UNIVERSITY OF NAIROBI

SCHOOL OF ENGINEERING

DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERING

SHORT-TERM WIND-SPEED-TO-WIND-POWER FORECASTING USING A HYBRID OF PARTICLE SWARM OPTIMIZATION AND ARTIFICIAL NEURAL NETWORKS

BY

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A thesis submitted in fulfillment for the Degree of Masters of Science in Electrical and Electronic Engineering, in the Department of Electrical and Electronic Engineering of the University of Nairobi

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LIST OF ABBREVIATION

ADALINE	Adaptive Linear Element Network
AIFNN	Annealing Integrated Fuzzy Neural Network
ANFIS	Artificial Neural Fuzzy Inference System
AR	Auto-Regressive
ARIMA	Autoregressive Integrated Moving Averages
ARTMAP	Adaptive Resonance Theory MAP
AWNN	Adaptive Wavelet Neural Networks
BMA	Bayesian Model Averaging
BNN	Back Neural Network
BPNN	Back Propagate Neural Network
CF-PSO	Constriction Factor Particle Swarm Optimisation
CKD	Conditional Kernel Density
ED	Economic Dispatch
EEMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Decomposition
ERCOT	Electric Reliability Council of Texas
ERNN	Elman Recurrent Neural Network
EWEA	European Wind Energy Association
FA	Fuzzy ARTMAP
FCM	Fuzzy c-Mean

FF-ANN	Feed Forward-Artificial Neural Network
FFNN	Feed Forward Neural Networks
FL	Fuzzy Logic
FNN	Fuzzy Neural Network
GANN	Genetic Artificial Neural Network
GM	Grey Model
GW	Giga Watt
GWEC	Global Wind Energy Council
HHT-ANN	Hilbert Huang Transform Artificial Neural Network
ICA-NN	Imperialistic Competitive Algorithm Neural Network
IMF	Intrinsic Mode Functions
K.E	Kinetic Energy
LM	Levernberg Marquardt
MA	Moving Averages
MAE	Mean Absolute Errors
MAPE	Mean Absolute Percentage Errors
MLP	Multi-Layer Perceptrons
MOS	Model Output Statistics
NNWT	Neural Network Wavelet Transform
NWP	Numerical Weather Prediction
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization

PSO-ANFIS	Particle Swarm Optimization- Adaptive Neuro-Fuzzy Interface
RBF	Radial Basis Functions
RMSE	Root Mean Square Errors
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition
SVM	State Vector Machines
UC	Unit Commitment
VARMA-GARCH	Vector ARIMA Generalised AR Conditional Heteroscedastic
WT	Wavelet Transforms

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ABSTRACT

Renewable energy has gained momentum over the last decade, with wind power technology leading by the number of projects implemented worldwide and academia as research[1]. Worldwide the growth of wind energy generation[2] has increased tremendously over the last 10 years, for instance, in 2000, installed capacity was 60GW and in 2010 it was 160GW. Furthermore, by 2015 the total global installation to 433GW.

With that kind of growth, energy sector professionals have had to keep pace finding better, reliable and efficient ways in the management of wind power farms and turbine designs that are cost effective. Numerical Weather Prediction software's (NWP) systems and meteorological tools are too expensive to acquire and maintain, therefore, these constraints have necessitated the development of accurate prediction system that are simple, fast and cheaper that can be used by system planners, power regulatory experts and the academic community through research.

Short term wind speed to wind-power predicting model is the main object for this research , the model will be optimized using a hybrid of particle swam optimization (PSO) and neural networks. Matlab modeling environment has been used extensively in this research work.

The hybrid prediction model performance will be evaluated, see chapter 4 and obtained the following values, using the mean square errors (MSE) of 0.26, the mean average error(MAE) of 0.62 and the mean average percentage error(MAPE) of 18.2.

CHAPTER 1:

INTRODUCTION

1.1. Background

Power and energy from either steam or horses was the main ingredient that propelled industrial revolutions in the 18^{th} and 21^{st} century. Modern methods of energy production being developed today lay a strong emphasis on Energy Efficient Designs and Environmental Conscience Power Generation.

Conventional sources of energy faces lots of challenges one being the cost of oil which is constantly increasing, making oil as a source of generation expensive especially when thermal sources are used in generating power, more still, the oil reserves are getting depleted more rapidly than earlier predicted

Green energy systems have been given attention in research and a huge number of green energy projects are being funded as seen through the wind power and electric vehicles projects. Wind energy is unpredictable in nature, this means that its applications are limited to the when and where the prevailing winds will be experienced. The development of wind power forecasting techniques and research has borne a center stage as per the following aspects of grid operations reliability, stability, power planning, maintenance, economic load dispatch and generator scheduling of the conventional energy sources, wind power integration to the traditional power grids[3] combined economic dispatch hybrid systems (wind–diesel hybrid) together with storage systems like pumped hydro to cut down running or operating cost by eliminating huge diesel generator loads. Properly designed wind power plants can be utilized to supply short interval power demand. For this to be achieved, forecasting as a tool can be used in power planning and scheduling of demand(load)[4].

Global warming from fossil fuel for instance oil, coal and natural gas used in various processes including the production of electrical power, has pioneered the birth of green energy research in better and cleaner energy sources [5][6] [7]. Hence, wind power has become a favorable area of energy research especially stabilizing wind power systems and the turbine blade design [8].

The electrical power consumers of today's modern world has grown to expect reliable and quality power at all times. While the conventional power generation still provide base load supply they are over-subsidized, expensive, the grid networks are ancient and are exhaustible, which leads to renewable energy being looked at as the cleaner and affordable alternative. Wind-speed-to-power forecasting, is therefore, an important area of interest in setting up wind power projects in a country especially for scheduling, dispatch and reserve allocations can be performed easily planned , like the European wind power development project; A.N.E.M.O.S as abbreviated as (A NExt generation wind resource forecasting systeM for the large scale integration of Onshore and offShore wind farms) [9].

Wind power is purely dependent on the prevailing wind flow, and since most modern power grids are a variation of hybrid systems/micro grids, the intermittency of wind can affect the grid negatively by limiting the total wind power being dispatched to the grid and total wind plant capacity [10]. Developing countries, energy is ever on an ever increasing demand, therefore, wind energy can be being pursued as an alternative power source though the ratio or the percentage of wind to other energy sources has to be checked. For instance the Greek island of Crete(20% to 40%) has high penetration of wind power and unpredicted changes can affect reliability and reduction in the operating economy[11]. Power operators hence to cover for the unexpected changes in speed, they maintain a huge spinning reserve[12].

Modern wind power plants are huge; requiring large pieces of land for both onshore and offshore wind farm, long and complex design stages, lack of standardization, erratic wind flow patterns, wind farm sites are often in remote places and huge farms require expansive pieces of land. The mechanical anemometer on the nacelle, is also a source of error in wind speed measurement.

These anemometers have calibration issues, measurement accuracy and raise the initial cost of the generation system, need to replace the mechanical speed measurement system with wind speed estimators designed on the turbine characteristics and data loggers which will provide reliable data that is used in the wind farm management and wind power planning.

Apart from these, there are several factors and challenges for an efficient hybrid power grid system before integrating into the generation mix, power system and dispatch planners look into the following challenges mentioned[13]:

(i) Wind power farm/plant capacities and energy balance management for short-term prediction of wind power, load profile management, energy storage/reserves, and system optimization.

(ii) Existing power grid network with special attention to: optimizing the present power network infrastructure, extensions and reinforcements, improving the grid interconnection or coupling points.

(iii) Grid-tied coupling connection and wind power integration, power quality and wind power plant/farm capacity while observing the grid codes.

(iv) For developed countries, market redesigns issues: market aggregation or the adapted market for power trading and spot market.

Therefore, this thesis and works recorded gives a development journey of a simple, wind-speed-to-wind-power prediction algorithm that works from a hybrid of Particle Swarm Optimisation and a cascade of Artificial Neural Networks. This hybrid model works on the scientific works illustrated from numerous research from various authors and numerical models like autoregressive integrated moving averages.

The Ngong' Hills wind farm by Kengen, is used as a case study it has a total of 31 turbines with only 16 Gamesa V52 being utilised as wind speed and wind power data was avaible, they have a generation capacity of 1.36MW of power.

1.2. Problem Statement

Different prediction models have various requirements, for instance Numerical weather prediction algorithms, require huge computing abilities as they have a lot of parameters to be considered, and also need huge financial backing to develop them. Other models that are simpler to develop are not so accurate themselves especially when considering longer forecasting horizons. Therefore, there is a big gap in finding an algorithm that is not only simple and less complex but designed to achieve an improved forecasting accuracy.

1.3. Justification

Unpredictable wind patterns increases the cost of wind power generation affecting the spinning reserves allocation, large ramp moments and other potential factors that influence the reliability of wind and stability of a power grid, hence, wind forecasts have become vital parameters for effective grid management with high wind penetrations (>5%).

Forecasting wind power dispatch, and the accuracy of the forecasting technique is an ongoing research problem [14] and several institutions are researching on different models for wind power prediction. Basin Electric Cooperative, has experienced poor forecasts where next hour generation forecasts errors are more than 50%[15]. Accurate wind power predictions has become an important power planning tool in regulating generation of power, scheduling and unit commitment of both conventional and nonconventional power sources as discussed in [16][17] for different forecast horizons example the short term horizon, that is forecasting for a period between 30 minutes to 360 minutes ahead.

Wind power integration into the grid is made possible through forecasting, the design and implementation of an efficient short term wind prediction for both wind speed and power will aid in planning both current and future renewable energies.

Globally, wind potential is huge as a power source that is competitive, both reducing the unit cost of energy and reduction of green gases. The Kenyan government has made tremendous power plans and is in the process of changing the base load power source from hydro to geothermal, wind and solar have been identified as vital sources of clean electrical energy, just as well, the first wind power was installed at Ngong Hills while, larger wind farms are being constructed in Turkana and Naivasha. Kipeto wind energy project already completed at Kajiado county, will also benefit especially in short term power forecasting[18].

Kenya has wind energy potential of 346 W/m2 with speeds of over 5.9 m/s in certain areas such as Kajiado, Marsabit, Meru, Laikipia, and Turkana Counties where wind power can be or is currently being explored as energy source for the future.

The current installed electricity generation from wind is 25.7MW developed at Ngong' Hills , a project undertaken by the Kenya Electricity Generating Company (KenGen) and a further 300 MW completed at Lake Turkana , by the Lake Turkana Wind Development company.

The following wind projects are currently under construction or in their completion phase that will benefit from this research.

(i) 13.6 MW Ngong' phase II wind farm,

(ii) 100MW Kipeto (Ngong') wind power

(iii) 6.8MW Ngong' phase III wind farm,

(iv) 100MW Isiolo wind farm

On the operational aspect of wind farms, the voltages and current profiles plus the frequency component on the generated values have erratic profiles which might introduce harmonics into the grid, interfere with the voltage levels due to variability of wind sources, again, turbine curtailment, this is the stalling/stopping of the turbine blades due to excess wind flow, is a major issue as it limits the aggregated power output from the farm.

With this kind of development in the country, accuracy in data logging for prediction becomes a fundamental requirement at project feasibility studies and consideration, later on, when the project is implemented, wind speed data is managed, several; authors have proposed wind speed estimation approaches that are used to create prediction models are given below [18];

(i) Equation for wind power relies on the wind turbine power coefficient of performance function $C_p(\lambda)$ and tip speed ratio, that are used to model higher order polynomials and the power coefficient is used to estimate the accuracy of the model, but the procedure requires real time calculation of the polynomial roots.

(ii) Look up table, requires external memory for accurate estimation, also, the execution time and accuracy depends on the size of the lookup table[19].

By now, the importance of intermediate and short-term wind forecasting should be clear and the complexity of such models, therefore, this has a created a gap in that cheaper and faster prediction techniques should

Artificial intelligence (AI) through efficient deep learning neural networks will play a major part in developing and designing faster predicting models that use fewer resources and designed for each specific need and time scale.

Prediction modeling is mostly based on historically recorded data and of importance is the wind speed and power, the data is used to develop algorithms on the given data set for analysis, assuming weather parameters like temperature, direction , air density are constant, this technique maintains speed and power of wind as base data for designing the model, this simplification is advantageous in that it reduces the development time since the prediction models are now simpler to design and highly accurate as the parameters are less.

Hybrid methods provided a promising gateway to improve speed of prediction and accuracy for the forecasted values, the hybrid model developed can me designed to be more efficient with a better improved accuracy by combining several artificial intelligence (AI) models for the forecasting engine.

1.4. Objectives

The objective here is to design a forecasting model by combining two algorithms particle swam optimization (PSO) and Artificial Neural Networks, the algorithm will predict wind values, that is wind speed and the wind speed will be converted to wind power for short term horizon [20]

The specific objectives are;

(i) To formulate a wind energy prediction technique based on Artificial Intelligence and statistical hybrid models.

(ii) To develop a forecasting engine based on the formulated prediction technique and cost function.

(iii) To evaluate the forecasting technique performance and compare with other models consider J. P. S. Catalao, H. M. I. Pousinho, and V. M. F. Mendes through their work in intelligent hybrid short term forecasting in Portugal obtained average MAPE of 5.99%[21].

1.5. Research questions

i) How can a hybridized network of nonlinear autoregressive neural networks and particle swarm optimization with statistical techniques models be combined to formulate a wind energy prediction technique?

ii) How will the forecasting engine be developed and integrate with the other techniques for the hybrid model proposed?

iii) How will the proposed model fair in comparison to the models currently being used?

1.6. Scope of work

Modern design of predictive architecture combines several aspects and parameters of the real world physical system. In forecasting, lots of historical data has to be processed and analyzed in order to design a forecasting engine or any other system that closely follows a real world problem and hence, the accuracy of the developed model is vital and therefore, a forecasting engine is optimized to reduce the prediction error.

Nonlinear neural networks was utilized to establish the moving average error between forecast and the actual data, the neural weights continuously optimized by a particle swarm algorithm in the following way:

i) Given that the Ngong' II wind farm has 16 , Gamesa G52 wind turbines, an aggregated average of the wind speeds is first determined and stored in an excel file.

ii) The data is then clustered into training, test and the validation data and fed into a nonlinear autoregressive net (narnet) at the input stage:

a) At this stage, a nonlinear neural network (narnet) is implemented to do an initial regression of the test data.

b) A cascadefeedforward neural-network is used to give a linear output of values from the first stage (a) above and target values. Here, the cascade feed forward net, its weights are optimized by the PSO algorithm.

c) Finally, the output stage which is composed of a closed-loop model, which is a nonlinear autoregressive neural network with external inputs (narxnet) is used to predict up to 2 hours.

d) The simulated wind speed data values are then converted to an equivalent aggregated mean wind power expected.

1.7 Concluion

Though most research in the country focus on the wind profiles and anticipated wind power potential, none has focused on wind power forecasting as a tool to explore the future wind farm capacity upon completion of the wind power project at a given site.

The running and efficient management of wind farms in Kenya will benefit from this research work especially in scheduling and dispatching generating systems , power system planning and maintenance of the grid network.

Raw aggregated wind data for the model was retrieved from the Ngong II wind farm , therefore, parameters like wind direction, site humidity or temperature are assumed constant for an easier and since simplicity of the model is paramount and therefore, we are not able to evaluate how these parameters affect the overall performance of the hybrid model.

CHAPTER 2:

LITERATURE REVIEW

2.1. Introduction

Power generated from the wind turbine, has to be integrated into the grid network. This if not carefully done will pose many challenges in terms of planning and power dispatch as to system stability has to take center stage and again accurate wind power forecasting is the biggest concern[22]. More so, the unpredictable wind patterns affects how much wind power is injected into the power grid, hence a probability model can be designed that caters for the intermittency or a statistical analysis as presented in [10].

Given that wind energy is erratic in nature as illustrated in [23] the accuracy of the forecasting model is desirable since wind prediction modelling is inherently complex and its flow is not easily predictable, the authors, proposed a hybrid Gaussian process with a numerical weather prediction for a day ahead prediction, performance evaluation and comparisons are made with the performance of artificial neural networks (ANN) using mean absolute error (MAE) as a metric for accuracy measurement.

This chapter introduces several works from other authors who have researched wind prediction using either speed or power or both to develop their models.

.Persistent models assume that prevailing weather conditions will persist into the next moment, therefore, this model suffers bias and is not accurate for longer forecasting horizons.

Physical models uses weather parameters and considers the topography of the area to predict, requires lots of data and complex to develop, but accurate for day ahead predictions.

Statistical models focuses on the dependency of forested data and the original data, statistical methods are used for these, like mean, correlations etc., this model uses time series based data or the neural network models in its design.

Hybrid models tries to combine several models to come up with a unique parameterized model for forecasting, the design utilizes the strengths of the models used while at the same time eliminating the shortfalls of each through compensation.

Spatial relation models tries to model through generalities such as, weather patterns between two closely located regions will be similar and as such, prediction in one site can be used on the other.

Artificial Intelligent models are designed to emulate human brain functions and are considered to be more versatile, since these models learns from the data presented and tries to make predictions based on the parameters designed into the model itself.

Table 2.1 : Literature Review and related works

Persistence and probability Models		
No.	Author	Contribution
1	T. Al Awami and M. a. El Sharkawi [10]	Proposed a model based on statistics and utilizing wind using a conditional probability density function, Beta and Extreme value, verifies that extreme value function outperforms the Beta function at high wind power forecasts while Beta functions perform better at moderate forecasts (6hours to 24 hours window). Persistence model is used for hourly wind predictions...
2	J. Juban, N. Siebert and G. N. Kariniotakis [23]	Proposed a probability prediction technique based on kalman filtering density estimation. This model performs equally as well as the persistence.
3	T. S. Nielsen, A. Joensen, H. Madsen, L. Landberg, and G. Giebel [24]	Developed a model based on probability and statistics, the model was used for predicting wind power values for up to a few hours.
4	Bri-Mathias Hodge and Michael Milligan [25]	Analyses the statistical distribution of the persistence error model distribution for 10 wind power plants in ERCOT, proposes a Cauchy distribution to model the distribution for forecast errors, and obtains the difference in confidence using Cauchy and normal distributions for comparison.
5	Sideratos, G. and Hatziargyriou, N.D.[26]	Presented a probability based wind power forecasting model using radial basis function (RBF) neural networks, it worked by predicting a set of quartiles with predefined nominal probabilities.
6	J. P. Palutikof [27]	Presented a methods to calculate extreme wind speeds, he used a classical methods are reviewed based on *generalized extreme wind values,(GEWV) distribution* and the *generalized pareto distribution(GPD).*

Physical Models		
7	Niya Chen, Zheng Qian , Nabney, I.T. and Xiaofeng Meng, [22]	Combined a Gaussian Process as a probabilistic component to the numerical weather prediction (NWP), the NWP was used for prediction of upto 1 day ahead. The method showed an improvement in performance of 9% to 14% to ANN mode.
8	R. J. Bessa, V. Miranda, A. Botterud, and J. Wang[24]	Used a kernel based model based with the Nadaya Watson Estimator to evaluate two wind farms, the performance of the model is benchmarked against a spline regression model.
9	Ghadi, M.J. ,Gilani, S.H. ,Sharifiyan, A. and Afrakhteh, H.[30]	Presented a new algorithm called the Imperialistic Competitive Algorithm-Neural Network (ICA-NN) method, it had a higher predictive accuracy and was used for short term forecast. Using data from Numerical Weather Prediction (NWP), the data was from online SCADA. Environmental factors (i.e. wind speed, temperature, Humidity, geographical conditions and other factors) are considered and the neural networks weight are adjusted using the then, Imperialist Competitive Algorithm .
Statistical and Time Series Models		
10	P. Gomes [4]	Presents a model that uses statistics for wind power and speed forecasting using Artificial neural networks (ANN) plus an autoregressive moving averages (ARMA) model. Statistical models try to establish correlation between in the variables used for performing estimation; it achieves this through training and prediction.
11	Bhaskar, K. and Singh, S.N. [29]	Proposed wind power forecasting using statistics without the use of the numerical weather prediction (NWP) inputs .The model was designed to have two stages, stage-I, comprised of a wavelet decomposition of wind time series data and an adaptive wavelet neural network (AWNN) that was used to decomposed signal for 30h ahead prediction, then stage-II, a model composed of a feed-forward neural network (FFNN) that was used for mapping the nonlinear wind speed and wind power output values.

12	S. Wang, M. E. Baran, and S. Member [30],	proposed an ARMA model for hourly prediction while focusing on power system reliability for a 50 unit power system, to achieve this, he used Monte Carlo production to simulate the actual system performance while introducing erratic system behavior.
13	Sideratos, G and Hatziargyriou N.D. [31]	Proposed a statistical model with an artificial intelligence techniques, the wind data values speed and direction, uniquely the method provided a way to estimate the quality of the meteorological data forecasts which improved the predictions and gave forecast of up to 48h.
14	Ozkan, M.B. and Karagoz, P.[32]	Proposed a hybrid model using statistics to predict short term wind power forecast of up to 48h ahead. Here weather events are clustered according to how important the forecasts are and also combined power forecasts from other different NWP sources and create hybrid final results. It required fewer historical data as opposed to neural networks (ANN) and support vector machines (SVM)
15	Junrong Xia, Pan Zhao and Yiping Dai [33]	Proposed a statistical hybrid model with numerical intelligence that applied fuzzy logic on neural networks for the forecasting architecture for a forecast of up to 36 hours at every half hour intervals with a reference point of wind.
16	Skittides [34]	Developed a statistical model based on the Principal Component Analysis (PCA). This model was used to give forecasts of wind data, speed, from an ensemble of similar events from the past. This model was used for predictions of up to 24h ahead and had better performance over the persistence model for forecasting up to 10 hours ahead.
17	Rachel Baile [35]	Proposed an autoregressive (AR) seasonal model using multi-fractal fluctuations, which could predict wind speed data up to 2-days ahead, the performance of the model showed an improvement over the standard models.
18	Jeon Jooyoung [36]	Modeled wind power into wind speed and direction with focus on intra-day prediction between 1hour to 72 hours ahead. The approach used a bivariate Vector ARMA generalized AR conditional heteroscedastic. Then a Conditional Kernel Density is used for modelling wind data values, speed, power and direction.

19	Guglielmo D'Amico [37]	Developed a non-parametric approach to predict wind speeds based on semi-markov chain model that could be reproduced as the statistical nature of wind speed accurately, the developed model is compared to the persistence model.
20	George Sideratos [38]	The method developed depends on artificial intelligence, inputs are wind speeds and direction interpolated at wind farms, after a preliminary prediction, the method then gives an estimation on the quality of meteorological prediction and it improves the predictions. It can predict up to 48hours ahead for wind farm operators in the electricity market.
21	Y. Min, W. Bin, Z. Liang-ii, and C. Xi [39].	Proposes an Ensemble Empirical Mode Decomposition and autoregressive integrated moving avarages (ARIMA) model that was used to estimate the wind characteristics. The wind speed time series is broken into Intrinsic Mode Functions and a singular residual series using the EEMD, the final predicted series is the summed up from the individual IMF and the residue component. They managed to achieve better result using this technique than using EMD-ARIMA model or the ARMA model.
22	X. Han, X. Zhang, F. Chen, Z. Song, and C. Wang [40].	Looked at the wind time series as a frequency component and used the wavelet theory to separate the data into low and high frequency sections. Then ARMA is used to forecast the high frequency sectors while least square support vector machine (LS-SVM) is used to predict the low frequency parts

Spatial correlation		
23	I.G Damousis et al [11]	Developed a fuzzy logic model that picked wind data values of speed and direction and trained by a genetic algorithm, the data from various stations located around the wind park and turbines. Then an autocorrelation and cross correlation functions were used to measure the improvement and the efficiency of the local and remote wind speed time series.
24	Y. Han and L. Chang [12]	They analysed the prediction accuracy of the forecast error from a distributed wind farm in the maritime Canada. The winds sites data considered are then aggregated as forecast error versus single wind farms; a spatial correlation function is developed to calculate an ensemble of wind forecast errors.

25	M. Khalid and A. V. Savkin [41]	Presented an alternative approach of improving short term prediction by proposing a model that extracts information from a wind site turbines and also from distributed observation points in the Australian wind farm. The model is a two stage model where wind speed is predicted using the model and then the data is converted to power by use of power curve model. The developed model performance is benchmarked with the persistence and grey predictor model with the mean absolute error and root mean square as the performance metrics.
26	L. Soder [42]	Presented a multidimensional ARMA series wind power forecasting technique, data from several regions is assumed to be correlated in terms of the forecast errors for wind speeds.
27	L. Xie et al [43]	Proposed a statistical model for spatio-temporal forecast correlation between wind speed and direction of sites located at different points, wind data is from Texas, improves the model by considering an advanced robust with look ahead capabilities, it is tried on a modified IEEE RTS 24 bus system

Artificial intelligence		
28	S. Saroha and S. K. Aggarwal[7]	Presented a time series multi-step Neural Network of neural networks and feedforward net optimised by a genetic algorithm(GA), trained using the Levenberg-Marquardt algorithm. The mean average error (MAE) and the mean average percentage error (MAPE) are used the performance metrics indicators. The model performance is benchmarked with the persistence model, GANN based models show better results using MAE and MAPE as benchmarking indicator against FFNN.based models
29	Thanasis G. Barbouniset al[44]	Presented an AI model to power generated from the wind turbines and information used for long term wind farm management of spinning reserves and economic scheduling..

30	Adnan Anwar [45]	Developed a Particle Swarm Optimization with a constriction factor parameter model (CF-PSO) tthat could optimally determine the parameters of an autoregressive (AR) model to achieve accurate predictions. The method is benchmarked with three models Forward-Backward approach, Geometric lattice approach, Least Squares approach and Yule-Walker approach, these models worked on error minimization of the AR model.
31	Andrew kusiak [46]	Proposed a method utilizing data from different timescales and forecast horizons, it was used for wind prediction of short and long term power.
32	X. Wu, B. Hong, X. Peng, and F. Wen [47]	Proposes a radial basis function (RBF) for short term prediction for upto an hour, this method had a superior evaluation of linear and nonlinear algorithms and faster convergence of results. The input values included wind speed, environmental temperature and power generation.
Hybrid Approach		
33	F. Keynia, N. Amjady and H. Zareipour [14]	Proposed a model that applies a filter on irrelevancy and a redundancy to a set of candidate inputs , the model used an optimized predictive engine that worked with an enhanced and modified particle swarm optimisation (EPSO) plus a hybrid neural network. Data is provided by the wind power producers in Alberta, Oklahoma and Canada , the model showed a considerable efficiency as compared to other techniques.
34	R. Ak, V. Vitelli, E. Zio, and S. Member [48]	This model used a multilayer neural network that is trained to identify and group interval-based outputs, the neural network is trained by a genetic algorithm for optimised prediction accuracy. This approach shows a significant improvement over the single-valued, crisp method.
35	P. K. Panigrahi, S. Mukhopadhyay ,A. Mitra, and P. Bhattacharya, [49]	They combined two methods wind values prediction,speed and wind power generation forecasting using a Discrete Hilbert Transform as a filter to characterize and forecast wind speed while a special neural network variant called radial basis function (RBF) converted the speed to power

36	J. Shi, W. Lee, U. S. A. Tx, and P. Wang [50]	proposed a HHT which is an adaptive analytical method used in a variety of data having both nonlinear and non-stationary dimensions, the model has an EMD and the HSA and is used extensively in geographical studies. Treats wind power output as signals with characteristics that can be forecasted just like wind. The time series of wind is taken separated into various frequencies, then using the signal as data input and it's joined with the wind velocity data to the ANN model. The HHT- ANN forecasting model is applied to a wind farm in Texas.
37	Michael Negnevitsky [51]	Developed an ANFIS system to predict future power generation for wind power from wind turbines, the developed system is for short term wind while it is evaluated with the persistence model.
38	Peter Johnson [52]	Proposed a hybrid model using fuzzy logic and artificial neural networks (ANN) in a hybrid model called ANFIS to predict very short term wind speed on frame of up to 2.5 minutes ahead.
39	Cameron W. Potter [53]	Developed an ANFIS system to predict wind vector rather than speed or power since wind turbines are directed towards oncoming wind, the system is used for very short term wind prediction.
40	Sivanagaraja Tatinati [54]	Proposed an adaptive model with Intrinsic Mode Functions (IMFs) utilizing empirical decomposition. In the model, IMFs and Least-Square-SVMs are used for IMFs with weak correlations, further, autoregressive models with Kalman filter were used with IMFs with high correlation factor, the model developed was called (hybrid EMD-LS-SVM-AR model).
41	Haque, A.U. Nehrir, M.H and Mandal,P[56]	Developed a hybrid model that used probability and wavelet transform with fuzzy ARTMAP (FA) network. Firefly (FF) algorithm was used as the optimizing algorithm. It used wind power data from a wind farm in, Colorado called Cedar Creek
42	Haque, A.U., mandal, P.,Nehrir, H.M and Bhuiya, [57]	Proposed a hybrid model from techniques in signal processing, artificial intelligence AI, and data mining. The signal processing aspect was used to filter out intermittent wind power time series data.

43	Jie Shi ,Zhaohao Ding , Wei-Jen Lee and Yongping Yang [58]	Proposed a model that combined GRA and wind speed distribution. Weights for each independent model was determined by considering different wind speed subsection and frequency and could give prediction of up to 15 minutes
44	L. Ran, Ke Yong-Qin and Z. Xiao-Qian [59]	Proposed a technique combining least squares (LS) and support vector machines (SVM) to improve prediction accuracy for short term wind velocity. The genetic algorithm in this model was used as the optimal parameter regularization selector for the LS-SVM kernel sigma.
46	J. Shi and Wen –Jen Lee [60]	proposes a weighed parallel forecasting algorithm for an improved short term prediction accuracy, the model operates by adjusting and increasing the performance sections of several models. The author compares the model with a SVM and ANN while using the mean relative errors as the performance metric.

Conclusion

Different models for forecasting have been looked at in this chapter, it is evident that the more complex a model is, the more accurate it can be, this is in the case of physical models especially the Numerical Weather Prediction models, this is mainly due to the fact that, it combines different parameters of the weather e.g., wind pressure, temperature, humidity, speed etc. and at the same time considers the topography. Physical models, are therefore, a more expensive and complex model of prediction, the other models discussed suffer accuracy limitations even though they might be simpler to design and use.

CHAPTER 3:

METHODOLOGY AND DESIGN IMPLEMENTATION

3.1. Introduction

Wind turbines generate power when wind cuts across the wind turbine blades; the blades are subjected to a force and hence turn in a given direction which could be clockwise or anticlockwise. Wind velocity characteristic determination is the initial consideration in designing a predictive system or in other words, it is the time series that is measured and converted into electrical power by a mechanical turbine. This chapter models wind turbines structure, wind speed data processing, nonlinear autoregressive models and the hybrid techniques predictive model.

Wind speed probability densities are used to simulate the variability nature of wind occurrences in nature; these models are discussed together with their basic functional equations in the preceding chapter. Algorithms discussed in this chapter outline the structure of Non-Linear Auto-Regressive Neural Networks (Narnet) and Cascade Feedforward - Particle Swarm Optimization (PSO) Forecasting model.

3.2. Wind Forecasting Approach

Currently, researchers are looking into grid stability with higher wind power penetrations. Accurate wind forecasting has been identified as an important area of both speed and power, the data is used for scheduling, capacity evaluation and determination of power costs e.g. tariffs

Wind forecasting and load forecasting allows wind turbine connection and disconnection scheduling with the conventional generators hence achieving low spinning reserve requirement and minimizing or maintain an optimal operating cost.

To design wind power forecasting models, two main approaches exist, either the single-steps or the several steps ahead wind power prediction[7]. Single step (deterministic, spot or point forecast) produce single forecast for each horizon as opposed to multi step that produce several time horizons.

All the forecasting models , statistical approach are the most promising since they can be simple in design though require a huge amount of information to be processed and analysed [25].

Wind power forecasting will bridge the gap for power system operators and generating companies in scheduling wind power to the general grid[25], areas in reserve requirements, unit commitment, generator scheduling and load management will directly benefit from the efforts carried out in developing efficient forecasting techniques.

Two major classifications, the physical models and the statistical models [26], broadly stated, the physical approach considers the physical layout like terrain, layout of the wind farm and temperate conditions and utilizes NWP models using a mathematical model of the atmosphere [27]. The statistical approach uses historical wind speed or power data [7][28] and is mainly used for short term predictions as it is more accurate than the physical models.

Physical techniques use meteorological and topological information as explained above but can also include the technical parameters of the wind turbine, this method utilizes the model output statistics (MOS) to estimate the local wind and to reduce prediction error, [29].

Wind power prediction modelling is dependent on data collection and data processing/ analysis, wind data collection is obtaining the actual wind speed data from field measuring devices such as anemometers and transmitted to central processing units in a remote location. Wind speed is then processed and the information utilized to make decisions including prediction.

The following listed data processing models, are the main numerical data processing models as given in [30]. Which are highlighted below:

i) Physical data design

ii) Statistics and numerical design

iii) Wind farm data design.

iv) Prediction data design for ensemble model.

3.3. Time scales classification for different forecasting methods

Since wind is a function of time, measured data from the site/farm can be processed according to the application and the desired accuracy. For instance, one might consider the hourly speed measurement, daily or weekly speeds. Then the data can be used for forecasting for different time scales and applications[31]. Wind data for speed and power are clustered into 4 main forecasting horizons, these are;

i) Very-short term wind speed or wind power forecasts: from a few second to 30 min, used in regulatory functions.

ii) Short-term wind speed or wind power forecasts: from 30 min to 6 hours, for ELD and load adjustment i.e. increase or decrease decisions.

iii) Medium-term wind speed or wind power: with a forecast horizon of a 6h to 1 day, for scheduling generators online and operational

iv) Long-term wind speed or wind power forecasts: with horizon of a 1-day to a week or more, used in U.C, spinning-reserve requirements and determination as well as scheduling maintenance to obtain the optimal operating cost.

Wind is stochastic in nature and hence accurate methods of forecasting are vital for maintenance scheduling, integration into the grid [26]The unpredictable nature of wind makes it practically unusable in so many ways, but by developing ways to be able to forecast this nature, the information can assist power system planners, developers and maintainers in wind power integration to the grid network, real time monitoring grid operations and control, grid network interconnection, power system voltage and frequency control, transmission capacity and expansion, integrity of the power grid system which include the power supply chain, generation, transmission and distribution and reduction of GHG emissions.

The power system requires a stable grid which is the main focus of the system operator, but a grid sustaining high penetration of wind is may experience reduced system reliability[32], since wind energy is uncertain and the systems currently online or connected to the system are fossil based, therefore, times when wind is unavailable the cost of fuel can be high as reserves have to be fired, system designers of wind power with thermal units try to minimize the cost function and emissions[10]. For achieving proper operation of both the wind turbines and conventional generators, forecasting has been identified as a tool for reserve allocation and optimal operating cost more so, for better performance in increasing the forecasting horizon, both short term and long term forecasts should run side by side.

Uncertainty of wind is varied and depends on the geographical location and the time scale, this is a challenge when these systems have to be incorporated to the grid, maintain the grid stability and balance the demand at the grid.

3.4. Wind Turbines

A wind turbine is the main converter or component that utilizes the strength existing in wind flow to generate electricity; it has the following components as shown in Figure 3.1. Different wind turbines have different wind capturing efficiencies and hence each blade is best suited to operate in specific wind site. Consider figure 3.3, it shows different turbine blades and their respective efficiencies.

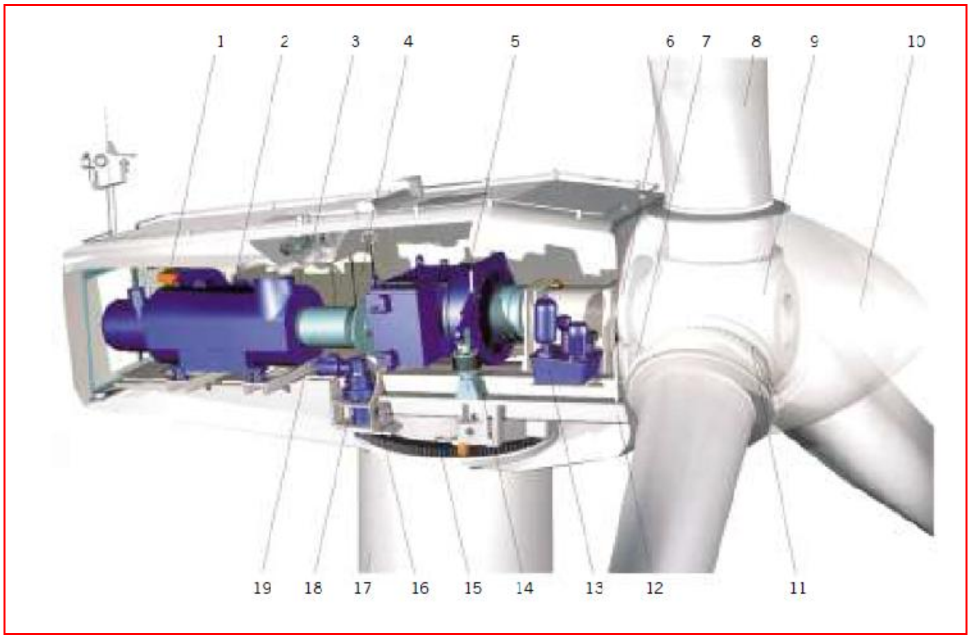

Figure 3.1: Gamesa G52 wind turbine (http://www.wind-power-program.com/Library/Turbine_leaflets/Gamesa/Gamesa_G52_850kw.pdf)

1	Service crane	9	Hub	17	Tower
2	Generator	10	Hub cover	18	Yaw gear
3	Cooling systems	11	Blade Bearing	19	Transmission high speed shaft
4	Top control unit	12	Bed frame		
5	Gearbox	13	Hydraulic unit		
6	Mainshaft with two bearings	14	Shock absobers		
7	Rock lock systems	15	Yaw ring		
8	Blade	16	Brake		

Consider a simple illustration of power generation from a wind turbine, the rotor is rotated from the upward (A1) side by the wind flowing through the rotor blades, a difference in pressure is then created between the upwind (A1) and downward (A2) sides of the blade, this then results into rotational motion of the blades that turn the mechanical rotor, further wakes, the trail of disturbed wind lift by the turbine, and flows downward consider Figure 3.2. below

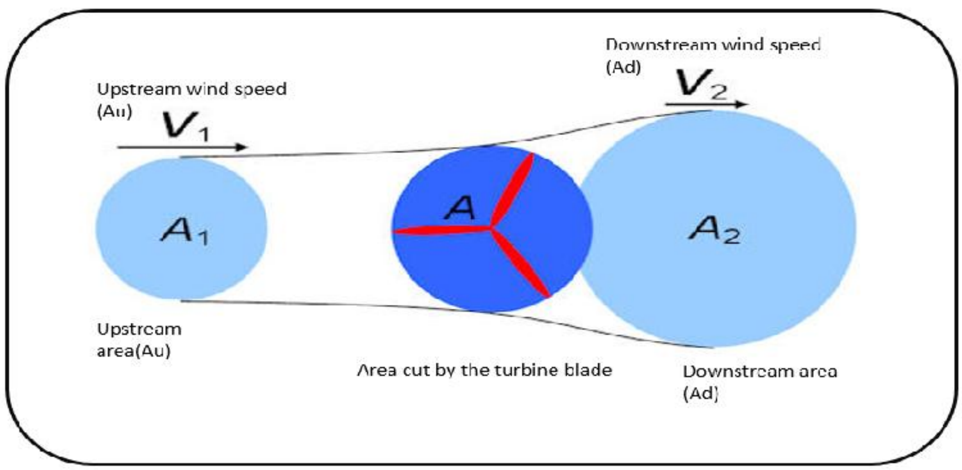

Figure 3.2:Wind across wind turbine blades

From the theory of motion, Kinetic Energy transferred by the wind velocity across the turbine blades is derived as shown by equation 3.1 and 3.2. the development of equations [3.1]-[3.15] are discussed in [33].

$$W = K.E_{upstream\,wind} - K.E_{downstream\,wind} \tag{3.1}$$

$W = \frac{1}{2} * (v_{up\_wind}^2 - v_{down\_wind}^2)$ *(assuming that the wind mass flow rate is unity).* (3.2)

Where K.E*upstream* = kinetic-energy of wind flow incident or across the wind turbine blades

K.E*downstream* = kinetic energy of wind flow through the turbine blades

V*up_wind* = Velocity of the wind flow incident or across the blades

V*down_wind* = Velocity of the wind flow through the blades

Wind turbine Power (P) is the rate of doing work, rate at which energy is dispensed, where $\overline{M}$ is the air mass flow rate, therefore;

$$P = \frac{\overline{M}}{2} * (v_{up\_wind}^2 - v_{down\_wind}^2) \tag{3.3}$$

But $\overline{M}$ is given as;

$$\overline{M} = \rho * A * (\frac{v_{up\_wind} + v_{down\_wind}}{2}) \tag{3.4}$$

Hence;

$$P = \frac{1}{4} * \rho * A * (\frac{v_{up\_wind} + v_{down\_wind}}{1}) * (v_{up\_wind}^2 - v_{down\_wind}^2) \tag{3.5}$$

To obtain the power max the rotors can extract, we have to differentiate with respect to down word wind, and equate to zero.

Using the principle of chain differentiation rule, and assuming the P (equation 3.3) is (y) we obtain:

$$\frac{dy}{dx} = \frac{1}{4} * \rho * A * [(v_{up\_wind}^2 - v_{down\_wind}^2) + (v_{up\_wind} + v_{down\_wind}) * (-2 * v_{down\_wind})] \tag{3.6}$$

$$3 * v_{down\_wind}^2 - 2 * v_{down\_wind} * v_{up\_wind} - v_{up\_wind}^2 = 0 \tag{3.7}$$

Solving and simplifying;

$$3 * v_{down\_wind}^{2} - v_{up\_wind}^{2} + 2 * v_{down\_wind} * v_{up\_wind} = 0 \quad (3.8)$$

$$v_{down\_wind} = \frac{1}{3} v_{up\_wind} \text{ or } v_{down\_wind} = v_{up\_wind} \quad (3.9)$$

Therefore, the maximum power output (Pmax) from the wind turbine will therefore be as shown by equation 3.10:

$$P_{MAX} = \frac{1}{4} * \rho * A * (v_{up\_wind} + \frac{1}{3} * v_{up\_wind}) * (v_{up\_wind}^{2} - \frac{1}{9} * v_{up\_wind}^{2}) \quad (3.10)$$

$$P_{MAX} = \frac{8}{27} * \rho * A * v_{up\_wind}^{3} \quad (3.11)$$

$$P_{MAX} = \frac{16}{27} * (\frac{1}{2} * \rho * A * v_{down\_wind}^{3}) \quad (3.12)$$

$$P_{MAX} = \frac{16}{27} * P_{TOTAL} \quad (3.13)$$

$$C_p = \frac{P_{MAX}}{P_{TOTAL}} = \frac{16}{27} = 0.593 \quad (3.14)$$

Where: $P_{TOTAL} = (\frac{1}{2} * \rho * A * v_{down\_wind}^{3})$ (3.15)

P_{TOTAL} is the total amount of power contained when the wind flows across the turbine, while Pmax is the maximum amount of electrical power that can be extracted by the wind turbine while observing all machine limits of the wind turbine.

Equation 3.15, is the Betz model and stipulates that the total power (P_{TOTAL}) extracted is relies on the cube of the wind velocity and the coefficient of performance, as given by equation 3.14, states that the maximum amount of power extracted can only be 59.3% of total power generated. This is mainly due to the internal turbine design and power conversion

3.5. Wind Farm Power Production

Wind farm evaluation, the Annual Energy Production (AEP) which is the energy from the wind turbine considering the total running hours of the turbine, this is further explained in [65, equation(8)], see equation 3.16 and the appendix G.

The following unction is used to estimate the AEP.

$$\mathrm{AEP} = \mathrm{T}\int_{v_{ci}}^{v_{co}} P_T(v)\, f(v)\, dv \tag{3.16}$$

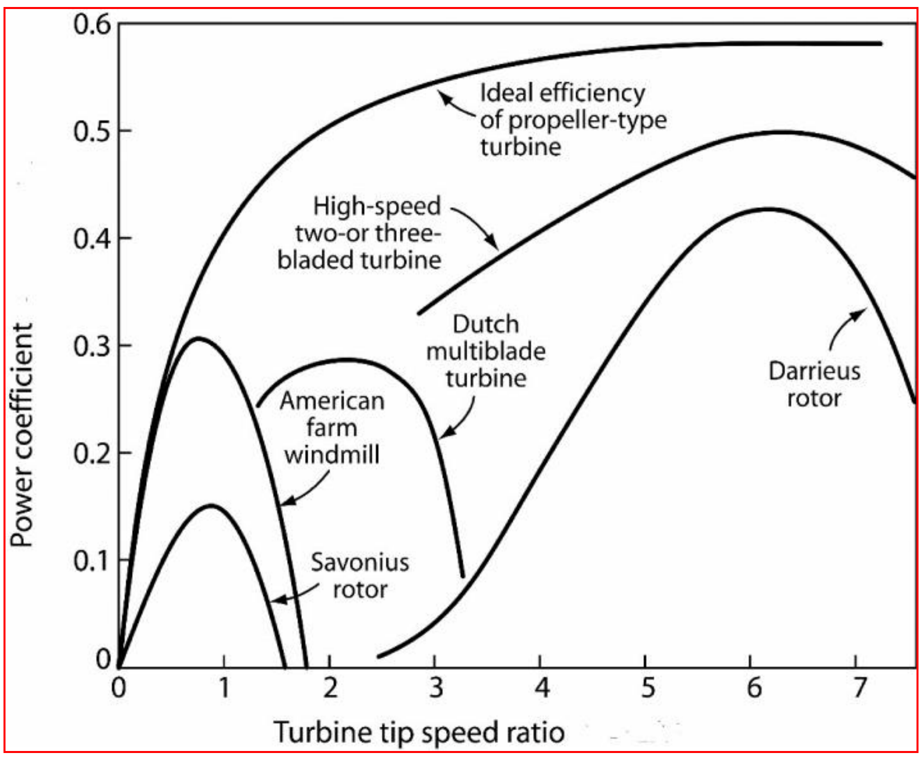

Figure 3.3 ; wind turbine performance curves

Performance efficiencies of different turbine blades, see [69, figure 6], these shows the variation in power generation while considering different blade designs for the wind turbine.

The Betz model, see equation 3.13, states that the theoretical total power output of any turbine to its maximum power output is limited to, see 3.14, 59.3%. This is also the coefficient of performance of though power loss through the turbine mechanical components and electrical efficiency reduces this power to about 0.35. The manufacturers curves as shown in figure 3.3 are used in determining the power derived from a particular wind blade type and is useful in relating the most appropriate wind turbine to a wind site, or can be approximated by equation 3.15 and equation 3.20,[11][35].

The power equation, as developed can then be plotted for a given turbine to give a plot as on shown below, figure 3.4. There are four distinct operating regions as marked, cut-in region, average region, rated region and the cut-out regions. The power generated closely follows the areas in the curve. They display the portions where the turbine can effectively generate power at cut-in velocity and the cut-out velocity points.

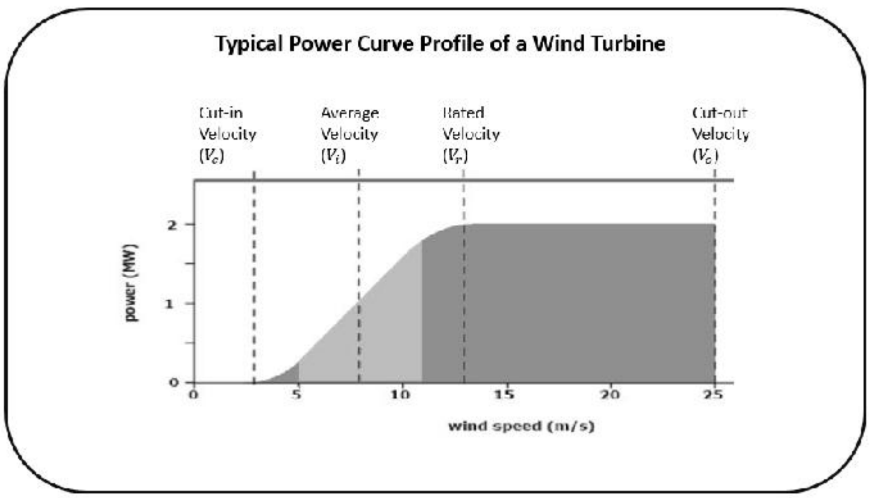

Figure 3.4 Wind power curve of a turbine as illustrated in [71,figure 3]

The power curves shown by equations 3.17 to equation 3.19, indicate the different power generation between the cut-in velocity to the cut-out velocity where the turbine will seize to operate and stall[37] , equation 3.17 -3.19 are illustrated in [68, eqn11].

$$P_{wind\_gen}(vel) = 0 \qquad \text{For } v_a < v_{cut\_in}, v_a > v_{cut\_out} \qquad (3.17)$$

$$P_{wind\_gen}(vel) = \frac{P_{rated} * (v_a - v_{cut\_in})}{(v_{rated} - v_{cut\_in})} \qquad \text{For } v_{cut\_in} < v_a < v_{rated} \qquad (3.18)$$

$$P_{wind\_gen}(vel) = P_{rated} \qquad \text{For } v_{rated} < v_a < v_{cut\_out} \tag{3.19}$$

From equation 3.12, equation, the theoretical power the wind turbine is given by the following equation 3.20 after substituting equation of an area of a circle and the coefficient of performance [38], see [68, eqn(2)] for the turbine power equation as illustrated in equation 3.20.

$$P_r(v) = \frac{1}{2} * \rho * \Pi * R^2 * C_p(\lambda, \beta) * v^2 \tag{3.201}$$

Where;

$P_r = Rated\ wind\ power\ of\ the\ rotor$

$\rho = air\ density$

$R =$ radius of the rotor blade

$C_p =$ rotor power efficiency

$\beta =$ tip speed ratio

$\lambda =$ blade pitch angle

Π = pi

According to[33], above equation is a theoretical one and the actual wind power equation deviates from that due to the followings:

1. Wind speed errors due to measuring instruments
2. Variations in air density
3. Misalignment of yaw and pitch
4. Shading effects and wake effects

Given that wind power and wind speed have a nonlinear relations, Weibull[39][40] and Rayleigh PDFs have also been captured to show their relation to wind speed and hence, we can, write the average power by the turbine from the wind speed probability function of either Weibull or Rayleigh. Hence, in theory expected power from a turbine can be estimated from the average values of power as given by equations, 3.21, 3.22 and 3.23.

Average power is given as a probability function as follows:

$$\overline{P(V)} = \int_{v_{min}}^{V_{max}} P(v_u) * f(v_u) dv_u = \int_0^{\infty} \frac{\rho * A * v_u^3}{2} * f(v_u) dv_u \tag{3.21}$$

$$\overline{P(V)} = \frac{\rho * A *}{2} \int_0^{\infty} v_u^3 * f(v_u) dv_u = \frac{\rho * A *}{2} \overline{V_u^3} \tag{3.22}$$

The value of $\overline{V_u^3}$ can be determined using the gamma function. The performance curve can be derived from the coefficient of power and torque, the power generation of the turbine can then be viewed as a term between the cut-in velocity and the cut-out velocity leading to formulation of equation 3.23;

$$\overline{P(V)} = \int_{v_{cut-in}}^{V_{Pmax}} \frac{c_p}{2} * \rho * A * v_u^3 * f(v_u) dv_u \tag{3.23}$$

Simplifying: With V_{Pmax} as the subject;

$$V_{Pmax} = \begin{cases} \left(\dfrac{2 * P_{max}}{c_p * \rho * A}\right)^{\frac{1}{3}} & c_p = \dfrac{\text{gen output}}{\text{wind power}} \\ \left(\dfrac{2 * P_{max}}{c_p * \rho * A * \eta_{gen}}\right)^{\frac{1}{3}} & c_p = \dfrac{\text{gen input}}{\text{wind power}} \end{cases} \qquad (3.24)$$

Given velocity and height where that velocity was measured, an extrapolation of second pair of velocity can be done using the extrapolation function and scaling as shown in figure 3.5 and equation 3.24. Therefore, wind shear, which is the time rate of change in wind speed at different altitudes, it allows the determination of wind flow profile and measuring of speeds at different heights over the surface i.e. coast lines, forests, hills or deserts.

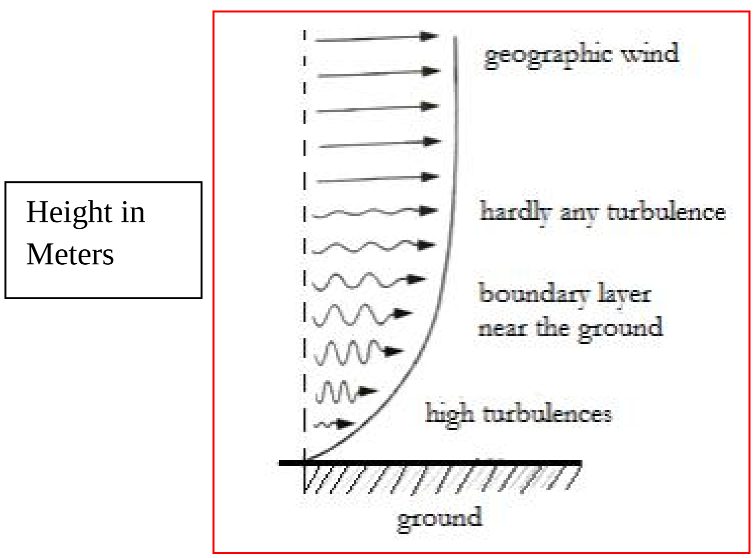

Figure 3.5: wind speed layers at different heights

This is a logarithmic wind profile due to the unique relationship between the wind rise and the elevation in a logarithmic pattern, as shown in the figure above.

The following equation is used to determine the wind velocities given a standard height,

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1}\right)^{\alpha} \tag{3.25}$$

$Where: \ \alpha =$
$roughness\ fator\ and\ gives\ the\ state\ of\ atmospheric\ stability$

Wind direction can be determined by wind rose, this is a diagram (see figure 3.6) representing the flow of the wind from various directions. The wind rose chart is divided in 8, 12 or 16 equal sectors that indicate wind flow from various directions and angles as shown. The following is the type of information that is contained in a wind rose:

1. The wind from a certain direction and amount in hours.
2. The time percentage of wind velocity from that specific direction.
3. The product of time percentage amount and third power velocity

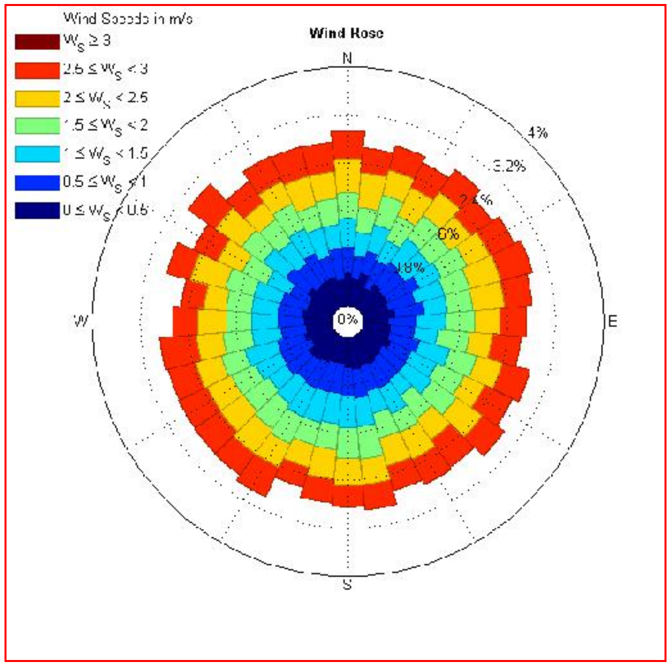

Figure 3.6: Wind Rose Chart

(**https://www.mathworks.com/matlabcentral/fileexchange/47248-wind-rose**)

3.6. Statistical Analysis: for Wind Speed Distribution Functions

A.Bizrah and M. Almuhaini [41] ,developed a wind speed modelling technique using probability density function, autoregressive moving averages (ARMA) and Markov-chain with several goodness fit function to check the model suitability .

There are two common wind speed probability density functions, Weibull and the Rayleigh functions. from the total power across the turbine as given by equation 3.26, the PDFs are used to estimate the wind speeds blowing in a given area, the unknown two parameters for the probability density functions (PDFs) i.e. shape and scale are obtain using the Maximum Likelihood Estimation methods or the Monte Carlo Methods though, though Maximum Likelihood Estimation technique is the best estimator of the Weibull or Rayleigh parameters of scale and shape.

The following equations in this section gives the wind speed PDF used in modelling and wind power analysis.

$$P_{TOTAL} = \frac{1}{2} * \rho * \frac{\pi}{4} * D^2 * v_u^3 \tag{3.26}$$

3.6.1 Gaussian (Normal) distribution function

$$f(x) = \frac{1}{\sqrt{2*\pi*\sigma^2}} * \exp -\left(\frac{(x-\mu)^2}{2*\sigma^2}\right) \tag{3.27}$$

Take $x = v_u$ and substitute, we obtain a normal distribution function of the wind speed.

3.6.2 Weibull PDF

The suitability of the developed Weibull see [71, equation (1)]distribution is dependent on the accuracy of k and c coefficients.

$$f(v_u) = \frac{k}{c} * \left(\frac{v_u}{c}\right)^{k-1} * \exp\left\{-\left(\frac{v_u}{c}\right)^k\right\} \tag{3.28}$$

Where;

c = scale parameter.

k = shape parameter

If $k > 3$ it implies a constant and steadier wind profile.

If $k = 2$, the weibull function changes into a Rayleigh PDF k and c are determined from the weighted sum of wind speed over a few years.

3.6.3 Rayleigh PDF

$$\mathbf{f(v_u) = \frac{2 * v_u}{c^2} * e^{-\left({}^{v_u}/_{c}\right)^2}} \tag{3.29}$$

The Rayleigh and the Weibull functions parameters can be estimated empirically as a gamma function;

$$V_m = c\Gamma\left(\frac{3}{2}\right)^N \tag{3.30}$$

Make 'c' the subject of the formula and obtain the following, equation 2.30.

$$c = \frac{2V_m}{\sqrt{\pi}} \tag{3.31}$$

The estimated Rayleigh function is then expressed as;

$$f(V) = \frac{\pi V}{2V_m^2} \exp -\left(\frac{\pi}{4}\left(\frac{V}{V_m}\right)^2\right) \tag{3.32}$$

The corresponding cumulative density function is also given as;

$$f(V) = 1 - \exp -\left(\frac{\pi}{4}\left(\frac{V}{V_m}\right)^2\right) \tag{3.33}$$

The standard deviation and the energy pattern formula is used to find the shape and scale parameters, the standard deviation is utilized using the equations;

$$\left(\frac{\sigma_v}{V_m}\right) = \frac{\Gamma\left(1+\frac{2}{k}\right)}{\Gamma\left(1+\frac{1}{k}\right)} - 1 \tag{3.34}$$

After solving equation 3.32, scale and shape parameter, (c and k), can be derived using equation 3.35 and 3.36.

$$c = \frac{V_m}{\Gamma\left(1+\frac{1}{k}\right)} \tag{3.35}$$

While 'k' is determined as

$$k = \left(\frac{\sigma_v}{V_m}\right)^{-1.090} \tag{3.36}$$

The energy pattern is a shown in equation 3.37

$$E_{PF} = \frac{\frac{1}{N}\sum_{i=1}^{N} V_i}{\left(\frac{1}{N}\sum_{i=1}^{N} V_i\right)^2} \tag{3.37}$$

$$k = 3.975 E_{PF}^{-0.898} \tag{3.38}$$

3.6.4 Mean wind speed/velocity

The mean wind velocity from equation 3.28, to find the approximated wind power, the mean velocity has to be weighted according to its power content, 3.29.

$$V_m = \frac{1}{N}\sum_{i=1}^{N} V_i \tag{3.39}$$

$$V_m = \sqrt[3]{\frac{1}{N}\sum_{i=1}^{N} V_i^3} \tag{3.40}$$

3.6.5 Standard Deviation

This SD measures inconsistency in wind speed data to determine the deviation from the average velocity. Hence, with a small standard deviation, it means that the data is uniform.

$$\sigma_v = \sqrt{\frac{\sum_{i=1}^{N}(V_i - V_N)^2}{N}} \tag{3.41}$$

3.7. Artificial Intelligent Algorithms for time series prediction systems

Forecasting is an already vital part in understanding several phenomena for instance, natural disasters, stock prices, electrical load demands changes and the economic performance of a country given a specific set of parameters as well the performance of wind farms in view of wind speeds prevailing in an area.

Forecasting, therefore, forms a huge part in our day to day decision making. The ability to forecast these areas is depended on the repeatability and understanding of the problem set we are focusing on.

As such, there is need to develop techniques to model the problem set and simulate them on a computer so as to better understand. Hence, the modelling and simulation, is a complicated task since, a thorough grasp of the exact area should be studied, documented and utilized.

The development or the design of the models, several tools can be used, we will design a forecasting by using hybrid techniques. It comes naturally that, where there is intelligence, a sort of brain has to be implemented to give abstractedness and form to any system or being.

The following section details the design of a hybrid non-linear-autoregressive-neural-network and Particle-Swarm Optimization model for a time series prediction engine for a wind farm in Kenya.

3.7.1 Non-Linear-Auto-Regressive Series

A time series is a sequence of numbers arranged serially and they normally represent real life data or values[42]. Mathematically, a time series can be expressed in a lagged autoregressive model or a moving average:

$$y_t = \alpha x_{t-1} + \beta \tag{3.42}$$

Where;

$\alpha = constant\ to\ be\ estimated$

$\beta = white\ noise\ term\ given\ zero\ mean\ and\ a\ variance$

$y_t = value\ to\ be\ predicted$

$x_{t-1} = previous\ data\ value$

For a first order autoregressive model, a more elaborate approach is used; the value to be predicted is expressed as shown below[43];

$$y_t = \beta_0 + \sum_{t=1}^{N} \beta_1 x_{t-1} + \varepsilon \tag{3.43}$$

$$\beta = (X^T X)^{-1} X^T Y \tag{3.44}$$

Where;

$y_t = value\ to\ be\ predicted$

$x_{t-1}(i = 1,2,\ldots,N) = past\ values$

N = auto-regression rank,

$\varepsilon = white\ noise\ term$

$\beta_{0,1\ldots N} = auto - regressive\ coefficients$

The to determine the autoregressive coefficients, the maximum likelihood method or the least squares can be used.

3.7.1.1 Non-Linear Autoregressive Neural Networks

Artificial Neurons were inspired by the way a brain-neurons functions, for instance, how new memories are formed by creating new connections between similar neurons and are activated by the firing action of the neurons and when similar neurons fire at the same time, their cumulative effect is summed over a node and a specific action is then performed for instance flexing a muscle.

Biological neuron structure is as shown in figure 3.7. The neuron is composed of the synapse, axon and the dendrites, together they combine to ensure the brain functions depending on the type of stimuli.

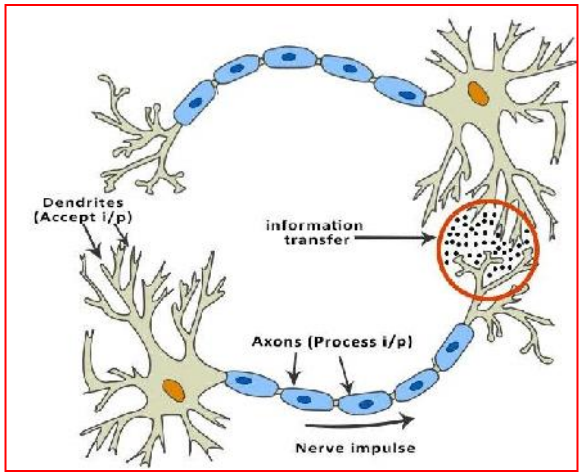

Figure 3.7: Biological neuron structure

NN are powerful and flexible, they are good in approximating nonlinear functions and give solutions where the input and output relationships neither are nor well defined or not easily computable.

Time series predictions are either linear or nonlinear, depending on the predictive model and the desired accuracy. Linear auto regression is achieved by using superposition principle[43][44]. A general autoregressive model is as shown in the equation below, The designing of the Nonlinear Autoregressive model in matlab can be done, through a set of equations as defined below;

$$y_{t+s} = \omega_0 + \sum_{j=1}^{D} \omega_j f(\iota_{o,j} + \sum_{i=1}^{m} \zeta_{i,j} x_{t-(i-1)d}) \tag{3.45}$$

$$x_t = (x_{t,} x_{t-1} \dots \dots \dots . x_{t-k})' \tag{3.46}$$

$$O_t = (O_{t,} O_{t-1} \dots \dots \dots . O_{t-k})' \tag{3.47}$$

As stated, ANN has faster learning curve, for predictive applications, the BPNN performs well as the error is fed back into the network and process is repeated.

Catalo et al [45],suggest that a three layered Feedforward- ANNs perform well in forecasting applications since the sigmoid function is nonlinear while the output function is linear and therefore, this shows that neural networks can be designed as a powerful algorithm for detecting patterns too complex for any algorithm to detect. ANN have dynamic learning features, are self-organized with a tolerance ability making it ideal for wind power forecasting modeling[46].

Short term forecasting is limited to several hours[6], ANN is an Evolution Algorithm that can be used for modelling different system and has uses in prediction of wind turbine output power as described in [47].

3.7.1.2 Structure of an Non-Linear Autoregressive Neural Network

Nonlinear-Autoregressive-Neural-Networks are represented by a mathematical expression that has a number of inputs, weights and a bias function that generate an output depending on the activation and transfer function. Consider the figure 3.8.below which shows the mathematical design of a neural network.

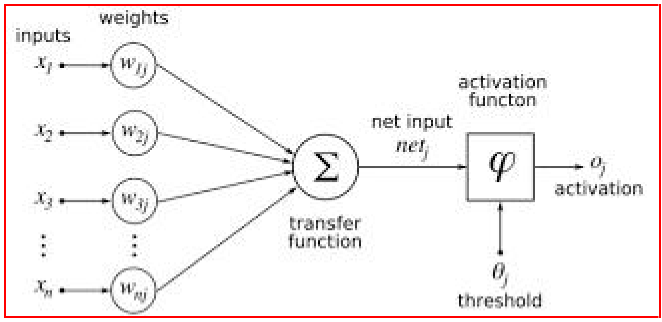

Figure 3.8: Artificial neural network architecture

In backpropagation neural network (BPNN), the weight update rule can be done using the delta rule or the gradient search method, which presents an excellent opportunity for weight adjustment in retraining the network for performance optimization.

The sensitivity factor is a partial derivative term and can be expanded through partial differentiation methods of calculus mathematics to evaluate the error (E).

The weights adjust the input node to the hidden node; $w_{i,j}$ it has a mean value lying between 0 and 1.

The activating function equation can be thought of as the training element of the neural network, Javad Mahmoudi et al gives it as a Bipolar Sigmoid function[7] though several activation functions both linear and nonlinear can be found in literature for instance , unit step ,signum, logistic or the hyperbolic functions.

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.47}$$

The Multilayer Perceptron (Bishop, 1995) is a complex connection of neurons arranged in layers , the hidden layers containing the hidden nodes are used to control the behavior of the network and the size too, the neuron and layer weights are adjusted using either of the following algorithms, Steepest-Descent ,Gradient-Descent, Back-Propagation, Levenberg-Marquardt[48].

The Bayesian Neural Network, (Mackay, 1992) uses the Hessian matrix introduced in the Levenberg– Marquardt algorithm to estimating the neural network weights. The BNN treats the network parameters or weights as randomly assigned values that obey probability distribution laws i.e. the normal distribution, the distributions are normally decided upon by the fact that they can favor less complex models to produce smooth fits.

The Radial Basis Function, by Moody and Darken Powell, has a structure similar to the multilayer perceptron and functions by utilizing the Gaussian where, the width of the Gaussian window is selected to control the fitted function smoothness. The outputs of the nodes are combined with a linear function to give the final network output. The network architecture closely resembles the multilayer perceptron architecture.

Generalised Regression Neural Network, by Nadaya and Watson , 1964, utilizes the parameter h, called the bandwidth, in determining the smoothness of the function to be fitted since increasing or decreasing the bandwidth parameter controls the size if the smoothing region,[49]

The *k*-nearest Neighbor, calculates the shortest distance between a reference point and all other points in a training set. The closest *k-point* in the training data points are then picked to set the predicted value as the weighted sum of the target output values for these *k*-points.

The Classifier and Regression Tree is a regression model that looks like tree-like ordered partition of the input size (Breiman, 1993). The input size is clustered into local sections classified into a sequence of repeating parts.

SVR by (Scholkopf and Smola, 2001; Smola and Scholkopf, 2003) uses a HD feature and to simplify the complexity of the model and a penalty added to an error function, the support vector regression can be transformed to a nonlinear model by use of a kernel.

3.7.2 PSO

This optimization technique is a simplistic model that copies social aspect of insects, certain fish species or birds e.g. sparrows, ants etc. The particles in the ensemble try to locate the best trajectory or paths of the best location of important resources for a colony. The particles investigate their environment while constantly releasing pheromones or biological markers when they locate resource to communicate between themselves and sharing information[15][50].

Position is a two dimensional space vector, x and y while the velocity will be V_x and V_y. Each agent in the group notes its initial position, distance plus velocity against the other agents: P_{best} and G_{best}. Consider fig 3.9, it shows the Cartesian coordinates as per equation (2.3) and equation (2.36), movement of the swarm elements within the Cartesian coordinate space is constrained with the following general simplistic rules.

(i) Solutions are constantly changing which are the positions and speed adjustment.

(ii) Consideration of the search space and all limitations given a certain search parameter or a number of all possible solutions.

(iii) Each member particle moves towards a global optimum solution at a certain rate.

(iv) All experiences both individual and group are recorded.

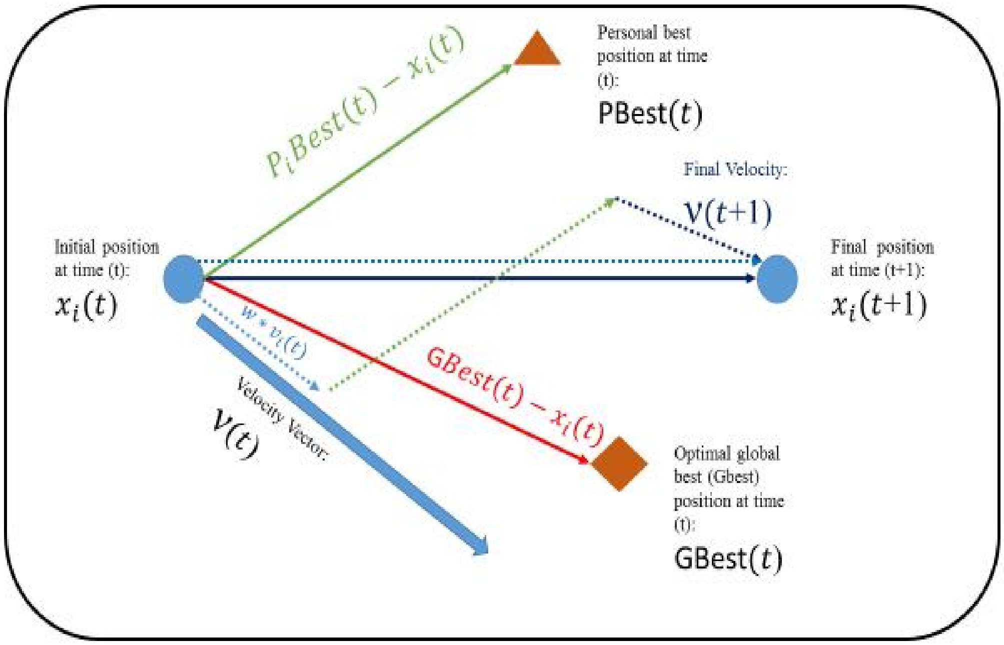

Figure 3.9: Cartesian Space for PSO agents

Many authors and texts are available, research on particle swarm optimization techniques have been done and variations to the canonical form, [51]. 3.7.2.1 PSO algorithm parameters

These are the variables that are considered in designing a PSO algorithm

A; the population of particles or agents

P_i ; Position of each agent say, a_i

F; objective function

v_i; Velocity of particle or agent, a_i

$V(a_i)$; neighborhoods of the agents, it's normally fixed.

$$x_t(i) = \text{old position} \tag{3.48}$$

After iteration $i + 1$, the new position is:

$$x_{t+1}(i) = x_t(i) + V_{t+1}(i) \tag{3.49}$$

The speed is updated similarly through the function;

$$V_{t+1}(i) = w * v_t(i) + C_1 * \text{rand}_1 * (p_{Best} - x_t(i)) + C_2 * \text{rand}_2 * (G_{Best} - x_t(i)) \tag{3.50}$$

C_1 and C_2 are the weighing coefficients

rand_1 and rand_2 are two random numbers between 0 and 1

w = diversification coefficient

$$\text{w\_damp\_new} = \overline{\text{w\_old}} - \left(\frac{\overline{\text{w\_old\_upper}} - \underline{\underline{\text{w\_old\_lower}}}}{\overline{\text{iter}}}\right) * \text{iter} \tag{3.51}$$

Where:

$\overline{\text{w}}\text{\_old\_upper} = 0.9$ and $\underline{\text{w\_old\_lower}} = 0.4$

$$C_1 + C_2 = 4 \tag{3.52}$$

3.8. PSO algorithm

PSO optimization algorithm; steps

1) Determine the initial conditions for each agent
2) Evaluate the searching points and parameters
3) Modify each parameter as per the new values

<u>PSO algorithm pseudo-code:</u>

1. Randomize the population.

$$x_i = (x_1, x_2, x_3 \dots \dots \dots \dots, \dots x_N)$$

$i = (1,2,3,4 \dots \dots \dots M)$ The iteration counter

M = swarm size or population size

N = number of parameters to be optimized

2. Evaluate every particle's position using the fitness function and minimize.
3. If fitness criterion is not met, update the counter by 1 , if met go to 4
4. Update the velocity according to equation 4.1

$$V_{t+1}(i) = w * v_t(i) + C_1 * rand_1 * (p_{Best} - x_t(i)) + C_2 * rand_2 * (G_{Best} - x_t(i)) \tag{4.1}$$

Where;

W= weight bias

Vt =velocity of the particle at time t.

Xt= position of the particle at time t.

C1,C2 = constriction factors 1 and 2.

Pbest = personal best position

Gbest = Group best position

5. Ensure the particles oscillates within the velocity (Vmax and Vmin) constraints according to equation 4.2

$$v_{max} \leq v_i \leq v_{min} \tag{4.2}$$

6. Update particle position according to equation 4.3

$$x_{t+1}(i) = x_t(i) + V_{t+1}(i) \tag{4.3}$$

Where Xt+1(i) = new position

Xt(i) = current position

Vt+1(i) = new velocity

7. Check the limits and evaluate.
8. Evaluate the fitness function and compare with the previous pbest. Logic decision, if the new value is better than the previous pbest, then set the pbest value equal to the new value and the pbest location equal to the

current location in the N dimensional search space, repeat for the gbest position.

9. Evaluate the stopping criteria has been met and update the iteration and repeat from step (5).

The process flow diagram is shown on fig 3.10

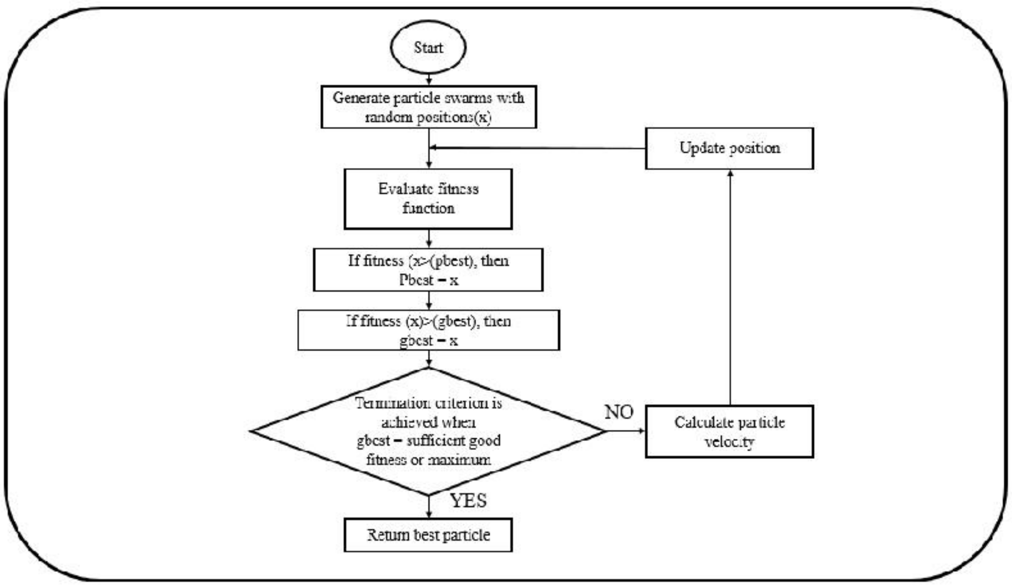

Figure 3.10: Particle swarm optimisation flow algorithm

3.9. Neural network (NN) pseudo code

1. Assign random weights to the elements in the network
2. Evaluate activation function of the hidden layers and the input elements in step 1.
3. Using the activation rate of step 2, determine the activation value of each output elements.

4. Determine the output nodes errors and recalibrate the network
5. Using error and weights of the output function, apply to the hidden layers and neuron nodes.
6. Recalibrate the network weights and repeat from 1.
7. Test for convergence and obtain the best solution.

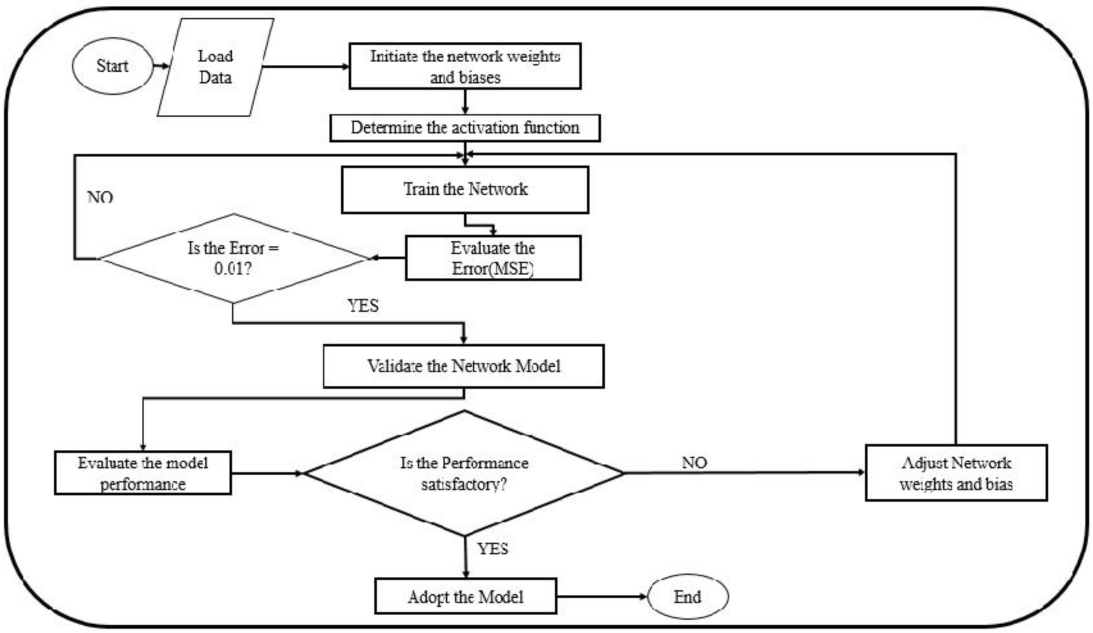

Figure 3.11: Backpropagation neural network algorithm flow chart

3.10. Predictive Model Design and the Hybrid PSO-NN Prediction Model

The implemented design is based on three stages neural network artificial intelligence model with optimized by a particle swarm algorithm, see figure 3.12

The first input stage is the data input stage where, data obtained from Ngong'II wind farm is processed and fed into the system. The first stage is the non-linear autoregressive neural network that has an aspect of the autoregressive integrated moving averages (ARIMA) [52].

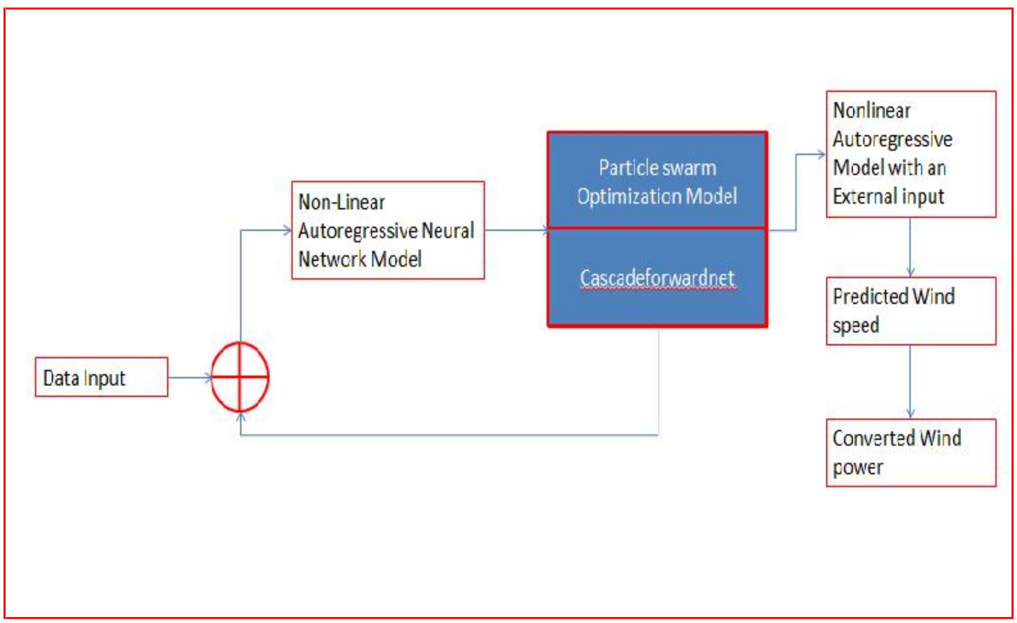

Figure 3.12: Three stage hybrid predictive models

The data is time series in nature, this data is classified into validation data and training data for the Narnet model. The model predicts a sequence of numbers which are passed to a feedforward network for input-output matching and weight adjustment and optimization using particle swarm optimization model and finally ,through a narxnet model for final forecasting.

For short term predictions, ANN algorithms are preferred since they have the ability to extract nonlinear relationships. It has many variants that can be adopted for specific functions.

Auto-regressive models are used since they are better at performing actual prediction as they take advantage of the auto-correlation and moving averages property. The hybridized cascadefeedforward net as depicted in stage two of the model is shown in figure 3.11, the design pseudo code is as shown ;

The feedforward network integrates the two autoregressive neural network.

1. Historical wind speed data, in this case, data collected from Ngong Hills wind power project, will be analyzed using statistical formulas.
2. Randomize the initial neurons to make up the initial PSO population
3. The historical data will be fed into the ANN network for processing
4. PSO will use data from step 2 to train the ANN network through weight and bias adjustment of the ANN network.
5. The MSE will be used to retrain the network for improved accuracy

6. The neurons will be rearranged to form new connections and a new network
7. PSO will be used to optimize the network for prediction accuracy

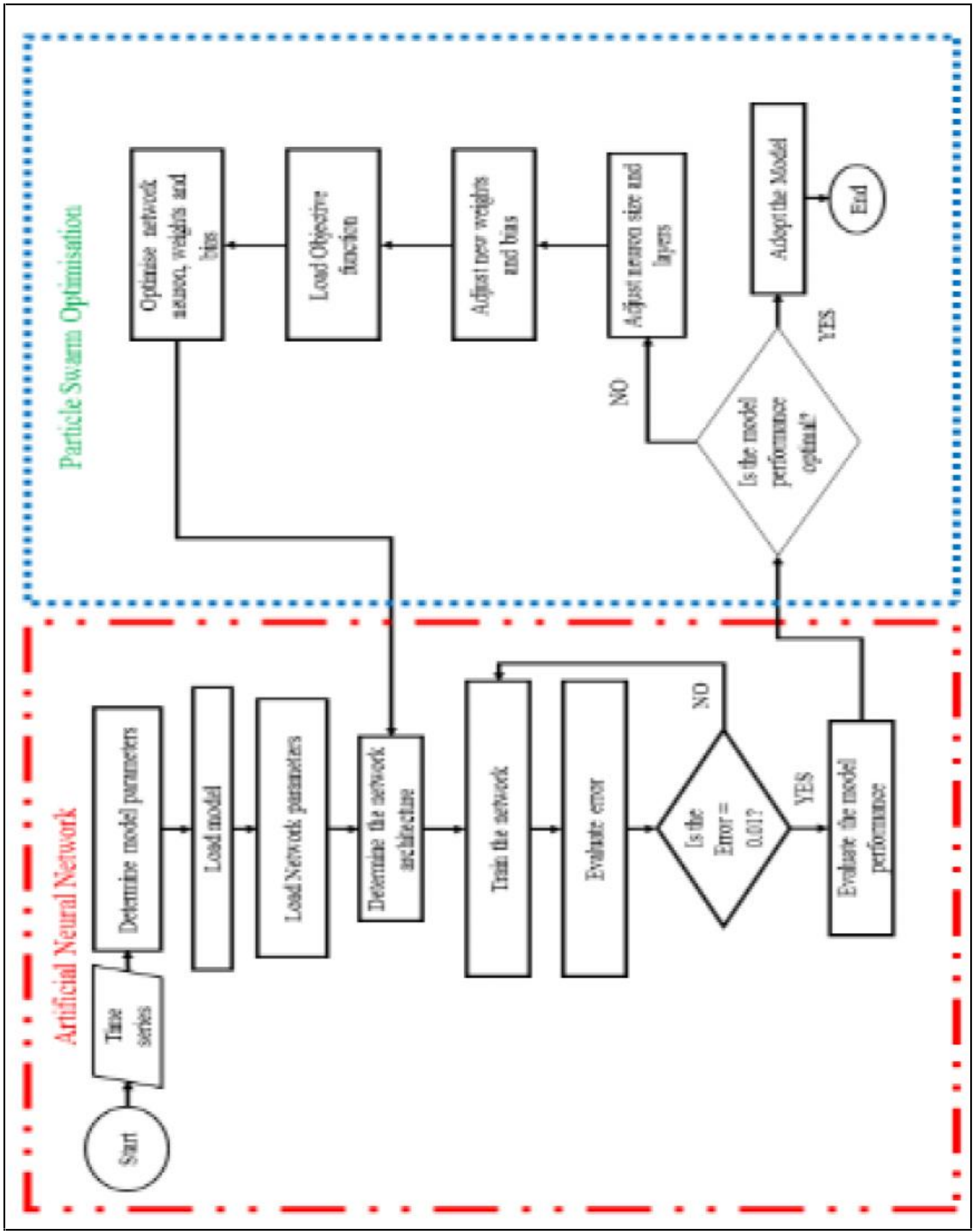

Figure 3.13: Combined Cascade Feedforward NN and PSO Process Flow diagram for Prediction Application

Conclusion;

Different measures of the wind speed predictions have been looked at, wind speed forecasting and turbines plus the betz model have been studied. More so, the statistical analysis and the two main intelligent models to be utilized in the design and implementation stage, chapter 4, have been introduced briefly here.

Optimization algorithms are inspired by nature, for instance, the movement in swarms of animals or insect have been studied for long and have been declared to have a distinct way under which they operate.

Ants have units of tasks and a hierarchy by which they handle matters and still have a form of hyper intelligence by which they respond to specific stimuli following a set of simplistic rules in that they exchange information depending on how members of the swarm judge the situation. For instance if they are searching for food and their home gets destroyed, they react somewhat immediately to solve the problem and rebuild the home or if they get attacked, they respond in the same way.

Brain neurons are also divided into tasks for instance; sensory, memory and muscular, an outlined in the structure of a biological neuron, the neuron has sections that help it carry out activities depending on the stimuli.

On a macro level, neurons and elements of a swarm can be thought of as similar in the way they operate, though a distinction will arise in the number of size of the unit under consideration. Artificial Neural Networks are good in finding solutions in a non-linear set of data which sets it apart from other algorithms and hence its application in prediction techniques.

The essence of forecasting is to allow a system to extrapolate a future value after feeding it some past data. From the literature review, probabilistic approach is most preferred as it allows the inclusion of uncertainties that are inherent with wind profile.

CHAPTER 4:

CASE STUDY; NGONG II WIND FARM AND DATA ANALYSIS

4.1. Introduction

This chapter introduces the Ngong' II wind farm .The wind farm under study is composed of 16 wind turbines Typical wind site parameters see table 1, the probability distribution curves, see figure 4.2 and the power from the turbines is shown in the figure 4.1.

Wind power plants and farms are capital projects and some initial investment scopes have to be established but the most important is the site suitability for the project. Table 1, summerises some of the parameters of the Ngong II wind farm. This chapter also discusses the model design and results achieved. The simulating environment is Matlab R2017a, the software was picked mostly because it is a detailed and well programmed simulation tool, it has several research modules that assist in leaning such as simulink

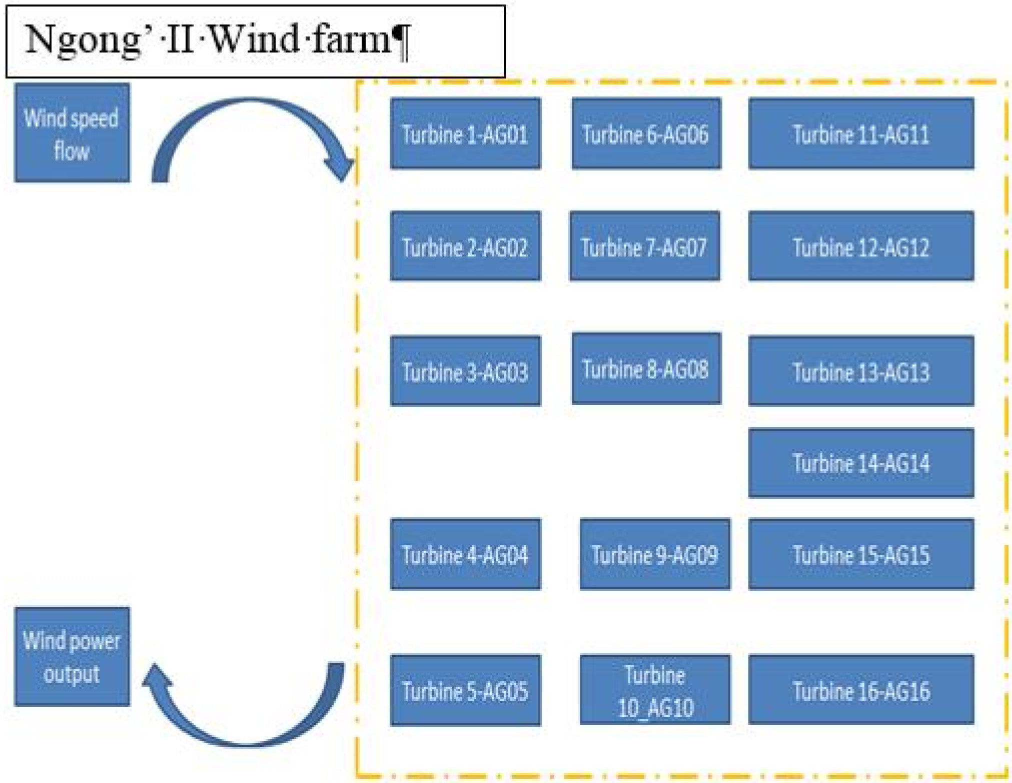

Figure 4.1: Ngong'II wind farm turbines

Table 4.1: Ngong II site summary

Site Summary	
Project site	Ngong Hills II
Power Installed (Watts)	13,600,000
Wind turbine used	Gamesa
Annual Production in kWh	3 kWh
Standard Deviation	3.5
Average Speed	9.4583 m/s
Coefficient k	2.9473
Coefficient c	10.6
Gamma(1 + (1/k))	0.892295
Alpha value	0.39054
Average speed at 40m	3.896273
Average speed at 60m	4.324533
Number of turbines	16
Capacity Factor	(approximated)25%

4.2. Plots and Charts Analysis

Figure 4.2, show the normal distribution of wind speeds at the Ngong' Hills using the data from wind turbine AG01 as a sample data reference.

Wind power has various charts and profiles defined to portray different information as regards the wind farm power plant capacity and wind turbine characteristics.

Between the distribution functions, wind profiles and the generated profiles ,the normal graph shows, figure 4.2 that the wind distribution or the Ngong'-II site is symmetrical about the mean i.e. the flow of high speeds over low speeds is balanced though there is a slight shift leaning to the left. From the site summary table1, average wind speed is 9.46 which translate to a power output of about 450kW of power.

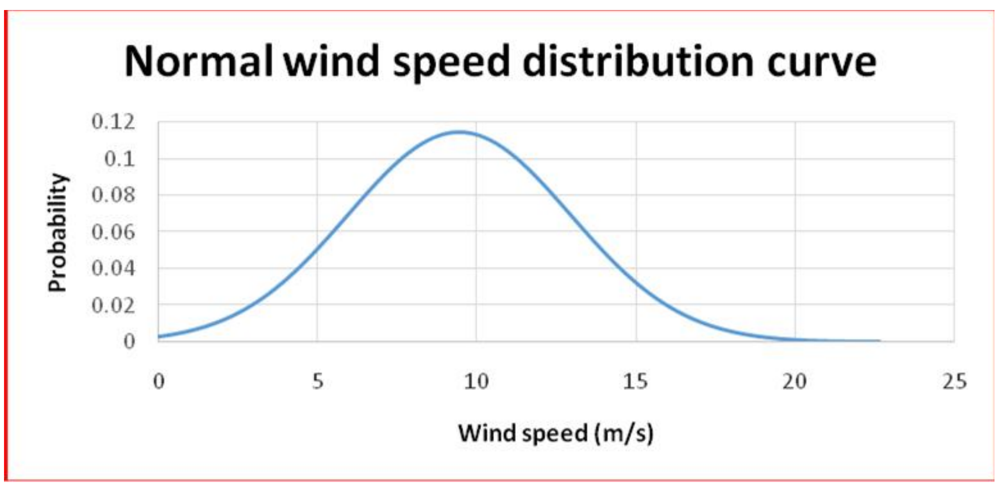

Figure 4.2: Normal distribution curve for wind speed[53]

Similarly, the combined cumulative and histogram displays the same analysis as the normal curve, see figure 4.3, the plot gives the gamesa as illustrated in [83, fig.4 and fig.5] These curves give an indication of the kind of turbine that can be effectively used to harvest power at this site.

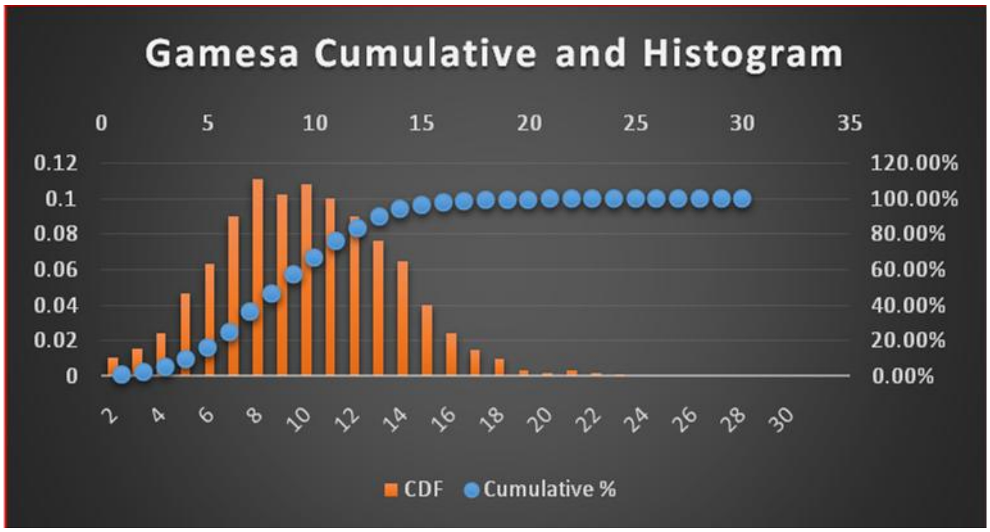

Figure 4.3: power curve verses wind speed distribution

The commercially available wind power curve data for gamesa-G52 power curve, see figure 4.4, below, from the plot we can see that the cutting speed is 4m/s, which us the minimum velocity required for power generation, next is the cutout speed fixed at 25 m/s at this velocity, more wind flow, makes the mechanical and electrical protection systems activate to protect the turbine form damage by stalling. The normal allowable operating points/ speeds are within the following speeds of 13 m/s to 24 m/s.

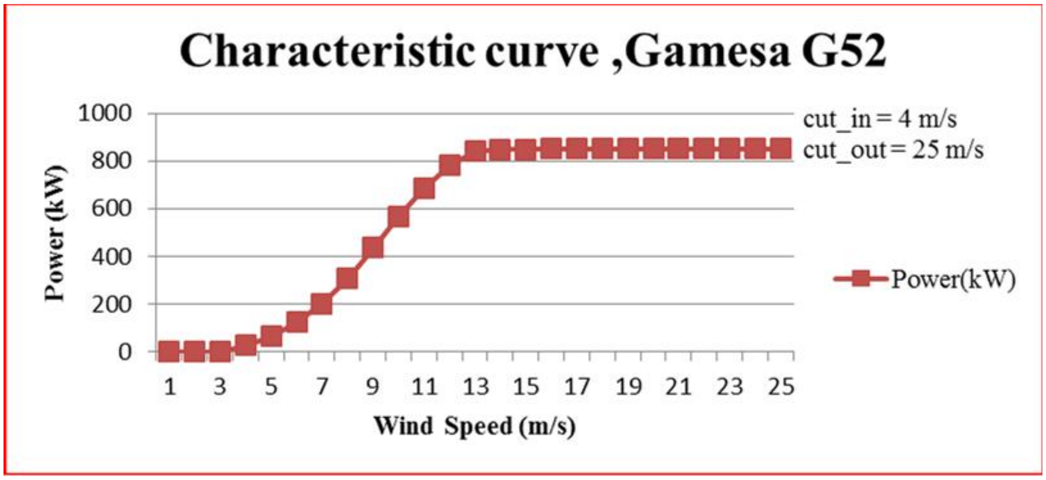

Figure 4.4: Gamesa G52 power curve

The column graph, figure 4.5, shows the monthly contribution per turbine for the whole year, the month of June indicates the lowest month approximately 1% in over production for the site while March is the highest month as the power produced was the largest, approximately 20%.

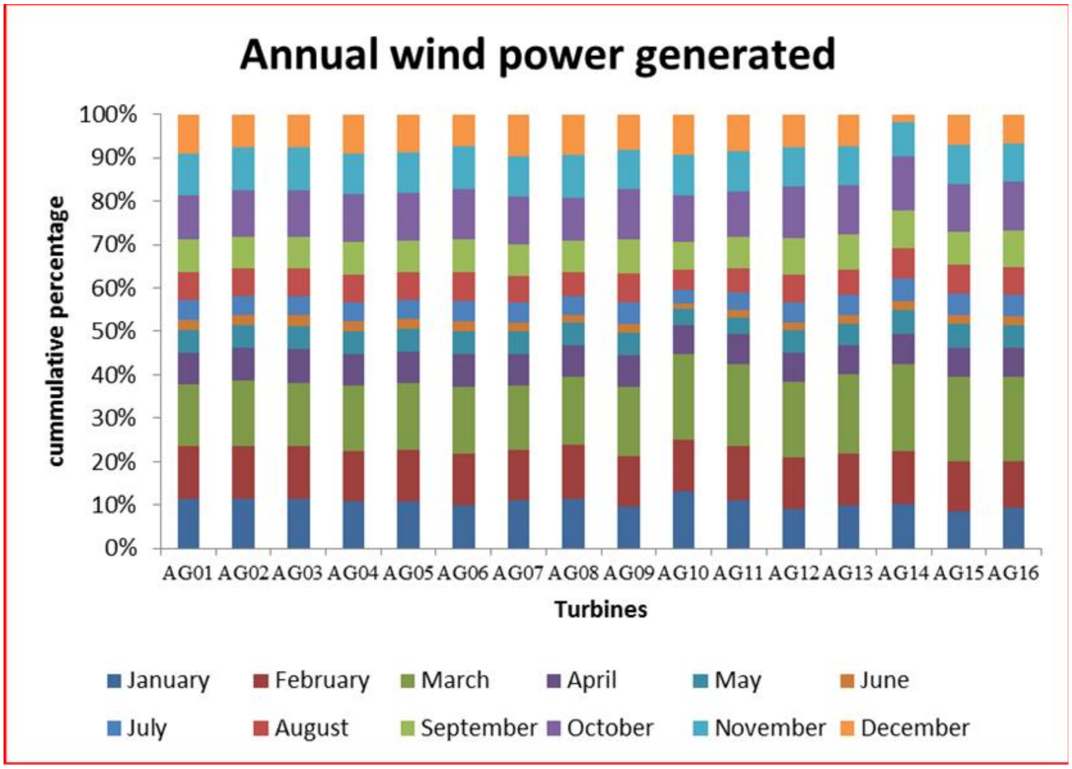

Figure 4.5: cumulated wind power contribution

The wind turbines at Ngong II site experiences mean monthly wind speed with the corresponding wind power generated at the site as shown by figure 4.6 and figure 4.7. the wind speeds varies for different months and the corresponding graphs are given in the appendix section.

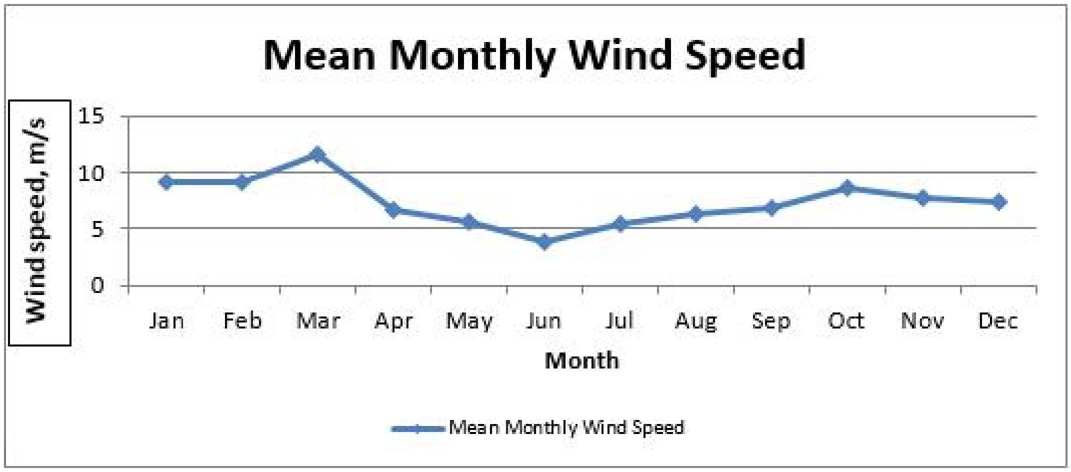

Figure 4.6: Mean Monthly wind speed

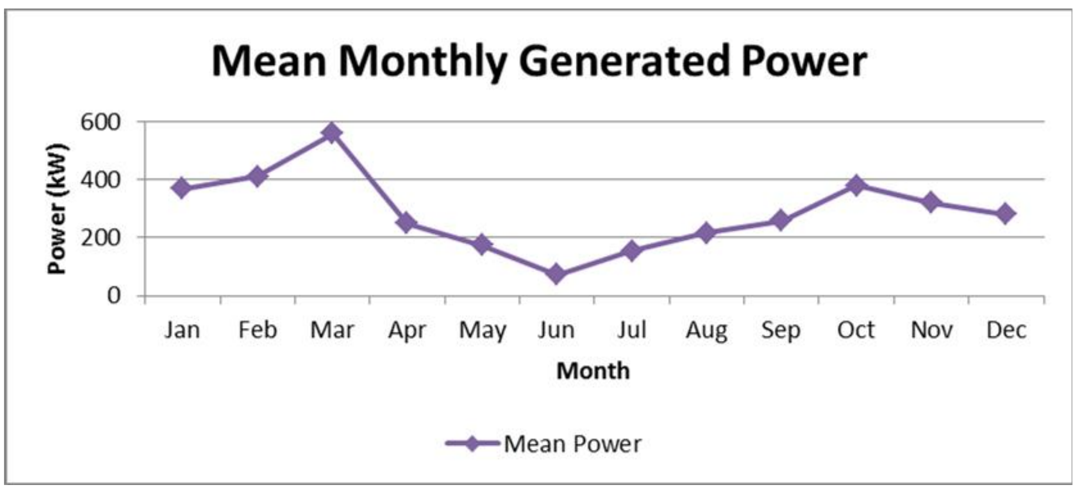

Figure 4.7: Mean monthly generated power

The mean speed chart and the mean monthly generated power show a similar trend since, the power generated is depended on the cube power of the measured prevailing speed across the site. Similarly, the performance of the individual 16 turbines show a similar profile as shown in the following figures 4.8 and 4.9, see appendix A.

It is important to focus on the two months for analysis purposes, hence the following two graphs for the two months, figure 4.8 and figure 4.9.

More so, it is of interest to note the variations in the daily power measurements for March and June. As opposed to an aggregated mean values used to plot charts for a bigger time scales see figure 4.8 and figure 4.9, note the difference in data point for March and June which can be attributed to the calendar days between the two months and most importantly, the resolution of the data recording devices.

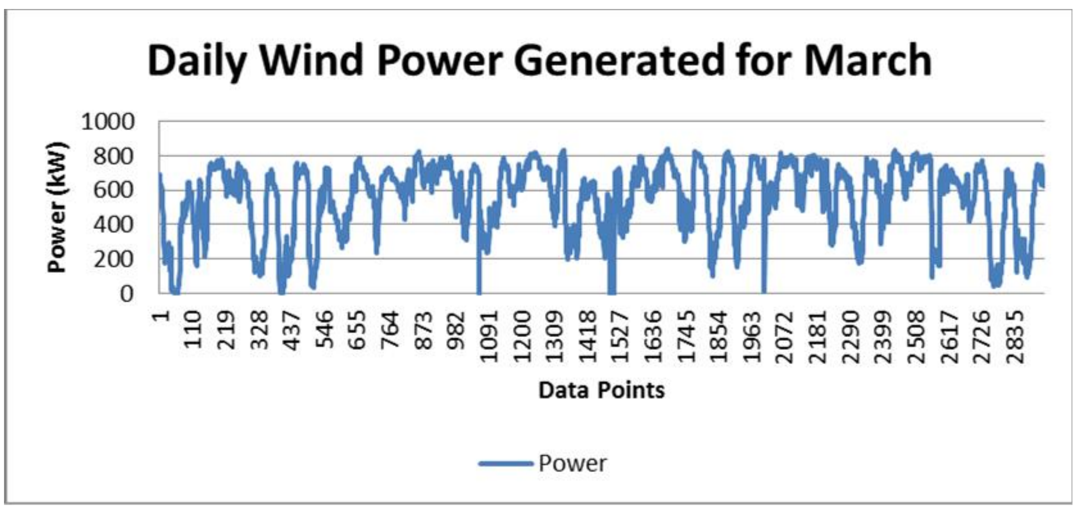

Figure 4.8: Daily wind generated for March

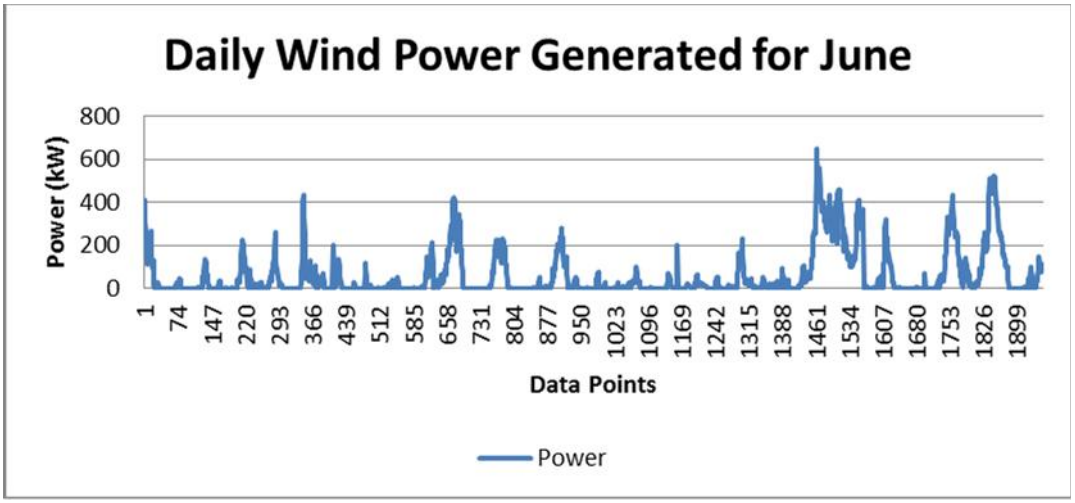

Figure 4.9: Wind power generated for june

4.3 Narnet Model

This narnet[54] model is used for data preparation and validation into testing and training as as shown in figure 4.10, the model is composed of 3 hidden layers and one output layer of 5-10-5-1 structure . The output from the model is a predicted set of data that is passed to the cascade feedforward network.

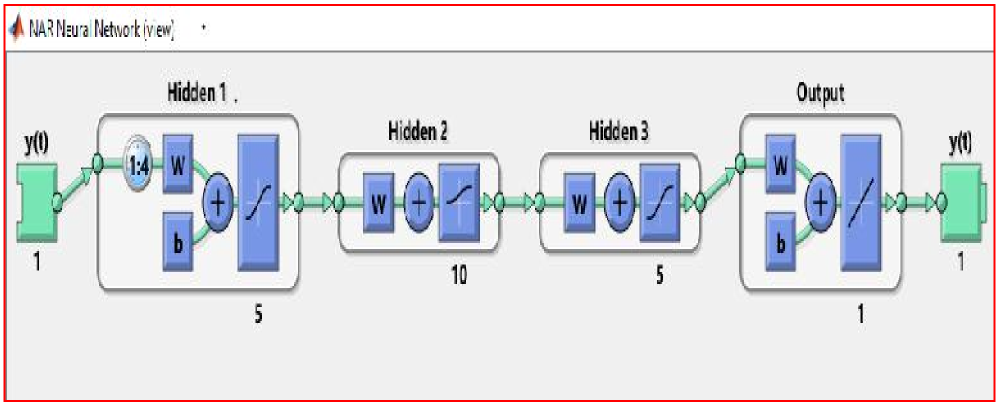

Figure 4.10 : Narnet Architecture

The model output is represented as a sequence of delayed data and the general equation is given below; see [3, equation (1)], where the predictive equation is a time delay as illustrated in equation (4.1)

$$y_t = f\big(y(t-1), \ldots, y(t-d)\big) \qquad (4.1)$$

The network performance charts are displayed below. They are the Best Validation performance, which gives the mean square error performance at 0.30287. The error histogram of 20 bins shows the data split into testing, validation and training. The regression chart displays the data adequacy for neural network training to the best fit line, the dotted line shows perfect fit between the output and the target while the solid line shows the approximation of the model to the best fit line. The data points indicates that majority of the data points are a good fit. The best performance occurred at iteration 32 as shown in figure 4.11. at this point, the mean square error is at its minimum point of 0.30287. Furthermore, the predictive model performance is further evaluated in figures 4.12, 4.13 and 4.14. Figure 4.12

is the error histogram of 20 bins and indicates that the 6000 samples lie within the 0.1523 error.

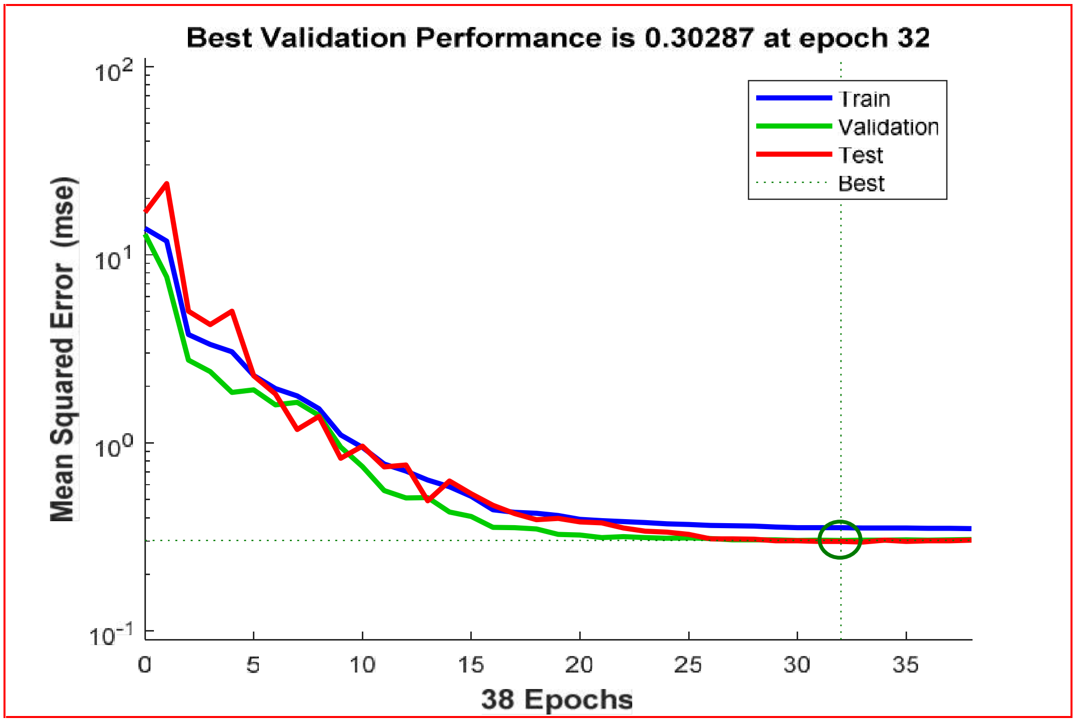

Figure 4.11: Narnet network performance

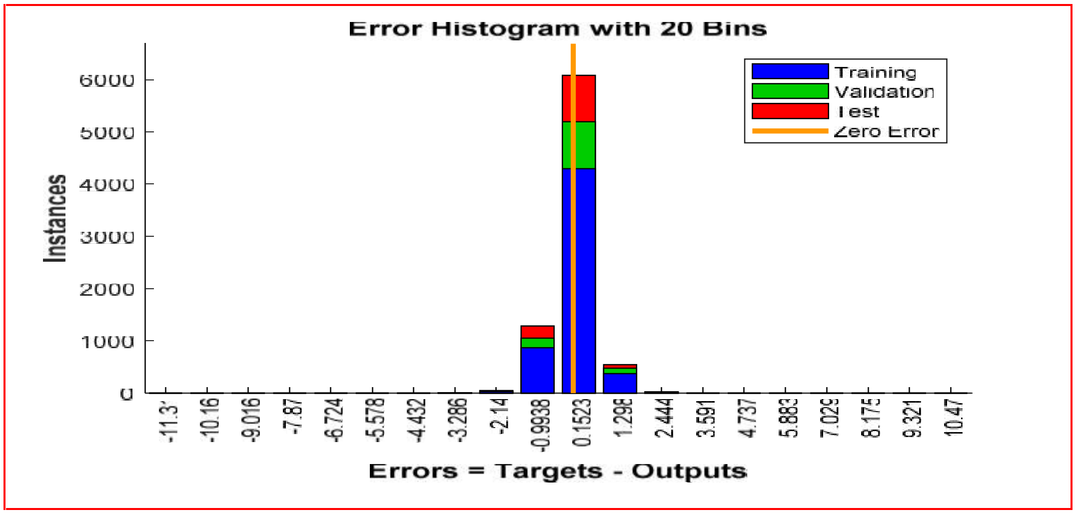

Figure 4.12: Network error histogram

Figure 4.13 gives the autocorrelation error parameter of the model performance at lag 0 with a 95% confidence level, though it also shows the model could be retrained to achieve better prediction abilities and improve the network performance. Figure 4.14 is the regression plots for the narnet model and it indicates that the model outputs are close to one (R-squared values) , therefore, the narnet model was trained

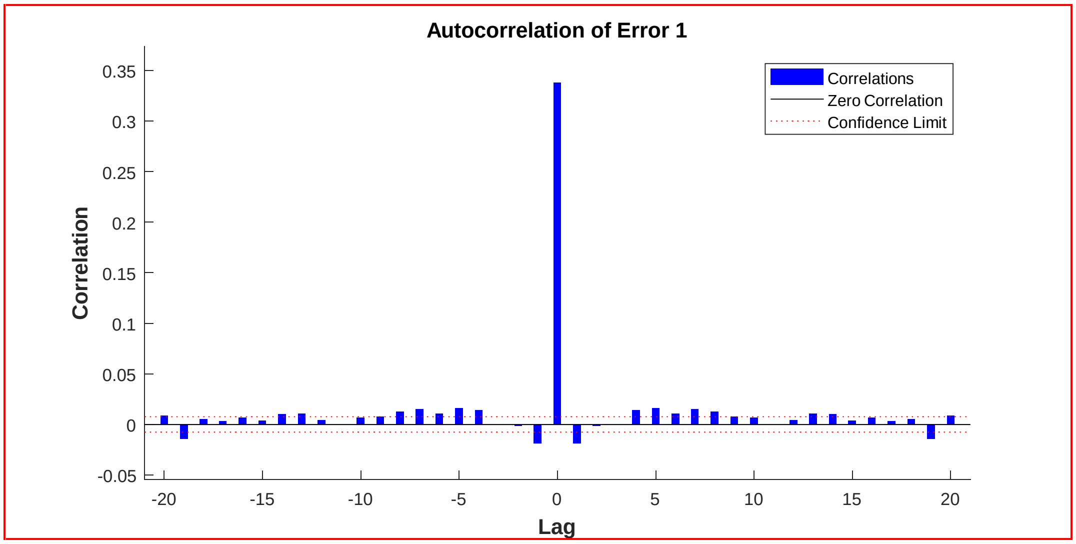

Figure 4.13: Network error 1 autocorrelation

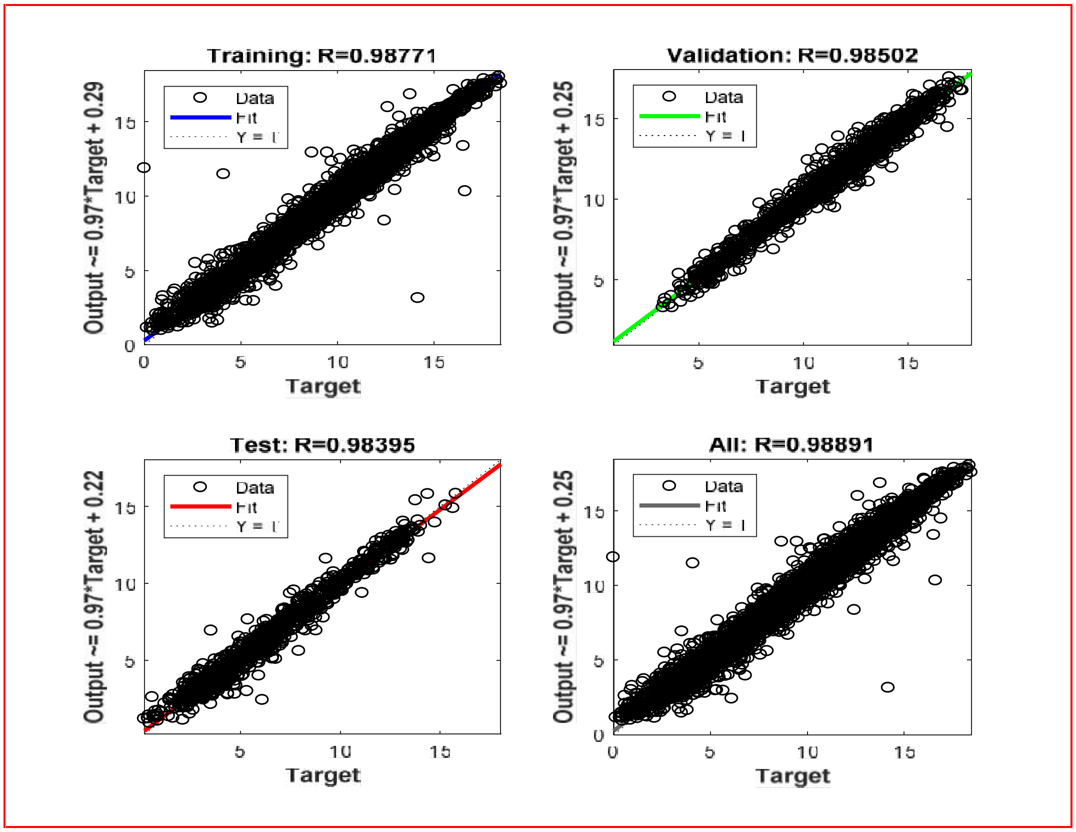

Figure 4.14: Network regressions

4.4 Cascade_feed_forward_net

The cascadefeedforward neural net is a fitting network and it maps the input-output data from stage 1(narnet model- figure 4.10), see figure 4.15 with one(1) hidden layer consisting of 5-neurons and 1-output layer (5-1 structure).

At this stage, the weights from the model are then continuously adjusted particle swarm optimization in every iteration using a mean square error (MSE)[2] cost function while the swarm is trained using the Levenberg- Marquardt algorithm.

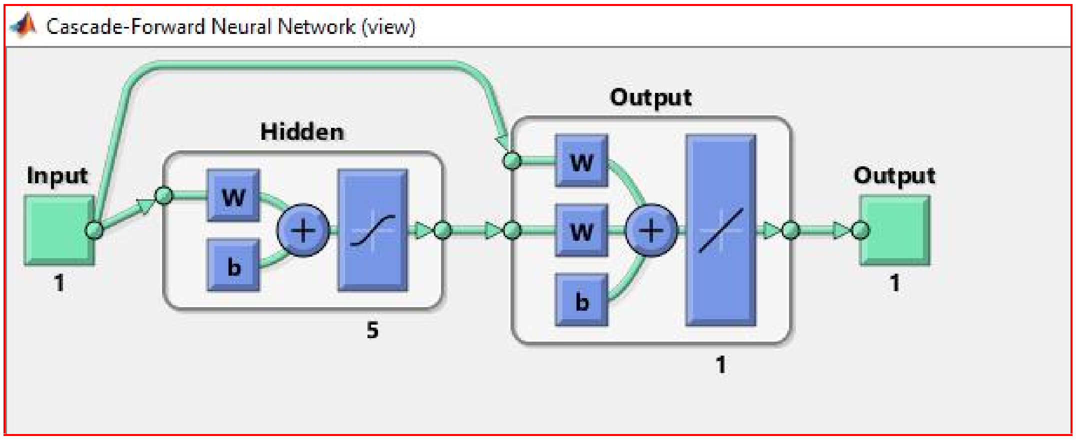

Figure 4.15: cascadefeedforward network architecture

The figure 4.16 is the PSO minimization curve, best performance occurs after the 60th iteration to obtain the best possible weights for the cascadefeedforward neural net.

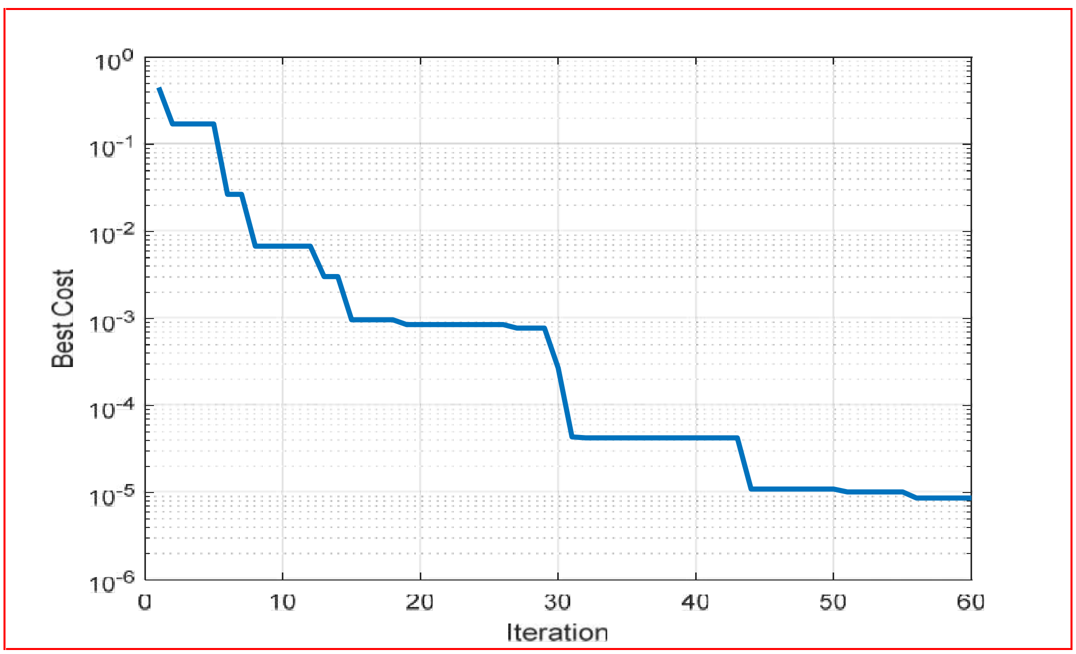

Figure 4.16: PSO Iteration graph

Figure 4.17 shows that the network reached a minimum at iteration 2 but reached the best performance at 18 and stopped as its best validation point of 0.27588 MSE Figures 4.18 and figure 4.19 are the regression errors and the error histograms. These plots indicates that the predictive errors have been minimised as shown by the performance plots.

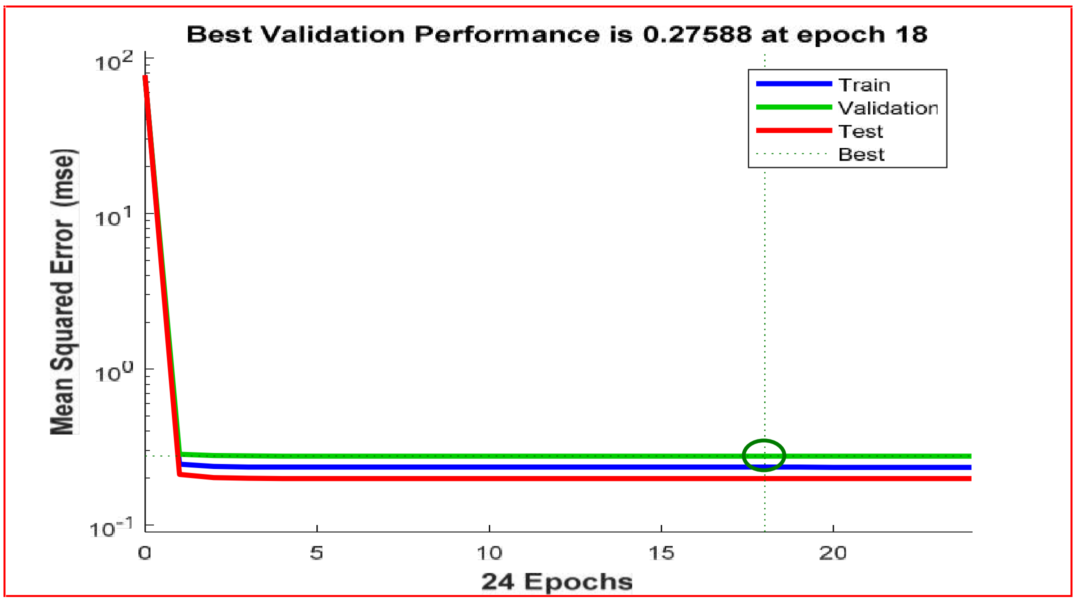

Figure 4.17: Cascadefeedforward network performance

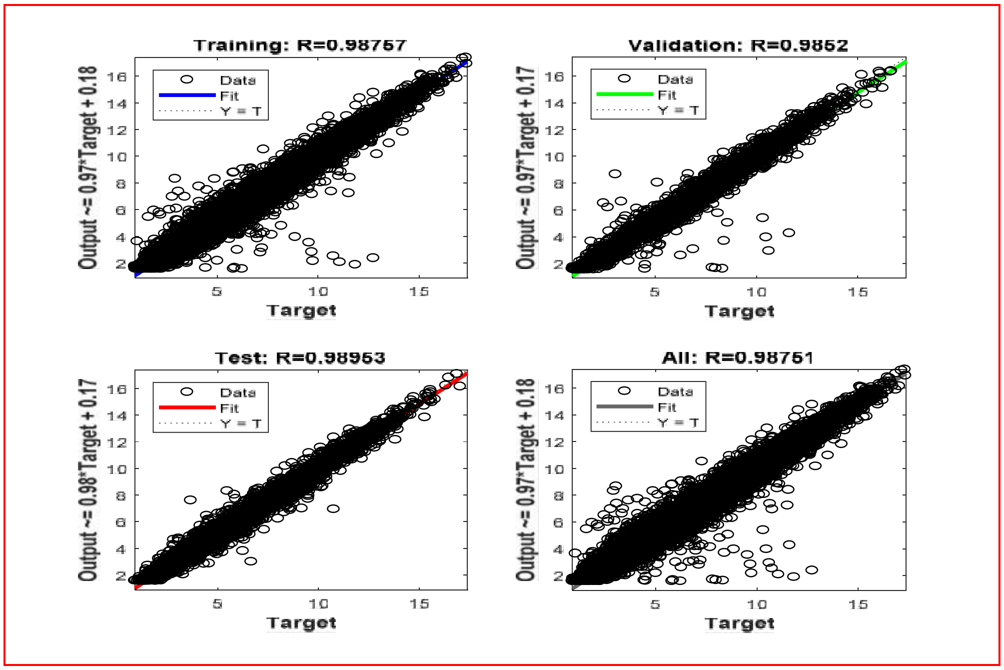

Figure4.18: Cascadefeedforward network regression

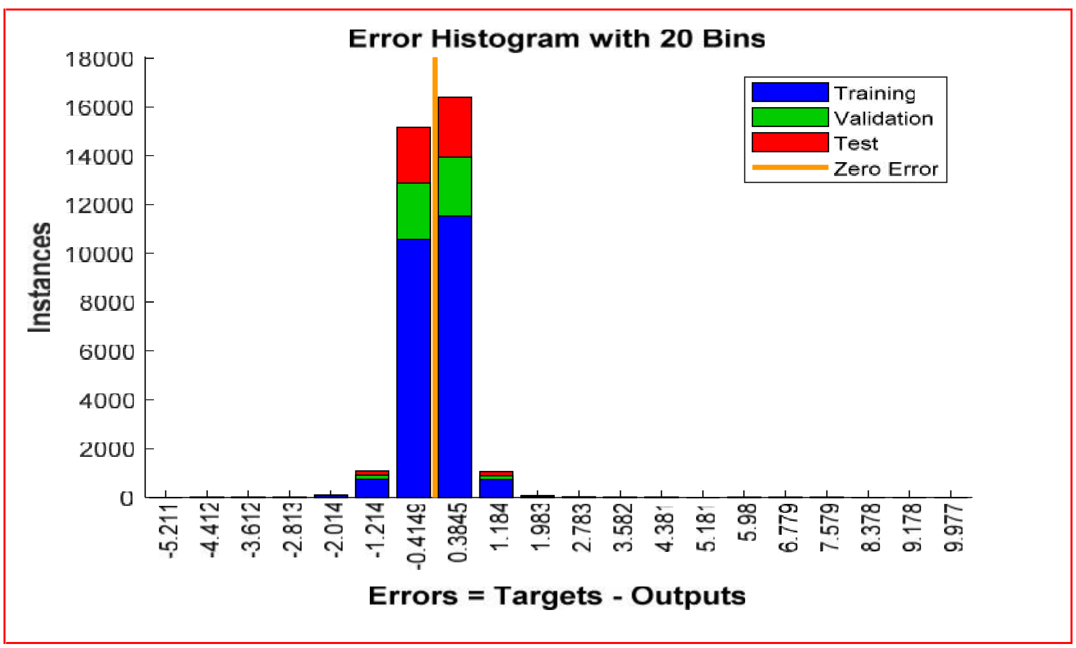

Figure 4.19: Cascadefeedforward network error histogram

4.5 Narxnet Model

This is the final stage of the forecasting engine. It has the network architecture as shown below, both the open loop and closed loop architecture. This model is the third stage in the predictive architecture, narxnet model with a 10-5-1 structure, figure 4.20 and 4.21.

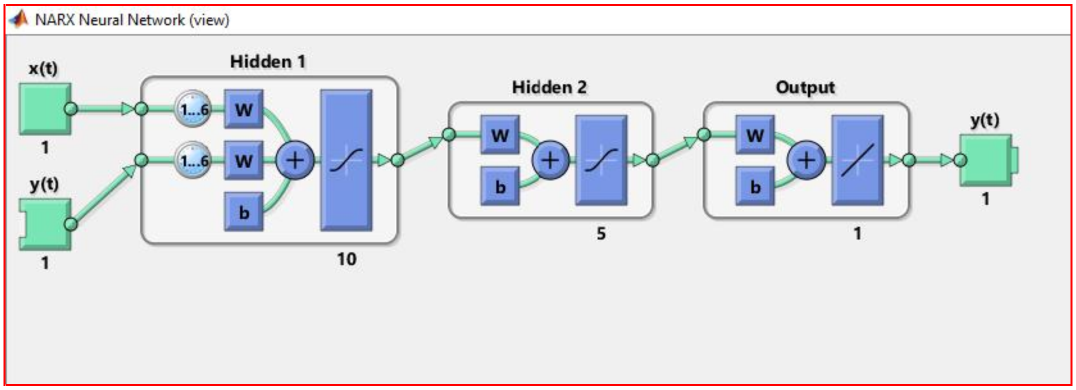

Figure 4.20: Narxnet open loop network architecture

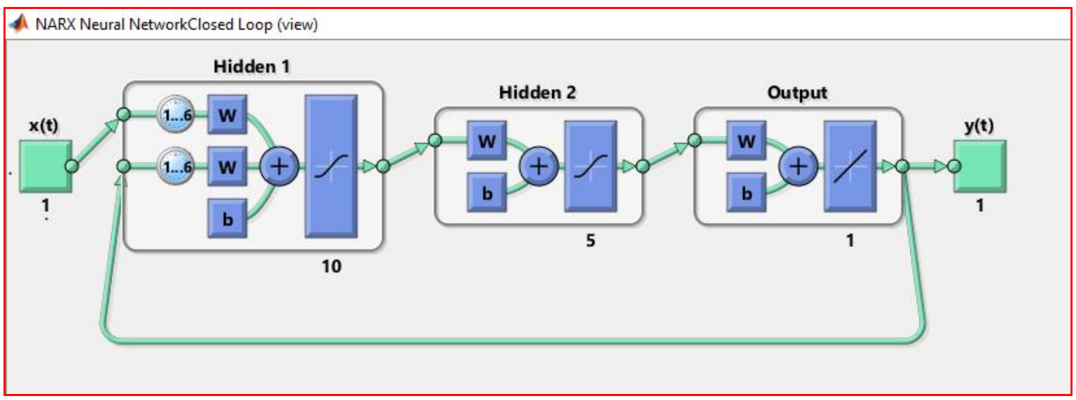

Figure 4.21: Narxnet closed loop network architecture

The performance mean square error is reduced to 0.21335, see figure 4.22, from the input stage which was at 0.30827. The nonlinear neural network with an external input has an improved performance since it reached its best iteration after 13 iteration.

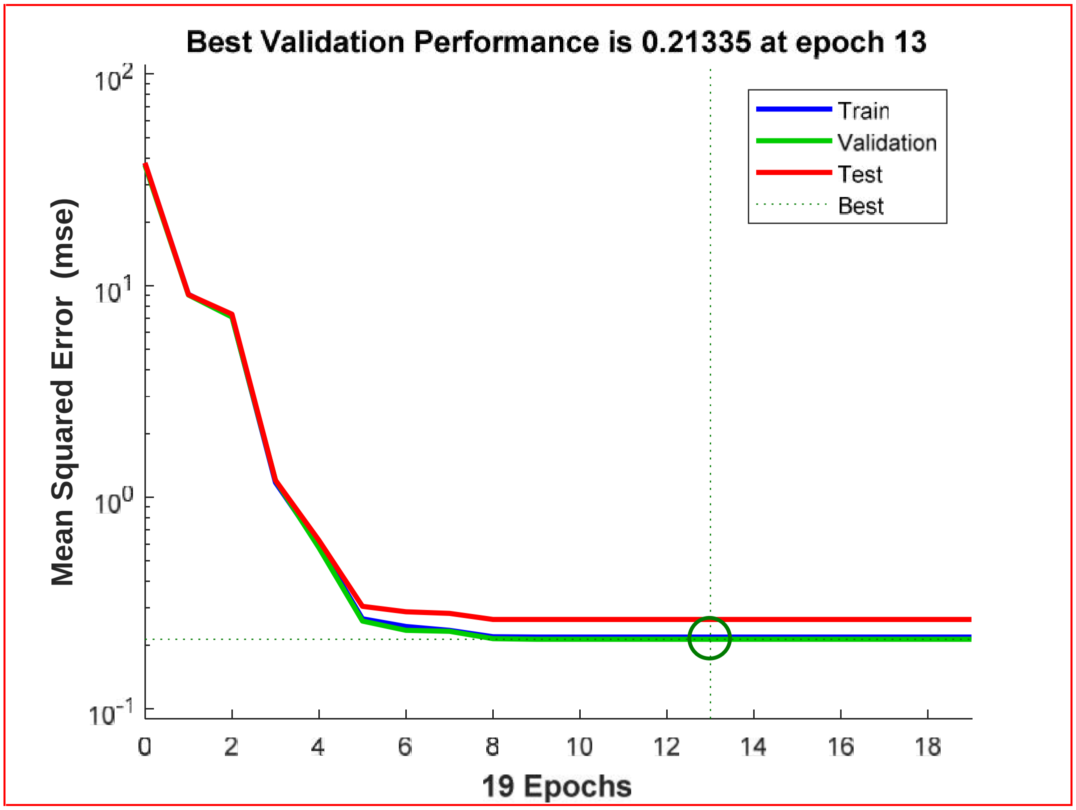

Figure 4.22: Narxnet network performance

Figure 4.23, 4.24 and 4.25 are the error histogram, regression plots and autocorrelation error plots respectively. See table 2 for the performance comparison and improvement of the predictive model from the first stage to the third stage.

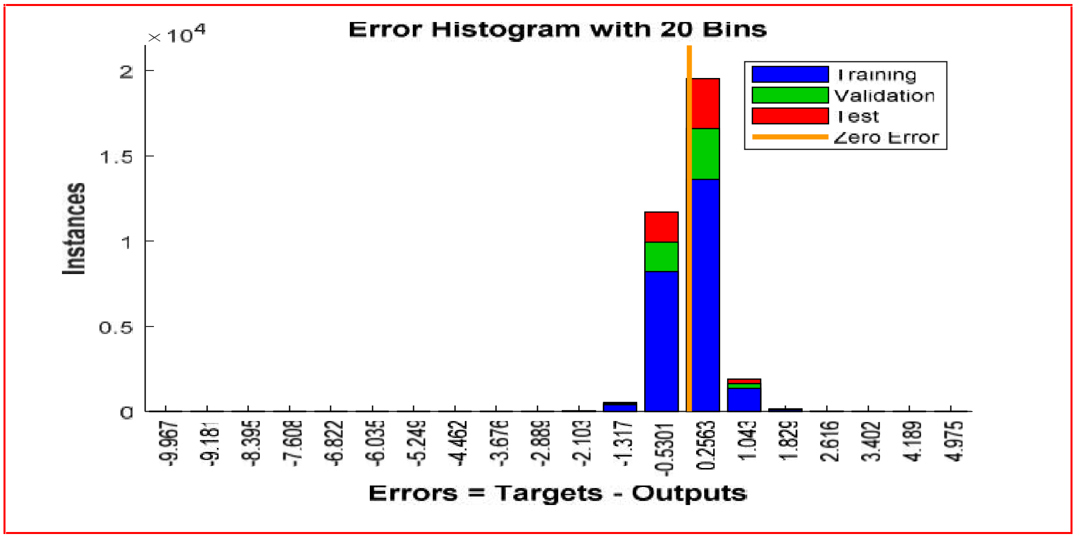

Figure 4.23: Narxnet error histogram

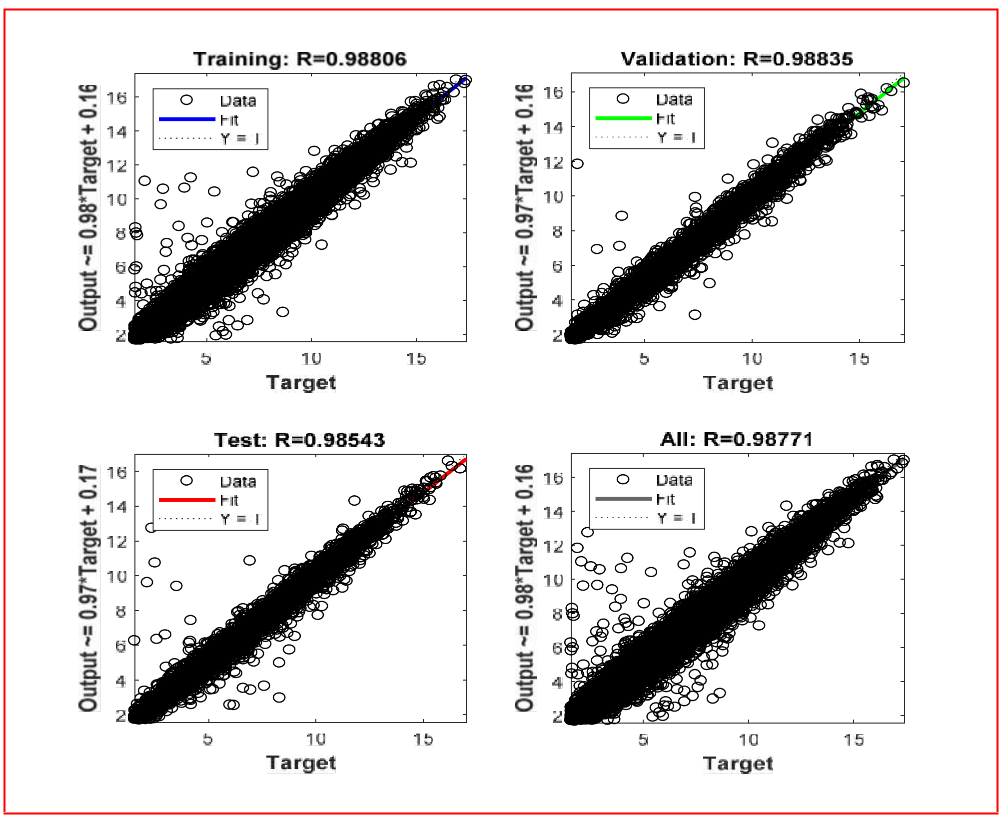

Figure 4.24: Narxnet network regression

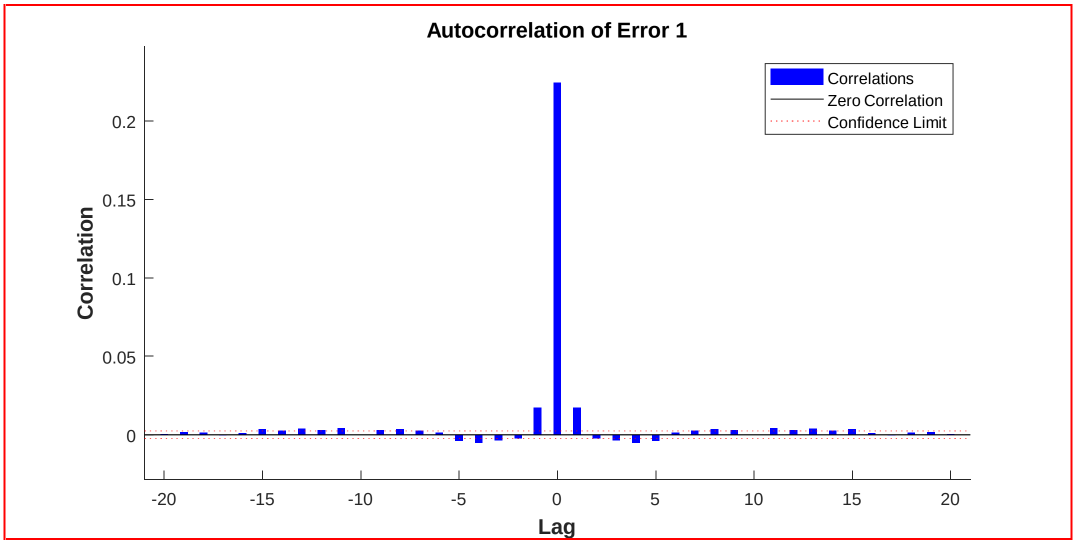

Figure 4.25: Narxnet network autocorrelation error

Table 4.2: Performance summary

Forecasting Engine Performance Summary			
Performance Parameter	**Narnet**	**cascadeforwardnet**	**Narxnet**
Performance	**0.3381**		**0.2247**
Regression Training	**0.98771**	**0.98757**	**0.98806**
Regression validation	**0.98502**	**0.9852**	**0.98835**
Regression Test	**0.98395**	**0.98751**	**0.98771**
Mean Square Error	**0.30287 at epoch 32**	**0.27588 at epoch 18**	**0.21335 at epoch 13**

Finally, the Narxnet model, as the third stage of the predicting model is used to predict wind speed for short term horizon of 2 hours, this is the aggregated mean speed output from the network the wind speed is then converted to wind power for the wind farm, see figures 4.26 and 4.27 for the graphed output values.

Table 3 gives the output performance of the 3 stage prediction engine as designed, the power is converted from wind speed values using weibull and Rayleigh probability density functions, see equation 6.2 and 6.3 [55].

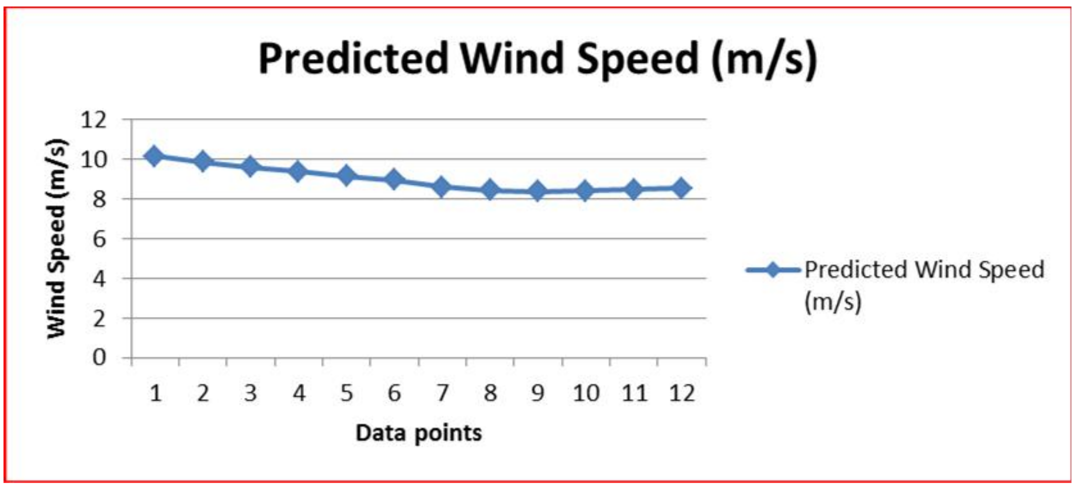

Figure 4.26: Closed loop narxnet predicted wind speeds

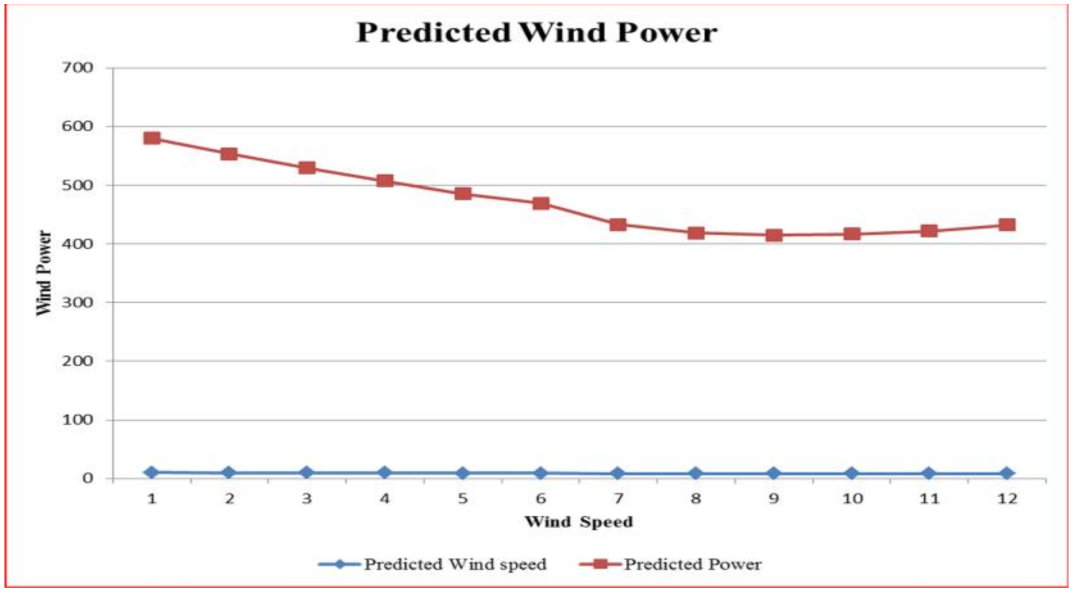

Figure 4.27: Narxnet closed loop predicted wind power

4.6 Weibull and Rayleigh distribution functions for Ngong II wind farm[55]

$$f(v_u) = \frac{2.95}{10.6} * \left(\frac{v_u}{10.6}\right)^{1.95} * exp\left\{-\left(\frac{v_u}{10.6}\right)^{2.95}\right\} \tag{6.2}$$

$$f(V) = \frac{\pi V}{2*9.46^2} \exp -\left(\frac{\pi}{4} * \left(\frac{V}{9.46}\right)^2\right) \tag{6.3}$$

Table 4.3: Predicted speed probability distribution

Predicted Wind speed	**Weibull Dist.**	**Rayleigh Dist.**	**Predicted Power**
10.14	0.0161	0.683	579.80
9.9	0.0165	0.698	553.37
9.6	0.0168	0.709	529.29
9.4	0.0171	0.720	507.01
9.1	0.0173	0.729	485.20
9.0	0.0175	0.735	468.97
8.6	0.0179	0.746	433.05
8.4	0.0180	0.750	418.22
8.4	0.0180	0.750	414.38
8.4	0.0180	0.750	416.56
8.5	0.0181	0.749	421.87
8.6	0.0179	0.746	432.36

4.7 Evaluation

Different authors use different metrics to evaluate the performance of their forecasting engines. Some of the statistical metrics used are MAE, MAPE,NMAE, RMSE, MSE, SDE and SSE, the mathematical fomula for the metrics are illustrated in the appendix (I) section of this thesis.

Specific forecasting models are constrained to specific geographical sites and as such it is never a guarantee that a model will perform well in another site given the geographcal dependency[56], classified accuracy of the forecasting models depending on the forecasting horizon as follows, short term prediction evaluated as the Mean Absolute Error lies in he range of 5% to 15 %, while for longer days, the performance deteriorates to 13% to 21% for prediction of between 1 and 2 days, if we increase the forecasting horizon to more than 3 days, the accuracy shifts to 20% to 25%.

The MHNN and EPSO [57] has an average MAE of 2.21.A predictive Deep Boltzmann Machine was introduced in [58] intelligent hybrid wind power forecasting engine composed of wavelets, ANFIS, support vectors and Grid Search algorithms, the forecasting is done per season i.e. winter, summer, spring and fall.

The performance of his model is shown in table 4 and compared to our forecasting model.

Our hybrid model is composed of three neural network architecture optimized by particle swarm, the performance compared to other models is as follows;

J. P. S. Catalao, H. M. I. Pousinho, and V. M. F. Mendes through their work in intelligent hybrid short term forecasting in Portugal obtained average MAPE of 5.99%[21].

Particle swarm based optimization of neural networks shows better improvements in the overall prediction accuracy than neural networks alone[59].

H. Shaker, D. Wood, and T. N. Alberta employed wavelet neural networks for net demand forecasting using direct and indirect methods [60].

Table 4.4 Performance comparison

Performance Comparison				
Metric / Model	**Narnet+CFF+ PSO+Narxnet**	**MHNN+ EPSO [91]**	**WT+ANFIS +SVM+GS [93]**	**WNN [95]**
Average MAE	**0.62**	**2.21**	**4.02**	**2.732**
Average MSE	**0.26**	**4.60**	**5.93**	**3.7995**
MAPE	**18.20**		**13.02**	

Several other models were analysed and a similar comparison made, we can note that the average MAE at 0.6174, the hybrid model developed shows a significant reduction in the prediction error as well as the average model mean square error at 0.264033. though the MAPE is quite high, this could be attributed to the huge aggregated data points used in the analysis.

4.8 Conclusion

The model was designed in this chaper, the three stage model – Narnet, cascade feedforward and the Narxnet is highlighted and the performance chartes for each submitted.

The cascade feedforward net was optimised using particle swarm algorith, the weights of the network were randomly initialised before feeding into the PSO algorithm, in this case, the whole ensemble, i.e the conection of neuranos and the layers was forming the swam of the PSO, and performance improved by weight adjustment as the particles.

The narnet and narxnet stages are designed after the autoregressive models and introduces the concept of ARIMA which after passing the data, predictive values are generated a the model is simulated.

Data was collected from ngong' II wind power plant operated by Kengen power company. See figures 4.6 and 4.7, these figures shows the mean-monthly wind speed/velocity and wind power generated for a period of 12 months on the site aggregated. The numbers of turbines considered is 16 , see figure 4.1 and the wind site summary for ngong' II, in table 1.

Matlab R2017a is used for model creation and simulation of the network. Matlab R2017a was chosen for being the most versatile modelling environment and has many features that were utilised the results from the model are analyzed in this section.

CHAPTER 5:

CONCLUSION AND RECOMMENDATION

5.1 Conclusion:

From the beginning, we set out to accomplish the following three objectives;

(i) To formulate a wind energy prediction technique based on Artificial Intelligence and statistical hybrid models.

(ii) To develop a forecasting engine based on the formulated prediction technique and cost function.

(iii) To evaluate the forecasting technique in comparison with other methods.

Objective (i) and (ii): The three stage predictive model was developed, see page 60, *it gives the architecture of the predictive model*. The internal system model has been elaborated in Chapter 4 as the neural networks i.e. nonlinear autoregressive neural networks and a cascade feedforward network whose, neural weights are adjusted and optimized using particle swarm algorithm has been developed.

The model has shown tremendous improvement in the general performance of the forecasting engine. We have demonstrated through, see page 86 for the performance summary of the model, modelling and simulation cascade of neural networks reduces the generalities associated with a single model, either Narnet or the Narxnet or the feedforward network. We, therefore, conclude that Autoregressive hybrid forecasting engine offers an improvement in the general performance and are designed to work on machines with limited computing abilities available for system planner as it is important to know how much power will be availed in a few hours' time or on spot, though special emphasis is laid to improve the prediction accuracy neural networks are basically intelligent.

Objective (iii): The model is evaluated and compared to other forecasting models available and, as per the evaluated performance, it has shown some improvement in the predictive and reduction in forecasting errors are small and minimized for such a simple model. We can attribute this to the automatic relationship between the combined nonlinear-autoregressive-neural-network models and particle swarm.

Time series prediction data used is a single input value to the network, and these leaves out several other parameters that can aid in improving the accuracy further, but we should know that with more inputs to be added, the more complex the model will.

In the design phase, the designer has to penalize and compare between model complexity and accuracy given that design time is always limited. For wind forecasting, several parameters have been omitted such as, temperature, humidity, wind direction etc.

5.2 Recommendation:

1. Increasing more parameters while still maintaining a similar goal of model simplicity as well using other neural network architectures and optimization algorithms such as genetic algorithms , cuckoo search to improve neural networks performance.

2. The benefits of researching on parameter estimation areas of forecasting functions and models, still wind power forecasting is very site-dependent and research can be done to develop systems that reduce the dependency in the case of regional forecasts and one model can be used across sites. But with simple modifications, a forecasting model can be utilized in different regions

3. Research on NWPs, taking into account local phenomena as well as extreme events other than what is normally the weather trend of a particular site, and also protect the power system, therefore, this kind of research is valuable in getting to understand the dynamics of a grid-tied renewable energy power system.

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APPENDICES

APPENDIX A: TURBINE POWER GENERATION PLOTS;

The plots were plotted using wind speed and wind power data obtained from Kengen wind power plant and site from Ngong Hills.

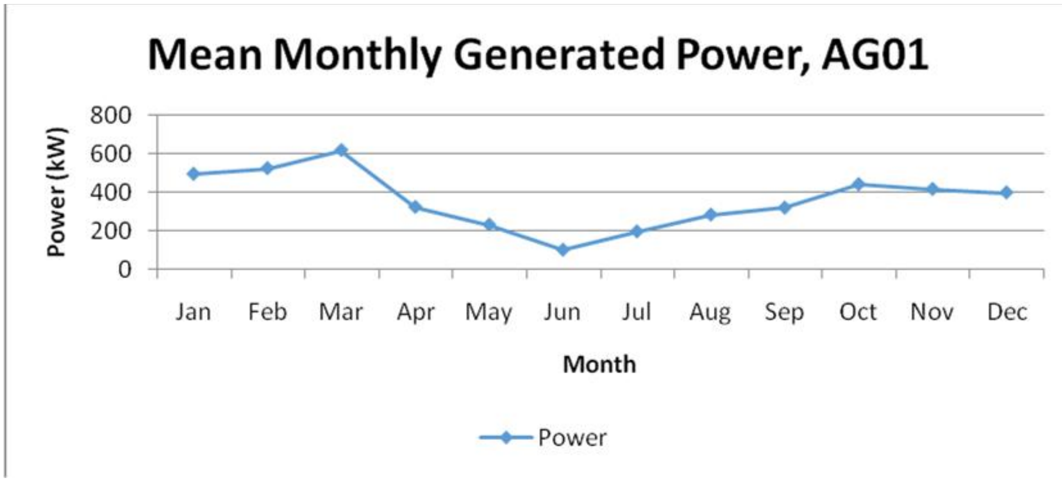

Figure A.1: Turbine AG01 power generated

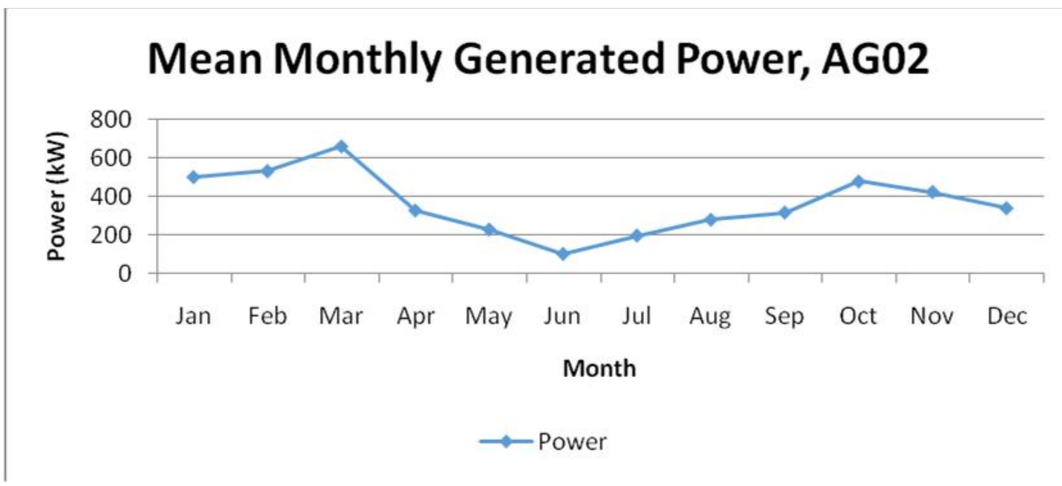

Figure A.2: Turbine AG02 power generated

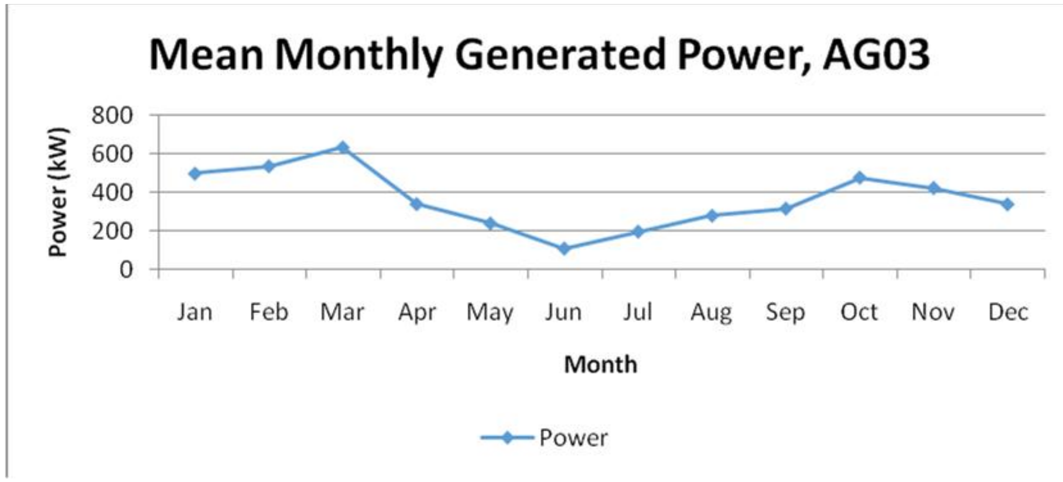

Figure A.3: Turbine AG03 power generated

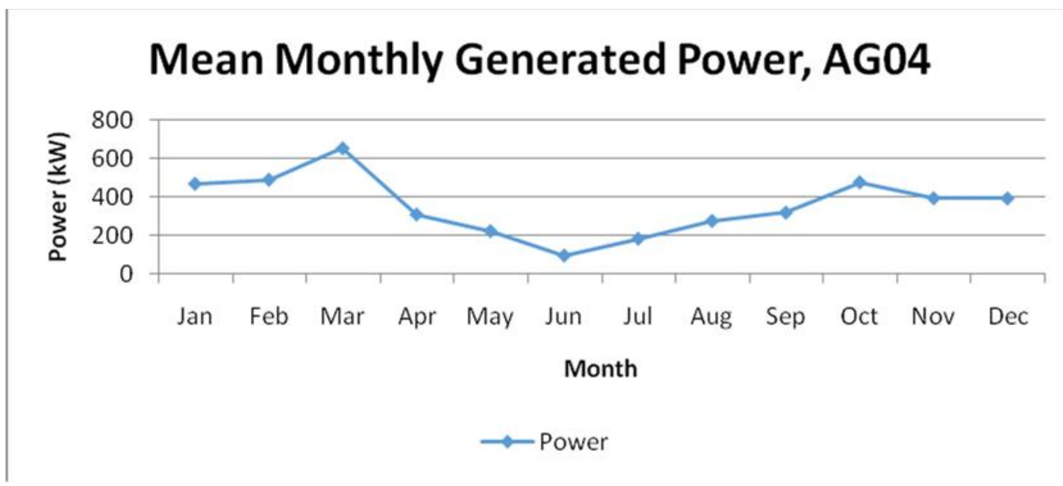

Figure A.4: Turbine AG04 power generated

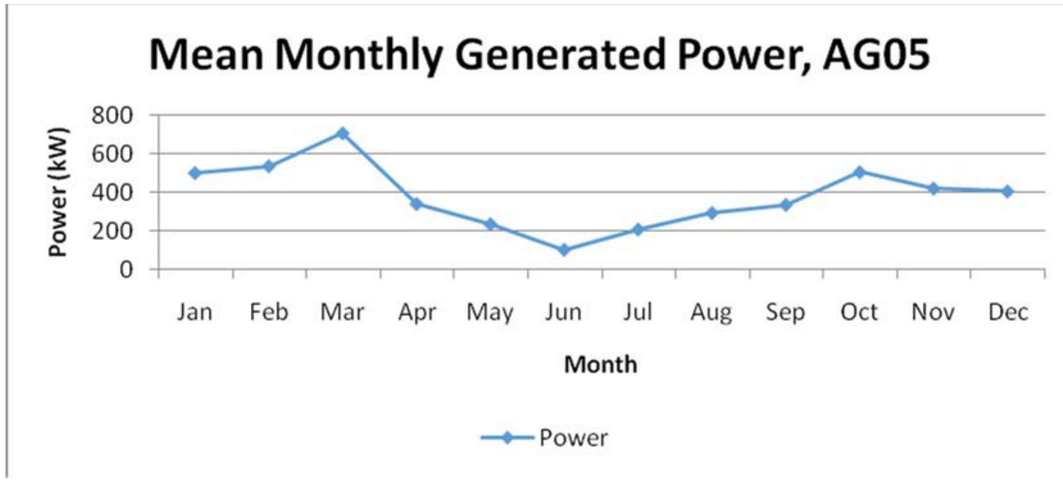

Figure A.5: Turbine AG05 power generated

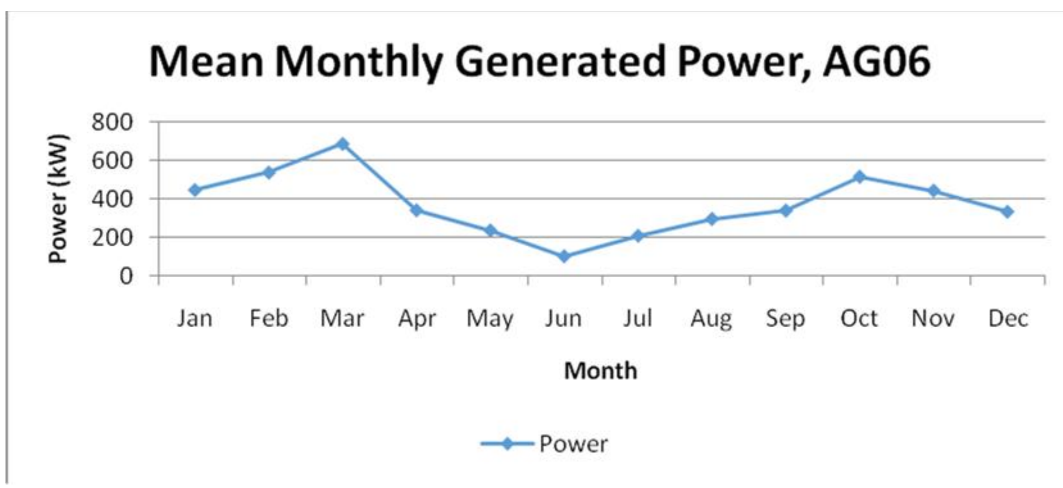

Figure A.6: Turbine AG06 power generated

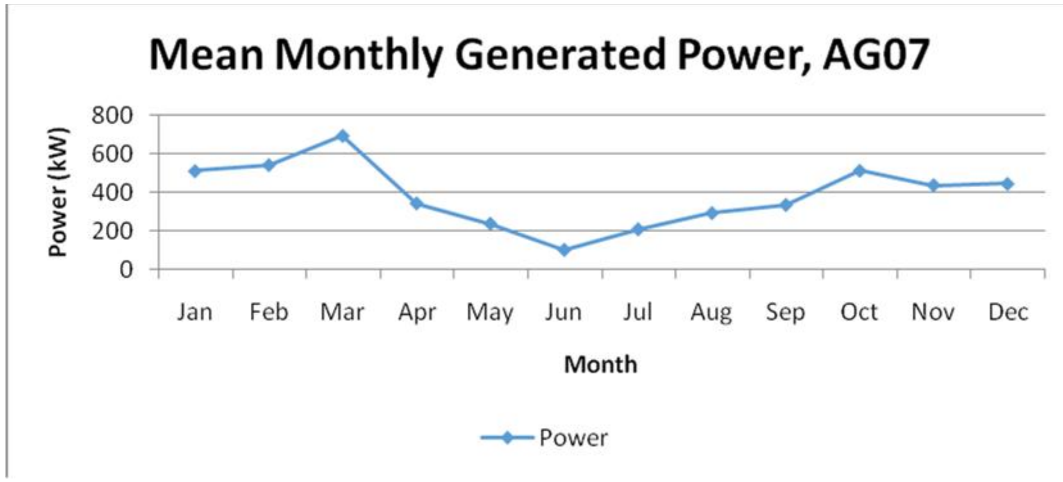

Figure A.7: Turbine AG07 power generated

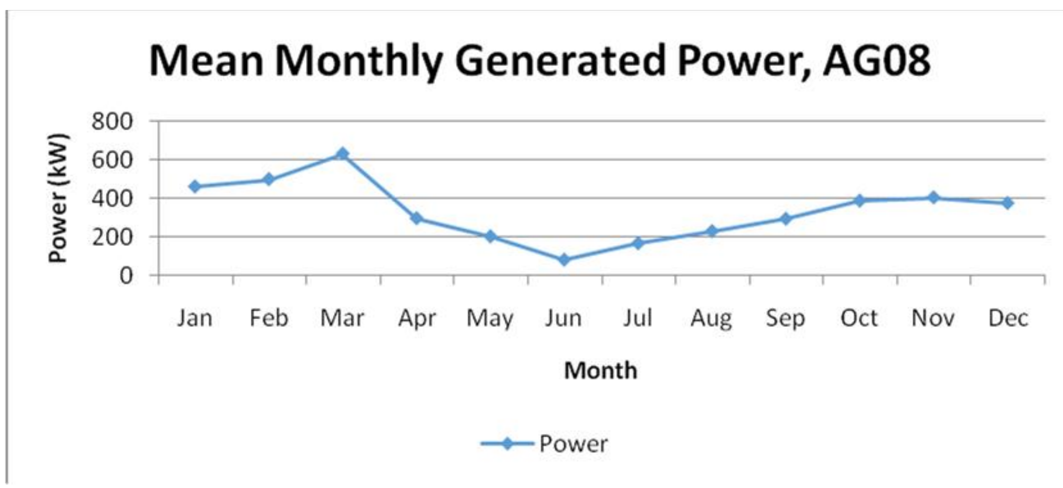

Figure A.8: Turbine AG08 power generated

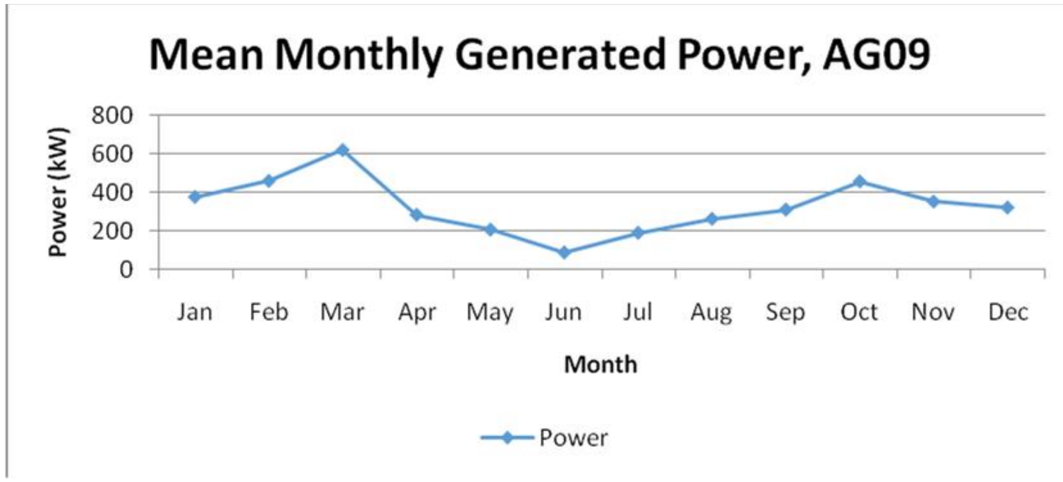

Figure A.9: Turbine AG09 power generated

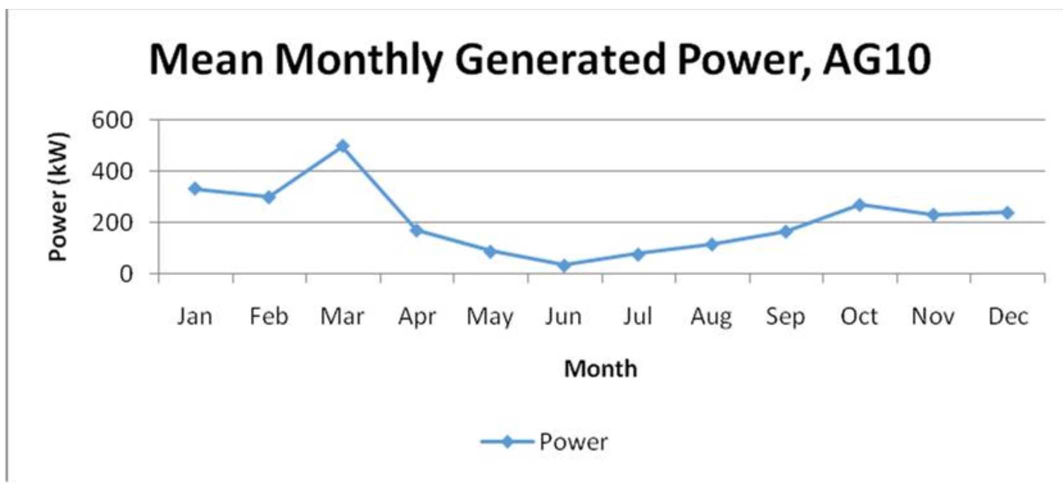

Figure A.10: Turbine AG10 power generated

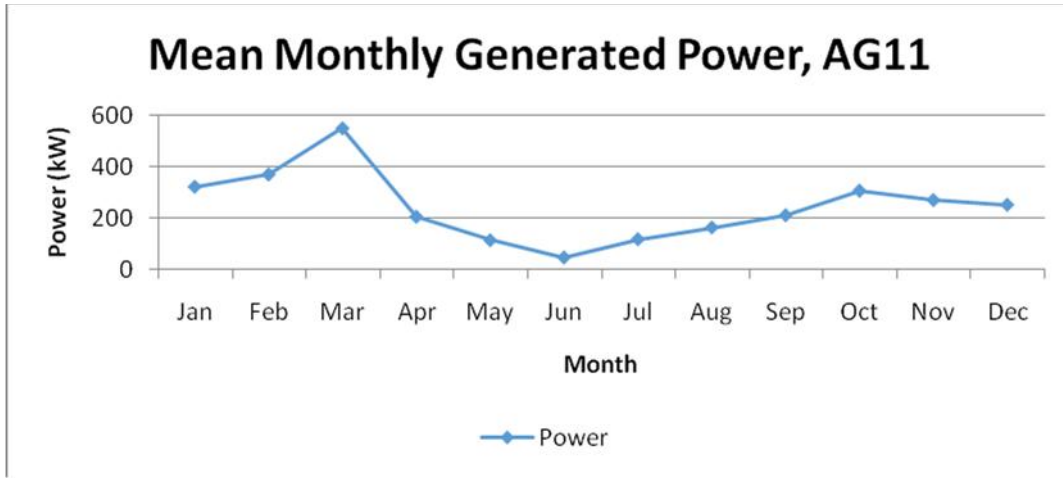

Figure A.11: Turbine AG11 power generated

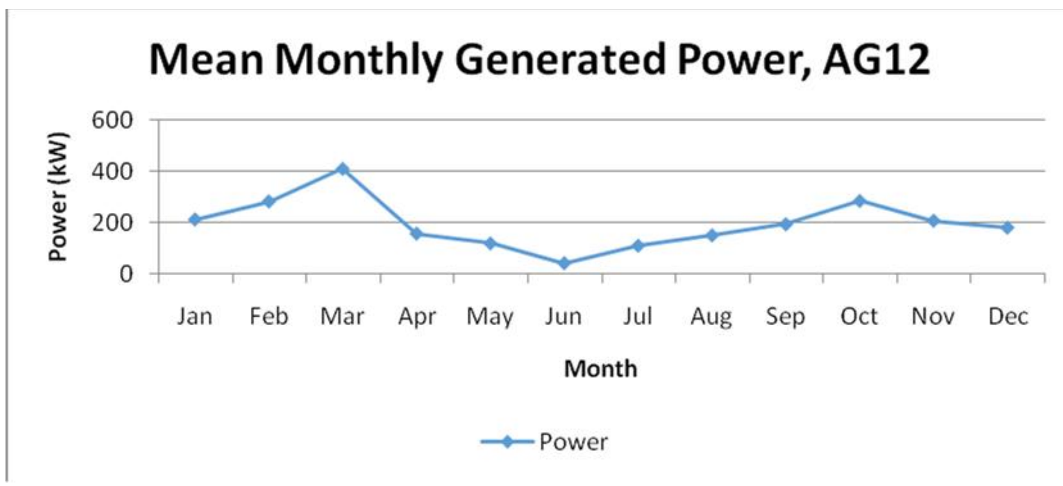

Figure A.12: Turbine AG12 power generated

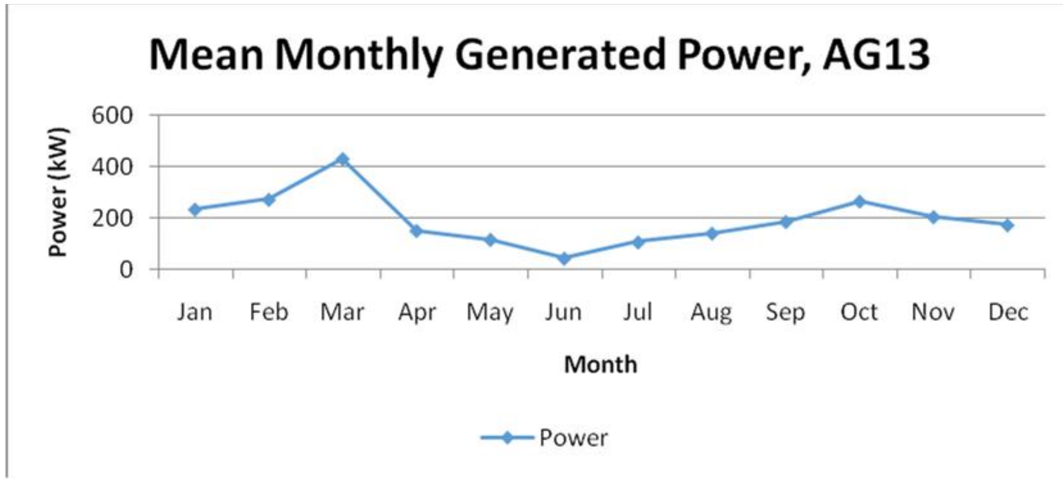

Figure A.13: Turbine AG13 power generated

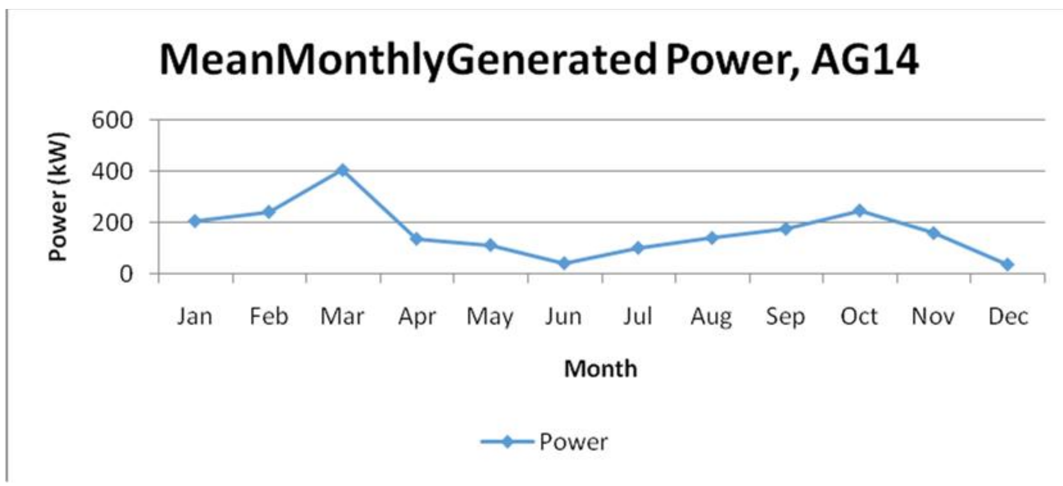

Figure A.14: Turbine AG14 power generated

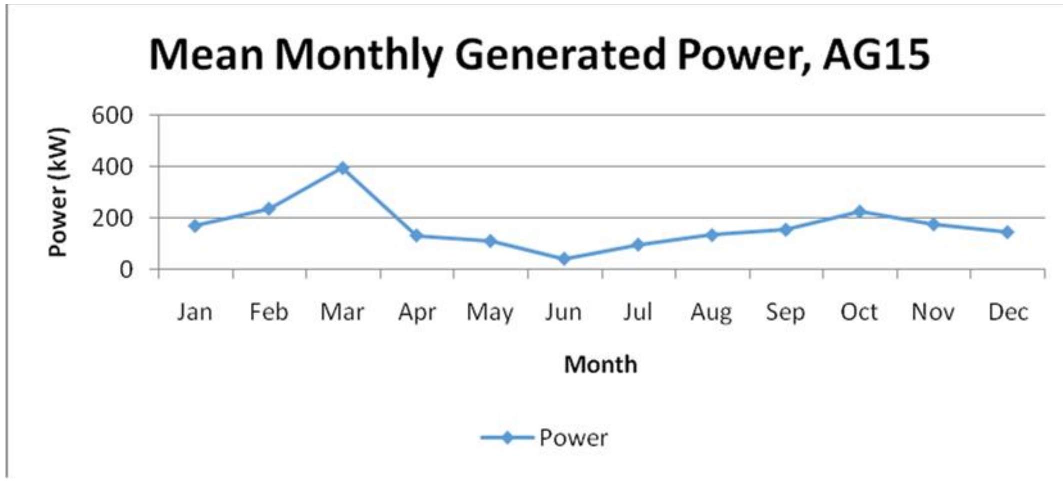

Figure A.15: Turbine AG15 power generated

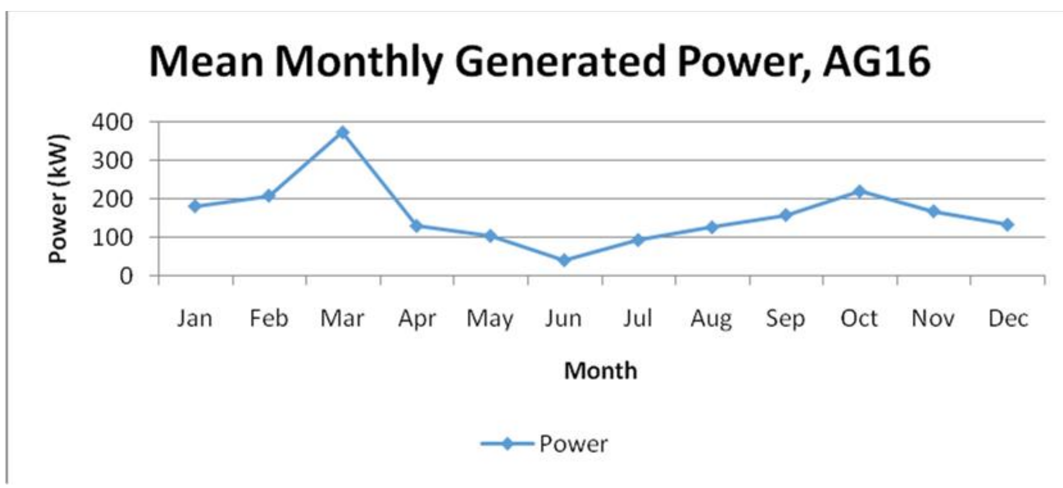

Figure A.16: Turbine AG16 power generated

APPENDIX B: NETWORK ARCHITECTURE CODES

APPENDIX B.1: The Narnet code:

```
close all, clear all, clc, format compact
%filename = 'C:\Users\Victor\Documents\MATLAB\Wind Power Prediction\Project Preogress\WData.csv'
data = readtable('Data.csv','ReadVariableNames',true);

N = 41703; % total number of wind speeddata points
Nu = 8000; %the  number of learning extracted samples

% data processing
y = data.AGGR;
y = y(all(~isnan(y),2),:);
%% -------------------------------------
%prepare data for the network
% training data processing
y_train = con2seq(y(1:Nu)');
% validation data processing
y_val = con2seq(y(Nu+1:end)');

%% --------------------------------------
%Create the NonLinear Autogressive Network
```

```
Input_Delays = 1:4; % input delay vector

Feedback_Delays = 1:4;

hiddenLayerSizes = [5 10 5]; % network structure (number of neurons)

net = narnet(inputDelays,hiddenLayerSizes);


% Change the layer activation fucntions

net.layers{1}.transferFcn = 'tansig';

net.layers{2}.transferFcn = 'logsig';

net.layers{3}.transferFcn = 'tansig';

net.layers{4}.transferFcn = 'purelin';


% create network

net.layerConnect = [0 0 0 0; 1 0 0 0; 0 1 0 0; 0 0 1 0];

net.biasConnect = [1; 0; 0; 1];


% Change the network parameters

net.trainParam.epochs = 1000;

net.trainParam.goal = 1e-5;

net.performParam.regularization = 0.5;

net.trainParam.lr = 0.1;

% Data division for training

net.divideFcn = 'divideblock';
```

```
net.divideParam.trainRatio = 0.7;
net.divideParam.valRatio = 0.15;
net.divideParam.testRatio = 0.15;

% training function
net.trainFcn = 'trainbfg';
%performance function
net.performFcn = 'mse';
% Prepare the networks
[i,is,Ls,ts] = preparets(net,{},{},ytrain);

% train network
[net,tr] = train(net,i,ts,is,Ls);
view(net)
Y = net(i,is,Ls);
perf = perform(net,ts,Y)
%% ----------------------------------------
% prepare validation data for simulation
y_initial = ytrain(end-max(input_Delays)+1:end); % initial values from training data
% aggregated
[i,is,Ls] = preparets(net,{},{},[y_initial y_val]);
```

```
% predict
predict = net(i,is,Ls);


% validate data
Yv = cell2mat(y_val);
% predict
Yp = cell2mat(predict);
% error
error = Yv - Yp;
```

APPENDIX B.2: The Cascade Forward net code

```
rng default % for reproducibility

input = Yv;

target = Yp;

net_CFF = cascadeforwardnet(5,'trainlm');

net_CFF = configure(net_CFF,input,target);

net_CFF.performFcn = 'crossentropy';

net_CFF.trainParam.lr = 0.01;

net_CFF = init(net_CFF);

[net_CFF,tr] = train(net_CFF,input,target);

view(net_CFF)

getwb(net_CFF);

i = net_CFF(input);


error_Normal = input - i;

L2 = 0.5*sqrt(mean(error_Normal).^2);


Cost_Function = @(x)loss(x, net_CFF,input ,target);

nvars = size(getwb(net_CFF));


[x, err_N] = pso(Cost_Function,nvars);
```

```
net= setwb(net_CFF, x');


% get the PSO optimized NN weights and bias
Particle_weights = getwb(net);
%%obtain the generating function for the cascadeforwardnet
net = configure(net,input,target);
view(net)
genFunction(net,'net')
```

APPENDIX B.3: The Narxnet Code

```
% create the network with delays

Input_Delays = 1:5:10;

Feedback_Delays = 1:5:10;

Hidden_Sizes = [10 5];

%------------------------------------

input = con2seq(i);

target = con2seq(Yv);

% nonlinear autoregressive neural network

net = narxnet(inputDelays,feedbackDelays,hiddenSizes);

[X_s,X_i,A_i,T_s] = preparets(net,input,{},target);

net = train(net,X_s,T_s,X_i,A_i);

error_N = cell2mat(yp) - cell2mat(Ts);

view(net)

Y = net(X_s,X_i,A_i);

perf = perform(net,T_s,Y)

% validation data

y_initial = target(end-max(input_Delays)+1:end);

[X_s,X_i,A_i,T_s] = preparets(net,{},{},[y_initial input]);

% predict on validation data

%predict = net(Xs,Xi,Ai,Ts);

predict_2 = net(X_s,X_i,A_i);
```

```
Yt = cell2mat(input);

% prediction

Y_P = cell2mat(predict_2);

Net_c = closeloop(net);

Net_c.name = [net.name 'Closed Loop'];

view(net_c)

[X_c,Xi_c,Ai_c,T_c] = preparets(net_c,input,{},target);


Y_closed  = netc(Xc,Xic,Aic);

y_pred = netc(cell(0,12),Xic,Aic);
```

APPENDIX B.4:The Particle Swarm code

```
function [x,err]=particleswarm(CostFunction,nVar)

% CostFunction= Cost_Function

% n_Var= Number of Variables

tic

Var_Size=[1 n_Var];   % matrix variable decision size


Var_Min=-5;        % Lower_Bound

Var_Max= 5;        % Upper_Bound




Max_It= 60;      % set iter_max

 n_Pop=50;       % set Population-Swarm-Size

we=1;               % Inertial weight factor

we_damp=0.8;     % Inertia_weightDamping_ratio

C_1=1.5;        % Pbest  Coefficient

C_2=1.5;        % Gbest  Coefficient

% set velocity constraints

V_Max=0.1*(Var_Max-Var_Min);

V_Min=-V_Max;

%% set the initial condtions
```

```
EP.Pos=[];
EP._Cost=[];
EP.Velocity=[];
EP.B.Pos=[];
EP.B._Cost=[];
member=repmat(EP,n_Pop,1);
GBest.Cost = inf;
for i=1:n_Pop
      % set Initial position
   P(i).Position = unifrnd(Var_Min,Var_Max,Var_Size);
      % set initial Velocity
   P(i).Velocity=zeros(Var_Size);
   % Eval
   P(i).Cost=Cost_Function(P(i).Position);

   % Update PBest
   P(i).B.Position=P(i).Pos;
   P(i).B.Cost=P(i).Cost;

   % iterate GBest
   if P(i).B_Cost<GBest.Cost
```

```
        GBest=P(i).Best;
            end
    end
 B_Cost=zeros(MaxIt,1);

%% PSO Main Loop
 for it=1:MaxIt
        for i=1:nPop
                % iterateVelocity
        P(i).Velocity = we*P(i)._Velocity ...
            +c1*rand(Var_Size).*(P(i).B.Pos-P(i).Pos) ...
            +c2*rand(Var_Size).*(GBest.Pos-P(i).Pos);
        % Add Velocity constraints
        P(i).Velocity = max(P(i).Velocity,Vel_Min);
        P(i).Velocity = min(P(i).Velocity,Vel_Max);
                %Iterate Position
        P(i).Pos = (P(i).Pos) + P(i).Vel;
                % apply the Mirror for velocity
        IsOutside=(P(i).Pos<Var_Min | P(i).Pos>Var_Max);
        P(i).Vel(IsOutside)=-P(i).Vel(IsOutside);

        % Add Pos Limits
```

```
        P(i).Pos = max(P(i).Pos,Var_Min);

        P(i).Pos = min(P(i).Pos,Var_Max);


        % Evaluate

        P(i).Cost = Cost_Function(P(i).Pos);

            % Iterate Personal Best

        if P(i).Cost<P(i).B._Cost

          P(i).B.Position=P(i).Pos;

          P(i).B._Cost=P(i)._Cost;

          % iterate Global Best

          if P(i).B.Cost<GBest._Cost

                    GBest=P(i)._Best;

                  end

              end


      end

        BCost(it)=GBest._Cost;

        disp(['Iteration ' num2str(it) ': Best Cost = ' num2str(BestCost(it))]);

       we_new=we*w_damp;


    end

    Best_Sol = GBest;
```

```
x=BestSol.Position;

err=BestSol.Cost;

%% Display_results

 figure;

%plot;

semilogy(BCost,'LineWidth',2);

xlabel('Iteration');

ylabel('Best_Cost');

grid on;

toc
```

APPENDIX B.5: Cost Function

```
function L2 = loss( wb,net, target, input)

% wb is the weights and biases row vector obtained from the PSO algorithm.

% It is transposed when transferring the weights and biases to the network t.

 net = setwb(net, wb');
 % The net output matrix is given by net(input). The corresponding error matrix is
given by
  error = target - net(input);
 % The mean squared error normalized by the mean target variance is
 L2 = 0.5*sqrt(mean(error).^2);
%L2 = mean(error.^2)/mean(var(Yv',1));
```

APPENDIX C: GENERALISED LEAST SQUARE REGRESSORS

$$Y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{C.1}$$

$$\varepsilon_t = \rho\varepsilon_{t-1} + \vartheta_t \tag{C.2}$$

$$Y_t = \beta_0 + \beta_1 x_t + \rho y_{t-1} - \rho\beta_0 - \rho\beta_1 x_t + \vartheta_t \tag{C.3}$$

$$Y_t - \rho y_{t-1} = \beta_0(1 - \rho) + \beta_1(x_t - \rho x_t) + \vartheta_t \tag{C.4}$$

$$Y_t^* = Y_t - \rho y_{t-1} \tag{C.5}$$

$$x_{2t}^* = \beta_1(x_t - \rho x_t) \tag{C.6}$$

$$x_{1t}^* = \beta_0(1 - \rho) \tag{C.7}$$

$$Y_t^* = \beta_0 x_{2t}^* + \beta_1 x_{1t}^* + \vartheta_t \tag{C.8}$$

$$Y_t - \beta_0 - \beta_1 x_t = \rho(Y_{t-1} - \beta_0 - \beta_1 x_{t-1}) + \vartheta_t \tag{C.10}$$

$$Y_1 = \beta_1 + \beta_2 x_1 + \varepsilon_1 \tag{C.11}$$

$$\sqrt{1-\rho^2}Y_1 = \sqrt{1-\rho^2}\beta_1 + \sqrt{1-\rho^2}\beta_2 x_1 + \sqrt{1-\rho^2}\varepsilon_1 \tag{C.12}$$

$$Y_1^* = x_{11}^*\beta_1 + x_{12}^*\beta_1 + \varepsilon_1^* \tag{C.13}$$

$$var(\varepsilon_1) = (1-\rho^2) * var(\varepsilon_1^*) = (1-\rho^2) * \frac{\sigma^2}{(1-\rho^2)} = \sigma^2 \tag{C.14}$$

APPENDIX D: DURBIN – WATSON TEST

$$H_0: \rho = 0 \;\; or \; H_0: \rho > 0$$

$$M = \frac{\sum_{t=2}^{T} (\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{T} \hat{\varepsilon}_t^2} \qquad \text{(D.1)}$$

M can be expanded and simplified into a quadratic equation as shown below:

$$M = 1 + 1 - 2d^2 \;\cong 2(1 - \; d^2) \qquad \text{(D.2)}$$

Equation 9D.2 has regions of operation and is therefore bound within the said region.

APPENDIX E: THE GEOMETRIC LAG

$$Y_t = \beta_0 + \sum_{N=1}^{\infty} \delta_0 \epsilon_1^N x_{t-N} \quad \text{(E.1)}$$

$$\beta_0 = \frac{\delta}{1- \varepsilon_1} \quad \text{(E.2)}$$

$$Y_t = \beta_0 + \sum_{N=1}^{\infty} \beta_N x_{t-N} + \varepsilon_t \quad \text{(E.3)}$$

APPENDIX F: THE POWER LAW EQUATION OF WIND SHEAR

$$\frac{u}{u_{ref}} = \left(\frac{z}{Z_{ref}}\right)^{\alpha} \qquad \text{(F.1)}$$

Where α is the height extrapolation coefficient, it can be determined using two methods commonly found in literature as stipulated in 9F.2 and 9F.3

Method 1: From the reference values;

$$\alpha = \frac{0.37 - 0.088\ln\,(u_{ref})}{1 - 0.088\ln\,(\frac{z_{ref}}{10})} \qquad \text{(F.2)}$$

Method 2: Using the roughness length;

$$\alpha = 0.24 + 0.096 log_{10} z_0 + 0.016 (log_{10} z_0)^2 \qquad \text{(F.3)}$$

APPENDIX G: WIND FARM ENERGY YIELD

These equations determines the total energy generated from a given wind-farm in a given year , calculated from wind_speed distribution curve and the wind turbine power_curve.

$$Mean\ power = E[power\ produced] = \int_{v=0}^{v=cut-out\ velocity} P(v)f(v)dv \quad (G.1)$$

$$\approx \sum_{wind\ class} P(v)h(v) \quad (G.2)$$

Where $h(v)$ is the probability that the wind class of that nature will blow.

$$E[power\ produced] = P_{Mean} \times Time \times Availability = \mu T \sum_{wind\ class} P(v)h(v) \quad (G.3)$$

APPENDIX H: WIND FARM PLAT CAPACITY-FACTOR

This is the rate at which the farm operates at the rated capacity. It is given as follows;

$$Capacity\ factor = \frac{actual\ enegy\ produced}{hypothetical\ energy\ produced} = \frac{E[energy\ produced]}{rated\ power \times Time} \qquad \text{(H.1)}$$

Typical capacity factors lie between 0.15 and 0.3

APPENDIX I: PERFORMANCE METRICS

APPENDIX I.1: MEAN ABSOLUTE ERROR

$$MAE(i) = \frac{1}{M}\sum_{t=1}^{M} |err(t + i|t)|$$

APPENDIX I.2: MEAN SQUARE ERROR

$$MSE(i) = \frac{\sum_{t=1}^{M} |err(t+i|t)|^2}{M-n}$$

APPENDIX I.3: MEAN ABSOLUTE PERCENTAGE ERROR

$$MAPE = \frac{100}{M}\sum_{h=1}^{M}\frac{|Power\_err(h+i|h)|}{Mean\_power}$$

APPENDIX I.4: SUM OF SQUARED ERRORS

$$SSE = \sum_{h=1}^{N} \left(\hat{P}_h - p_h\right)^2$$

APPENDIX I.5: STANDARD DEVIATION ERROR

$$SDE = \sqrt{\frac{1}{M}\sum_{h=1}^{M}(pred\_err_h - mean\_err)^2}$$

$$mean\_err = \frac{1}{M}\sum_{h=1}^{M} pred\_err_h$$

$$pred\_err_h = \frac{1}{M}\sum_{h=1}^{M} Pred\_power_h - acctual\_power_h$$