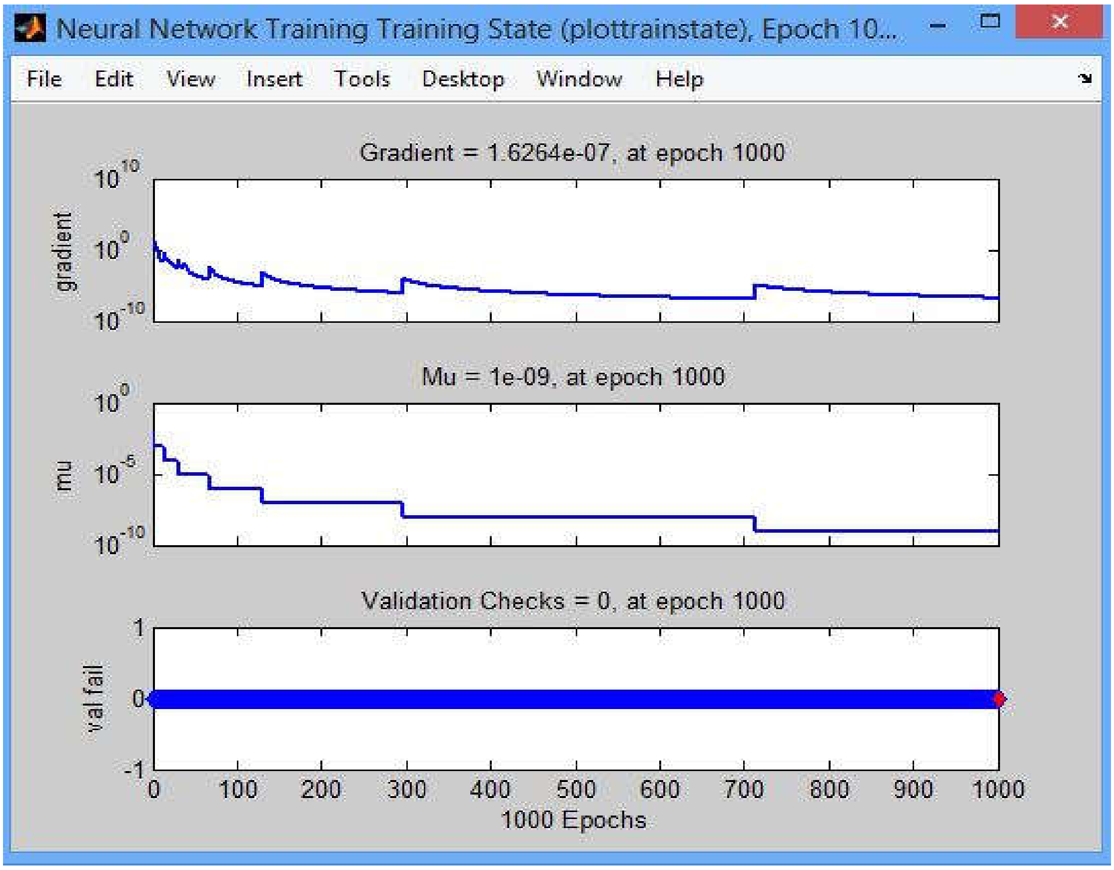

Figure 4.3The Training State Window

Also presented is figure 4.4 showing the Neural Network training tool of the best network.

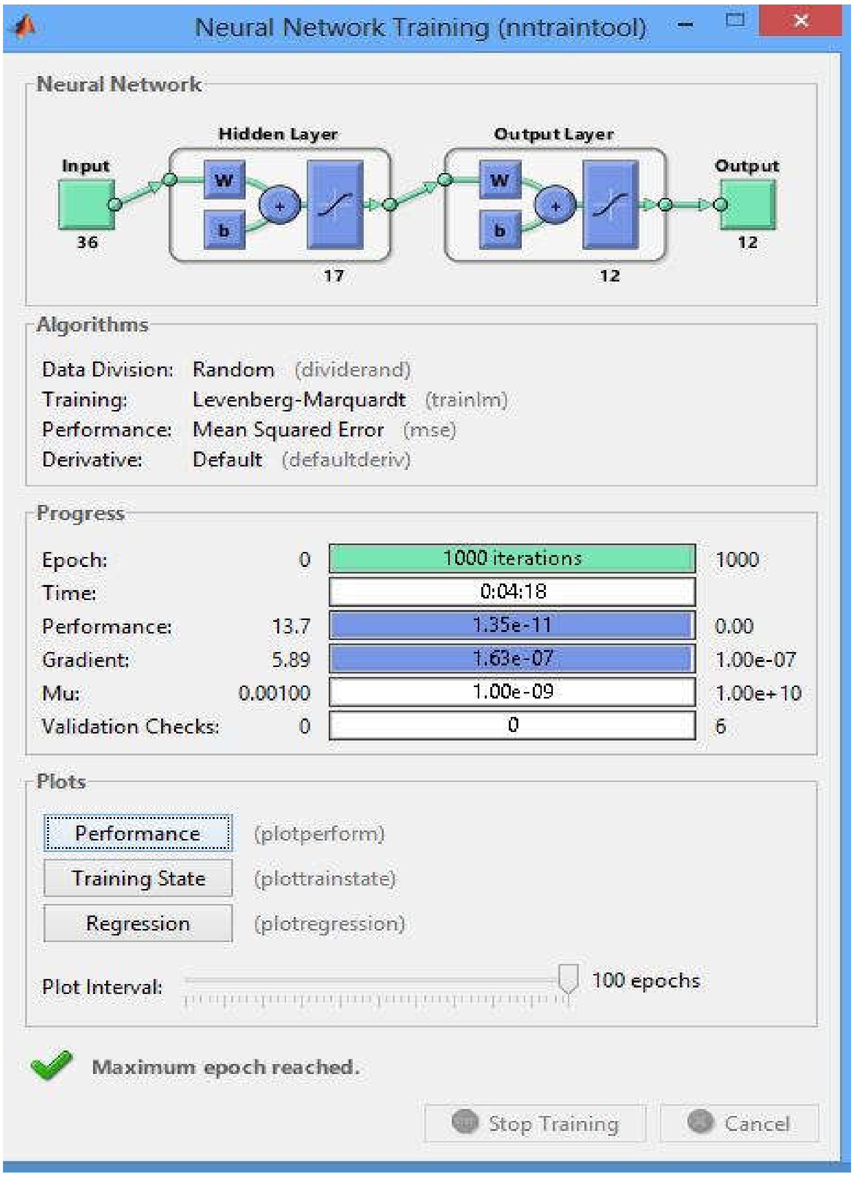

Figure 4.4: Neural Network Training Tool for the Best Network

The trained network optimized weight for each of the two layers (hidden layer and output layer) and connected biases that gave the best network output-target relationship were documented and attached in tables A.4.1-A.4.4 of the appendix.

4.3 Comparison of Simulated Results

The simulated results of the developed model were found to be exactly the same as those obtained from NIMET Kano office because the performance error from the trained model was $1.35e^{-11}$, figure 4.5 and 4.6 are the comparison plot between actual and forecast Monthly averages of wind speed for January to December of 2014 and 2007 while table A.4.5 and A.4.6(attached in appendix) shows a comparison between the actual monthly averages of wind speed obtained from NIMET and the output of the best network obtained from the trained neural network model.

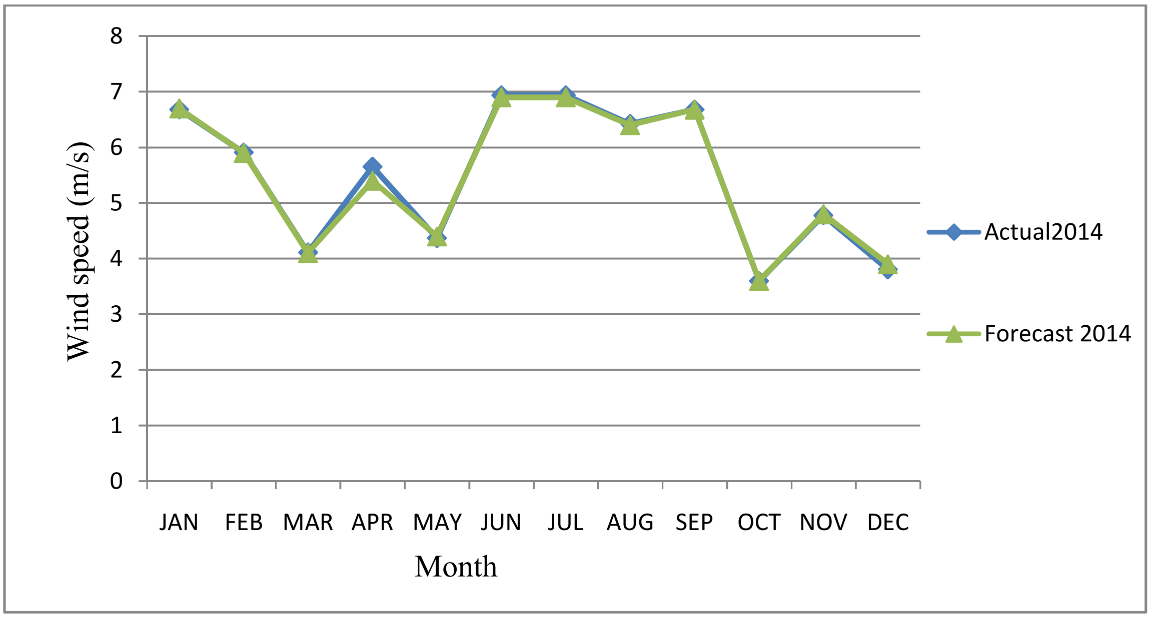

Figure 4.5 Comparison Plot Between Actual and Forecast Average Monthly Wind Speed for 2014.

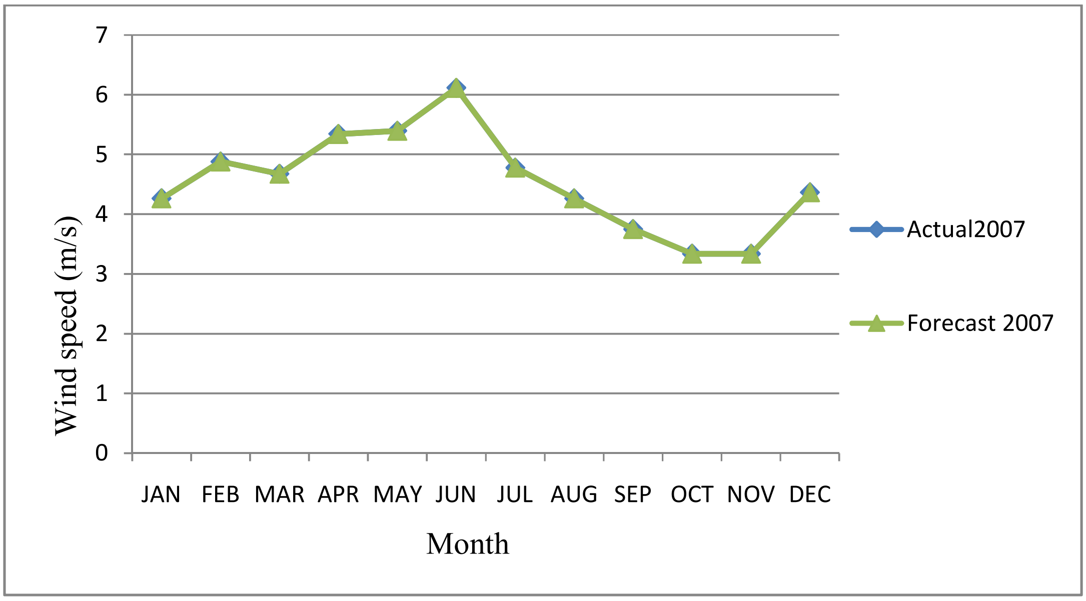

Figure 4.6 Comparison Plot Between Actual and Forecast Average Monthly Wind Speed for 2007.

4.4 CONCLUSION

The ability to predict accurately the wind speed of Kano state was achieved by the use of Artificial Neural Network. The forecasted wind speed of Kano state was compared to that obtained from NIMET and the results shows an excellent performance of prediction using ANN.It can be concluded that the aim and objectives of this project has been successfully achieved.

CHAPTER FIVE
CONCLUSIONS, CONTRIBUTIONS AND RECOMMENDATIONS

5.0 INTRODUCTION

This chapter gives the summary of the research, contribution made to knowledge and the recommendation for further improvement on the subject matter

5.1 CONCLUSIONS

The Monthly average wind speed forecast using R2012b ANN Toolbox was designed, the implementation of the network architecture, training of the neural network and simulation of the best results were done successfully with a very high degree of accuracy resulting into Monthly average wind speed with $1.35e^{-11}$ forecast error. A set of optimized weights and the associated biases after training the network from wind data obtained from NIMET (1970 to 2014)were also obtained. The degree of accuracy of the forecasts was verified by comparing the simulated outputs from the network with obtained data from NIMET. Several networks architecture were trained and simulated before arriving at the best Mean Square error performance of $1.35e^{-11}$.

Similarly it has been established that wind speed value is the major consideration for siting a wind generator, however Kano has reasonable probability of mean wind speed and hence good siting of wind generator.

5.2 CONTRIBUTIONS

The following contribution has been made to fill the knowledge gap on wind speed forecasting

1. A model for prediction of wind speed in Kano has been developed

2. Only Maximum Temperature, Minimum Temperature and Relative Humidity forms the predictor variables in predicting wind speed with a high degree of accuracy excluding atmospheric pressure and sunshine hours in most of the reviewed literature.
3. This model eliminates the task of conversion of the measured wind speed from knots to the standard unit (m/s) as it's been done in all our synoptic stations since the prediction output (wind speed) is in m/s.

5.3 RECOMMENDATIONS

Further research could be carried out to improve the results of this research by

1. Considering the effect of season.
2. Hybridization of Neural network with fuzzy logic
3. Incorporating Genetic algorithm for optimization of the input/target data.

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