A RISK ANALYSIS AND RELIABILITY FORECASTING METHOD FOR WIND ENERGY SYSTEMS

by

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ABSTRACT

Two of the most significant challenges facing the world in the 21st century are improving energy security and mitigating the effects of climate change. To counter these challenges, renewable energy sources, such as wind, are considered a possible solution and have gained importance worldwide. With many jurisdictions setting high wind-energy targets for the coming decades, risks have grown as the demand for new wind turbines has outstripped the growth of its suppliers.

Integrating significant amounts of wind-electricity into existing networks raises reliability concerns due to variable nature of wind. A method for estimating the reliability of wind-energy systems is presented which is a combination of a forecasting method (probabilistic approach) and *RL* (Resistance-Load) technique (risk-based approach), demonstrated through a case study, and verified using real-time wind farm data.

LIST OF ABBREVIATIONS AND SYMBOLS USED

AC	Alternating Current
AWEA	American Wind Energy Association
CDF	Cumulative Distribution Function
CoV	Coefficient of Variation
CRP	Carbon Fibre Reinforced Plastic
FMEA	Failure Modes and Effects Analysis
GE	General Electric
GHG	Greenhouse Gas
GRP	Glass Fibre Reinforced Plastic
GWEC	Global Wind Energy Council
HAWT	Horizontal Axis Wind Turbines
HVDC	High Voltage Direct Current
IEA	International Energy Agency
LoF	Line-of-Fit
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
NERC	North American Electric Reliability Corporation
OECD	Organization for Economic and Co-operation Development
OHC	Outer Hair Cells
PDF	Probability Density Function
PMG	Permanent Magnet Generators
PPCC	Probability Plot Correlation Coefficient
TIV	Transport and Installation Vessel

VAWT	Vertical Axis Wind Turbines
WEO	World Energy Outlook
WTG	Wind Turbine Generator

A	Turbine Swept Area
c	Scale Parameter
C_p	Power Coefficient
$f_{RL}(r,l)$	Joint Distribution of R and L
$F(v)$	Cumulative Distribution Function (CDF)
h_{ref}	Reference Height for Measured Wind Speed
k	Shape Parameter
L	Load
$loss_n$	n^{th} Type of System Loss
L_h	Hourly Simulated Load
N_T	Number of Wind Turbines
p_n	Cumulative Probability for n^{th} Ordered Value
$P_{Net(h)}$	Net Hourly Wind Farm Output
P_{out}	Wind Turbine Output
R	Resistance
R^2_{PP}	R-Squared for Probability Plot
R^2_{LoF}	R-Squared for Line-of-Fit Plot
T_{loss}	Total System Losses
u	Uniform Distribution
v	Wind Speed

v_{ref}	Measured Wind Speed at a Given Height
z_p	Normal Score
α	Wind-Shear Exponent; Probability Percent for Student-t Distribution Table
μ	Mean
ν	Degree of Freedom (nu)
ρ_{air}	Density of Air
φ	Standard Normal Cumulative Distribution Function
σ^2	Variance
σ	Standard Deviation
GW	Gigawatt (10^9)
kW	Kilowatt (10^3)
MW	Megawatt (10^6)
MWh	Megawatt-hour
Mtoe	Million tonnes of oil equivalent
TWh	Terawatt-hour

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CHAPTER 1 INTRODUCTION

Maintaining or improving energy security and mitigating climate change will be the two most pressing challenges facing the 21^{st} century. The evidence to support this is, for example, stated by the International Energy Agency (IEA) in *World Energy Outlook (WEO), 2010*:

> "*The energy world faces unprecedented uncertainty. The global economic crisis of 2008-2009 threw energy markets around the world into turmoil and the pace at which the global economy recovers holds the key to energy prospects for the next several years. But, it will be governments, and how they respond to the twin challenges of climate change and energy security, that will shape the future of energy in the longer term.*" [1].

With the uncertainty in economic growth, it is difficult to predict the outlook for energy with confidence. According to WEO, the emerging economies, such as, China and India will drive global energy use, resulting in an increased total primary energy demand. The increase in energy demand will include fossil fuels accounting for over one-half of the increase in total primary energy share [1].

For many years, fossil fuels, namely oil, coal and natural gas, have served as the principal primary energy source in meeting world's energy needs [2]. In 2007, their contribution accounted for over 80% in meeting the world total primary energy demand (see Figure 1.1). The IEA has projected an increase of 36% in the world primary energy demand between 2008 and 2035, from around 12,300 Mtoe (million tonnes of oil equivalent) to over 16,700 Mtoe, or 1.2% per year on average [1]. A large part of this increase in energy demand is expected to come from non-OECD countries reflecting faster economic growth, industrial production, population and urbanization [1].

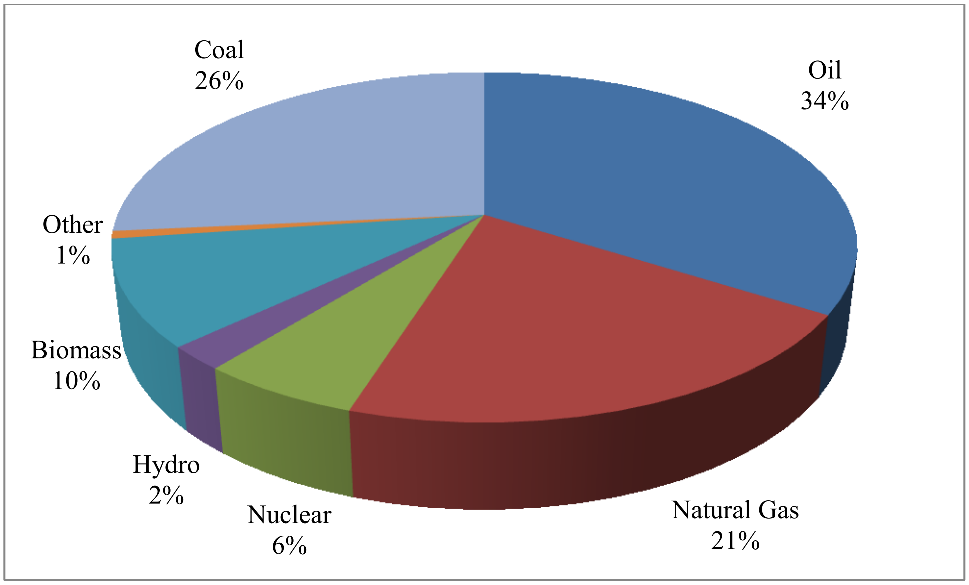

Figure 1.1 Fuel share of world total primary energy supply in 2007 [3]

Based on IEA's projections for 2035, oil is expected to remain the dominant fuel in the primary energy-mix, although its share will drop from 34% in 2007 to 28% by 2035. The demand for coal sees a steep rise until 2020 and gradually declines while the growth in natural gas is expected to surpass the demand for other fossil fuels due to its environmental and practical attributes [1]. Since fossil fuels are finite sources of energy on earth, their increasing demand to meet the growing needs raises concerns over security of supply.

The extensive consumption of fossils has led to an increase in anthropogenic greenhouse gas (GHG) concentrations in the environment resulting in the rise of global average temperatures since the mid-20th century [4]. Greater warming over land than over the ocean, melting of ice-caps, changing wind patterns and tropical storms are some of the impacts attributed to climate change [5].

To counter the twin challenges of maintaining or improving energy security and mitigating climate change, low-carbon emission technologies have gained considerable interest around the world, resulting in an increased electricity generation from renewables, such as wind, solar, biomass and geothermal. The thesis focus is on wind energy, one of the renewables, and how it can be made more secure and reliable in the future.

1.1 The Growth of Wind Energy and the Wind Industry

High demand for wind-generated electricity and increasing number of turbine installations are indictors reflecting the growth of wind energy and the wind industry, respectively. Since 2000, worldwide, renewable-based electrical generation has grown by almost 900 TWh; although most of this increase came from hydroelectricity, wind-electricity experienced a seven-fold growth [6]. Expectations of significant supplies of electricity from wind-energy systems (i.e., individual wind turbines or groups of turbines in a wind farm) in the future are now a commonplace; for example, the Global Wind Energy Council (GWEC) in its *Global Wind Energy Outlook 2010*, projects that world wind energy production will increase over tenfold by 2030—emphasizing the importance of wind as a key contributor to improving energy security and reducing greenhouse gas emissions [7]. For example, Figure 1.2 shows the increasing level of global wind-energy generation projected by the GWEC to 2030, assuming an advanced growth scenario.

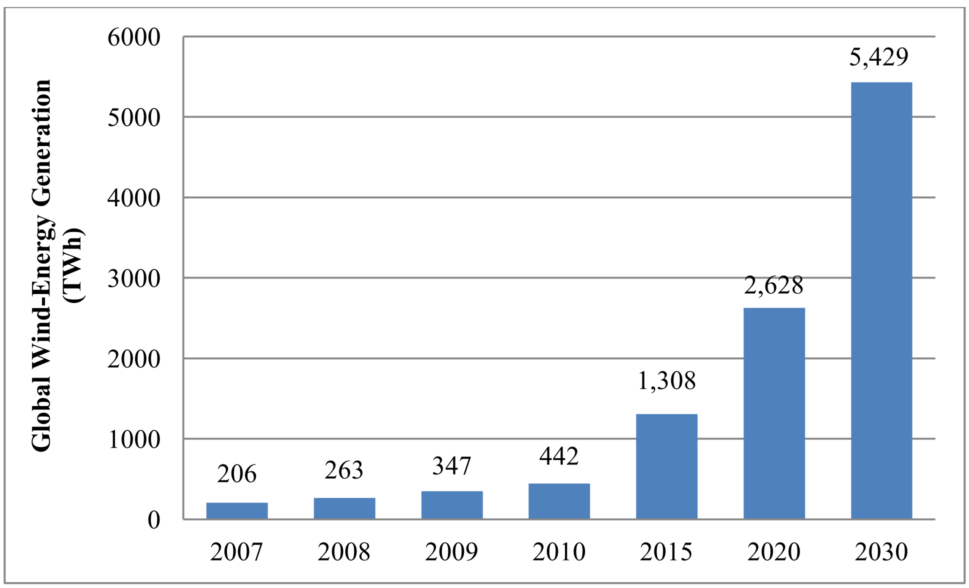

Figure 1.2 Future projections for global wind-energy generation [7]

To meet future projections of wind-generated electricity, the demand for new wind turbines has grown at a rapid pace. Each year since 2001 has seen a rise in wind installed capacity; see Figure 1.3, except in 2010 which experienced a slowdown for the first time in more than two decades [8]. Also, the investment in new wind turbines saw a decline for the first time and the market for new turbines reached an overall capacity of 37.64 GW, down from 38.31 GW in 2009. Yet, a major contribution towards the growth in wind energy was attributed to China which alone accounted for more than half of the world wind market 2010, adding 18.9 GW of new installed capacity. Many nations such as Germany, Spain, U.K, France and Italy are considered major wind energy markets where the annual wind turbine sales range between 0.5 and 1.5 GW; while other nations such as Poland, Belgium, Brazil, Japan and Mexico emerged as a medium sized markets for new wind turbines in the range of 100 and 500 MW. Despite the slowdown in 2010, altogether 83 countries worldwide used wind energy for electricity generation and 52 countries increased their total installed capacity; hence, the year 2010 witnessed world wind capacity reaching over 195 GW after 159 GW installed in 2009 and 120 GW in 2008 [8].

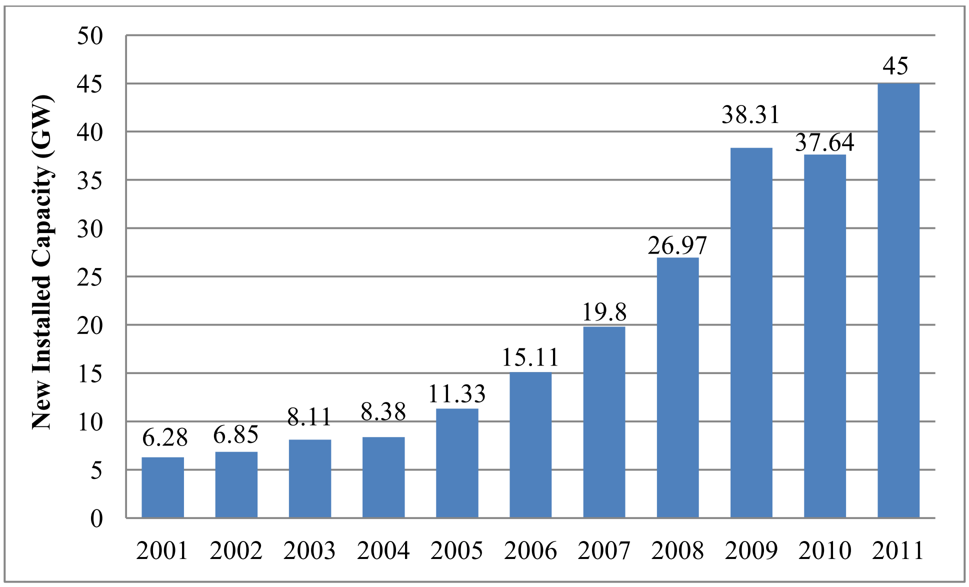

Figure 1.3 Worldwide growth in new wind installations [8]

One of the outcomes of the growth in demand for wind energy is the increasing size of wind turbines. Wind turbines of the early 1920s ranged in size from 1 to 3 kW, while the largest wind turbine of 1940s was a result of industrialization; world's first megawatt-size wind turbine named Smith-Putnam rated at 1.25 MW was used to feed electricity to a local utility network for several months during the World War II [9]. The interest in wind energy faded as the oil prices dropped following WW II; it was the oil shock of 1970s that the interest in wind turbines rose again and wind energy is now seen as essential to meet the need for clean and renewable electricity.

Wind turbines have grown in size; become more complex with time as the industry has been producing bigger and higher capacity (commercial or utility scale) wind turbines rated from 650 kW to 7 MW [10]. Currently, E-126 model, rated 7.5 MW stands as the highest capacity wind turbine to date [11]; while some manufacturers are talking about 10 MW wind turbines in the future [10].

1.2 Wind Turbine Basics

Wind turbines are machines for generating electricity that use energy from the wind. The rotor blades and the nacelle of a wind turbine are held aloft with the support of a tubular steel tower. The mechanical rotation of the blades due to kinetic energy of the wind results in generation of electricity by a generator [12]. Figure 1.4 explains the working principle of a wind turbine and lists some of the major components.

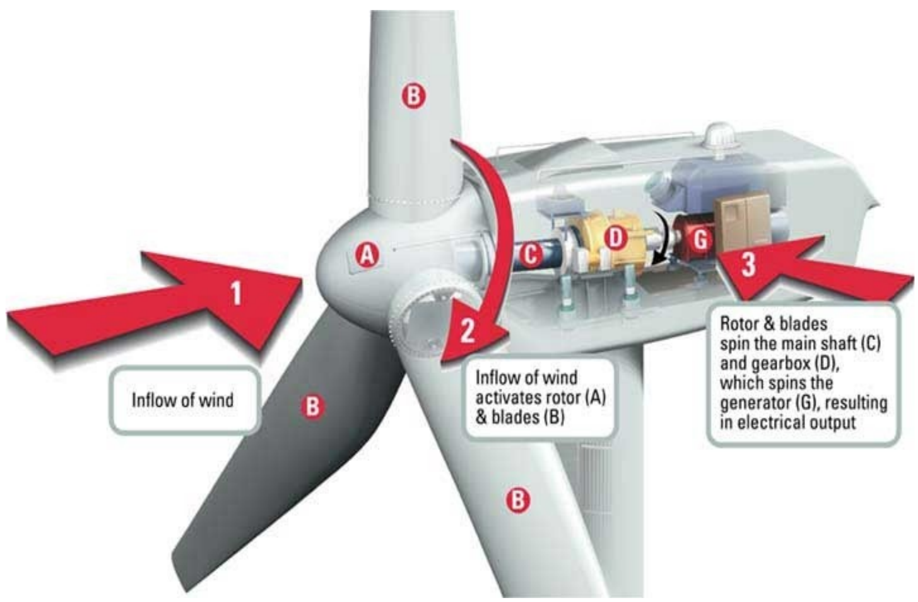

Figure 1.4 Working principle and components of a wind turbine [13]

Wind turbines are divided into two categories, - Horizontal Axis Wind Turbines (HAWT), and Vertical Axis Wind Turbines (VAWT) depending on the rotation of the main shaft (axis). The horizontal axis turbine resembles a "propeller-type" design, while the vertical axis turbine resembles like an "egg-beater". The main components of a wind turbine are:

- Rotor hub and blades, which convert the wind's energy into rotation of the shaft;

- A nacelle (enclosure) containing a drive train, usually including a gearbox and a generator;
- A tower, to support the rotor and drive train; and
- Electronic equipment such as controls, electric cables, ground support equipment, and interconnection equipment.

Wind turbine towers are mostly tubular and made of steel. The blades are made of fiber glass-reinforced polyester or wood-epoxy. Based on their installation, wind turbines can be onshore (land-based) or offshore (sea-based). Onshore wind turbines are usually installed in hilly or mountainous regions which are generally 3 km or more inland from the nearest shoreline. Offshore wind turbines are installed 10 km or more from the land, have a fixed bottom or foundation based tower, and are installed where the water depth is not more than 40 m. Some offshore wind turbines are deep-water turbines and are known as floating wind turbines. More important for offshore wind turbines is that the buoy, which is tethered to the sea-bed with cables, should keep the turbines from pitching and rolling violently in ocean swells [14].

1.3 Risk and Reliability

With the expansion of wind energy, the elements of risk and reliability concerns have also grown. Reliability issues have arisen over wind-generated electricity which faces uncertainty due to variable nature of wind to meet a dynamic load; and risks have grown as the turbine manufacturers try to keep up with the demand for new wind turbines while maintaining the quality of their product.

1.3.1 Risk

The term risk, in general, can be defined as "*a possibility of incurring a loss*" [15]; whereas mathematically, it is the probability of such a loss [15]. Identifying and studying risks is useful to avoid the occurrence of events that can lead to a negative result. A risk analysis for wind energy is important because wind is considered as one of the solutions to overcome our energy and climate change issues.

Spreading at a rapid pace—and with the order books already full for the coming years—the industry is confronted with challenges and risks in meeting the growing demand for new wind turbines. Events like shortage of raw materials, shortage of installation vessels and equipment failures have raised quality and quantity concerns worldwide. It is therefore necessary to determine whether the wind industry holds enough potential or if the world is only banking on an energy source that is surrounded by risks.

1.3.2 Reliability

A system in general is considered reliable if it performs a certain task successfully under a set of operating conditions. In case of a wind-energy system, meeting a jurisdiction's electrical load is the prime concern, while the operating conditions may vary in different regions.

To ensure the reliability of a system, it is important to identify the uncertainties that can affect a system's performance, or its reliability. The uncertainties present in a wind-energy system can occur in the form of energy source (wind speeds), the conversion process (wind turbine and electrical network), and energy services (electrical load). An energy system with such randomness in itself can deter the efforts towards overcoming the twin challenges of energy security and climate change; therefore, reliability forecasting is important.

1.4 Thesis Objectives

This thesis develops a reliability forecasting method for wind-energy systems which can be employed to calculate the probability of success for a wind farm in meeting a jurisdiction's electrical load; the method is a combination of a forecasting method (a probabilistic approach) and *RL* (Resistance-Load) technique (a risk-based approach). Due to uncertainties present in renewable energy sources, it is hard to predict their future values with confidence; hence a probabilistic method is employed. The forecasting method uses probability distributions to study and simulate random variables, while the *RL* technique employs reliability equations to calculate the probability of $R > L$ for a given year. Higher the probability of $R > L$, greater is the system reliability. The *RL* technique, in general, has been widely used to estimate system reliability, but here, it is being introduced to energy security. The reliability forecasting method will be demonstrated with the following objectives:

1) *Analysing the probability distributions:* The presence of uncertainties in a wind-energy system requires that the random variables be identified first and then their probability distributions studied. The probability distributions are best represented through distribution parameters which are calculated using historical data.
2) *Simulating random variables:* Simulations can be performed to generate the most probable replications of the real-world. The random variables are replicated for a given year using their distribution parameters calculated in the previous step to obtain the simulated values of generation and load (or *R* and *L*).
3) *Verifying the forecasting method:* Steps 1 and 2, representing the probabilistic simulations, will be verified using real-time wind farm data to ensure the validity of the forecasting method.
4) *Calculating the probability that R is greater than L:* The simulated values of *R* and *L* can be employed for an *RL* analysis to calculate the probability of $R > L$ (or reliability) for a wind-energy system with the help of reliability equations.

The thesis also includes a qualitative risk analysis of the wind industry that examines various issues arising during a wind turbine's lifecycle; that is, from the stages of manufacturing a turbine to its operational stage in a wind farm.

1.5 Thesis Organization

The thesis is divided into six chapters and three appendices. Chapter 2 reviews existing reliability work and introduces the new approach employing the *RL* (Resistance-Load) technique to energy security.

Chapter 3 discusses in detail the method and simulation steps to obtain future *R* and *L* values, and reliability equations to forecast wind farm reliability.

Chapter 4 presents the results of a case study. Results are divided into, first, the verification of forecasting method and second, reliability forecasting or calculating the probability of $R > L$ using the *RL* technique.

Chapter 5 presents a discussion and significance of the case study results. Further applications of the *RL* technique to wind-energy systems are also described.

Finally, chapter 6 presents the concluding remarks for the thesis and lists some limitations of the method. Related future work is also suggested.

Appendix A and B comprise of historical wind speed and load data analysis results respectively, while appendix C presents a discussion on the risk analysis of the wind industry.

CHAPTER 2 BACKGROUND

The focus of this chapter is to examine the background work in the current state of risk and reliability research for wind-energy systems. The chapter begins with a qualitative risk analysis by enlisting the risk categories here, although a major part of this chapter looks at the application of existing techniques for wind farm reliability and how to make wind-energy systems more reliable. The chapter concludes by discussing the drawbacks of existing reliability approaches and introduces the *RL* technique while simultaneously explaining how *RL* can be a better approach in forecasting reliability.

2.1 Qualitative Risk Analysis

With many nations having their wind energy targets established for the coming decades, the demand for multi-MW wind turbines has grown. New wind turbines with larger and heavier components such as bigger blades, taller towers and heavier nacelles are being manufactured to meet the growing needs of wind-generated electricity. This is leading to various types of risks during a turbine's lifecycle. For example, larger turbines consume more raw materials, need more space for transportation and installation, increased surveillance during its operation and higher investments. A failure at any stage of its lifetime can result in a loss in terms of energy or money, or both. The risks can be subdivided into four main categories that may arise during a turbine's lifecycle; these are:

1) Manufacturing and Installation risks
2) Operational risks
3) Environmental risks
4) Financial risks

Manufacturing risks arise as some of the key raw materials, such as, the rare-earth metals (for making permanent magnets) and acryonitrile (used in production of carbon fiber) could face a possible shortage of supply in the future resulting in their rising costs and making wind turbines expensive; while installation risks are seen as lack of sufficient installation vessels and shortage of electric cables to link the wind farms exist. Wind variability, increased gearbox failures, and wearing out of bearings has given rise to some of the operational challenges resulting in failure of wind-generated electricity.

Environmental concerns have risen due to low-frequency noise of wind turbines, while killing of bats and birds have drawn attention from various environmental groups. All such risks that surround wind-turbine industry and where huge investments are expected to flow raises a financial risk and it is worth asking—"Are the investments safe?" A further detailed discussion of the four risk categories is continued in Appendix C.

2.2 Quantitative Reliability Assessments

Although the past decade has witnessed the unprecedented growth of wind energy worldwide, its growing complexity is calling into question the reliability of wind-energy systems. For example, turbine failures due to quality concerns and generation risks associated with the variability of wind speeds mean that wind-energy systems are more prone to failure in meeting end-use electricity demand than traditional generation-systems. As a result, considerable effort is being made to improve the reliability of wind-energy systems through the application of various analysis techniques. This section reviews some of this research, including equipment failure analysis and the impact of wind speed variability. The *RL* technique is then introduced as a means to assess and forecast reliability.

2.2.1 Equipment Failure

Failure Modes and Effects Analysis (FMEA), a general purpose failure analysis technique, is now being used in the study of wind turbine designs and how they can be simultaneously made both more reliable and more economical [16]. FMEA considers a wind turbine as a system, requiring the identification of those components that can lead to a system failure and assigning them a risk ranking based on their severity, occurrence, and detection. Although this can help improve turbine design, it lacks information on how well a wind turbine or a group of turbines would perform in meeting a community's load, given the uncertainties present in wind speeds, load, and system losses.

Ozgener and Ozgener performed reliability analysis on a wind turbine (specifically the generator) and showed that the factor of reliability (that is, the reliability of individual components) is 0.37 at 4380 hours of operation, giving it a failure rate of 2.28×10^{-4} h^{-1} [17]. The study also revealed that if 25% of all electric, electronic, and mechanical components could be improved, the failure rate would reduce to 2.10×10^{-4} h^{-1}, thereby increasing the lifetime of a wind generator from 25,000h to 30,000h. Failure rate of $1.3 \times 10^{-4}\ h^{-1}$ was achieved when the defects were brought down by 75%. Other factors that can impact the reliability of wind turbines and can lead to loss of electrical generation, such as turbine blade degradation and downtime due to equipment replacement, were not included in the analysis. The authors did not provide information on how well a set of similar turbines would perform if they were installed to meet a jurisdiction's electricity load. Similar results have also been obtained by Iniyan, Suganthi, and Jagadeesan [18].

A recent study conducted by Herbert, Iniyan, and Goic examined the overall reliability of a wind farm based on the performance of wind turbine components [19]. The results indicated that failure rates were lower during the first year of service when compared with subsequent years due to increased breakdowns and longer maintenance time. A Weibull probability distribution was applied to study the reliability of the wind farm comprising of 15 wind turbines, each of 225 kW capacity. The study listed performance parameters such as technical availability (94%), real availability (82.88%), and capacity factor (24.9%), on average, between 2000 and 2004. The analysis included a spare-part optimization study at different risk levels such as 90%, 80%, and 70% to evaluate the requirement of components during the time of unpredictable failures. The results were—five, eight, and ten spare parts for 70%, 80%, and 90% risk levels respectively, with gearbox replacement being the highest as compared to other sub-components. The spare part optimization results were useful for determining minimum shutdown periods and increasing power generation. Since this work only focused on the reliability of wind turbine components it did not discuss whether the wind farm was successful in meeting the load. Furthermore, the performance of the components in terms of their lifetime and future reliability were not considered. The study suggested that as the complexity of wind turbines increases, so does the concern over their reliability.

Edimu, Gaunt, and Herman have used probability distributions for studying reliability indices of energy systems to give a better understanding of risks as compared to using average values for parameters like failure rates and restoration times [20]. According to this study, using mean values of indices ignores the shape of the Probability Density Function (PDF) index and limits the quality of the index interpretation. The study was performed on a composite electrical-power system, using Monte-Carlo simulation techniques; failure was defined by the outages of generating unit(s), transmission line(s), or a combination of generation and transmission outages. The study found that the use of continuous PDFs in reliability analysis of unconventional sources such as wind and solar is extremely useful as the generation models reflect high levels of variability. Since this work was limited to generation and transmission aspects, no evaluation of generation against load was presented to indicate the overall reliability of the wind-energy system.

2.2.2 Wind Variability

Abul'Wafa has proposed a probabilistic method to examine the contribution of wind power to the overall reliability of an energy system [21]. The system modeling and evaluation consists of three steps: wind speed modeling, wind turbine generator (WTG) system modeling, and system risk modeling. The wind speed model simulates the variation of wind speed over specified period of time for a selected geographical site, the WTG model comprises of different WTG units totalizing 425.82 MW of installed capacity, while the system risk model involves studying the risks and reliability when the generation is compared against the load. The results indicate that there are limits to reliability with higher penetrations of wind electricity. The probabilistic method does not identify the probability distributions considered for wind speeds and loads in the case study, which if not addressed correctly, can produce incorrect reliability results. The method also omitted information on grid availability over time for which the reliability was calculated.

Degeilh and Singh's work on wind farm reliability [22] focused on minimizing the variance of aggregated wind farm output by optimally distributing a set number of wind turbines at known sites. Using three years of wind data from a NREL/3TIER study of the western U.S. provided the statistics for evaluating each site's possible mean power output, variance, and correlation with the other sites. The approach considered the impact of wind-power output variance reduction on a power system against a modeled load to study the reliability variation. The results showed that power-output variances were most reliable when the sites are not significantly correlated. A Monte-Carlo simulation was run for every hour over the three year period to determine the level of reliability of each wind turbine, had a mechanical or electrical failure taken place. Xie and Billinton conducted a similar reliability study of wind speed between two wind test sites; it showed a poor reliability of the wind farms due to high correlation of the sites [23]. A relative comparison such as this indicated loss of electrical generation but did not address the overall reliability of the system on energy services of a jurisdiction in meeting its energy needs, putting energy security at risk.

2.2.3 Reliability Assessment

The North American Electric Reliability Corporation (NERC) maintains reliability standards for bulk power system across North America by enforcing standards for power system reliability and annually checking resource adequacy using 10-year forecasts and summer and winter forecast plans [24]. According to NERC, the reliability standards are defined as planning and operating rules that electric utilities must follow to ensure the most reliable system possible. The reliability analysis involves a stepwise "Event Analysis" technique; the principal components of this analysis technique are:

- Identifying and understanding the cause of the event,
- Ensuring timely action of corrective steps or evaluation of recommendations,
- Learning lessons from such an occurrence to avoid repetition of similar events,
- Integrating risk analysis to the event analysis process, and
- Sharing the enhancements across the industry to maintain high reliability standards

The focus of such an analysis technique is inclined towards increasing the reliability of power transmission and distribution networks while discussing key issues and trends that could affect system performance. It lacks information on how the uncertainty in renewable energy sources such as wind generation can impact overall system reliability in meeting the expected load demand, limiting NERC's reliability results.

An analysis report by NERC on integrating renewables states that unique operating and planning characteristics would be required to accommodate and effectively manage their variable nature to ensure reliability standards [25]. To integrate significant amount of variable generation to the bulk power system, the analysis techniques and tools will require probabilistic approaches. According to this report, variable generation manufacturers are encouraged to support the development of probabilistic approaches or models for bulk power system reliability. Such approaches would require the use of probability density functions to address the randomness associated with renewable generation, the transmission network, and load demand. The findings suggest that an addition of risk assessment along with probabilistic techniques would be required to design the future bulk power system [24].

Another reliability approach often used by resource planners includes calculating system Loss of Load Expectation (LOLE) or Loss of Load Probability (LOLP) values [25]. These values are obtained through reliability simulations where resource adequacy is indicated by calculating reserve margins and expected demand profiles, including forced outage rates and maintenance schedules. The reliability simulations also include probabilistic cost simulations for meeting a demand curve from specified generating units over the simulation period [25].

2.2.4 Reliability Assessment Using *RL*

The uncertainties involved in a wind-energy system occur in the form of variable wind speeds (source), system losses including failures (conversion process), and variable load (services). From the reliability work discussed above, the assessment techniques either focus on uncertainties in wind as an energy source, the wind-conversion process, the electricity services using wind, or a combination of these. This kind of analysis limits the system reliability assessment where uncertainties can be ignored, potentially producing results that can be detrimental to energy security of a jurisdiction.

Some engineering systems are designed to have a certain "resistance", *R*, against an applied "load", *L*. "Resistance-Load" is a risk-analysis technique widely used for the reliability assessment of systems. The importance of this technique and its utility to both engineering and non-engineering applications make it a useful risk-assessment tool. Some examples where *RL* has been employed for reliability assessment include [15]:

1. Structural reliability: Factors such as the structural strength of beams having a specified cross-section. The beams have certain resistance R to withstand a load L; failure occurs when $L > R$.
2. Trading: Stock market trading involves an asking price and a buying price. Treating the selling price as the load L and buying price as resistance R, the stock will fail to be sold if $L > R$.

3. Communication: A local network is connected to the internet through a gateway device with a certain throughput capacity. The gateway's throughput capacity is the resistance R and the sum of the user's internet activity is the load L. A user will experience a slowdown of response whenever $L > R$.

Reliability analysis using the *RL* technique for energy security considers the random nature of electrical generation and load simultaneously. For a wind-energy system, the uncertainties associated with the net electrical generation and the energy services can be addressed using R and L, respectively. A wind-energy system will be considered reliable when its generation R will exceed the load L. The *RL* technique is used to calculate the probability of $R > L$ (represented as $P[R > L]$) which is the expected reliability of a wind farm calculated over a given year.

2.3 Summary

This chapter introduced the four main risk categories, followed by a detailed description about various application techniques aimed at improving reliability of wind-energy systems. The existing techniques fail to address the uncertainty in energy source, conversion process and energy services simultaneously, hence *RL* technique is introduced to energy security. As claimed by NERC that a combination of risk-based approach with probabilistic methods would be required to design future bulk power systems; *RL* technique can be combined with probabilistic methods to forecast reliability of wind-energy systems. The following chapter presents the reliability forecasting method.

CHAPTER 3 METHOD

This chapter presents the method of forecasting reliability using the *RL* technique. An energy system is considered reliable when its electrical generation (R) is greater than load (L). The method of forecasting reliability (or calculating the probability of $R > L$) can be summarized as follows:

1. Identifying random variables of the system
2. Analysing probability distribution of random variables through historical data
3. Calculating respective probability distribution parameters
4. Simulating, using step 3, random variables to acquire R and L values
5. Implementing reliability equations to calculate probability of $R > L$

Following these steps, the expected probability of $R > L$ for a wind-energy system for a given year can be obtained. A detailed discussion of the method is now presented.

3.1 Identifying Random Variables

For the purposes of the method, there are three time-dependent random variables:

1. Wind speeds (v)
2. System losses (*loss*) [26]
3. Load (L)

Wind speeds and system losses together contribute to a variable electrical output (or R value), while the load (or L value) can be considered independent of them.

Random variables are generally represented using probability distributions. Correct identification of a probability distribution is important and can be done with the help of graphical analysis tools such as histogram and probability plots.

To estimate future reliability, it is necessary to forecast values of R and L using simulation techniques, such as, random variate generation and Monte-Carlo simulation to obtain the most likely scenario. Sections 3.2 and 3.3 describe the steps required to model R and L values respectively, while section 3.4 discusses the reliability equations used for calculating the probability of $R > L$.

3.2 Modeling the *R* Value

R represents the total electrical output of a wind farm for a given year that can vary with wind speeds and system losses. These two random variables can be identified for their probability distributions through historical data records of wind speeds and system losses. A sample histogram as shown in Figure 3.1 describes a Weibull probability distribution.

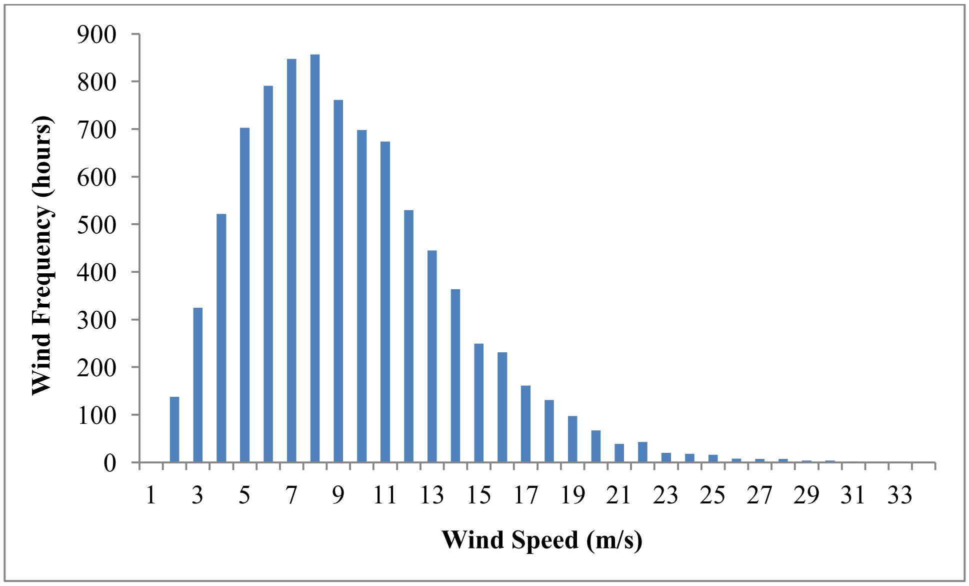

Figure 3.1 A sample histogram for a Weibull distribution

A Weibull distribution can be further verified by performing a normality test using a probability plot, a graphical technique to assess whether or not a probability distribution adequately describes a data distribution [27]. In some cases, the data may follow a normal distribution and consequently, is difficult to separate from a Weibull distribution due to similarity of the curves. A probability plot following a straight line confirms a normal distribution of the data points ([28] and [29]). It is easy to detect the spread of data points from the straight line when the data set is small, but for a larger data set, the deviation at the end points of the trend line is a better indication of non-normality. Figure 3.2 gives a sample probability plot confirming a Weibull distribution.

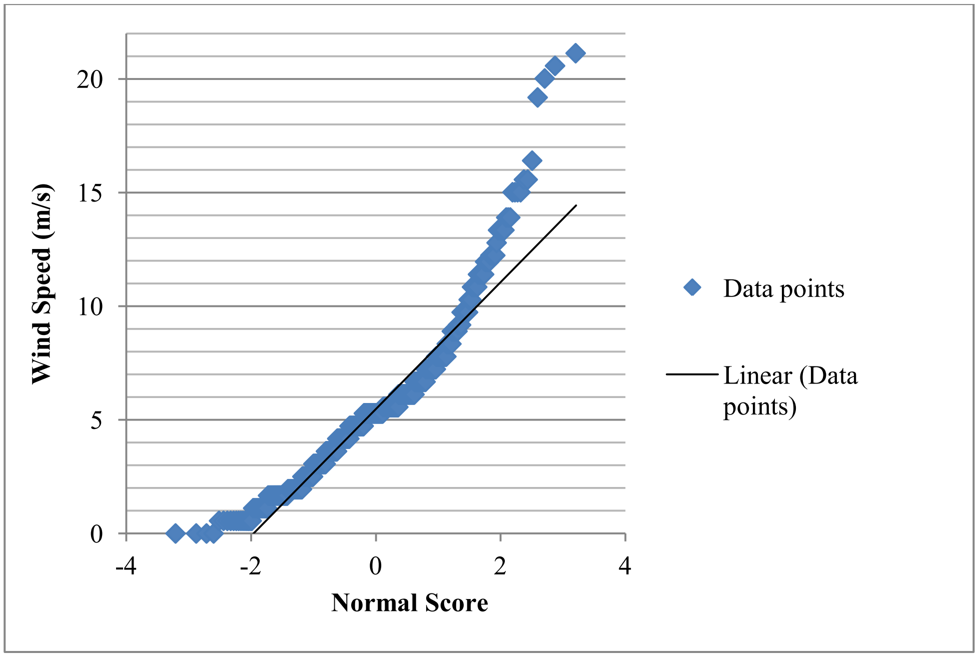

Figure 3.2 A sample probability plot

The deviation from the trend line is measured using probability plot correlation coefficient (PPCC $=\sqrt{R_{PP}^2}$) which gives the goodness-of-fit measurement for a distribution. Based on experience, an $R^2{}_{PP} \geq 0.95$, with no systematic curvature implies an adequate fit for normality, but higher the $R^2{}_{PP}$ value, more rigorous is the test for fitting a data distribution; for example, an $R^2{}_{PP} \geq 0.99$ to separate a normal distribution from a Weibull distribution can be used [27].

Since probability distribution of wind speeds v can be represented using a two-parameter Weibull distribution, its cumulative distribution function (CDF) is given by equation (3.1) [30].

$$F(v) = P[V \leq v] = \int_0^v f(v)\,dv = 1 - \exp\left[-(v/c)^k\right] \tag{3.1}$$

where c and k are the scale and shape distribution parameters, respectively. If twice the logarithm of the Weibull CDF is taken, then equation (3.1) can be rearranged as equation (3.2).

$$\ln[-\ln\{1 - F(v)\}] = k \ln v - k \ln c \tag{3.2}$$

which is similar to $y = a\mathrm{x} + b$ form, the straight line equation. One can now evaluate (ln v, ln[-ln{1-$F(v)$}]) pair by linear regression analysis to study the line-of-fit plot and obtain the values of Weibull distribution parameters using equations (3.3) and (3.4).

$$k = a \tag{3.3}$$

$$c = \exp(-b/a) \tag{3.4}$$

While $F(v)$ can be estimated by any of the methods listed in Table 3.1, where n is the number of data points and x is the x^{th} data point arranged in ascending order.

Table 3.1 Methods for estimating *F(v)*

Method	*F(v)*
Mean Rank	$\frac{x}{(n+1)}$
Median Rank	$\frac{(x-0.3)}{(n + 0.4)}$
Symmetrical CDF	$\frac{(x-0.5)}{n}$

Simulating wind speeds require generating new values of random variables with a specified distribution which involves the following two steps [31]:

1. A sequence of random numbers distributed uniformly between 0 and 1 is obtained; $u \sim U(0,1)$ representing a uniform distribution.
2. The sequence is then transformed into a sequence of random values of the desired distribution. This step is sometimes called *random variate generation*.

To generate a random distribution using a CDF, inverse transform algorithms are a common practice. Such inverse transform algorithms are based on the observation that for a given distribution having a distribution function $F(v)$, the value of $F(v)$ is uniformly distributed between 0 and 1.

To simulate wind speeds for known values of Weibull distribution parameters c and k (as calculated above), random variate generation and inverse transformation algorithm, both described through equation (3.5), and solving for $u = F(v)$ with $0 \le u \le 1$, can be used.

$$v = F^{-1}(u) = c[-\ln(1-u)]^{1/k} \tag{3.5}$$

Since u represents a uniform distribution between 0 and 1, $(1 - u)$ is also considered to be uniformly distributed and the simulated wind speeds can be obtained using equation (3.6) [31].

$$v = F^{-1}(u) = c[-\ln u]^{1/k} \tag{3.6}$$

In brief, the following two steps summarize a random Weibull distribution simulation for obtaining new wind speeds:

1. Generate $u \sim U(0,1)$
2. Return $v = c\,[-\ln u]^{1/k}$

The second random variable contributing to a variable R, that is, system losses can be identified for its probability distribution using histogram and probability plot techniques (as done for wind speeds). For a normal or lognormal distribution of system losses, the respective distribution parameters, that is, mean and variance can be obtained from historical records. These parameters can be used to simulate new set of system losses through Monte-Carlo simulation technique; a technique used to model a phenomenon with uncertainties in the input which rely on repeated random sampling for computation of results.

After obtaining simulated losses and wind speeds, the net hourly generation $P_{Net(h)}$ from a wind farm comprising N_T wind turbines can be calculated using equation (3.7).

$$P_{Net(h)} = N_T \times P_{out} - T_{loss} \tag{3.7}$$

Where P_{out} is the electrical output from a single wind turbine given by equation (3.8), where A is the turbine swept area (m^2); ρ_{air}, the air density (kg/m^3); C_p, the power coefficient (percent); and v is hourly simulated wind speed (m/s) obtained using equation (3.6).

$$P_{out} = \frac{1}{2} A \rho_{air} C_p v^3 \tag{3.8}$$

And T_{loss} is the sum of the total simulated losses, calculated using equation (3.9).

$$T_{loss} = (loss_1 + loss_2 \ldots. + loss_n) \times (N_T \times P_{out})/100 \tag{3.9}$$

Where $loss_1 \ldots\ loss_n$ are the system losses, such as, turbine generator unavailability, transmission losses, and wake-induced losses, all measured as percentages.

The modeled electrical generation or R value over a year is the summation of the net hourly generations, as shown in equation (3.10).

$$R = \sum_{h=1}^{8760} P_{Net(h)} \tag{3.10}$$

The mean and variance values for a discrete and normally distributed R are given by equations (3.11) and (3.12), respectively.

$$\mu_R = \frac{1}{8760} \sum_{h=1}^{8760} R \tag{3.11}$$

$$\sigma_R^2 = \frac{1}{8760} \sum_{h=1}^{8760} \left(P_{Net(h)} - \mu_R\right)^2 \tag{3.12}$$

For a lognormally distributed R, natural logarithm of mean and variance values must be obtained. The standard deviation is calculated by taking square root of the variance.

3.3 Modeling the *L* Value

In *RL*, load can be either normally or lognormally distributed [15]. Since an energy system's load is independent of wind speed and losses; simulating an energy load only requires a study of historical load trends of the jurisdiction. Since normal and lognormal distributions are closely related to one another, a probability plot is preferred over a histogram as it becomes difficult to separate the two based on histogram alone. To identify normal or lognormal distribution for system load through a probability plot, following steps are used [27]:

1. Let the data be determined by a random variable X having N number of data points, which can be denoted by x_n (for n = 1,2…N). Sort these values in ascending order such that $x_1 \leq x_2 \ldots \leq x_N$.
2. Check for each values of $x_n > 0$ for $n = 1,2\ldots N$. If any negative value or a zero value is encountered, a lognormal distribution cannot fit the data. If all values are positive, then go to step 3.
3. All the positive data points are then transformed by taking natural logarithms and will form the ordinate axis of the probability plot.

4. An empirical cumulative probability is then calculated for each sample size of N points using equation (3.13).

$$p_n = (n - 0.5)/N \quad \text{for } n = 1, 2 \dots N \tag{3.13}$$

   where p_n is the cumulative probability for the n^{th} ordered value.

5. The abscissa is constructed from the normal scores, $z(p)$. The normal scores for N data points can be obtained by taking the inverse of CDF of the standard normal distribution.
6. The lognormal probability plot is then constructed from the points $\{z(p_n), ln[x_n]\}$.

The data points for the plot would fit a normal and lognormal distribution if a straight line pattern is observed. A linear regression analysis using least square method can provide a quantitative measure of the goodness-of-fit and is represented by R^2_{PP}. A higher R^2_{PP} value is used to choose between a better fit of distribution. A normal probability plot can be constructed by not transforming the data points, which is, by not taking natural logarithms.

For an identified probability distribution, its respective distribution parameters, that is, mean and variance can be obtained which are used for simulating a new load for a given year. The mean of a set of numbers x_1, x_2, …. x_n is denoted by $\bar{x}$ and is called arithmetic mean. A sample mean is calculated from observations obtained by sampling a statistical population, using equation (3.14).

$$\overline{X_n} = \frac{x_1 + x_2 \dots + x_n}{n} \tag{3.14}$$

Where n is the number of observations for a variable x.

If a series of observations is sampled from a larger population or from a probability distribution which gives the probabilities of each possible result, then the probability distribution can be used to construct a "population mean" (μ_x), which is also the expected value for a sample drawn from this probability distribution. For small samples the two means may differ from each other, but the "Law of Large Numbers" states that larger the size of the sample, the more likely it is that the sample mean will be close to the population mean [32].

Variance is used as a measure of how far a set of numbers are spread from the expected value (or mean). If a random variable X has a mean value μ, then the variance of X for a population of size N is given by equation (3.15).

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2 \tag{3.15}$$

A normally distributed load is an example of a probability distribution for which a simple closed form expression does not exist, as possible in the case of the Weibull distribution where inverse transformation technique could be directly applied (for example, see equation (3.5)). To simulate a normal distribution for known mean and variance parameters, it is necessary to use numerical methods for inverse transformation technique [33]. For simulating a normally distributed load, the Box and Muller transformation algorithm can be used [34].

For simulating a lognormal distribution, random variates are generated based on the fact that, if Y is normally distributed with mean μ and variance σ^2, then e^Y is lognormally distributed with parameters μ and σ^2 [35]; the algorithm can be written as,

1. Generate normally distributed Y with mean μ and variance σ^2
2. Return $X = e^Y$

After obtaining the simulated load (normally or lognormally distributed), the total load (or L value) at the end of a year can be obtained from the summation of the hour load using equation (3.10) and replacing $P_{Net(h)}$ with L_h (hourly simulated load). For a discrete and normally distributed L, the mean and variance can be obtained using equations (3.11) and (3.12), replacing R with L, $P_{Net(h)}$ with L_h and μ_R with μ_L. Variations in load (increasing or decreasing) for a given year can be addressed by calculating new values of μ_L and σ^2_L to indicate the expected change.

For a lognormally distributed L, natural logarithm of mean and variance values should be obtained. The standard deviation is calculated by taking square root of variance value.

3.4 Calculating Probability of $R > L$

For any system, the reliability or probability $R > L$ can be defined using equation (3.16) [36].

$$P[R > L] = \int_{-\infty}^{\infty}\int_{r>l}^{\infty} f_{RL}(r,l)\, dr\, dl \tag{3.16}$$

where $f_{RL}(r,l)$ is the joint (bivariate) distribution of R and L , which can also be written as equation (3.17) [15].

$$f_{RL}(r,l)\ dr\, dl = P[r < R \le r + dr \cap l < L \le l + dl] \tag{3.17}$$

The reliability can be estimated by numerical integration, but requires knowledge of $f_{RL}(r,l)$, which may be difficult to estimate due to the large amount of data required to form a bivariate histogram and then to fit a joint distribution to it. Instead, the joint distribution can be simplified to equation (3.18) assuming R and L are independent of each other [15].

$$f_{RL}(r,l) = f_R(r) \times f_L(l) \tag{3.18}$$

With this, $f_R(r)$ and $f_L(l)$ can be estimated separately, which requires less data than $f_{RL}(r,l)$; the new reliability is given by equation (3.19).

$$P[R > L] = \int_{-\infty}^{\infty}\int_{r>l}^{\infty} f_R(r)\, f_L(l)\, dr\, dl \tag{3.19}$$

If R and L are distributed normally or lognormally, the event $[R > L]$ is same as [15],

1. $[R-L > 0]$ for normal distribution
2. $[R/L > 1]$ for lognormal distribution

For a normal distribution of R and L, the mean and variance are given by equations (3.20) and (3.21), respectively.

$$\mu_X = \mu_R - \mu_L \tag{3.20}$$

$$\sigma_X^2 = \sigma_R^2 + \sigma_L^2 \tag{3.21}$$

where X denotes R-L. For simulated values of R and L, the system reliability can be estimated using equation (3.22).

$$P[R > L] = P[R - L > 0] = P[X > 0] = 1 - \varphi(-\frac{\mu_x}{\sigma_x}) \tag{3.22}$$

where φ_x is standard normal cumulative distribution function and σ is the standard deviation.

Similarly, for a lognormal distribution of R and L, the mean and variance are given by equations (3.23) and (3.24), respectively.

$$\mu_{\ln x} = \mu_{\ln R} - \mu_{\ln L} \tag{3.23}$$

$$\sigma_{\ln x}^2 = \sigma_{\ln R}^2 + \sigma_{\ln L}^2 \tag{3.24}$$

Where X denotes R/L. The system reliability can be estimated (for simulated R and L values) using equation (3.25).

$$P[R > L] = P\left[\frac{R}{L} > 1\right] = P[X > 1] = P[\ln X > 0] = 1 - \varphi(-\frac{\mu_{\ln x}}{\sigma_{\ln x}}) \tag{3.25}$$

Equations (3.22) and (3.25) are the reliability equations and indicate the probability of $R > L$. The probabilities or value of φ_X can be obtained from normal distribution probability tables [15].

3.5 Summary

This chapter identified wind speeds, system losses and load as the three random variables for a wind-energy system. It showed how their probability distributions could be analysed through historical data using analysis tools such as histograms and probability plots. Wind speeds can be represented using Weibull distribution, while load and losses through normal or lognormal distributions. The steps for calculating respective distribution parameters and simulation steps for replicating the random variables were discussed; it was shown how values of R and L could be obtained. Finally, the probability of $R > L$ was determined by substituting the mean and standard deviation values of R and L into the reliability equations. The implementation of the method is presented through a case study performed on a wind farm and its results are discussed in the following chapter.

CHAPTER 4 CASE STUDY

This chapter demonstrates the application of the forecasting method and the *RL* technique through a case study of a wind farm located in, and supplying electricity to, the City of Summerside, Prince Edwards Island, Canada. The wind farm has 12 MW installed capacity and comprises of four Vestas V-90 wind turbines, each rated at 3 MW. The chapter begins with an identification of probability distributions of random variables by analyzing wind speeds and load using monthly data and yearly data, respectively. Simulated values of generation and load (that is, R and L) are produced using historical records from 2006 to 2009 for the year 2010 which are compared with real-time data from Summerside wind farm for verification purposes. To forecast reliability for a year in future, R and L values are simulated using data from 2006 to 2010 and reliability equations are then implemented. The chapter concludes by calculating an expected reliability (or probability of $R > L$). The case study is implemented in Microsoft Excel 2007.

4.1 Verifying the Forecasting Method

Before employing the method to forecast future R and L values, it was necessary to verify it. This was done by backcasting the expected values of R and L for 2010 using historical data from 2006 to 2009 and comparing them with the actual 2010 values. With limited wind farm data (the Summerside wind farm began operation at the end of 2009), local wind speeds (2006-09) and system losses (approximate values) were used to estimate wind farm output R, while hourly historical load (2006-09) was available from Summerside.

Hourly wind speeds for 2006 through 2009 were obtained from Environment Canada's online climate data website and were analysed for their probability distributions. The wind speeds are a two-minute average, sampled every five seconds at the end of each hour and are measured at an elevation of 10 m above ground level [37]. From the 10 m data, the wind speed for a given height can be calculated using equation (4.1) [38],

$$v = v_{ref}(h/h_{ref})^{\alpha} \tag{4.1}$$

where v is the wind speed at a higher elevation h and v_{ref} is the reference wind speed at a given height h_{ref} (in this case, 10 m). The exponent α is the wind-shear and typically assumed to be 0.2 [38]. The turbines at Summerside have a hub height of 80 m, the value of h.

An analysis of wind speed data for identification of the probability distribution was conducted for each month; sample results for February 2008 are displayed using a histogram and probability plot in Figure 4.1 and Figure 4.2, respectively.

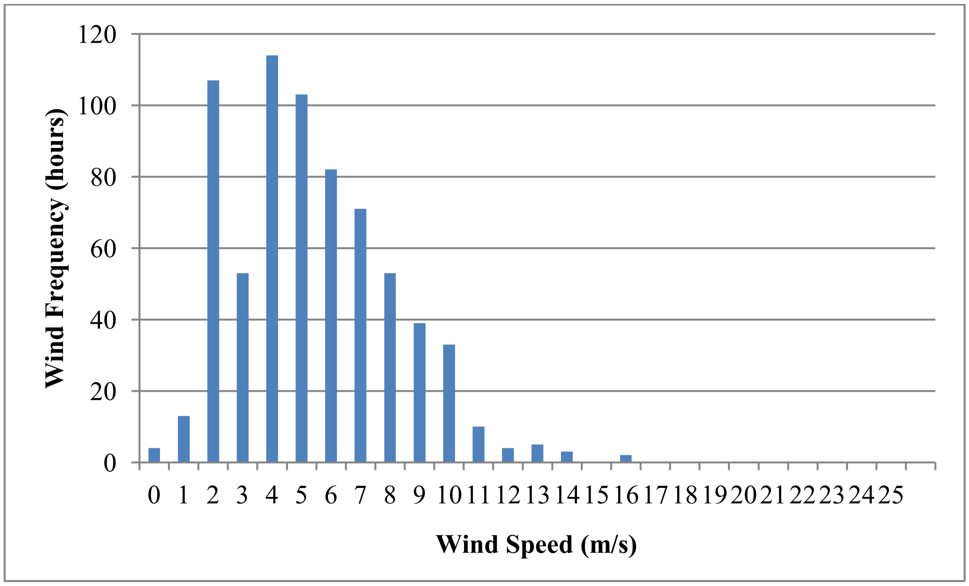

Figure 4.1 Wind speed histogram for February 2008

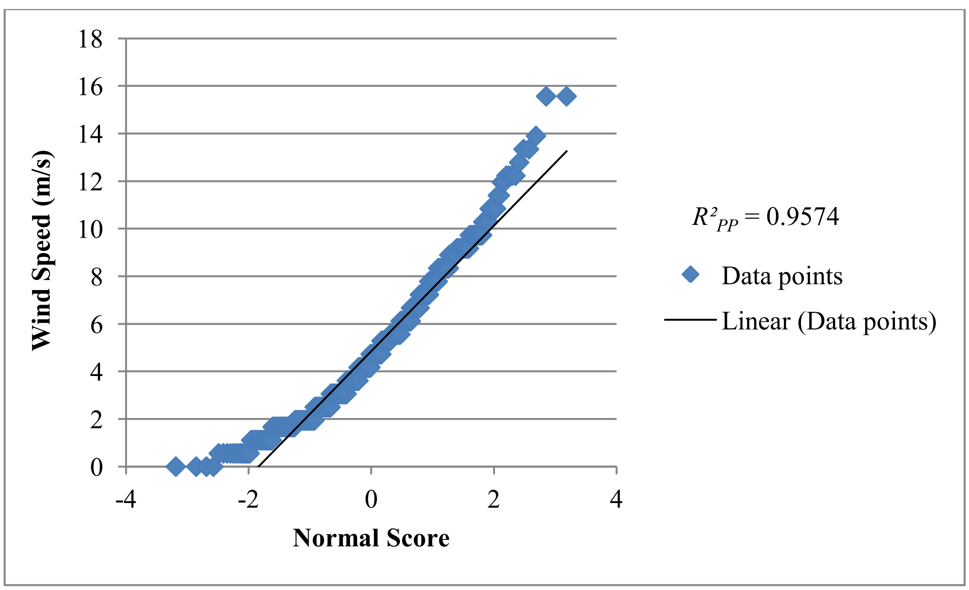

Figure 4.2 Probability plot for February 2008

An $R^2_{PP} \leq 0.9850$ and deviation from the trend line implied a Weibull distribution. The distribution parameters c and k for February 2008 were calculated using equations (3.3) and (3.4). Linear regression analysis was applied to study the line-of-fit (*LoF*) plot for estimating c and k values. The value of R^2_{LoF} (0.9867) indicated a good fit between actual data points and predicted data points. Figure 4.3 displays the results for Weibull parameter calculations.

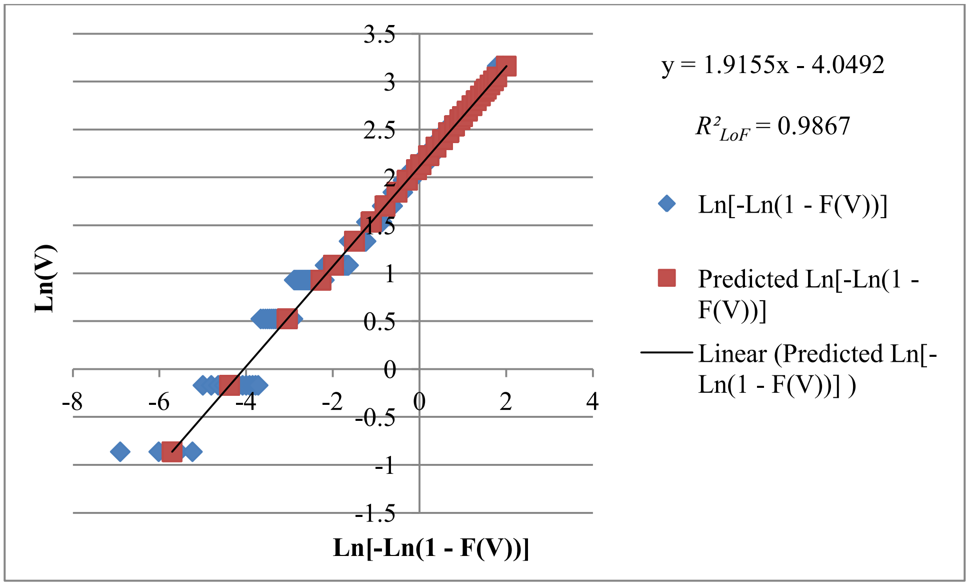

Figure 4.3 Results for Weibull parameter calculations for February 2008

Similar wind speed data analysis was performed for all the months from 2006 through 2009 and a four-year average of Weibull parameters was calculated for each month (monthly results of wind data analysis are displayed in Appendix A of the thesis). This was necessary to study historical wind speed data distribution and an average of distribution parameters was required to simulate future wind speeds that could possibly occur for 2010. For known values of c and k, wind speeds for 2010 were simulated every hour using Excel's inbuilt random generator and equation (3.6).

System losses were estimated from a wind-integration study conducted by the Nova Scotia Department of Energy; the losses and their respective values are shown in Table 4.1.

Table 4.1 Losses and their approximate values [26]

Type of Loss	Value
WTG Unavailability ($loss_1$)	3%
Collection and Substation Unavailability ($loss_2$)	0.5%
Electrical and Transmission Loss ($loss_3$)	2%
Utility/Grid Unavailability ($loss_4$)	0.5%
Icing and Blade Degradation ($loss_5$)	3%
Wake Induced Turbulence Loss ($loss_6$)	5%

The lack of wind-production data made it necessary to assume a normal distribution for the losses; system losses were also assumed to be constant for verification purposes.

The output from a single wind turbine, P_{out}, was calculated using equation (3.8), with the hourly simulated wind speeds v and Vestas V-90 specifications for A (6,362 m^2), ρ_{air} (1.225 kg/m^3), and C_P, power coefficient values corresponding to a given wind speed v [39]. The total system losses T_{loss} were calculated using equation (3.9), while the net hourly generation $P_{Net(h)}$ was obtained from equation (3.7). The final R value was reached using equation (3.10); Table 4.2 gives a result comparison.

Table 4.2 Verifying *R* value (N.A. – Not available; n.a. – Not applicable)

Parameters	2010 Summerside Data (Actual)	2010 Simulated Results	Percent Error
Maximum wind speed (m/s)	N.A.	37.36	n.a.
Peak generation (MWh)	11.69	11.82	1.1%
Total yearly generation [*R* value] (MWh)	30,278	30,323	0.14%

The L value for 2010 was simulated using distribution parameters calculated from a historical load trend analysis of the loads from 2006 to 2009. Histogram and probability plots were used for load data analysis; Figure 4.4 shows a histogram plot for load data.

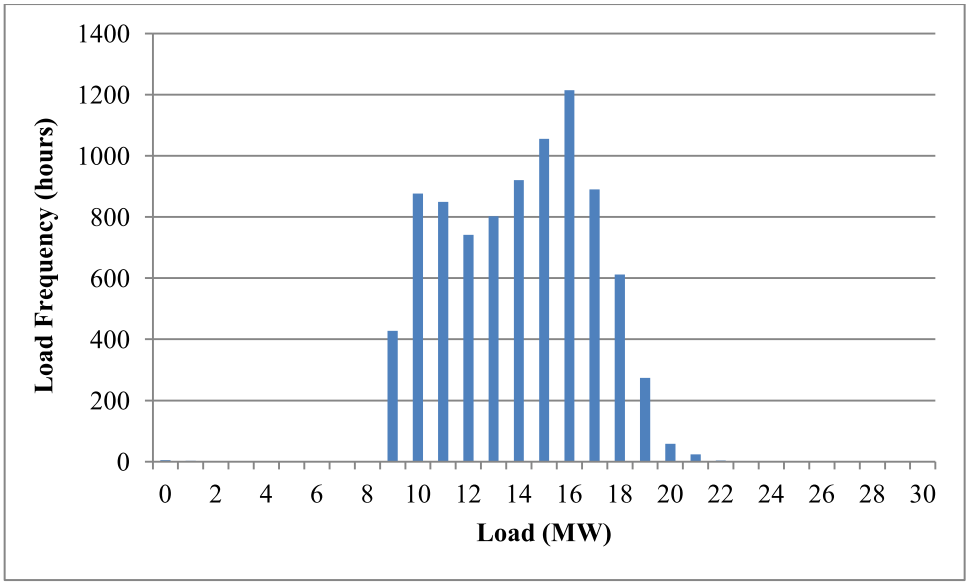

Figure 4.4 Load histogram for 2007

Since the histogram has a zero value, load follows a normal distribution because a lognormal distribution cannot have a negative or zero value. Table 4.3 lists the results of load data analysis and their corresponding histograms and probability plots are shown in Appendix B of the thesis.

Table 4.3 Type of distribution from load data analysis

Year	Type of distribution	Explanation
2006	Normal	Indicates zero value in histogram plot
2007	Normal	Indicates zero value in histogram plot
2008	Normal	Based on probability plot with higher goodness-of-fit for normal distribution R^2_{PP} = 0.9701, than lognormal R^2_{PP} = 0.9566
2009	Normal	Indicates zero value in histogram plot

The distribution parameters, mean and variance, were then calculated and a four-year average of the parameters was used to simulate a load using Excel's random generator to obtain hourly values for 2010. Table 4.4 gives a comparison of the forecast results with the actual data from Summerside.

Table 4.4 Comparing the actual and forecast *L* value for 2010

Parameters	2010 Summerside Data (Actual)	2010 Forecast Results	Percent Error
Peak load (MWh)	22.1	23.5	6.4%
Total yearly load [*L* value] (MWh)	120,440	118,804	-1.4%

The difference in peak load values showed an error of 6.4%, while the *R* and *L* simulated values indicate an error of less than 2% of the actual data for 2010, which meant that the steps employed in the forecasting method can be considered acceptable pertaining to Summerside's wind speed and load data.

4.2 Calculating Probability of *R* > *L* Using Reliability Equations

Probability calculations for $R > L$ can be performed for any given year. The *RL* technique can be employed to compare the performance of wind-energy systems over the years if historical values of *R* and *L* are available, while simulated *R* and *L* values can be used to calculate an expected reliability. The operating conditions for a year in future may change, such as, an increase or decrease in load or wind farm capacity, or both. These variations can be addressed by recalculating the values of distribution parameters μ_R, σ_R and μ_L, σ_L for *R* and *L*, respectively.

For demonstrating the *RL* technique, the probability of $R > L$ is calculated using five years of historical data from 2006 through 2010 for wind speeds, system losses and load to forecast *R* and *L* values for a given year, say 2011. No expected variations in load and wind farm capacity have been assumed for this example. The five-year average of monthly Weibull distribution parameters were obtained for simulating new wind speeds; Table 4.5 lists those scale and shape parameters.

Table 4.5 Five-year average of monthly Weibull parameters for 2006-2010 wind data

Month	**Scale Parameter (*c*)**	**Shape Parameter (*k*)**
January	9.59	1.75
February	9.34	1.89
March	9.67	1.76
April	9.80	1.85
May	8.98	2.18
June	8.29	2.07
July	7.81	2.31
August	7.2	2.15
September	8.32	1.99
October	8.85	1.80
November	9.18	1.78
December	10.95	1.79

As no historical record was available for losses, a normal distribution was assumed, while the loss values from Table 4.1 were taken as the mean. Using the mean values, Monte-Carlo simulation technique was applied which helped to simulate system losses and to study the uncertainties associated with them. Standard deviations were calculated by assuming three different values of Coefficient of Variation (CoV), 5%, 15%, and 25% [40]. To study the variations in system losses, the Monte-Carlo simulations were performed for the year 2011 at hourly intervals.

Of the six categories of losses listed in Table 4.1, $loss_2$ and $loss_4$ (substation and grid unavailability, respectively) were not included in Monte-Carlo simulation as their mean values are close to zero (~0.5%) and CoV is usually defined for non-zero means, hence they were assumed constant. Table 4.6 provides a summary of the Monte-Carlo simulation results and expected R values obtained using simulated wind speeds and losses for 2011.

Table 4.6 Monte-Carlo simulation results and the expected value of *R*

Parameters	CoV		
	5%	15%	25%
Maximum possible loss value (%)	14.7	17.6	19.9
Minimum possible loss value (%)	11.9	9.4	7.2
Peak wind farm output (MWh)	11.69	11.46	11.93
Total yearly generation *R* (MWh)	30,453	30,275	30,271
Mean [μ_R] (MWh)	3.47	3.45	3.45
Standard deviation [σ_R] (MWh)	3.40	3.38	3.38

The load data for 2010 followed a normal distribution and a five-year average of load distribution parameters (from 2006-2010) provided mean and standard deviation values of 13.61 MWh and 2.90 MWh, respectively. These values were used for simulating a new hourly load for 2011 using Excel's inbuilt random number generator. The simulated *L* value obtained at the end of the year was 117,824 MWh.

The analysis showed that both the *R* and *L* simulated values were found to have a normal distribution. For normally distributed values of *R* and *L*, the probability of $R > L$ was calculated from equation (3.22) and normal distribution probability tables were used for the corresponding values of standard normal cumulative distribution function, φ_X. The mean (μ_R) and standard deviation (σ_R) values used for *R* are listed in Table 4.6 for different CoVs; while for *L*, the values were μ_L=13.59 MWh and σ_L=2.93 MWh. The probabilities were calculated for 100%, 75%, and 50% of load and the results are listed in Table 4.7.

Table 4.7 Expected probability of $R > L$ for a given year

CoV	5%			15%			25%		
Load	**100%**	**75%**	**50%**	**100%**	**75%**	**50%**	**100%**	**75%**	**50%**
μ_X	-10.12	-6.53	-3.53	-10.14	-6.55	-3.55	-10.14	-6.55	-3.55
σ_X	4.48	4.04	3.70	4.47	4.02	3.68	4.47	4.02	3.68
P [R > L]	1.2%	5.3%	17.1%	1.1%	5.1%	16.8%	1.1%	5.1%	16.8%

The expected probability of $R > L$ in meeting a full-load is 1.2%, while half-load can be met with approximately 17% probability for all CoV values and under similar operating conditions. An increase in probability values can be seen a result of reduced load, that is, from meeting the jurisdiction's full-load to half-load. Results for 15% and 25% CoV values remained unchanged, indicating that variations in system losses have a less significant impact on wind farm reliability as compared to variations in load. The higher probability of $R > L$ reflects greater reliability in meeting a jurisdiction's load during a given year.

4.3 Summary

This chapter demonstrated the reliability forecasting method and the application of RL technique in calculating the probability of $R > L$ for Summerside wind farm under specified operating conditions of wind speeds, system losses and load. The forecasting method was first verified by simulating generation and load scenarios for 2010, which were compared with Summerside's real-time wind generation and load data, respectively. Small percentage error in R and L values, that is, less than 2%, verified the steps of the forecasting method. A five-year average of probability distribution parameters for wind speeds and load were calculated from historical data analysis from 2006 to 2010. Hourly wind speeds and load were simulated for a year in future, and R and L values were obtained. System losses being unavailable were assigned a normal probability distribution for analysis purposes. Simulation techniques such as random variate generation and Monte-Carlo simulation were employed. For a normally distributed R and L, reliability equation (3.22) was used for calculating the probability results. A low reliability (1.2%) is forecasted for the wind farm in meeting Summerside's full-load, while half-load can be met with 17% reliability. Further discussion on results in presented in the next chapter.

CHAPTER 5 DISCUSSION

This chapter presents a discussion on the results analysis of the case study performed and lists some of the assumptions made. It begins with a recalculation of reliability for an anticipated increase in Summerside's load and its impact on the reliability of the wind farm. A justification for the difference in data analysis, that is, monthly data for wind speeds and yearly data for load for identifying probability distributions is then presented. An hourly comparison of forecasted results with Summerside's 2010 actual performance for $R > L$ hours in meeting its full-load and half-load is also presented. An application of the *RL* technique for estimating number of wind turbines is then described. Such information can be useful to wind farm operators to increase their wind farm's reliability to desired levels. The chapter concludes by enlisting the case study assumptions.

5.1 Results Analysis

The case study results for the Summerside wind farm showed that the probability of $R > L$ being 1.2% for a full-load and nearly 17% for a half-load for all CoV values. Since a jurisdiction's total load can change over time, a sample calculation with a 10% increase in Summerside's load was performed and the probability of $R > L$ was recalculated. Here, the increase changed the load distribution parameters μ_L and σ_L which were recalculated and then substituted in equation (3.22). The probability values declined from 1.2% above to 0.8% for the full-load, while half-load could be met with a probability of 14.3%, down from 17%. This provided an expected reliability of the Summerside wind farm for an anticipated increase in the city's load in the near future.

Since wind speeds can show high variability and can be difficult to predict, the identification of probability distribution and calculations of Weibull distribution parameters were done with 12 separate months of wind data rather than a single year. For each month's analysis, the hourly wind speeds taken from the Environment Canada website provided sufficient data points; for example, more than 700 data points that were analyzed using histogram and probability plots, and then the distribution parameters were calculated.

On the other hand, load, being less variable than wind speeds, used annual data; the histogram and probability plots were drawn for load using 8760 data points and the distribution parameters, that is, mean and variance were calculated for each year. Since load is more predictable (for example, morning and evening peak loads), the load data analysis was restricted to yearly assessment for identification of its probability distribution. Figure 5.1 shows predictability of the peak load during any given day obtained for the year 2010, while Figure 5.2 shows the seasonal peak load variations during summer and winter months for the same year. The peak load was found to be less dynamic and varied within a specified range from 17 MW to 22 MW. A subsequent analysis of the seasonal average load for Summerside showed less variation with a range of 11.3 MW to 15.5 MW.

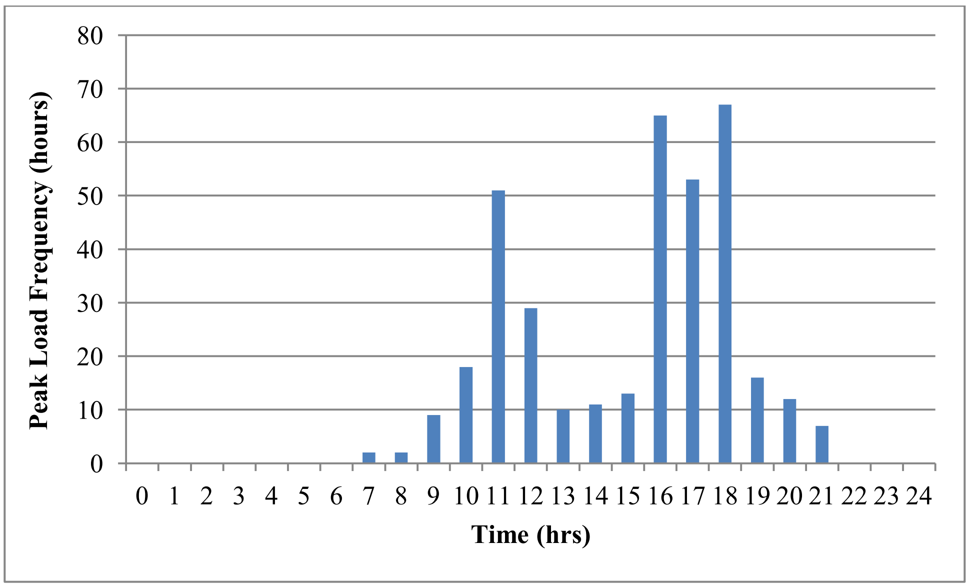

Figure 5.1 Daily morning and evening peak load histogram for 2010

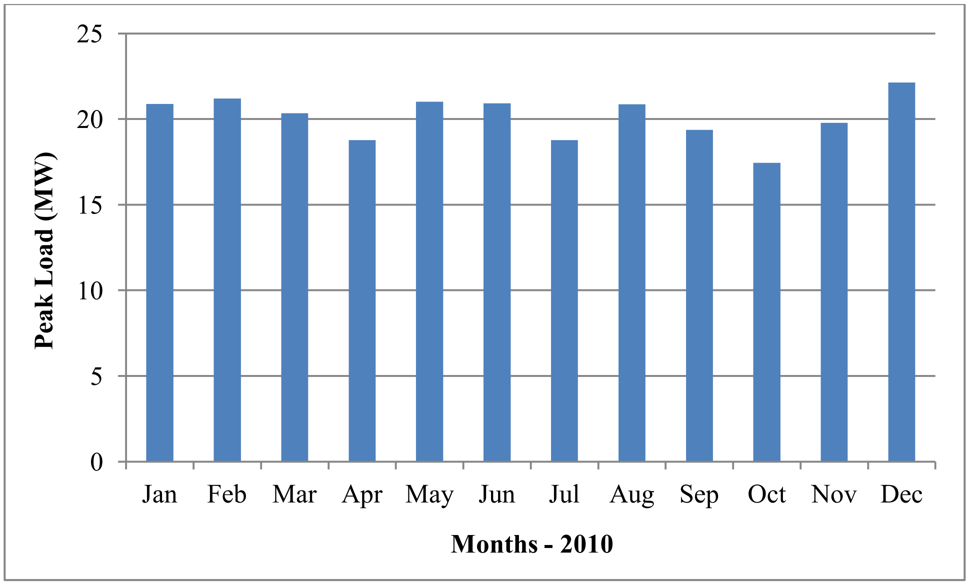

Figure 5.2 Seasonal variations in peak load for 2010

Although wind speeds are best represented using a Weibull distribution, some exceptions of normally distributed wind data were observed during the historical data analysis. The probability plots for those wind speeds followed a straight-line pattern and indicated higher values of $R^2{}_{PP}$; the $R^2{}_{PP}$ values exceeded 0.985 which confirmed a normal distribution. Table 5.1 gives a list of months that were excluded from the analysis due to normality of wind speed data.

Table 5.1 Normal distribution for wind speed data

Month – Year	$\boldsymbol{R^2{}_{PP}}$ **value**
May 2007	0.9875
July 2009	0.9884
September 2009	0.9863
December 2006	0.9877

Figure 5.3 and Figure 5.4 show a normally distributed wind data for December 2006 through a histogram and a probability plot, respectively.

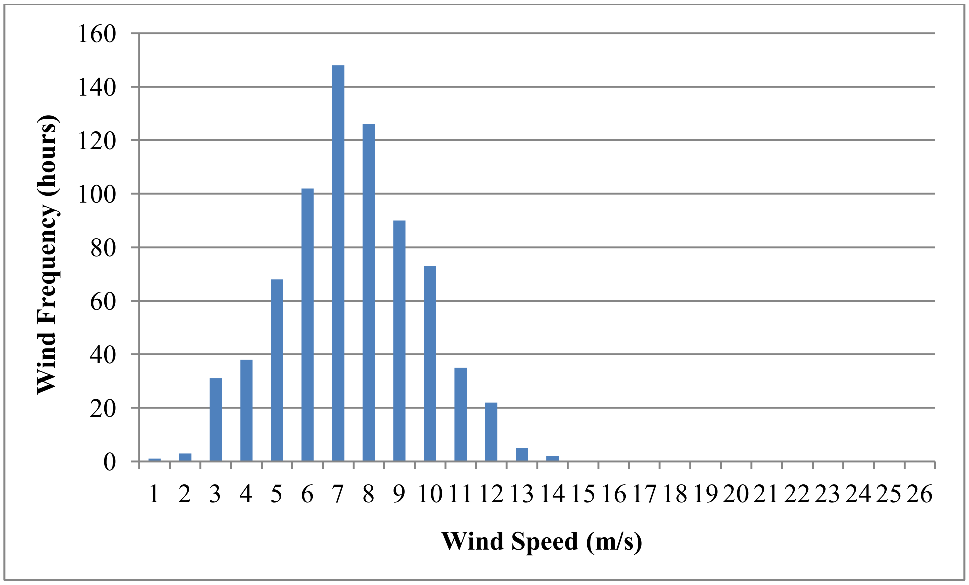

Figure 5.3 Normally distributed wind data histogram (Dec-2006)

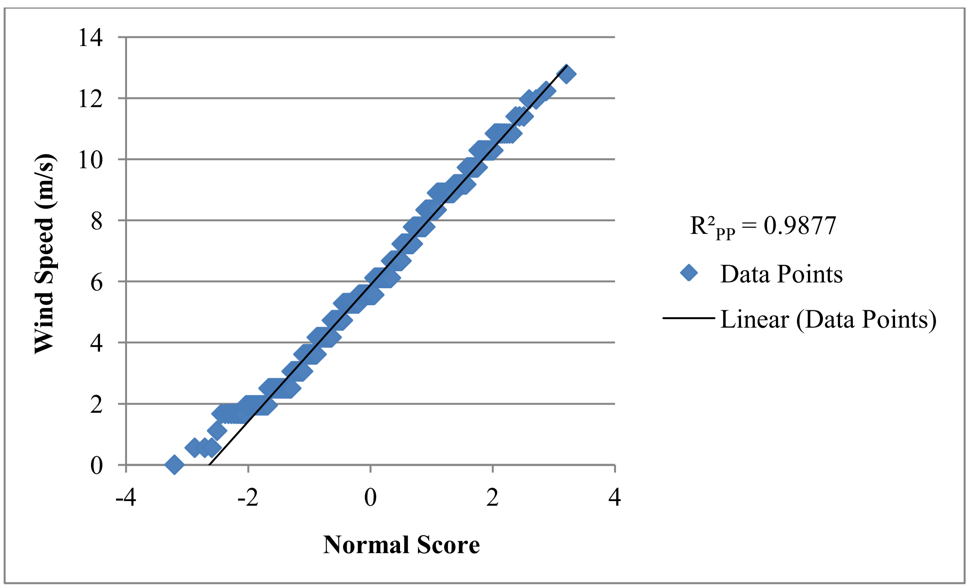

Figure 5.4 Probability plot with $R^2_{PP} \geq 0.985$ (Dec-2006)

The probability results (that is, the percentage values) cannot be considered equivalent to the number of hours (or time) in a year when the wind farm output would exceed the load; rather, the results should be interpreted as follows: a lower probability indicates a limited number of wind output hours exceeding the load, while a higher probability indicates more hours of excess generation. Table 5.2 shows the forecast of hourly supply versus full-load results compared with Summerside wind farm performance during its first year of operation. According to the definition, a wind-energy system can be considered reliable only for $P[R > L]$ (see equation (3.16)), while the failure is defined as $P[R \leq L]$, that is, an unreliable system [36].

Table 5.2 Comparison of supply versus load hours (full-load) for 2010

Criteria	Actual 2010 Hours	Forecast			Outcome
		Hours	Time	Probability	
$R < L$	8509	8612	98.3%	98.8%	Unreliable
$R = L$	1	0	0%	0%	Unreliable
$R > L$	250	148	1.7%	1.2%	Reliable

The reliability results forecast for Summerside showed a probability of $R > L$ of 1.2%, which corresponds to 148 hours (or 1.7% of the time) when wind generation exceeds the load. A higher percentage would have indicated more number of hours with excess of wind-generated electricity, or in other words, greater wind farm reliability. Reasons for lower reliability of the wind-energy system can be attributed to a low annual mean generation from the wind farm (approximately 3 MW) when compared with Summerside's average load (approximately 13 MW) per year. Table 5.3 gives an hourly comparison of the forecasted performance where excess wind-generation could meet Summerside's half-load more reliably (with nearly 17% probability), that is, for 1876 hours (or over 21% of the time).

Table 5.3 Comparison of supply versus load hours (half-load) for 2010

Criteria	Actual 2010 Hours	Forecast			Outcome
		Hours	Time	Probability	
$R < L$	6902	6884	78.6%	82.9%	Unreliable
$R = L$	0	0	0%	0%	Unreliable
$R > L$	1858	1876	21.4%	17.1%	Reliable

Hourly comparisons such as this can be useful in studying the short-term availability of wind-generated electricity which can provide information to a wind farm operator to plan for the import or export of electricity as needed. To improve its energy security, the city of Summerside is also connected to West Cape supply (a wind farm having 9 MW installed capacity) and can purchase electricity from New Brunswick Power (a power utility company), when needed. This dependence on other resources for electricity is indicative of the uncertainty associated with wind energy (or an energy source).

Since hourly historical load data was available from 2006 through 2009, the wind farm's 2010 generation was also compared with different loads from these years. This was done to estimate how the wind farm would have performed over these years for a given Summerside load, had it been operating since 2006. The reliable hours of wind-electricity (that is, $R > L$ hours) were found to be 297, 217, 192 and 179 hours from 2006 to 2009, respectively. A decreasing number of hours of reliable wind-generation were a result of consistent rise in Summerside's load since 2006; but, a high value of 250 hours of excess generation for 2010, up from 179 in the previous year, indicated an overall reduction in energy consumption during 2010. The 2010 L value at the end of the year was 120.4 GWh, down from 122.4 GWh during 2009. Such a variation reflected the uncertainty involved in the end-user demand (or energy services).

The number of iterations performed for simulating system losses using the Monte-Carlo technique were done for 8760, 26280 and 43800 values, which is equivalent to one, three and five years of hourly data points, respectively. The variations in losses simulated over the three time periods showed negligible variations, hence 8760 iterations were chosen for the case study. Also, the final probability results were similar for 15% and 25% CoV values which demonstrated that variations in system losses, one of the random variables, had less significant contribution towards reliability results as compared to variations in the load; hence, choosing one year of iterations was considered a reasonable choice.

The probability results are anticipated values indicating expected annual performance of the wind farm which has been designed to operate under a defined set of conditions, such as expected wind speeds, load, and system losses. The contribution of these results can be useful in studying wind energy projects which have been proposed with significant installed capacity and large number of wind turbines. Such projects usually provide information on the percentage share of the energy mix that would be met using wind-generated electricity, but often fail to address how reliable a wind farm would be in meeting a jurisdiction's load. It is necessary from the viewpoint of energy security to have an estimated reliability of a wind-energy system which employs a variable source of energy, instead being entirely unaware of its potential performance: the higher the probability value, the greater is the wind-energy system's reliability.

5.2 Applications of the *RL* Technique

The *RL* technique can be useful in determining additional number of wind turbines required to improve wind farm's reliability. For example, to achieve reliability (that is, $P[R > L]$) value of 75%, a new mean generation μ_R should be calculated to estimate additional number of wind turbines. For a normally distributed R and L, new μ_R value can be calculated using reliability equation (3.22), for which the inputs, such as $P[R > L]$ values over 50% can be obtained using student-t distribution table for corresponding α value (representing probability percentage) and v (representing degrees of freedom) [42]; and σ_R can be substituted in terms of μ_R using a CoV value obtained from Table 4.6. For example, a sample calculation for 60% reliability (up from the current 1.2%) in meeting Summerside's full-load would require 12 additional wind turbines, assuming each rated at 3 MW or an additional capacity of 36 MW to its existing generation.

The application of the *RL* technique is not limited to wind energy. A jurisdiction may employ multiple energy sources where estimating the overall reliability of an energy system holds greater significance than reliability of one energy resource. The forecasting method can be applied to any energy source that is random in nature, such as, wind or solar and their expected generation can be combined with the generation of other sources such as oil, natural gas and coal to obtain a new mean value μ_R—the total generation from all energy sources. The new mean can be used to find a jurisdiction's energy system reliability against a modeled load (or μ_L value) by calculating the probability of $R > L$ using reliability equations. Hence the wide applicability of *RL* analysis is an advantage to energy security as it can be combined with different energy sources, either renewables or non-renewables, or both.

5.3 Case Study Assumptions

The reliability forecasting method using historical data analysis and application of the *RL* technique presented has limitations which required assumptions being made due to limited data availability.

For example, missing hourly wind data from the Environment Canada datasets were handled in one of the two ways:

1. A block of up to five consecutive hours of missing wind data were assigned an average wind speed of the previous and next hour value. Using average wind speeds for missing wind data have been applied and suggested in [41].
2. A block of more than five consecutive hours of missing wind data was considered as non-existent. Assigning an average value for a greater number of hours was rejected due high variations of wind speeds; hence, the histograms and probability plots were drawn with only available monthly wind data. Table 5.4 gives a list of months of missing wind data from 2006 through 2010.

Table 5.4 Missing wind speed data (2006-2010)

Month – Year	Available wind speeds (hrs)	Missing wind speeds (hrs)
January 2006	688	56
March 2009	654	90
April 2008	686	34
May 2008	0	744
May 2009	738	6
September 2008	708	12
November 2010	714	6

Limited data availability from Summerside meant that it was necessary to use system losses from the Nova Scotia Wind-Integration study report. These losses were assigned a normal distribution and their variance values were calculated using different CoV values; the final results being similar for 15% and 25% CoV. Data availability would have helped analysing the probability distribution for system losses as done for wind speeds and load.

5.4 Summary

This chapter presented a discussion on the case study results obtained for forecasting reliability for Summerside wind farm. Monthly historical data of wind speeds and yearly data for load was used for identification of probability distributions. Wind speeds are generally represented using a Weibull distribution, but some exceptions of normal distributions were observed; those months were excluded from the analysis. An hourly comparison of generation and load forecasted values showed an excess of wind-generated electricity for 148 hours in meeting a full-load and for 1876 hours in meeting a half-load for Summerside. Reliability of the wind farm was also calculated for an anticipated 10% increase in load which further reduced the probability of $R > L$ to 0.8% from the current 1.2% for a full-load. An application of the RL technique was used to estimate number of wind turbines that could make Summerside wind farm more reliable; an additional capacity of 36 MW can increase its reliability value to 60%. Some assumptions were considered to address the missing wind data from Environment Canada website. Due to limited data availability from Summerside, system losses were taken from Nova Scotia Wind-Integration study report. Next chapter presents the concluding remarks for the thesis.

CHAPTER 6 CONCLUSION

The challenges of addressing energy security and climate change are expected to drive the growth of renewable-based electrical generation. Wind energy is now considered by many as one of the possible solutions to counter these challenges. As a result, worldwide growth in wind energy is expected to increase as more wind turbines are installed to meet the demand for clean electricity.

Despite this, wind energy has risks and uncertainties that need to be addressed, perhaps the most significant being that due to its variability, it cannot be considered as a reliable source of energy for meeting an electrical load. Such uncertainty raises concerns regarding the ability of wind-energy systems to contribute significantly towards a jurisdiction's energy security.

Given the need for reliability in wind-energy systems, the contribution of this thesis has been a method intended to forecast an expected reliability while simultaneously addressing the uncertainties of wind, wind turbines, electrical network (including losses), and load. The method is a combination of a forecasting method and a risk-based technique: the forecasting method is used to model future generation and load (or R and L) scenarios through simulations, while the RL technique, a risk-based approach for calculating reliability of systems—either engineering or non-engineering—was introduced to energy security.

The method begins with an identification of random variables—or the sources of uncertainty—within a wind-energy system whose values can change with time; they were identified as wind speeds, system losses and load. Random variables are generally represented using probability distributions, for example, normal, lognormal or Weibull. A correct identification of a probability distribution is important for addressing the uncertainties of a system; an incorrect identification can produce wrong reliability results that can be detrimental to energy security. Graphical analysis tools, such as, histograms and probability plots can be used for identification purposes. Since normal, lognormal and Weibull distributions possess similarity of curves, a rigorous test using probability plots is necessary to separate these distributions. A higher R^2_{PP} value can be used; usually, an R^2_{PP} value of 0.95 or more indicates a normal distribution, but an R^2_{PP} value of over 0.985

can also be selected. Wind speeds, losses and load were analysed for their probability distributions using historical data records. Histograms provided a visual identification, and probability plots were used to study the best-fit of a distribution for a given data set. Using these analysis tools, the objectives of identifying the random variables and their corresponding probability distributions was achieved.

Following this identification, the probability distribution parameters were obtained. A Weibull distribution is represented through its scale c and shape k parameters, while normal or lognormal distribution through its mean μ and variance σ^2. Based on the fact that a Weibull Cumulative Distribution Function (CDF) can be rearranged to represent the straight line equation, its parameters (c and k) were calculated using the line-of-fit plot which employed linear regression analysis technique. For normal or lognormal distributions, the parameters, that is, its mean and variance were obtained from historical data analysis. For a large data set, for example, yearly data with 8760 observations, the arithmetic mean was considered similar to population mean based on the principle of "Law of Large Numbers"; and in case of limited data availability and for a known mean value, a Coefficient of Variation (CoV) was assumed. With this, the objective of obtaining the probability distribution parameters was met.

To forecast reliability of a wind-energy system, future generation and load (or R and L) scenarios must be simulated. A variable wind output is a function of wind speeds and system losses, while the load can be considered independent of them. To model an R and L value, the random variables, that is, wind speeds, losses, and load were simulated using simulation techniques, such as, random variate generation and Monte-Carlo simulation. All simulations were done using Microsoft Excel 2007 software. Simulating hourly wind speeds required Weibull distribution parameters, a uniform distribution obtained using random variate generation, and inverse transformation technique. For normally distributed system losses, Monte-Carlo simulation technique was used to generate hourly values; while Excel's inbuilt random generator was used for simulating an hourly load. Using these hourly scenarios the final R and L values were obtained at the end of the year. Hence, the objective of replicating the random variables and obtaining the simulated R and L values was achieved.

A wind-energy system can be considered reliable only when its generation exceeds the load (or $R > L$). To achieve the final two objectives of the thesis, that is, verifying the forecasting method and to calculate the reliability of a wind-energy system, a case study was done on Summerside wind farm; a 12 MW wind farm which began operating since October 2009 and supplies electricity to the city of Summerside (meeting its residential and industrial load).

To verify the forecasting method, historical records of the three random variables, that is, wind speeds, system losses and load were obtained from 2006 to 2009 using which the new values of generation and load were simulated for 2010; Summerside provided the real-time hourly data for the same year. After identifying the probability distributions—Weibull distribution for wind speeds and normal distribution for load and losses—their respective probability distribution parameters (as a four-year average) were calculated. Hourly simulated wind speeds were generated, while losses were assumed constant for verification purposes, and a simulated R value was obtained for 2010. A summation of hourly simulated load provided the final L value at the end of the year. The result comparisons of actual and simulated R and L values showed an error of less than 2%, and the objective of verifying the forecasting method was achieved.

Using this forecasting method and five years of historical data from 2006 to 2010, future R and L values were simulated. A five-year average of Weibull distribution parameters for simulating wind speeds and Monte-Carlo technique for simulating losses were used to obtain a future R value. The L value was simulated using Excel's random generator for which the inputs—five year average of mean and standard deviation—were used. The R and L values were found to be normally distributed and reliability equation (3.22) was used to calculate reliability (or probability of $R > L$) which was obtained using normal probability distribution tables. The probabilities were calculated for full-load, 75% load and half-load; and the results were 1.2%, 5.3% and 17.1%, respectively. An hourly comparison of forecasted values showed an excess of wind-generated electricity for 148 hours that could reliably meet a full-load and 1876 hours to meet a half load. With this, the objective of calculating an expected reliability of a wind-energy system achieved.

An application of the *RL* technique was also used in forecasting the reliability of Summerside wind farm with an anticipated increase in load. A 10% increase in Summerside load was assumed for the future which changed the load distribution parameters. The new mean and standard deviation values were obtained and reliability was recalculated. The new reliability results showed a probability of $R > L$ at 0.8% which declined from the current 1.2% in meeting Summerside's full-load.

An additional number of wind turbines were also calculated using the *RL* technique. For a desired reliability and a known load, a new mean generation value was obtained. A sample calculation for 60% reliability of the wind farm in meeting Summerside's full-load was performed which resulted in an additional 36 MW capacity requirement or 12 new wind turbines assuming each rated at 3 MW. Such results can be useful to wind farm operators to estimate how many more wind turbines are actually needed to improve their wind-energy system's reliability and to what levels.

At present wind energy only constitutes a small share of the current energy mix. As indicative from the results, it is yet to prove itself in terms of reliably contributing towards energy security and also towards climate change. Due to the risks and uncertainties involved, forecasting reliability of wind-energy systems will remain the prime concern as the growth of wind energy continues in the future. Also, as stated by North American Electric Reliability Corporation (NERC) future bulk power systems would require an application of both—probabilistic methods and risk analysis techniques—a reliability forecasting method such as the one presented is a combination of these approaches.

Many wind energy projections only focus on additional installed capacities to be added in the future, but lack information on how well those wind farms will actually perform against a given load. As a result, these projections tend to overlook the uncertainties and the risks involved in energy source (wind variability) and the dynamism of energy services (variable load). Adding wind energy by setting up wind farms worldwide cannot guarantee an equivalent supply of reliable wind-electricity, hence, it will be important to have knowledge about the potential performance of wind-energy systems. This generic method can be applied to forecast any wind-energy system's reliability with available historical data for wind speeds, system losses and load. With the information on reliability forecasting of wind-energy systems, the world can look forward to a more secure energy future and simultaneously respect environmental concerns, or in other words, counter the twin challenges of energy security and climate change.

6.1 Limitations of the Method

The availability and access to risk-analysis software can be a limitation. The kind of reliability assessment presented here is generally performed with the help of commercially available risk-analysis packages. These packages have inbuilt capability to identify the probability distributions and generate random numbers that results in using lesser number of equations while also reducing the simulation time. Due to such features, the risk-analysis packages can be expensive and usually have limited access, unless purchased. The easy applicability of the method described in the thesis can be seen from the fact that Excel software which is widely available to many users can also be used to demonstrate the reliability forecasting method employing the *RL* technique, when access to expensive software can be problematic. The lower percentage error verified the steps, the equations used to demonstrate the reliability forecasting method, and the acceptability of Excel software for this study.

To implement the reliability equations, R and L must have similar probability distributions, both normally distributed for equation (3.22) and lognormally for equation (3.25), as the simulated data may result in change of the probability distributions of R and L. Following the simulations, the forecast values for R and L must be verified for their correct probability distributions using histogram and probability plots before applying them to reliability equations. The possibility of a change in probability distribution is high in the case of R value which is obtained by simulating two random variables at the same time, that is, wind speeds and system losses, using Excel's built-in random number generator and Monte-Carlo simulation, respectively; while in the case of the L values, the required probability distribution can be specified beforehand—as normal or lognormal—an inbuilt capability of Excel software. The *RL* analysis application will fail if a difference in probability distributions of R and L occurs.

6.2 Future Work

In addition to the work presented above, several enhancements can be made in the following ways:

1. With an expected know value of wind-generated electricity, a jurisdiction can evaluate its actual greenhouse gas reductions possible over a given year.
2. With hourly information available on wind-generated electricity from a wind farm, some applications, such as charging of electric vehicles and storing wind energy (in ETS units for space heating) can be better planned.
3. Another possible future work using this approach can be helpful in forecasting reliability of solar-energy systems which also involves a renewable and variable source of energy.

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APPENDIX A Historical Wind-Data Analysis Results

Additional results on the probability distribution identification of historical wind data (2006-2009) through histogram and probability plots are shown in this section. A histogram only provides visual identification, while a probability plot is constructed to confirm the best-fit for a Weibull distribution.

Including each month's wind data analysis results of the past four years would have resulted in large number of histograms and probability plots, hence, this has been addressed by selecting three different months from each of the previous four years; Table I gives a brief summary.

Table I Historical year and months selection for wind data analysis results

Year	Months
2006	January, February and March
2007	April, May and June
2008	July, August and September
2009	October, November and December

Each month's result analysis includes a histogram and its corresponding probability plot. Any R^2_{PP} value of more than 0.985 rejects a Weibull distribution and confirms normality of wind speed data.

Figure I and Figure II show wind data analysis for January 2006 hourly wind speeds.

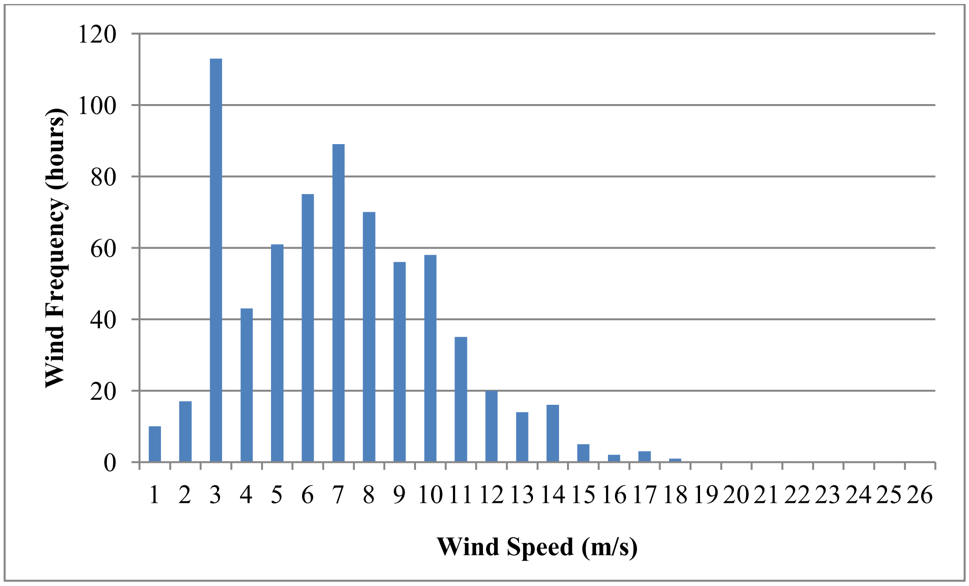

Figure I Histogram for January 2006 wind speeds

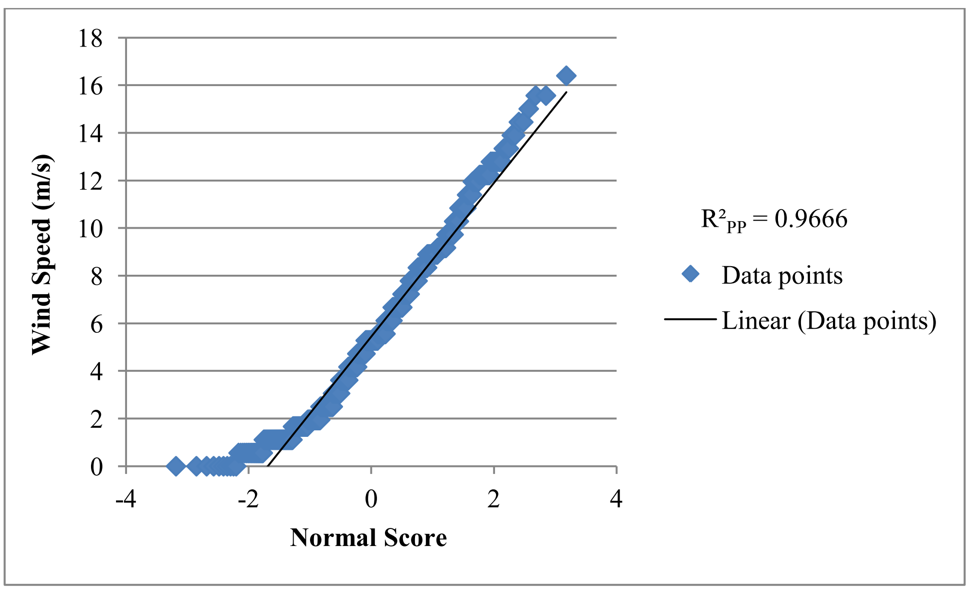

Figure II Probability plot for January 2006 wind speeds

Figure III and Figure IV show wind data analysis for February 2006 hourly wind speeds.

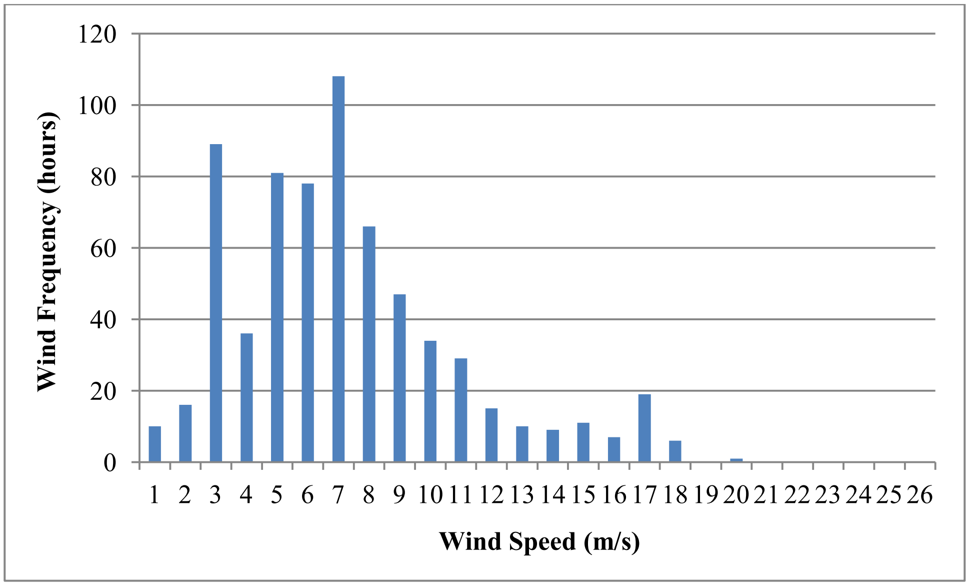

Figure III Histogram for February 2006 wind speeds

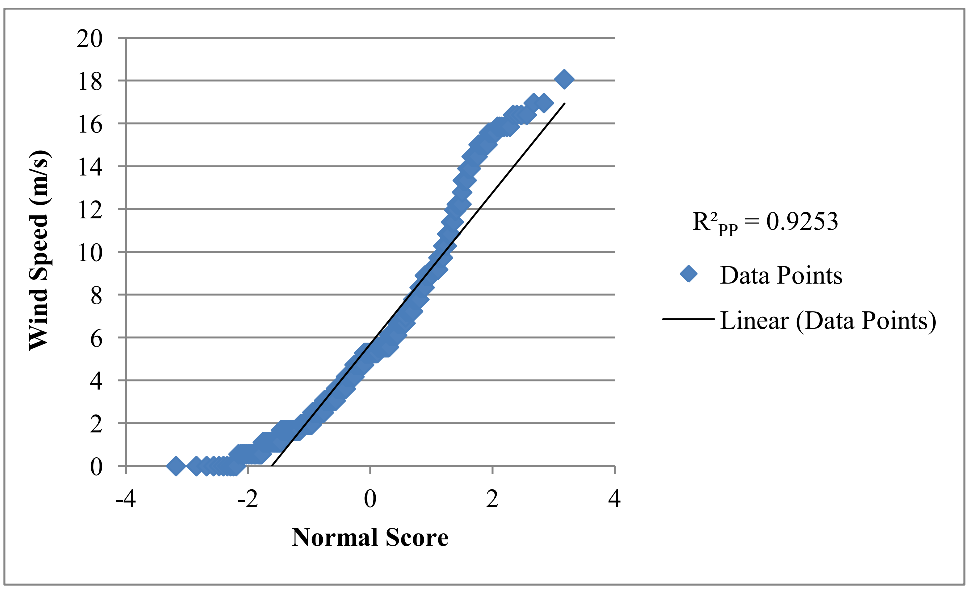

Figure IV Probability plot for February 2006 wind speeds

Figure V and Figure VI show wind data analysis for March 2006 hourly wind speeds.

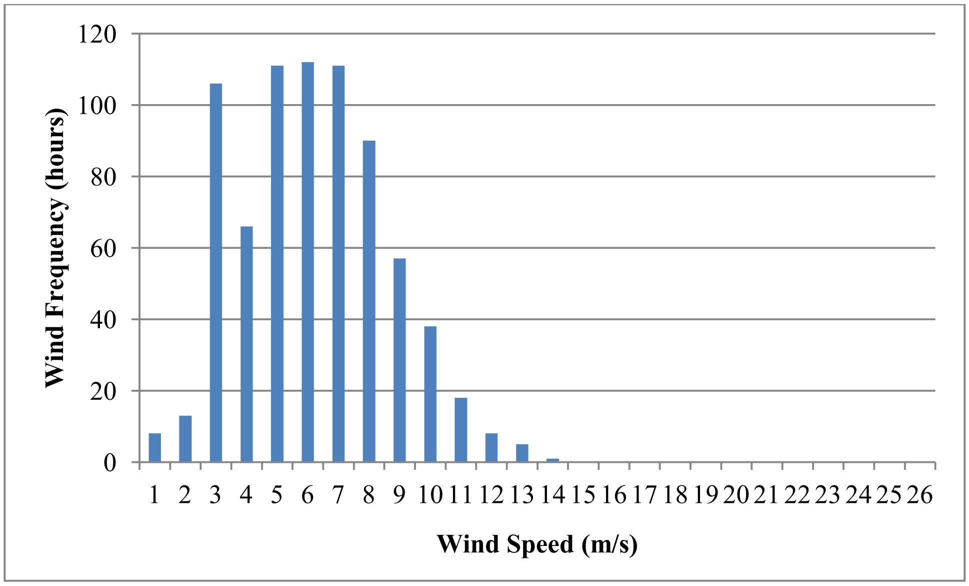

Figure V Histogram for March 2006 wind speeds

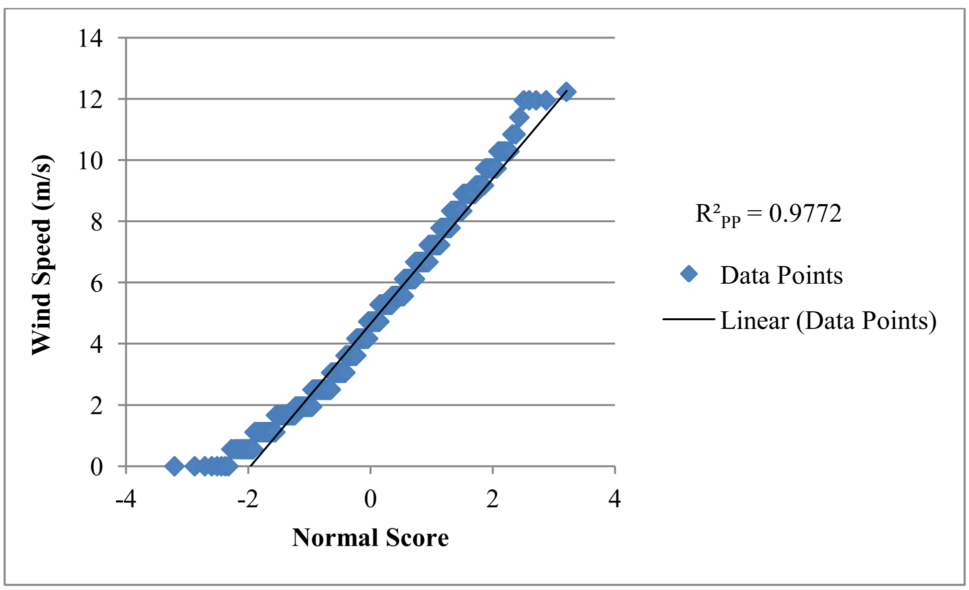

Figure VI Probability plot for March 2006 wind speeds

Figure VII and Figure VIII show wind data analysis for April 2007 hourly wind speeds.

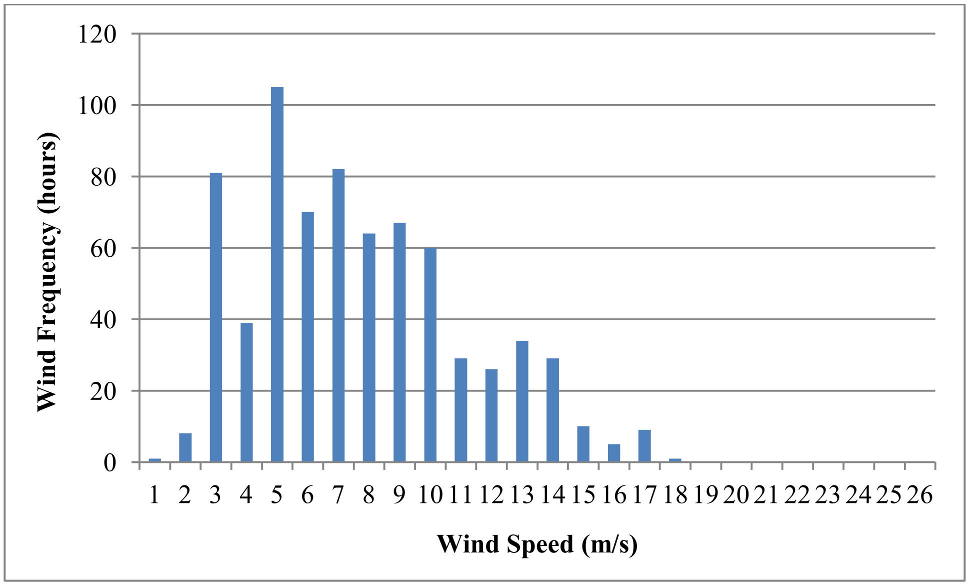

Figure VII Histogram for April 2007 wind speeds

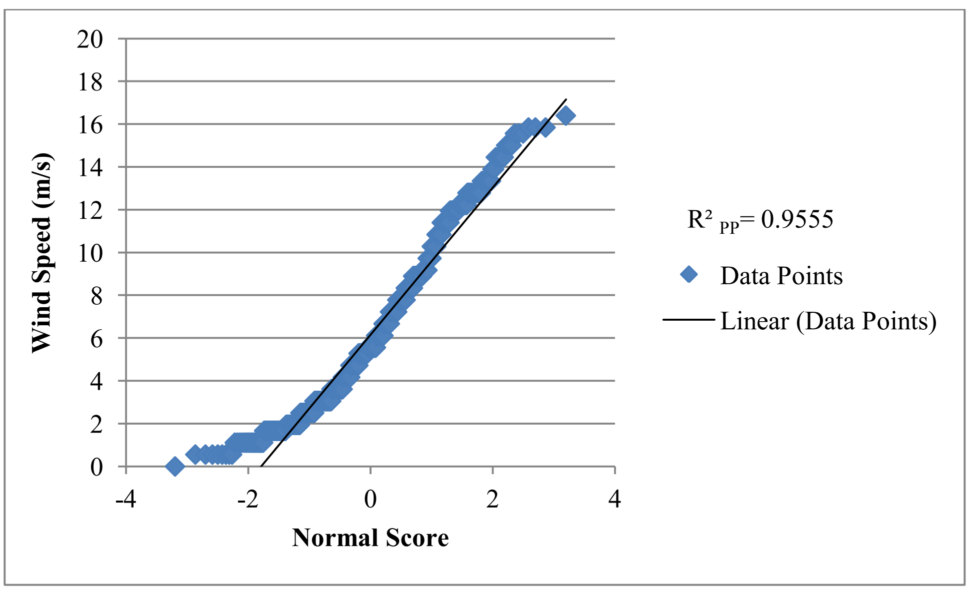

Figure VIII Probability plot for April 2007 wind speeds

Figure IX and Figure X show wind data analysis for May 2007 hourly wind speeds.

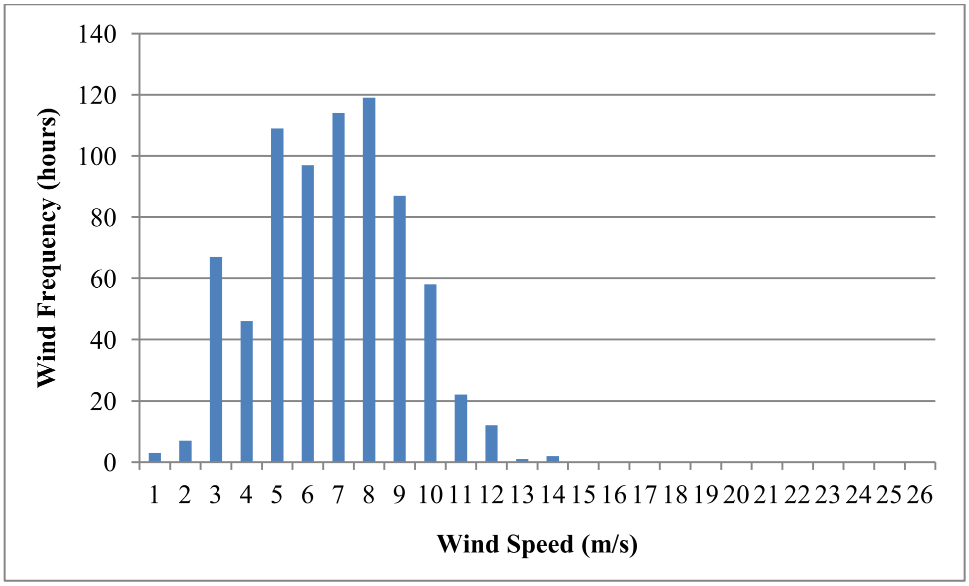

Figure IX Histogram for May 2007 wind speeds

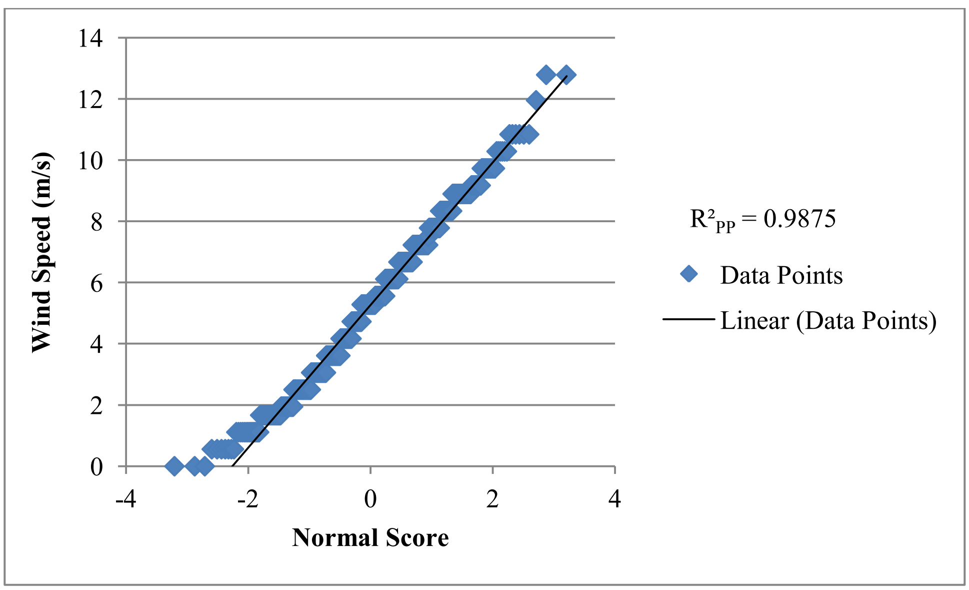

Figure X Probability plot for May 2007 wind speeds

Figure XI and Figure XII show wind data analysis for June 2007 hourly wind speeds.

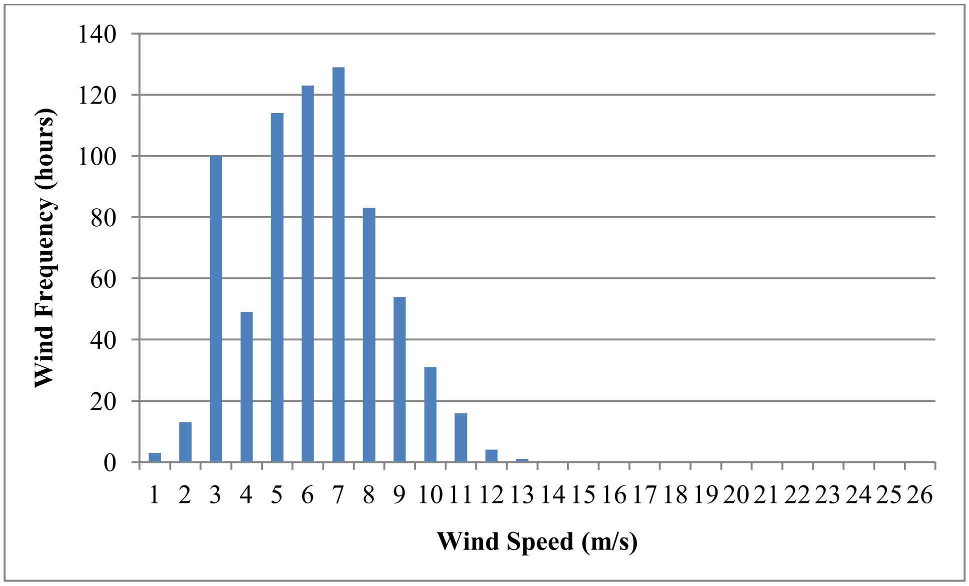

Figure XI Histogram for June 2007 wind speeds

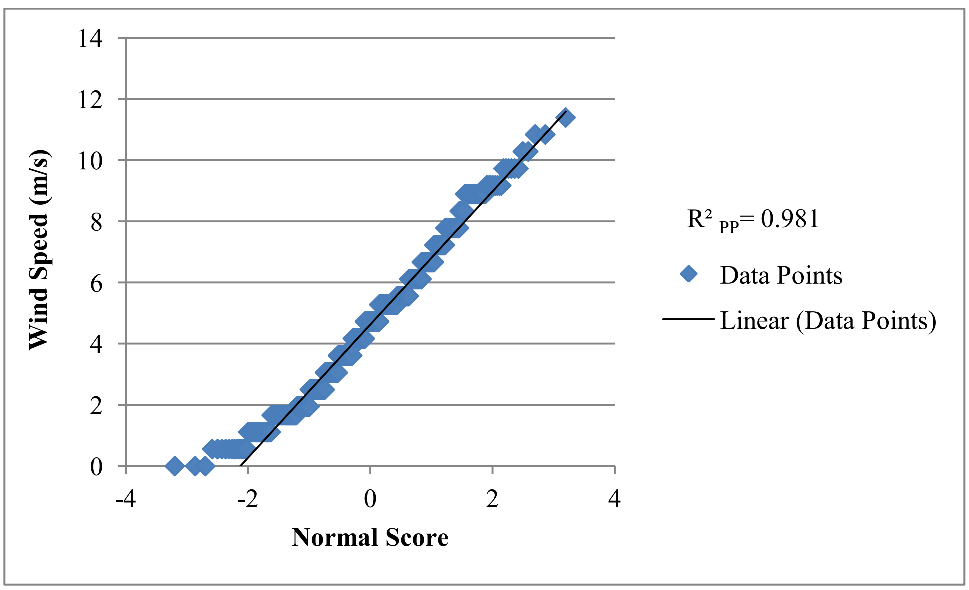

Figure XII Probability plot for June 2007 wind speeds

Figure XIII and Figure XIV show wind data analysis for July 2008 hourly wind speeds.

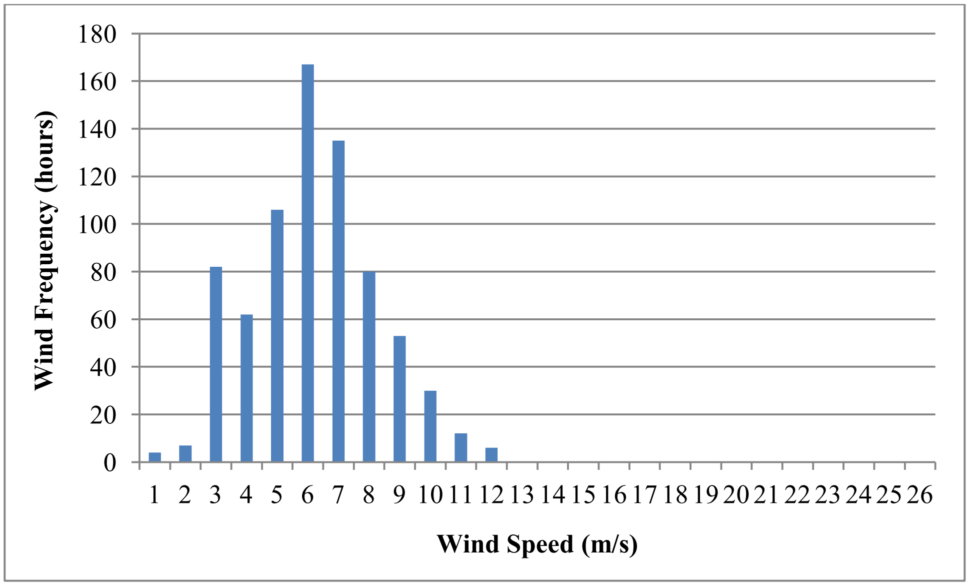

Figure XIII Histogram for July 2008 wind speeds

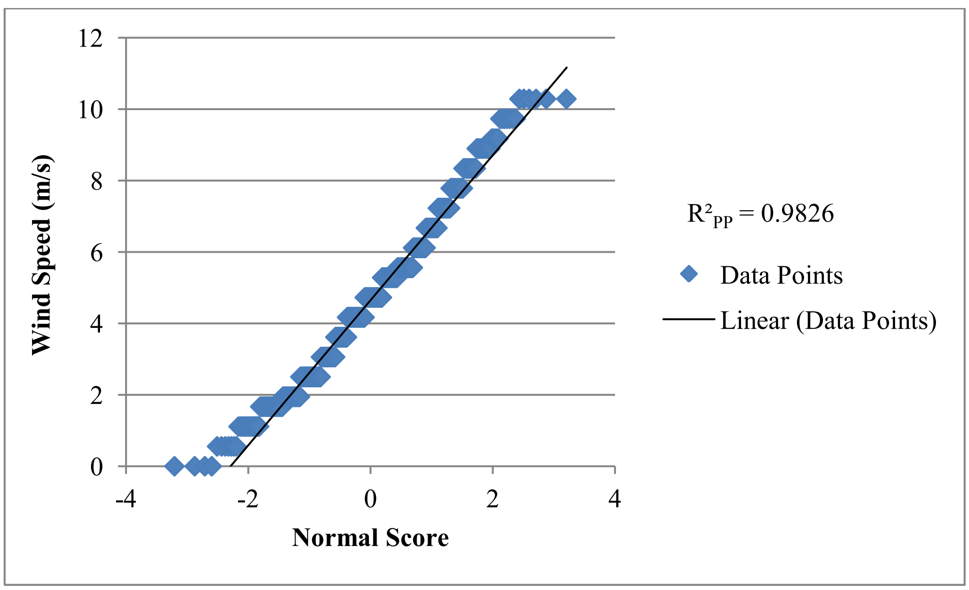

Figure XIV Probability plot for July 2008 wind speeds

Figure XV and Figure XVI show wind data analysis for August 2008 hourly wind speeds.

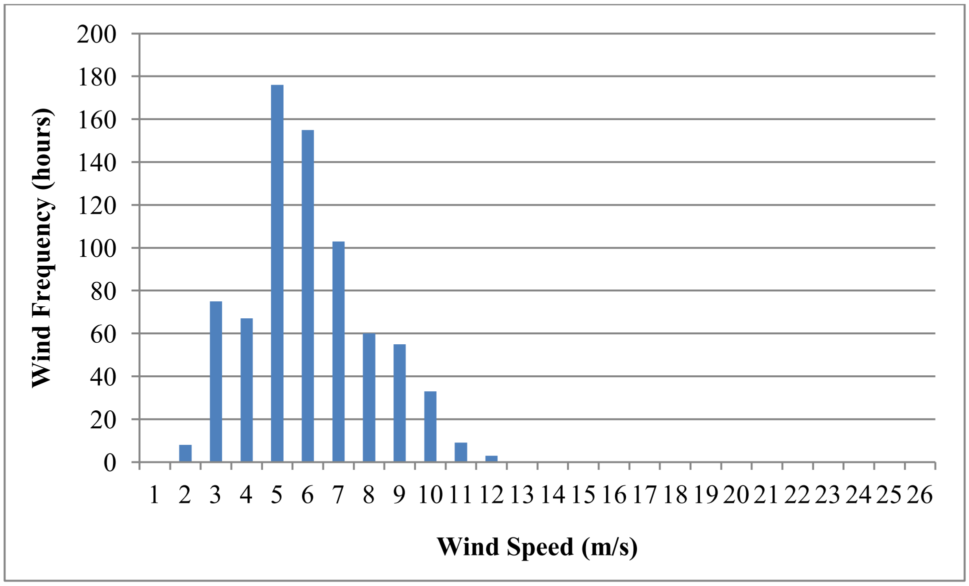

Figure XV Histogram for August 2008 wind speeds

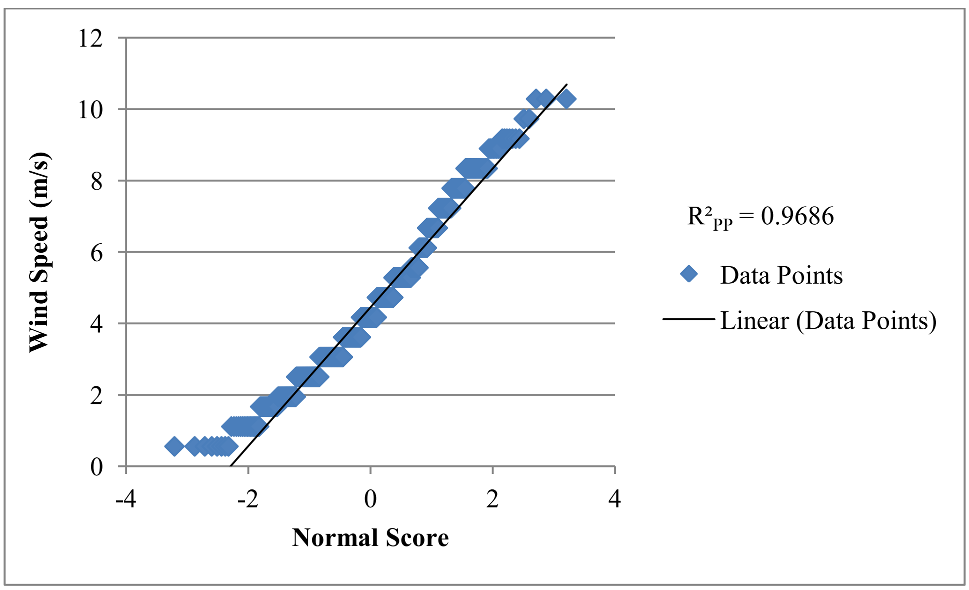

Figure XVI Probability plot for August 2008 wind speeds

Figure XVII and Figure XVIII show wind data analysis for September 2008 hourly wind speeds.

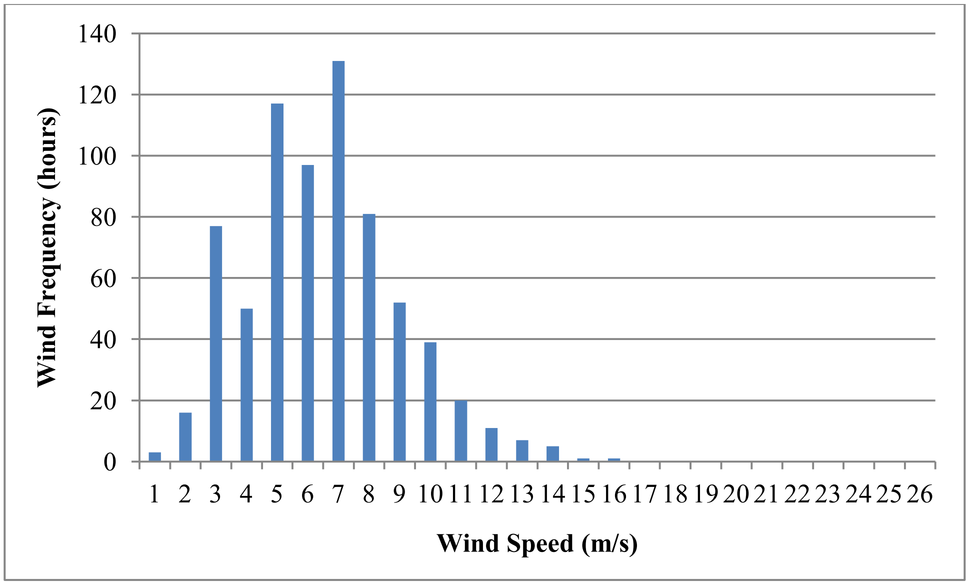

Figure XVII Histogram for September 2008 wind speeds

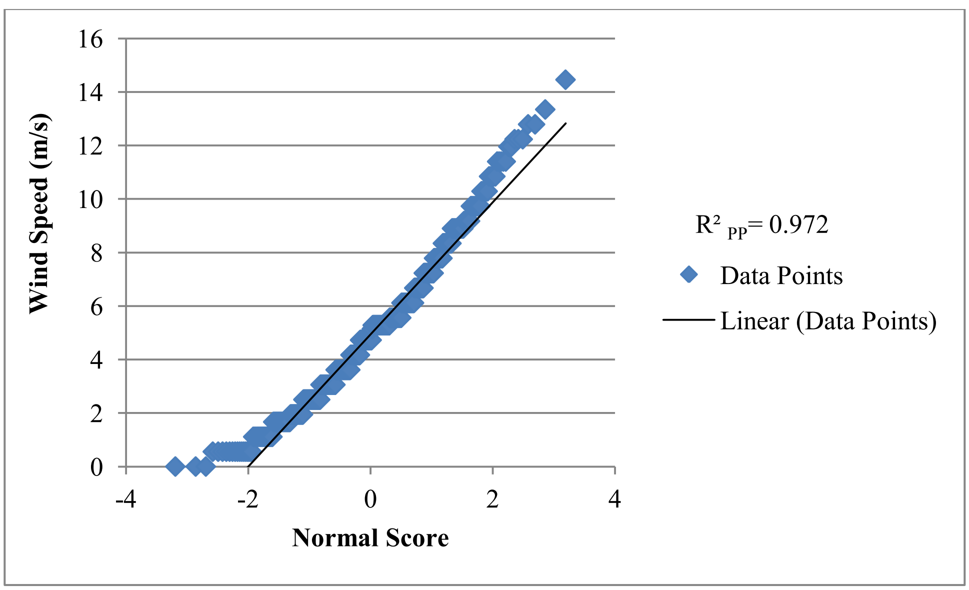

Figure XVIII Probability plot for September 2008 wind speeds

Figure XIX and Figure XX show wind data analysis for October 2009 hourly wind speeds.

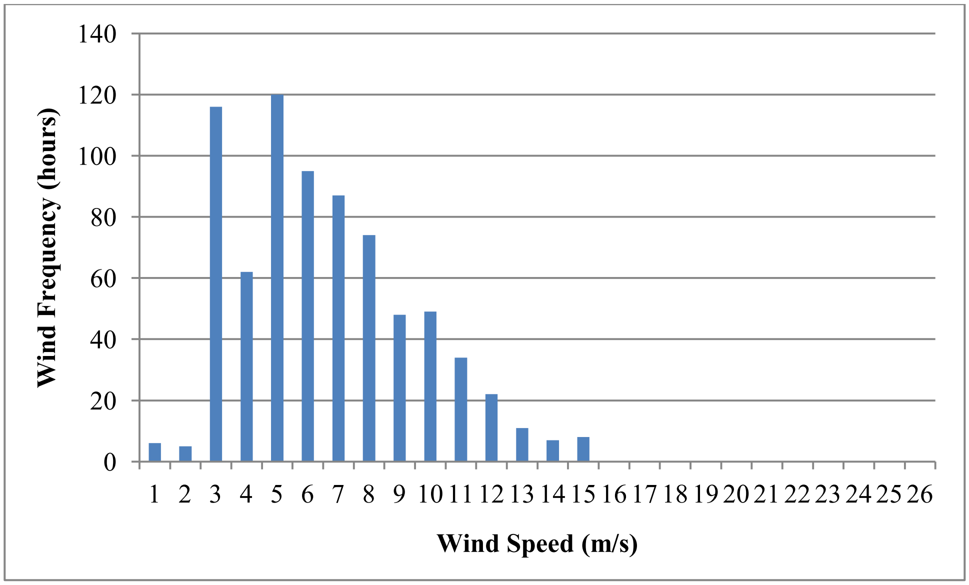

Figure XIX Histogram for October 2009 wind speeds

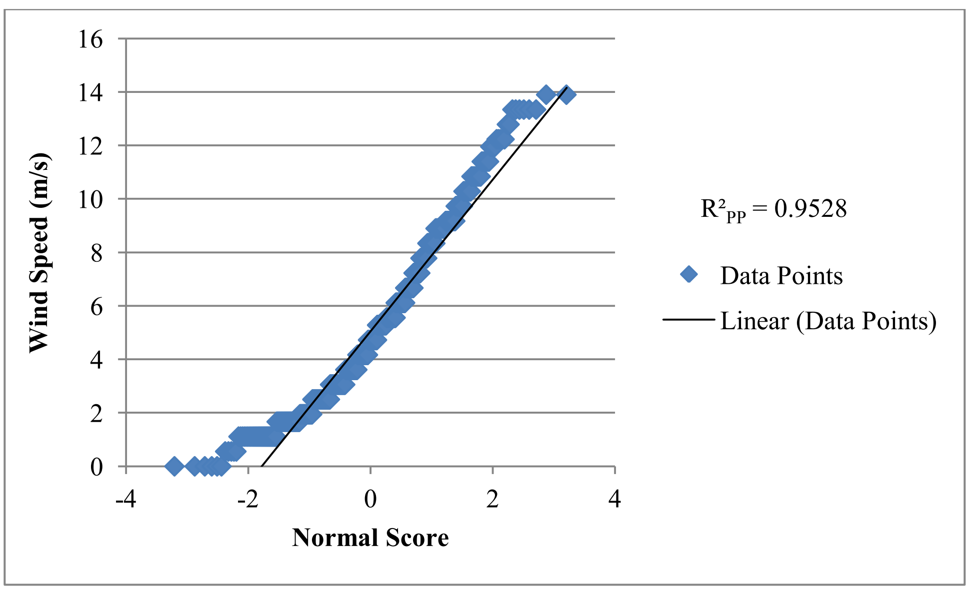

Figure XX Probability plot for October 2009 wind speeds

Figure XXI and Figure XXII show wind data analysis for November 2009 hourly wind speeds.

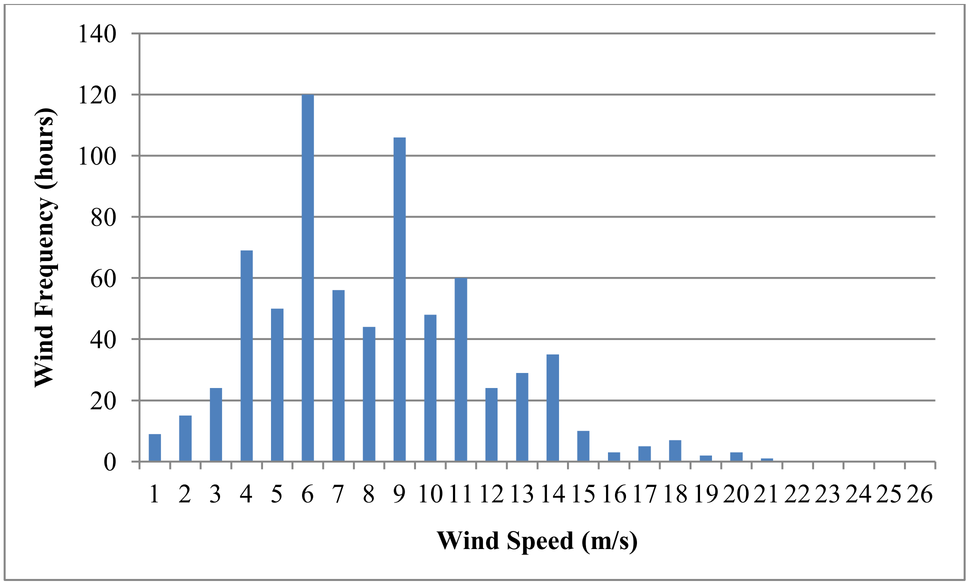

Figure XXI Histogram for November 2009 wind speeds

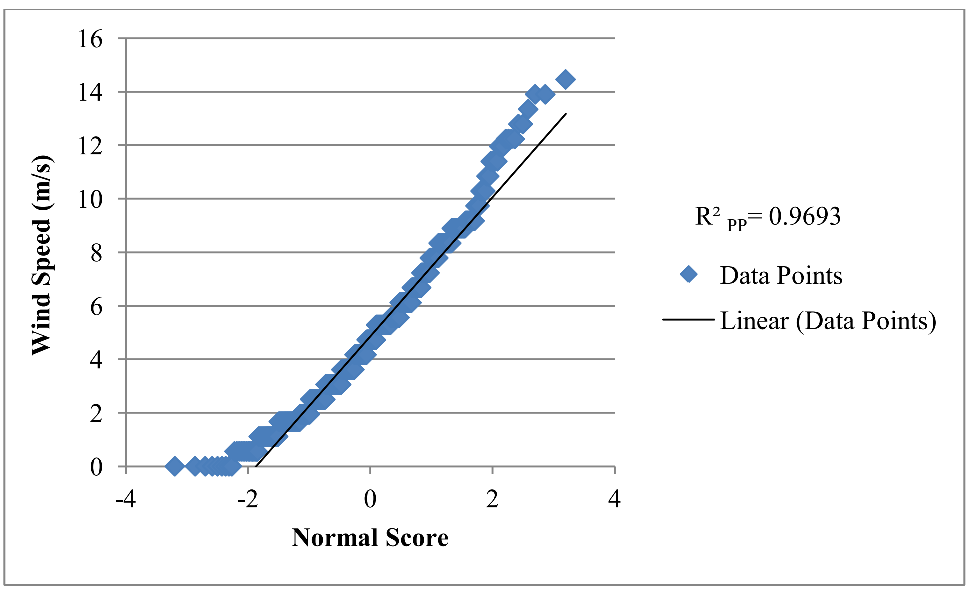

Figure XXII Probability plot for November 2009 wind speeds

Figure XXIII and Figure XXIV show wind data analysis for December 2009 hourly wind speeds.

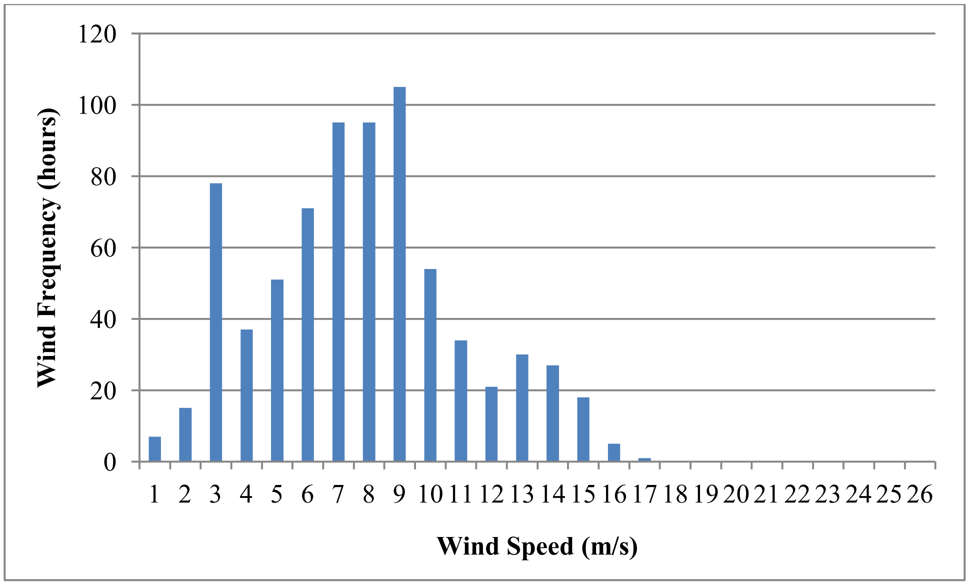

Figure XXIII Histogram for December 2009 wind speeds

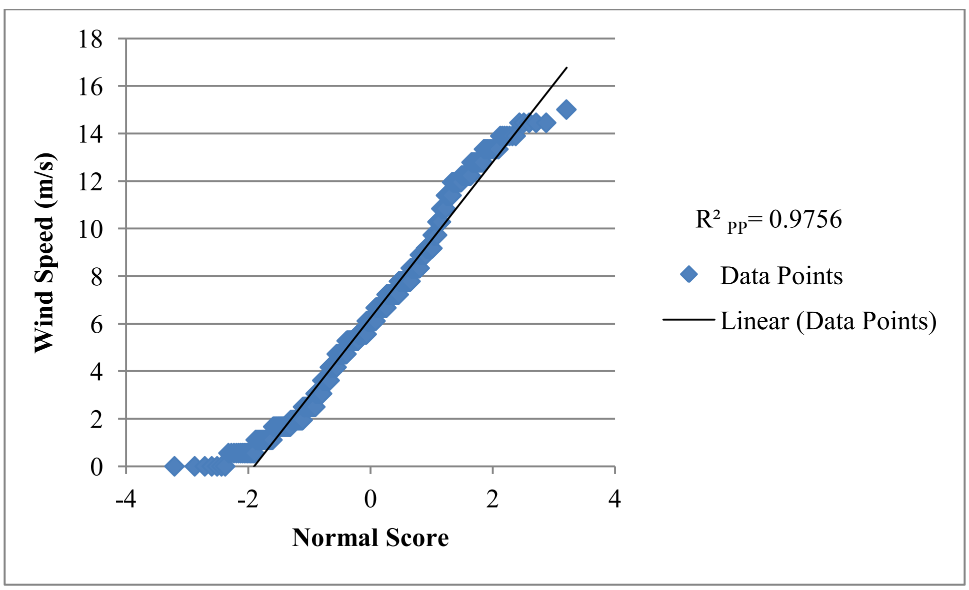

Figure XXIV Probability plot for December 2009 wind speeds

APPENDIX B Historical Load-Data Analysis Results

Results for probability distribution identification of historical load data (2006, 2008, 2009 and 2010) are shown here. Yearly data has been used to draw histograms and probability plots. A negative or a zero value will reject a lognormal distribution. Figure XXV shows the histogram for the year 2006 implying a normally distributed data.

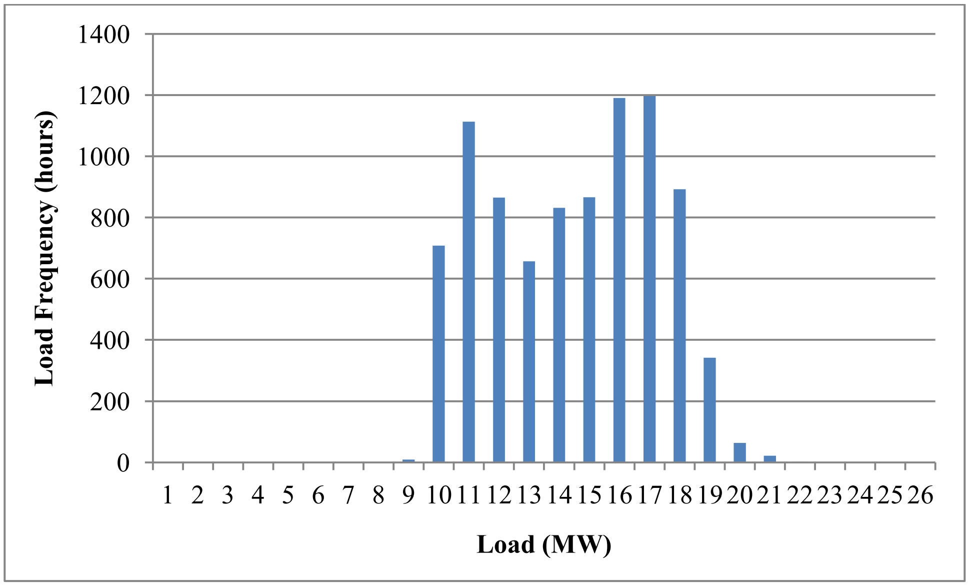

Figure XXV Histogram plot for 2006 load data

Figure XXVI shows a histogram plot for the year 2008 load data.

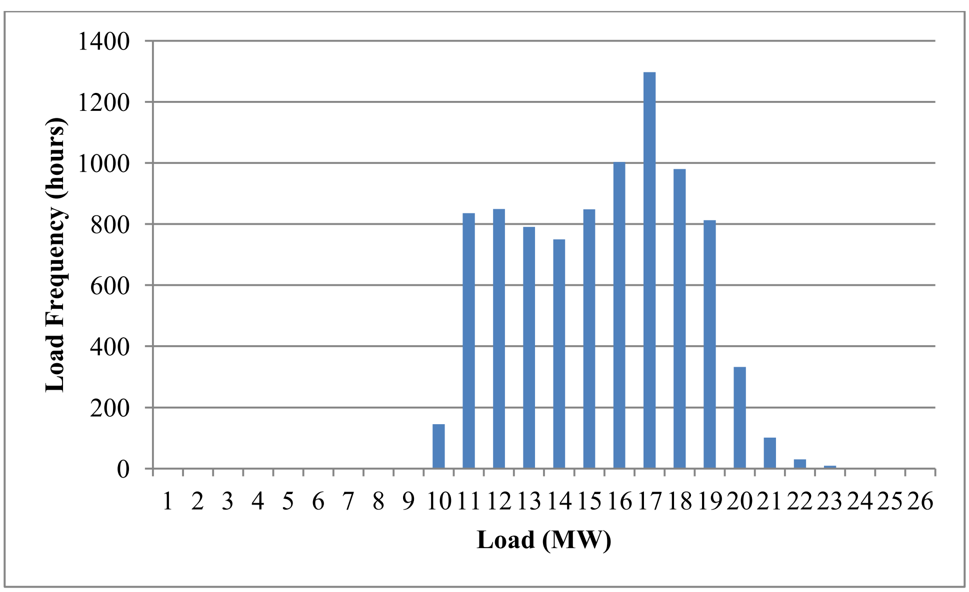

Figure XXVI Load histogram for year 2008

Since the histogram (above) shows all positives values, probability plots were drawn to study the best-fit for the data distributions between normal and lognormal. A higher R^2_{PP} value was used to select the best-fit between the two probability distributions. Probability plot for a lognormal fit showed an R^2_{PP} value of 0.9556 (see Figure XXVII), while it was 0.9701 for a normal fit (see Figure XXVIII); hence, a normal distribution was selected for year 2008 load data.

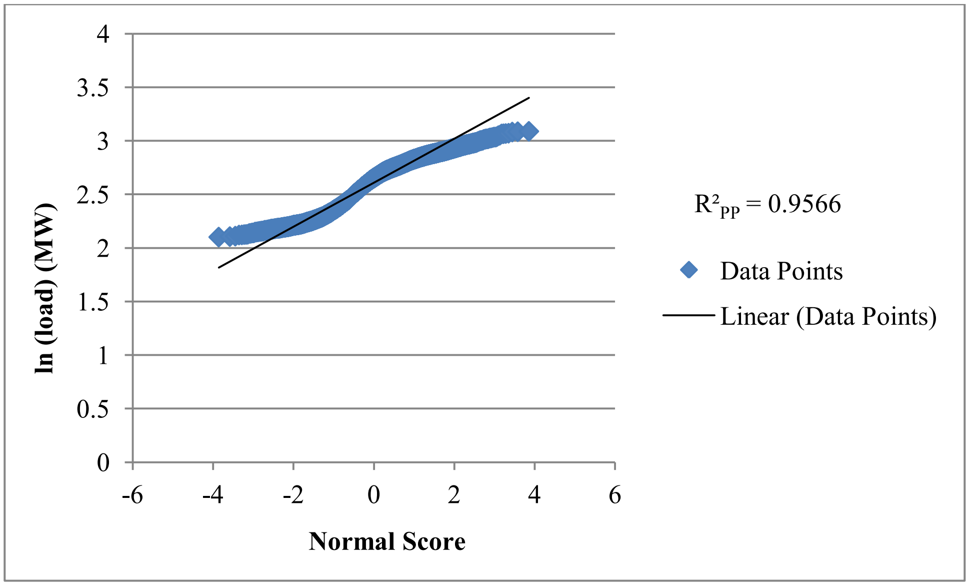

Figure XXVII Porbability plot of a lognormal fit for 2008 load data

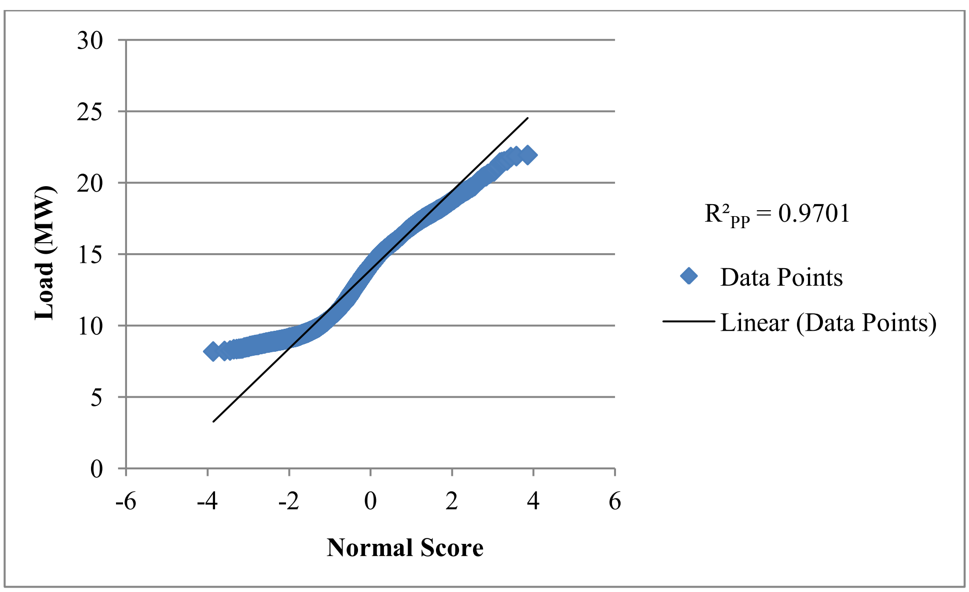

Figure XXVIII Porbability plot of a normal fit for 2008 load data

Load data analysis for the year 2009 and 2010 indicated a zero value in histogram plots (see Figures XXIX and XXX, respectively) implying a normal distribution.

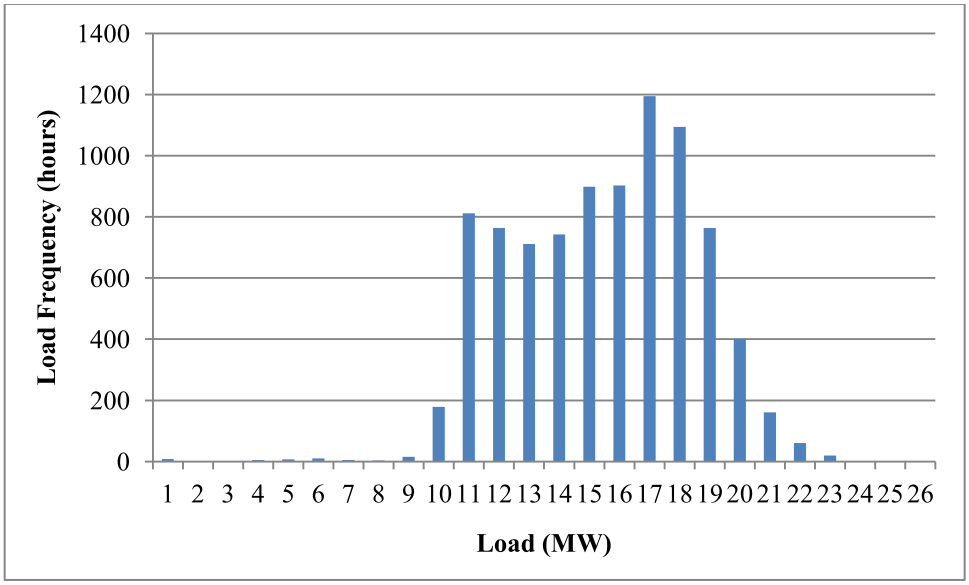

Figure XXIX Histogram plot for 2009 load data

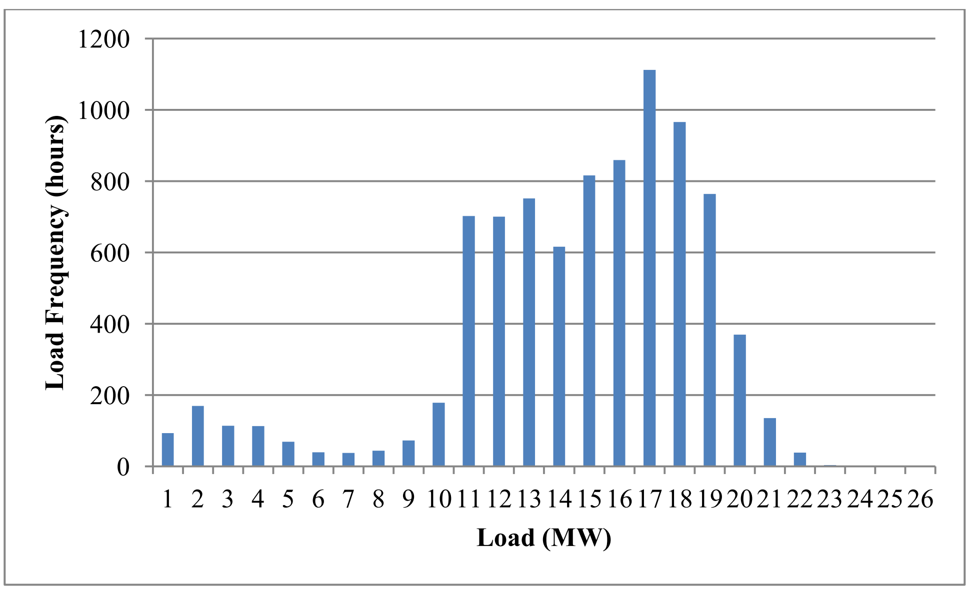

Figure XXX Histogram plot for 2010 load data

APPENDIX C Qualitative Risk Analysis

Continuing from the background chapter of the thesis, a detailed risk analysis on the four risk categories is presented below.

C.1 Manufacturing Risks

With the growth of wind industry, little concern is now being given towards quality control as manufacturers focus on mass production to meet the demand for new wind turbines [43]. Successful working of wind turbines is essential to ensure reliable operation of a wind farm. Many wind energy projects, onshore and offshore, have been affected by the risks surrounding the industry. A reason being that various flaws develop with wind turbines; some of them occurring at the manufacturing stage itself. The list below indicates some flaws that can lead to failure of wind turbines to generate electricity, putting energy security at risk [43]:

1) Cracks sometimes can appear soon after manufacturing, specifically in blades,
2) Mechanical failure because of alignment and assembly error is common,
3) Electrical sensors may fail due to sudden power surges, and
4) The hydraulic braking system causes problem, although non-hydraulic braking system is more reliable.

Manufacturing and installation risks for wind turbines are explained in detail through the following sub-categories.

C.1.1 Shortage of Raw Materials

The risk that wind turbine industry faces at the manufacturing level is the possible shortage of raw materials and consequently, their rising costs; for example, the rise in cost of some commonly used materials like steel, copper and permanent magnets that are important for manufacturing wind turbines. This can result in wind turbines and eventually, wind power becoming expensive. A study conducted by German Energy Agency in February 2005 found that increasing the amount of wind power could increase consumer costs by 3.7 times [44]. Tables II and III give a comparison of raw materials required for manufacturing different rating of wind turbines.

Table II Percentage raw material used in a 1.5 MW wind turbine [45]

	Weight (%)	Permanent Magnet	Concrete	Steel	Aluminum	Copper	GRP	CRP	Adhesive	Core
Rotor										
• Hub	6.0			100						
• Blades	7.2			2			78		15	5
Nacelle										
• Gearbox	10.1			96	2	2				
• Generator	3.4			65		35				
Frame	6.6			85	9	3	3			
Tower	66.7		2	98						
(Total %)	100.0	0.0	1.3	89.1	0.8	1.6	5.8	0.0	1.1	0.4

Notes: Tower includes foundation. GRP = glass fibre reinforced plastic. CRP = carbon fibre reinforced plastic. Core = forms the core of the blade and comprises of balsa wood or low-density polymer foam.

Table III Percentage raw material used in a 4 MW wind turbine [45]

	Weight (%)	Permanent Magnet	Concrete	Steel	Aluminum	Copper	GRP	CRP	Adhesive	Core
Rotor										
• Hub	6.0			100						
• Blades	7.6			2			68	10	15	5
Nacelle										
• Gearbox	10.1			96	2	2				
• Generator	2.7	3		93		4				
Frame	6.6			85	9	3	3			
Tower	67.0		2	98						
(Total %)	100.0	0.08	1.34	89.6	0.8	0.51	5.37	0.76	1.14	0.38

Notes: Tower includes foundation. GRP = glass fibre reinforced plastic. CRP = carbon fibre reinforced plastic. Core = forms the core of the blade and comprises of balsa wood or low-density polymer foam.

From the tables above, it is evident that steel forms nearly 89% of the total turbine weight. Steel goes into every component of the wind turbine and rotor hub comprises all steel, irrespective of the turbine size. The size of steel castings for large turbines, especially the blade hub units, is one of the manufacturing challenges. The tower also comprises largely of steel and adding a tower height of additional 10 meters is approximately $10,000 investment. Rising cost of steel has been a concern as prices have doubled since 2004 [46].

Copper requirement for making generators has been extensive (35% for 1.5 MW turbine), whereas for high rating wind turbines this has been replaced by permanent magnets which is an advantage because the copper prices have been rising steeply, risen over 200% since 2004 [46], but the shortage of rare-earth metals for making permanent magnets is a potential future risk. As of 2010, China controls nearly 97% of the world's processed rare-earth metals and is the leading maker of rare-earth permanent magnets [47]. Presently, China has reduced a massive 72% export quota for the second half of 2010 raising concerns for leading manufacturers such as Siemens, Vestas and Goldwind that uses Permanent Magnet Generators (PMG) [47]. An estimate of 2,000 kg (4,400 lbs) of rare-earth or neodymium (used in making powerful magnets for generators) based alloy goes into a high energy PMG for a size of a 3.5 MW wind turbine [47].

As wind turbines get bigger in size, so does the turbine weight. Efforts are being made to make turbine components lighter and stronger, for example the turbine blades. Small turbine blades are made of steel or aluminum, but are heavier [48]. Blades of large wind turbines are made from fibre-glass reinforced with polyester or epoxy resin. Lighter blades have less material requirement than do other wind turbine components, resulting in a lower overall cost. Moving from small wind turbines to multi-MW turbines, fatigue resistant performance is extremely important, with designers and manufacturers using more of glass or carbon fibre over the traditional polyester fibres [49]. However, the use of carbon composites requires more accuracy and increases manufacturing costs [48].

Increased prices of other raw materials including acrylonitrile (used in the production of carbon fibre) has gone up by 48% since 2004 [46]. Many major turbine manufactures produce their own blades and there may not be a shortage of supply at present, but the availability and price of carbon fibre—a major sub-component for larger blades—remains a problem [46].

C.1.2 Risks in Equipment Transportation

With the growth of wind industry, it has become a common sight to see oversized transport loads moving wind turbine components from factory floor to the project sites. A basic risk that arises is the handling of these highly sensitive, high-tech and expensive components that weigh several tons and extend over 100 feet in length. Apart from getting attention from everyday road travelers, transportation of such massive components has never been easy and has resulted in project delays, equipment damages and even frustration and road-rage caused due to traffic delays.

The shipment of equipment can be sea-based, railroad or truckloads depending on where the wind turbine is being manufactured and the project site location. According to American Wind Energy Association (AWEA), 2008 alone saw an installation of 8,300 MW wind energy in US, equivalent to 5,000 wind turbines and resulting in an estimated 40,000 specialized transport hauls. A single turbine can require up to eight hauls – one nacelle, one hub, three blades and three tower sections [50]. The project size today is getting bigger, for example, projects as big as 4 GW are being planned for the future and are expected soon which will increase the transportation requirements across many nations. The risks associated with transporting the turbine equipments have resulted in the following incidents in the past [50]:

1) In Idaho and Texas, oversized loads laden with tall turbine parts have slammed into interstate overpasses leading to hundred thousand dollar repairs and eventually project delays and cargo claims.
2) States of New York, California and Wisconsin have suffered property damage and traffic tie-ups as result of dropped loads and miscalculated turns.
3) In a severe accident in late 2008, a woman was killed when her mini-van was struck by an oversized load carrying wind turbine cargo.

Wind turbines, already big enough, are expected to get even bigger in future. Some blades are already more than 50 yards long and those are reaching the limits of what can be shipped on interstate highways and rail cars [50]. The cost of transportation on per turbine basis varies from \$100,000 to \$150,000 and since wind-energy projects are getting bigger, the costs are likely to go up [51]. It is unclear whether getting bigger will eventually help making us energy secure or not, but more likely, it will be an addition to the risks that the industry is already facing.

C.1.3 Risk of Shortage of Installation Vessels

The shortage of installation vessels is a prime concern for offshore wind farms as many nations are eyeing for mega projects—UK Government's aim to install 33 GW offshore wind capacity by 2020 is an example. In addition to the shortage of transport and installation vessels (TIVs), lack of sufficient wind turbines engineered for offshore environment, lack of appropriate grid capacity and interconnections, shortage of skilled workers and slow planning process are some reasons that will affect the project development [52].

The installation vessels play an important role in wind farm development as required for:

1) Transporting wind turbines (3-5 MW range) to offshore locations,
2) Erecting, installing and maintaining them throughout their service life, and
3) Finally dismantling them.

Wind turbines of modest size can be assembled on land and then taken by vessels out to sea, but carrying them upright raises stability issues and carrying them horizontally requires spacious deck. Wind industry facing a shortage of such vessels has entered into the practice of adapting vessels from the offshore oil and gas sector. This leads to further risk as the vessels may become scarce whenever oil prices rise and there is a need to decommission installations where oil and gas reserves have been fully exploited [52].

The TIVs are heavy and complex—building one takes years rather than months and the investors seek strong assurance of potential profit before commissioning new vessels [52]. According to RWE Innogy (a firm for developing renewable energy in Europe), the plan towards manufacturing their own installation vessels would help them overcome one of the most important supply bottlenecks for constructing wind farms at sea [53]. Hence, the risk remains as the availability of vessels may lag behind the demand as more number of offshore projects are given green signal in the future.

C.1.4 Installation Risks with High Voltage Cables

As most wind farms are usually several kilometers away from the grids, they need to be connected through electric cables for power transmission. Offshore wind farms usually comprise high rating wind turbines (such as, 5 MW capacity) and are nearly 50-60 km away from the shoreline [53]. With more number of turbines getting installed, the requirements for electrical equipment increases and installing electric cables are seen as a challenge from manufacturing and installation perspectives [53]. HVDC (High Voltage Direct Current) transmission is considered more efficient way to transmit power because of heavy losses associated with AC (Alternating Current, ie having sinusoidal waveform pattern) transmission over any significant distance [53]. As claimed by Narec, “80% of the problems with offshore installation is the cables because it is very difficult to do it" indicates the concern with high voltage cable installations [53].

The risk involved with cable installation is high [53]. According to Ernst & Young LLP, projects are being held up by the shortage of construction vessels and high-voltage cables needed to link wind farms to the electricity grid [54]. Hence, the development of wind industry still needs to overcome various challenges and will require significant innovations to prove itself.

C.2 Operational Risks

Loss of production is often the greatest penalty of a wind turbine fault. Operational risks range from non-availability of the wind to the downtime of a wind turbine due to maintenance requirements. Minimizing operational risks is essential for high reliability of wind farms. This section discusses the operational risks that may arise due to any of the following reasons.

C.2.1 Wind Variability

A significant reason why wind energy is criticized is due to the variable nature of wind and becomes a potential risk in terms of failure to generate electricity—the main purpose for which wind turbines are installed for. Wind speed variability is a significant factor contributing towards a highly variable source of power from a wind farm which depends on changing climatic conditions [55]. Wind, does not necessarily blow when it is most needed and may not be close to the load centers [56]. As more wind capacity is added to the electrical network, wind reliability becomes a critical issue.

Weather forecasting is useful as it can help the grid operator to schedule for the fluctuations of wind generated power by bringing in thermal generation or relying on pumped-hydro, but, on the other hand an inaccurate forecast can create havoc and cause wholesale prices to spike erratically [56].

C.2.2 Gearbox Failure Issues

Wind turbine gearbox failures have been a concern and the industry has been trying to improve gearbox reliability—a major and expensive component of wind turbines. Gearboxes, which are designed for a lifetime similar to that of wind turbines, have yet to achieve the goal of surviving at least twenty years. Higher than expected failure of gearboxes (happening within three years after installation) are adding to the cost of wind energy [57]. Being a massive metal component, gearbox housings and shafts tend to bend due to changing winds and these deflections result in damaging gearbox bearings and affecting gear alignments [57]. Due to this, the lighter-built bedplates on which the gearboxes are mounted, the strength of which is affected by changing winds, aggravates the problem of early gearbox failures [57]. This kind of uncertainty is making wind turbines costlier since turbine manufacturers add large contingencies to the sales price to cover the warranty risk due to the possibility of premature gearbox failures [58].

A possible solution to gearbox failures is seen in using direct drive systems. Enercon claims that gearless, direct drive, variable speed technology is the way forward for the large turbines [59]. In direct drive systems, wind rotor hub is attached directly to the ring generator, which is carried on an axle having just two roller bearings, thus avoiding the multiple bearings and gears of competing products.

C.2.3 Generator Failure Concerns

With the wind turbine's ongoing problems with gearbox failures, the problem of generator failures has added another concern for the industry. According to North American Wind Service Alliance, a network of independent wind energy equipment repair shops, widespread failure of generators in American wind farms is becoming an increasingly serious issue [60]. It has been observed that generators in wind turbines still under warranty fail as often, if not more so, than those in older units. Quality issues have been reported with some of the designs along with mechanical wear on bearings, which to an extent, is considered behind generator failures [60].

The potential risk seen beyond failures is the shortage of generators for wind turbine retrofits, with almost no supply to the aftermarket third-party, repair industry [60]. The urgent need to overcome this risk is that the manufacturers get on top of the problem otherwise these failures will continue to add large sums to wind farm operation and maintenance costs. The price tag for a generator varies from $80,000-$120,000, while hiring a crane to lift multiple units can go up to $40,000 [60].

C.2.4 Maintenance Risks

Wind turbines must be available to generate electricity when the wind blows and it can happen only if the turbines are properly operated and maintained. Maintaining wind turbines is a major work including, working with machine tools, cranes, electricity, performing heavy mechanical repairs and working at height, which is all potentially dangerous [61]. Working on wind turbines is risky, and requires improved awareness of safety on the job. Following is a list of safety measures that should be kept in mind to mitigate risks during maintenance work [61].

C.2.4.1 Working with Cranes

Before starting the maintenance work, a complete list of actions must be planned and discussed with all the workers, staff and operators (crane operator in this case). To make sure that the maintenance is done safely, the crane operator must have similar work experience, should understand the instructions clearly and if needed, must be aware of hand-signals used during the work. An inspection of the crane before starting the job is equally important because cranes can fall over resulting in severe damage.

C.2.4.2 Climbing Gear

It can be life saver if used properly, but at the same time it is bulky and cumbersome to use. If a worker is tied off incorrectly, the damage caused is as bad as not wearing the gear at all. It is important to tie off the gear to the tie off points which are approved to handle the load. Checking the gear of the fellow technicians is considered a good practice.

C.2.4.3 Working with Electrical Systems

Working with electricity on a metal structure is a job of a trained worker. The measuring instruments (eg. volt-ohm-meter) leads must be of higher rating than the working voltage level. For most of the wind turbines today, 600 volts insulation rating is replaced by a 1000 volts insulated leads to avoid the unexpected danger of high working voltage levels.

C.2.4.4 Weather Conditions

Working on exterior of the wind turbine could be risky in extreme weather conditions. It is difficult to work in windy conditions, so climbing from outside should be avoided for wind speeds over 40 mph. Maintenance of turbines in colder regions have their own limitations.

C.2.4.5 Working as a Team

Working on turbine maintenance is potentially dangerous and working alone should be avoided as it can help prevent accidents and injuries.

C.3 Environmental Risks

Since wind energy is believed to counter the twin challenges of energy security and climate change, certain environmental risks have been associated with it as the side-impacts of increasing wind energy development, as claimed by environmentalists, various environmental groups and public. Some of these issues, not as big as component failures, do exist and are getting more attention with the rapid development of wind industry. Efforts are being made to address these problems through proper sitting, public education and with the use of improved technology, but the outcomes remain uncertain if the focus of the industry is not brought on these issues [62]. Some environmental issues are listed below.

C.3.1 Wind Turbine Noise

Source of wind turbine noise can be subdivided into mechanical and aerodynamic noise, of which noise due to gearbox and generator is comparatively less than the noise created by turning of blades. School of Medicine at University of Washington which conducted a detailed study, concluded that, apart from high frequency noise from mechanical components, wind turbine noise has infrasound component (sound below audible level) that could influence the physiology of the ear [63]. In most studies of wind turbine noise, low-frequency noise is neglected on the basis that the sound is not perceptible, but fails to take into account that Outer Hair Cells (OHC) are stimulated at the frequencies that are not heard [63].

C.3.2 Bird and Bat Killings

A major environmental risk has been seen in killing of birds and bats as a result of collision with the structure or getting killed by the rotating blades. Many believe that killing of birds by vehicles, collision with tall buildings and from power transmission lines is much greater than killings from wind turbines, but adding another source of avian killer is more of a concern. Research is being done on these issues and some of the findings are as follows [64]:

- Wind farms kill millions of birds round the world, and high mortality rate of raptors is a particular concern.
- Wind farms that fall in line of migratory routes are more dangerous and those which do not; they may come under that category because migratory routes can shift but wind sites cannot.
- Collision probability models have been studied and rotor hub is found to be the most dangerous part rather than the rotor speed.
- Observations have revealed that wind turbines can cause changes in (anti predator) behavior of squirrels interfering with their normal life.

Bat killings by wind turbines have been known since 2004, with the assumption that their killing is similar to that of birds. An examination of 188 hoary and silver-haired bats killed at a wind farm in southwestern Alberta in Canada between July and September 2007 showed no external injuries, as was expected, had the bats been smashed by the blades. The reason of killing was bursting of blood vessels in the lungs caused by air pressure difference due to spinning blades, rather than any sort of contact with them [65]. A research done at University of Calgary found that increasing the turbine height increases the bat killings exponentially [65]. Compared to killing of the birds, bats cannot withstand sudden pressure drops created by rotating blades as their blood capillaries are much weaker than that of birds, resulting in filling of lungs with fluids and blood.

C.4 Financial Risks

Energy comes for a price and its affordability becomes a prime concern in a situation where energy prices are not stable. Financial risks can be considered in two ways—first, investing huge sums of money for a technology that stands on a risky edge with the probability of incurring a loss and second, the risk of rising cost of wind electricity borne by the consumers. These risks can be explained on several basis like, high cost of equipment, frequent failures, turbines not producing output (during non-availability of wind), high maintenance costs, problems of integrating wind electricity, and need for sufficient backup. All these actions are driven by monetary investments and a technology that still needs to prove itself, its worth asking—are we putting the money at risk?

Harnessing wind energy involves large sums of money. Wind turbines, is where the majority of the money is invested—in manufacturing, operating and maintaining them throughout their service life. Other expenditures include connecting wind farms to the grids and providing backup during low or no wind periods. The sudden expansion of wind industry with limited manufacturers in the market has already made itself one of the fastest multi-billion dollar industry in a short span of time. With growth expected to increase further and order books already full for next couple of years, huge investments are expected to take place in this sector. Figure XXXI shows the expected future investments in wind industry.

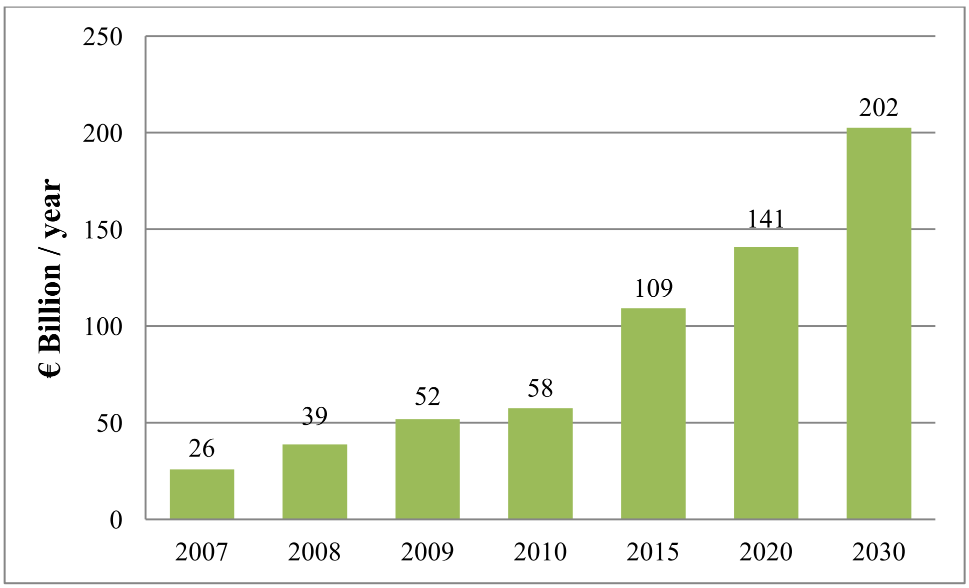

Figure XXXI Expected future investment by wind industry [7]

The investments are expected to increase by more than three times the current level within next two decades. With the respect that wind industry is looking towards a huge expansion, high investments as shown above puts the industry into a financial risk. With a few global manufacturers like Vestas, Seimens, GE (General Electric) and Gamesa, whose products are considered reliable than others, have faced troubles with their wind turbines in terms of unpredicted failures. The risks discussed in previous sections describe what the industry already faces despite its continued growth. The major concern—which will impact not only the manufacturers and grid operators, but consumers as well, is—are we ready to lose billions of dollars if the industry fails to perform?

To overcome the financial risk, it is important that wind industry needs to balance its expansion with reliability of its product at the same time. The focus should be more towards overcoming the present challenges which can make wind industry better prepared for the future, rather than ending in a deep trouble by witnessing frequent failures and costly maintenance, when affordability can cause a set back to its further growth.