Integration of Renewable Energy into Nigerian Power Systems

By

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Declaration

I, Awodiji Olurotimi Olakunle hereby declared that the thesis titled "Integration of renewable energy into Nigerian power systems" is my original work. No parts or whole had earlier been submitted to any other University.

Signature: Signed by candidate ……………………………………….

Date: ……………………………………………

Dedication

To my lovely wife, Olukemi Roseline,

To my Children, Oluwadamilola David, Omotoke Debbie and Oluwatomisin Esther

To my parents, Late Mr. and Mrs. Awodiji

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Abstract

Many countries are advancing down the road of electricity privatization, deregulation, and competition as a solution to their growing electricity demand and other challenges posed by the monopolistic nature of the existing structure. Presently, Nigeria has a supply deficit of electricity as a result of the growing demand. This imbalance has negatively affected the economy of the country and the social-economic well-being of the population. Hence, there is an urgent need to reform the power sector for greater efficiency and better performance. The objectives of the reform are to meet the growing power demand by increasing the electric power generation and also by increasing competitiveness through the participation of more private sector entities.

The renewable energy integration is one way of increasing the electricity generation in the country in order to cater for the growing demand adequately. Examples of the renewable energy that is available in the country include wind, geothermal, solar and hydro. They are considered to be environmentally friendly, replenishable and do not contribute to the climate change phenomena. The country presently generates the bulk of its electricity from both thermal (85%) and hydroelectric (15%) power plants. While electricity generation from the thermal power stations constitutes the largest share of greenhouse emission, this is mostly from burning coal and natural gas. The effect of this high proportion of greenhouse emission causes climate change which is referred to as a variation in the climate system statistical properties over a long period of time. It has been observed that many of the activities of human beings are contributory factors to the release of these greenhouse gases (GHG). But, as the traditional sources of energy continue to threaten the present and future existence on the planet earth, it is, therefore, imperative to increase the integration of the variable renewable energy sources in a sustainable and eco-friendly manner

over a long period of time. The variability and the uncertainties of the renewable energy source's output, present a major challenge in the design of an efficient electricity market in a deregulated environment. The system deregulation and the use of renewable sources for the generation of electricity are major changes presently being experienced in power system. In a deregulated power system, the integration of renewable generation and its penetration affects both the physical and the economic operations.

The main focus of this research is on the integration of wind energy into Nigerian power systems. Up till now, research on the availability of the wind energy and its economic impacts has been limited in Nigeria. Generally, the previous study of wind energy availability in Nigeria has been limited in scope. The wind energy assessment study has not been detailed enough to be able to ascertain the wind energy potential of the country.

To cope with this shortcoming, a detailed statistical wind modeling and forecasting methodology have been used in this thesis to determine the amount of extractable wind energy in six selected locations in Nigeria using historical wind speed data for 30 years. The accuracy test of the statistical models was also carried using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Chi-Square methods to determine the inherent error margin in the modeling and analysis. It is found that the error margin of the evaluations falls within the expected permissible tolerance range. For a more detailed wind assessment study of the Nigeria weather, the seasonal variation of the weather conditions as it affects the wind speed and availability during the two major seasons of dry and rainy was considered.

A Self-Adaptive Differential Evolution (SADE) was used to solve the economic load dispatch problem that considers the valve-point effects and the transmission losses subject to many constraints. The results obtained were compared with those obtained using the "standard"

Differential Evolution (DE), Genetic Algorithm (GA), and traditional Gradient Descent method. The results of the SADE obtained when compared with the GA, DE, and Gradient descent show the superiority of SADE over all the other methods.

The research work shows that the wind energy is available in commercial quantity for generation of electricity in Nigeria. And, if tapped would help reduce the gap between the demand and supply of electricity in the country. It was also demonstrated that the wind energy integration into the power systems affects the generators total production cost.

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Nomenclature

AE	Absolute Error of the forecast
AR	Auto Regressive
ARMA	Average Regression Moving Average
AVE	Average Energy
BPE	Bureau of Public Enterprise
CAISO	California Independent System Operator
DE	Differential Evolution
DISCOS	Distribution Companies
ECN	Electricity Corporation of Nigeria
ECNZ	Electricity Corporation of New Zealand
EPSR	Electric Power Sector Reform Act
FACTS	Flexible Alternating Current Transmission System
FERC	Federal Electricity Regulatory Commission
GA	Genetic Algorithm
GENCOS	Generating Companies
IPP	Independent Power Producers

IMF	International Monetary Fund
LMP	Locational Marginal Price
MA	Moving Average
MAE	Mean Absolute Error
MISO	Midcontinent Independent System Operator
MLE	Maximum Likelihood Estimator
MMLE	Modified Maximum Likelihood Estimator
MOM	Method of Moment
NDA	Niger Dam Authority
NERC	Nigerian Electricity Regulatory Commission
NETA	New Electric Trading Arrangement
NEPA	National Electric Power Authority
NEM	Nigeria Electric Market
NIMET	Nigeria Meteorological Agency
NYISO	New York Independent System Operator
NWP	Numeric Weather Prediction
PD	Power Density
PHCN	Power Holding Company of Nigeria
RMSE	Root Mean Square Error

ST	Short-Term
STD	Standard Deviation
TCN	Transmission Company
WECS	Wind Energy Conversion System

Chapter 1

Introduction

Historically, the electricity industry was monopolistic in nature. It is also vertically in a structure where the task of generation, transmission, and distribution of electrical power all lies with electric power utilities. These electric power utilities are mostly owned by the government of such countries or in some instances, it could be privately owned. But, in the early1990 to 2000, electricity reforms begin to sweep across many countries worldwide. The need to replace and change the fundamental structure of the old vertically monopolistic power markets with a more competitive, and a more participant's driven method called deregulated electricity market becomes more prominent. The deregulated electricity market approach unbundles the initial structure into separate independent entities of generation (Genco), an open access non-discriminatory transmission (Transco) and distribution (Disco) respectively, with each of the entities performing their functions separately. There are different factors that have driven the reforms in different countries, but this can be broadly categorized into economical, technical and political.

The technical factor includes the advancement in the transmission of electricity over a long distance from the remotely located generating stations to the load centers. Also, the development of efficient electricity generation methods has made it possible to complete the building of smaller generating power plants within a short period of time, unlike most gigantic power plants that take a longer time to complete in the past. Ordinarily, only the monopolistic investor would have been able to make such investment of building gigantic power plants in the past because of the huge capital base requirements. Also, the advancement in some of the modern technologies has made the grid to be more efficient through the deployment of FACTS devices and other control methods. This has made the separation of generation and transmission section easier in the deregulated electricity market.

But, beyond technical factors are political factors in the policy direction of the different countries. Since most of the electricity utilities in the vertically integrated structure are wholly owned by the state, the decision to deregulate becomes the issue of policy. The state can decide to deregulate and also choose otherwise depending on its electricity policy which determines its actions.

The economic factor is primarily responsible for the overall decision to carry out the reform in the electricity market. The main economic idea that is responsible for the deregulation was that a highly functional, competitive electricity market can reduce cost and minimize the average energy prices [1]. With the success of deregulation in most of the other sectors of the economy, such as telecommunication, transportation, aviation and oil, and gas, hence the deregulation of the power sector was expected to replicate the same success achieved in the other sectors. Therefore, the quest for global competitive electricity market, for the enhancement of efficiency, and to broaden participation in the electricity industry is believed amongst the pro-deregulation agitators as a means of breaking the monopoly of the state-run utilities. This is necessary for cost benefits and better service delivery. A competitive electricity market is used for the goal of achieving the public interest, only when the structure of the market takes into consideration the peculiarities of the power system [2]. Another reason that led to deregulation amongst countries worldwide is the external pressure from the International Monetary Fund (IMF) and the World Bank that suggests that an open competitive market in the electricity sector as a precondition for financial assistance or accessibility to loans to fund their respective capital projects.

The renewable energy technologies compared to the conventional energy technologies are cleaner in nature with lower environmental impact. Renewable energy sources cannot be depleted over time. But, other non-renewable sources are not and can be depleted in the future. The large-scale increase in the renewable energy integration in the electricity market and its use in electricity generation is as a result of the reduction in the fossil fuel reserves of the traditional methods and also the concern about their impact on the climate change. The variability and the uncertainties of the renewable energy source's output are the major characteristics that pose a challenge in the design of an electricity market. The renewable energy penetration has affected the existing electricity market structures, policies, electricity bidding methods, economic load dispatch and many other operations of the power system.

But, with the increase in the renewable energy penetration into the transmission network comes many challenges to the service provider. One of such is the limited transmission line infrastructure, as a result of its natural monopoly which is a factor that can limit the renewable generation development. Transmission capacity is necessary to transmit the generated power to load centers and also for the purpose of balancing the system. The renewable energy integration into the existing network is difficult because the power system network was not originally designed to accept this kind of production, thereby causing line congestion as a result of the increase in its output [3].

1.1 Background to the Thesis

There presently exists a severe shortage of electricity supply in Nigeria. The difference between the demand and supply of electricity is so large and the effects of the inadequacy can be felt in every sector of the economy. The government's decision to solve the electricity problem in the country led to the deregulation of the power sector. The deregulation includes the unbundling of the state-owned utility company into many entities and the participation of independent power producers (IPP). In addition to power sector deregulation, there is also the need to achieve energy mix for the power sector. In order to achieve this objective, the renewable energy policy was formulated as a policy guideline for harnessing the available renewable energy sources and integrating it into the deregulated electricity industry. However, when electricity market design is being deliberated upon with the penetration of high renewable energy in a deregulated environment, an important concern is the likely effect of negative pricing at different locations. In locations with high penetration of renewable generation usually, have times of low energy prices mainly because renewable generation's marginal cost is usually zero. But during the period of the year when renewable energy generation increases relative to load (load is low), energy prices, then become negative (the willingness of the generator to pay the load for the generated power). This occurs when there is a restriction by the transmission limits for the control of the variable resources [4]. The effect of the negative prices experienced, therefore, serves to create a degree of the opportunity cost that is related to non-dispatchability of the generation.

The total reliability conditions of the system are subject to change as surplus renewable resources are added and additional ancillary services provisions will be needed as power system characteristic changes.

The major roles and challenges of designing electricity market are to first remove needless obstacles, and provide motivations that boost the behavior of the participants. Also, to provide security that will reduce the effects of variability, uncertainty and associated risk, all this is to be achieved within the recognized permissible legal and regulatory framework. Therefore, the integration of variable renewable sources of power generation and the deregulation of the power sector is the major changes the power system is experiencing in Nigeria.

1.2 Need for the Research

It is argued that the integration of wind energy into the newly deregulated electricity market in Nigeria will help to reduce the difference between the electricity demand and supply, and also help resolve the country's electricity challenges for both present and future electricity demand in achieving both social and economic development.

1.3 Objectives of the Thesis

The integration of renewable energy source is critical to the future energy roadmap for the sustainable development of Nigeria. Several renewable energy sources are readily available in the country to be harnessed for the purpose of generating electricity. The objectives of this thesis are to carry out a wind assessment study of the country for the purpose of integrating wind energy into the newly deregulated electricity market in Nigeria, and to study the economic impact of the integration of the wind on the cost of energy production of generating electricity based on the peculiarity of the existing Nigerian power system network configurations.

1.4 Research Methodology

An extensive review of relevant literature was carried out at the beginning of the research. This review includes the various deregulation processes in different parts of the world. A comprehensive wind speed resource assessment analysis of some six selected locations in the Northern part of Nigeria was done to determine their suitability for the location of wind farms for the purpose of generating electricity. In order to achieve the energy mix in the power system, the economic load dispatch study was carried out using different meta-heuristic optimization methods: Differential Evolution (DE), Genetic Algorithm (GA), and Self-Adaptive Differential Evolution (SADE) and the tradition Gradient descent method.

1.5 Contributions of the Research

The contributions of the research are:

1. Detailed wind energy assessment study of the selected locations in Nigeria using statistical modeling and forecasting techniques for the purpose of wind energy generation and integration into the newly deregulated electricity market for social-economic development of the country.
2. The application of fast and efficient self-adaptive differential evolution (SADE) algorithm to solve the economic load dispatch problem of Nigerian power systems with renewable energy integration considering transmission losses.

1.6 Outline of this Thesis

The thesis is organized as follows:

Chapter 2

This chapter deals with the general overview of deregulation worldwide with a depth study of deregulation in Europe, North America, and Nigeria. It also discussed the reasons behind deregulation and the factors that influence it. Particular emphasis was placed on Nigeria with the holistic analysis of the privatization program with the integration of renewable energy.

Chapter 3

This chapter emphasizes on wind availability, forecasting, and modeling of the potential windiest locations in Nigeria was investigated.

Chapter 4

This chapter discusses the use of the optimization techniques that were employed in scheduling the wind-thermal operations of the Nigerian power system network in the deregulated environment.

Chapter 5

This chapter presents the simulation results and discussions of the previous two chapters in details.

Chapter 6

This chapter introduces the conclusion and recommendations for future work.

1.7 List of Publications

1. **O.O. Awodiji** and K. A Folly, "*Impact of wind farm Integration on Electricity Production Cost",* Southern African Universities Power Engineering Conference SAUPEC 2017 Stellenbosch University January 30th – 1st February 2017).
2. **O.O. Awodiji** and K.A. Folly, **"***Comparison of Economic Load Dispatch of Nigerian Thermal Power Plants Using Genetic Algorithm and Differential Evolution Methods",* Southern African Universities Power Engineering Conference SAUPEC 2015 University of Johannesburg January 27th -29th 2015).
3. **O.O. Awodiji** and K.A. Folly**,** "*Economic Load Dispatch of Power System Using Genetic Algorithm with Valve Point Effect"*, 6th International Conference, ICSI 2015, held in conjunction with the Second BRICS Congress, CCI 2015, Beijing, China, June 25-28, 2015, Proceedings, Springer International Publishing).

4. **O.O. Awodiji** and K.A. Folly, **“***Economic Load Dispatch of Wind-Thermal Generation in a Deregulated Electricity Market Using Differential Evolution”,* Renewable Energy, Smart Grid, and Computational Intelligence Applied to Smart Grid, August 29th -30th, University of Cape Town). 2014.

Chapter 2

Literature Review

2.1 Historical Evolution of Market Deregulation

The U.S electricity market in the late 18th century was unregulated. The first regulatory framework was developed between the city of New York and Wisconsin in the early 19th century [2]. But, in 1920 the Federal Power Commission was created in the U.S with the responsibility to regulate wholesale electricity markets and interstate transmission network. In 1935, the Public Utility Holding Company Act (PUHCA) was passed, and this led to the emergence of vertically integrated utilities organized mostly on a state by state basis with final sales to customers controlled by state utility commissions. With the passage of the Public Utility Regulatory Policies Act (PURPA) in 1978, the participation of the independent power producers in the electricity market was made possible. The real phase of electricity market deregulation started in 1996 with the creation of the wholesale power competition throughout the U.S by the Federal Energy Regulatory Commission (FERC). FERC seeks to promote competition in the wholesale market through open access policy and nondiscriminatory transmission provision of public utilities. The wholesale electricity market is under the direct supervision of FERC in the U.S while the retail market is directly being controlled by each state regulatory commission. As a result, the power market deregulation differs in each state with each state having its own separate markets [5] [6].

The electricity market of PJM is one of the largest liberalized markets in the U.S with coordinating activities in several states. It acts as an impartial, independent party which controls a competitive wholesale electricity market and deals with the high-voltage electricity to ensure uninterrupted supply of several million people [7]. The California ISO (CAISO) is one of the leading electricity markets in U.S. Its activities cut across several states and supplies electricity to over 30 million people on its network. Apart from the initial hitches of blackouts and bankruptcy that characterize the market in 2001, as a result of transmission capacity inadequacy and the inability of the wholesale to meet their demands because of the low retail electricity price, the CAISO has been able to provide for electricity market trading, analysis of electricity bids, transmission capacity, and reserves needed to keep the grid in balance. CAISO uses locational marginal pricing method that forms a very transparent system that bills, electricity, based on the costs of generation and delivery [8]. Other wholesale electricity markets in the U.S include NYISO, ERCOT, and MISO etc.

The pioneering deregulation of the electric power utilities started in Latin America in the early 1980s. Chile was the first country to privatize its electric power utilities in 1982. This was followed by Argentina, Peru, Bolivia and Colombia in 1992, 1993 and1994 respectively. The other countries were, however, hesitant about the deregulation process, but later embraced the process as a preferred alternative owing to the success recorded by Chile in its deregulation process. Generally, the deregulation of the electricity market in the Latin America essentially is the reason behind the improved power sector of these countries [9].

The electrical power utility deregulation in the Oceania is dated back as early as 1987 when the New Zealand government decided to reform its power sector by the setting of the Electricity Corporation of New Zealand (ECNZ) with the mandate to own and manage the facilities of the Ministry of Energy. The ECNZ in 1988 was able to establish the system operator named Transpower, and also successfully set up a wholesale market in New Zealand. The new electricity market in New Zealand has performed very well over the years and was rated among most of the successful electricity markets in the world. In 1990, Australia started the electricity sector deregulation as a result of the recommendation of the Industry Commission reforms that included the state-owned electricity industry. The state of Victoria and New South Wales established a pool market in 1994 and 1996 respectively. The National Electricity Market of Australia was formed in 1998 and it is the product of the two early markets. The Australia's electricity successfully implements the wholesale spot market. The formation of the national energy regulator was the next step of the reform, which replaces the earlier mixed federal and state regulators [10].

The Asian countries also participated in the reform process of their electricity market. Japan began the reform process of its electricity industry in 1995 by promoting the participation of independent power producers into the wholesale electricity market so as to foster competition [11]. These independent producers are ineligible to bid for services within their area but only those that are outside were allowed. The Japanese electricity reform has gone through several changes and modification since inception with the expansion of the retail competition to the residential sector in 2016 and provision for the future unbundling of the transmission and distribution sectors. The power industry in China has experienced a series of changes since 1985. Some of these changes include the end of the monopoly of exclusive participation in power generation investment policy. Between1985-1987, the Chinese government introduces policies to boost new investors to participate in power generation markets, but there were no changes as the vertically integrated remained government responsibilities [12].

2.2 The Deregulation Process in Europe

The deregulation of electricity started in England in 1989 when the parliament adopted the electricity act signifying the commencement of reform in the electricity sector. The pool, electricity market model was approved for the new electricity industry. But, not until 1998 when the full deregulation of the electricity market was achieved [13]. Although the pool market has performed well for the satisfaction of the majority, it was still heavily criticized for its susceptibility to market power by large generators and also its inability to execute bilateral contracts. As a result, the pool market was substituted by the new market called New Electricity Trading Arrangement (NETA) throughout England and Wales in 2001 [13] [14]. Under the new NETA market that emerged, electricity is treated like any other available commodity where bilateral contract amongst parties is allowed. Norway was second to England in Europe in the deregulation of its electricity market in 1990 by the adoption of the Energy Act. The Swedish electricity market was reformed in 1995, and in conjunction with the Norwegian electricity market established the Nord Pool that was launched in 1996. This is a power market, which includes both bilateral and voluntary pool modes. Thereby, it has avoided flexibility of England's initial pool market. The Nord pool power market was specifically designed to accommodate both the bilateral and the pool modes. Finland became the third country to join the Nord pool in 1998 and Denmark became a member in 2000. The European Union also set a deadline of the year 2007 among member countries after many years of intense negotiation through the Electricity Directive 96/92/EC that all electricity market must be fully deregulated. Although the directive highlights some guidelines for the gradual opening of the power sector, it wasn't specific as to defining a common guideline for the electricity reform in the member state. As a result, the reform follows a different structure in all the member countries. In Germany, the Electrical Economy Right New Regulation was adopted in 1998 for the full deregulation of the power sector [15]. The electricity market was fully opened, and allowing the end users to make a choice of suppliers. Greece and Spain are also members of the European Union with fully deregulated electricity industry.

2.3 The Deregulation Process in Africa

In Africa, most of the countries still operate the traditional vertically integrated electricity sector with the exception of Uganda and Nigeria which has fully deregulated its electricity industry. The electricity deregulation processes in Uganda began in 1999, with the unbundling of the Uganda Electricity Board (UEB) into three subsidiaries, independent companies, namely: The Uganda Electricity Generation Company Limited (UEGCL) that is saddled with the responsibility to provide electricity generation services. The Uganda Electricity Transmission Company Limited (UETCL) which is to provide the transmission services of electricity to the distributor, and the Uganda Electricity Distribution Company Limited (UEDCL) which distributes electricity to end consumers [16].

The electricity reform bill of the government of Nigeria was passed into law in 2005 thereby paving way for the full deregulation of the country's power sector. Soon after, the state-owned National Electric Power Authority (NEPA) was unbundled into eighteen successor companies with the formation of a holding company known as Power Holding Company of Nigeria (PHCN) and the regulator called the Nigerian Electricity Regulatory Council (NERC). The government of Nigeria has embarked on the most comprehensive power sector reform in the African continent [17].

Nigeria remains the only country in Africa that has fully deregulated its electricity industry. Most other African countries electric utilities are still vertically integrated into nature, but many plans to reform their energy sector in the future for greater efficiency and increase participation.

Electricity generation in Nigeria began as early as 1896 with the installation of the first generating station in Lagos by the British Colonial Government [18]. Ever since then, the electric power sector has evolved through so many stages covering a long period of time of more than a century. The Electricity Corporation of Nigeria (ECN) established in 1962 to oversee the generation, distribution, and retail of electricity while the establishment of the Niger Dam Authority (NDA) was solely for hydroelectric power development in the country. These two institutions were merged together in 1972 to form a new organization known as National Electric Power Authority (NEPA) [19]. NEPA, from inception, was a public utility organization and have the monopoly of electricity generation, transmission, and distribution within and outside the country. With the increase in economic activities over the years as a result of industrial growth, population increase and improve lifestyle; energy demand has been increasing steadily without a corresponding increase in generation. Electricity demand in the country far exceeds the supply from NEPA and this shortfall causes recurrent outages and unreliable power supply to the customers [20]. Nigeria presently has a total installed capacity of 7876.4 MW with only less than 4000 MW available capacities for a population of 180 million people. Poor maintenance of the generators, inadequate transmission and distribution networks are some of the factors responsible for the discrepancies in the installed and the available capacity in the country. The transmission network consists of almost 5000km of 330kV lines and 6300km of 132kV lines with 6098MWA transformer capacity for the 330/132Kv network and 8090MWA transformer capacity for the 132/33 kV network. The transmission network coverage is very poor with most parts of the country, not covered; the current maximum wheeling capacity is 4000MW. The Nigerian distribution network is equally characterized by weak and inadequate network coverage, overloading of the transformer and obsolete equipment. The Federal Government of Nigeria had embarked on a comprehensive power sector reform to solve the energy crisis in the country. The reform is expected to proffer solution to the energy crisis, and also, act as the roadmap for the full deregulation of the power sector. The electric power sector reform act 2005 (EPSR) is the statutory document that laid out the model and framework for deregulating the electricity industry. The reform has two main components: which are restructuring and privatization.

The implementation of the reform started with the creation of an initial holding company called the Power Holding Company of Nigeria (PHCN) in 2005. Although the processes were characterized by delays and postponements several times, it eventually started with a tentative timetable for the implementation schedule to follow. The Bureau of Public Enterprise (BPE) was established to carry out the deregulation and privatization of publicly owned establishment for the Federal Government of Nigeria [21]. Power Holding Company of Nigeria is made up of eighteen successor companies which include: six generation companies (GENCOs), one transmission company (TCN) and eleven distribution companies (DISCOs). The generation sector was deregulated through core investor sale and concession. The generating companies (GENCOs) will be responsible for operating the existing generating stations, and also, making the necessary investment to improve generation. The six-generation companies are made up of both thermal and hydropower stations. More new Independent Power Producers will be licensed in addition to the ongoing National Integrated Power Project (NIPP) to participate in the generation of electricity in the country. It is expected that in line with the deregulation objectives, more participants in the generation sector will bring about the desired competition in the electricity market and improve electricity generation in the country.

The transmission sector remains regulated and managed by the Independent System Operator (ISO). ISO’s responsibility includes overseeing the market operations that involve the trading of the wholesale energy amongst market participants. The newly emerged transmission company from the unbundling of the PHCN is called the Transmission Company of Nigeria (TCN). TCN is responsible for guaranteeing the technical security and reliability of the interconnected power system, achieving the technical quality of the electrical power supply, and also, providing non-discriminatory access to the transmission system as stated in the electric EPSRA 2005. The competition level in the electricity markets is highly dependent upon the transmission system robustness, therefore, the government enters into a management contract agreement with an international electricity company to manage the Transmission Company of Nigeria on its behalf for an agreed period of time through a Memorandum of Understanding (MOU). There is also a core investors' sale (sale of equity) agreements between the Federal Government and the new distribution companies that provide for the DISCOs to manage the existing distribution network in the country. The eleven distribution companies are restricted to operate within specific geographical areas in the country. The distribution companies distribute electrical power to the consumers in their various operating areas.

The Nigerian Electricity Regulatory Commission (NERC) was inaugurated in 2005. Its establishment forms an integral part of the reform process. The responsibilities of NERC include: to regulate electricity tariffs and the quality of service rendered, to effectively oversee the power sector [22], and to monitor and discourage anti-competitive behavior among various participants, including mergers and acquisition which involves licensed electricity companies. NERC is also responsible for issuing licenses to the generating companies, transmission services, distribution companies, system operators, and trading companies as part of its many functions.

The national integrated power projects (NIPP) are gas turbine power stations located mostly in the southern parts of the country to harness the abundant natural gas in those areas. Owing to the relatively short duration of construction and installation of the equipment of the gas turbine power station (between 18-24 months) it is expected that approximately 5000 MW of electricity will be injected into the National grid to boost electricity generation and improve electricity supply to both domestic and industrial consumers [23]. This short-term solution is expected to meet the shortfall in supply, pending the completion of other medium and long-term power projects. The Nigerian Bulk Electricity Trading is a public liability company owned by the Federal Government of Nigeria. NBET (Bulk Trader) was established in 2010, in line with the "Roadmap for Power Sector Reform" for trading licenses, holding a bulk purchase and resale license, to engage in the purchase and resale of electrical power and ancillary services from independent power producers and from the successor generation companies [24].

2.4 Overview of Deregulated Electricity Model

The analysis of deregulated electricity markets globally shows that the method of reform differs in all the various countries that were studied. The varied market structure adopted by most of the countries is largely due to both economic and political reasons coupled with the prevailing domestic conditions. But, it can be observed that they all bear similarities of competitive electricity markets. The first among these similarities is the unbundling of the former electric utility company into generation, transmission and distribution services which are now managed and run by different companies thereby resulting in a deregulated electricity market. Also, the regulatory authority supervises and enforces strict regulation on market guidelines and operations. The regulator is empowered by law to impose sanctions and penalties on any erring participants and also settle all forms of dispute that may arise. Under the deregulated electricity market structure, the generation and distribution are competitive while the transmission remains monopoly but with an open access and non-discriminatory policy. The monopoly of the transmission is not unconnected with the associated huge cost of investment, and also due to both environmental and ecological factors. This means that all participants need to have equal and non-discriminatory network access without prejudice. In achieving the fairness of non-discriminatory network access to all market players, an Independent System Operator (ISO) is assigned with the responsibility of managing the grid. Some parts of the responsibilities entail: balancing the bids/offers submitted through an increase/decrease, calculating the available transfer capability (ATC) of the network, dispatch/re-dispatch and providing ancillary services for system balancing, etc. Another similarity in some of the developed deregulated electricity market is the issue of hedging the risk of contracts thereby causing electricity prices to fluctuate. The market participants can either directly obtain the contracts from ISO, or the regulator or participate in the trading of these contracts like any other commodity in a secondary market. The two basic forms of the market upon which others are developed from are the pool market and bilateral contract market. The bilateral market offers the producers and consumers the opportunity for direct negotiation of the quantity of energy trading and the price. All the participants' schedule will be submitted to the ISO requesting for approval to undertake a transaction, the ISO then carries out some network analysis in line with the volume of transaction submitted and if the network is considered suitable to accommodate the transaction without the network balance being threatened after which the ISO can now accept this schedule. Once the ISO now accepts the transaction, the ISO then requires the participants to share in the cost of network losses either by providing the necessary power or through payment. Also, the participants are billed by the ISO for using the network to carry out transactions. The pool market does not provide a direct link between the seller and the buyer, the ISO operates a day ahead bids/offers arrangements for the market participants where the generators and loads are economically dispatched so as to minimize cost. Most of the deregulated electricity markets always include both market in its daily operations [25]. Therefore, while a direct trading between seller and buyer is going on, the market participants can also simultaneously take part in the spot market where energy is traded as a pool market. It has been shown that the electricity markets that offer their participants the flexibility to make a choice between bilateral contracts and spot market have performed well.

In Figure 2.1 the deregulated electricity market is illustrated in its general form.

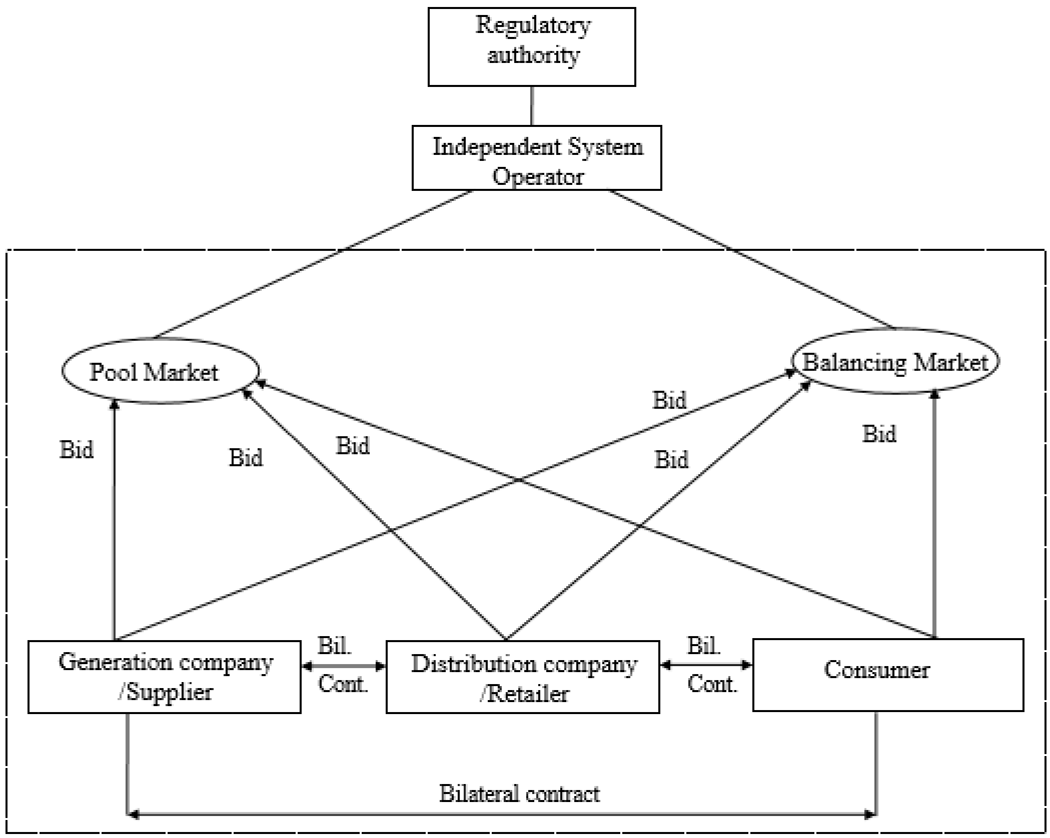

Figure 2.1: Deregulated Electricity Model **[26]**

2.5 Overview of Electricity Market Model

Economic efficiency is the major stated reason why governments have chosen to restructure and deregulate generation markets [27]. Electricity markets were developed as a way of enabling competition in electricity generation where competition had previously been seen as impossible. Electricity cannot be stored economically in large quantity and demand and supply must be matched at all parts of the system in real time. It had generally been accepted that a centrally planned and managed system was necessary to do this, but market mechanisms were developed in the 1980s, which promised significant improvements in the way electricity was generated and sold. It was shown at the time that such markets could achieve much higher levels of economic efficiency than the vertically integrated monopolies they replaced. Economic efficiency here refers to both short-term (static) and long-term (dynamic) efficiency. Short-term efficiency is maximized when at any time the system is using the lowest cost combination of plants to meet system demand and the lowest cost reserve is available to the system in the case of outages or changes in demand. Electricity markets provide this when they operate a transparent real-time auction, accepting generation offers from lowest to highest price until demand is met. Most buyers and sellers in electricity markets also seek the certainty and risk management benefits of electricity contracts across the market. But a transparent real-time market is essential to allow competition, transparent price setting and the basis for contract prices. During the day-ahead market, suppliers offer generation services, buyers submit bids for energy, and ISO procures ancillary services on behalf of buyers. These markets are then cleared through security constrained unit commitment auction, the resulting clearing prices are used for financial settlement [27] [28].

Long-term efficiency relates to the way in which the market develops over time. This includes providing timing signals for investment to enter the size and type of plant that the market requires and for the exit of older or higher cost plant that cannot compete with new and more efficient technology. Previously, the vertically integrated and centrally planned systems increased their capacity as they saw fit and passed on these costs to customers via regulated tariffs. The risk of the investment was passed on to customers rather than borne by the investor. Questions that are pertinent include: Do we have a transparent market that results in the economic (least cost) dispatch of the plant to meet demand at any time? Is the market price a good guide for long-term contract prices? Does the market encourage appropriate entry and exit of the plant? Who bears the risk of new entry?

To ensure power system security and reliability, ancillary services are needed, including frequency and voltage control and black-start capability. ISOs or their equivalent organizations purchase ancillary services from service providers. Frequency control ancillary services are commonly traded on a market that has marked similarities to the electricity market.

2.5.1 Competitive Markets

Market trading of electricity as a commodity can have significant consequences for customers. With open access, suppliers will target those customers with the most attractive load and profit profiles. It will, therefore, follow that market trading will lead to load disaggregation and potentially higher supply costs for residual customers. Market trading has also led to greater price volatility and an increased premium for risk. Therefore, a competitive market is a market whereby there are a number of producers and consumers with the ability to freely choose which producers they want to acquire services from. In the case of competitive electricity markets, generators (renewable and conventional), are producing electricity and consumers both large and small can freely choose their electricity service, provider.

The components of the typical competitive market are shown in Figure 2.2. It comprises of the generating companies (Genco), the independent power producers (IPP), the wholesale market, the retailer, and consumers.

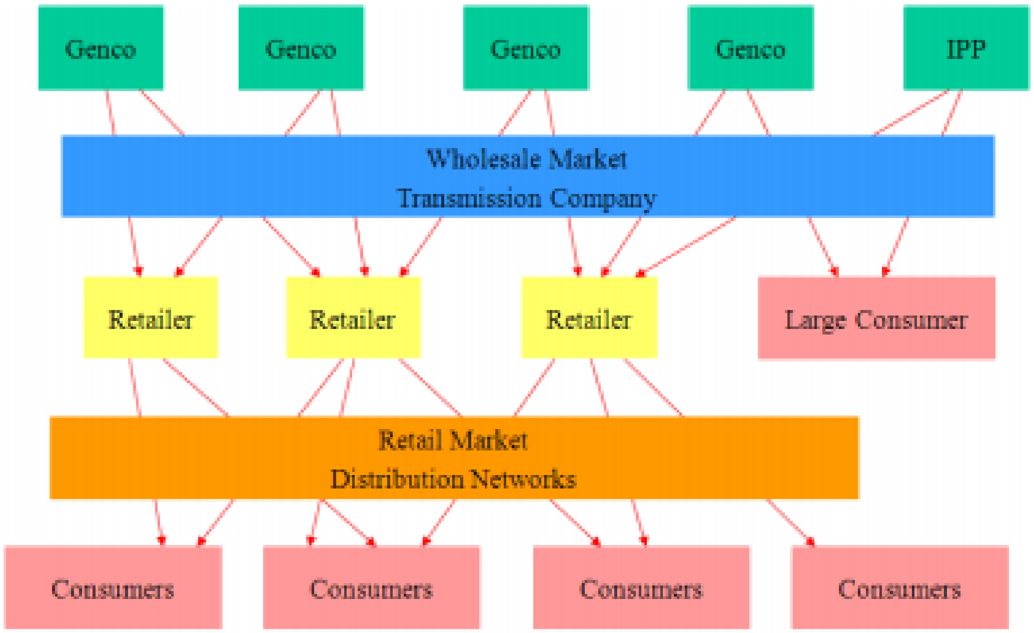

Figure 2.2: Competitive Electricity Model **[29]**

2.6 Renewable Energy in Deregulated Market: Experience of Other Countries

Many countries, such as Germany, Spain, France, UK, and the US have a significant proportion of renewable energy mix. Although the level of integration of renewable energy varies from one country to another, most of the experience of such integration in the individual deregulated electricity market is almost similar.

2.6.1 Impact of Wind Integration on Wholesale Market Clearing Price

It was found that the wholesale electricity spot prices in the UK would be significantly affected by the amount of wind generation in every hour, more especially if it relies significantly on the wind generators to meet a large share of its renewable energy target [30]. Mostly, an increase in the availability of wind generation usually results in a decrease in the wholesale market clearing prices mainly because the availability of the wind generation reduces the demand for thermal generation output [31] [32]. This is mostly because market clearing prices are proportional to the marginal costs of generation, with conventional generators having higher marginal costs compared to wind generators.

A lower market clearing price will reduce power prices for all consumers; therefore additional wind power can reduce the cost of electricity to a wide range of consumers. However, according to [33], it can be deduced that the federal tax credits and state renewable portfolio standard policies result in lower market clearing prices, it distorts wholesale power markets, displace generation from the base load power facilities, and unfairly impact the compensation received from existing generation assets.

Figure 2.3 illustrates how additional wind power within a competitive market might theoretically impact the electricity clearing for all generators.

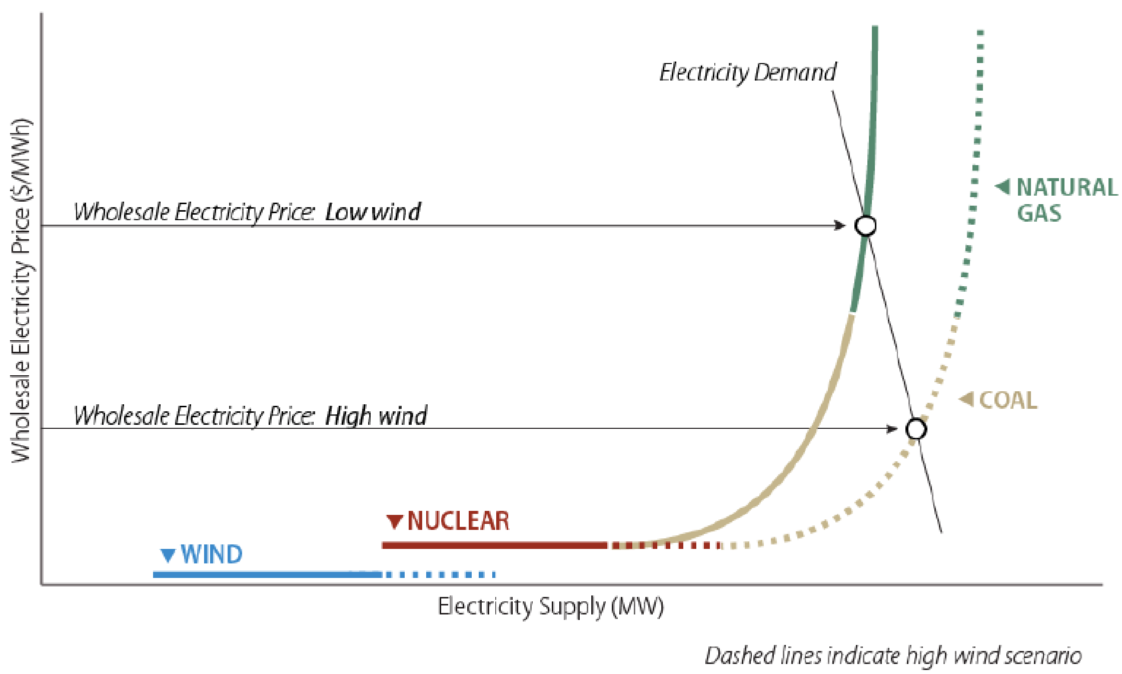

Figure 2.3: Illustration of Potential Wind Power Effects on Wholesale Electricity Prices **[34]**

Figure 2.3 shows two different scenarios of low and high wind availability. During the period of high wind, the wholesale electricity price curve shift to the right, thereby reducing the wholesale electricity price paid to both conventional and wind generators as against the price paid during the period of low wind availability.

2.6.2 Wind Power Contribution to Negative Wholesale Power Price

The negative pricing phenomenon occurs when the supply of electricity exceeds the demand. When this happened, the base load generators, like coal, prefer to stay running and pay to put their electricity on the grid by placing negative auctions, bids rather than take their generators offline and incur high ramping costs when demand goes back up. The cost of paying end users to consume their electricity is less than the ramping cost of restarting their turbines. But, considering the role of wind generation in the occurrence of negative prices, during the period of high wind power in-feed and low demand, the market reacts with bids underneath variable costs in order to avoid ramping-down baseload power plants, which are expensive to restart. Thus the likely impact of negative pricing on resource adequacy remains one of the most persistent issues related to variable renewable energy sources and competitive market design [35]. Negative wholesale power prices serve as a market indicator for extra requirements that target system flexibility.

2.7 Wind Energy Policy in Nigeria

The wind is a natural phenomenon related to the movement of air masses caused primarily by the differential solar heating of the earth's surface. Seasonal and locational variations in the energy received from the sun affect the strength and direction of the wind. The annual average wind speed in Nigeria at 10m heights varies from about 2 m/s in the coastal areas to about 4 m/s in the far north. At 50m, the range is 2m/s to 8m/s. It is possible to convert wind energy to rotary mechanical energy and electrical energy for a variety of uses. In view of the energy available in the wind, there is a need to embark on a wind energy development program in Nigeria. Wind energy is the energy contained in the movement of air in the form of the wind, which can be used to turn the blades of windmills or wind turbines, which in turn could drive electrical generators to produce electricity. Large modern wind turbines operate together in “wind farms” to produce electricity for utilities, while smaller ones can meet localized and smaller energy needs. Wind energy has few ecological and social drawbacks. The complaints about bird strike concerns that exist in many developing countries will probably not be deterrents to the development of the wind energy in Nigeria.

Wind energy policy in Nigeria includes the commercial development of the wind energy resource and to integrate wind energy with other energy resources into a balanced energy and electricity mix. Also, necessary measures shall be taken to ensure that this form of energy is harnessed at sustainable costs to both suppliers and consumers in the rural areas. The nation shall ensure the development of indigenous small-scale wind generating devices and energy storage devices.

The set objectives of the wind energy policies are the development of wind energy as an alternative renewable energy resource. To develop the local capability in the country with the wind energy technology and use wind energy for provision of power to rural and urban areas. The development of wind energy technology in areas where it is technically and economically feasible to feed into the grid.

The strategies for the realization of the wind energy policies and objectives are to encourage research and development in wind energy utilization and integration. It also includes the development of skilled manpower for the provision of basic engineering infrastructure for the local production of components and spare parts of wind power systems. Intensifying work in the wind data acquisition and development of wind maps and implement a web-based wind prospecting tool to encourage the implementation of wind projects and also by providing appropriate incentives to producers, developers, and consumers of wind power systems [36].

Chapter 3

Wind Energy Forecasting and Modelling

Among all the other forms of renewable technologies, the wind energy had found more integration into the grid than the others form of renewable sources. The availability of wind generation is mainly weather dependent, unlike the conventional generators whose availability is mainly due to mechanical availability. Wind generation intermittency and variability are the major difficulties encountered in power system mainly due to the inaccuracy in the forecasting of the expected energy generation from a particular wind farm. This is due to both the stochastic nature of wind and also the nonlinear wind speed to the electrical energy characteristic of a wind farm [37]. Therefore, advanced wind forecasting tools are necessary for the integration of wind generators into the power system. The location of wind farms affects the power generated from wind turbines and has an impact on the power grid. The assessment of the potential location is very important to the wind energy integration in power systems. The evaluation of wind farm depends mostly on the quality of the available wind, the mean wind speed and the economic and environmental factors.

The integration of wind farms and their power output into the grid affects the operation of the existing transmission systems. Therefore, a demand is placed by the grid operator on newly integrated wind power plants before connecting to the grid so that the transmission constraints are not violated. The grid operator could also set regional bounds on wind farms as a result of economic and geographical concerns.

Since the expected profit from a wind farm is the driving force for power plant investor, and the revenue from the wind farm is directly linked to the expected total generation. Therefore, for locations with strong wind speed, investors prefer to establish wind farm of substantial sizes in order to increase revenue.

The market operation, planning, and scheduling of generators, dispatch, and provision of the ancillary market all depend on the accuracy of the wind forecasting. If the wind prediction variation is much, then the error will affect planning, operations, price and market behavior in a competitive market. The market will experience distortion whose severity will depend on the degree of variation and the need for emergency backup from the ancillary market to cushion the effect of the variation at a relatively higher price.

3.1 Wind Modelling Techniques

The prevailing wind resource at a location varies continually with time and is dependent on seasonal variation. Availability of wind is very difficult to predict using all known weather parameters. This is partly due to the interactions between forcing mechanism such as the rotation of the earth, weather effect, and obstruction to the direction of wind flow, the topography of the earth's surface, hub height above the earth's surface, etc. [38].

For the purpose of siting a wind farm in a particular location, the information on the wind variation along with its influence on the power output of the wind energy conversion system is of great importance for optimal integration of the wind energy systems in the power network [39]. The adequate knowledge of the wind variation, wind direction, and wind turbulence are useful parameters to be considered for wind site selection and sizing. Prior to the development of a wind farm, large wind resource measurements are collected over an extended period of time at a proposed wind location. The wind measurements could be weather data consisting of the wind speed, wind direction, air temperature, atmospheric pressure, humidity, and gust readings. The wind speed measurement is then modeled using any of the established statistical techniques, from where wind speed distribution is obtained by determining the wind potential at that site. The analysis of the wind speed distribution obtained is often used in the wind energy industry for the evaluation of the wind resource potentials and for siting of wind energy conversion system (WECS) at different locations across the field [40] [41] [42]. Most common wind modeling techniques include the Weibull, Rayleigh, Gamma, Lognormal, Exponential, Beta, Log-logistic, Gaussian distribution function etc. [43] [44]. The Weibull function is one of the most widely used, and the standard technique for modeling of the wind speed measurement due to its wide range of versatility, flexibility, and it's useful for describing the wind variation at a site [45]. The inability to accurately model the wind using an accurate statistical function will result in large errors in the predictability of wind potential at a given site. The prediction errors in the wind speed distribution will invariably give rise to the wrong classification of the site's wind power which is a function of the wind power density [46]. The Rayleigh function is extensively used in modeling of the wind at a steady wind site for energy application. The Rayleigh distribution is a special case of the Weibull distribution which is found to typically represent the wind characteristics at some sites. The Gamma function, has found its applicability in the modeling of low wind speed site, as well as in multi-level Poisson regression modeling.

3.2 Wind Speed and Forecasting Techniques

The prediction of the future occurrence of an event could either be through the estimation of some model or site parameters which are believed to influence the future event or through an inferred study of patterns or historical measurement of wind farm measurement taken over an extended period of time. In recent years, several forecast models have been proposed and developed in the literature for the short to long-term wind speed predictions. The accuracy of each forecast model depends on the modeling techniques and also its intended area of applications. The several forecast techniques can be summarized into the following: persistence-based; physical-based; statistical based which include the time series and artificial neural network based; and hybrid-based technique.

3.2.1 Persistence-Based Technique

The persistence-based technique widely used in industries (such as wind energy, weather stations, local airport, government agencies, etc.) as a benchmark for performance comparisons with other developed forecast models. The used of the persistence-based is usually aimed at very-short-term wind predictions. The persistence-based technique is the simplest forecast model being used to predict the future power outputs based on the present or the immediate past wind power [47] [48]. This model is developed on a general assumption that the future wind speed-power will be the same as the recently measured wind speed power over a past time period *t*.

One merit of the persistent-based technique is its forecast skill when utilized in predictions ranging from very short-term to short-term time horizon (minutes to less than 6-hour forecasts). However, its performance, accuracy decreases with the increasing time horizon. As a result, the applicability of this forecast model in wind prediction is often considered for a very short to short-term time horizons because of its remarkable forecast accuracy when used in a discrete time step.

3.2.2 Physical -Based Technique

The physical-based technique also known as the numeric weather prediction (NWP) technique was first developed and implemented in the 1920s and was later modified in the 1950s for prediction of the future state of the atmosphere based on the present weather conditions at a location [49]

[50]. The NWP model was developed by meteorologists and widely accepted as the most accurate technique for long-term weather forecast [51] [52]. This model is based on the mathematical model that solves complex non-linear relationship of the present weather conditions to predict the future state of atmospheric conditions. The model uses information such as the mass of air, temperature, pressure, relative humidity, surface terrain information, air (wind) velocity etc. to produce the future meteorological information. Due to the complexity of this model in acquiring weather predictions in short time horizon, the computations (simulation programs) are run 1-2 times per day. Hence, this limits the use of NWP model for short-term weather forecasts. The short-term weather forecasts require the incorporation of an accurate digital elevation model to the NWP model to denote the pattern of the wind flow over the considered terrain structure [53]. For long-term weather forecasts, the accuracy of the prediction depends on the NWP model and it performs well if the raw weather conditions information over a relatively large area is known [54] [55].

3.2.3 Statistical -Based Technique

The statistical-based technique is the most widely used forecasting models for the prediction of future events based on historical events or measurement. The use of the statistical technique is aimed at predicting the availability of wind ranging between very short and short-term predictions. Unlike the physical based method that uses complex mathematical equations for its predictions, the statistical technique is based on the pattern recognition between historical measurements taken over an extended time period. This technique adopts the differences (errors) between the predicted and the real (actual) measurements to adjust its model parameters [56]. The statistical-based technique is grouped into the time series based and the artificial neural network.

3.2.3.1 Time Series Technique

The aim of the time series technique is for the development of a forecast model that can tune the forecast parameters such that the forecast error between the predicted and the actual values are small. The time series-best known as the conventional statistical technique is based on the auto-recursive algorithm. The time series technique is aimed at the prediction of future value based on historical measurements taken at successive time intervals. The forecast skills and accuracy of this technique, decrease with increasing time steps, especially when seasonal components exist in the time series. As a result, the time series model performs well using uniformly spaced time series as compared to its use with stochastic time series [57]. The various time series techniques which have been adopted in predictions of the time series data include the following: Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Exponential Smoothening (ES), Grey Predictor, and Kalman filters etc.

3.2.3.1.1 Moving Average (MA)

The moving average technique is the simplest and the most popular statistical technique used for prediction of a univariate time series. The moving average technique is considered as an accurate forecast tool for short-term prediction where there were no trends in the past time series (events). However, where trends are in past data, the use of MA technique will perform poorly because of the residual error in past data which is propagated into the future predictions. The MA model technique usually fits with the time series by replacing past measurement with an average of past data that moves by a forward time step.

If $P_1, P_2, P_3 \ldots\ldots P_m$ is the successive past power measurement at a successive time t; $\alpha_t, \alpha_{t-1}, \alpha_{t-2}, \ldots \alpha_{t-m}$ is the white noise errors at time $t, t-1, \ldots t-m$; $\theta_1, \theta_2, \ldots\ldots \theta_m$ is the moving average of parameters: the m^{th} order of the moving average with parameters $\varphi_1, \varphi_2, \ldots\ldots \varphi_m$ is defined as:

$$M_{ma}(m) = \mu + \alpha_t + \theta_1\alpha_{t-1} + \theta_2\alpha_{t-2} + \theta_3\alpha_{t-3} \ldots\ldots.. + \theta_m\alpha_{t-m} \tag{3.1}$$

$$= \alpha_t + \sum_{j=1}^{m} \theta_1\alpha_{(t-1)} \tag{3.2}$$

where $M_{ma}(m)$ is the moving average forecast for successive future events beyond time t, μ is the mean of the time series (often assumed to be zero).

The moving average technique is accurate for stationary time series data without cyclic or seasonal trend. Another disadvantage of the simple moving average model is that the forecast accuracy decreases when there is a strong trend in the historical time series data. But, in order to handle the problem associated with seasonal trend, the historical time series with the trend is transformed from the non-stationary time series into stationary series data by using modeling techniques such as differential transformation as well as the iterative non-linear fitting etc. This will enhance minimization of the forecast error which may occur when using the MA model for seasonal or non-stationary time series data.

3.2.3.1.2 Auto-Regressive (AR)

The autoregressive (AR) technique is another time series forecast technique which has been used for the modeling and prediction of time series based on its previous pattern or successive past data. The autoregressive technique is often described by a weighted sum of its previous values and the presence of white noise error.

If $P_1, P_2, P_3 \ldots\ldots P_m$ is the successive past power measurement at a successive time *t;* the autoregressive model of n^{th} order at which the model will go backward to predict the future value is defined as:

$$M_{ar}(n) = \varphi_1 P_{t-1} + \varphi_2 P_{t-2} + \varphi_3 P_{t-3} \ldots\ldots + \varphi_n P_{t-n} + \alpha_t \tag{3.3}$$

$$= \sum_{i=1}^{n} \varphi_i \, P_{t-i} + \alpha_t \tag{3.4}$$

where φ_i is the auto-regressive parameter, α_t is the white noise error, and $M_{ar}(n)$ is the auto-regressive forecasts for period beyond time *t.*

3.2.3.1.3 Auto-Regressive Moving Average (ARMA)

The Auto-Regressive Moving Average (ARMA) is a stationary time series model which is made up of the autoregressive and the moving average. The ARMA model is often used for the modeling of stationary time series, which takes into account the past event, forecast error, and the lagged term (random white noise) [58] [59].

The ARMA (n, m) order of the model is defined as the past time steps the model will go to predict the future value as illustrated by:

$$M_A(n, m) = \sum_{i=1}^{n} \varphi_i \, P_{t-1} + \alpha_t - \sum_{j=1}^{m} \theta_j \, \alpha_{t-j} \tag{3.5}$$

where φ_i is the auto-regressive parameter, α_t is the white noise error, θ_j is the moving average parameter, P_t is the past power value at a time *t*, *n* is the autoregressive order and *m* is the moving-average order. The ARMA technique is suitable for short term forecasts, but forecast accuracy drops with increasing time horizon (that is, the performance of the ARMA differs with time horizons). One advantage of the ARMA technique is its performance when utilized for short term forecasts, where the time series is stationary with no seasonal trends. For a non-stationary time series, the ARMA model performs poorly when used for forecasts of time series events.

3.2.3.1.4 Auto-Regressive Integrated Moving Average (ARIMA)

The Auto-Regressive Integrated Moving Average (ARIMA) is a time series technique used for the filtering of seasonal trends in non-stationary time series as compared with the ARMA which is used for modeling of the stationary time series. For non-stationary time series, the trend can be decomposed (by applying one or more differential transformation to the non-stationary data to achieve stationary time series). Thereafter, the ARMA model applies to the transformation, and this technique is defined as the ARIMA modeling [60].

3.2.3.1.5 Exponential Smoothening (ES)

Exponential smoothening (ES) is a technique used for cyclic and seasonal trend time series. This technique is often used for smoothing the irregularities or seasonal variation in a time series because the seasonal variation in the time series cannot be easily removed. The exponential smoothing technique is a weighted averaging forecast technique that is based on an unequal allocation of weights to time series with a smoothing constant. The use of the exponential smoothening technique is more complicated than the simple moving average (MA) technique because greater weights are given to the recent data while lesser weights are given to past data as compared to the equal weight allocation given to the past data in the MA technique. In addition, the weights allocated to the past data declines in an exponential manner with increasing forecast time (i.e. greater weight is given to the more recent forecasts and takes less consideration of the long past events or forecasts) [61]. With an unequal assignment of weights to the recent value, it is easier to adjust the noise or forecast errors in the past values or data to tune the ES model for future forecasts.

3.3 Time Scale Wind Prediction Techniques

The time step or an interval between the current and future values of a forecast model has been defined as the forecast time horizon. The future value of an unknown event can be predicted at different time horizons such as seconds to few minutes ahead, minutes to a few hours ahead, hours to 1-day ahead; one day to a week or more etc. Several forecast wind models have been proposed in the literature for prediction of wind speed and power output of a WECS at different locations over a wide range of forecast time. However, the accuracy of various forecast models considered differ with the quality of the available wind measurement, the atmospheric stability of the considered sites, forecast skills of the developed models, as well as its intended applications (such as electricity market bidding and clearing, economic load dispatch planning, operational security in day ahead marketing, maintenance scheduling and resource planning etc. In addition, the choice of a wind forecast model (such as the persistent-based, physical-based, statistical-based, ANN or the hybrid model etc.) depends on the intended forecast time horizons, as well as the computation speed requirement for acquisition of the forecast results.

3.3.1 Very Short-Term Forecasting

The very short-term forecasting has received a wide attention in deregulated electricity markets and trading applications. Often times, the very short-term forecast usually refers to as persistence-based technique because the forecast time ranges from a few seconds to 30-minutes ahead. The very short time wind forecasts are used in applications such as; electricity market settlements; regulatory actions such as in the response to a fault tackling, quick load changes in turbine control etc. [62]. The persistence-based technique, time series-based technique and hybrid technique (e.g. the ANN and fuzzy logic) are examples of the very short-term forecast models that have been utilized within this forecast time range.

3.3.2 Short-Term Forecasting

The short-term forecasting is based on the time series prediction ranging from 30 minutes to a day ahead. The short-term power forecast is useful for determining an incremental cost that a varying wind power generation can incur for power network instability. It is worth mentioning that the varying power generation at a given wind farm can change the scheduling of other power plants in order to stabilize the net imbalance between the wind farm outputs and the loads on the network. The short-term forecasts are useful in applications such as; the power system management (e.g. economic load dispatch decisions, unit commitment), security, purpose in day-ahead electricity trading, generator offline or online decisions etc [63].

3.3.3 Long-Term Forecasting

The long-term forecasts are usually based on the prediction of regional atmospheric patterns, ranging from 1 day to 1 week ahead. For this forecast horizon, a large meteorological data are required for developing the forecast model to produce an accurate forecast [64]. For wind power forecasts, the prediction is aimed at maintenance and planning of wind farm operations, conventional power plant decisions such as unit commitment and electricity markets, etc. In addition, the long-term power forecast is aimed at providing stability support to the power grid, especially during peak load demand.

3.4 Wind Resource Assessment

3.4.1 Mean Wind Speed

The mean wind speed is an important site parameter that is considered in the wind profile determination at any given site. The mean wind speed (MWS) is used to measure the wind potential at a known site for small-scale to large-scale energy project. The mean wind speed (m/s) at wind sites was obtained using the equation:

$$V = \frac{1}{N}\sum_{i}^{N} v_i \tag{3.6}$$

where v_i is the wind speed sampling at t^{th} time, and N is wind speed data points number.

3.4.2 Air Density Variation with Height(s)

The air density is a site parameter considered when measuring the wind potentials at a site. The air density at a site affects the operation and performance of the WECS. The wind power generation of the WECS is directly proportional to the air density at given height (h), as a function of the atmospheric pressure and air temperature. As the air temperature of 15 °C above the ground level, the density of dry air has a constantly approximated value of 1.225 kg/m3. The use of constant air density usually underestimates or overestimates the actual air density value at a wind site. Some of the mathematical models available for modeling of the prevailing air temperature and atmospheric pressure are discussed below:

(i) For a known air temperature and atmospheric pressure readings at a hub height *h*, the air density at the site can be obtained using:

$$\rho = \frac{P}{RT} \tag{3.7}$$

where ρ is the time varying air density (kg/m^3) at the site, P is the atmospheric pressure *(hPa.)*, and T is the air temperature (K) and R is the molar gas constant (287.05J/(K.mol.)).

(ii) When information about the atmospheric pressure and the air temperature readings of the wind site are unavailable, the air density can be determined using the experiential formula proposed [65]. The mathematical relationship that exists between the air density for a reference height h is defined as:

$$\rho(h) = 1.225e^{-0.001h} \tag{3.8}$$

where ρ(h) is the varied air density (kg/m^3) at the considered hub height (m) h. Thus, the determination of the wind profile at a new height h_2 is crucial because it influences the turbine performance at that height, as well as reduce the lifespan of the turbine rotor blades due to fatigue [66]. The hub height is related to the wind speed by the mathematical relationship below:

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1}\right)^{\alpha} \tag{3.9}$$

where v_1 is the reference wind speed at a 10 m hub height h_1; v_2 is the new wind speed at hub heights h_2; and α is the exponent which depends on the site surface roughness:

(iii) When the information about air temperature and atmospheric pressure readings of the sites are available, the moisture content in the air is taken into consideration.

The site's varying air densities at the considered hub heights were obtained using [67].

$$\rho(h) = \frac{P}{RT}e^{-(\frac{gh}{RT})} \tag{3.10}$$

where *ρ(h)* is the time varying air density as a function of hub height (kg/m³), *R* is the molar gas constant (287.05J/(K.mol.)), *P* is the atmospheric pressure (hPa.), *T* is the air temperature (K), *g* is the gravitational constant (9.81m/s²), and *h*, the height.

3.4.3 Wind Turbulence Intensity

High wind turbulence intensity often affects the performance of the energy output of the WECS, thereby causing great stress on the wind energy system components. The speed and direction of the wind flow often change rapidly while passing through the terrain surface or obstacles such as the vegetation, hills, trees, buildings, and mountains. The standard deviation of the wind speed is the most common indicator of the turbulence intensity of a site. The turbulence is defined as the rapid disturbances or irregularities in the flow of the wind speed and direction at any given site. In addition, the turbulence intensity is often defined as the ratio of wind speed standard deviation to the mean wind speed, typically measured over a time period *t*. Other reasons for high turbulence intensity at a windy location are due to the weather effects, as well as non-uniformity of the terrain surface which varies significantly from one wind site to another.

For this study, the wind turbulence intensity (T) at 10, 20 and 60 m hub heights is determined by using:

$$T = \left(\frac{v}{\delta}\right) \tag{3.11}$$

where δ is the standard deviation of wind speed and *v* is the wind speed.

Using the Maximum Likelihood Estimator (MLE), the standard deviation in terms of the sampled wind speed *(vi)* and the mean wind speed *(v)* is defined by:

$$\delta = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{1}(v_i - v)^2\right)} \tag{3.12}$$

where *N* is a number of wind data points, and δ is the standard deviation of the wind speed.

3.4.3.1 Shape and Scale Parameters

The statistical shape and scale parameters are crucial site parameters which are often considered in wind resource assessment at any given site. The estimated shape and scale parameters of the site are essential for the development of the statistical distribution model, as well as in the evaluation of the wind resources for wind energy project. The estimated values of shape and scale parameters are important for selection of a suitable site for wind farm development. The various shape and scale parameters available in wind resources assessment include the Weibull, Rayleigh, Gamma, lognormal and Inverse Gaussian.

3.4.3.1.1 Shape Parameter

The shape parameter of a given site is a dimensionless entity used in wind site assessment to denote the nature of prevailing wind. The shape parameter value of a given site is generally used to denote the nature of the prevailing wind such as gusty, moderate or steadier wind. A value of $k<1.50$ corresponds to a highly variable or gusty wind, $k = 2$ corresponds to a moderately gusty wind and $k=3$ indicates a regular and steadier wind.

There is a wide range of techniques available for estimation of the site shape parameter. The available estimation techniques for estimating the most widely used Weibull parameter are

Maximum Likelihood Estimator (MLE) [68] [69], Modified Maximum Likelihood Estimator (MMLE) [70], Method of Moments (MOM) [71] [72], Analytical or Standard Deviation Method [73] [74], Graphical Method (Least Square), Energy Pattern Factor etc. The Graphical Method (Least Square) is a technique used in engineering and mathematical problems for estimating the Weibull parameter when modeling an experimental data with a linear relationship. For time series data, the appropriate Weibull techniques often utilized for estimation are the standard deviation method and the MLE. The choices of the listed techniques are dependent mainly on its simplicity and accuracy. To use other estimation methods, the applications required the transformation of the time series wind speed data into bins or cumulative frequency distribution. When the wind speed data are available in time series format, the analytical method and the MLE can be applied for estimating the Weibull distribution for wind energy analysis. The analytical method has found its applicability in this study due to its simplicity and flexibility. However, the analytical technique does not give an accurate estimate of the Weibull parameter values when used for the different wind measurement. Rather, it gives an approximate value based on the standard deviation and means of the wind speed.

The shape parameter of a Weibull distribution function using the MLE is defined as:

$$k = \left(\frac{\sum_{i=1}^{N} \ln(v_i) v_i^k}{\sum_{i=1}^{N} v_i^k} - \frac{\sum_{i=1}^{N} \ln(v_i)}{N}\right)^{-1} \tag{3.13}$$

Where *k* is the Weibull shape parameter using an iterative procedure, *N* is the number of non-zero wind speed data points [75].

The shape parameter of a gamma distribution function is defined as:

$$k_g = \left(\frac{v^2}{\delta^2}\right) \tag{3.14}$$

where k_g, δ are the gamma shape parameter and the standard deviation

The shape parameter of the lognormal distribution k_l was estimated as:

$$k_l = \mu = ln\left(\frac{v^{-2}}{\sqrt{var + v^{-2}}}\right) \tag{3.15}$$

3.4.3.1.2 Scale Parameter

The scale parameter is used in wind resource assessment to denote the strength of the prevailing wind at a given site. The scale parameter of the Weibull distribution c was estimated using the MLE defined in Eqn. (3.16):

$$c = \left(\frac{\sum_{i=1}^{N} {v_i}^k}{N}\right)^{\frac{1}{k}} \tag{3.16}$$

where c is the scale parameter of the Weibull distribution, and k is the value of the Weibull shape parameter.

The scale parameter of the Rayleigh distribution c_r was estimated using the MLE defined as: [76]

$$c_r = \sqrt{\left(\frac{1}{2N}\sum_{i=1}^{N} v_i\right.^2\Bigg)} \tag{3.17}$$

where c_r is the scale parameter of the Rayleigh distribution and v_i is the wind speed observations at i^{th} time step(s).

The scale parameter of the Gamma distribution c_g was estimated as:

$$c_g = \left(\frac{\delta^2}{v}\right) \tag{3.18}$$

where c_g is the scale parameter of the Gamma distribution.

The scale parameter (sigma) of the lognormal distribution c_l was estimated as [77]

$$c_l = \sqrt{ln\left(1 + \frac{var}{v^2}\right)} \tag{3.19}$$

where c_l is the scale parameter of the lognormal distribution.

3.5 Statistical Modelling of the Wind Speed Measurement

The application of a statistical model to wind speed measurement is for the determination of a suitable model to be used for the wind energy evaluation at a potential site. The probability wind distributions are used to describe the distribution of the wind speed, as well as the period of time a particular wind speed v prevails at a site. The knowledge of the wind speed distribution at a site can be used to evaluate the performance of the WECS, as well as developing a site power curve model.

The predominantly statistical modeling techniques available in the wind resource assessment are the Weibull, Rayleigh, Gamma, Logistic, Exponential, Lognormal, distributions etc.

3.5.1 Weibull Distribution Function

The Weibull distribution is the most widely used statistical distribution which has found various applications in life data analysis; reliability engineering; partial discharge analysis and insulation aging; wind energy study; as well as in the modeling stochastic deterioration etc. [78] [79]. In the wind energy study, the Weibull model is the standard statistical function used among several statistical distribution functions for modeling of the wind speed at a given site. In the modeling of site wind speed using the Weibull distribution function, the wind speed variations are described by using its shape and scale parameters.

The Weibull cumulative distribution function (CDF) is defined by:

$$F_w(k,c) = 1 - exp\left[-\left(\frac{v}{c}\right)\right]^k \tag{3.20}$$

where F_w is the Weibull CDF, k and c, are the shape parameter and scale parameter respectively.

For Weibull 2-parameter distribution, the CDF is expressed as:

$$f_w(k,c) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{3.21}$$

where f_w is the Weibull PDF.

3.5.2 Rayleigh Distribution Function

The Rayleigh function is widely used in statistical distribution function, is defined by:

$$F_r(k,c) = 1 - exp\left[-\frac{v}{c}\right]^2 \tag{3.22}$$

where F_r is the CDF of the Rayleigh distribution, c is the Rayleigh scale parameter at k = 2.

If k = 2 put into Eqn. (3.22), the Rayleigh density function for a continuous wind distribution is defined by:

$$f_r(k,c) = \frac{2v}{c^2} exp\left[-\left(\frac{v}{c}\right)\right]^2 \tag{3.23}$$

where f_r is the Rayleigh pdf.

3.5.3 Gamma Distribution Function

The gamma distribution function has found its applicability in the low wind speed data and for Poisson regression modeling errors in multi-level. The PDF is given by:

$$f_g(k,c) = \frac{v^{k-1}}{c^{k\tau(k)}} exp\left[-\left(\frac{v}{c}\right)\right] \quad k,c > 0 \tag{3.24}$$

where f_g, k, c, are the probability density function, shape parameter and scale parameter of a Gamma distribution, respectively.

The cumulative distribution function of a Gamma distribution is defined as:

$$F_g(k,c) = \frac{1}{c^{k\tau(k)}} \int_{o}^{v} t^{k-1}\, exp\left(-\left(\frac{t}{c}\right)\right) dt \tag{3.25}$$

where F_g, $\tau(k)$ are the Gamma cumulative distribution and Gamma function of *(k)*, respectively.

3.6 Accuracy Tests of the Statistical Models

To determine whether the predicted wind distributions obtained as obtained in the statistical models were accurate for describing the wind speed prevalence at the wind farm, accuracy tests need to be conducted on the models. There are several testing techniques available for the validation of the accuracy of the predicted wind distribution obtained from the statistical models. They include the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Chi-Square Test, Correlation Coefficient (R), Coefficient of Determination (COD), mean square error (MSE), Standard Deviation of the Absolute Error (Std.) etc. The various tests for determining the accuracy of the statistical models are explained as:

3.6.1 Root Mean Square Error (RMSE)

The RMSE is used for comparison purposes between the predicted and the actual (measured) values the actual deviation. RMSE is also more advantageous than the mean absolute error in detecting extremely large errors because the mean absolute error is less sensitive to extreme values. RMSE is therefore obtained as follows:

$$RMSE = \left[\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}\right]^{\frac{1}{2}} \tag{3.26}$$

N is the number of wind speed data points. x_i is the i^{th} actual wind pdf; y_i is the i^{th} predicted wind distribution.

3.6.2 Chi-Square Test

It is used for testing purpose between the predicted and actual wind distribution. It can be applied to discrete distributions while others are restricted to a continuous distribution. It is defined mathematically as:

$$x^2 = \frac{\sum_{i=0}^{n}(y_i - x_i)^2}{N - n} \tag{3.27}$$

where x_i, y_i , and N are defined in Eqn. (3.26) n is the number of constant wind speed data.

3.6.3 Mean Average Error (MAE)

This is the average of all absolute error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x| \tag{3.28}$$

where n is the number of error and $|x_i - x|$ is the absolute error.

3.7 Estimation of the Wind Power Density

The available wind power moving across the rotor blade surface per unit swept area is defined by:

$$p = \frac{1}{2}\rho(h)v^3 \tag{3.29}$$

where v is the mean wind speed, $\rho(h)$ is the air density, and p is the power density.

The maximum power across the swept area is given mathematically as:

$$P_o = \frac{1}{2}\rho(h)Av^3 \tag{3.30}$$

where P_o is the maximum wind power and A is the swept area, $\rho(h)$ is the time varying air density.

The mechanical power of the WECS is defined by:

$$P_m = C_p\frac{1}{2}\rho(h)Av^3 \tag{3.31}$$

where P_m and C_p are the mechanical power and the rotor power coefficient respectively.

3.7.1 Actual Wind Power Density

The actual wind power density is given as:

$$P_A = \frac{1}{2}\rho(h)\int_0^{\infty} v^3\, f(v)dv \tag{3.32}$$

where $f(v)$ is the Weibull wind distributions and P_A is the wind power density.

3.8 Analysis of the Wind Energy Generation

Therefore the mechanical power of the WECS from Eqn. (3.31) is re-defined as:

$$P_m = C_p * \frac{1}{2}\rho(h)A\int_0^{\infty} v^3 f(v)dv \tag{3.33}$$

where P_m is the mechanical power, C_p is the rotor power coefficient , v is the wind speed, A is the swept area, $f(v)$ is the Weibull wind distributions, and $\rho(h)$ is the time varying air density. For accurate wind assessment, the information about the wind conditions on the site is determined and used to develop the site power curve.

The electrical outputs can then be estimated as:

$$P_s = C_p * \eta\frac{1}{2}\rho(h)A\int_0^{\infty} v^3\, f(v)dv \tag{3.34}$$

where P_s is the electrical power outputs of the WECS, C_p is the rotor power coefficient, $\rho(h)$ is the time varying air density, A is the swept area, $f(v)$ is the Weibull wind distributions, v is the wind speed, and η is the efficiency.

The energy outputs of the WECS based on the turbine power curve is given as:

$$E_s = N_h * C_p * \eta \frac{1}{2} \rho(h) A \int_0^\infty v^3 \, f(v) dv \tag{3.35}$$

where E_s is the energy of the WECS, N_h is the number of working hours of the WECS generating electric power, C_p is the rotor power coefficient, $\rho(h)$ is the time varying air density, A is the swept area, $f(v)$ is the Weibull wind distributions, v is the wind speed, and η is the efficiency.

Chapter 4

Economic Load Dispatch with Wind Energy

4.1 Overview of Economic Load Dispatch

The traditional Economic load dispatch (ELD) is an essential task in the regulated electricity market operation, ELD objective is to share power generation to equal load demand at minimal cost while meeting all the power units and system constraints [80]. But in a deregulated electricity market, each of the utility may have to contest with others so as to increase its own profits, while considering the non-utility generators, the renewable energy generators and other third-party transactions in the optimal scheduling problem [81]. The transactions in this market among utilities are based on price offers and submission of bids, and each utility uses the market prices for the scheduling of power transaction with others. The ELD operation becomes far more complex and difficult with the integration of variable wind energy generators. The volatility of this source and the output variation makes the optimal scheduling operation in a deregulated market with integrated wind energy a difficult task to achieve. A constrained optimization problem is formulated for the purpose of solving the optimal scheduling problem in the deregulated market. For economic dispatch studies, the online generators are characterized by functions that relate their costs of production to their power outputs. The quadratic cost functions are commonly used to model generator's cost for simplification of the mathematical formulation. The input-output of units is inherently non-linear with valve-point loading or ramp rate limits and having multiple local minimum points in the cost function. The ELD problem is traditionally solved using conventional mathematical techniques such as lambda iteration and gradient schemes. These approaches require that fuel cost curves should increase monotonically to obtain the global optimal solution. Also, different approaches such as linear programming and nonlinear programming have been applied to the economic load dispatch problem. The main drawback of linear programming methods is that they are associated with the piecewise linear cost approximation, although they are fast and reliable and the nonlinear programming approaches are complex [82].

But, with the advent of an evolutionary algorithm which are stochastic based optimization techniques that search for the solution of problems using a simplified model of the evolutionary process found in nature, this type of constrained optimization problems can easily be solved providing better results [83]. The success of evolutionary algorithms is partly due to their inherent capability of processing a population of potential solutions simultaneously, which allows them to perform an extensive exploration of the search space [80].

4.1.1 Problem Formulation

A. Objective function

Minimize the total fuel cost (or the total costs) of the whole power system:

$$min\sum_{i=1}^{N} f_1(P_{Gi}) = min\sum_{i=1}^{N}(a_i + b_iP_{Gi} + c_iP_{Gi}^2) \tag{4.1}$$

where a_i, b_i *and* c_i refer respectively to the cost coefficients of the consumption characteristics of the i-units and P_{Gi} refers to the output of the i-units where N is the number of connected generators. Note that, when the thermal generating unit changes its output, there is a nonlinear cost variation due to valve point effect. Typically, the valve point effect arises because of the ripple-like effect of the valve point as each steam begins to open. This is illustrated in Figure 4.1, the fuel cost of a thermal generating unit considering the nonlinear effect of the valve will be a nonlinear function as given in Eqn (4.2).

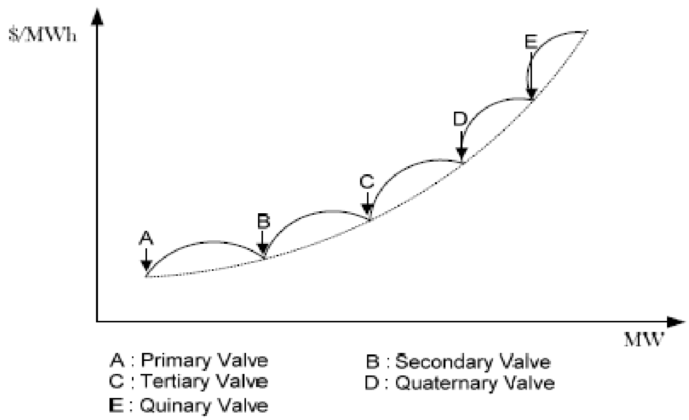

Figure 4.1: Valve Point Effect **[84]**

$$min\sum_{i=1}^{N} f_1(P_{Gi}) = min\sum_{i=1}^{N}[(a_i + b_iP_{Gi} + c_iP_{Gi}^2) + \left|e_i \sin(f_i\left(P_{Gi}^{min} - P_{Gi}\right))\right|] \qquad (4.2)$$

Where e_i and f_i are cost coefficients.

The transmission loss can be calculated using the B loss coefficient method as:

$$P_L = \sum_{i}^{n}\sum_{j}^{n} B_{ij}P_iP_j \qquad (4.3)$$

where P_L is the power loss and B_{ij} is the B loss matrix.

B. Wind Power Output

The estimated sum of the electrical power output of all the connected wind farms can be calculated from the Eqn. (4.4) as:

$$P_s = \sum_{j=1}^{m} P_{wj} \tag{4.4}$$

where m is the number of connected wind generators and P_{wj} is the power output of the wind turbines. Neglecting the maintenance and other associated costs, it is assumed that the marginal cost of the wind power plant is zero since the wind is free.

C. Constraints

a. Power balance constraint

$$\sum_{i=1}^{N} P_{Gi} + \sum_{j=1}^{m} P_{wj} - P_D - P_L = 0 \tag{4.5}$$

where P_D is the power demand

b. Inequality constraint considering generation unit capacity

$$P_{Gimin} \leq P_{Gi} \leq P_{Gimax}$$

$$Q_{Gimin} \leq Q_{Gi} \leq Q_{Gimax}$$

$$P_{wj} \leq P_{wj}^{max}$$

$$Q_{wt}^{min} \leq Q_{wt} \leq Q_{wt}^{max}$$

$$V_i^{min} \leq V_i \leq V_i^{max}$$

4.2 Overview of Optimization Problems

“Almost every problem in engineering, science, economics, and life can be formulated as an optimization or a search problem. While some of the problems can be simple and can be easily solved by traditional optimization methods (i.e., Gradient descent, Simplex Methods, and Response surface Methods) which are based on mathematical analysis, most of the problems are very hard to solve using analysis-based approaches [85]. *Nevertheless, these hard optimization problems can be solved by inspirations from nature, since nature is known as a system of vast complexity and it always generates a near-optimum solution. Natural computing is concerned with computing inspired by nature, as well as with computations taking place in nature. The most common examples of natural computing are an evolutionary computation, neural computation, cellular automata, swarm intelligence, molecular computing, quantum computation, artificial immune systems, and membrane computing* [86]. *Together, they all made up the computational intelligence field. Among the nature-inspired computational field, evolutionary computation is the most influential* [87]. *It is a computational method for obtaining the best possible solutions in a huge solution space based on Darwin’s survival-of-the-fittest principle. Evolutionary algorithms are a class of effective global optimization techniques for many hard problems. More and more biologically inspired methods have been proposed in the past two decades* [88]. *The most prominent ones are particle swarm optimization (PSO), ant colony optimization (ACO), and immune algorithm (IA). These methods are widely used due to their particular features compared with other evolutionary computation techniques. All these biologically inspired methods are population-based. Computation is performed by autonomous agents, and these agents exchange information by social behaviors. The algorithm models the behavior of knowledge propagation of*

animals [89]. *There are also many other nature-inspired metaheuristics for search and optimization. Metaheuristics algorithms are a class of intelligent, self-learning algorithms for finding near-optimum solutions to hard optimization problems, mimicking intelligent processes and behaviors observed from nature, sociology, thinking, and other disciplines. Metaheuristics may be nature-inspired paradigms, stochastic, or probabilistic algorithms. Metaheuristics-based search and optimization are widely used for fully automated decision-making and problem-solving. While each metaheuristics-based method has its specific strength for particular cases, it was actually the same performance as that of random search in consideration of the entire set of search and optimization problems* [89].*"*

4.2.1 Gradient Descent Optimization

"The most intuitive methods of this class rely on an accurate estimate of the local gradient and proceeding in the steepest direction. Depending on the nature of the problem either minimization or maximization, the method is called ''steepest descent'' or ''steepest ascent'', respectively [90]. *The simplest naive form is to assess the quality of neighboring points and, if there are better points, to proceed towards the best of these. Then, new neighboring points are evaluated and this process continues until there is no neighbor better than the current point. The other starting points lead to (sometimes even quite bad) local optima. Each optimum has its own basin of attraction, indicating that any steepest descent search starting from a point within that basin will end up at that particular basin. This, of course, is the definition of a local search method* [91]. *In some cases, especially those where the landscape being searched looks like a long, narrow valley (in the case of minimization), steepest descent does very poorly. Unless the valley is approached at a perfect right-angle, it takes many small steps to reach the optimum. The more sophisticated conjugate*

gradient (CG) methods determine the new direction based not solely on the current gradient, but on old gradients as well [92]. *This leads to a much better search behavior. The inclusion of the second derivative (the Hessian matrix) is often used in curve-fit problems or nonlinear least squares routines. The quantity that is minimized must follow an x^2 distribution, which is often the case with errors from a fit* [93]. *Calculation of the Hessian is possible precisely because of the assumption of the x^2 distribution. The standard method, which combines the steepest descent and Hessian approaches, is the Marquardt–Levenberg method, using the former far from the optimum and the latter in the neighborhood of the optimum* [85].*"*

4.2.2 Evolutionary Algorithms

"Evolutionary Algorithms are stochastic based optimization techniques that search for the solution of problems using a simplified model of the evolutionary process found in nature [84]. *These algorithms provide an alternative for obtaining global optimal solutions, especially in the presence of non-continuous, non-convex, and highly nonlinear solution spaces. The success of evolutionary algorithms is partly due to their inherent capability of processing a population of potential solutions simultaneously, which allows them to perform an extensive exploration of the search space* [94].*"* Examples include Genetic Algorithm (GA), Differential Evolution (DE), Evolutionary Systems (ES) and Evolutionary programming (EP) etc.

4.2.3 Genetic Algorithm

Genetic Algorithm searches a solution space for optimal solutions to a problem. The key characteristic of GA is how the searching is done. The algorithm creates a "population" of possible solutions to the problem and lets them "evolve" over multiple generations to find better and better solutions [95].

"The simplest form of the genetic algorithm involves three types of operators: selection, crossover (single point), and mutation. The selection operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce. The crossover operator randomly chooses a locus and exchanges the subsequences before and after that locus between two chromosomes to create two offspring [96]. *For example, the strings 10000100 and 11111111 could be crossed over after the third locus in each to produce the two offspring 10011111 and 11100100. The crossover operator roughly mimics biological recombination between two single−chromosome (haploid) organisms. Also, the Mutation operator randomly flips some of the bits in a chromosome. For example, the string 00000100 might be mutated in its second position to yield 01000100. A mutation can occur at each bit position in a string with some probability, usually very small (e.g., 0.001)* [97]*."*

The following steps were used to solve a problem using GA:

1. Create a population of random candidate solution named *pop*.
2. Until the algorithm termination conditions are met, do the following (each iteration is called a generation):
    a. Create an empty population named *new-pop.*
    b. While *new-pop* is not full, do the following:
        i. Select two individuals at random from *pop* so that individuals who are more fit are more likely to be selected.
        ii. Crossover the two individuals to produce two new individuals.
    c. Let each individual in *new-pop* has a random chance to mutate.
    d. Replace *pop* with *new-pop.*
3. Select the individual from *pop* with the highest fitness as the solution to the problem.

The population is a collection of candidate solutions that are considered during the course of the algorithm. Over the generations of the algorithm, new and often “good” members are “born” into the population, while older and “bad” members “die” out of the population. A single solution in the population is referred to as an individual. The fitness of an individual is a measure of how “good” the solution represented by the individuals. The selection process is analogous to the survival of the fittest in the natural world. Individuals are selected for crossover based upon their fitness. The fitter the individual the more likely the individual will be able to reproduce and survive to the next generation. The crossover occurs by mingling the solutions together to produce two new individuals. During each generation, there is a small chance for each individual to mutate, which will change the individual in some small ways.

The real value coding was used for the Genetic Algorithm in this work. But, in choosing the algorithm operator and parameters, there is a need for a balance between the convergence reliability and convergence velocity. The GA main operations include:

1. Population

The algorithm creates a population of possible solutions to the problem and lets them evolve over multiple generations to find better and better solutions.

2. Fitness

In this work, an attempt was made to minimize the building energy use and therefore, the lower the energy use, the higher the fitness of an individual selection. In achieving the fitness, the solutions are ranked in order of the “best” to the “worst”.

3. Selection

The selection operator is used to select solutions from the current population that will be used to form the next population of solutions. In this work, a convergence with a few building simulations as possible is used (that is, reliable convergence with a high convergence velocity). The tournament operator randomly selects n-solutions from the population, the winner solutions, which have a better ranking, out of the tournament are carried forward for recombination.

4. Crossover

The recombination operator controls the mixing of “genetic information” selected from paired individuals through a process known as “crossover” (each individual in the pair resulting from a separate tournament selection). It takes place by swapping bit values between the two individuals. The “uniform crossover” operator was used in this thesis, each pair of bits is swapped with a 50% probability (an average of 50% of the bits will be swapped).

5. Mutation

The mutation operation primarily maintains diversity from one generation to the next. This operator assists the GA to produce a better solution. The uniform mutation type was used in this thesis to replace the value of the gene with a uniform random value. The upper and lower bounds for the gene is user-specified.

6. Elitism

In order to guarantee that the search is able to continue until the specified number of simulations is reached; the search is automatically re-initialized if the population collapses onto a single solution.

7. Termination

The GA was stopped after a fixed number of algorithm iterations (generations). Since the recombination and mutation operators are probabilistic; it is possible that a selected solution is simply copied from one generation to the next (this also occurs for the "elite" individual).

4.2.4 Differential Evolution Algorithm

"Differential Evolution (DE) is a heuristic evolutionary method for solving constrained optimization problems. DE is a powerful algorithm that improves the population of individuals over several generations through the operators of mutation, crossover, and selection [98]. *Differential Evolution offers great convergence characteristics and requires few control parameters which remains fixed throughout the solution process and requires minimal tuning. Unlike most of the other meta-heuristic techniques such as GAs and evolutionary strategies where perturbation occurs in accordance with a random quantity. DE make use of weighted differences between solution vectors to perturb the population. DE combines simple arithmetical operators with the classical operators of recombination, mutation, and selection to evolve from a randomly generated starting population to a final solution* [98]. *At every generation G during the optimization process, DE maintains a population P^G of NP vectors of candidate solutions to the problem at hand.*

$$P^G = \left[X_1^G, \dots \dots X_i^G, \dots \dots, X_{NP}^G\right] \tag{4.6}$$

Each candidate solution X_i is a D- dimensional vector, containing as many integers –valued parameters as the problem decision parameters D.

$$X_1^G = \left[X_{1,i}^G, \ldots, X_{j,i}^G, \ldots \ldots X_{D,i}^G\right], \quad i=1,\ldots\ldots NP \quad (4.7)$$

$$J=1,\ldots\ldots,D$$

There are several strategies to be employed for optimization. This chosen strategy starts by defining and evaluating the initial population through calculating the fitness value of each individual. After which, until the condition set for termination is not reached, then the necessary individuals are picked, and a new one is produced according to the selected DE scheme. This individual is evaluated and compared with the previous old one, and only the one with the best fitness value will be chosen among the others and passed for the population of the next generation.

Step 1: Parameter setup

The user chooses the parameters of population size, the necessary boundary constraints of optimization variables, and the mutation factor (F), the crossover rate (CR) and the stopping criterion of a maximum number of generations (G_{max}).

Step 2: Initialization

Set generation G=0. Initialize a population of NP individuals with random values generated according to a uniform probability distribution in the D-dimensional problem space. These initial values are chosen randomly within the user-defined bounds.

$$x_{j,i}^{G=0} = x_j^{min} + rand_j[0,1]\left(x_j^{max} - x_j^{min}\right) \quad (4.8)$$

where, i=1,….,NP and j=1,…., D. $x_{j,i}^{G=0}$ *is the initial value (G=0) of the j^th parameter of the i^th individual vector.* x_j^{min} *and* x_j^{max} *are the lower and upper bounds of the j^th decision parameter, respectively. The corresponding fitness value of each vector is evaluated and stored.*

Step 3: Mutation operation

The mutation operation in DE (DE/rand/1) is achieved by adding a weighted difference vector between two selected individuals to the third individual. The mutation strategy perturbs the best vector of the current population by a single difference of two other randomly selected vectors (X_{r1} *and* X_{r2}*). For each target vector, a mutant vector (*V_i^G*) is produced using the formula:*

$$V_i^G = X_{r1}^G + F(X_{r2}^G - X_{r3}^G) \tag{4.9}$$

where X_{r1}^G *is the current generation. Vector indices* r_2 *and* r_3 *are randomly chosen with* r_2 *and* $r_3 \in \{1\ldots NP\}$ *and* $r_2 \neq r_3 \neq i$*. F is a user-defined constant called mutation factor, which is typically chosen from within the range [0, 1].*

Step 4: Crossover operation

The main purpose of this operation is to increase the diversity of the population. The crossover operation creates a trial vector (U_i*) by mixing the parameters of the mutant (*V_j*) with the target vectors (*X_i*) according to a selected probability distribution.*

$$U_i^G = \begin{cases} V_i^G, if rand_j(0,1) \leq CR \text{ } or \text{ } j = Rnbr(i) \\ X_i^G, otherwise \end{cases} \tag{4.10}$$

The crossover constant CR is a user-defined value, which is usually selected from within the range [0, 1]. $rand_j$ *is the trial parameter with randomly chosen index* ϵ *[0, 1]. Rnbr (i) is the trial parameter with randomly chosen index {1… D}, which ensures that the trial vector gets at least one parameter from the mutant vector.*

Step5: Selection operation

The selection operator is applied in the last stage of the DE procedure. The selection operator chooses the vector which is going to compose the population in the next generation. This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that then allowed to advance into the next generation. The selection process may be outlined as:

$$X_i^{G+1} = \begin{cases} U_i^G, iff\left(U_i^G\right) \leq f\left(X_i^G\right) \\ X_{best}^G, otherwise \end{cases} \tag{4.11}$$

where f is the function to be minimized.

The strength of DE's approach is that it is robust and often displays better results than GA and other evolutionary algorithms. It can also be applied to varieties of real-valued problems despite noisy, multimodal, multidimensional spaces, which usually makes the problems very difficult for optimization. In DE the parameter CR and F do not require the same fine tuning which is necessary for other evolutionary algorithms."

4.2.5 Self-Adaptive Differential Evolution (SADE)

"A learning strategy adaptation schemes were introduced into the original DE algorithm and a SADE was developed. The SADE algorithm can automatically adapt the learning strategies and the settings of parameters during evolution [99]. *To achieve good performance for a particular problem by using the original DE algorithm, all the available learning strategies must be tested in the mutation phase and also fine-tune the corresponding critical control parameters CR, F, and NP. The performance of the original DE algorithm is highly dependent on the strategies and parameter settings. Even when the most suitable strategy and the corresponding control parameters for a specific problem are found, it may still require a huge amount of computation time* [100]. *Also, during different evolution stages, different strategies and different parameter settings with different global and local search capabilities might be preferred* [99]. *Therefore, the SADE algorithm was developed that can automatically adapt the learning strategies and the parameter settings during evolution. The SADE does not require the choice of a certain learning strategy and the setting of specific values to critical control parameters CR and F. The learning strategy and control parameter CR, which are highly dependent on the problem's characteristic and complexity, are self-adapted by using the previous learning experience* [101]. *Therefore, the SADE algorithm can demonstrate consistently good performance on problems with different properties, such as unimodal and multimodal problems."*

The strategy *"rand/1/bin/"* was used to change the control parameters *F* and *CR* during the simulation. The *NP* control parameter did not change during the run, but each individual in the population was extended with parameter values. The adjusted *F* and *CR* were applied at individual levels where the better values of the encoded parameters lead to better individuals with better chances of survival and likelihood of producing better offspring.

The new control parameters $F_{i,G+1}$ and $CR_{i,G+1}$ were calculated as follows:

$$F_{i,G+1} = \begin{cases} F_i + rand_1 * F_u & if\ rand_2 < \tau_1 \\ F_{i,G} & otherwise, \end{cases} \tag{4.12}$$

$$CR_{i,G+1} = \begin{cases} rand_3 & if\ rand_4 < \tau_2 \\ CR_{i,G} & otherwise. \end{cases} \tag{4.13}$$

The control parameters *F* and *CR* are produced in a new vector. $rand_j,\ j \in \{1, 2, 3, 4\}$ are uniform random values that fall within the range [0, 1]. τ_1 *and* τ_2 are the probabilities to adjust the control parameters *F* and *CR* respectively. τ_1, τ_2, F_i and F_u have values 0.1,0.1,0.1 and 0.9 respectively. The new *F* takes a value from [0.1, 1.0] and the new CR from [0, 1] in a random manner.

Chapter 5

Simulation Results and Discussions

5.1 Introduction

An evaluation of the potential of wind generation in six selected northern cities of Nigeria namely: Jos, Maiduguri, Katsina, Kano, Bauchi, and Kaduna was carried out at 10m height.

The calculation of the parameters was done using MATLAB R (2015a) and Microsoft Excel spreadsheet (2013). The Nigerian Meteorological Agency (NIMET), provided the data for the simulations.

Nigeria is geographically divided into the Northern and Southern parts. Wind speed is generally weak in the southern part with the exception of the offshore and coastal regions. The offshore region includes Lagos, Ondo, Delta and Rivers State. The other locations in this region have a low wind speed and are generally unsuitable for the development of the wind energy for commercial quantities. The Northern region experience very strong wind mostly in the hilly parts and this made the region suitable for the siting of wind farms for generation of electricity in commercial quantities [102]. Hence, the studies of wind assessment and resource of six selected cities, namely: Jos, Kano, Kaduna, Bauchi, Katsina, and Maiduguri were carried out for the purpose of wind farm development in Nigeria.

A 30 year (1980-2010) historical wind data were obtained and analyzed. The selected sites property are as follows: Kaduna (Latitude-10.1590$°N$, Longitude-8.1339$°E$, Altitude- 626m), Bauchi (Latitude-10.637$°N$, Longitude-10.0807$°E$, Altitude- 616m), Katsina (Latitude-

$12.5139°N$, Longitude-$7.6114°E$, Altitude- 519m), Kano (Latitude-$12.0022°N$, Longitude-$8.5920°E$, Altitude- 484m), Maiduguri (Latitude-$11.8311°N$, Longitude-$13.1510°E$, Altitude- 325m) and Jos (Latitude-$9.8965°N$, Longitude-$8.8583°E$, Altitude- 1290m).

The cup-generator anemometer located at each sites MIMET's stations were used to capture the wind-speed data on the height of 10m at a sample time of wind speed measurement of 10minutes for the different locations considered. The Weibull distribution function is used in this thesis because of its acceptability and suitability for wind energy potential assessment.

The monthly mean wind speed values were computed and shown in Table 5.1 and graphically in Figure 5.1 and 5.2 respectively. Figure 5.3 shows the annual mean wind speed. Jos has the highest mean wind value of 9.63m/s in the year with Maiduguri having the lowest mean wind value of 2.21m/s for the year

Table 5.1: Monthly mean wind Speed (m/s) at 10m Height

	January	February	March	April	May	June	July	August	September	October	November	December
Jos	9.32	9.43	9.14	9.12	9.21	8.83	8.92	8.35	7.43	7.83	8.53	9.63
Kano	7.88	8.43	7.92	8.62	9.16	9.17	8.33	7.11	6.83	6.42	6.66	7.73
Kaduna	6.83	6.48	5.78	5.43	5.46	5.54	5.19	4.73	3.81	3.42	4.92	6.13
Katsina	8.87	7.84	6.64	7.63	8.94	9.94	8.87	7.01	6.42	5.52	5.4	6.95
Bauchi	5.17	5.72	5.51	7.08	5.32	4.29	4.21	4.26	3.89	4.11	4.45	4.34
Maiduguri	2.61	2.93	3.41	3.42	3.82	3.93	3.36	3.53	2.21	2.33	2.21	2.24

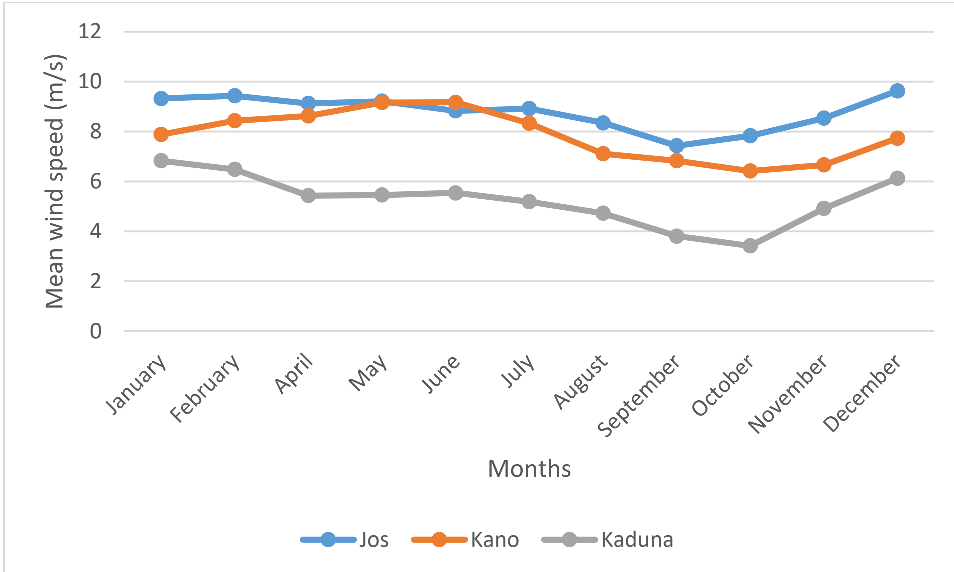

Figure 5.1: Monthly Mean Wind Speed for Jos, Kano, and Kaduna at 10m Height

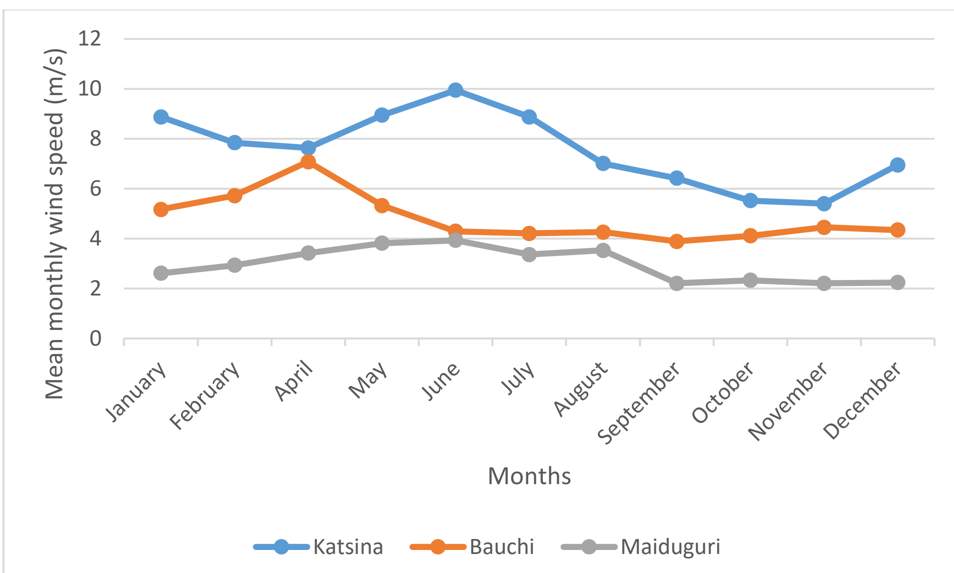

Figure 5.2: Monthly Mean Wind Speed for Katsina, Bauchi, and Maiduguri at 10m Height

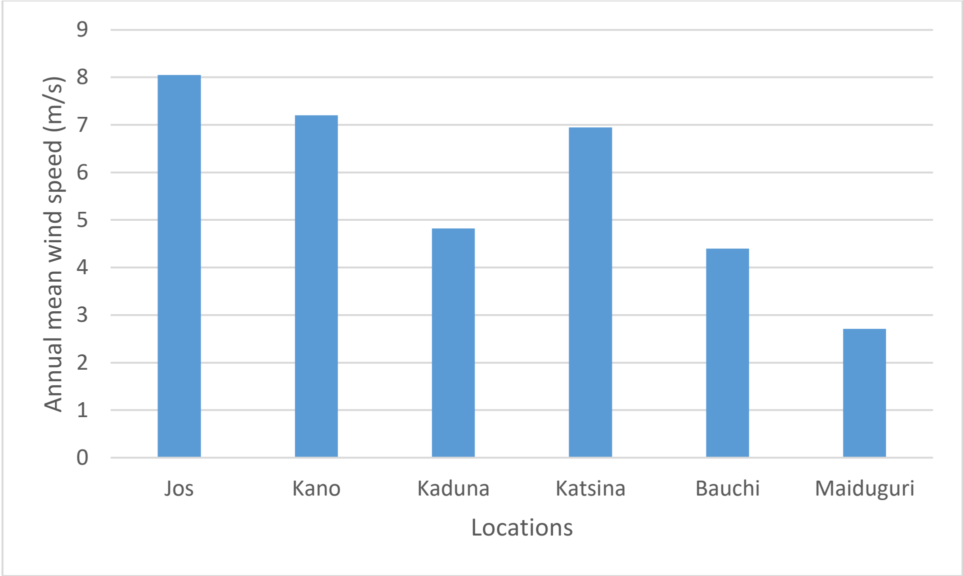

Figure 5.3: Annual Mean Wind Speed.at 10m Height

Table 5.2 shows the computation of the value of k and c of the Weibull parameters at 10m height. The power densities and average mean power were computed as shown in Table 5.3. Jos has the highest power density of 602.79W/m^2 with the mean energy of 447.62kWh in January with Kaduna has the lowest power density of 25.68W/m^2 and mean energy of 20.21kWh in October. According to the international wind power classification [103], it can be established that wind resource in Jos, Kano, and Katsina fall into class 7 ($400 < PD < 1000$) while Bauchi, Kaduna and Maiduguri fall into class 3 ($150 < PD < 200$). In view of the different categorization of the various locations as shown, Jos, Kano and Katsina are thus right for the development of wind energy. Also, Maiduguri, Kaduna and Bauchi are suitable for the development of marginal wind power projects.

Table 5.2: Computation of Weibull Parameters (k and c) at 10m Height

	Jos		Kano		Kaduna		Bauchi		Katsina		Maiduguri	
	k	c	k	c	k	c	k	c	k	c	k	c
January	4.24	9.85	2.09	8.6	5.89	7.26	2.86	5.69	4.14	9.73	7.88	2.74
February	3.91	9.68	2.97	8.95	4.29	6.97	2.49	6.23	2.89	8.36	4.47	3.26
March	4.51	8.31	3.12	8.6	3.87	6.2	2.14	6.15	3.47	7.12	6.11	3.57
April	6.22	9.35	5.17	9.03	6.52	5.72	2.84	7.72	5.13	8.22	10.46	3.49
May	6.72	10.6	5.1	9.76	6.3	5.73	2.95	5.81	5.72	9.42	7.03	3.96
June	5.33	9.67	3.87	9.86	8.54	2.76	2.47	4.67	5.12	10.48	7.47	4.04
July	5.42	9.73	4.12	9.37	8.22	5.35	2.49	4.52	4.31	9.66	7.34	3.49
August	6.04	8.48	3.76	7.5	6.02	5.06	2.38	4.75	4.72	6.59	1.12	3.68
September	5.16	7.91	4.27	7.2	6.04	4.12	2.32	4.45	2.43	6.52	3.13	2.32
October	4.68	7.16	4.64	6.4	5.31	3.59	2.11	4.52	3.64	6.25	2.12	2.54
November	5.31	6.16	3.42	7.11	5.13	5.29	2.06	4.86	4.47	5.62	5.39	2.32
December	7.43	5.84	3.92	7.89	6.09	6.38	1.91	4.82	3.47	7.64	4.27	2.43

Table 5.3: Power Densities (W/m^2) and Average Energies (kWh/month) at 10m Height

	Jos		Kano		Kaduna		Bauchi		Katsina		Maiduguri	
	PD	AVE	PD	AVE	PD	AVE	PD	AVE	PD	AVE	PD	AVE
January	602.79	447.62	410.25	305.43	209.64	156.24	114.23	84.21	561.45	417.35	98.25	75.54
February	542.63	364.8	476.92	322.63	193.47	129.48	158.16	108.54	384.02	256.94	158.36	105.05
March	483.45	362.35	384.63	287.64	142.57	105.64	147.34	128.24	223.78	163.78	169.89	127.47
April	536.47	386.24	406.41	293.78	101.47	73.84	130.34	112.34	305.65	221.39	138.23	103.64
May	473.25	352.73	513.68	381.48	100.73	77.46	89.32	64.12	476.29	360.47	145.87	107.58
June	428.66	309.85	572.62	411.32	101.47	73.49	70.45	50.33	653.2	468.72	171.56	122.21
July	422.12	313.4	415.76	309.48	85.72	63.98	69.58	51.32	500.72	371.86	152.64	111.65
August	370.32	275.94	263.75	198.24	66.4	50.24	71.4	53.25	228.72	169.92	74.56	54.58
September	258.52	187.32	222.18	160.32	38.01	26.87	60.21	45.2	183.14	128.73	62.58	45.26
October	322.24	238.45	178.76	133.63	25.68	20.21	71.51	52.19	166.76	121.03	71.49	53.64
November	461.72	332.39	221.39	160.34	80.42	57.71	114.13	82.87	105.72	76.45	104.58	74.25
December	576.42	431.38	326.12	242.32	140.93	106.45	98.54	74.58	268.15	195.82	80.25	59.54

The computation of *k* and *c* Weibull distribution parameters for the locations was extended to 30m and 60m height respectively as shown in Tables 5.4 and 5.5 respectively. The calculation of the Weibull parameters for these new heights was achieved by direct application of the Eqn. (3.9) in chapter 3.

Table 5.4: Computation of Weibull Parameters (k and c) at 30m Height

	Jos		Kano		Kaduna		Bauchi		Katsina		Maiduguri	
	k	c	k	c	k	c	k	c	k	c	k	c
January	4.39	12.31	3.24	12.64	3.62	9.38	3.15	7.38	3.65	11.86	2.92	7.08
February	4.21	11.23	3.32	12.35	5.13	9.12	2.79	8.42	3.42	10.87	2.64	7.32
March	5.48	10.45	3.64	11.89	7.24	8.32	2.47	8.12	5.73	9.45	3.39	7.63
April	4.32	10.13	5.72	12.21	4.12	7.65	3.21	9.87	6.42	10.24	4.67	7.84
May	5.52	11.41	5.75	11.69	8.21	7.61	3.47	7.85	5.83	11.62	3.82	8.15
June	5.74	12.59	4.73	11.39	6.10	7.27	2.63	6.32	4.69	12.34	2.89	7.92
July	4.21	12.32	4.45	11.64	7.33	7.34	2.59	6.04	4.79	11.94	3.16	7.75
August	5.31	10.31	4.38	10.78	7.42	6.75	2.43	6.17	5.34	9.02	3.08	6.67
September	5.32	9.42	4.69	9.72	5.21	5.43	2.12	6.43	4.57	8.85	3.14	5.78
October	4.62	9.89	5.62	10.94	5.13	5.04	2.03	6.04	5.04	7.59	2.34	5.87
November	5.23	9.08	3.64	11.16	5.07	6.92	2.05	6.62	3.72	7.62	2.56	6.21
December	5.12	9.22	4.82	12.32	5.52	8.34	2.58	6.53	3.54	9.72	2.36	5.78

Table 5.5: Computation of Weibull Parameters (k and c) at 60m Height

	Jos		Kano		Kaduna		Bauchi		Katsina		Maiduguri	
	k	c	k	c	k	c	k	c	k	c	k	c
January	5.21	13.11	3.32	13.17	4.12	10.65	3.24	8.71	3.71	12.81	2.81	8.24
February	5.38	12.22	3.24	13.34	5.54	10.34	3.04	9.23	3.35	12.11	2.97	8.72
March	5.84	12.34	3.71	13.56	7.45	9.24	2.62	9.21	4.16	10.65	3.21	8.92
April	4.72	11.89	6.42	13.17	4.62	8.68	3.51	11.12	6.17	11.37	4.12	8.74
May	5.31	11.40	5.78	12.84	8.64	8.29	3.52	8.72	6.82	13.32	3.53	9.24
June	5.76	10.52	4.56	12.32	6.21	8.96	3.03	7.31	6.15	14.54	2.72	9.32
July	5.76	11.42	4.64	12.36	8.48	8.25	2.91	7.22	5.30	13.25	3.42	9.45
August	5..34	12.59	4.79	11.28	7.12	7.32	2.82	7.32	5.62	10.78	3.15	8.72
September	5.28	10.56	5.76	11.71	5.26	6.45	2.13	7.41	5.33	10.23	3.32	7.62
October	4.62	12.36	3.89	11.71	5.31	5.48	2.31	6.72	5.43	9.13	3.06	6.45
November	5.63	10.35	4.12	13.12	4.62	8.62	2.21	7.23	4.03	8.74	2.43	6.72
December	5.71	9.45	4.84	13.69	5.32	9.51	2.36	7.41	4.62	11.32	2.62	7.32

Figures 5.4-5.15 show the changes of the power density (PD) and the average energy (AVE) throughout the year for the locations. It can be established that a reduction in the wind availability or strength affects the power density and the average energy. The power density varies proportionately to the average mean of the particular location. It increases or decreases depending on the wind strength and makes the electrical power output calculation to be wind dependent. It

can be seen that Jos has the highest monthly wind power density in the month of January and the lowest in the month of September. The same is applicable to the average energy. Kano's highest mean power density occurs in the month of June with the lowest average energy in the month of October thereby corresponding to its lowest mean power density and average energy respectively. The same relationship also exists between the mean power density and the average energy for the Katsina, Bauchi, Kaduna, and Maiduguri.

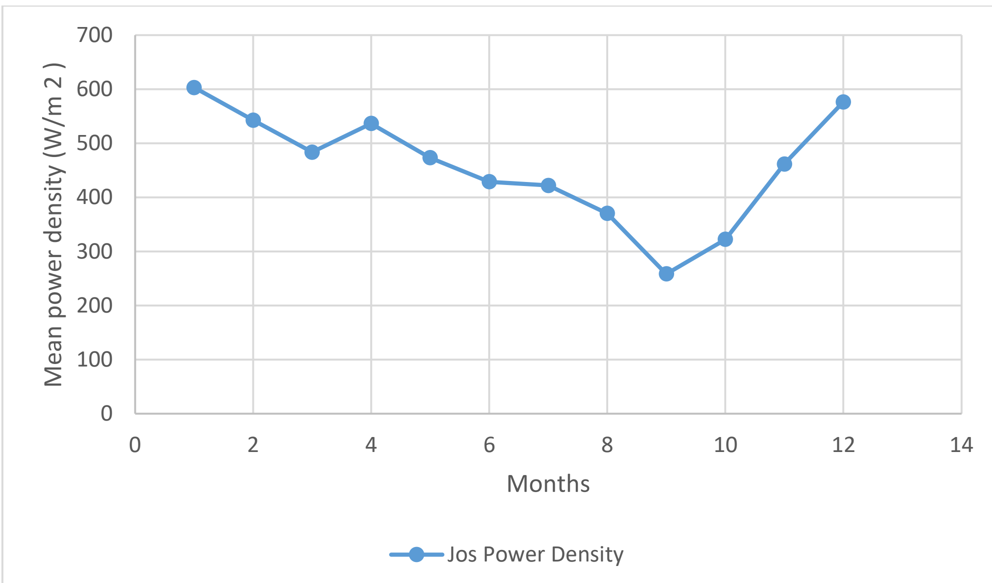

Figure 5.4: Mean Wind Power Density for Jos at 10m Height

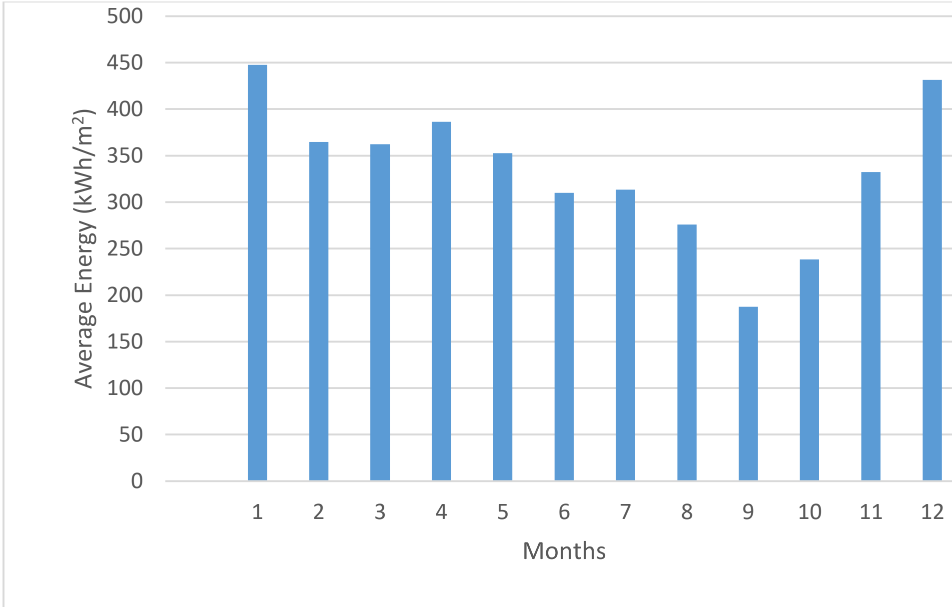

Figure 5.5: Mean Energy for Jos at 10m Height

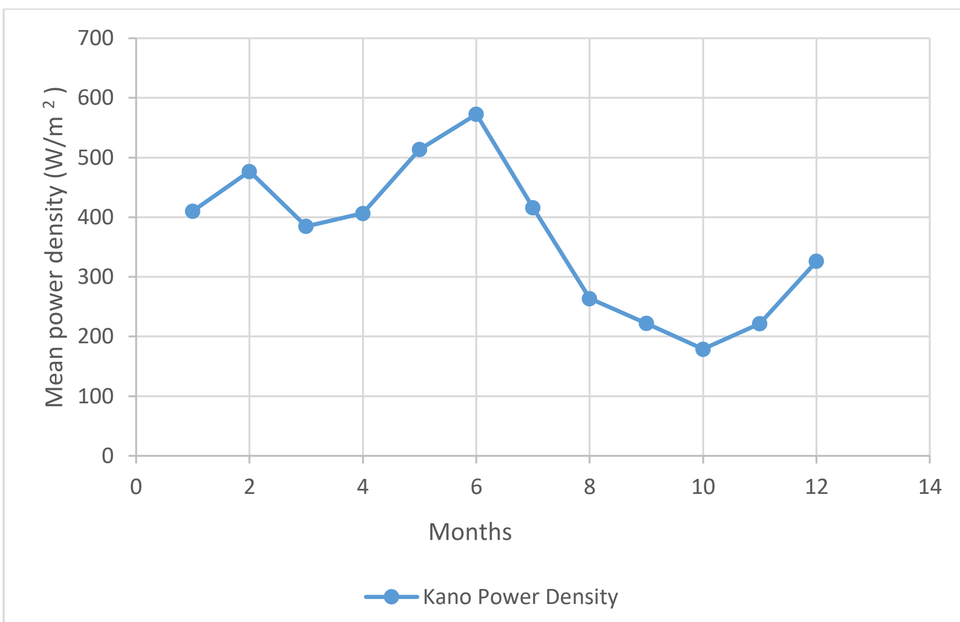

Figure 5.6: Mean Wind Power Density for Kano at 10m Height

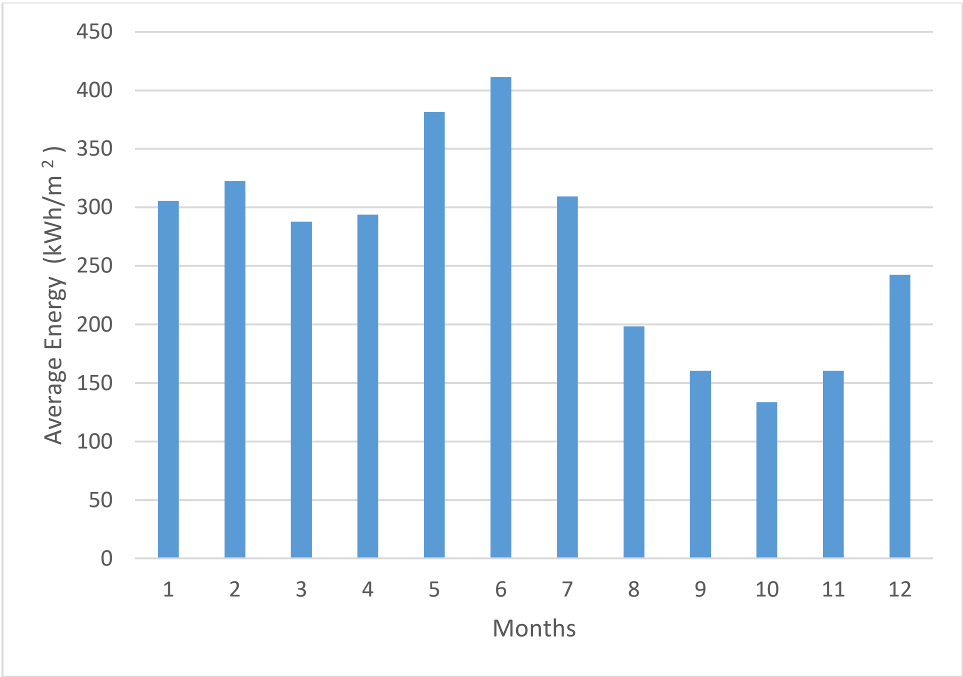

Figure 5.7: Mean Energy for Kano at 10m Height

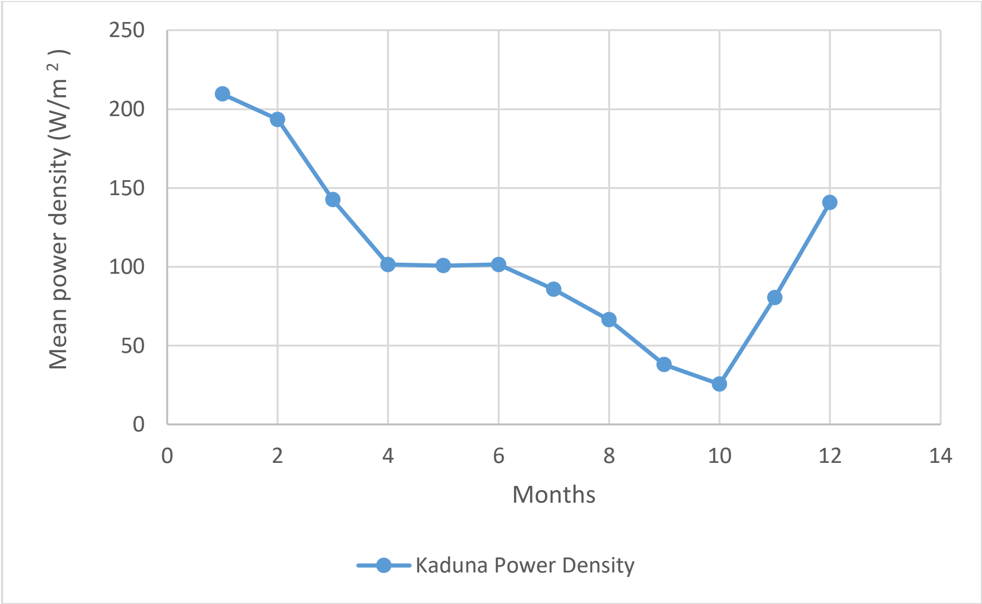

Figure 5.8: Mean Wind Power Density for Kaduna at10m Height

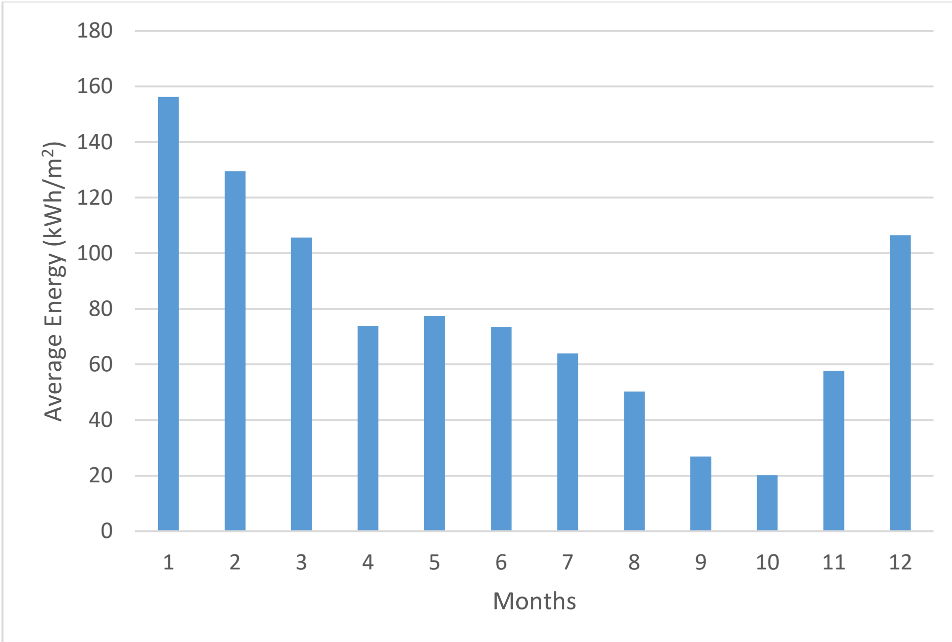

Figure 5.9: Mean Energy for Kaduna at 10m Height

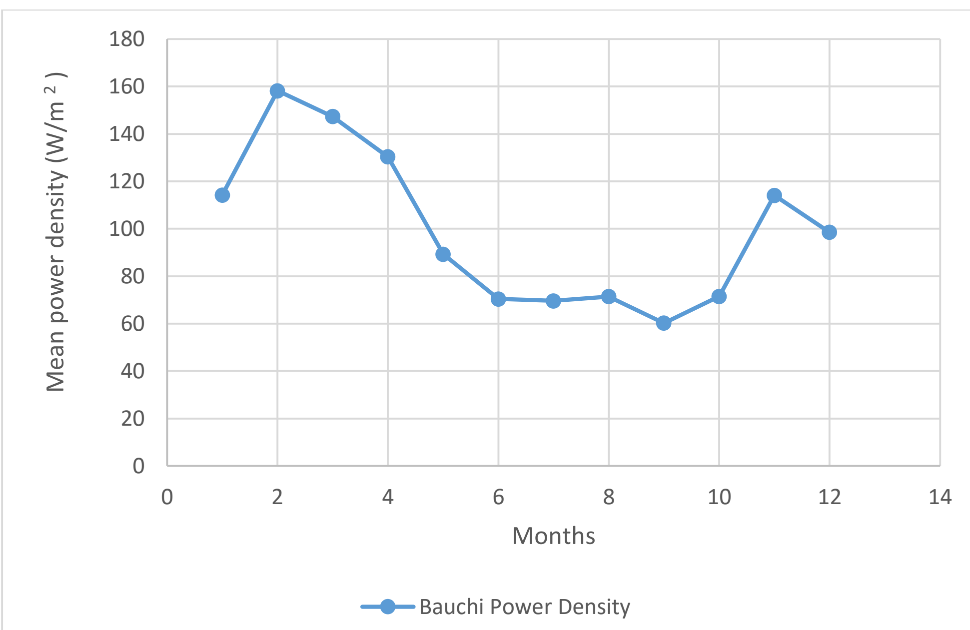

Figure 5.10: Mean Wind Power Density for Bauchi at 10m Height

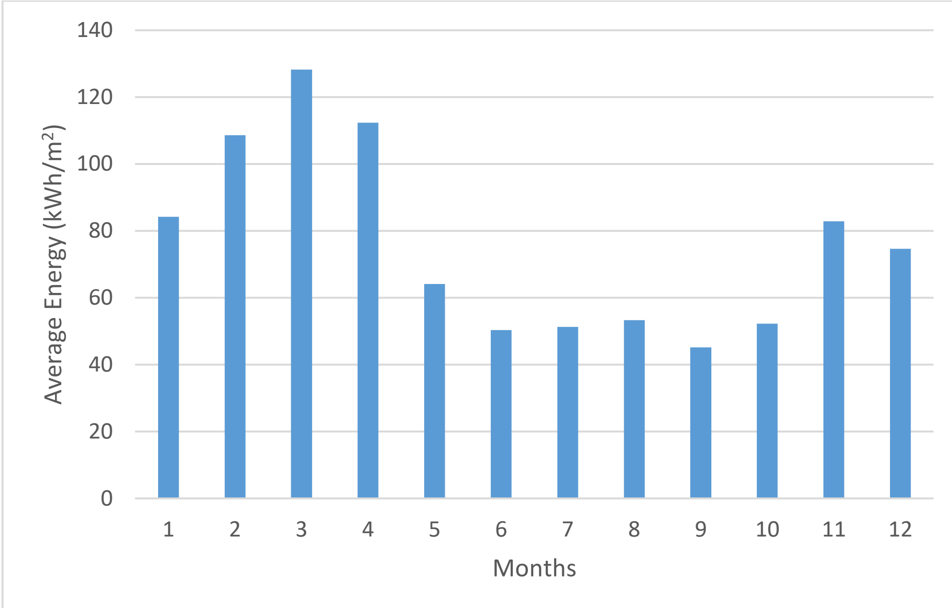

Figure 5.11: Mean Energy for Bauchi at 10m Height

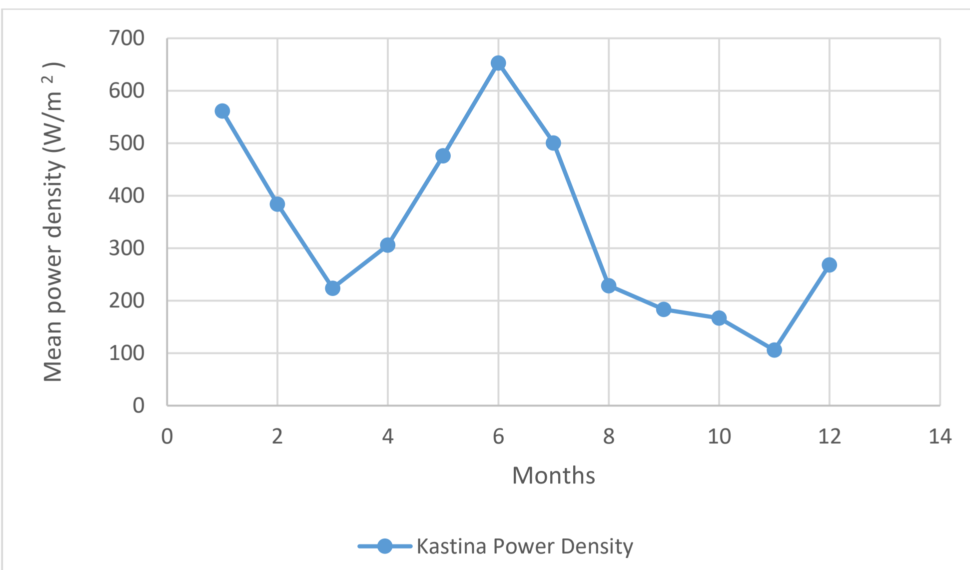

Figure 5.12: Mean Wind Power Density for Katsina at 10m Height

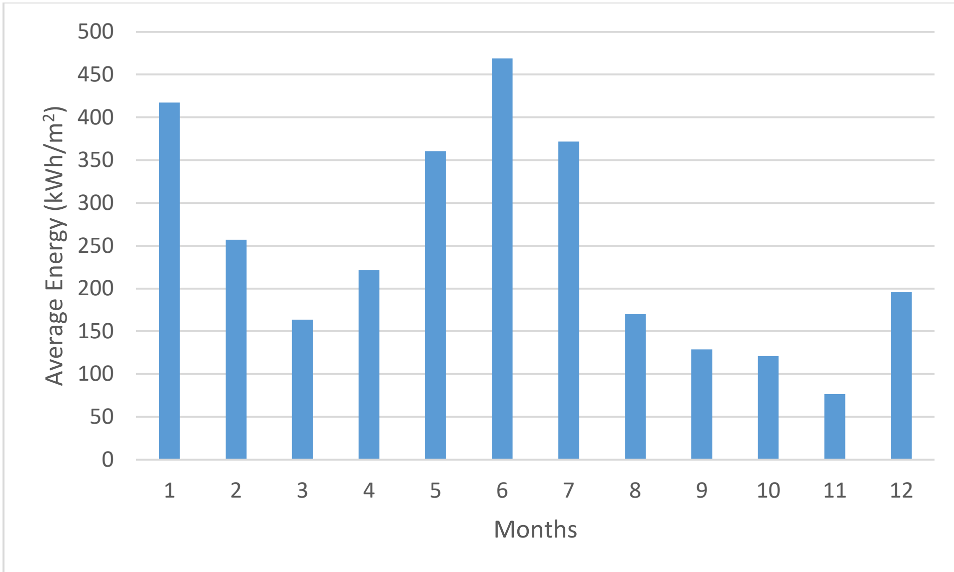

Figure 5.13: Mean Energy for Katsina at 10m Height

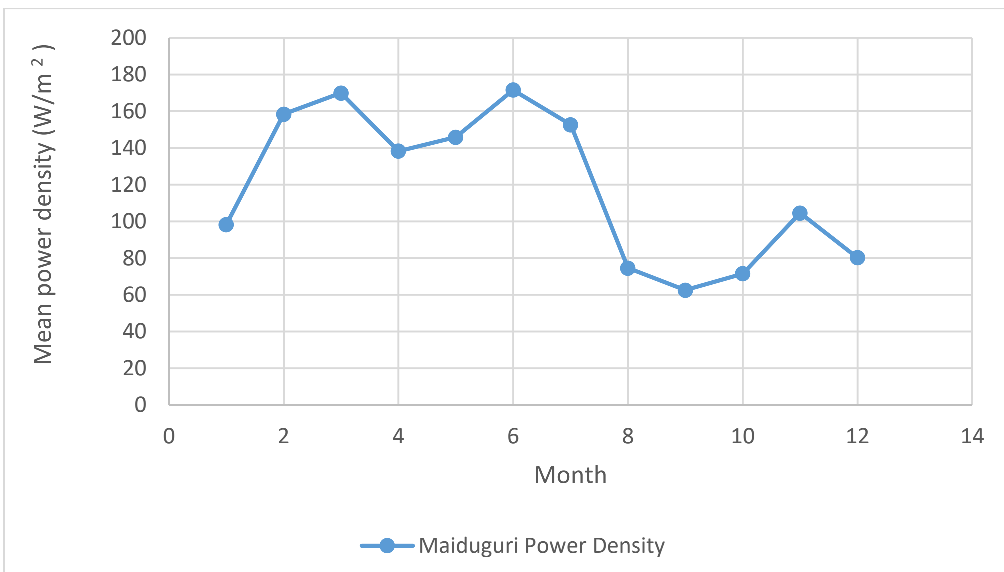

Figure 5.14: Mean Wind Power Density for Maiduguri at 10m Height

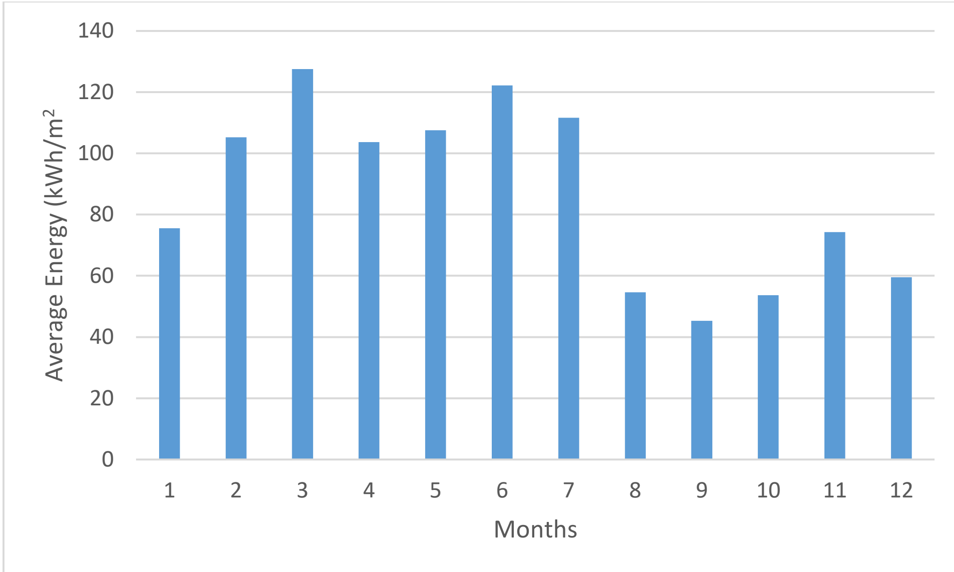

Figure 5.15: Mean Energy for Maiduguri at 10m Height

5.2 Wind Energy Forecast Error of the Selected Locations

The RMSE, MAE, and Chi-square are statistical methods used for the validation of the accuracy of the predicted wind distribution for the selected locations across the country. The validation process was carried out at 10m, 30m and 60 m height respectively. The month of July 2010 was chosen for all the locations for the purpose of the statistical analysis. The results for the different methods of MAE, Chi and RMSE for the heights 10m, 30m and 60m respectively were computed by the comparison of the results from the models with real measurement. The results obtained are presented in Tables 5.6 to 5.11.

Table 5.6: Weekly Forecast Error (m/s) for Jos in the Month of July 2010

WEEK	**Jos**								
	10 m			**30 m**			**60 m**		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	0.34E-5	0.42E-5	7.42E-3	6.34E-5	7.16E-5	4.71E-3	0.23E-4	0.45E-5	1.36E-3
2ND	0.51E-5	0.64E-5	7.56E-3	6.78E-5	7.32E-5	4.78E-3	0.25E-4	0.37E-5	1.33E-3
3RD	0.31E-5	0.45E-5	7.54E-3	6.23E-5	7.27E-5	4.22E-3	0.26E-5	0.41E-5	1.42E-3
4TH	0.46E-5	0.56E-5	7.76E-3	6.46E-5	7.53E-4	4.67E-3	0.28E-5	0.43E-5	1.38E-3
5TH	0.41E-5	0.43E-5	7.38E-3	5.76E-5	6.38E-5	4.89E-3	0.21E-5	0.23E-5	1.17E-3

Table 5.7: Weekly Forecast Error (m/s) for Katsina in the Month of July 2010

	Katsina								
	10 m			**30 m**			**60 m**		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	1.73E-5	2.43E-5	3.28E-3	0.49E-5	0.87E-5	2.16E-3	5.56E-5	7.76E-5	6.23E-3
2ND	2.46E-5	5.23E-5	4.34E-3	0.72E-5	1.43E-5	2.34E-3	6.45E-5	6.72E-5	6.45E-3
3RD	1.43E-5	2.17E-5	3.14E-3	0.35E-5	0.85E-5	2.67E-3	4.39E-5	5.65E-5	5.37E-3
4TH	1.36E-5	2.34E-5	3.45E-3	0.61E-5	1.23E-4	2.68E-3	5.58E-5	7.21E-5	6.53E-3
5TH	3.94E-5	6.58E-5	6.78E-3	0.66E-5	1.48E-5	2.34E-3	6.56E-5	1.08E-4	7.67E-3

Table 5.8: Weekly Forecast Error (m/s) for Kaduna in the Month of July 2010

WEEK	**Kaduna**								
	10 m			**30 m**			**60 m**		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	0.64E-5	2.37E-5	3.45E-3	0.52E-5	0.92E-5	3.13E-3	5.93E-5	6.73E-5	4.17E-3
2ND	1.34E-5	2.43E-5	4.34.E-3	0.81E-5	1.36E-5	2.85E-3	4.59E-5	8.17E-5	3.76E-3
3RD	2.46E-5	3.23E-5	3.10E-3	0.54E-5	1.99E-5	2.25E-3	4.35E-5	4.91E-5	2.33E-3
4TH	1.45E-5	4.56E-5	3.27E-3	0.63E-5	1.16E-4	4.57E-3	6.56E-5	6.68E-5	4.25E-3
5TH	1.36E-5	3.37E-5	6.27E-3	0.74E-5	1.23E-5	2.64E-3	8.27E-5	3.09E-4	6.54E-3

Table 5.9: Weekly Forecast Error (m/s) for Kano in the Month of July 2010

WEEK	Kano								
	10 m			30 m			60 m		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	1.31E-5	1.56E-5	2.45E-3	0.25E-5	0.27E-5	3.45E-3	4.93E-5	7.73E-5	4.58E-3
2ND	0.36E-5	3.34E-5	4.34E-3	0.67E-5	1.63E-5	2.96E-3	6.59E-5	9.17E-5	5.31E-3
3RD	0.73E-5	2.15E-5	2.10E-3	0.41E-5	1.17E-5	2.86E-3	4.35E-5	5.91E-5	4.78E-3
4TH	1.56E-5	2.34E-5	1.27E-3	0.37E-5	1.43E-4	2.56E-3	5.56E-5	7.68E-5	6.81E-3
5TH	2.76E-5	3.54E-5	5.39E-3	0.62E-5	1.38E-5	2.75E-3	8.27E-5	1.09E-4	6.67E-3

Table 5.10: Weekly Forecast Error (m/s) for Bauchi in the Month of July 2010

WEEK	Bauchi								
	10 m			30 m			60 m		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	1.56E-5	3.29E-5	2.49E-3	1.34E-5	2.67E-5	1.36E-3	4.24E-5	6.34E-5	5.24E-3
2ND	1.23E-5	4.38E-5	3.52E-3	1.67E-5	1.61E-5	2.56E-3	3.65E-5	7.11E-5	4.32E-3
3RD	1.84E-5	3.42E-5	3.47E-3	1.51E-5	0.82E-5	2.72E-3	5.67E-5	6.24E-5	6.35E-3
4TH	1.56E-5	3.28E-5	4.52E-3	1.48E-5	1.41E-4	3.15E-3	5.31E-5	5.34E-5	5.12E-3
5TH	2.75E-5	5.42E-5	5.41E-3	1.46E-5	1.72E-5	2.19E-3	6.33E-5	2.16E-4	4.67E-3

Table 5.11: Weekly Forecast Error (m/s) for Maiduguri in the Month of July 2010

WEEK	Maiduguri								
	10 m			30 m			60 m		
	MAE	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***	***MAE***	***RMSE***	***Chi***
1ST	0.34E-5	2.23E-5	4.74E-3	0.47E-5	1.41E-5	2.11E-3	5.41E-5	5.76E-5	5.51E-3
2ND	1.13E-5	2.65E-5	3.21E-3	0.66E-5	1.65E-5	2.36E-3	4.11E-5	7.56E-5	6.17E-3
3RD	1.34E-5	2.45E-5	3.33E-3	0.41E-5	1.38E-5	2.59E-3	4.67E-5	6.76E-5	4.19E-3
4TH	1.45E-5	2.11E-5	2.44E-3	0.47E-5	2.21E-4	2.71E-3	4.36E-5	5.43E-5	6.32E-3
5TH	2.25E-5	3.18E-5	4.35E-3	0.56E-5	1.43E-5	2.23E-3	6.31E-5	3.19E-4	7.34E-3

5.3 Nigeria Weather Seasons Effect on Wind Prediction

The dry season and rainy season are the two main seasons in Nigeria. The tropical continental air mass from the Sahara desert brings the dry season, while the rainy season comes as a result of the air mass originating from the far South Atlantic Ocean generally known as the tropical maritime air mass. This seasonal variation is caused mainly due to the changes in the wind that heavily influence the season. This causes a change in the availability of the wind at a different season in a year, thereby affecting the wind forecasting and prediction for the generation of electricity. Table 5.12 shows the wind characteristics variation due to seasonal changes for the covered period. The computed results show that the mean wind speed is season dependent for all the locations. Jos has the highest mean wind speed of 8.98m/s during the dry season with an average power density of 598.21w/m^2. Maiduguri has the lowest mean wind speed of 2.62m/s and average power density of 113.81w/m^2 during the dry season. The duration of each season varies depending on its location. While in some locations, the rainy season starts early in April and ends in September, in other locations the dry season covers nearly the same period of October to March or May.

Table 5.12: Wind Characteristics Variation due to Seasonal Changes.

Season	Mean wind speed (10m)	k	c	Average power density(W/m^2)	Monthly-seasonal (duration range)
Jos					
Rainy	8.64	5.79	9.29	385.9	April- September
Dry	8.98	5.23	7.8	598.21	October-March
Kano					
Rainy	8.12	4.38	8.78	333.01	May- September
Dry	7.5	3.35	7.91	399.06	October- March
Kaduna					
Rainy	4.56	6.94	4.79	102.36	June-September
Dry	5.59	5.09	5.94	132.12	October- May
Katsina					
Rainy	8.14	4.56	8.48	391.29	June-September
Dry	6.87	3.67	7.4	284.18	October- May
Bauchi					
Rainy	4.84	2.58	5.32	107.84	June-September
Dry	4.8	2.26	5.38	94.82	October- May
Maiduguri					

Rainy	2.81	6.09	3.5	124.21	June-September
Dry	2.62	5.04	2.81	113.81	October- May

The estimated power output obtained from this turbine is shown in Table 5.13. Jos has the highest wind energy output compared to other locations. This is closely followed by Katsina, Kano, Kaduna Bauchi, and Maiduguri respectively. The total annual power output of the wind turbine in the selected locations is 3627MW

Table 5.13: Wind Power Output

Locations	Power Output/year (MW)
Jos	1290
Katsina	921
Kaduna	282
Kano	846
Bauchi	179
Maiduguri	109
Total	3627

The power output of the wind turbine is shown in Fig.5.16. The operating characteristics of the wind turbine can be found in [104].

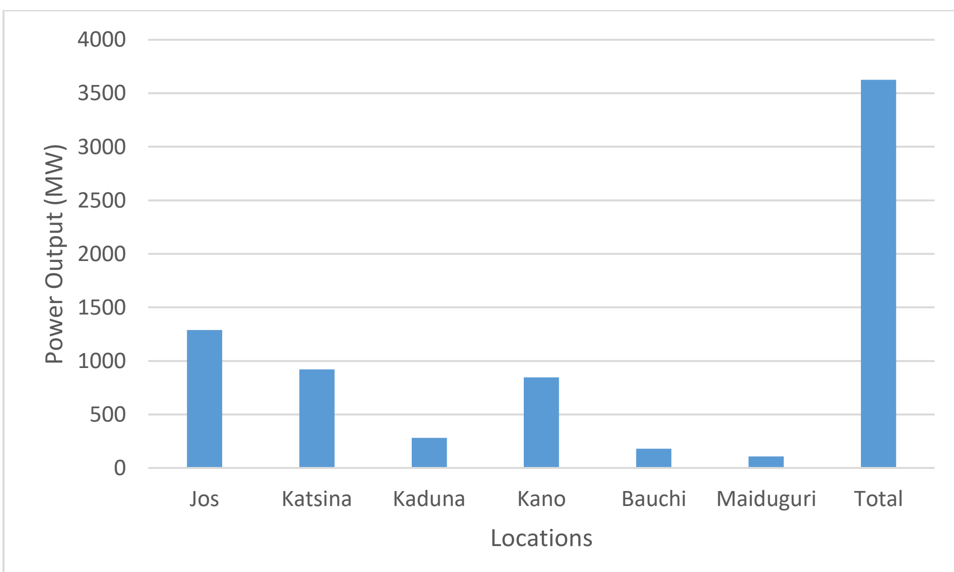

Figure 5.16: Power Output of the Wind Turbines

The Northern part of Nigeria has a large expanse of land and geographically well situated for setting up of wind farms in the country. The results show that the electrical output of the wind farms can be grid-connected.

5.4 Nigerian Case Study

The Nigerian national grid is a fast growing power system with different operational challenges at different operating points. The network suffers from reactive power compensation problems leading to widespread voltage fluctuations together with high technical losses and overloading of components during heavy system loading mode [105]. The standardized 2010 model of the Nigerian network comprises 7 generators, out of which 3 are hydro whilst the remaining generators are thermal, 28 bulk load buses and 33 extra high voltage (EHV) lines of 330kV [106].

The transmission network will play a major role in the post-deregulation era in Nigeria. Presently, there is technically a limitation on the wheeling power of the transmission network which is about 6000MW, the available transfer capability of the existing transmission network in Nigeria is grossly inadequate to sufficiently transmit the electricity from the generators to the load centers with the addition of the output from the wind generators. But, with the planned expansion of the transmission network infrastructure in the country, it is expected that once completed, it will increase the wheeling capacity of the transmission system to transmit more power from all other forms of energy sources [107] [108]. The renewable generation licenses shall be issued to independent power producers for generation and transmission expansion. They shall participate in the day-ahead market electricity trading through competitive offers and bids submitted to the independent system operator. The government's future plan is to encourage the renewable generators by providing accessible incentive facilities to ease their operations and also act as guarantor for the investment by minimizing their exposure to risk [109].

Therefore, connecting the wind farms via transmission lines, the independent system operator carries out dispatch with the existing conventional thermal generators for trading activities to begin in the market. The wind energy presently does not contribute any megawatt to the national grid, but it is projected that the contribution will be approximately 50% of all renewable energy integration by the year 2023. The other forms of renewable energy sources will contribute the other half. With a typical demand profile of 10000MW, it is expected that the total contribution of all renewable energy supplies in Nigeria will grow by 10% by 2020, 20% by 2025 and 30% by 2030 respectively [110].

5.4.1 Algorithm Formulation of the Different Optimization Methods

5.4.1.1 Differential Evolution (DE)

The Salient steps of DE based ELD realization

Step 1: At the initialization stage, the relevant DE parameters are defined. Also, relevant power system data required for the computational process are actualized from the data files.

Step 2: Run the Newton-Raphson load flow to determine the initial load bus voltage, transmission loss, and active power loss respectively.

Step 3: The objective function for each vector of the population is computed. The vector with the minimum objective function value (the best fit) so far is determined.

Step 4: Update of the generation count.

Step 5: Mutation, crossover, selection, and evaluation of the objective function.

Step 6: If the generation count is less than the preset maximum number of generations go to step 4. Otherwise, the parameters of the fittest vector are returned as the desired optimum value. Hence run the final *develd* to obtain the final value of the power loss, total fuel cost, and the appropriate generation schedule.

Table 5.14: Parameter Settings for DE-based ELD

Control Parameters	Differential Evolution
Maximum number of generation gen^{max}	200
Population size, NP	100
Scaling factor for mutation, F	0.8
Crossover constant, CR	0.5

5.4.1.2 Genetic Algorithm (GA)

GA works with a population of strings consisting of a generation. A string divided into substrings, with each representing a problem variable. In the present ELD problem, the defined problem variables correspond to the power generation of the units. With each string representing a possible solution that is made of substrings, each corresponding to a particular generating unit. The length of each substring is decided based on the maximum/minimum limits on the power generation of the unit it represents and the method of solution accuracy desired. The string length, which depends on the length of each substring, is chosen based on a tradeoff between solution accuracy and solution time. Longer strings may provide better accuracy, but result in higher solution time.

The various stages involved in the solution Algorithm for GA are the following:

1. Choose the Population size, number of generations, substring length and the number of trials.

2. Generate initially randomly coded strings as population members in the first generation.

3. Decode the population to get power generation of the units in the strings.

4. Execute load flow considering the unit generations in step (3) except for the slack bus, in order to evaluate the transmission system losses, slack bus generation, the line flows and hence any violation for the slack bus generation and violation the line flow limits.

5. Evaluate the fitness of population members.

6. Execute selection based on reproduction. Steps (2)-(6) are repeated for all the number of generations and the minimum augmented cost is noted for the first trial. This operation is carried out for the selected number of trials and the overall minimum for the augmented cost is taken as the solution point.

Table 5.15: Parameter Settings for GA-based ELD

Control Parameters	Genetic Algorithm
Maximum number of generation gen^{max}	200
Population size, NP	100
Uniform mutation rate	0.5
Uniform crossover rate	0.9
Selection Method	Elitism

5.4.1.3 Self-Adaptive Differential Evolution (SADE)

The formulation of the SADE algorithm for the solution of the economic load is the same with the classical DE with the exemption of the values of *CR* and *F* that are not constant but changing in the simulation.

Table 5.16: Parameter settings for SADE- based ELD

Control Parameters	Differential Evolution
Maximum number of generation gen^{max}	200
Population size, NP	100
Scaling factor for mutation, F	From [0.1-1.0]
Crossover constant, CR	From [0-1]

5.5 Results and Discussions

The simulation studies are carried out on Nigerian 31-bus network. This study assumes the installation of wind turbines on the buses that correspond to the six selected wind locations. The Nigerian thermal power plant characteristics are shown in Table 5.17 with each plant cost coefficients and their corresponding minimum and maximum power outputs [84].

Table 5.17: Nigerian Thermal Power Plants Characteristics

Units	a_i ($/MWh^2)	b_i ($/MWh)	c_i ($/h)	e_i ($/h)	f_i ($/h)	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)
Sapele	6929	7.84	0.13	600	0.052	137.5	550
Delta	525.74	6.13	1.2	260	0.028	75	300
Afam	1998	56	0.092	450	0.048	135	540
Egbin	1278	13.1	0.031	850	0.094	275	1100

$= US dollar

The experiment aimed at optimizing the fuel cost and for simplicity purpose, the fixed wind speed turbine is selected. In the problem formulation for the economic load dispatch with wind integration, two different cases with and without transmission losses were considered. The solution of the problem was solved using four different methods: DE, GA, SADE and conventional gradient descent for comparison. In this work, the ELD is applied to the four thermal plants of Egbin, Sapele, Delta and Afam and the six wind farms located in Jos, Kaduna, Kano, Katsina, Bauchi, and Maiduguri. The simulations were run on a Dell Laptop with Intel ® Core ™ i5 -5200U CPU @ 2.20GHZ with a RAM size of 8GB. The convergence rate for each of the algorithms varies, thereby adding different computational burden to the system. The SADE has the fastest convergence rate of about 55minutes amongst the different algorithms, followed by the DE (about 1hour) and the GA (above 1hour) respectively. The gradient descent method is slow to converge with the simulation running for about an hour before it finally converges. The results of the ELD with and without transmission losses considered are shown in Table 5.18 and Table5.19

respectively. Table 5.20 shows the cost of generation obtained with and without losses for the different optimization techniques

Table 5.18: Results of Economic Load Dispatch without Losses

	Gradient Descent (MW)	DE (MW)	GA (MW)	SADE (MW)
Egbin	968.58	1020.85	1060.52	1045.23
Sapele	486.68	471.69	476.58	466.58
Delta	286.42	260.62	240.3	250.47
Afam	520.33	510.24	480.36	495.36
Jos	24.41	25.32	28.25	26.62
Katsina	21.57	21.78	22.14	20.84
Kano	15.62	14.87	13.56	14.48
Kaduna	19.63	18.43	20.58	21.69
Bauchi	12.24	11.96	12.43	13.26
Maiduguri	12.52	12.24	12.65	13.47
Total generation	2368	2368	2368	2368
Demand	2368	2368	2368	2368

Table 5.19: Results of Economic Load Dispatch with Losses

Power stations	Gradient Descent (MW)	DE (MW)	GA (MW)	SADE (MW)
Egbin	1015.48	1026.49	1043.52	1068.51
Sapele	471.32	476.34	481.62	446.58
Delta	278.54	263.54	256.21	265.28
Afam	533.14	529.79	512.14	513.52
Jos	25.41	26.4	27.62	26.15
Katsina	22.47	22.56	22.56	21.45
Kano	15.85	15.52	16.23	16.54
Kaduna	20.35	19.22	20.52	21.14
Bauchi	11.53	13.56	12.62	13.14
Maiduguri	12.65	12.79	12.86	13.24
Total generation	2406.74	2406.21	2405.9	2403.55
Demand	2368	2368	2368	2368
Losses	38.74	38.21	37.9	37.55

Table 5.20: Cost of Production for the Different Methods

	DE($/hr)	GA($/hr)	SADE($/hr)	Conventional($/hr)
Without losses	7360.34	7498.27	7150.15	8634.41
With losses	7542.57	7621.36	7325.4	8715.55

The generators schedule reflects the best possible contributions of all the individual generators based on the demand for that hour. Table5.20 shows the cost of production obtained from the simulation results of the four different methods. The SADE gives the least production cost as compared to other methods. Also, considering the case with losses, the SADE gives the least transmission losses as compared to others. This task of economic dispatch is being carried out by the system operator to first ascertain if the transmission network has the capability to accommodate the volume of trading activities for that day. Once the ISO guarantees the reliability of the transmission network, then trading activities can commence and marginal cost price for that hour can be achieved by a number of bids and offer received. The present transmission wheeling capacity of the Nigerian network is 6000MW, it is expected that the transmission network can sustain the number of trade activities in the interim pending the completion of the various ongoing renewable projects across the country. But, as the penetration of the renewable energy into the grid increases the volume of trading activities, there will be a need for transmission expansion so as to increase the available transfer capability (ATC) and to maintain the reliability of the transmission system during operation.

The most important step in any wind farm projects is a good wind feasibility study which shows detail analysis of all the necessary parameters, identify any likely risk and further recommend the best way to proceed with the project. Therefore, considering the wind assessment results of the selected location for the siting of wind farms in Nigeria, and the calculated amount of wind power output, the return on investment in the long term will be profitable and yield a good result for investors.

Chapter 6

Conclusion and Recommendation for Future Work

6.1 Conclusion

The electricity industry in Nigeria has undergone a dramatic change in the last 15years. The demand for higher economic efficiency, increase competitiveness, as well as the political decision of market opening, has resulted in the deregulation of the power sectors. The existing high voltage networks, the increasing efficiency of generation technology have facilitated this restructuring. The next phase of the deregulation process is the integration of renewable energy into the existing liberalized Nigerian electricity markets.

In realizing the objective of integrating renewable energy into the Nigerian power systems, the wind energy was considered as a case study in this research amongst the other available renewable energy sources in the country. The country is divided into the Southern and Northern parts. From past work surveyed, it was found that the wind speed in the south is lower compared to the northern part of the country. As a result, six locations were selected from the Northern part of the country as a case study for assessment of wind energy potential and development in Nigeria.

Based on the in-depth analysis of the stochastic nature of wind power output in this thesis, the Weibull distribution parameters of the selected wind speed for different time interval are obtained respectively, and also the probability density function of wind power output for different intervals is achieved. These functions were used to calculate output probabilities at each interval.

The economic load dispatch problem was formulated using the quadratic cost function model incorporating wind energy and considering the valve point effect. The solutions were found with and without transmission losses considered subject to many constraints. The constrained optimization problem was formulated for scheduling the online generators and was solved using three different evolutionary algorithms and gradient descent method for results comparison purposes.

The wind assessment, modeling, and forecasting were carried out for the selected locations of Bauchi, Kano, Kaduna, Katsina, Jos and Maiduguri in the northern part of Nigeria. It can be inferred that a significant amount of wind energy can be harness all year round from these locations, and they are considered suitable for the siting of wind farms for the purpose of electricity generation in the country. Also, the self-adaptive differential (SADE) evolution techniques give the least cost generator result, amongst all the optimization methods used in solving the formulated economic load dispatch problem with wind energy of the Nigerian power system. The power sector reform in Nigeria is an ongoing process and the integration of renewable energy is among the several aspects of the reform stages. It is expected that the next stages will strengthen the development of the electricity supply industry and the electricity market respectively.

6.2 Future Research Works

The deregulation of the electricity market brings numerous challenges. The integration of renewable energy presents greater tasks to the power system as a result of the variability and uncertainties associated with its outputs. Therefore, more detail research is still required in the area of reliable weather forecasting and modeling. Also, the complexity of the design of an efficient market for the power system with high renewable penetration required more future work. The coordination of several congestion management schemes would be necessary for the effective trading of the commodity in the market. Therefore, more attention should be given to the congestion management of the transmission network since the whole deregulation policy is hinged on the open access, nondiscriminatory of the transmission network. Manipulation of pricing through gaming in the market by the participants should be properly checked using the advanced mathematical methods. A further research topic is made up by the ancillary services that are important for the efficient performance of the network. Among them, the consideration of reactive power in congestion situations, frequency and voltage stability and trading enforcement forms a special challenge. Many of the risks in a deregulated market arise, mainly, through price volatility, but also because of uncertainties regarding regulatory and technical issues. Therefore, all of this different kind of risks should be further investigated. Also, the use of game theory in the deregulated electricity market is a field where the future research will focus on. This entails the investigation of marketplaces with a large number of players.

The renewable power is clean and also free at the point of use, but, it cannot be totally relied upon because of its intermittent nature. Most grid operators managed this intermittency by keeping polluting power stations online to make up for the shortcomings. Artificial Intelligence (AI) is expected to play a crucial role in the smart grid systems through demand-side flexibility, so as to eliminate the need to keep the polluting thermal power stations online for the management of the renewable energy intermittency. Therefore, the application of AI in smart grid in this area opens up research opportunities for the improvement of integration of renewable energy in power systems. In solving future economic load dispatch problems of wind-thermal-hydro cost minimization and scheduling, multi-objective functions should be considered that incorporate multiple fuel cost and emission. The solution of the self-adaptive differential evolution in a single objective function shows better results compared to the Genetic Algorithm, Differential evolution, and gradient descent, but, other meta-heuristics methods with better convergence could be explored to solve the multi-objective function optimization problem.

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APPENDIX

Appendix A

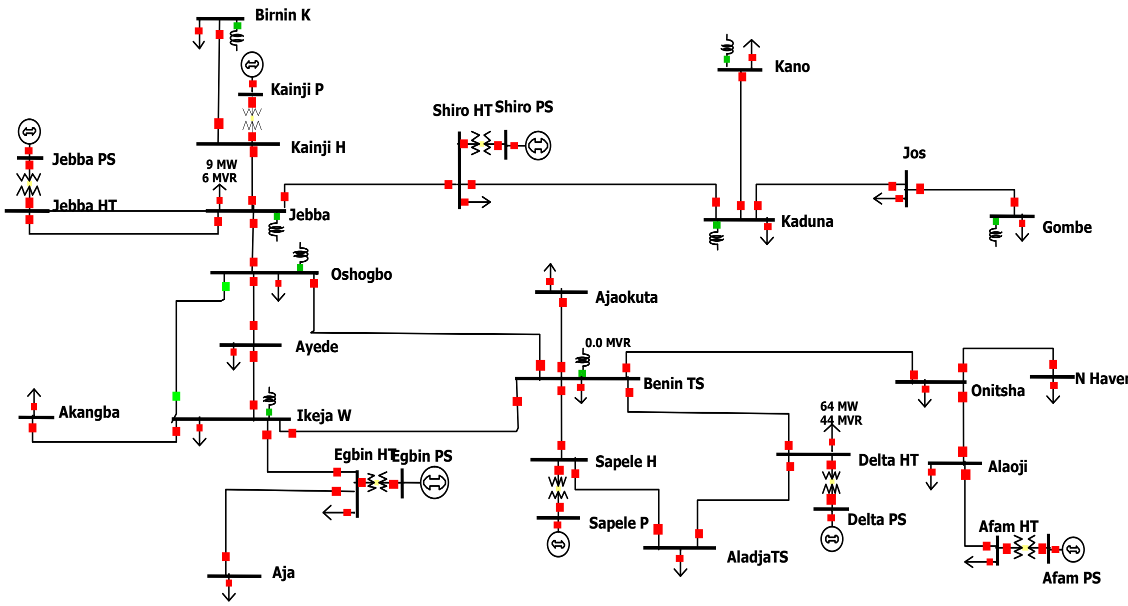

Figure A.1: Modified Single Line Diagram of Nigeria 31-bus Grid Systems

Table A1: Nigeria 31- bus Network Data

Bus No	Bus Code	Voltage Magnitude	Angle Degree	Load MW	Load Mar	Generator MW	Generator Mvar	Injected Qmin	Injected Qmax
1	1	1	0	0	0	830	0	450	-255
2	2	0.99	0	0	0	200	0	450	-250
3	2	1	0	0	0	150	0	450	-250
4	2	1	0	0	0	250	0	450	-250
5	2	1.03	0	0	0	490	0	450	-250
6	2	1.04	0	0	0	350	0	450	-250
7	2	1.03	0	0	0	450	0	450	-250
8	0	1	0	156.8	79.9	0	0	0	0
9	0	1	0	8.6	5.6	0	0	0	0
10	0	1	0	429.9	258.4	0	0	0	0
11	0	1	0	201	136.7	0	0	0	0
12	0	1	0	166.2	97.8	0	0	0	0
13	0	1	0	58.4	28.4	0	0	0	0
14	0	1	0	144.7	88.4	0	0	0	0
15	0	1	0	115.2	42	0	0	0	0
16	0	1	0	82.1	44.5	0	0	0	0
17	0	1	0	112.6	50	0	0	0	0
18	0	1	0	184.9	60	0	0	0	0
19	0	1	0	102.9	17.5	0	0	0	0
20	0	1	0	60.3	70	0	0	0	0
21	0	1	0	26.8	10.5	0	0	0	0
22	0	1	0	292	114.9	0	0	0	0
23	0	1	0	193.5	101.2	0	0	0	0
24	0	1	0	139.4	61	0	0	0	0
25	0	1	0	109.7	64.2	0	0	0	0
26	0	1	0	0	0	0	0	0	0
27	0	1	0	64.3	44.2	0	0	0	0
28	0	1	0	119.3	65.7	0	0	0	0
29	0	1	0	61.5	10.3	0	0	0	0
30	0	1	0	0	0	0	0	0	0
31	0	1	0	0	0	0	0	0	0

Table A2: Nigeria 31-bus Line Data

Bus	Bus	R	X	Transformer	Transformer
nl	nr	p.u.	p.u.	Tap >1 at bus nl	Tap <1 at bus nl
25	1	0	0.00648	0	0.975
26	2	0	0.01204	0	1
27	3	0	0.01333	0	1
28	4	0	0.01422	0	0.95
29	5	0	0.01638	0	1.025
30	6	0	0.01351	0	0.95
31	7	0	0.01932	0	1
10	8	0.0055	0.04139	0.9425	1
11	8	0.00987	0.07419	0.4155	1
8	15	0.00538	0.0405	0.2269	1
21	8	0.00766	0.05764	0.323	1
8	26	0.00098	0.00739	0.1657	1
8	27	0.00287	0.02158	0.1209	1
9	11	0.00206	0.01547	0.78	1
9	29	0.0048	0.03606	0.8083	1
30	9	0.00159	0.01197	0.2683	1
31	9	0.00016	0.00118	0.0266	1
11	10	0.01163	0.0875	0.4903	1
10	22	0.00036	0.00266	0.0595	1
24	10	0.00538	0.0405	0.227	1
10	25	0.00122	0.00916	0.2054	1
11	24	0.00412	0.03098	0.1736	1
12	13	0.00774	0.05832	0.3263	1
18	12	0.00904	0.06799	0.381	1
29	12	0.00189	0.01419	0.318	1
13	19	0.01042	0.07833	0.4389	1
15	14	0.00605	0.04552	0.2551	1
14	28	0.00049	0.00369	0.0828	1
15	17	0.00377	0.02838	0.159	1
26	16	0.00248	0.01862	0.1044	1
27	16	0.00102	0.00769	0.0431	1
20	30	0.01218	0.09163	0.5135	1
25	23	0.000028	0.00207	0.0464	1

Appendix B

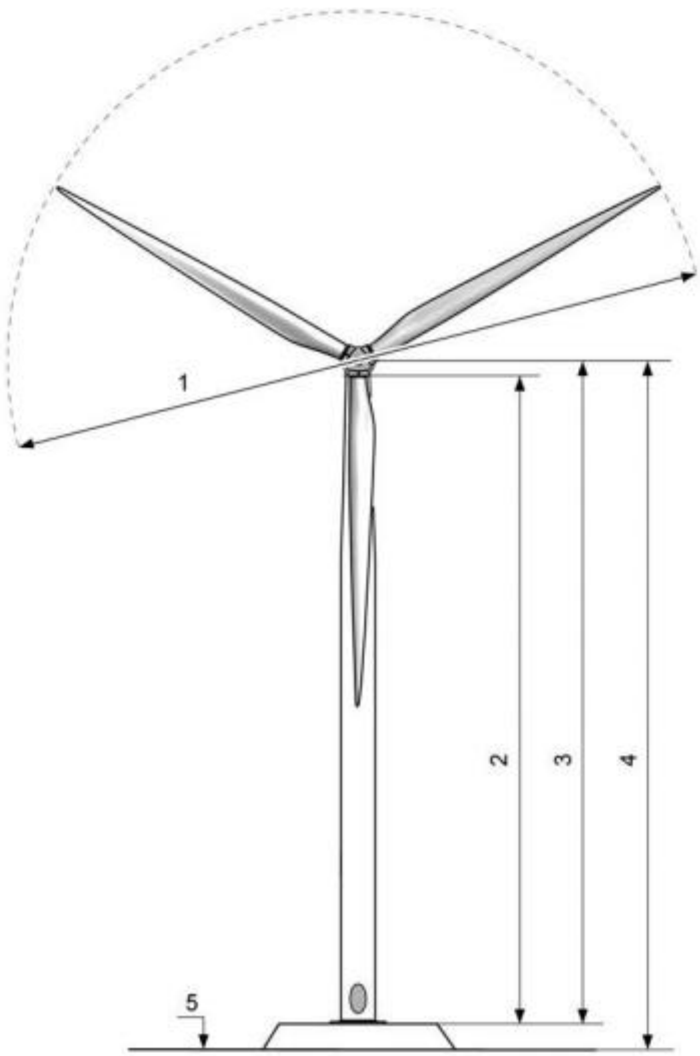

Figure B1: Dimension of Wind Turbine Generator (WTG)

1. Rotor diameter
2. Tower height
3. Rotor height
4. Hub height
5. Ground top level

Table B1: Wind Turbine Technical Data

1	Rotor diameter	95m
2	Tower height	96.2m
3	Rotor height	97.7m
4	Hub height	100m
5	A- Factor	9.59
6	Form Factor	2
7	Annual average wind speed	8.5m/s
8	Vertical average sheer compound	0.2
9	Extreme wind speed (10 minute average)	42.5m/s
10	Survival wind speed (3-second average)	59.5m/s
11	Automatic stop limit (10 minute average)	25m/s
12	Characteristics turbulence intensity according to	
	IEC61400 (15m/s)	18%
13	Air density	1.225kg/m2
14	Altitude	1000 above sea level
15	Permissible relative ambient humidity	30% to 99%

Table B2: Wind Turbine Operating Data

1	Rated power	2.1MW
2	Rotor Speed	12.1 to 17.6 r.p.m
3	Power regulation	Active pitch regulated
4	Rated wind speed	11m/s (without turbulence)
5	Cut in wind speed (30- second average)	3.5m/s
6	Cut-out wind speed (3-second average)	34m/s
7	Cut-out wind speed (10-second average)	25m/s
8	Restart wind speed (10- minute average	23m/s

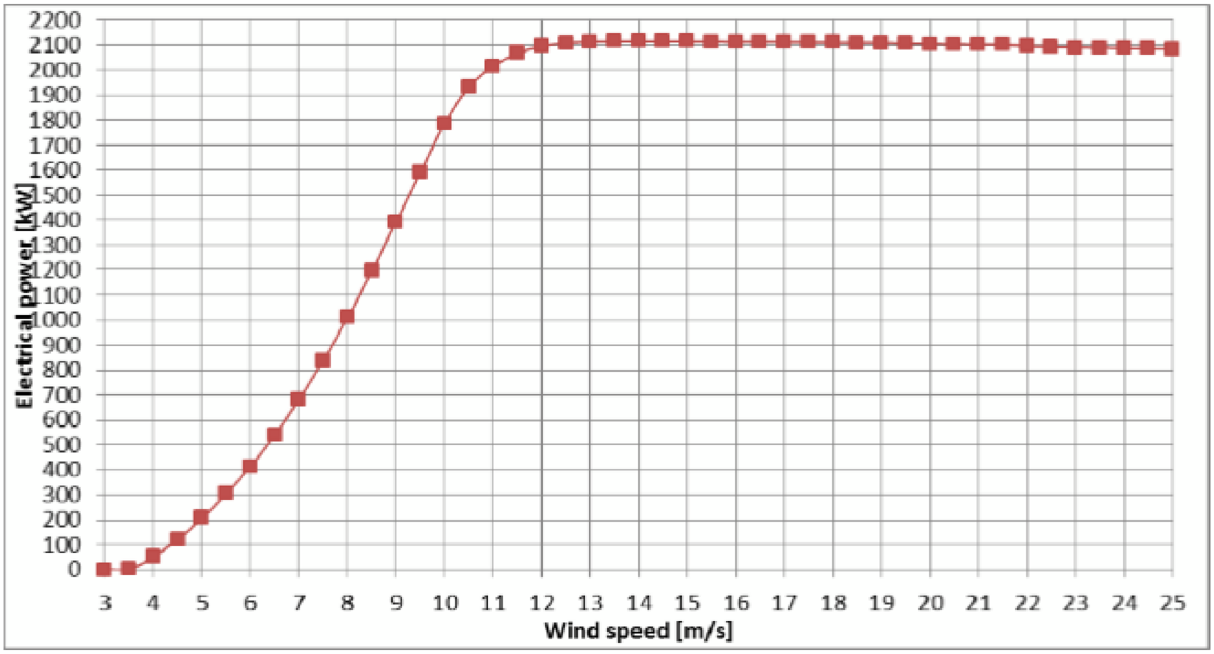

Figure B2: Power Curve

Table B3: Generator Data

Type	Asynchronous 3- phase induction generators with
	slip rings operated with rotor circuit inverter
	system (DFIG)
Rated frequency	50Hz (+5%/-6%)
Number of poles	4
Synchronous speed	1500rpm
Speed at rated power	Rotor short-circuited : 1511rpm
Operation speed range	1200-1800rpm
Rated generator speed	1568rpm
Efficiency	96.80%
Max rotor slip	20%
Power factor compensated	0.94 lagging and 0.94 leading