Uncertainty in long term predictions- A new approach to reduction.

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A master's thesis report as a part of 10^{th} semester

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Abstract:

Long term estimation of wind resource has a mean deviation of wind speed. The uncertainty associated with the wind speed has an impact on energy production, which influences wind farm's viability, thereby, adding greater investment risk for the investors.

This study answers, if an uncertainty due to long term predictions can be reduced. This is done by defining an initial process for this study, where different cases are studied and analysed initially. Results from the case studies, show that there are inconsistent time periods associated with uncertainty.

A new method called, consistent period method is defined and when predictions are made using this method, has led to the reduction of uncertainty. Therefore, it is concluded that the above approach can be used for reducing uncertainty in the long term prediction using short term measured time series.

Preface

This M.Sc thesis was written as a part of 10th semester of the study programme Sustainable Energy planning and Management, in the Department of Development and Planning at Aalborg University in the fall of 2007.

The experience gained through this study was exceptional. Initially finding a company for collaboration has been difficult, however, having a network is very important in meeting right kind of people. Collaborating with DONG Energy A/S has resulted in exchange of ideas in both ways.

At the outset, I would like to thank Poul A.Østergaard, for his contact with DONG Energy A/S initially and also for arranging supervisor for this study. Many thanks to, Martin Méchali, for having arranged meeting in Fredericia at DONG's premises and Raymond Downey, who has been instrumental in helping me with, defining the thesis topic. Thanks are also to EMD International A/S for licensing WindPro software for this study period.

Special thanks to my supervisor Thomas Sørensen, for his immense support and his availability when ever I needed help. Lastly, I thank my family for the support they rendered through out this thesis period.

Aalborg, January 10th, 2008

Praveen Siddabathini

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1. Wind Energy Expansion and Challenges

Wind Energy is one of the new entrants into the energy sector and its growth is further influenced by climate change[1], which calls for reducing CO_2 in the atmosphere.In contrast, some section of thinkers[2] claim that the climate change is blown out of proportion and is not true, nevertheless, clean technologies are needed for future as there is a migration trend of population towards cities in the coming decades, which invariably necessitates for sustainable consumption of resources thereby, keeping the environment safe for posterity.

To keep the environment safe for posterity, it is the duty of everyone to adapt to the sustainable consumption of resources. Sustainable consumption is synonymous with sustainable development, as the latter is defined with respect to energy and other resources as a development which does not reduce the development options of the future by deteriorating the natural environment (Daly and Cobb 1990, 482)

In the present day scenario, one of the conditions that are required for sustainable development is 'Pollutants (like CO_2 and radioactive waste) should not be generated faster than the environment can absorb or neutralize them' (Nørgaard 1998), As can be seen from climate change, it is evident that the global atmospheric concentration of CO_2 increased from a pre industrial value of 280 ppm to 379 ppm in 2005. The growth rate was larger during 1995-2005 which amounted to 1.9 ppm per year (Bernstein et al. 2007 4)

This shows that there has been considerable damage occurred in the climate and its effects can be seen by increase in green house gases, especially CO_2. Since there is no

[1] According to IPCC (Intergovernmental panel on climate change), climate change refers to a change in the state of the climate that can be identified (e.g.using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time,whether due to natural variability or as a result of human activity

[2] In the article of the magazine '21st Century Science & Technology' it is argued that IPCC style of scientific study is not devoid of politics and mentions how an independent and objective scientific research should be based, comparing it to the report by United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR) on the global risks associated with radiation (Jaworowski 2007)

immediate solution that exists to reduce this damage, however, there are long term plans which can be put in place for reducing the greenhouse gases. One of the plans would be to increase the share of renewable energy sources, at the same time learning to live with the problem.

1.1 Energy sector’s challenges due to climate change

This climate change effects across all sectors from water, human health, agriculture, Infrastructure, tourism, transport and energy. So, there is necessity that the energy sector is well adapted to this problem. According to IPCC (2007) the following steps can be taken to adapt to climate change, related to the energy sector are stated below:

1. Strengthening of overhead transmission and distribution infrastructure,
2. Underground cabling for utilities,
3. Energy efficiency,
4. Use of renewable sources,
5. Reduced dependence on single sources of energy.

The above suggestion clearly indicates the use of renewable energy sources are a must for mitigating the climate change. For this to happen there needs to be proactive strategies which should aim at introducing new technologies. New Technologies like wind energy should be encouraged with financial incentives and also accommodating them in national energy policies.

Drawbacks of the new technologies are that they do not fit well in the organisation of the old technologies (fossil fuel and uranium technologies), consequently, there is heavy organisational resistance against these new technologies, as this assumption has been confirmed in the Danish case over the last 25 years (Hvelplund 2001 43)

Despite the resistance, Danish model of wind energy has been a success, which has set an example, fuelling the growth of wind energy around the world. Also, to be noted here is the proactive policy, set in motion by the European commission directive (1997; 2001) which asks the member states, to set a national target for inclusion of power produced from renewable energies, as a percentage of total electricity production.

The European commission has set a target of 40GW to be installed in EU by 2010, however, at the end of 2005 the target has been reached well ahead of time (European Commission 2007), this led to readjusting of the target by European wind energy association (EWEA) for the year 2010, which now stands at 70 GW.
Estimates from EWEA shows that electricity consumption in the European Union (EU) is expected to double from 2000 to 2030 and wind energy could meet more than 20% of EU power demand by 2030 (Kjær 2006).

1.2 Growth of wind power- A Historical Overview

From 1800-1973

As mentioned before, commercially the wind power is a new entrant in the energy sector, but, its uses have been recognized in the late 19th century by Charles F. Brush (1849-1929) who has built the first automatically operating wind turbine for electricity generation (Danish Wind Industry Association 2003)

Figure 1.1:Poul la Cours wind laboratory in Askov, Denmark, 1897 (courtesy: Poul la Cour Museum, Denmark)

There was not much development in the wind power commercially between 1900 and the oil crisis of 1973, however, the foundation for modern wind turbines which could generate electricity were laid by inventors Poul la Cour and Johannes Juul in Denmark and Ulrich Hütter in Germany (European Commission 2005).

From 1973-1990

After the oil crisis in 1973, there was a considerable interest from electric companies in making large wind turbines, and in 1979, two 630 kW wind turbines were built. Despite a good start, the growth has been stalled due to high prices of electricity, and also due to the cost involved in making few wind turbines.

After a brief pause, in the year 1980-1981, the 55kW wind turbines were developed due to which the cost per kilowatt hour (kWh) of electricity dropped by 50% and in addition to that, the development of European Wind Atlas Method by Risoe National Laboratory, Denmark, has further helped in lowering kWh costs (Danish Wind Industry Association 2003).

Risoe National Laboratory was originally established as a centre for nuclear research, but, today it is well known for its research in wind energy. This recognition is by far can be attributed to the Danish energy policies of 70's and 80's which were not received well by the public, mainly due to the opposition towards nuclear energy (Kørnøv et al. 2007 389). Risoe was given the responsibility to certify wind turbines for safety by the Danish government, which was aimed at protecting investors directly and developing more safer wind turbines indirectly (Danish Wind Industry Association 2003)

From 1990 to 2000

As can be seen, the conditions were not favourable in the late 80's, however, with the coming of Brundtland report (1987) and subsequent 'Earth Summit in 1992 (UN 1997), has given boost to the development of wind energy and its research across the world. The white paper of EU was a result of Earth Summit, which has called the member states to set targets nationally reaching a target of 12% for the entire EU (European Commission 1997)

From 2000 to present

After the white paper of EU in 1997, which has set targets for member countries and also research under the EU fifth framework program which ran from 1998-2002 (European Commission 2000) has emphasised on the research, which need to be taken for efficient penetration of renewables into the energy sector.

Two notable projects taken under this framework are WEMSAR (Wind Energy Mapping using Synthetic Aperture Radar) and ANEMOS (Development of **A** **NE**xt Generation Wind Resource Forecasting Syste**M** for the Large-Scale Integration of **O**nshore and Off**S**hore Wind Farms)

WEMSAR is a tool, which is used in the retrieval of satellite based data and combines it with the local measurements. Models from WEMSAR will help in improving the efficiency of forecasting and also the reduction of cost in planning and siting of the wind turbine parks.

The second project, ANEMOS aims to forecast short term wind power which directly helps end users, to realise economic and technical benefits from a single wind farm to regional or to national level, with a time scale ranging from minutes up to several days ahead (European Commission 2006).

This tool is not a single tool, but a mix of various tools developed using different statistical methods and conditions i.e., offshore, onshore, flat, complex, interconnected and island systems. The outcome of the project was to help wind power prediction on a daily basis and to help in adding more capacity, the latter helps in reducing risk to the investor, thereby directly resulting in setting up more wind farms (European Commission 2005; 2006)

It was identified in the fifth framework that more research needs to be done within the areas of resource assessment, in tandem with meteorology research.

1.3 Research areas and influence of growth

As the wind energy expanded, new areas of research have emerged, and special methods have been developed like environmental impact assessment, which plays a very decisive role in the location of a wind farm.

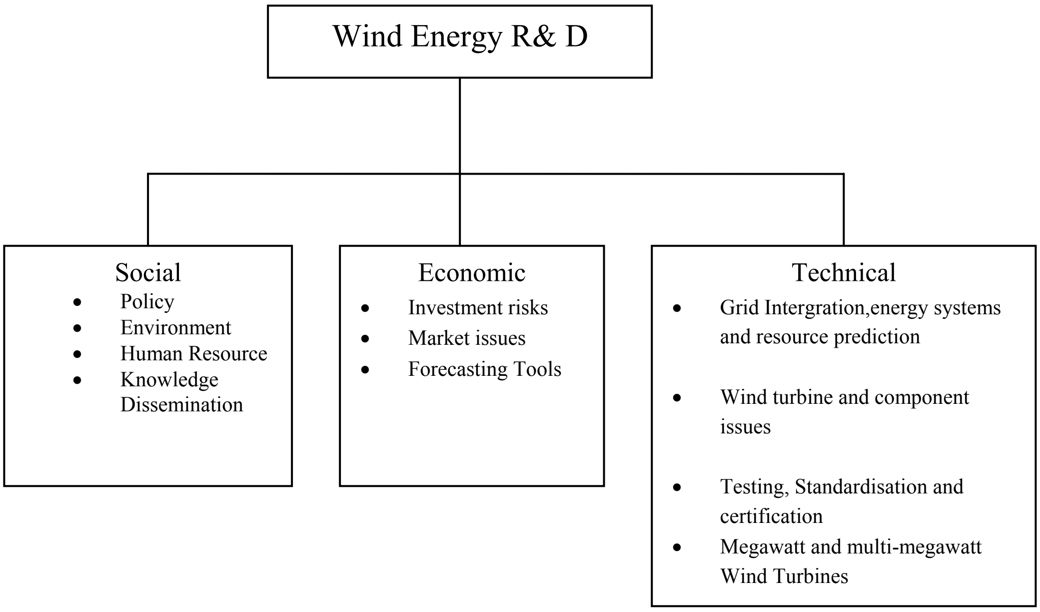

Figure 1.2: Wind energy priority areas of research (Courtesy : EWEA)

The above figure shows the research areas that have been classified into three major categories, based on EWEA's priority research areas. These are explained very briefly down below.

Social R& D:

Research needs to be focused on finding out, the impact of policies towards expansion of wind energy from country to country, as proactive policies always face opposition from the established players in any sector (Hvelplund 2001 69)

For the wind power to expand there needs to be dissemination of knowledge. This can happen by having courses at the universities and establishing separate chairs for research supported by the government and the private institutions.

Economic R&D:

To realise full economic potential of wind power with other forms of energy, country specific and operation specific tools should be developed, there by reducing investment risks.

Technical R&D:

This is the area, which requires continuous research. Grid integration tools are necessary as wind power, which fluctuates in producing power, needs to be accommodated into grid and excess of this power can be used to develop storage systems. Also, operation and maintenance tools are to be developed for site specific requirement, so that the Wind farms could be operated in optimum conditions, there by maximizing operation output. Wind resource estimation is also one of the areas for future research, as reducing the estimation errors, will help in reducing investment risks associated with it.

1.4 Wind resource Estimation – The concept of 'Uncertainty'

In section 1.3, under 'Technical' R&D, it was mentioned that research needs to be done in the area of wind resource estimation. Before explaining further it is necessary to know why we need to estimate a wind resource. Wind resource of an area is usually estimated, when there is non-availability of long term measured time series defined for that area or region.

Wind resource estimation starts with having an overview of the available wind resource and identifying the sites for low and high winds, quantifying them to see, if they are useable for further study (Landberg et al. 2003, 261-271). This seems to be easy method, but, economically, it is not a good option.

There are other methods that are useful when estimating a wind resource. One of the methods is Measure-Correlate-Predict (MCP) method. It must be noted that, estimation is always an approximation, hence is not devoid of errors.

When there is non-availability of long term measured time series of a location, the alternative way is to find a near by location which has long-term measured time series. By convention this is termed as a reference location or site, and by using reference location together with local station or site, a local wind resource can be estimated. Estimation through long term prediction using a reference site gives rise to different uncertainties.

Source of Uncertainty	Wind Speed [%]	[m/s]	Energy Output[1] [%]	Wh/ Annum
Anemometer accuracy	2.0	0.14		
Correlation accuracy		0.19		
Period representative of long-term	1.3	0.10		
Total wind		**0.26**		**2.22**
Wake and topographic calculation	-	-	3.0	1.11
Wind variability (1 year)	6.0	0.43		3.75
Overall (1 year)				**4.49**

Table 1.1: Various Uncertainities are shown that are assumed in wind resource estimation in case of cuilliagh mountain site, Ireland (EWEA, 2003)

From the Table 1.1, Cuilliagh mountain site is predicted with Malin head as a reference site and the uncertainty values are tabulated. In case of Malin head, the historical period at this site is representative of the climate over longer periods and this gives an variability or deviation of 6% in the annual mean wind speed (Gardner et al. 2003, 268-282).

The uncertainty value of 6% in the annual mean wind speed is further confirmed by Veldkamp (2006, 47-62), where in 1,722 station pairs were taken and 30,020 predictions were calculated, which gives a deviation or Coefficient of variation (COV[3]) of 6%.

In addition to the above, Raymond's (2006) thesis also confirms the variability percentage, as predictions have shown, variability in the yearly average of wind speed is found to be 6.6% (Downey 2006 25),
Now the question arises, whether this uncertainty value could be reduced, as reduction of this value will lower the investment risk, thereby more wind farms can be realised. In addition to that, this will reduce the costs involved in components manufacture and also extension wind campaigns.

1.5 Problem Definition

Based on the above discussion and focussing on primary problem area, the following research question is formulated:

How can uncertainty be reduced in long term prediction using short term measured time series and how will, choosing the time period has influence on uncertainty?

Basing on the research question, this analysis restricts uncertainty with relation to measured time series while trying to find the reduction in error. To start with the first part of the question, a process needs to be defined and tested to get a general view of the uncertainty over long periods of time. This analysis uses Measure-Correlate-Predict (MCP) method in WindPRO[4] and within MCP, it uses Linear Regression model of first order polynomial. However, using other Regression models and different MCP methods is not the focus of this study. Only Dutch wind sites are

[3] In this context, Coefficent of variation is defined as the ratio between standard deviation 'σ' to the predicted wind speed 'μ', hence COV = σ/μ (Downey 2006)
[4] WindPRO is a Windows 98/ME/NT/2000/XP modular based software suite for the design and planning of both single WTG's and Wind farms (EMD).

considered for predicting long term measured time series mainly due to availability and the length of measured time series.

1.6 Analysis Outline

This study was initiated in continuation of the previous work in the 9th semester. Company's perspective was selected as this is inline with my interest as well it meets university requirements. A problem was identified in the long term prediction of wind speed using short term time series. DONG energy A/S and EMD International A/S have collaborated for this study.

This analysis contains six chapters and one Appendix. Each chapter is described briefly below.

Chapter 1 presents the background for this study and it discusses the research, which needs to be taken up for the spread of wind energy, and it identifies the problem related to this study, there by ending with the problem definition.

Chapter 2 discusses about the research design that was used as a starting point and it mentions, case study as an invaluable tool for this explorative research. It briefly describes a scenario and gives a model by which this case study will be taken up, and finally it presents the data collection methods used for this study.

Chapter 3 builds up the theory for uncertainty and describes the MCP methodology used in this research; also, it presents a process by which each case can be studied.

Chapter 4 starts with study of cases using the methodology from chapter 3.Here, four wind sites, namely, Beek, Eindhoven,Soesterberg and Deelen are studied. The results of the case study, helps in forming a new concept called 'consistent period' . The cases are further tested within this consistent period and results are analyzed.

Chapter 5 defines consistent period method and using the 'units of analysis' or individual cases are studied using this method. It also find the relation between correlation and COV.

Chapter 6 states the conclusion by reviewing the research question, how it was answered, and also reviews the case study research used in this study, finally it discusses the results and limitations for this study.

2. Research Design and Methodology

This chapter explains how this analysis was initiated and gives a brief description of the case and later explaining data collection methods. It discusses the research strategy for this study, and how this strategy will be used to arrive at the solution for the research question.

2.1 Introduction

As a part of the guidelines of this course and inline with the previous semester's work, company's perspective was selected. DONG Energy (Danish Oil and Natural Gas) company has been a part of this collaborative work, as DONG's interests in Wind Energy is well known in the Energy sector. With initial contact from Martin Méchali, Project Engineer, DONG Energy, and subsequent meeting arranged at DONG's premises in Fredericia, various topics of interest were discussed and 'Uncertainty topic' was found to be inline with my interests, so, this research methodology was formulated based on the exchanges and meetings thereafter.

2.2 Research Design

From the problem defined in the Section 1.5, the purpose of the focus area here is to reduce the uncertainty in Wind estimation. It was also mentioned in Section 1.3 that research in Wind resource estimation is one of the areas for future research.

Reducing uncertainty will have a huge impact on the investment in new projects, as some of the projects are discarded due to lack of clarity in the viability of a wind farm. Secondly, it will reduce prolongation of wind campaigns and also help in the reduction in costs of designing Wind turbine components. It is therefore necessary that, there needs to be an initial process that has to be set up and the methods are to be chosen accordingly. Basing on the initial results and observation of the results, further study is carried out and a hypothesis is made accordingly.

This study does not involve in propositions in the first place, rather it is explorative. According to Yin (2003, 22) '*Some studies may have a legitimate reason for not having any propositions. This is the condition-which exists in experiments, surveys, and other research strategies alike-in which a topic is the subject of 'exploration''*. Also, he further states that explorative study should state the purpose. Hence, the purpose of this explorative study is to reduce the uncertainty in Wind estimation.

In this study long periods of measured time series are taken and correlated with a reference site. Each correlation and estimation is done taking half year, one year and two years of measured time series. This is later plotted as graphs for easy observation and analysis. Basing on the above process it raises a question, 'Before what length of time period can the measured time series be used as they are without long term estimation'?

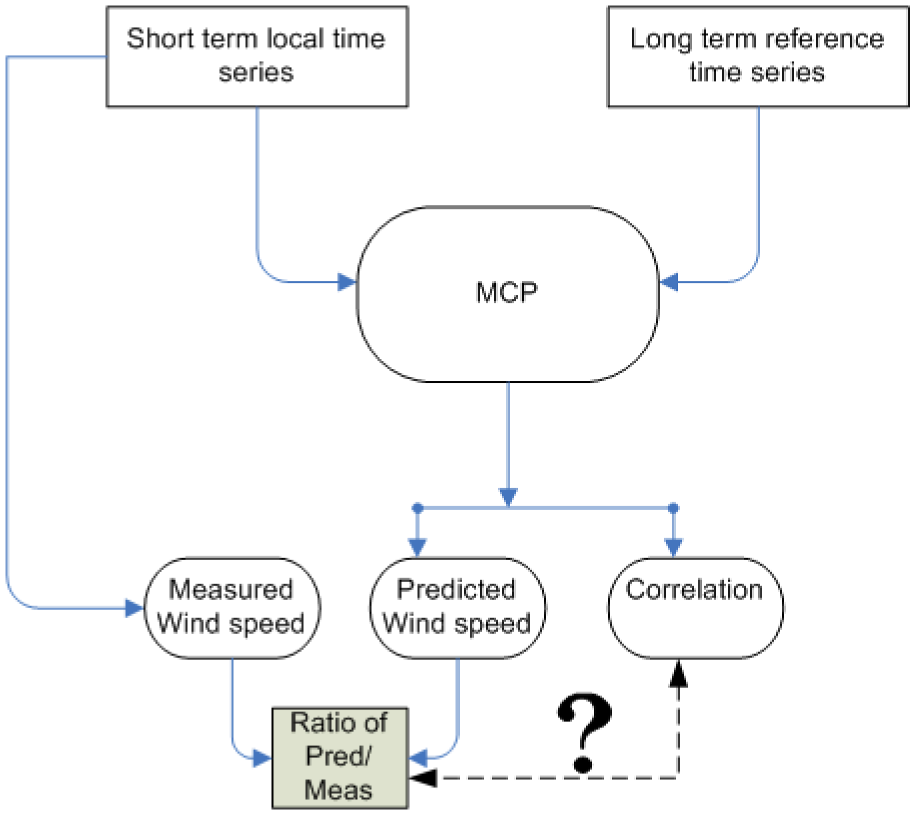

Figure 2.1: Initial method to find out the predicted Wind speed

Not only that, in Figure 2.1, the initial method is represented graphically and since this study is of explorative nature, there needs to be number of iterative processes to be done taking the above model. It is also attempted to find out the relation between the correlation and COV of the predicted time series.

As we have earlier been introduced to the 'concept of uncertainty' in section 1.4, this uncertainty can be assumed to be a function of

- Correlation between local and reference data
- Length of Time period of local measurements
- Landscape
- Quality of the data

Whether the above assumption will prove to be correct, will only be known when the long term estimation is done and observations are made. Case studies form an important part of analysis in this report.

2.3 The Case Study

Initial analysis as depicted in Fig 2.1 is taken as a basis for each case study. In this case Dutch wind sites were chosen for initial analysis. In designing the case studies different units of analysis were chosen which will be explained later. The observations made during initial analysis will be used to test the assumptions made in Section 2.2.

According to Yin (200342) '*the same case study may involve more than one unit of analysis. This occurs when, within a single case attention is given to sub unit or sub units''*. The purpose of the study is to find, if an uncertainty in wind estimation can be reduced and the concept mentioned in the previous section is used for initial analysis taking two sub units (in this case Beek Vs Eindhoven and Deelen Vs Soesterberg), whose results would analyse if an Uncertainty can be reduced or not.

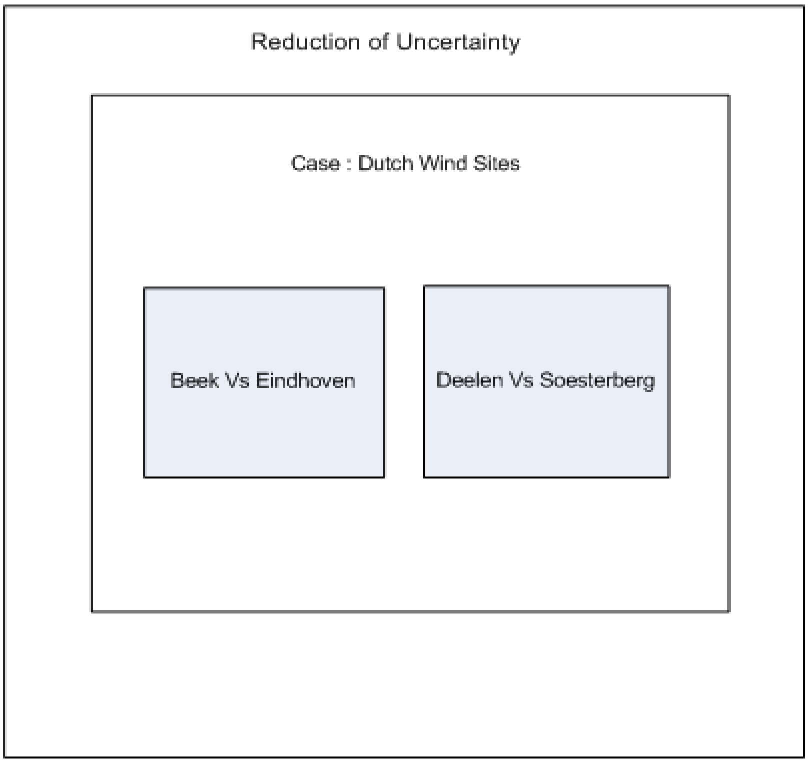

Figure 2.2: Embedded type of case design, inspired from Robert Yin (Yin 2003, xvi, 181)

Figure 2.3: : Geographic map showing the position of Wind sites, map modified from EUMETNET (2007, 1)

Brief description of the case study:

This case study can best be described by having a scenario, where in we have only one year measured time series of site A and 40 years of measured time series of site B. Now, site A is assumed to be a place where the probable wind farm is to be placed, while site B is a near by reference mast from a meteorological station.
Since we do not know the conditions that would have been at the site A for 40 years, we try to build a relation between site A to site B. By using that relation we can predict the long term conditions at site A.

The long term prediction of site A carries uncertainties in the predicted wind speed. These uncertainties depend on many factors, and some of which are assumed in Section 2.2. Reducing uncertainty will reduce the investment risk associated with site A. Suppose site A's uncertainty is 15%, then, there will not be any investments as the wind farm is not viable, and most often, many potential wind farms are not realised due to less research taken in this area.

Having understood the scenario, the Dutch case is explained

Dutch wind sites are located on the south central and southern part of the Netherlands, and are shown in Figure 2.3. These sites have a long term measured time series of more than 40 years, and are available for free from Royal Netherlands Meteorological Institute (KNMI). The wind speeds are available as hourly wind speeds normalised to 10m measuring height with roughness Z_0= 0.03m.

There are four sites namely, Deelen, Soesterberg, Beek, Eindhoven, are used for this study. Out of the four, two sites are assumed as local sites, while the other two are assumed to be reference sites.
In the first case study, Deelen is taken as local site and Soesterberg is taken as reference site. Deelen is predicted taking half year, one year, two years and three years with long term reference site Soesterberg, by following the procedure for 'Initial Analysis' mentioned in Section 3.2.

Each prediction is analysed by answering these questions

- How well is the correlation between local and reference sites?
- What is the effect of length of time period on predictions?
- How will the quality of data influence predictions?

Deductive approach is used in this case study and concepts are refined after making empirical observations. Here, error in estimation for each unit of analysis is deduced from predictions and many 'units of analysis' are added for statistical study and further observations.

2.4 Data collection

The Data collection for this study was done in number of ways. The measured time series were obtained from The Royal Netherlands Meteorological Institute (KNMI) as they are available for free. Literature about technical publications within the field of wind estimation was obtained from winddata.com. EWEA's website has up-to-date information on every aspect of Wind Energy and EU's website has wealth of information regarding the research being taken up within the Wind energy.

WindPro was used to set up the process, as studying the literature associated with this tool was important, for understanding of the methods involved in MCP.

Interaction and comments with Raymond Downey from DONG and Thomas Sørensen from EMD International A/S in the middle of the study were recorded digitally and comments were utilised in refining the process.

The first visit was made at DONG's premises have been useful in identifying the problem for study and subsequent literature which followed has led to better understanding of the problem. The second visit was made in the first week of November, 2007 to present the results of the initial study and also to agree on the restriction to be set for this study because of time constraints.

3. Uncertainty in Wind Estimation

This chapter discusses the types of uncertainty related to wind estimation, which gives a better understanding of the necessity to reduce error in wind estimation. It also discusses the various methods that can be used to reduce uncertainty, while briefly focusing on the working of the method chosen in this study. Finally it discusses the methodology used for explorative study from which a case study is used to connect the methodology.

3.1 Types of Uncertainty in Wind resource assessment

Wind resource estimation results in several types of uncertainty, however, uncertainties can be classified into two types: uncertainty in the wind measurement and prediction methodology, and the natural variability of wind parameters (Fontaine and Armstrong 2007, 1-10)

Wind Measurement Uncertainty

Most of the Wind measurement campaigns use cup anemometers for logging wind

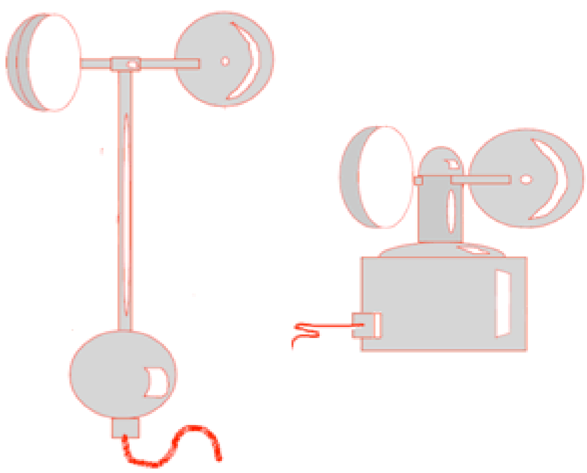

Figure 3.1: Two Cup shaped Anemometers are shown, one on the left, which is of good design and other Anemometer of poorly designed (Pedersen et al. 1999, 11-60)

speeds. This is due to the fact that cup anemometers are robust and can withstand the local conditions. Uncertainties in measurement can occur due to wrong calibration of the instrument. So, before any wind campaign is done, the selection of good calibrated cup anemometer is essential.

As shown in the Figure 3.1, the second cup anemometer is of poor design, which has short shaft, which allows flow over body to influence the rotor. The body has sharp edges and asymmetric protrusions, which effect the sensitivity in different directions.

Different uncertainties exits in the calibration of cup anemometers like, uncertainty of wind tunnel, transducers and instrumentation uncertainty and statistical uncertainty in derivation of mean values (Pedersen et al. 1999, 11-60).

According to IEC (1999, 11-60) mechanical friction due to temperature difference is of concern in calibrating cup anemometers, because, the friction coefficients are temperature dependent, so, anemometers are to be calibrated depending on where they are to be placed for measurement campaign.

Overspeeding of Anemometers

Rapid changes in wind speed causes the anemometers to respond to positive changes in wind speed than to negative changes and the mean indication from the cup anemometer is higher than true average wind speed. This is however, is not a major source of error in the wind measurement.

Lightening

The mast top anemometer is affected by the lightening rod as the wake passes through the downwind direction. When the wake passes over the advancing cups, less drag is experienced and the anemometer will record higher wind speeds than usual and conversely it records less, when the wind passes over retreating cups (Fontaine and Armstrong 2007, 1-10).

Precipitation

According to IEC report, there is likelihood of correlation of wind speed and rain associated with it. Logging of the data could be incorrect due to expose of cables and other wired equipment to the wet weather.

Sheltering effects

Uncertainty in wind measurement can be a result of buildings that have come up near the wind measurement mast and growing of trees which restrict the free flow of air to the mast, thereby incorrect recording of the wind speed.

Equipment maintenance

Wind measuring equipment is a complex set up, where in irregular maintenance causes the equipment to stop functioning and factors like icing can cause equipment to remain stuck.

ISO guidelines must be followed in measuring Uncertainty

Source of uncertainty	**Uncertainties**	
	Min. (%)	Max. (%)
Quality of sensor calibration	1.0	5.0
Changes in sensor calibration	0.2	3.0
Uncertainty caused by sloping wind on the anemometer	0.2	1.5
Measurement of too high wind speed as a results of sensor dynamic	0.2	1.0
Flow distortion caused by mast	0.5	2.0
Flow distortion caused by boom	0.5	2.0
Flow distortion caused by mountings and other protruding objects	0.1	2.0
Unsymmetrical horizontal flow at the anemometer	0.2	2.0
Sensor and data logging uncertainty	0.2	1.0
Total uncertainty	**1.3**	**7.4**

Table 3.1: List of uncertainties mentioned in IEA report (Pedersen et al. 1999, 11-60)

Summarizing, different types of uncertainties are shown in Table 3.1, and uncertainties should not exceed 1.5% for good installations and greater than 7% error, the measurements are discarded (Pedersen et al. 1999, 11-60)

Prediction methodology Uncertainty

Wind Shear Extrapolation

Usually the wind measured at a mast height of 10m is extrapolated to get the wind speed at the hub height. If we take the graph of wind speed versus hub height, the line joining the points on the graph is twisted near the lower heights, this is called Wind shear (Danish Wind Industry Association 2003). Using the wind flow models will introduce uncertainties and wind shear depends on direction, time as can be seen in Figure 3.2. Common wind flow models extrapolate by applying direction sector wise, while not considering wind speed or time of the day (Fontaine and Armstrong 2007, 1-10).

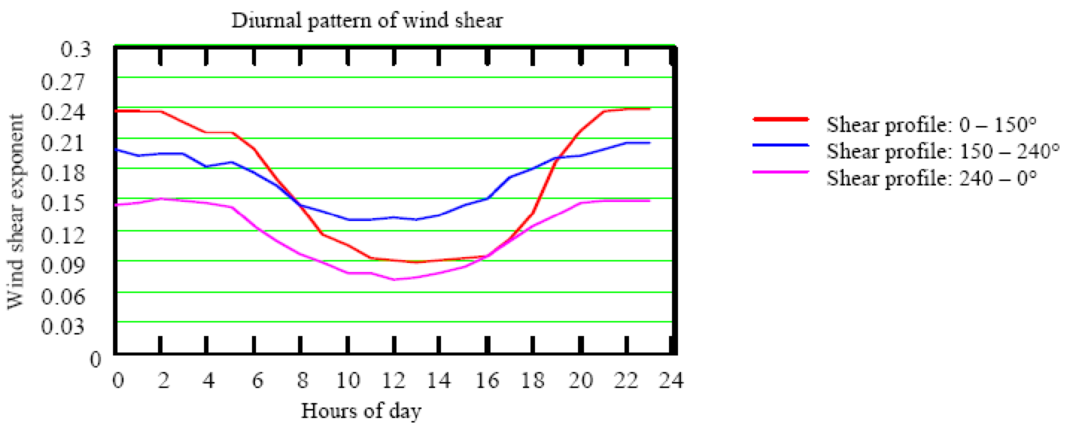

Figure 3.2: Wind shear variations according to the time of the day and direction (PB Power, 2007)

Uncertainty due to complex terrain

In the previous topic, the wind speed from a mast was extrapolated vertically using a wind flow model, this can be for a specific wind turbine location, while knowing a regional wind climate and extending the wind over a proposed wind farm using

Figure 3.3: Mountainous terrain with mast positions in Sicily, Italy (EMD, 2007)

roughness maps and terrain classification will give rise to uncertainty in the prediction of wind speed. This is called horizontal extrapolation. Simple terrain like Denmark, will not add much to the predicted wind speed, however, a complex terrain like Sicily, Italy will have much impact on the predicted wind speeds.

Long term wind prediction

The method used for predicting long term wind speed using short term measured time series is known as MCP method. Here the short term measured time series is usually from a local wind site which was setup for short term wind campaign, and the long term reference site is usually a meteorological station. Uncertainty depends on the number of years of wind data, trend of wind data and temperature variations.

Estimation error of long term wind data is found by taking the standard deviation of the ratio of predicted to the measured wind speed. In Section 1.4, according to Veldkamp the estimation error is 6% and in this study we will try to see if this error can be reduced.

Reference,location	Station,Pairs	Predictions	Mean Ratio Pred/Meas	COV, V
Anderson	53 sites	unknown	1.0	0.035
Bass	82	Unknown	1.0	0.05
Landberg,Portugal	5	Unknown	0.9	0.06
Veldkamp, Netherlands	1,722	30,020	1.0	0.06
Raymond,Netherlands	4	Unknown	1	0.06

Table 3.2: Wind speed variation with MCP methodology (Veldkamp 2006, 47-62)

From the Table 3.1, it can be seen that the long term estimation error on an average is around 6%. Veldkamp (2006, 47-62) mentions that '*predictions do not improve at all with smaller distances*', however, it must be noted that the topography of Netherlands is almost similar throughout.

We have seen uncertainties which exist in wind measurement and later how using prediction methodologies will give rise to uncertainties. The third uncertainty, natural variability of wind parameters is beyond scope of this study; hence it will not be discussed here. It will be interesting to know, how uncertainties mentioned above are measured, so that a clear understanding of the methods will be advantageous.

3.2 MCP methodology

The general guidelines followed when performing an MCP analysis are similar. However, the difference lies in the actual relationship that is used to build the transfer function from the concurrent reference site to the concurrent local site.

MCP analysis requires two measured time series, the local measured time series and the reference measured time series. The long term reference site is used to predict the short term measured time series of a local site.

Methodology

According to Anderson (2004) the general method for MCP process can be described below with some modified terminology.

- Obtain the measured time series of the site that is to be predicted, which will referred as 'Local site'.
- Near to the local site, find a site that has a very long term measured time series and consider this site to be a reference station and hence it is called 'Reference site'
- Compare the 'Reference site' for the matching time period of the local site and name it as 'Concurrent period'
- Establish a relationship for this concurrent period from 'Reference site' to the 'Local site'.
- This relation is called correlation[5] and defined as having a relation between two time series, and this relation can be linear, polynomial, non linear or aggregated monthly level
- Now using the above relation, estimate the wind in the 'Local site' taking the long term measured time series from the 'Reference site'.

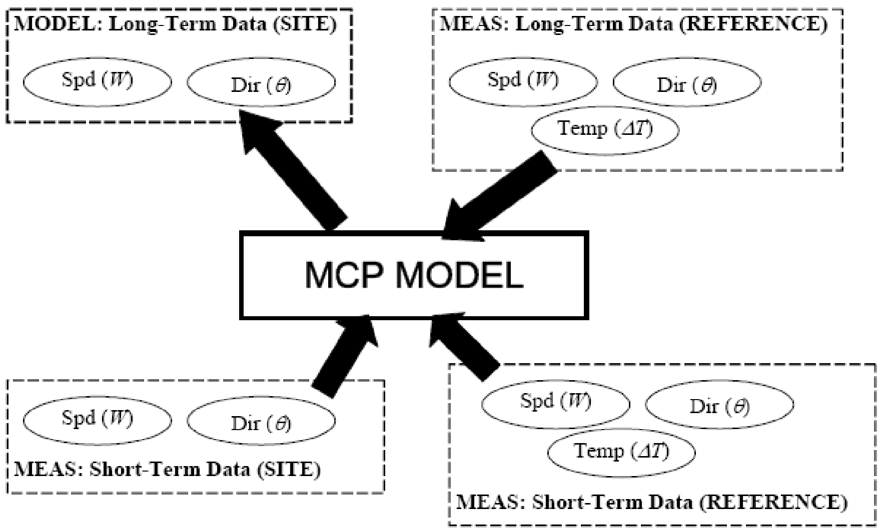

Figure 3.4: MCP model from WindPro (EMD, 2007)

[5] Analysing correlation gives an overview of how well the two data sets are related, if the correlation is poor, the long term estimation will also be poor, sometimes this gives massive errors in the calculated energy production (Thøgersen and Nielsen 2006,464)

The Transfer function[6] differs basing on the method chosen for correlation in the concurrent period and later using the relation obtained during the correlation, is used to predict the wind speed.

As this study uses WindPro software to carry out MCP analysis, an understanding of the MCP method used in this study will be useful, however, to get an overview, different MCP methods available in WindPro are mentioned below. They are,

- Linear Regression MCP
- Matrix method MCP
- Weibull scale MCP
- Wind Index MCP

However, only linear regression method is discussed.

Linear Regression MCP

Regression model in WindPro builds the transfer function based on the concurrent data and this function transfers the long term reference data to the local site for that length of the period of the reference site.

The regression model used is the first order, two component and twelve sector regression.

Here local site estimation is dependent on the reference site, it means, if we assign variables to the reference site as 'x' which is an independent variable and assign 'Y' to the local site, then we have an equation

$$Y = f(x) + e$$

e is the random error (residual).In this study we do not include residual error 'e.' Regression parameters are estimated using Least squares algorithm which calculates summed squared difference of the estimated wind speed and actual measured wind speed in a particular bin. The idea here is to reduce the summed square difference, so

[6] Transfer function referred above is a relation that is obtained between wind speed and direction at the reference site and the wind speed at the local site. Most MCP techniques use a direction sectored regression analysis to establish this relation (Anderson 2004).

the least squares method chooses set of regression parameters in $f(x)$ which reduces the squared sum.

$$SS_R = \sum_{i=1}^{n} \left[Y_i - f(x_i)\right]^2$$

Method to calculate Long term corrected wind data

According to Thøgersen (2006, 455-484), long term corrected wind data is calculated using Bootstrap and Monte-Carlo simulation techniques and is described in the following steps.

1. Fit the Wind speed model with corresponding residuals from 0 to 359 degrees along 12 sectors.
2. Similarly fit the wind veer model with corresponding residuals
3. Use the reference time series
4. Calculate the sample of the on site wind speed data using the wind speed model, i.e., $W_{\text{site}}=f\ (W_{\text{ref}})+e$.
5. Similarly calculate for the wind veer model
6. Repeat the steps 2 to 5 till all the samples in the data, reach the number in long term reference data points.
7. Now generate a table data and fit Weibull table data for comparison.

In this study, we estimate the wind speed and wind veer. Apart from Linear regression of first order, second order polynomial methods are embedded in WindPro which are at user's disposal.
Referring again to the research question of this study, which asks us to see if there can be reduction of uncertainty in wind estimation, leads us into a methodology that is adopted initially which leads into a case study basing on this methodology in the next chapter.

The initial analysis is described below

Initial Analysis

Initial analysis as the name suggests is an initial process that attempts to see the distribution of various parameters in the long term estimation. It starts with finding the wind sites with long periods of recorded measured time series.

List of steps involved in initial analysis

Preparation phase

1. Select two wind sites which have long term measured time series.
2. Clean the measured time series in the WindPro application and remove any unwanted errors like, small wind speeds, directional errors etc..
3. Create a filter which can process these kind of files in future
4. Choose two wind sites, out of which, one will be counted as ‘ Local wind site’ and the other one as ‘Reference wind site’
5. Record the long term wind speeds of the two sites and choose the time series for MCP prediction basing on half year, one year, two years or three years of wind data from the local site. Dicing[7] , Slicing[8] and Randomization[9] can be used in choosing from the measured time series.
6. Using WindPro application, make a separate file for each selected data from step 5. This is done especially for long term data as 40 years of statistics contains more than 360,000 lines of data for one site. If two sites are used, it demands enormous computing power and time, which is not advisable.
7. Take an Excel sheet and make a column with the following fields as shown in the Table 3.2.

Year	Measured	Predict	Ratio	Correlation	Cumulative	Norm Dist	Weibull mean
1991	4.4	4.33	0.984091	0.881	0.07142857	0.015679	4.4
1992	4.4	4.41	1.002273	0.8781	0.14285714	0.216893	4.7
1993	4.4	4.42	1.004545	0.8802	0.21428571	0.270432	4.4
1994	4.4	4.42	1.004545	0.9064	0.28571429	0.270432	4.4

[7] Dicing is a method of selecting each alternate month of wind data and using it for correlation (Anderson 2004)
[8] Slicing is a method of selecting the first half of the wind statistics of a time period for correlation and later selecting other half for correlation (Anderson 2004)
[9] Randomization is selecting randomly a set of months for correlation in one random pick up from the entire period.

Table 3.3 : A model table which will be used to record the predicted values.

Prediction Phase

1. Insert two meteo objects in WindPro and load the local and reference measured time series for the entire period in each of the objects.
2. Now, find the Weibull corrected local measured time series for the entire period and put that one in 'Measured' column of the Table 3.2
3. Load the local measured time series in meteo object taking separate files as mentioned in step 6 of 'Preparation phase'.
4. Take the Weibull corrected wind speed and put the value in 'Weibull mean' of Table 3.2
5. Now start MCP module and load the time series from the drop down menu in 'Measure' tab, check if the loaded time series are the chosen ones.
6. Load the values in 'Correlate' tab by clicking the button 'Load data'. Note down the value of correlation coefficient and put the value in the table under column' Correlation'
7. Load the values into predict tab and predict using linear regression default settings and it is important to 'uncheck' residual resampling from the default settings. The value we get is the predicted wind speed for that particular file, which may be yearly, two years or three years.
8. Take the ratio of 'Predicted' to the 'Measured' wind speed and fill it in the ratio column.
9. Now sort the ratio in ascending order and give it a cumulative probability from 0 to 1
10. Calculate the Normal Distribution from the mean and standard deviation of ratio of the wind speeds.
11. Repeat the steps for each half year, year, two years or three years and note down the values.

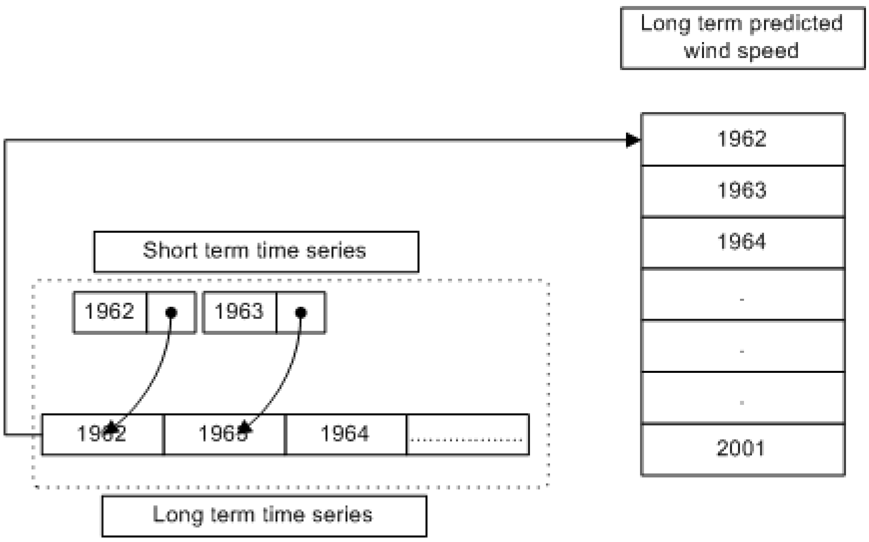

Figure 3.5: A model showing each year is predicted with long term reference and long term wind speed is generated

Analysis Phase

1. Once we get all the tabular values like in Table 3.2, it is time for analysis of the values, the values are normalised and various graphs like Cumulative distribution Vs Ratio, Ratio Vs Correlation etc... are plotted
2. Standard error is found out for measured and predicted wind speeds
3. Time graphs are plotted for measured and predicted wind speeds basing on the observations from step 1.

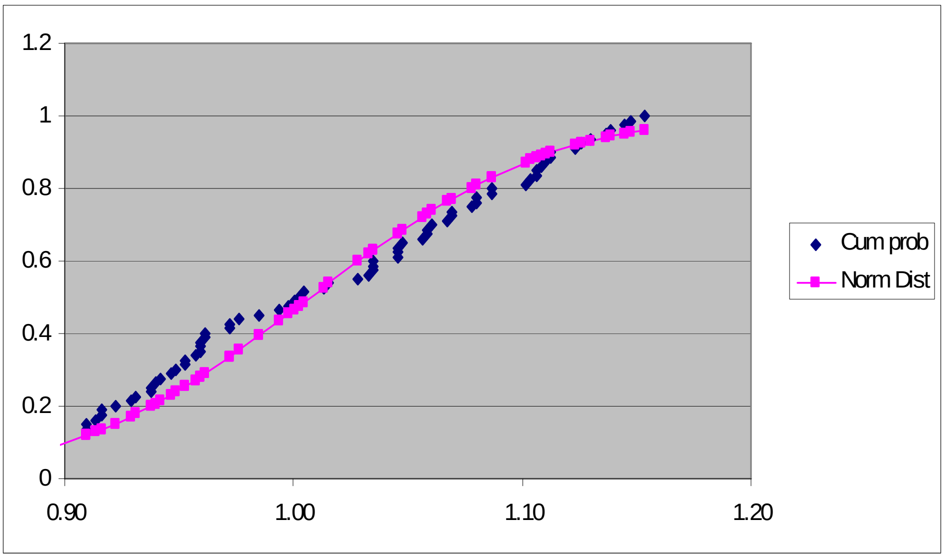

Figure 3.6: A Cumulative probability Vs Ratio graph is shown.

This process is a robust process as for each year, the prediction has to be done manually for each year, which is laborious and also it cannot be automated because, the analyses phase has to be done by observing the results, obtained from various parameters. This is the optimum process that can serve as a starting point for testing with different types of measured time series (As mentioned in step 5 of 'Preparation Phase') and methods.

This above process forms as basis for a case study which will be thoroughly investigated in the next chapter.

4. Case Study: Dutch Wind Site

This chapter utilizes the theory developed in chapter 3 and in accordance with the research question an initial process is described and this case study utilizes that process for studying the case of four wind sites and subsequent observations are made.

4.1 Dutch Wind Sites: Introduction

When this study was initiated it was intended to find a great length of time period of measured time series that are available for research. Previous work by Anderson (2004) Veldkamp (2006, 47-62) and Raymond (2006) have all made a choice to use these statistics as they are available for free from the Royal Netherlands Meteorological Institute (KNMI) and are of great length in time wise.

All the wind speeds are hourly wind speeds normalised to 10m measuring height over a open terrain with roughness z_0 = 0.03m. This case uses four wind sites, taking two of them as a reference wind sites and the other two being local sites. The distance between the reference and the local site is kept to minimum between 50 to 75 kms.

Name of the site	Availability	
	From	To
Deelen	1961	Present
Soesterberg	1958	Present
Beek	1961	Present
Eindhoven	1960	Present

Table 4.1: List of wind sites with their period of available measured time series

The above Table 4.1 shows schematically, the availability period of each of the wind sites. However, for this study Deelen was taken as a local wind site and was predicted with Soesterberg with nearly 44 years, while Beek was taken as local wind site and was predicted with Eindhoven with 40 years of measured time series.

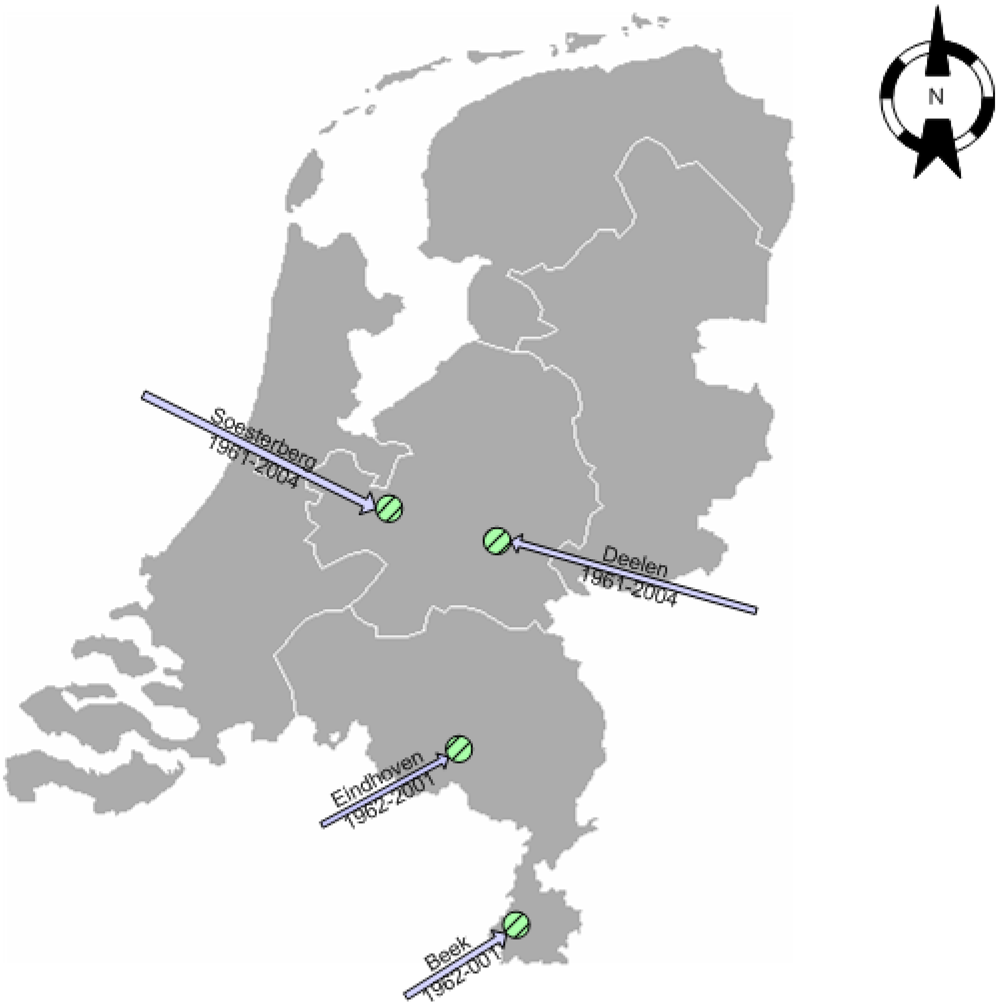

Figure 4.1: Geographic map showing the position of Wind sites, map modified from EUMETNET (2007, 1)

From the methodology discussed in Chapter 3, this case study utilizes the procedure for analysis of the first pair of wind sites.

4.2 Predicting Deelen with Soesterberg

Deelen has been selected as a local site for prediction using long term measured time series from Soesterberg. Though, the measured time series for Soesterberg are available from 1958 onwards, in order for the time periods between the local and reference sites to be the same, the starting year for both the sites were taken to be from 1961 onwards. Deelen's time series is cleaned from any errors and later, this data set of 44 years is made into small time periods of half year, one year, two year and three years. This ends the 'Preparation Phase' of the measured time series.

In the prediction phase, each period of time series of Deelen is loaded into WindPro and subsequent values are noted. For example, each half year of Deelen would constitute predicting 88 times with the long term reference site, Soesterberg.

Site	Length of each period	No.of Predictions
Deelen	Half year	88
	One year	44
	Two years	22
	Three years	14
	Total	168

Table 4.2: Number of predictions of Deelen with Soesterberg

Half year predictions were done slicing each year into two parts and then, each part is predicted with the long term reference. For example, year 1961 is sliced into two halves, from Jan 01st to June 30th and is named as 1961a and the other half is named 1961b.

Each of the predicted values are noted down and tabulated for review in the 'Analysis Phase'.

Prediction Results

Each of the predictions after being tabulated, they are analysed numerically as well as graphically. Table 4.3 presents the prediction results based on the length of time period chosen. The deviation of the measured to predicted wind speeds is compared and also the average correlation of the local site to the reference is noted. Correlation is an important parameter that needs to be analysed, and to find, if there is a relation between correlation and standard deviation of the wind speeds. Though, there has been a relation established between higher correlation and the probability of greater matching of wind speeds between local and the reference sites, however, it is interesting to find the relation between different predictions. WindPro finds correlation from reference to local site by weighted mean of each sector.

Type of Period (1961-2004)	Measured COV	Predicted COV	Avg.correlation
½ year	10.46%	7.49%	0.84188977
1year	7.64%	7.1%	0.84778636
2years	7.12%	6.28%	0.847864
3years	5.99%	5.94%	0.84743571

Table 4.3: Deviations of wind speed in percentage from measured to predicted and average of weighted mean sector wise correlations.

In the Table 4.3 there is no significant reduction in the COV from the measured to predicted. It is the same for half year to three years prediction; also, correlations are almost similar for each period of correlation. This necessitates analysing the results graphically.

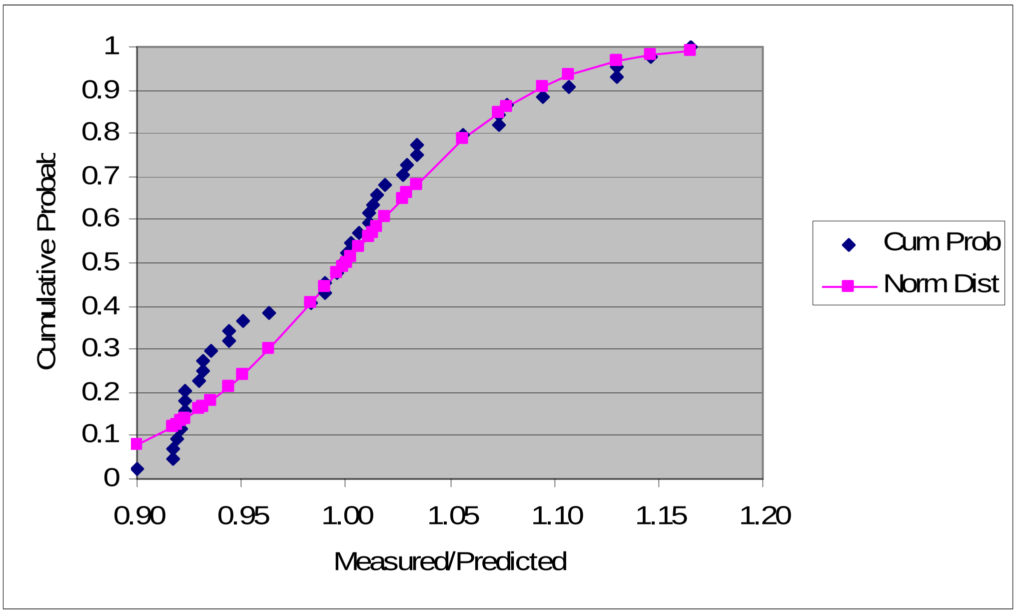

Figure 4.2: Cumulative distribution of the ratio of predicted to the measured

In the Figure 4.2, a plot is made between ratio of the predicted/measured wind speeds to the cumulative probability of the yearly prediction. This cumulative distribution in the graph is assumed to follow a Normal distribution, so a normal distribution is plotted over this graph. It is observed that, there are clusters of data which do not follow normal distribution and hence the graph of cumulative distribution is skewed.

This leads us into finding the cause of this skewness of the graph. Firstly, these clusters can be assumed for a particular time period in the 44 years of data and referring to Figure 4.3, this assumption can be verified, as this graph compares predicted wind speed to the measured wind speed.

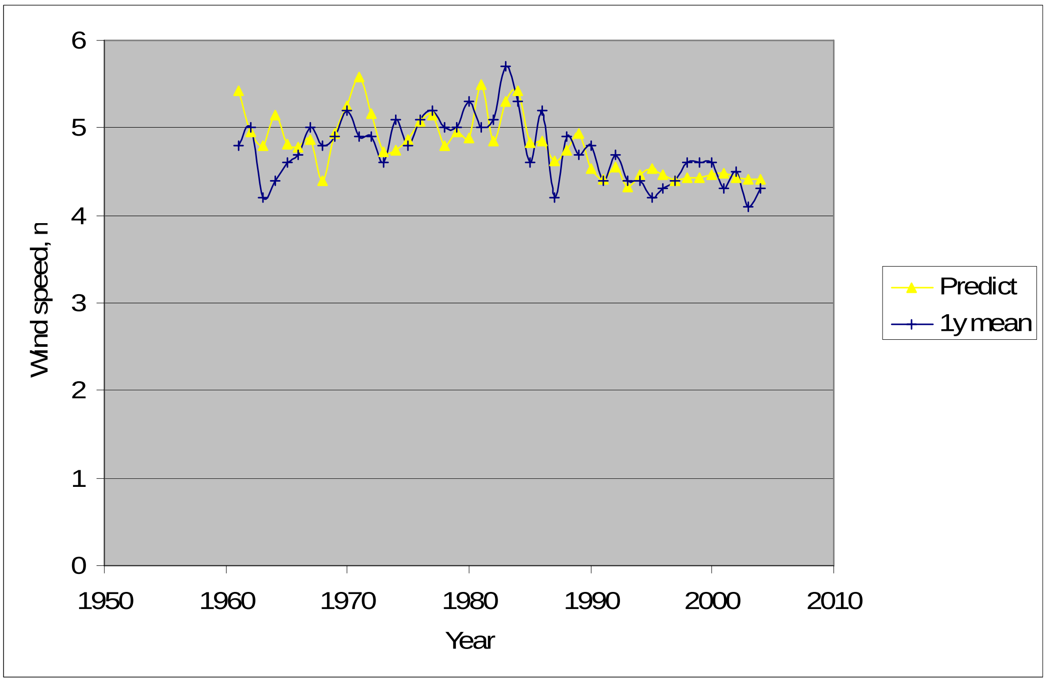

Figure 4.3: Comparison of predicted to measured wind speeds along the time scale

The graph shows different trends in the time period and the transfer function is different for various time periods, hence we can infer that there is inconsistency with the time periods.

Drawing from the graph above, we can clearly see, from 1991 onwards the wind speeds follow a different pattern than the rest of the years. There is also a shorter duration where in this kind of trend can be observed from the graph and also can be confirmed from the tabular values.

The causes of this inconsistency can be from different sources as mentioned by Thøgersen (2006, 455-484), which includes changing of the position of mast, changing of height of the anemometer or houses or trees have come up causing the wrong measurements.

He further states '*As a rule of thumb reference data can be used as far back as the latest source of inconsistency'* (Thøgersen and Nielsen 2006, 471), from this statement and previous observations from predictions, it will be worth while to take only the consistent period or use the data after the latest source of inconsistency.i.e., from 1991 onwards for further predictions.

4.3 Consistent period prediction (1991-2004)

For this case study, basing on the observations made before, the consistent period was chosen to be from 1991-2004, which amounts to a total of 14 years of measured time series. Using the methodology mentioned in the 'Initial Analysis' of Chapter 3, we straight away follow the steps mentioned in the 'Prediction phase'. Only half year, one year and two years are considered as periods for prediction using long term reference, Soesterberg.

Type of Period (1991-2004)	Measured COV	Predicted COV	Avg.correlation
½ year	8.02%	2.19%	0.87377857
1year	3.86%	1.32%	0.87893571
2years	3.80%	1.09%	0.88167143

Table 4.4: Deviation of wind speed from measured to predicted in percentage, average of correlations are also shown.

From prediction the results are noted in Table 4.4, observations from table shows that there is a decrease of error in the wind speeds from 8.02% to 2.19% for half year predictions while, for one year and two years the decrease is from 3.86% to 1.32% which shows that the error from measured to predicted is reduced by nearly 75%.From this we can infer that limiting prediction to consistent period will reduce uncertainty..

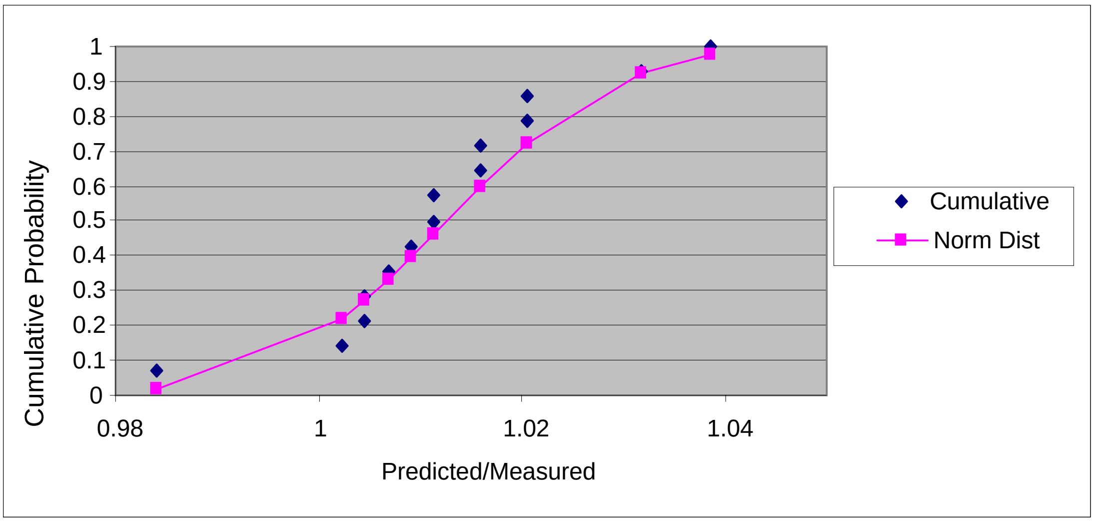

Figure 4.4: Cumulative distribution of the ratio of predicted to the measured wind speeds of the consistent period 1991-2004.

Cumulative distribution of the ratio of the predicted wind speeds to the measured wind speeds, now almost follow normal distribution as can be seen from Figure 4.4. As a part of analysis a recent twenty year period (1985-2004) is taken to see, if there is a deviation from consistent period. This analysis involved in predicting yearly data with long term reference.

4.4 Predicting Beek with Eindhoven

Figure 4.5: Geographical location of the Beek and Eindhoven, map modified from EUMETNET (2007, 1)

Beek lies to the south of the Netherlands and Eindhoven to the north-west of Beek's wind site. Availability of measured time series were from 1961 for Beek and for Eindhoven they are from 1960 onwards. However, for the prediction purpose only 40 years of measured time series are considered. As shown from Figure 4.6, Beek is considered as local wind site, while Eindhoven was considered as reference wind site. Following the procedure as mentioned in chapter 3 for 'Initial Analysis', Beek's measured time series are cleaned from any errors and each half year, one year, two years and three years of data from the entire period are taken out for later predictions. In the 'Prediction Phase' of 'Initial Analysis', each period of the time series of Beek is loaded into WindPro application for MCP analysis and values are noted. For half year predictions, there are in total, 80 predictions are made from the entire period of 40 years.

Prediction Results

Each of the predictions are analysed numerically as well as graphically. In the numerical analysis, Table 4.3 presents the prediction results based on the length of time period chosen. The deviation of the measured to predicted wind speeds is compared and also the average correlation of the local site to the reference is noted.

Type of Period (1962-2001)	Measured	Predicted	Avg.correlation
	COV	COV	
½ year	10.46%	7.49%	0.84188977
1year	7.64%	7.1%	0.84778636
2years	7.12%	6.28%	0.847864
3years	5.99%	5.94%	0.84743571

Table 4.5: Wind speed deviations in percentage, before and after prediction basing on the time period chosen

From the above table, there is no significant reduction of error, except for half year prediction the error decreased from 10.46% to 7.49%, however, for other years, there is not much reduction. Analysis of the cumulative distribution of ratio of the wind speeds from Figure 4.6, shows as similarity with the previous case, i.e., Deelen with Soesterberg**,** as we find that the graph has clusters of data and is skewed. It does not follow the normal distribution; by this we can assume that there is different trend of the time series along the entire length of the time period.

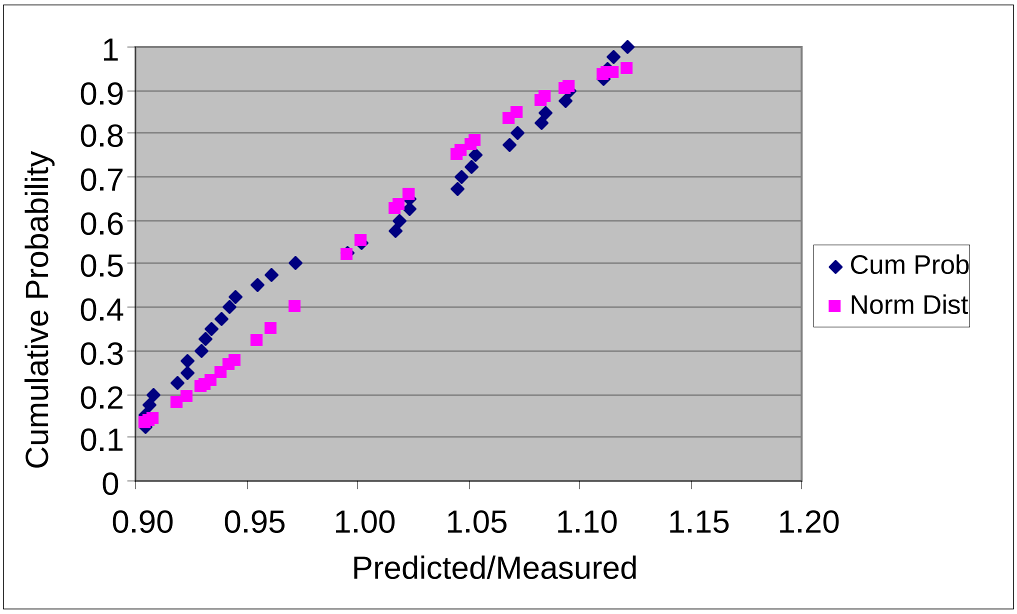

Figure 4.6: Cumulative distribution of the predicted wind speed to the measured for one year predictions

We can get a clear picture by way of having a time graph plotted similar to the one from previous case. However, in Figure 4.8, the predicted wind speed follows a different pattern along the years. In this case the last period from 1985-2001 follow a different pattern, so, this can be assumed to be a consistent period for prediction. This period can be tested to see, if the error in the measured time series can be reduced.

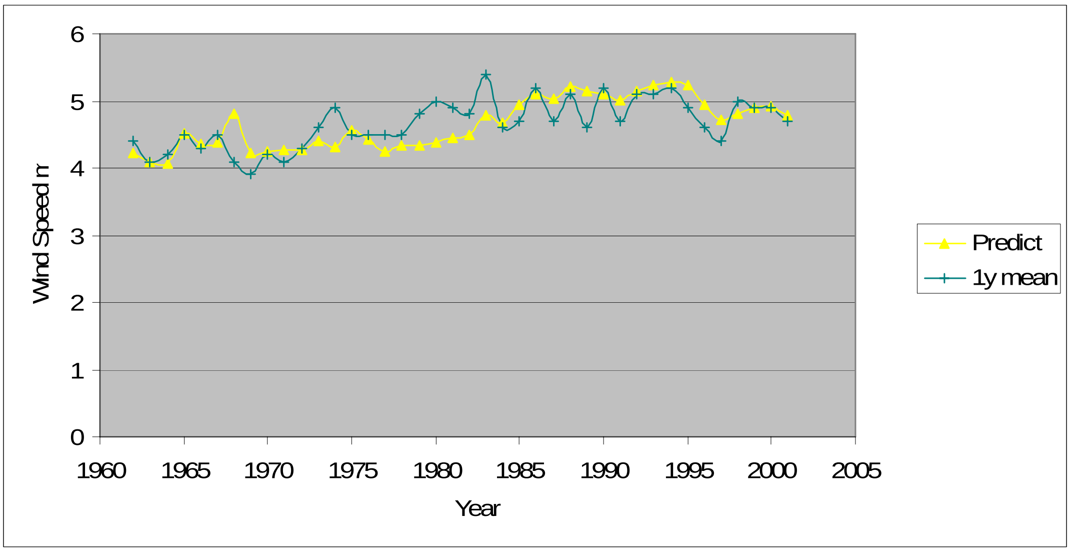

Figure 4.7: Time graph showing the predicted wind speed with the measured

4.5 Consistent Period prediction (1985-2001)

A total of 17 years of measured time series are taken from the consistent period and are predicted with the long term reference site Eindhoven. The methodology followed is from chapter 3, which has a method 'Initial Analysis'. Since we readily have measured time series based on half year, one year, two years and three years, predictions can be immediately be performed

Type of Period (1985-2001)	Measured COV	Predicted COV	Avg. correlation
½ year	7.44%	3.71%	0.81397647
1year	5.08%	3.3%	0.82196471
2years	2.97%	2.85%	0.825875

Table 4.6: Standard deviation of the measured to the predicted wind speed.

Predictions based on the each of three years for the consistent period is left out, as the aim is to have more predictions for analysis, in contrary, three years would not give more predictions for 17 years of data.

Referring to Table 4.6, the error in the measured wind speeds is high for half year, however, as the length of time period of data increases from half year to one year, two years, it can be observed that the error decreases. It is interesting to note that, for predictions, in addition to, decreasing of error from half year, there is also a decrease due to type of period selected.

For example, in the predictions, the error due to half year prediction is reduced from 3.71% to 2.85% as the time period increases from half year to two years. It means, there is not only a horizontal decrease of error, but also there is vertical decrease as the time period increases.

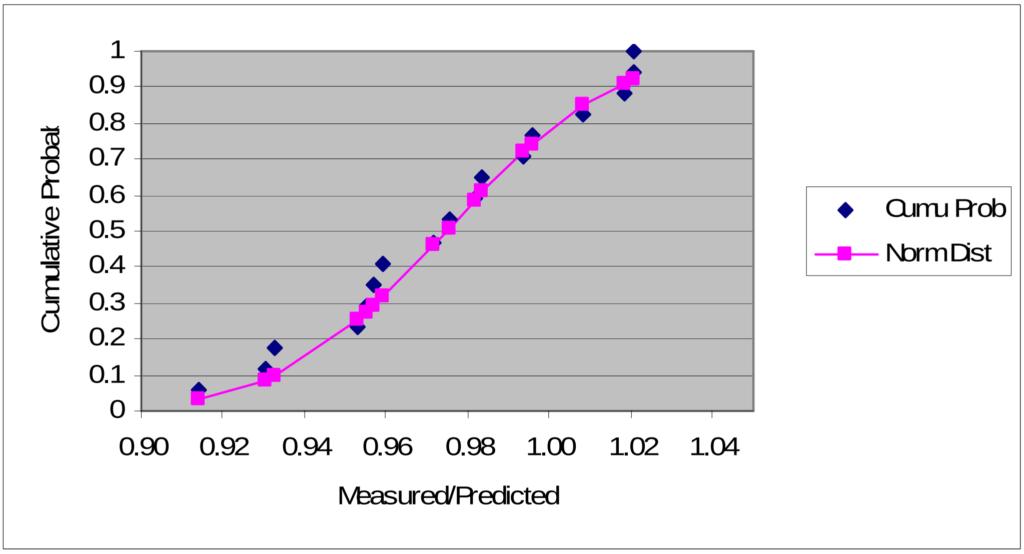

Figure 4.8: Cumulative distribution of the ratio of wind speeds for one year predictions in the consistent period (1985-2001).

Cumulative distribution of the ratio of the wind speeds closely follow a normal distribution as can be seen from Figure 4.9 and this is different from the 40 year period and can be purely attributed to choosing the consistent period of predictions.

Also, the consistent period differs for the two predictions, as Deelen with Soesterberg, the consistent period was chosen from 1991-2004, while for Beek with Eindhoven, the period was chosen from 1985-2001. From this we can infer that consistent period differs from site to site for the above cases.

4.6 Conclusion

Chapter 4 utilizes the theory and methods developed in Chapter 3 by way of taking wind sites as cases for study. The criteria was to have wind sites which have great length of measured time series. 'Initial Analysis' has led to the discovery of inconsistent time periods over greater lengths, and reducing standard deviation for the periods of inconsistency, is a futile attempt. However, using the consistent period for prediction has yielded results in the case of Deelen with Soesterberg. As this is an embedded case of study, discussed in chapter 2 and referring to Figure 2.2, the second unit of analysis i.e., Beek with Eindhoven were chosen and the methodology discussed in chapter 3 is utilised for arriving at conclusion with this unit of analysis.

Both cases resulted in inconsistent time periods, and by selecting consistent time periods have led to the reduction of error in wind estimation. From this we can say, the research question is answered, but not fully and to completely answer the research question, there needs to be more number of cases which can be tested with the methodology developed in chapter 3 and consequent observations made in chapter 4 with the case studies.

It is attempted to find the relation between ratio of the wind speeds and correlation coefficients by plotting graphs, however, no significant result was found. Relation between correlation and COV is found in Chapter 5, as more number of cases have been investigated.

The next chapter focuses primarily on taking different cases which aim to find if an uncertainty can be reduced, by using the methods developed in this chapter as well as previous chapters.

5. Consistent period methodology

In chapter 4, two cases were taken and predictions were done, however, in the initial stage, there was no reduction of error due to prediction, but, after finding the inconsistency in the time period and confining the predictions to the consistent time period, it was observed that the reduction of error is possible. The question arises, if this methodology can be applied to many cases or is it only for the cases studied before. This chapter examines the possibility of testing the method, which was used previously by extending it to number of cases.

5.1 Introduction

Each of the cases studied in chapter 4 are considered as independent of each other and the results from these case studies have helped in defining a method called consistent period method. This theory is now tested with other cases. According to Yin (200332), multiple cases should be considered like multiple experiments and he further states '*'under these circumstances, the mode of generalization is 'analytic generalization,' in which a previously developed theory is used as a template with which to compare the empirical results of the case study''*.

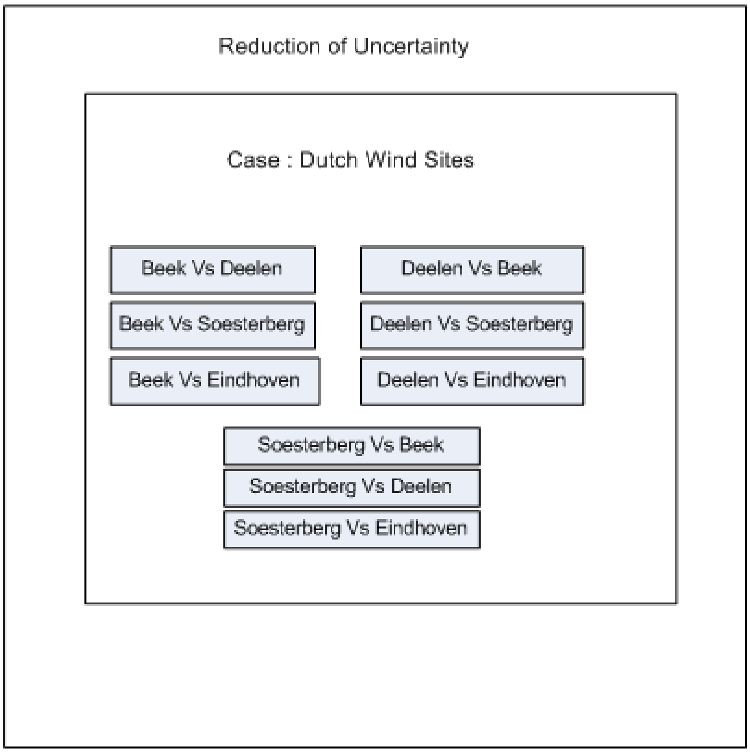

Figure 5.1: Embedded type of case study, involving 9 sub units of analysis.

The template that will be used here is the ‘consistent period method’ and testing more number of cases with this method can lead us into generalisation. ‘*‘If two or more cases are shown to support the same theory, replication may be claimed*’’ (Yin 2003, 32).Therefore, in this chapter, not one case, but many number of cases are tested using the methodology developed and the results are analysed for reduction of error.

Referring to Section 2.3, the type of design adopted for this study is ‘Embedded Type’ of design with more number of ‘units of analysis’. This can be visualised diagrammatically in Figure 5.1, where 9 units of analysis were embedded within the case, and this case itself is based on the theory developed in chapter 3 and chapter 4.

Each ‘unit of analysis’ is taken as an independent unit and is tested for reduction; the procedure for reducing error by consistent period method is discussed down below.

5.2 Consistent period method

In simple terms, consistent period method is based on the theory developed in chapter 3 and 4 and is stated below:

1. Proceed with selecting two sites, one as a local site and other being reference site and follow the steps mentioned in ‘Preparation Phase’ from ‘Initial Analysis’ of Chapter 3
2. From Chapter 4, we have observed that half year predictions are included, however, in this step, only one year predictions are included.
3. After one year prediction of local site with long term site, analysis is done for error in prediction to the measured wind speeds and also correlation.
4. Time graphs are plotted to find the period of consistency by using the measured and predicted wind speeds.
5. Select the first consistent period from the graph by visual observation and predictions are performed on this, to find out the reduction of error from predicted to the measured wind speed.
6. After this, select the second consistent period, probably a reduced time period from the previous selected time period and perform predictions. These results are compared with previous consistent predicted results.

Predictions in this chapter follow the above method and only three cases or 'units of analysis ' are presented here and other cases are presented in appendix..

5.3 Analysis of Different cases-Results

Beek with Soesterberg

By using the consistent method mentioned in the previous section, each of these three cases are analysed and the results are noted. Our aim here is to see if consistent period method works.

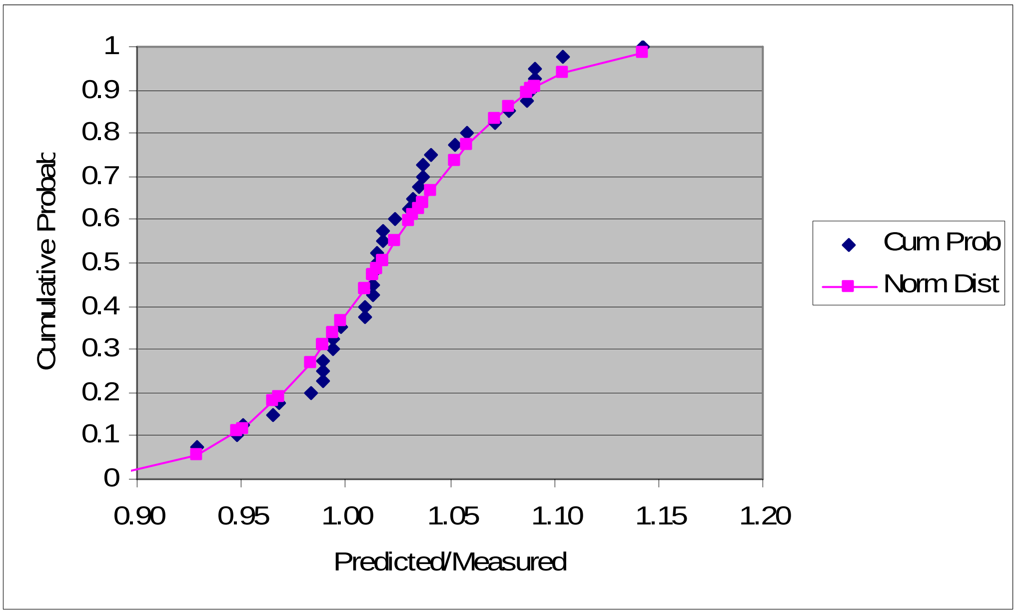

Figure 5.2: Cumulative distribution of predicted with measured wind speed (1962-2001)

In the above Figure 5.2, the clusters of wind data are observed, which again reminds us of the cases studied in chapter 4, and it is necessary that we look for the causes of these clusters. From the knowledge gained in the previous cases, we can look for particular time periods where the wind speeds follow a pattern. So, from Figure 5.3, there are different patterns that can be observed and also the cumulative distribution of wind speeds, almost follow a normal distribution.

The error in the predicted wind speed for forty years is 5.6%, while the measured wind speed error is found to be 7.3%, two consistent periods can be taken from the time graph. The first consistent period is from 1984-2001, consisting of 18 years and the second one is from 1984-1997 which consists of 14 years of measured time series.

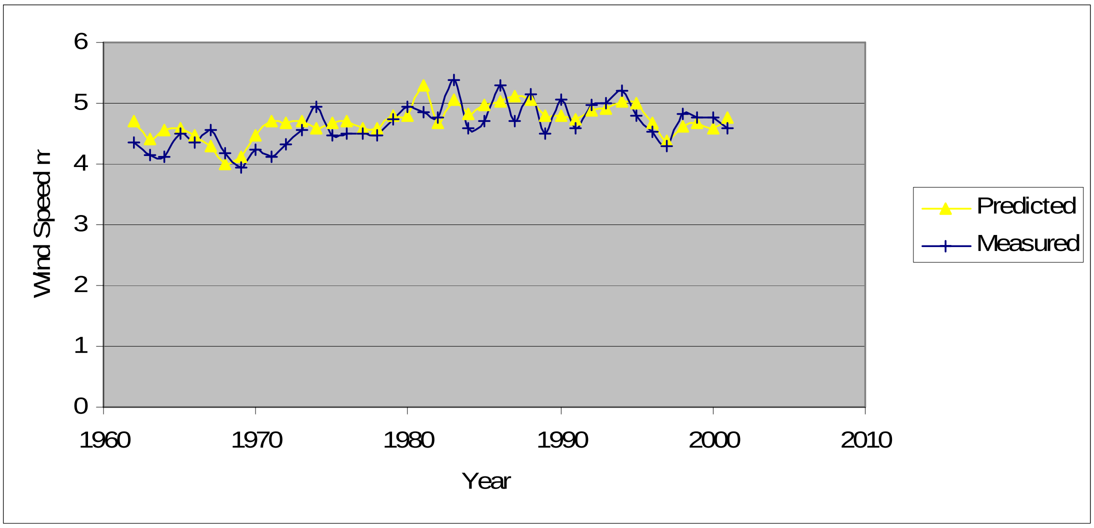

Figure 5.3: Time graph showing the trends of measured to the predicted wind speed.

After the prediction of consistent period of measured time series, it is found that the measured wind speed error is decreased to 5.6%, while the predicted has decreased from 5.6% from forty years to 3.9% in the consistent period 1984-2001.

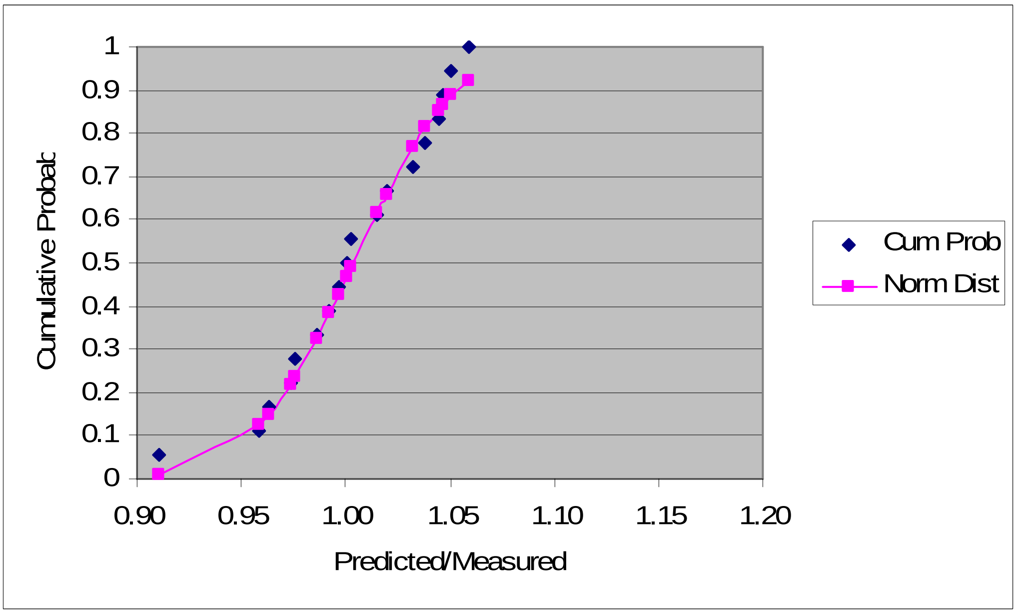

Figure 5.4: Cumulative distribution of predicted to measured wind speed (1984-2001)

Using the step 6 of the consistent period method, another time period is selected, probably reducing the length of the time period of the previous consistent period, and is predicted for long term estimation and observations made from results show that there is no decrease of error, .i.e., predicted error is 4% which is 0.1% more than the last consistent period. Observing Figure 5.5, we can see that, except one data point, all others almost follow a normal distribution.

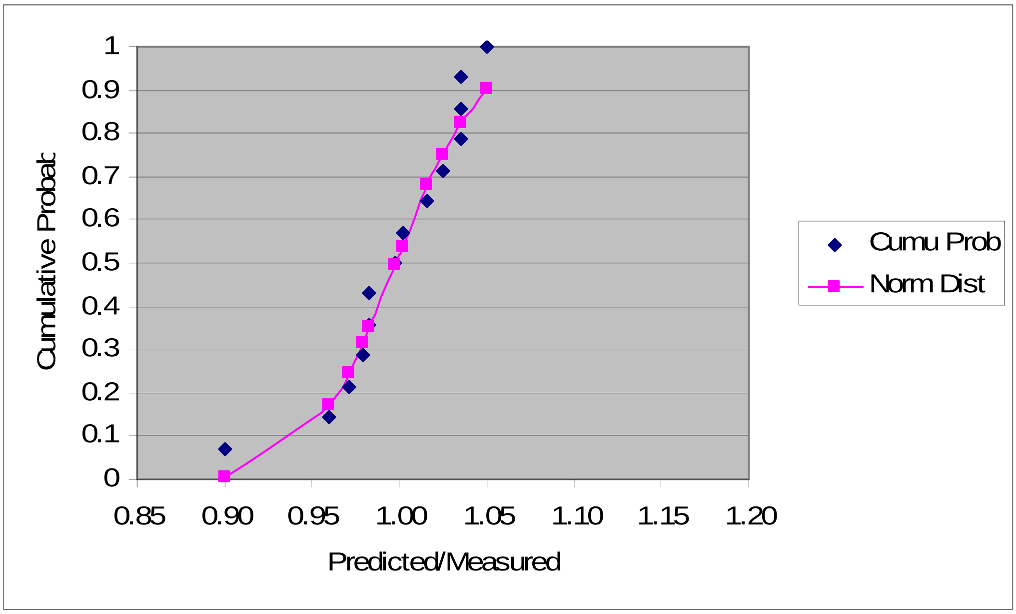

Figure 5.5: Cumulative distribution of predicted to measured wind speed (1984-1997)

Deelen with Eindhoven

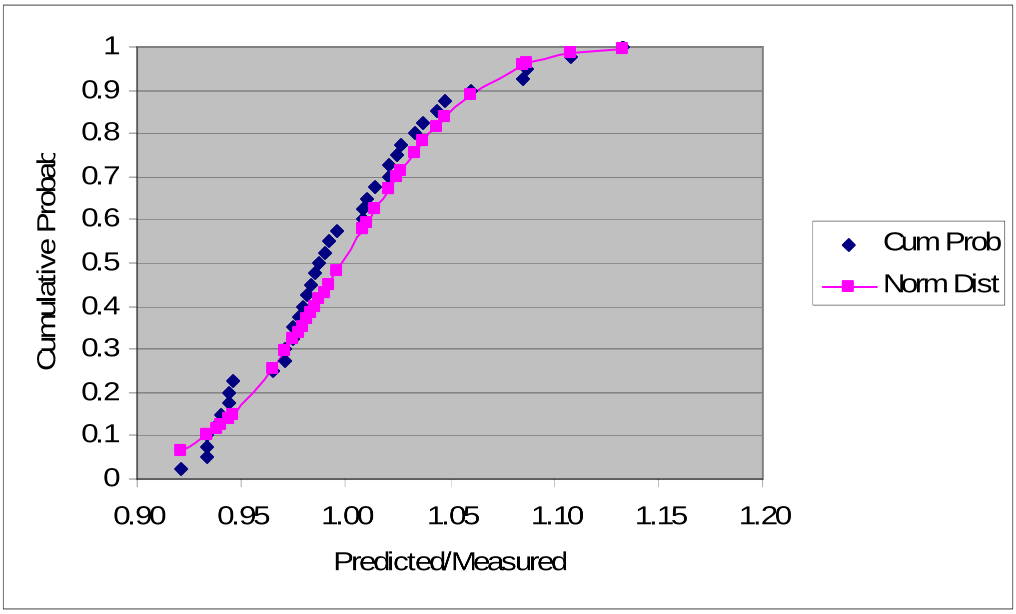

Figure 5.6: Cumulative distribution of predicted with measured wind speed (1962-2001)

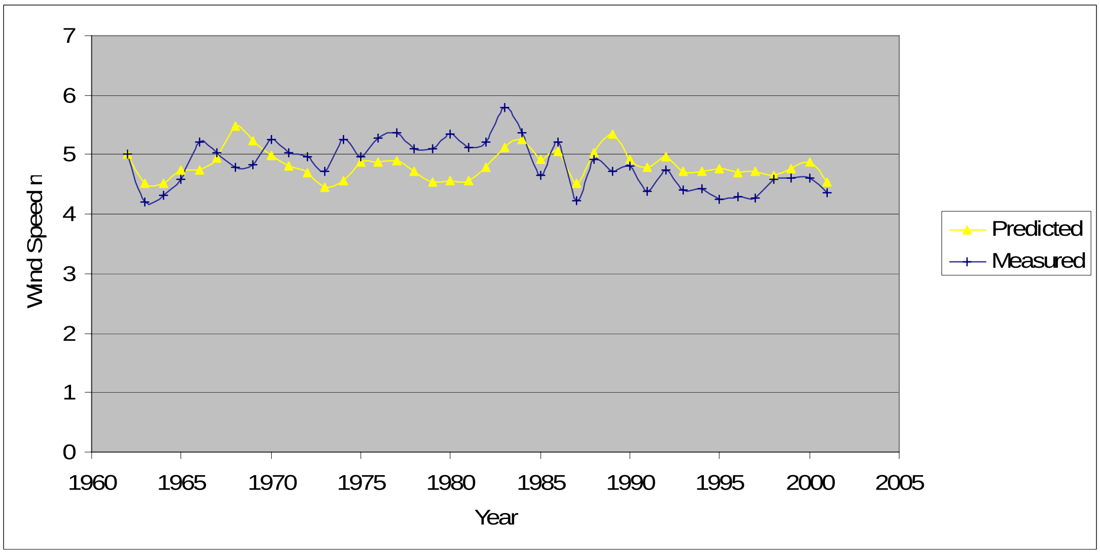

Figure 5.7: Time graph showing the trends of measured to the predicted wind speed.

Deelen is taken a local wind site, while the Eindhoven is taken a reference site, following the procedure for consistent period method, the above graphs from Figure 5.6 and Figure 5.7 are obtained, by analysing the first graph from Figure 5.6, there are three clusters of data which are skewed, and in the time graph this can be confirmed. The next step is to identify these time trends and assume them as consistent periods. i.e., period 1985-2001 which has a total of 17 years is considered as one consistent period, while another consistent period is from 1990-2001 which is made up of 12 years.

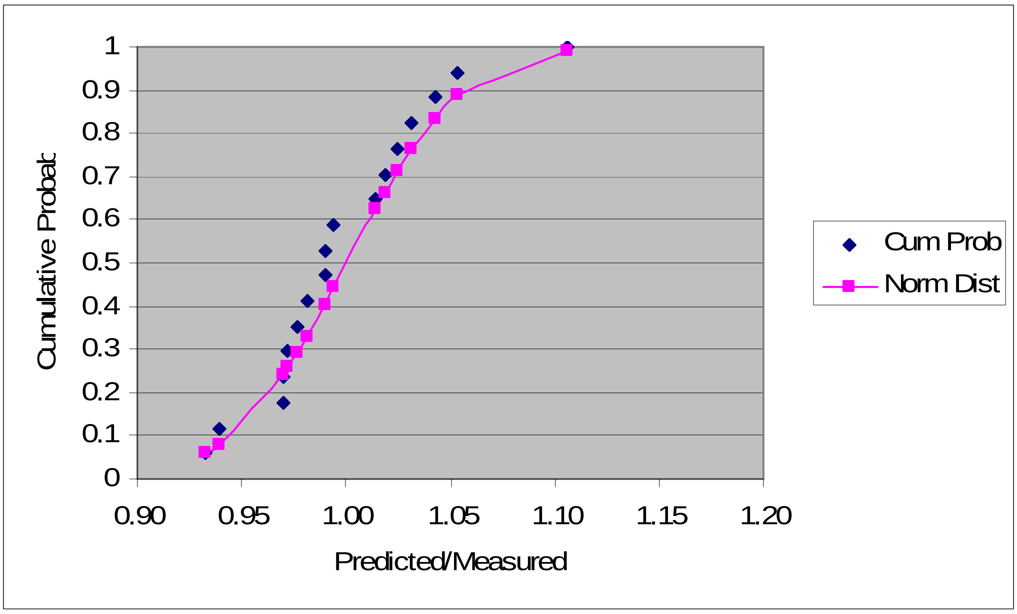

Figure 5.8: : Cumulative distribution of predicted with measured wind speed (1985-2001)

Normal prediction for 40 years is found to be 5.04%, while the prediction for consistent period from 1985-2001 is 4.3%, which is a reduction of nearly 1% in estimation of error. Figure 5.8 shows the cumulative distribution of the wind speed ratios follow normal distribution, except for very few ratios, deviating from the normal distribution, this could be attributed various factors mentioned in Section 3.1 of Chapter 3.

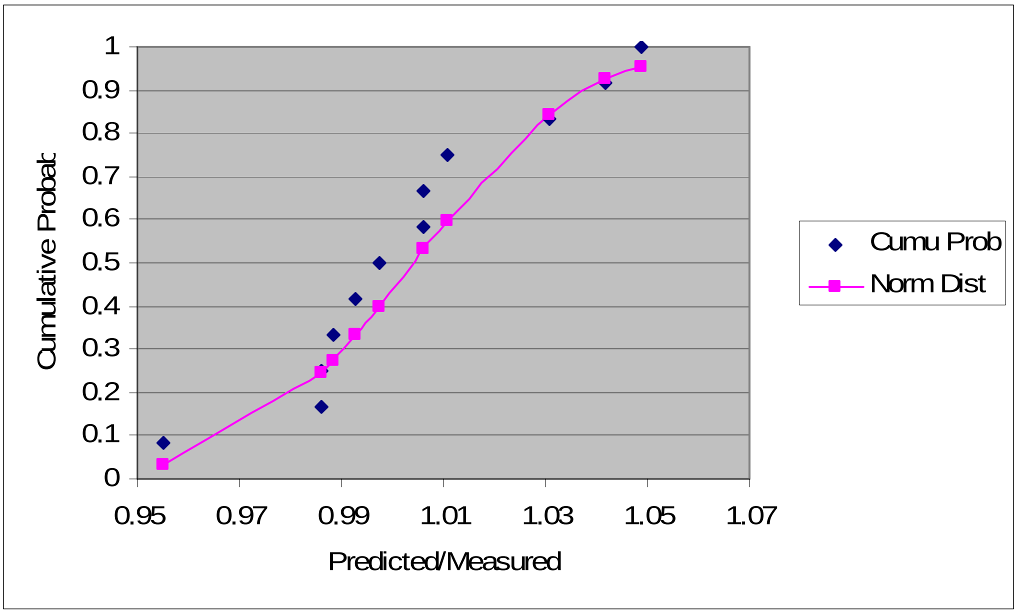

Figure 5.9: Cumulative distribution of predicted with measured wind speed (1990-2001)

Observations from Figure 5.9, suggest that it is similar to Figure 5.8, however, the error in long term prediction for this time period (1990-2001) is 2.6%, which is a significant reduction, when compared to the other time periods of this case.

Soesterberg with Eindhoven

This is the last case of this Chapter, which will be studied and the results will be evaluated to see, if they follow a similar pattern. Here, Soesterberg is taken as a local site, while Eindhoven is taken as a reference site for predictions.

Following the procedure mentioned in 'Consistent period method', Soesterberg is predicted each year with Eindhoven's 40 years time series. From the Figure 5.10, a particular pattern of wind speed can be found only by keen observation. However, when this pattern is analysed using the time graph from Figure 5.11, our assumption can be confirmed. The prediction error from 40 years is found to be 7.3%, while the

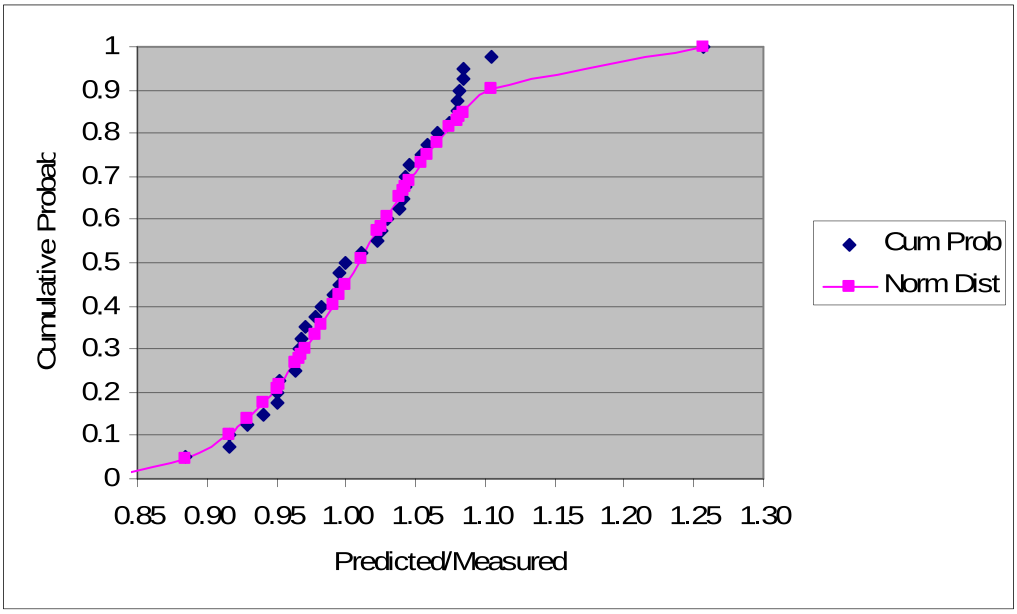

Figure 5.10: Cumulative distribution of predicted with measured wind speed (1962-2001)

measured error is only 6.2%; this 40year prediction is totally different from the other two cases. This type of error sometimes is not uncommon, but, it is of particular interest to be noted about this increase of error in long term prediction.

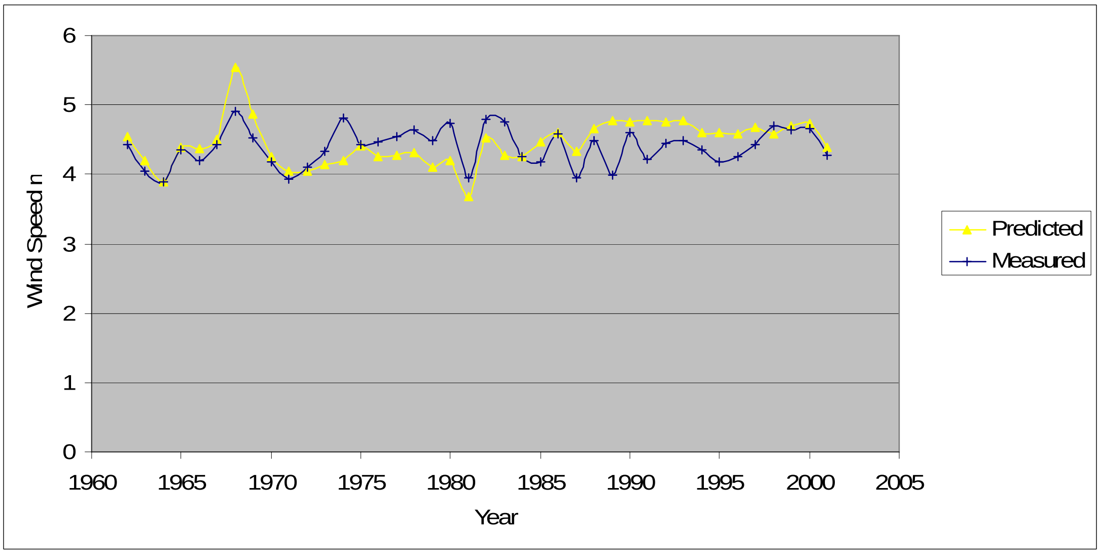

Figure 5.11: Time graph showing the trends of measured to the predicted wind speed.

Using the time graph, a new time period from 1985-2001 having 17 years of measured time series is selected. It is long term predicted and the error in the long term predictions is found to be 3.1%, this seems to agree well with the previous two cases, which involved in reduction of error in the consistent period.

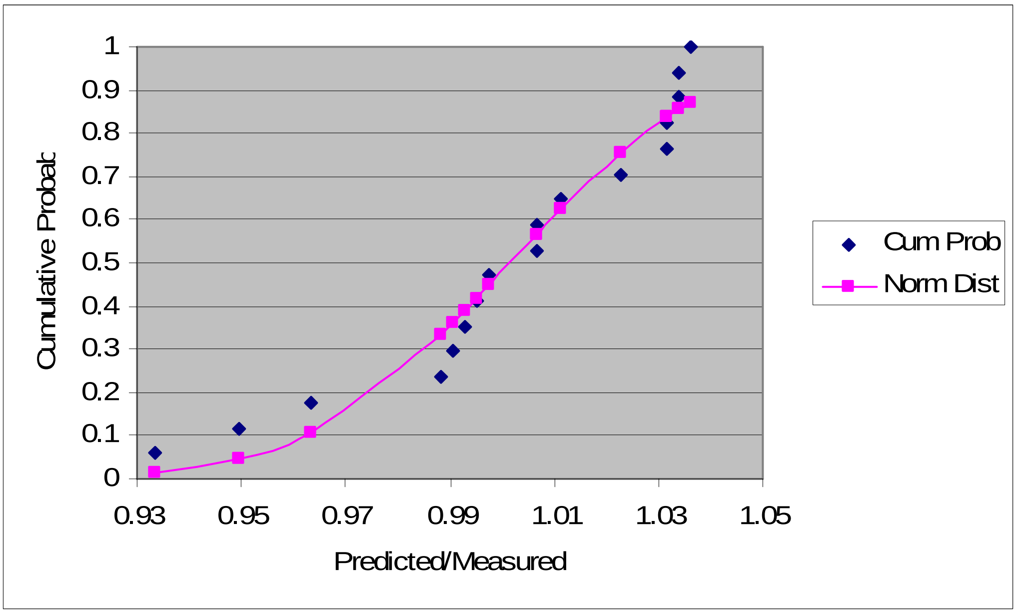

Figure 5.12: Cumulative distribution of predicted with measured wind speed (1985-2001)

From Figure 5.12, the cumulative distribution of ratios do not follow perfectly a normal distribution, however, the error can be reduced.

Referring again to the 'Consistent period method', another time period is selected. Period from 1990-2001, having 12 years of measured time series is chosen and is long term predicted, the error in this case is found to be 2.6%,which is still lesser, when compared to the previous error of 3.1% .

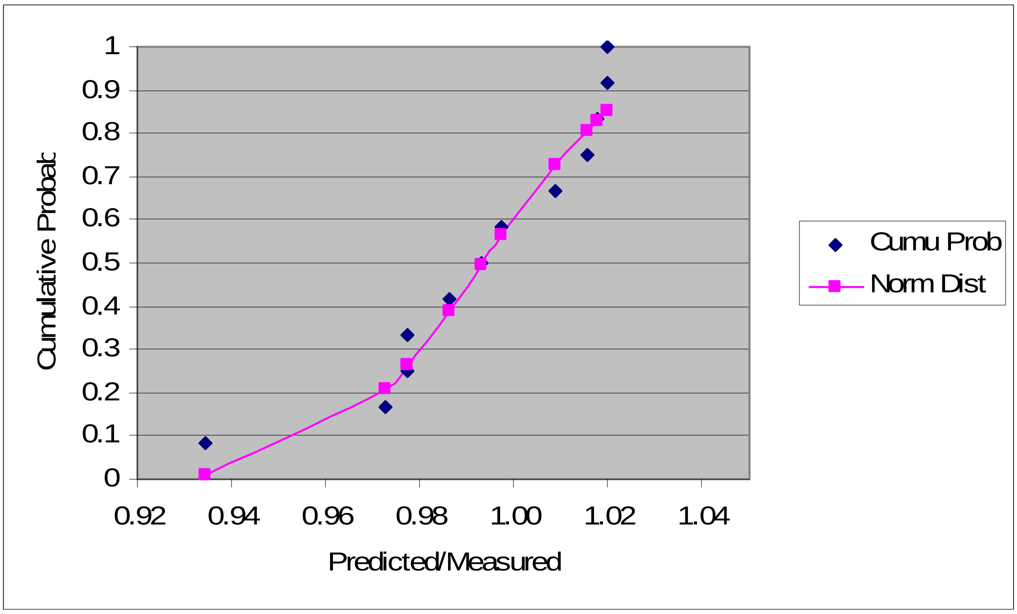

Figure 5.13: Cumulative distribution of predicted with measured wind speed (1990-2001)

From Figure 5.13, the predictions are plotted as a cumulative probability with ratios of wind speeds. These data points follow normal distribution well

5.4 Summary

The above cases use the procedure mentioned in Section 5.2, and these cases were considered as 'units of analyses' within an embedded case. The theory developed in Chapter 3 & 4 and modified in Chapter 5 by giving a new method for reduction of uncertainty in long term estimation, which is tested using three cases and the rest of cases appear in Appendix, as other cases also utilise the same methodology.

Also, referring to Yin, '*'If two or more cases are shown to support the same theory, replication may be claimed*'' (Yin 2003, 32), which tells us that, in this embedded case study, replication can be claimed by following the method as mentioned in Section 5.2 and the testing of subsequent cases. The positive results of these cases affirm that the methodology works.

5.5 Results review

The following results are presented in tabular form; these results are organised based on three classifications:

1. Normal long term predictions
2. First consistent period prediction
3. Second consistent period prediction

Normal Long Term Prediction

Name of site	Years	Beek			Deelen		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	40	x	x	x	7.3	6.8	0.7005625
Deelen	40	8.2	8.3	0.7288	x	x	
Soesterberg	40	6	6.3	0.7039	6	5.8	0.84665

Table 5.1 Values of COV of the predicted wind speeds and the average correlation of the Normal long term measured time series.

Name of site	Years	Soesterberg			Eindhoven		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	40	7.3	5.6	0.67573	7.7	7.98	0.7999725
Deelen	44,40	7.1	7.1	0.84779	8.2	5.04	0.820685
Soesterberg	40	x	x	x	6	7.3	0.806055

Table 5.2: Values of COV of the predicted wind speeds and the average correlation of the Normal long term measured time series

Observing Table 5.1 and Table 5.2, we can see that, there is not much reduction in the uncertainty due to predictions. Some of these errors are near to 6%, which agree with Veldkamp (2006, 47-62) and Raymond's (2006). In Table 5.2, the numbers of years are denoted consecutively, when the length of the time period is different. As an example, Deelen has number of years 44, 40, which implies, Deelen was predicted for 44 years with Soesterberg and 40 years with Eindhoven.

First Consistent period prediction

Name of site	Years	Beek			Deelen		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	17	x	x	x	5.6	4.2	0.72480588
Deelen	17	5.9	4.2	0.74724	x	x	
Soesterberg	17	5.2	3.1	0.7261	5.2	3.3	0.87404706

Table 5.3: Values of COV of the predicted wind speeds and the average correlation of the first consistent measured time series.

Name of site	Years	Soesterberg			Eindhoven		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	18,17	5.6	3.9	0.67573	5.08	3.31	0.82196471
Deelen	20,17	5.9	3.9	0.87417	5.9	4.3	0.84023529
Soesterberg	17	x	x	x	5.2	3.1	0.8285

Table 5.4: Values of COV of the predicted wind speeds and the average correlation of the first consistent measured time series.

The first consistent period is the first consistent time series, which was chosen from the time graph and is long term predicted, and now, referring to Table 5.3 and Table

5.4, we can see that there is a significant reduction in the error when compared to the Normal long term prediction. Please note that in Table 5.4, the number of years are mentioned, consecutively 20, 17. This implies Deelen was predicted with Soesterberg for 20 years and with Eindhoven for 17 years.

Second consistent period prediction

Name of site	Years	Beek			Deelen		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	12	x	x	x	5.6	4.1	0.72775833
Deelen	12	4.2	3.2	0.8424	x	x	
Soesterberg	12	4.1	3.1	0.72823	4.1	2.1	0.87983333

Table 5.5: Values of COV of the predicted wind speeds and the average correlation of the second consistent measured time series.

Name of site	Years	Soesterberg			Eindhoven		
		Meas.	Pred.	AvgCorr.	Meas.	Pred.	AvgCorr.
Beek	14,12	6.2	4	0.70543	5.32	3.76	0.81915833
Deelen	14,12	4	1	0.87894	4.2	2.6	0.8424
Soesterberg	12	x	x	x	4.1	2.6	0.828125

Table 5.6: Values of COV of the predicted wind speeds and the average correlation of the second consistent measured time series.

The second consistent period is the one that is selected by reducing the time period of the first consistent period and after selection, predictions are done. From Table 5.5 and Table 5.6, it can be observed that, error has been reduced considerably, .i.e., Prediction error for Deelen with Eindhoven in the first consistent period is 4.3%, while in the second consistent period, it was reduced to 2.6%.

In Table 5.6, the number of years for Deelen is mentioned as 14, 12, which denotes, Deelen was predicted with Soesterberg for 14 years and with Eindhoven for 12 years. This notation was used for easy understanding and accommodating the values in the tables.

5.6 Relation between Correlation and COV

Referring to Figure 2.1, it was intended to find the relation between Correlation and COV; therefore, this section attempts to answer the question using the results from the predictions done before.

Normal long term period

Local site with Reference site	Avg .correlation	COV
Beek Vs Deelen	0.7006	6.8
Beek Vs Soesterberg	0.6757	5.6
Beek Vs Eindhoven	0.8	8
Deelen Vs Beek	0.7288	8.3
Deelen Vs Soesterberg	0.8478	7.1
Deelen Vs Eindhoven	0.8207	5
Soesterberg Vs Beek	0.7039	6.3
Soesterberg Vs Deelen	0.8467	5.8
Soesterberg Vs Eindhoven	0.8061	7.3

Table 5.7: Values of average correlation and COV of different sites from 1961-2004

Table 5.7, shows the values obtained from the normal long term prediction from the years 1961-2004.Here, each of these values are generated by prediction of one year of local site time series with 40 years of reference site time series. These values are graphically presented to find if there is any kind of linear relationship that exists between them.

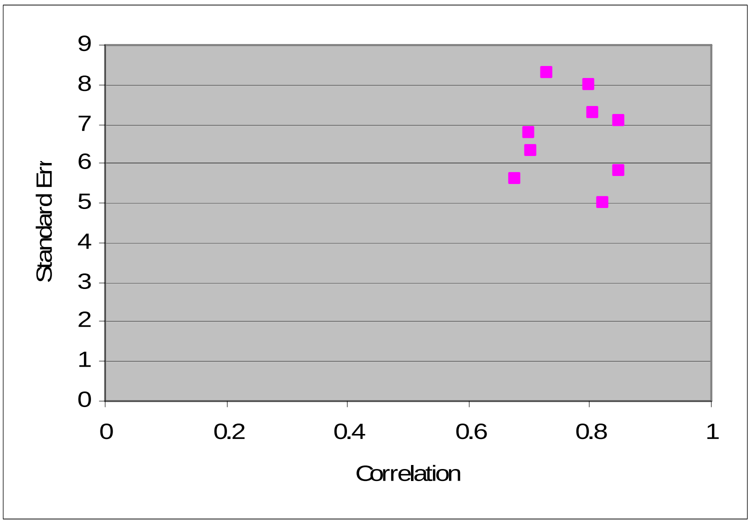

Figure 5.14: Scattered values of correlation with COV, showing no relation

In Figure 5.14, the data points are scattered randomly, so, we cannot assume, there exist a linear relation between correlation and COV.

First Consistent period

Local site with Reference site	Avg .correlation	COV
Beek Vs Deelen	0.72480588	4.2
Beek Vs Soesterberg	0.675725	3.9
Beek Vs Eindhoven	0.82196471	3.31
Deelen Vs Beek	0.74723529	4.2
Deelen Vs Soesterberg	0.874165	3.9
Deelen Vs Eindhoven	0.84023529	4.3
Soesterberg Vs Beek	0.7261	3.1
Soesterberg Vs Deelen	0.87404706	3.3
Soesterberg Vs Eindhoven	0.8285	3.1

Table 5.8: Values of average correlation and COV of different sites from 1985-2001

The average correlation and COV values are derived from the first consistent period which spans from 1985-2001 and has time series ranging from 17, 18 and 20 years for different sets.

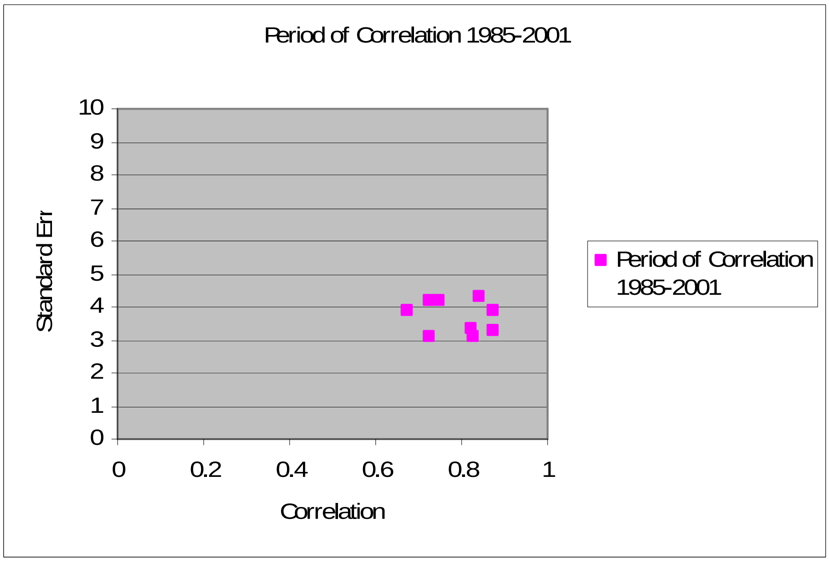

Figure 5.15: Scattered values of correlation with COV, showing a very weak relation

These values are plotted as shown in Figure 5.15, and observations from the figure imply that the data points seem to be close, yet, they are still scattered, showing that there is a very weak relation between correlation and COV.

Second Consistent period

Local site with Reference site	Avg .correlation	COV
Beek Vs Deelen	0.727758	4.1
Beek Vs Soesterberg	0.705429	4
Beek Vs Eindhoven	0.819158	3.76
Deelen Vs Beek	0.8424	3.2
Deelen Vs Soesterberg	0.878936	1
Deelen Vs Eindhoven	0.8424	2.6
Soesterberg Vs Beek	0.728225	3.1
Soesterberg Vs Deelen	0.879833	2.1
Soesterberg Vs Eindhoven	0.828125	2.6

Table 5.9: Values of average correlation and COV of different sites from 1985-2001

Table 5.9, presents the values from the second consistent period, these values are plotted as graph to find the relation between correlation and COV.

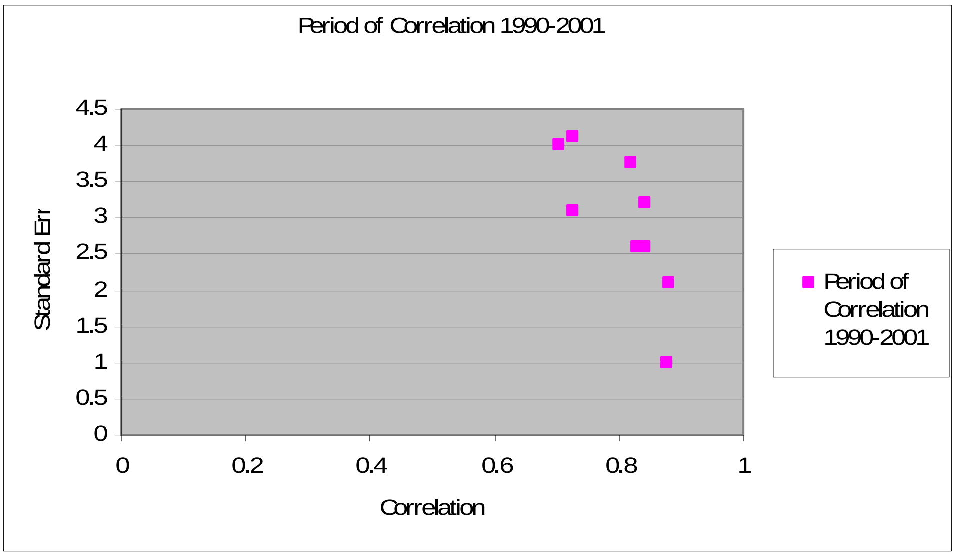

Figure 5.16: Scattered values of correlation with COV, showing weak relation

The above graph in Figure 5.16 shows the values distributed, showing a weak relation between correlation and COV. As the correlation increases there is decrease in the COV, however, this is not very strong.

For easy understanding and to draw a trend line, each of the correlation values are subtracted from 1 and are plotted as separate graph as shown in Figure 5.17.

An equation is generated by drawing the trend line and the correlation values of the data points on the graph is found to be 0.5317, which is a weak relation between Correlation and COV.

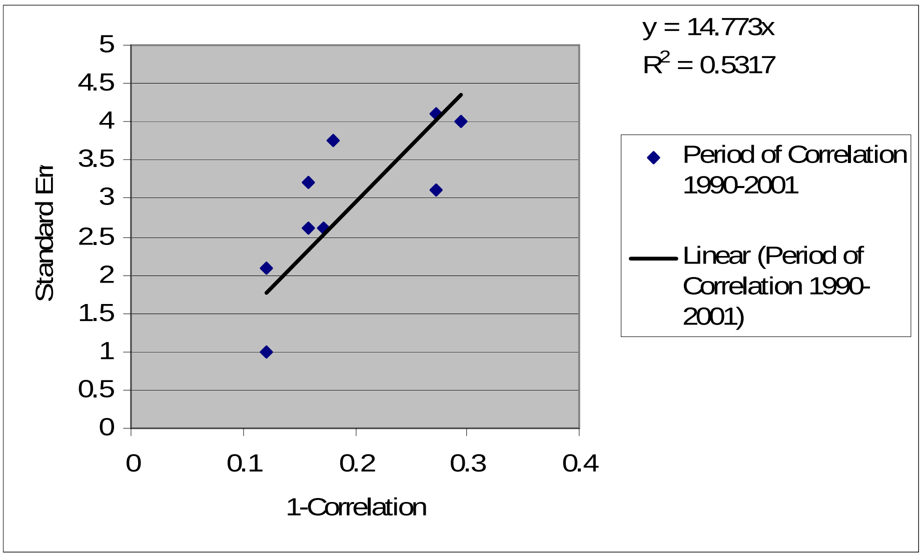

Figure 5.17: Trend line along the data points is drawn to find the relation between correlation and COV

Summary

- By having a normal long term period, there cannot be any relation between correlation and COV.
- Consistent period offers a little possibility for relating correlation and COV
- There exists a very weak relation with the first consistent period.
- Second consistent period offers a possibility even more, as some of the values follow the common trend line, however, the relation between data points is weak
- The results are valid only for the sites that were studied and cannot be extended for other sites.
- Overall, there cannot be any significant relationship that can be established between correlation and COV.

6. Conclusion

Uncertainty in the wind speed is directly related to the development of wind farms. When the uncertainty is reduced, the investment risks associated with this can be minimized, thereby adding more capacity. In addition to reducing investment risks, cost of manufacture of turbine components can be reduced as well, and prolongation of wind campaigns can also be minimized. So, if there is a way, that can be found to reduce this uncertainty, then, it would be a boon for wind industry, basing on this the research question was formulated:

How can uncertainty be reduced in long term prediction using short term measured time series and how will, choosing the time period has influence on uncertainty?

The research question is answered in the following sections and results and limitations are also discussed.

6.1 Consistent period method – A way to reduce uncertainty

Initially a case of long term prediction was explored using the procedure developed in chapter 3, which was called as ‘Initial Analysis’. Observing numerical results has not yielded any reduction of uncertainty, however, when normal distribution of the data was superimposed on the cumulative distribution of ratios of wind speeds, led to the discovery of clusters of wind data. When plotted as a time graph, these data followed a pattern confirming to the clusters. The period to which these cluster belong were identified and these periods were named as ‘Consistent periods’

These ‘Consistent periods’ were long term predicted, and the results show a reduction in the uncertainty. Consistent period method was defined in chapter 5, which was based on the methodology developed in chapter 3 and 4. This is illustrated in Figure 6.1, which shows different stages for reducing uncertainty.

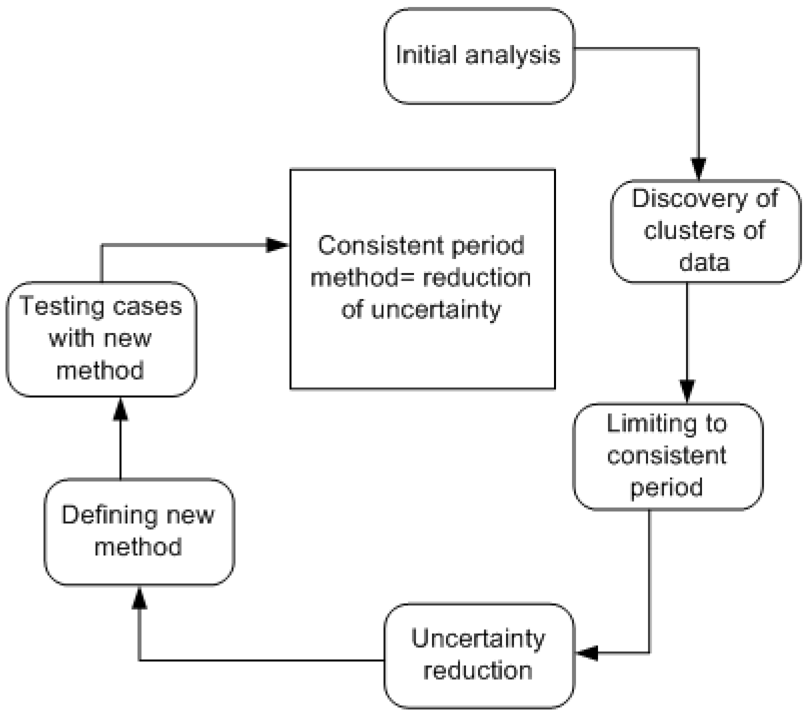

Figure 6.1: Schematic representation of the process to reduce uncertainty

This answers the first part of the research question and the second part of the research question, which seeks to find, a relation between selection of time period and uncertainty, can be answered by referring to the predictions in chapter 4 and 5, which can be summarized below:

- Selecting long term time series, say 40 years, has little effect on uncertainty.
- Sometimes, the predictions will lead to more error, due to data inconsistencies. E.g. clusters are found in the data in most of the predictions.
- 40 years of period has not yielded any significant reduction.
- Selection of consistent period has huge impact on the reduction of uncertainty, as this can be observed for half year, one year and two years predictions.

Overall, choosing a consistent period has a greater impact on the reduction of uncertainty than otherwise.

6.2 Results, limitations and further research

Research design using embedded type of design (Yin 2003) has helped in solving the research questions. Each case study was considered as a 'unit of analysis' and was investigated using explorative ways. The theory developed is modified along the path and making use of the results; the methodology was modified, finally giving 'consistent period method'. This method was tested with different cases and replication was claimed, as case studies resulted in reduction of uncertainties in the long term prediction. By this, it was proved that this method works for reducing uncertainty.

Results

Relation between correlation and COV

One of the interesting questions was to find out the relation between COV and correlation. In section 2.2, it was assumed that uncertainty was a function of correlation between local and reference sites, and also, it is known that higher the correlation, greater is the long term prediction. Now the question arises, whether there is a relation between uncertainty and a good long term prediction?

Uncertainties are caused due to various factors as mentioned in chapter 3, like, growing up of trees around the mast, or houses may have come up, clogging of the anemometer. In chapter 5, section 5.6, the relation between correlation and COV was found using more time series. It was found that, during the normal long term prediction, there exists no relation between correlation and COV, while the first consistent period shows a very weak relation, and observations from the second consistent period shows possibility for a weak relation. As the correlation increases the error decreases, however, the scatter was still present, and the linear relation obtained between the data points shows a very weak relation, i.e., correlation between data points have been found to be 0.5317, which is a weak relation.

Relation between consistent period and inconsistent period

Uncertainty was found to be related to the inconsistent time period. This conclusion was arrived after many predictions using large number of time series. In chapter 4, the first case study, gives us an opportunity to look at the inconsistencies in the length of the time series. When the consistent period is taken and long term predictions were performed, the results show a huge reduction in COV. This was also confirmed; when more data sets were taken in Chapter 5 and predictions were done. This shows, limiting predictions to the consistent period has helped in reducing the error.

Limitation and further research

In this study only Dutch wind sites were considered due to the availability of long term time series, as it is expensive to obtain time series from different parts of the world. Time series from Winddata.com, do not have considerable long reference time series, when compared to Dutch time series, however, the material in the website was useful in framing the background for this study. Time constraint for this study was also major factor in restricting to less number of sites for prediction.

The methodology used in this study can be generalised, as applying this methodology has indicated the reduction of error for Dutch wind sites.So, it can be extended for different sites in the world, though it cannot be guaranteed. Using prediction tools along with the methodology takes enormous time; this limits the possibility for adding more sites to predictions.

A separate tool, which can automate this process, if developed would be very useful, taking into exception; where there is a visual observation that has to be made, for picking the consistent period, i.e., time graphs. Inclusion of many site combinations, many correlations and also having different landscapes included, will help in giving a clearer picture of uncertainty in long term predictions. This will directly help in reducing investment risks associated with establishing new wind farms.

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A.1 Appendix

In this appendix the remaining 4 cases from the embedded case design are discussed and their results are given below

Beek with Deelen

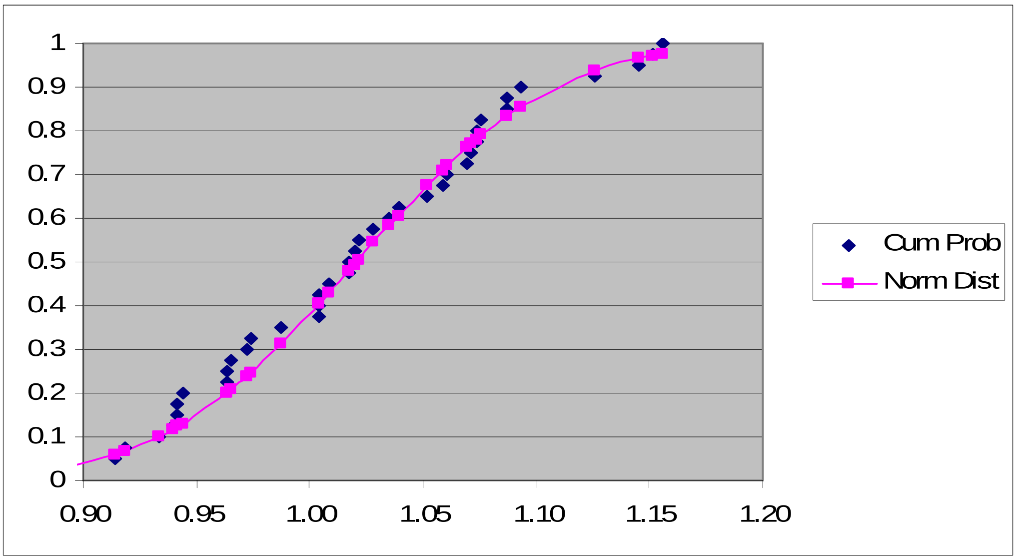

Figure Error! No text of specified style in document.**.1:** Cumulative distribution of predicted with measured wind speed (1962-2001)

The long term prediction error of Beek with Deelen is found to be 6.8%, from measured error of 7.3%, which shows that the error did not been reduce significantly. Plotting cumulative distribution of the ratio of the wind speeds, shows clusters

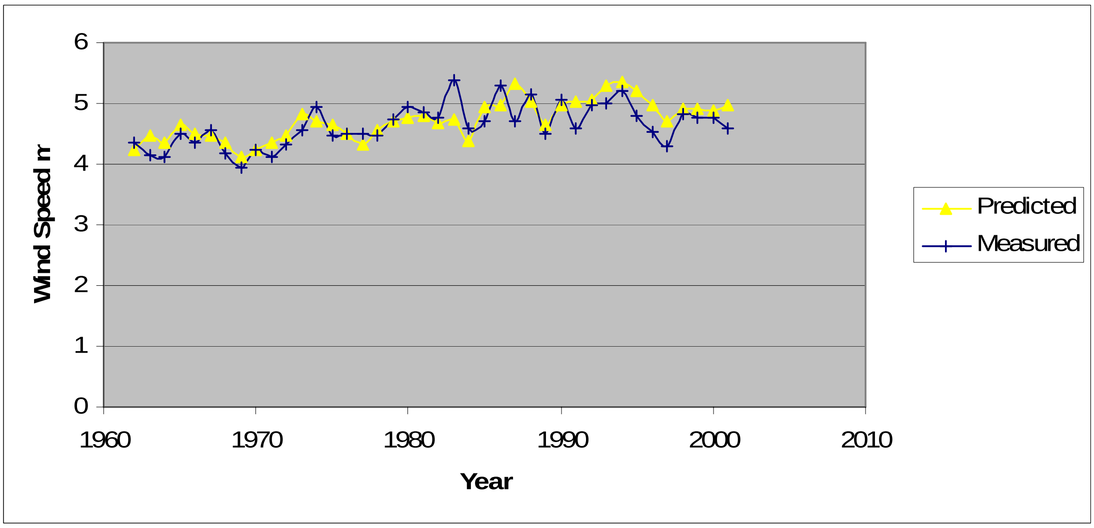

Figure Error! No text of specified style in document.**.2:**Time graph showing the trends of measured to the predicted wind speed and observations from Figure A.2, shows us a pattern of the time period, which affirms these clusters of data. Now taking the first consistent period and performing predictions gives out an prediction error of 4.2% from the consistent measured time series error of 5.6%. The cumulative distribution is plotted in the Figure A.3

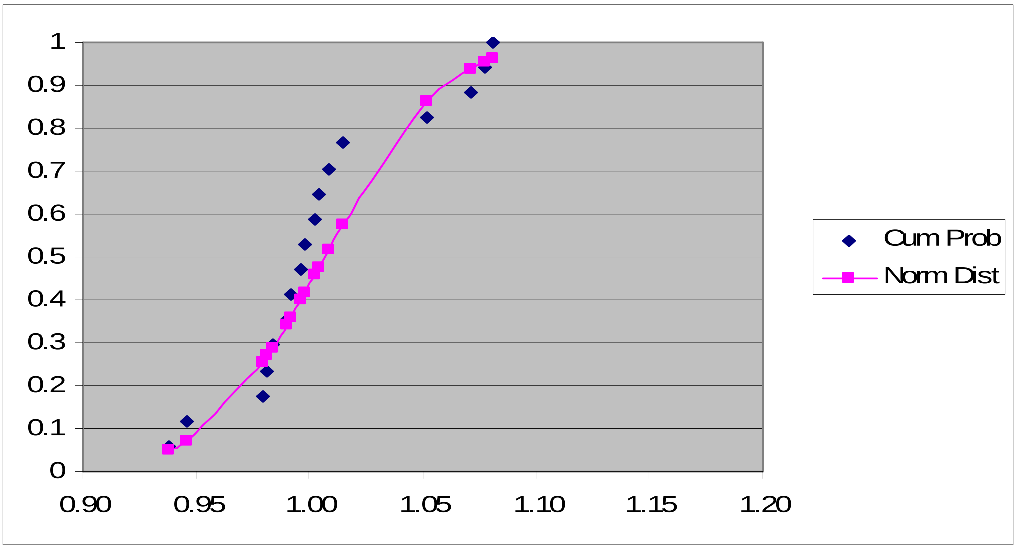

Figure Error! No text of specified style in document.**.3:** Cumulative distribution of predicted with measured wind speed (1985-2001)

Now, second conistent period is taken, which is from 1985-1996, whose cumulative distribution is shows below, which does not strictly follow normal distribution,

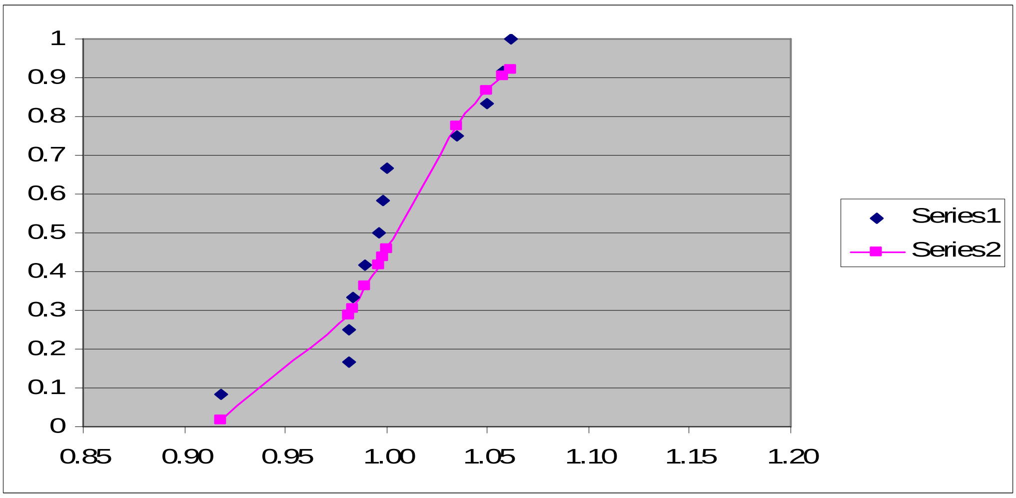

Figure Error! No text of specified style in document.**.4:** Cumulative distribution of predicted with measured wind speed (1985-1996)

however, the reduction of error in the prediction is found to be 4.1%, which tells that, there is no significant reduction, even though, a second consistent period was taken to test, if the error can be reduced.

Deelen with Beek

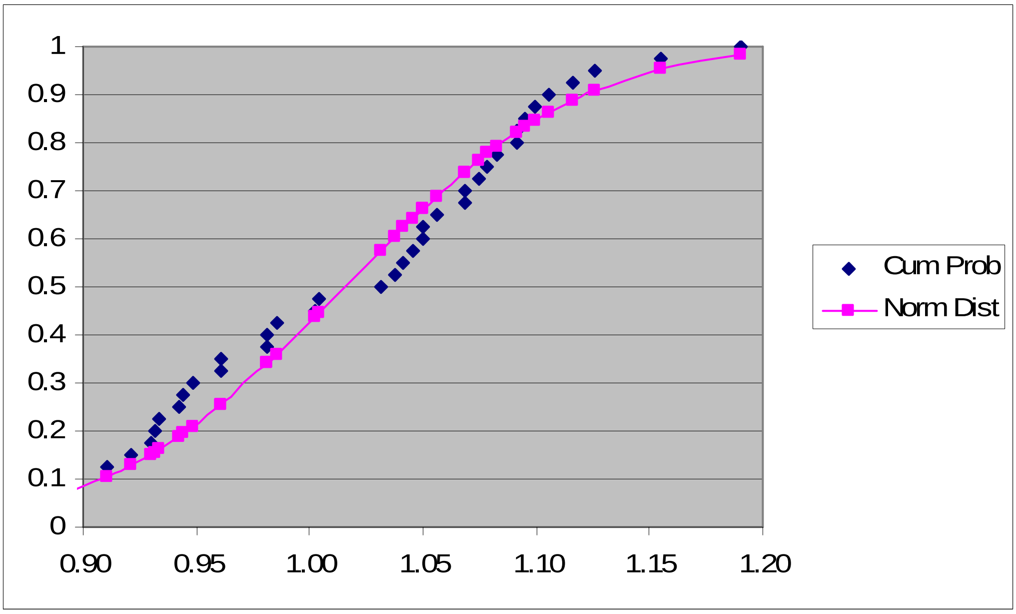

Figure Error! No text of specified style in document.**.1:** Cumulative distribution of predicted with measured wind speed (1962-2001)

Deelen is taken as a local site and Beek as a reference site and each year of Deelen is predicted with long term Beek of 40 years time series. Figure A.5 shows the cumulative distribution plot and observation of this plot shows the presence of clusters of data. The error due to prediction is found to be 8.3%

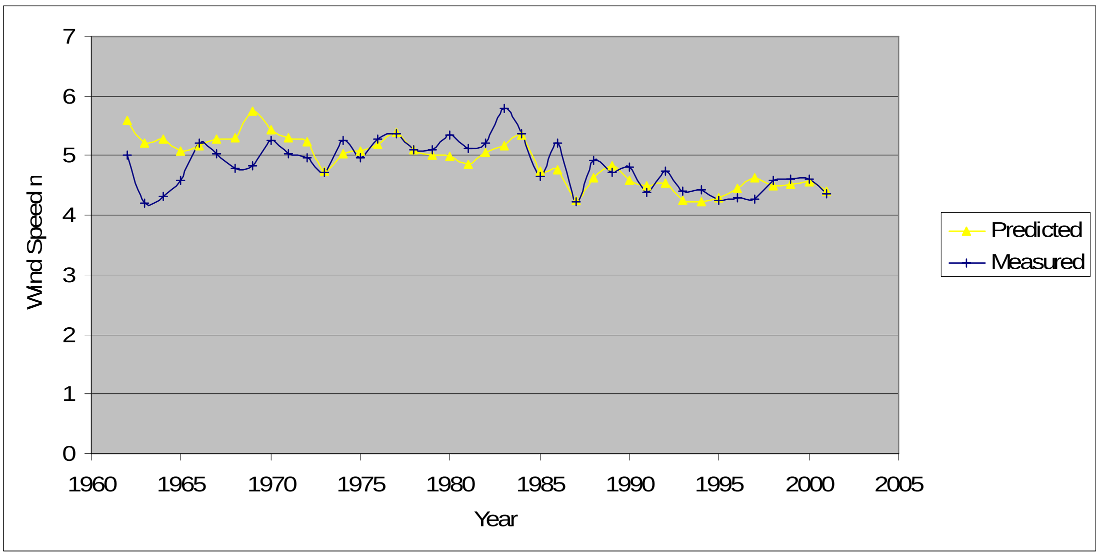

Figure Error! No text of specified style in document..**2:**Time graph showing the trends of measured to the predicted wind speed

Using the time graph from Figure A.6, we can select the first consistent period. Now, predictions are made and cumulative distribution of ratios are plotted and this follows normal distribution.The error due to prediction is reduced from 5.9% to 4.2%

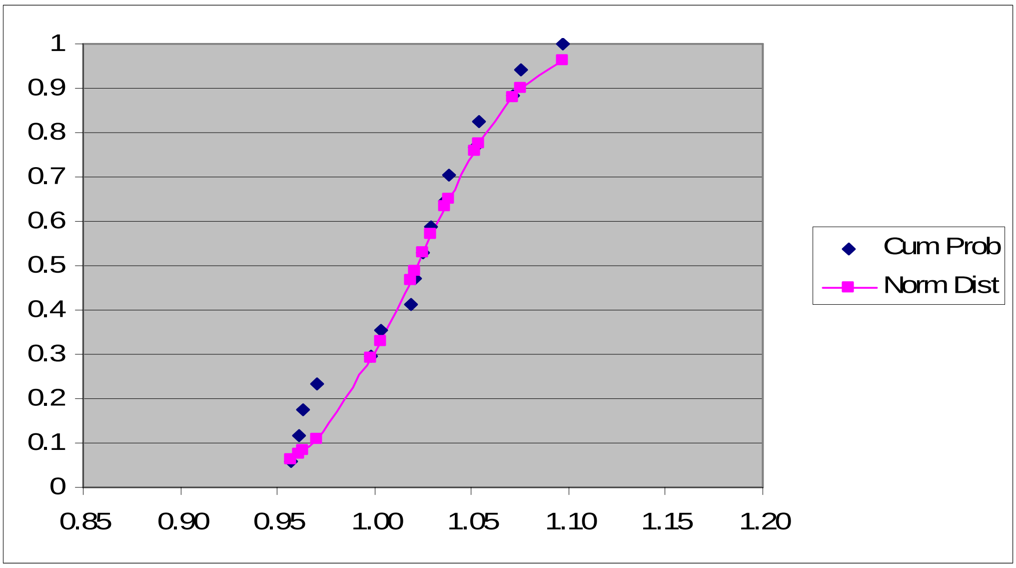

Figure Error! No text of specified style in document..**3:**Cumulative distribution of predicted with measured wind speed (1985-2001)

Second consistent time series is selected using the time graph and predictions are performed. The error due to prediction is found to reduce slightly from the first consistent period, i.e., 3.2%

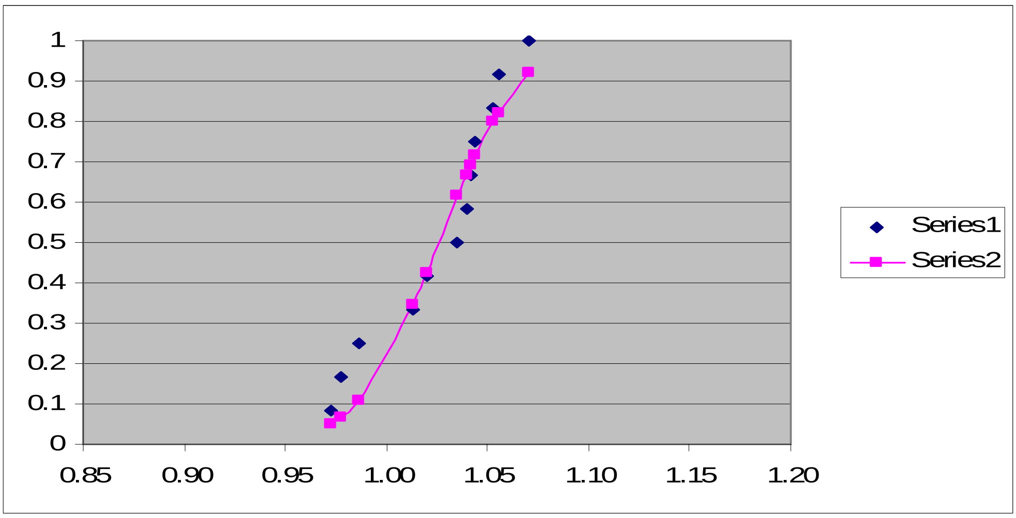

Figure Error! No text of specified style in document.**.4:** Cumulative distribution of predicted with measured wind speed (1990-2001)

Soesterberg with Beek

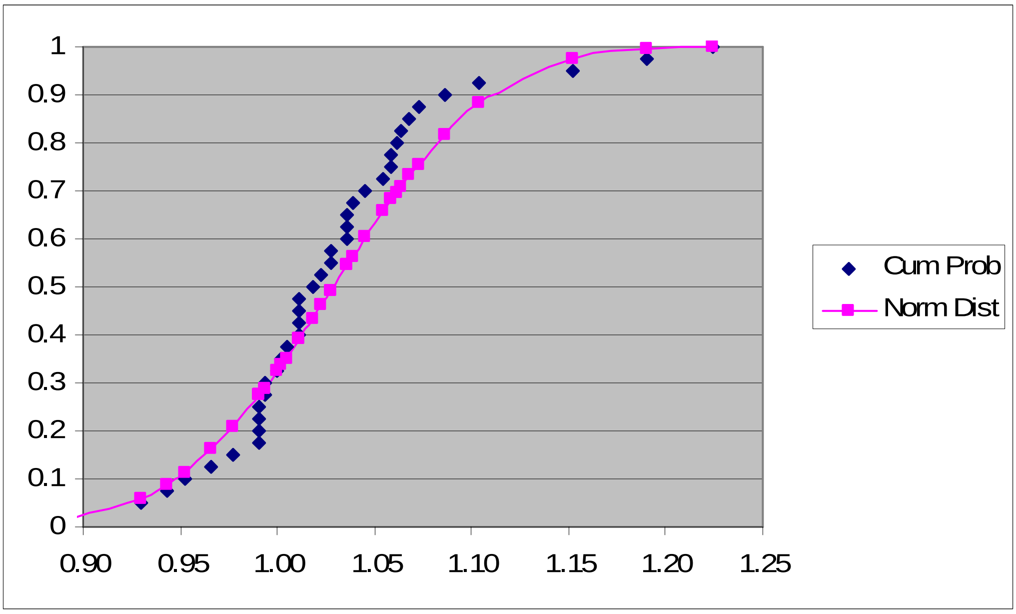

Figure Error! No text of specified style in document.**.1:** Cumulative distribution of predicted with measured wind speed (1962-2001)

Soesterberg is taken as a local site and Beek as a reference site and after predictions the graph as shown in Figure A.9 is plotted for analysis. This follows the similar trend from the two cases before, i.e., presence of clusters of data, which makes the graph skewed. The error due to prediction is found to be 6.3%

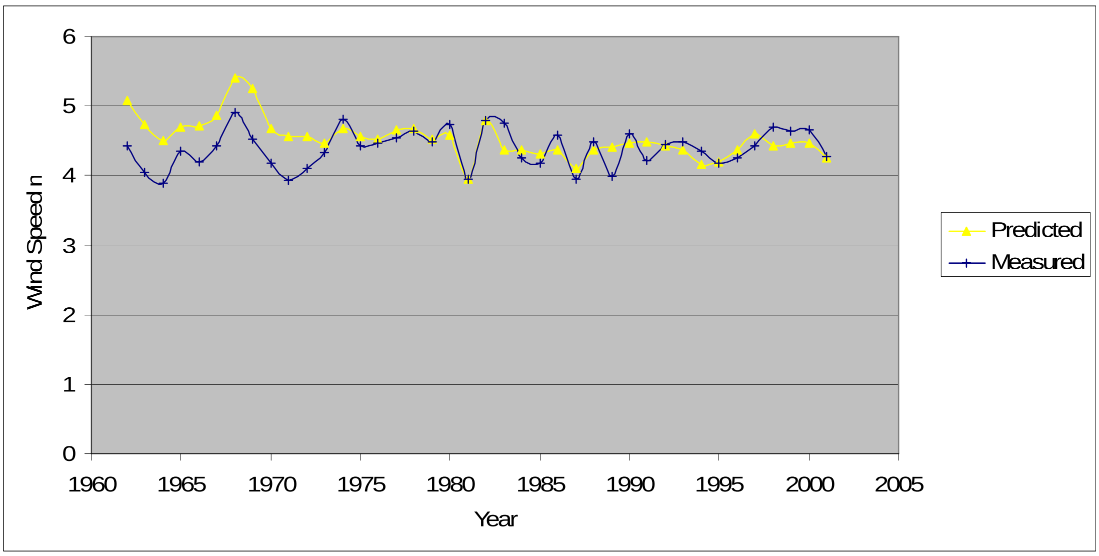

Figure Error! No text of specified style in document.**.2:** Time graph showing the trends of measured to the predicted wind speed

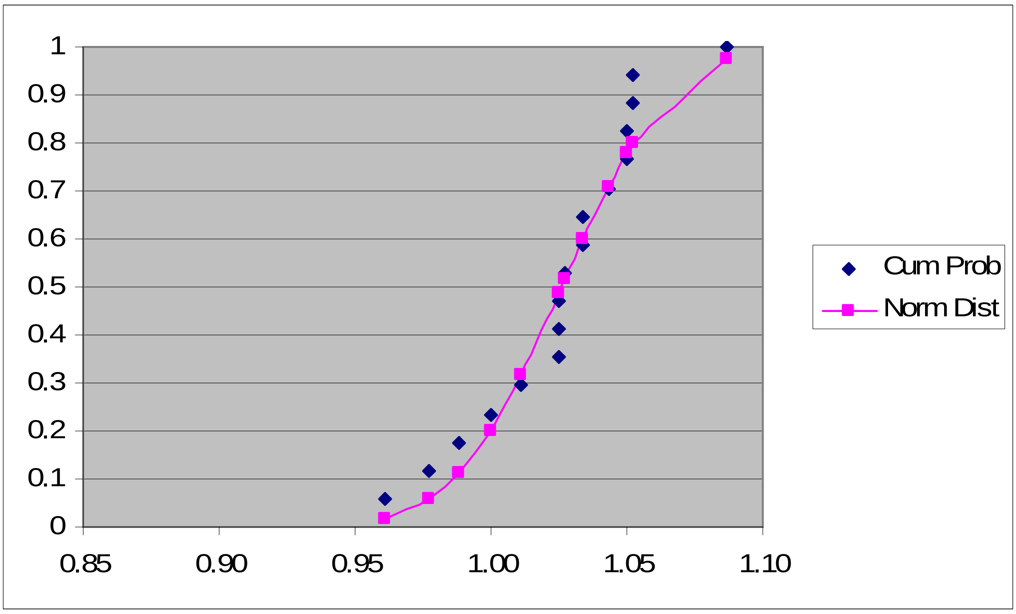

Figure Error! No text of specified style in document.**.3:** Cumulative distribution of predicted with measured wind speed (1985-2001)

Taking the first consistent period by using the time graph as shown in Figure A.10, the predictions are made and the error due to predictions is found to be 3.1%.

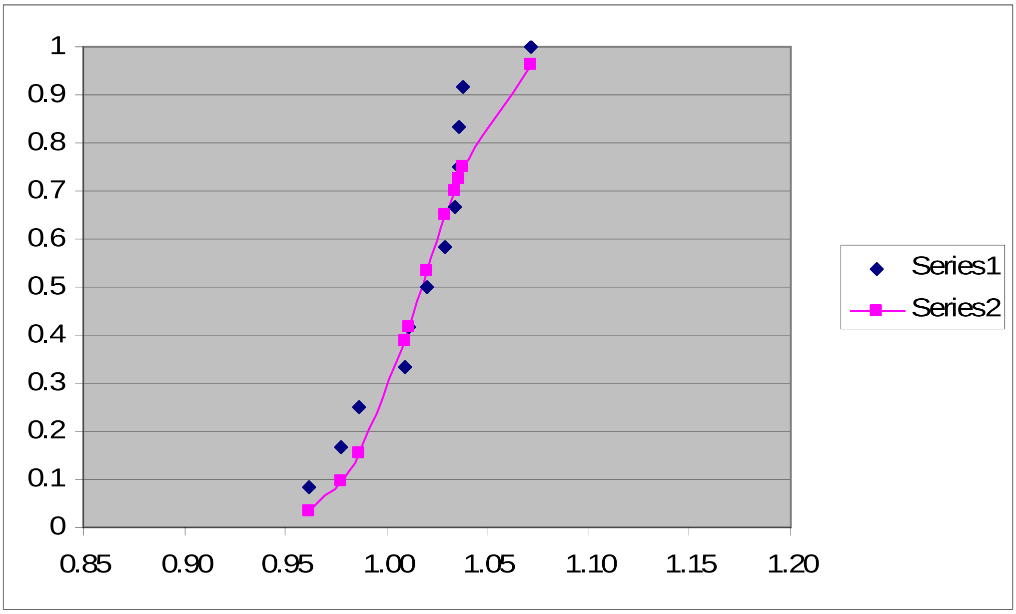

Figure Error! No text of specified style in document.**.4:** Cumulative distribution of predicted with measured wind speed (1990-2001)

The second consistent period’s time series is taken and predictions are performed and the error due to the predictions is found to be 3.1%, which shows that there is not at all any decrease in the error.

Soesterberg vs Deelen

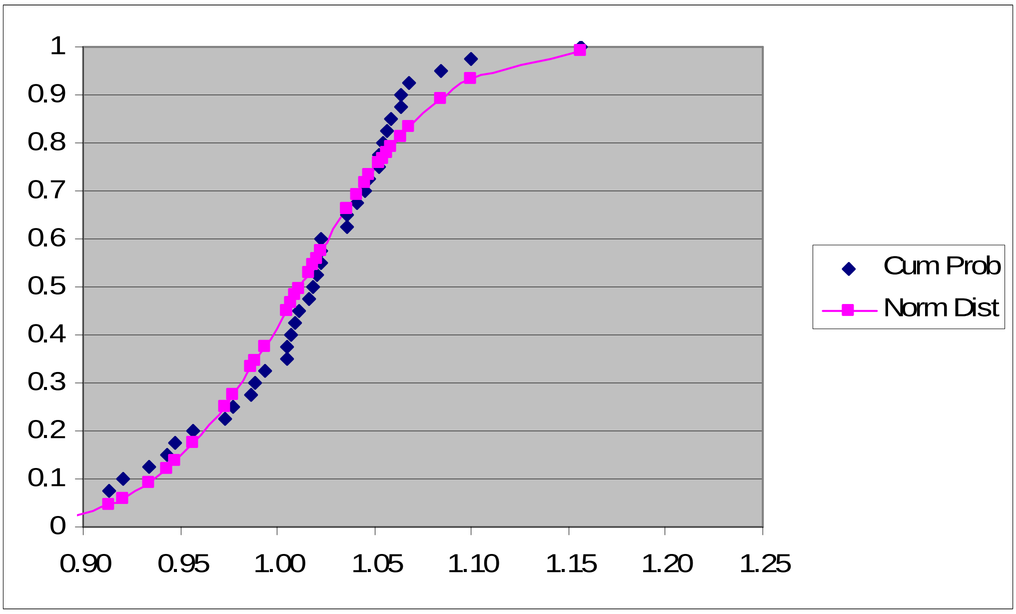

Figure Error! No text of specified style in document.**.1:** Cumulative distribution of predicted with measured wind speed (1962-2001)

In this final case, Soesterberg is taken as a local site, while Deelen is considered as a reference site. After predictions are done, the graph shown in Figure A.13 is plotted and time graph shown in Figure A.14 is also plotted. The error due to prediction is found to be 5.8%

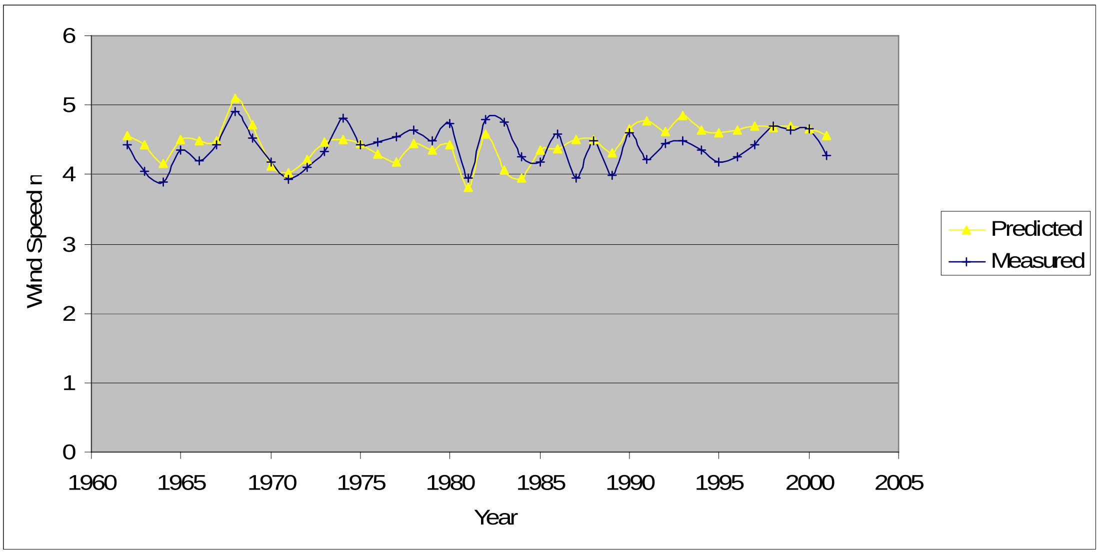

Figure Error! No text of specified style in document.**.2:** Time graph showing the trends of measured to the predicted wind speed

The first graph almost follows normal distribution, however, observing the time graph, shows that there are different pattern of wind speeds.

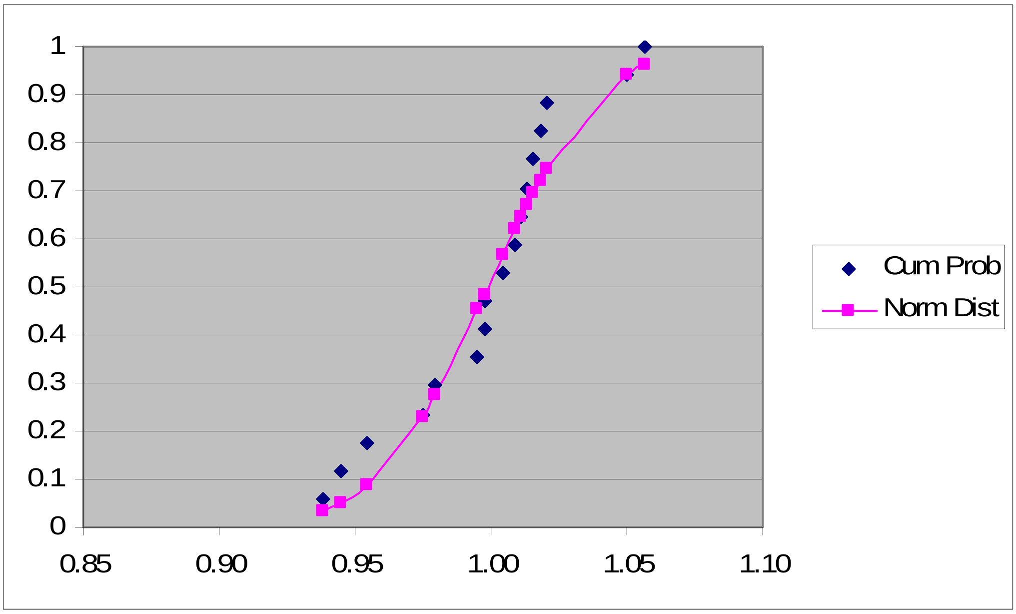

Figure Error! No text of specified style in document.**.3:** Cumulative distribution of predicted with measured wind speed (1985-2001)

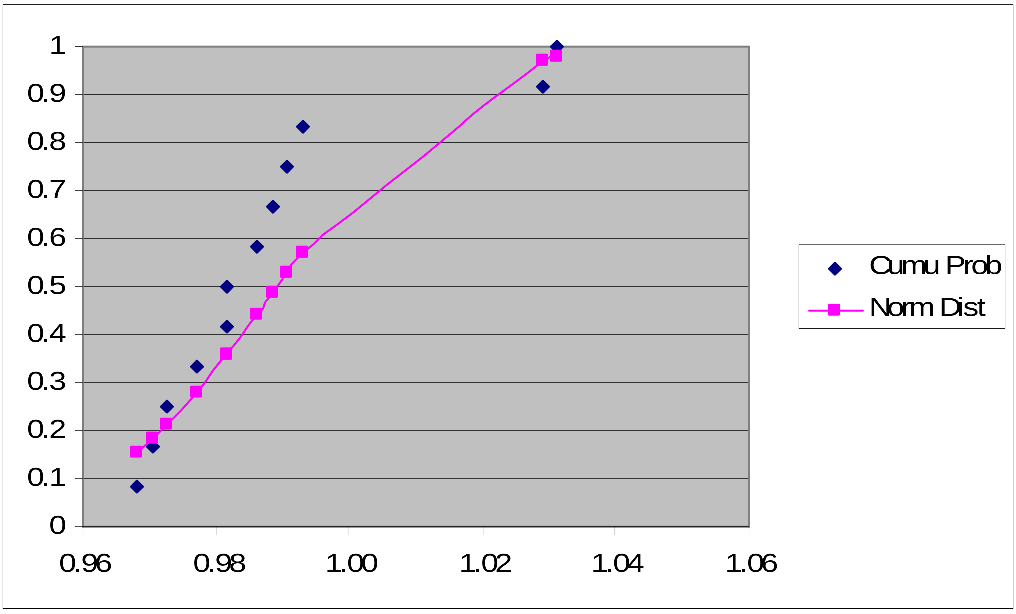

Figure Error! No text of specified style in document.**.4:** Cumulative distribution of predicted with measured wind speed (1990-2001)

Best consistent period is selected and predictions are performed. The error due to prediction for first consistent period is found to be 3.3%.

Second consistent period is selected and predictions are performed, the prediction error is found to be 2.1%, which shows that choosing the right consistent period will have a significant impact on the uncertainty.