WIND POWER PREDICTION MODEL BASED ON PUBLICLY AVAILABLE DATA:
SENSITIVITY ANALYSIS ON ROUGHNESS AND PRODUCTION TREND

Dissertation in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE WITH A MAJOR IN WIND POWER
PROJECT MANAGEMENT

UPPSALA
UNIVERSITET

Uppsala University Campus Gotland
Department of Earth Sciences

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[10th December, 2019]
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Approved by

Supervisor, Dr. Karl Nilsson

Examiner, Dr. Stefan Ivanell

10th December, 2019
Abstract

The wind power prediction plays a vital role in a wind power project both during the planning and operational phase of a project. A time series based wind power prediction model is introduced and the simulations are run for different case studies. The prediction model works based on the input from 1) nearby representative wind measuring station 2) Global average wind speed value from Meteorological Institute Uppsala University mesoscale model (MIUU) 3) Power curve of the wind turbine. The measured wind data is normalized to minimize the variation in the wind speed and multiplied with the MIUU to get a distributed wind speed. The distributed wind speed is then used to interpolate the wind power with the help of the power curve of the wind turbine. The interpolated wind power is then compared with the Actual Production Data (APD) to validate the prediction model. The simulation results show that the model works fairly predicting the Annual Energy Production (AEP) on monthly averages for all sites but the model could not follow the APD trend on all cases. The sensitivity analysis shows that the variation in production does not depend on ‘the variation in roughness class’ nor ‘the difference in distance between the measuring station and the wind farm’. The thesis has been concluded from the results that the model works fairly predicting the AEP for all cases within the variation bounds. The accuracy of the model has been validated only for monthly averages since the APD was available only on monthly averages. But the accuracy could be increased based on future work, to assess the Power law exponent (α) parameter for different terrain and validate the model for different time scales provided if the APD is available on different time scales.
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<td>Annual Energy Production</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>APD</td>
<td>Actual Production Data</td>
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<tr>
<td>ABL</td>
<td>Atmospheric Boundary Layer</td>
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<tr>
<td>DNS</td>
<td>Direct Numerical Simulations</td>
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<td>LES</td>
<td>Large Eddy Simulation</td>
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<td>MIUU</td>
<td>Meteorological Institute Uppsala University mesoscale model</td>
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<tr>
<td>MCP</td>
<td>Measure Correlate Predict</td>
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<tr>
<td>NWP</td>
<td>Numerical Weather Prediction</td>
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<tr>
<td>RANS</td>
<td>Reynolds Averaged Navier-Stokes</td>
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<tr>
<td>SMHI</td>
<td>Swedish Meteorological and Hydrological Institute</td>
</tr>
<tr>
<td>TSO</td>
<td>Transmission System Operator</td>
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<tr>
<td>WRA</td>
<td>Wind Resource Assessment</td>
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<td>WAsP</td>
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1 Introduction

1.1 Background

The installed capacity of wind power has reached to 597 GW and is expected to reach 839 GW by 2023 (International Energy Agency, 2018) (World Wind Energy Agency, 2019). The rapid growth in the wind power industry has given the insight to reduce the investment cost and increase the installed capacity of wind turbines. Wind Resource Assessment (WRA) has a pivotal role in a wind power project. The increasing potential for wind power in the Nordic countries has increased the amount of literature on the uncertainties of wind power due to the varying Nordic climate.

Aldén & Ridbäck (2019) presented a report on the new and ongoing wind power research in Sweden. The report highlights the need for research in wind power to achieve the political objective of 100% renewable electricity generation by 2040. The renewable energy policy fact sheet reports that Sweden has surpassed its target in 2013 to achieve 50% renewable energy by 2020 and has set a new goal for 100% renewable electricity by 2040 (International Atomic Energy Agency, 2017). These reports highlight the need for an increase in detailing the wind resource of Sweden.

In recent years, there has been an increasing amount of literature on wind-power forecasting. A very few studies are performed for the long-term prediction which is used for the wind farm design. Landberg (1999) introduced a wind power prediction model using the High-Resolution Limited Area Model (HIRLAM) and adapted that to site-specific using Wind Atlas Application and Analysis Program (WAsP). Madsen et al. (2005) suggested a structured procedure to evaluate the prediction process for wind power, the procedure uses a combination of ‘Persistence’ and ‘moving average predictors’ model. Barbounis et al. (2006) presented a long-term wind power forecasting model which forecasts 72 hours of wind power using three local Recurrent Neural Network (RNN) model.

Zhang et al. (2014) introduced a new hybrid Measure Correlate Predict (MCP) model for long-term prediction at a target site by using logic to MCP short-term & long-term and weight the long-term estimation concerning reference site. Jimenez et al. (2007) performed offshore WRA and compared them using WAsP & PSU/NCAR (known as MM5) mesoscale model. The WAsP prediction was based on six different actual measurements and MM5 was predicted based on the National Centers for Environmental...
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Prediction (NCEP) global model. Sideratos & Hatzigiorgiou (2007) presented a statistical method of wind power forecasting using two steps of prediction, initially the method uses Numerical Weather Prediction (NWP) model and later it uses fuzzy logic to estimate the quality of the forecast. Nilsson et al. (2018) developed a simplified model for predicting the energy production using the available wind resource from the nearby meteorological station, mean wind speed from MIUU and wind turbine data i.e. power curve of the turbine.

Zhang et al. (2015) performed a comparison of NWP and probabilistic wind resource methods, where the different stages of WRA are explained. The WRA stages include site prospecting, measurement campaign, microscale vertical extrapolation, long-term extrapolation, wind farm layout design, gross energy production estimation, energy losses assessment, uncertainty estimation. Bailey et al. (1997) prepared a handbook for the fundamentals of conducting a monitoring program. The handbook clubs the above-mentioned WRA steps into major three steps which are preliminary area identification, area wind resource evaluation and micro-siting.

Various literature has been published for predicting day-ahead wind power to stabilize the electrical grid. Sideratos & Hatzigiorgiou (2012) proposed a new model that could predict wind power using NWP, it reduces the uncertainties of NWP and weather stability using the Radial Basis Function Neural Networks (RBFNN). Filik & Filik (2017) performed a comparison of performance for Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) model for various case studies using local meteorological instruments. Abhinav et al. (2017) considered the influence of stratification in wind forecasting and developed a Wavelet-based Neural Network (WNN) forecast model using NWP model.

A slight aberration in wind speed causes a major aberration in the wind farm power output due to the relationship between these two parameters (Murthy & Rahi, 2017). It requires on-site measurement of the wind resource, whereby capital costs are responsible for the permit to measure wind, equipment rental during the measurement period. The above-listed models were mostly used for stabilizing the power grid or perform forecasting for the day-ahead market to bid with the Transmission System Operator (TSO). Nilsson et al. (2018)’s simplified statistical model was able to predict the energy production for Gotland scenarios which are mostly flat surfaces. But to verify whether the model works for all scenarios with different roughness and to increase the detailing of wind resource map i.e. MIUU a dissertation would be required. So that based on the detailed analysis, the risk factor in investment and cost for WRA can be reduced based on Nilsson et al. (2018) model.
1.2 Aim

This thesis aims to investigate the freely available wind data from Swedish Meteorological and Hydrological Institute (SMHI) based on the algorithm developed by Nilsson et al. (2018) (for Gotland alone) to increase the detail of wind resource mapping i.e MIUU map. The algorithm is run in a MATLAB script, that uses the wind data and predicts the wind power production based on the installed wind turbine's power curve. The predicted wind power is then compared with the APD and sensitivity analysis is performed based on the terrain roughness and 'distance between wind farm and measuring station'.

1.3 Research Questions

1. How can freely available wind data be used to estimate time-varying power production from wind turbines?

2. How accurate is the model in different types of terrain?

3. How accurate the model works based on the distance between the wind farm and the measuring station?

1.4 Limitation

The scope of this project is limited to onshore sites and also the terrain analysis is done using Google Earth software. To calculate the exact roughness and terrain properties a GIS software like windPRO would be required, to analyze the wind flow over terrain highly advanced CFD software like WindSim, OpenFOAM, CFX, etc. are required which are time and cost consuming.

1.5 Outline

Chapter 2 introduces wind flow models, Power law and the wind measurement guidelines for a site. Based on the understanding from literature, chapter 3 explains the methodology used for the thesis to estimate the wind power and analyze various case studies. The methodology starts explaining from the basic step of collecting data until the estimation of wind power and validate that with the APD. Based on the explained procedure, the results are reported, reviewed and discussed in chapter 4. Following the discussion, the report is concluded summarizing the results and findings in chapter 5.
2 Theoretical Background

2.1 Introduction

The issue of uncertainty in wind resource extrapolation has received considerable attention. Numerous studies have been attempted to explain wind resource extrapolation models. Various extrapolation models have been used in the industry as part of the WRA. They can be classified into linear and non-linear models. The WRA models will be explained to analyze the uncertainty in wind power prediction.

2.2 Linear Wind Flow Model

For linear WRA, the traditional approach relies on Jackson and Hunt type wind flow model. WAsP model, an industry-standard software developed by Danish Technical University (DTU) is used for site-specific calculations. WAsP defines wind climate and flows over different terrains. It is limited to neutrally stable wind flows for simple low hills terrain same as Jackson and Hunt model (Emeis, 2018). However, the model cannot define weather processes. The generalized model process is shown in figure 2.1. The model is simple and fast to run on simple systems, does not demand high configurations.

2.2.1 Statistical Data Approach

The statistical model predicts wind power based on the historical data of wind speed and wind rose frequency for individual sectors in a region known as Weibull distribution (Nilsson, 2010). The model uses measurement data and variables that can be used for prediction based on the Artificial Neural Network (ANN) or recursive least square method. The statistical model might use NWP model (Sideratos & Hatziargyriou, 2007). Note: This model does not consider the meteorological conditions for the prediction (Wang et al., 2011).
2.3 Non-Linear Wind Flow Model

Non-Linear wind flow model includes numerical and CFD models such as global circulation models, high-resolution limited-area models, mesoscale models which can be categorized as NWP models. Also non-linear wind flow model has Large Eddy Simulation (LES) models and Reynolds Averaged Navier-Stokes (RANS) model which are categorized as micro-scale models.
2.3.1 Global circulation model

The global forecast model provides a resource map with a poor spatial resolution of 100 km. When we compare the roughness length with other models, global circulation model has a very poor roughness length (Arnqvist, 2018).

2.3.2 High-resolution limited-area model

High-resolution limited-area model is a local forecast model with an average spatial resolution between 10-50 km. The model uses a technique of ‘lateral boundary coupling’ which joins the inner model and outer low-resolution model from the lateral boundary. The model can be used for simulating regional climate (Kida et al., 1991).

2.3.3 Mesoscale model

The mesoscale model has a good resolution of the boundary layer and a horizontal resolution of 0.1-10 km (Arnqvist, 2018). It is mostly used for a large scale wind resource mapping. The Mesoscale model can provide virtual data sets that can be used as an input for microscale models, instead of using measured wind data sets (Carvalho et al., 2013). It has a low operational cost, high sampling resolution and also sometimes 100% data availability. Mesoscale models have principles such as Navier-Stokes equation which defines the forces acting on the wind, energy equation that determines the temperature field, humidity equation that determines the humidity field, turbulent kinetic energy equation that describes the atmospheric turbulence (Arnqvist, 2018). Mesoscale models are divided into two groups 1) Terrain and physiographically-induced mesoscale systems and 2) Synoptically-induced mesoscale systems (Pielke Sr, 2013). MIUU model is an example of mesoscale model, that is mainly used for the energy estimation in this wind power prediction model.

2.3.4 CFD based microscale models

Micro-scale models are used for site-specific assessments. In industry, RANS model is used for modelling due to computational constraints. RANS model equations govern the mean flow and the effect of turbulence on the mean flow properties. The RANS model can perform modelling of all scales of eddies based on time average fields (Arnqvist, 2018). In RANS model, a very fine grid data can be used to model the roughness with the help of laser scan over the topography. For research and other purposes, models like LES is used. LES uses the principle of low pass filtering the Navier-stokes equation. LES computes large scale motions of turbulent flow directly and only sub-grid scale motions are modelled which reduces the computational cost significantly compared to Direct Numerical Simulations (DNS) (Zhiyin, 2015).
2.4 Describing the boundary layer profile with the power law

The power or logarithmic law is used when the wind power is predicted from a lower height wind data. The power law (equation 2.1) helps to predict the wind speed at hub heights using the power law exponent. The power law component ($\alpha$) (Equation 2.2) can be resolved if the measured wind speed at two heights is known. During WRA the most common method of extrapolating the wind speed at hub heights is using the Power law. The $\alpha$ is calculated directly if the wind measurement is available at two heights and fit a curve to the data. If only one anemometer is used for measuring wind speed at the site then $\alpha$ is calculated based on the surrounding terrain. If the terrain information is unavailable, then the value of $\alpha = 1/7$ can be used, which is so-called 1/7 power law (Lubitz, 2009).

$$U(z) = U_{ref}(z_{ref}) \left( \frac{z}{z_{ref}} \right)^\alpha$$

$$\alpha = \frac{\ln(U/U_{ref})}{\ln(z/z_{ref})}$$

Where

- $U$: Wind speed
- $z$: Hub height
- $U_{ref}$: Reference wind speed
- $z_{ref}$: Reference hub height
- $\alpha$: Power law exponent

Lubitz (2009) performed a study which compared the predicted wind speed using power law with the measurement data. The results showed that the power law accuracy is better for lower level, but when predicting wind speed at the upper level without upper-level data is very difficult. The prediction also requires knowledge on upper-level wind profile, if not this leads to uncertainty in the prediction. The figure 2.2 shows the varying $\alpha$ value based on the roughness of the terrain from high buildings till sea surface. The $\alpha$ value is a function of terrain roughness or complexity based on the turbulence level.
2.5 Meteorological Institute Uppsala University Mesoscale model (MIUU)

The MIUU model is a wind resource map with average wind speed for entire Sweden, which is suitable for detailed study of the wind field in complex terrain. The MIUU mesoscale numerical model is a three-dimensional hydrostatic non-linear model with terrain-following coordinates for Sweden. The model was developed by the Department of Meteorology at Uppsala University, Sweden (Enger, 1990). The model is governed by prognostic equations for wind, temperature, humidity and turbulent kinetic energy. To reduce the effect of boundaries in the model, the model area considered is larger than the area of interest (Bergström & Barthelmie, 2002). The model uses a horizontal telescopic grid with high resolution especially in the areas of interest. In the vertical direction, log spacing is used for lower levels and linear spacing is used for higher levels. The model starts from a minimum height of $Z_0$, where $Z_0$ is the roughness length and extends up to a maximum height of 10000 m. Specification of roughness length, height above sea level and the temperature is required for each grid point at the lower boundary. Estimation of temperature above land surface is done using solar radiation and the usage of land. For temperature above sea surface, recorded monthly average values are used. The important parameters varied to cover a wide area are:

1. Geostrophic wind
   a) Strength and direction
2. Thermal stratification
   a) Daily temperature variation
3. Surface roughness

4. Topography

5. Temperature differences between land and sea

The MIUU model has been run for 4 months mainly in January, April, July and October. So that all 4 seasonal variations can be observed and modelled. The model has been run for 4 seasons with 3 geostrophic wind speeds and 8 wind direction sectors so totally $4 \times 3 \times 8 = 96$ model runs. As a result, mean wind speed or wind energy potential at different hub heights are obtained (seasonal or annual) based on the weightage provided to the climate data of geostrophic wind. The figure 2.3 shows the mean wind speed from the MIUU model at heights 12m and 33m. The MIUU model is used to map wind resource for a resolution of 0.5 - 10 km. Usually the power law is used for wind speed extrapolation when the exact site measurement time series is available. But when exact site measurement is not available MIUU model can be used for wind resource mapping (Bergström, 2007). MIUU model acts as a base for the estimation of wind power in this report.

Figure 2.3: Mean wind speed from MIUU model (Olauson et al., 2015)
2.6 Mesoscale to microscale modelling

The technological advancements in the wind turbine industry lead to the development of multi-megawatt turbines by reducing the cost per kilowatt-hour. The hub heights are increasing beyond 100 m and the rotor diameter is increasing beyond 150m with rated power increasing above 10 MW. The wind turbines stretch significantly across the Atmospheric Boundary Layer (ABL), where the boundary layer starts right from the ground surface. This makes the modelling difficult in and around the wind farm. A more practical microscale representation of the ABL becomes more likely to be combined with mesoscale models using statistical or physical downscale methods. In general, the large-scale & site-scale data are related and down-scaled to create a high-resolution time series if not distributions of quantities of interest in connection to climate (Sanz Rodrigo et al., 2017).

2.6.1 Statistical downscaling

The statistical downscaling is the method of reconstructing long term high-resolution time series from a short term measurement campaign and a long term model integration. The model has low-cost computational cost and high resolution of the local condition using the local measurement. The model is categorized into three methods: regression method, weather generators and weather classification (Sanz Rodrigo et al., 2017).

2.6.1.1 Regression Method

The regression methods include multiple linear regression, Canonical Correlation Analysis (CCA) and ANN. The conventional name for the regression methods in WRA is MCP which has been used to relate short-term on-site data with the long-term measurement from nearby meteorological stations. Regression methods in the context of wind power forecasting are called Model Output Statistics (MOS) prediction, which statistically relates output from numerical weather prediction models to power measurements. This method is mostly used during wind farm operation, it can also be used to assess the climatic variability and uncertainties during the planning phase (Sanz Rodrigo et al., 2017).

2.6.1.2 Weather generators

Weather generators can generate artificial time series with practical high-frequency variance that is not shown in the numerical model. This approach is a probabilistic model and is used by the generation of accurate weather data that correspond to future climate projections for climate change studies (Sanz Rodrigo et al., 2017).
2.6.1.3 Weather classification

The weather classification method groups atmospheric realizations into similar weather types of reduced bins. The method can generate a fair long term estimate of the mean wind resource and uncertainty (Sanz Rodrigo et al., 2017).

2.6.2 Physical downscaling

The physical downscaling method is mainly used to increase the resolution of atmospheric models for the area of interest. Generally, this method comes under the mesoscale model that increases the accuracy of the global circulation model (GCM) to a resolution of a few kilometres (Sanz Rodrigo et al., 2017).

2.7 Site-specific conditions

The wind turbines are designed based on the site-specific loads. The site-specific conditions are assessed based on ‘topographical complexity, wind conditions, air density, earthquake, electrical network conditions and soil conditions’. Also, factors such as ‘maximum wind speed, shear of vertical wind profile, flow inclination, turbulence due to roughness, turbulence due to wakes and wind-speed distribution’ are considered (Madsen & Risø, 2008, Pg 18-19).

According to IEC 61400-1, the site-specific assessment is done based on the following parameters,

1. Wind Speed
   a) Mean, distributions, sector-wise
   b) extreme wind speed

2. Turbulence matrix
   a) depends on wind speed & direction
   b) mean & standard deviation
   c) with and without wind farm turbulence

3. Flow inclination
   a) Mean, mean absolute & extreme values
   b) situation of occurrence

4. Maximum wind speed gradient
   a) value and situation of occurrence (Strack & Riedel, 2004)
The sites are classified based on their roughness class (See table 2.1) mostly the site is divided into sectors and the roughness class is calculated. For example, if a site is divided into 3 sectors and 1/3 of the site has roughness class 2 & 2/3 of the site has roughness class 3 then the roughness class is calculated based on the formula 2.3 (Nielsen & SORSEN, 2006, Pg 165).

\[
\left(\frac{1}{3} \times 2 \right) + \left(\frac{2}{3} \times 3\right) = 2.67
\]

<table>
<thead>
<tr>
<th>Roughness Class RC</th>
<th>Roughness Length, (Z_0) [m]</th>
<th>Energy Index [%]</th>
<th>Landscape</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0002</td>
<td>100</td>
<td>Water surface.</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0024</td>
<td>73</td>
<td>Completely open terrain with a smooth surface, such as concrete runways in airports, mowed grass.</td>
</tr>
<tr>
<td>1</td>
<td>0.03</td>
<td>52</td>
<td>Open agricultural area without fences and hedgerows and very scattered buildings. Only softly rounded hills.</td>
</tr>
<tr>
<td>1.5</td>
<td>0.055</td>
<td>45</td>
<td>Agricultural land with some houses and 8-meter tall sheltering hedgerows within a distance of about 1,250 meters.</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>39</td>
<td>Agricultural land with some houses and 8-meter tall sheltering hedgerows within a distance of about 500 meters.</td>
</tr>
<tr>
<td>2.5</td>
<td>0.2</td>
<td>31</td>
<td>Agricultural land with many houses, shrubs and plants, or 8-meter tall sheltering hedgerows within a distance of about 250 meters.</td>
</tr>
<tr>
<td>3</td>
<td>0.4</td>
<td>24</td>
<td>Villages, small towns, agricultural land with many or tall sheltering hedgerows, forests and very rough and uneven terrain.</td>
</tr>
<tr>
<td>3.5</td>
<td>0.8</td>
<td>18</td>
<td>Large cities with tall buildings.</td>
</tr>
<tr>
<td>4</td>
<td>1.6</td>
<td>13</td>
<td>Very large cities with tall buildings and skyscrapers.</td>
</tr>
</tbody>
</table>

Table 2.1: Roughness Classes (Ragheb, 2012, Pg 2-3)
2.8 Wind measurements

The wind measurements are done using various methods and instruments in the industry. To proceed with actual WRA, site-specific wind measurement is required, also the bank accepts only actual site measurement for investment support. If there are gaps in the documentation of wind measurement, it gives way for increased uncertainties in the measurement. The following sections define the general criteria for the technical specifications and documentation required for measurements (Measnet, 2016).

2.8.1 Wind speed

The measurement of wind speed on site-specific location is performed corresponding to the IEC 61400-12-1. When performing an anemometer based mast measurement, the anemometer needs to be calibrated and supplemented by a remote sensing measurement so that the wind speed can be extrapolated to hub heights considering the uncertainties involved in this technique. The initial wind measurement height could be starting from 2/3 of the planned hub height which is highly relevant for determining the hub height wind conditions.

For assessing the wind shear and wind profile at the site, an additional anemometer is installed at a significant height difference from the measurement height. The heights chosen for measurement needs to be mostly within the planned wind turbine rotor diameter swept area. These additional anemometers are installed as per the IEC 61400-12-1 specification on separate booms so that the flow distortion is minimized to a maximum degree. For determining the uncertainties, flow distortion in the wake of the met mast needs to be considered.

The anemometer booms are installed in 45° offset for the tubular mast and 90° for lattice mast if the prevailing wind direction is known beforehand. Also, no other instruments are installed in the anemometer booms. The wind speeds are measured in an interval of 10 min average; the average, standard deviation, minimum and maxima values must be recorded. The wind measurement data is considered to be incomplete if even one of the following criteria is fulfilled:

1. If the metmast data does not cover at least 12 consecutive months
2. The filtered data availability from the primary sensor and backup sensor installed as per the IEC 61400-12-1 is less than 90%
3. The data availability is less than 95% which is filled by the MCP method based on further measured data at the site.

Re-calibration for sensors needs to be performed after 12 months if not testing is performed to validate the calibration of the sensors over the measurement period. In
case, if there is a deviation in the calibration test this needs to be taken into account for the uncertainty assessment (Measnet, 2016).

2.8.2 Wind direction

The measurement of wind direction is done as per the IEC 61400-12-1 specifications. Wind vanes can be used to measure the wind direction, it shall be mounted on separate booms concerning the boom orientation and length according to IEC 61400-12-1. The reason behind mounting the wind vanes on separate booms is to minimize the flow distortion in 360° direction. The wind veer is assessed at the site using an additional wind vane at a significantly lower height. Also, additional wind vane increases data availability. Same as in measuring the wind speed, the measurement heights for the wind direction is also chosen which lie inside the planned wind turbine rotor swept area. During installation, the alignment of wind vanes are done to correct the wind direction offset data.

The criteria for the measurement frequency and incompleteness are same as the wind speed parameter. If the measurement is considered to be incomplete based on the criteria then the deviation must be included for the uncertainty assessment (Measnet, 2016).

2.8.3 Flow inclination

The variation in the flow inclination angle is highly dependent on the slope of the site-specific terrain. Hence, for complex terrain suitable sensor needs to be installed so that the flow inclination can be derived for the measuring position (Measnet, 2016).

2.8.4 Temperature and Atmospheric stability

The air temperature is measured during the wind measurement campaign especially for sites where extreme temperatures are habitual according to IEC 61400-12-1. There should be one sensor installed within the top 10 m of the met mast. The sensors must be calibrated and shielded properly to minimize the bias and uncertainties due to solar radiation. Specifically for non-neutral stability condition sites related to wind energy, ultrasonic anemometers are installed to measure stability by heat flux. This can be substituted by installing two sensors at different heights and stability can be measured based on the difference in values. The long-term mean temperature for a site should be extrapolated only if appropriate long-term data is available (Measnet, 2016).

2.8.5 Pressure

The air pressure is measured using barometers on site very close to the planned wind turbine hub height if not it can be corrected according to ISO 2533. Same as temperature
parameter, the air pressure needs to be extrapolated only if appropriate long-term data is available (Measnet, 2016).

2.8.6 Humidity

Humidity is measured on-site, where extreme weather conditions are expected. Same as the temperature parameter, the humidity sensor needs to be installed within the top 10 m of the met mast. Also, the humidity needs to be extrapolated only if appropriate long-term data is available (Measnet, 2016).
3 Methodology

3.1 Overview

The chapter explains the methodology implemented for this thesis from collecting measurement data till interpolation of AEP for a wind farm (figure 3.1) and perform a sensitivity analysis of the APD based on the different terrain roughness and ‘distance between wind farm and measuring station’.
Figure 3.1: Process flowchart from data collection to AEP estimation
3.2 Input Data

The model uses freely available wind data from SMHI, annual mean wind speed from MIUU, the power curve of the turbine, terrain classification based on Google Earth Pro.

3.2.1 Measurements

Initially, when the site selection is in process, wind data for the particular site is not available, the wind farm design is based on the information from the nearest representative meteorological station. Data for wind flow analysis, which is performed considering the topography and roughness level of the terrain is needed to perform wind farm design (Bechrakis et al., 2004). The wind measurement data is obtained from the nearby representative meteorological station i.e. SMHI for this model. The wind is measured at a height of 10 m and is a ‘mean over 10 min of every 1 hour’. Also, the data is unavailable for 50 min every hour, which reduces the accuracy of the data. The measured wind speed has a bad resolution i.e. the variation in the wind speed is very high, using low-resolution wind data affects the model outputs (Swedish Meteorological and Hydrological Institute, 2019) (Panebianco & Buschiazzo, 2013). So the data is normalized before using it for the interpolation of wind power.

3.2.1.1 Data validation

The wind data needs to be validated before using for the prediction process. The data validation is performed based on the following criteria.

1. The wind data that is going to be used needs to be as close as possible to the site. So that the estimation uncertainties can be reduced to a larger extent (Velo et al., 2014).

2. The measurement site needs to be the most representative site of the area of interest. The representative site is chosen to match the wind flow information considering the topography and roughness level of the terrain (Bechrakis et al., 2004).

3. The wind data needs to be available for almost 25 years so that the mean wind speed value calculated after re-normalization is long term correlated (Brower, 2012).

4. The data availability percentage is set to be more than 80% for the data to be normalized and long term correlated. The suggested percentage is based on the Liléo et al. (2013) report. The results from the report concluded that the long term correlation method does not impact the uncertainty involved in estimating the long term wind speed if the data set availability is provided to be more than 75-80%.

5. The data availability accuracy is calculated using the equation

\[
\text{Data availability} = \left( \frac{\text{No. of bins}}{\text{No. of years} \times 8760} \right) \times 100\%
\]
3.2.2 MIUU data

As discussed in section 2.5, the power law is used to extrapolate wind using real time series but due to unavailability of actual site measurement, MIUU data is used. The MIUU data is used to calculate the distributed wind speed based on the global average wind speed (Swedish Energy Agency, 2019). The data is collected from Vindlov website, the mean wind speed is available for all over Sweden at heights 110 m, 120 m, 130 m, 140 m. The 110 m MIUU data is used for this model to correlate the wind speed at hub height, as all case studies which have been considered has hub heights near to 110 m. To avoid large uncertainties, the power law is being used which is mention in the equation (3.1) to calculate the MIUU value for the desired hub height. The power law was chosen instead of Log law due to its simplicity and that the difference between MIUU height and wind turbine height is low, making the error committed also rather low. The $\alpha$ is given by $\alpha = Ae^{-bv}$ where $v$ is the monthly wind speed, A and $b$ are empirical parameters (Hussain, 2002).

\[
\text{MIUU Value} = \text{Known MIUU value} \times \left( \frac{\text{desired hub height}}{\text{MIUU value height}} \right)^{\alpha} \tag{3.1}
\]

Where

$\alpha$ value of 0.14 is chosen for simulation based on neutral condition

Touma (1977) performed a study on the dependence of the wind profile power law based on 12 months of data for various stability conditions. The study suggested that the $\alpha$ value 0.14 or 1/7 gives good approximation only for neutral conditions. So for correlation approach, the $\alpha$ value of 0.14 is used considering neutral stability (Touma, 1977) (Hussain, 2002). The MIUU value is then multiplied with the re-normalized wind speed bin values to get distributed wind speed (i.e. wind speed profile) which is then later used to interpolate the energy production.

3.2.3 Power curves

The energy estimation is done based on the power curve of the planned wind turbines. Here for this model, the power curve of the turbines installed in the case study locations are used. The power curve distribution and capacity factor ($C_p$) are shown in below figures.

A point to be remembered is that these power curves are idealized ones. Hence there is always a slightly higher or lower estimation of AEP in WRA. The ideal power curve refers to the following optimal conditions

1. Wind is steady with no flow distortion
2. There is a laminar flow
3. Wind is spatially uniform
4. There is no wake influence by the turbine
5. There is no yaw error
6. The turbine generates steady-state power output (Trivellato et al., 2012)

Based on these power curves and distributed wind speed, energy production is interpolated.

Figure 3.2: Power curve for Näsudden wind farm - Vestas V90-3MW (EMD International A/S, 2019)

Figure 3.3: Power curve for Klintehamn wind farm - Vestas V80-2MW (EMD International A/S, 2019)
Figure 3.4: Power curve for Smöjen wind farm - Vestas V63-1.5MW (EMD International A/S, 2019)

Figure 3.5: Power curve for Betåsberget wind farm - Vestas V90-1.8MW (EMD International A/S, 2019)
Figure 3.6: Power curve for Högtjärnklacks wind farm - Vestas V100-1.8MW (EMD International A/S, 2019)

Figure 3.7: Power curve for Nötåsen wind farm - Vestas V90-1.8M (EMD International A/S, 2019)
Figure 3.8: Power curve for Sängsjön wind farm - Vestas V90-1.8MW (EMD International A/S, 2019)

Figure 3.9: Power curve for Sjisjka wind farm - Vestas V90-2MW (EMD International A/S, 2019)
3.2.4 Terrain classification

The model has been ran for 9 case studies with varying terrain roughness class (see table 3.1) and different types of terrain (see table 3.2).

<table>
<thead>
<tr>
<th>S.No</th>
<th>Wind farm</th>
<th>Meteo Data</th>
<th>Wind farm roughness class</th>
<th>Meteo roughness class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Näsudden</td>
<td>Visby Flygplats</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>2</td>
<td>Klintehamn</td>
<td>Visby Flygplats</td>
<td>2.1</td>
<td>0.9</td>
</tr>
<tr>
<td>3</td>
<td>Smöjen</td>
<td>Färösund Ar</td>
<td>1.1</td>
<td>2.3</td>
</tr>
<tr>
<td>4</td>
<td>Betåsberget</td>
<td>Hallhåxåsen</td>
<td>2.5</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>Högtjärnklacks</td>
<td>Borlänge Flygplats</td>
<td>2.9</td>
<td>1.3</td>
</tr>
<tr>
<td>6</td>
<td>Nötåsen</td>
<td>Sundsvalls</td>
<td>2.9</td>
<td>2.5</td>
</tr>
<tr>
<td>7</td>
<td>Sängsjön</td>
<td>Åsele</td>
<td>2.6</td>
<td>2.8</td>
</tr>
<tr>
<td>8</td>
<td>Sjisjka</td>
<td>Latnivaara</td>
<td>2.8</td>
<td>1.6</td>
</tr>
<tr>
<td>9</td>
<td>Tavelberget</td>
<td>Åmot</td>
<td>3.2</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Table 3.1: Wind farm and Meteo Data Roughness Class

The wind farm layouts and topography are shown in the below figures to understand the terrain types and surroundings.
Figure 3.11: Näsudden wind farm (Vindbrukskollen, 2019d) (Google Earth Pro, 2019d)
Figure 3.12: Klintehamn wind farm (Vindbrukskollen, 2019c) (Google Earth Pro, 2019c)
Figure 3.13: Smöjen wind farm (Vindbrukskollen, 2019g) (Google Earth Pro, 2019g)
Figure 3.14: Betåsberget wind farm (Vindbrukskollen, 2019a) (Google Earth Pro, 2019a)
Figure 3.15: Högtjärnklacks wind farm (Vindbrukskollen, 2019b) (Google Earth Pro, 2019b)
Figure 3.16: Nötåsen wind farm (Vindbrukskollen, 2019e) (Google Earth Pro, 2019e)
Figure 3.17: Sängsjön wind farm (Vindbrukskollen, 2019) (Google Earth Pro, 2019)
Figure 3.18: Sjiiska wind farm (Vindbrukskollen, 2019f) (Google Earth Pro, 2019f)
Figure 3.19: Tavelberget wind farm (Vindbrukskollen, 2019) (Google Earth Pro, 2019)
### Table 3.2: Wind farm terrain classification

<table>
<thead>
<tr>
<th>S.No</th>
<th>Wind farm</th>
<th>Meteo Data</th>
<th>Distance btwn wind farm &amp; Meteo</th>
<th>Terrain Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nässudden</td>
<td>Visby Flygplats</td>
<td>62</td>
<td>Flat terrain surrounded by sea</td>
</tr>
<tr>
<td>2</td>
<td>Klintehamn</td>
<td>Visby Flygplats</td>
<td>33</td>
<td>Flat terrain with high forest trees</td>
</tr>
<tr>
<td>3</td>
<td>Smöjen</td>
<td>Fårösund Ar</td>
<td>21</td>
<td>Flat terrain with few high trees and surrounded by sea</td>
</tr>
<tr>
<td>4</td>
<td>Betåsberget</td>
<td>Hallhåxåsen</td>
<td>58</td>
<td>High hills surrounded with few ponds</td>
</tr>
<tr>
<td>5</td>
<td>Högtjärnklacks</td>
<td>Borlänge Flygplats</td>
<td>43</td>
<td>Medium hills surrounded with few ponds</td>
</tr>
<tr>
<td>6</td>
<td>Nötåsen</td>
<td>Sundsvalls</td>
<td>46</td>
<td>High hills with a large lake nearby</td>
</tr>
<tr>
<td>7</td>
<td>Sängsjön</td>
<td>Åsele</td>
<td>8</td>
<td>High hills with a large lake and few ponds</td>
</tr>
<tr>
<td>8</td>
<td>Sjisjka</td>
<td>Latnivaara</td>
<td>42</td>
<td>High hills surrounded with few ponds</td>
</tr>
<tr>
<td>9</td>
<td>Tavelberget</td>
<td>Åmot</td>
<td>28</td>
<td>Low hills with a large lake and few ponds</td>
</tr>
</tbody>
</table>

### 3.3 Data modification

The data modification is performed to normalize the wind data and get a distributed wind speed based on the annual average wind speed value i.e. MIUU. The normalization modifies the time series to vary around 1 instead of varying around the mean values (Nilsson et al., 2018). Data modification is performed by the following 3 steps
1. The measurement data from SMHI is modified by adding normally distributed noise to account for bad resolution of wind speed i.e. the variation in the wind speed is very high.

   a) The normally distributed random noise values are generated using MATLAB function with a standard deviation value of 0.4, which is then added to the wind speed bin values. Joffre & Laurila (1988) performed an analysis to study the standard deviations of wind speed obtained from the wind measurement. The analysis suggested that normalized wind speed at 10 m height is well approximated with a standard deviation value of 0.4 for lower wind speeds considering the smooth surface. Hence standard deviation value of 0.4 is used to generate normally distributed random noise values for all case studies considering lower wind speed and smooth surface. As a result, we get a normalized wind speed.

2. There is a possibility that the normalized wind speed might have negative values. To remove the negative values, a conditional statement is introduced in the MATLAB script which identifies the negative wind speed values and corrects them to 0 m/s. The correction gives re-normalized wind speed data.

3. The final step is to modify the data to have a distributed wind speed.
   a) From the re-normalized wind speed, mean wind speed value is calculated. (The mean wind speed that is calculated is long term correlated, as the data set with more than 25 years availability is only accepted for the model)
   b) The calculated MIUU value for the turbine’s hub height and mean wind speed from the re-normalized wind speed is used to obtain a distributed wind speed based on the below equation

\[
\text{Distributed wind speed} = \left[ \frac{\text{Bin values}}{\text{Mean wind speed}} \right] \times \text{MIUU value}
\]

3.4 Output Data

The output data (i.e. estimated energy production) is obtained by performing a few steps which are explained below

1. The distributed wind speed and power curve of the wind turbine installed in the site is used to interpolate the power generated for the wind speed bin values (hourly).

2. The hourly values are summed up monthly to have the monthly production data. 12 estimated values are obtained for each year in order to reduce uncertainties.

3. For this model, the simulations are run for the years 2016-2018. So from the 36 estimated values (\(12 \times 3 = 36\)) minimum, maximum and mean values are calculated. So, 12 minimum, maximum and mean values are obtained.
3.5 Validation data

The output data is validated with the monthly APD of the wind farm which is obtained from Vindstat AB (Vindstat AB, 2019). The APD unavailability is defined in the table 3.3.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Wind farm</th>
<th>Data Unavailability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2016</td>
</tr>
<tr>
<td>1</td>
<td>Näsudden</td>
<td>X</td>
</tr>
<tr>
<td>2</td>
<td>Klintehamn</td>
<td>X</td>
</tr>
<tr>
<td>3</td>
<td>Smöjen</td>
<td>X</td>
</tr>
<tr>
<td>4</td>
<td>Betåsberget</td>
<td>1 month</td>
</tr>
<tr>
<td>5</td>
<td>Högtjärnklacks</td>
<td>X</td>
</tr>
<tr>
<td>6</td>
<td>Nötåsen</td>
<td>5 months</td>
</tr>
<tr>
<td>7</td>
<td>Sängsjön</td>
<td>X</td>
</tr>
<tr>
<td>8</td>
<td>Sjisjka</td>
<td>3 months</td>
</tr>
<tr>
<td>9</td>
<td>Tavelberget</td>
<td>X</td>
</tr>
</tbody>
</table>

Where

X Complete data available

Month Data was not available for specified number of months

Table 3.3: Data availability

The validation process is explained in steps below,

1. The minimum, maximum and mean values are calculated from the available APD.

2. The estimated AEP is always slightly higher than the APD considering the idealized power curve as mentioned in section 3.2.3. The assessment performed by Portabella & Stoffelen (2006) for the impact of uncertainty shows that the uncertainty % was 10 percent due to wind variability. Hence, 10% of the energy estimated is reduced from the total estimation.

3. The APD and the estimated AEP are compared based on the min, max and mean values by plotting them in a graph.

As mentioned in the second point, the uncertainty accounts not only for wind variation but also for turbine availability, wake loss, electrical loss, curtailment due to grid issues, yaw & pitch mechanism losses.


3.6 Sensitivity analysis

The sensitivity analysis is performed for the results obtained from the output data and validation data (i.e. APD and estimated energy production). The sensitivity analysis includes production trend comparison, production difference based on the ‘distance between wind farm and measuring station’, production difference based on the ‘wind farm roughness’ and comparing production difference VS roughness difference %.

The production trend comparison is done based on the estimated energy production and the APD to verify whether the actual production trend falls in line with the estimated production trend.

The production difference % is calculated between estimated energy production and APD. The difference % is then compared with ‘distance between wind farm and measuring station’, ‘wind farm roughness’ and ‘roughness difference %’ (i.e. difference in roughness between wind farm terrain and measuring station terrain).

3.7 Discussion

There could be possible other alternative options for data collection or MIUU data wind resource mapping like New European Wind Atlas (NEWA), Global wind atlas, etc. The above explained methodology is adopted based on the data availability during the start of the thesis. Also, the NEWA was released in the year 2019 hence there could be possibility for uncertainty of data. Hence the standard MIUU model was chosen for the wind resource mapping.
4 Case study results and discussion

4.1 Introduction

The estimations have been performed for the various case studies as mentioned in table 3.1. Sensitivity analysis and the results are discussed in the following sections highlighting the variations. The results are presented in the order where the estimated AEP trend almost fall in line with the APD. The estimated AEP does not include wake, operational and grid/transmission losses. Hence, 10% of the energy estimated is reduced from the total estimation as mentioned in section 3.5.

4.2 Case study results

4.2.1 Case study 1: Näsudden wind farm

Näsudden wind farm is located in the south-west part of Gotland island. To define the terrain profile, the wind farm is surrounded by farmlands and the terrain is almost flat completely. The wind farm is located along the coast of Baltic sea. The meteo data was used from "Visby Flygplats" which is at a distance of 62 km from the wind farm. The roughness class for the wind farm and meteo are same with a value of 0.9.

Näsudden has Vestas V90 wind turbines with a nominal power of 3 MW at a hub height of 90 m and the mean MIUU value for the wind farm location is 8.7 m/s. The three-year annual mean estimation graph (figure 4.1) is simulated for the minimum, maximum and mean values of production value. The three-year estimation trend also almost fall in line with the APD. The production estimation almost falls inside the variation bounds of the APD curve.
4.2.2 Case study 2: Klintehamn wind farm

The Klintehamn wind farm is located near the west shore of Gotland island. The terrain profile has small buildings nearby and tall hedgerows surrounding the wind turbines which are installed near the coast. For Klintehamn also “Visby Flygplats” meteo data was used and the distance is 33 km from the wind farm. The roughness class for the wind farm is 2.1 and the meteo roughness has a value of 0.9.

Klintehamn has Vestas V80 wind turbines with a nominal power of 2 MW at a hub height of 67 m and the mean MIUU value for Klintehamn site is 8.0 m/s. The three-year estimation trend (figure 4.2) follows the APD trend. The total mean estimated production is 6.5 TWh and the total mean APD is 4.29 TWh.
4.2.3 Case study 3: Smöjen wind farm

Smöjen wind farm is located in the north-east part of Gotland island. The terrain profile has tall hedgerows less than 8 m, few ponds in-between the turbines which are installed near the coast and in few places flat surfaces. For Smöjen, the "Fårösund Ar A" meteo data was used which is at a distance of 21 km from the wind farm. The roughness class for the wind farm is 1.1 and the meteo roughness has a value of 2.3.

Smöjen has Vestas V66 wind turbines with a nominal capacity of 1.5 MW at a hub height of 67 m, the mean MIUU value is 7.7 m/s. The three-year estimation trend (figure 4.3) is exactly in line with the APD trend. The total mean estimated production is 3.8 TWh and the total mean APD is 3.13 TWh. The model works perfectly for this site since the time series was obtained from a very short distance from the wind farm.
4.2.4 Case study 4: Betåsberget wind farm

Betåsberget wind farm is located in the middle of Sweden. The terrain elevation profile goes from flat to hilly and also there are hedgerows, vegetation and surrounded by few ponds. "Hallhåxåsen" meteo data was used for the power estimation of Betåsberget wind farm which is located at a distance of 58 km. The roughness class for the wind farm is 2.5 and the meteo roughness has a value of 2.

Betåsberget has Vestas V90 wind turbine with a nominal power capacity of 2 MW at a hub height of 105 m, the mean MIUU value for the location is 5.3 m/s. Although the three-year estimation trend (figure 4.4) does not fall in line, the estimation curve falls inside the APD variation bounds. The total mean estimated production is 4.25 TWh and the total mean APD is 4.47 TWh. The mean estimated and mean actual production values are almost the same since there is less turbulence due to smooth surface over hills.
4.2.5 Case study 5: Högtjärnklacks wind farm

Högtjärnklacks wind farm is located between Borlänge and Gävle city. The site has an elevation profile rising from flat to hilly with small hedgerows, surrounded by many ponds and there are few small buildings nearby. "Borlänge Flygplats" meteo data was used for the estimation of Högtjärnklacks wind farm, which is located at a distance of 43 km. The roughness class for the wind farm is 2.9 and the meteo roughness has a value of 1.3.

Högtjärnklacks wind farm has Vestas V100 wind turbine with a nominal power capacity of 1.8 MW at a hub height of 95 m. The mean MIUU value for the wind farm is 6.8 m/s. The three-year estimation trend (figure 4.5) slightly follows the actual production trend. But the estimation curve falls almost completely inside the APD variation bounds. The smooth surface over the hills compliments for less turbulence. The total mean estimated production is 6.54 TWh and the total mean APD is 6.59 TWh.
Figure 4.5: Högtjärnklacks three-year estimation for 2016-2018

4.2.6 Case study 6: Sängsjön wind farm

Sängsjön wind farm is located near Åsele city. The terrain profile rises from flat to hilly valleys with small hedgerows and surrounded by many large lakes. "Åsele" meteo data was used for the estimation of Sängsjön wind farm, it is located at a distance of 8 km. The roughness class for the wind farm is 2.6 and the meteo roughness has a value of 2.8.

Sängsjön wind farm has 3 Vestas V90 with a power capacity of 1.8 MW and 1 Vestas V90 with a capacity of 2 MW. All 4 wind turbines are installed at a hub height of 105m. For estimation, Vestas V90 1.8 MW wind turbine power curve was used. The mean MIUU value for the site is 6.6 m/s. The three-year estimation trend (figure 4.6) slightly follows the APD trend. But the estimation curve almost falls inside the variation bounds of APD. The total mean estimated production is 5.07 TWh and the total mean APD is 6.18 TWh.
4.2.7 Case study 7: Sjisjka wind farm

Sjisjka wind farm is located in the north most of Sweden. The terrain elevation rises from flat to hilly with tall hedgerows in flat surface and small hedgerows in the hilly surfaces. Based on the terrain profile the roughness class for the wind farm is 2.8 and the meteo roughness has a value of 1.6. The meteo data used for the wind power estimation of Sjisjka wind farm is "Latnivaara", which is at a distance of 42 km from the wind farm.

Sjisjka wind farm has 30 Vestas V100 with a power capacity of 2.6 MW installed at a hub height of 80 m. The mean MIUU value for the wind farm is 6.3 m/s. The three-year estimation curve (figure 4.7) and the APD trend do not fall inline but the estimation curve comes completely within the APD variation bounds. The total mean estimated production is 6.32 TWh and the total mean APD is 5.77 TWh.
4.2.8 Case study 8: Tavelberget wind farm

Tavelberget wind farm is near Gävle city. The terrain elevation profile rises from flat to hilly, there are high hills with dense hedgerows. There are small and very large lake nearby. Based on the terrain profile the roughness class for the wind farm is 3.2 and the meteo roughness has a value of 1.5. The "Åmot" meteo data which is at a distance of 28 km from the wind farm is used for the wind power estimation.

Five Vestas V90 wind turbine with a power capacity of 2 MW at a hub height of 105 m is installed in Tavelberget wind farm. The mean MIUU wind speed for the wind farm is 7.3 m/s. The three-year estimation trend (figure 4.8) do not fall in line with the APD curve. But the estimation curve slightly comes inside the APD variation bounds. The total mean estimated production is 6.76 TWh and the total mean APD is 6.46 TWh.
4.2.9 Case study 9: Nötåsen wind farm

Nötåsen wind farm is located near Sundsvall city. The terrain has small hills next to a very large lake. There are small hedgerows and a small village nearby. Based on the terrain profile the roughness class for the wind farm is 2.9 and the meteo roughness has a value of 2.5. "Sundsvalls Flygplats" meteo data was used even though there was another meteo data nearby but the data was inconsistent. Sundsvalls meteo data is at a distance of 46 km from Nötåsen wind farm.

Gamesa G114 wind turbine is installed in Nötåsen wind farm with a nominal power capacity of 2 MW at a hub height of 104 m. The mean MIUU value is 5.8 m/s for the wind farm location. The three-year estimation trend (figure 4.9) does not follow the APD trend. But the estimation curve comes slightly within the APD variation bounds. The total mean estimated production is 6.88 TWh and the total mean APD is 6.13 TWh.
4.3 Analysis

The estimation results from different case studies are analyzed based on their alignment with the APD trend. The alignment is categorized whether the estimation from the model was able to follow the trend and falls within the APD variation bounds (See table 4.1). The MIUU value plays a major role in the estimation model if exact MIUU value for the location is not used then the estimation value varies to a greater extent. For Gotland cases, the model works perfectly fine following the trend and APD. For mainland cases, the estimation comes within the APD variation bounds but the model couldn’t follow the production trend. Either the model follows the trend or falls within the APD variation bounds.

Further analysis showed that the cases which did not follow the trend mostly had small or big lakes nearby or the terrain was not flat. Taken together, it leads to a conclusion that the model finds it difficult to follow the trend if there are lakes nearby or if the terrain is not flat. But the model was able to estimate the AEP almost equal to the APD by considering 10% uncertainty as explained in the section 3.5.
Sensitivity analysis was performed by comparing the production difference % with ‘distance between the wind farm and measuring station’ (see figure 4.10) and ‘wind farm roughness class’ (see figure 4.11). Also, the production difference % is compared with the roughness class difference % (see figure 4.12). The figure 4.10, 4.11, 4.12 shows that production variation is not linear based on the distance or the roughness. It is difficult to make a statement that the production difference is based on the roughness difference % or distance parameter because it is varying differently. However, the simulation results show positive results for the model predicting wind power with very less production difference % for most of the cases.

The possible errors for the model might be due to poor measurement data (i.e. the measured data might be too far from the wind farm, the measurement site may not be an exact representative site of the wind farm, poor data accuracy), idealized power curve is used for interpolation as explained in section 3.2.3. There could also be a possibility for difference since the model does not consider the actual turbine out of operation hours and the actual wake/grid losses for the turbine. The accuracy of terrain classification may be less as it is done using Google Earth Pro (see section 3.2.4) and the Power law exponent (α) value used for the MIUU value calculation is 0.14 considering neutral stability (see section 3.2.2). Maybe if the α value used is based on the appropriate stability of the wind farm terrain and using actual information about wake/grid losses, turbine out of operation hours there could be less difference in result for most cases.

In summary, from these results, it is evident that the monthly trends and production levels are well estimated for Gotland cases using the model. For the mainland cases, the production levels are well predicted using the model. The model was able to predict the monthly wind power production for various wind farms across Sweden within the APD variation bounds. Since the APD is available only as monthly average the model could not be validated for weekly, daily or hourly basis. Further work needs to be performed to assess the uncertainties involved, due to the use of constant α value irrespective of the terrain roughness and the general trend of overestimating the energy production.
Case study results and discussion

<table>
<thead>
<tr>
<th>Case Study</th>
<th>Trend</th>
<th>APD variation bounds</th>
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<tr>
<td>Näsudden</td>
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</tr>
<tr>
<td>Klintehamn</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Smöjen</td>
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<tr>
<td>Högtjärnklacks</td>
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<td>Sjisjka</td>
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<td>Tavelberget</td>
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<tr>
<td>Nötäsen</td>
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</tbody>
</table>

Where
X  Follows
-  Do not follow

Table 4.1: Case study trend

![Figure 4.10: Difference based on distance](image)

Figure 4.10: Difference based on distance
Case study results and discussion

Figure 4.11: Difference based on roughness

Figure 4.12: Variation in estimation
5 Conclusion

The thesis introduces a time series based wind power prediction model which can be used for initial WRA during the screening phase of a wind power project. The model can produce time-based wind power prediction results based on the freely available wind data from a nearby representative measuring site with the help of global average wind speed value from MIUU. The power curve of the wind turbine that is planned to install, is used to interpolate the wind power with the help of distributed wind speed.

The graphical results from different case studies show that the model was able to estimate time-varying wind power production on monthly averages using freely available wind data. The terrain for different case studies are analyzed and the roughness classes are calculated to identify the factors influencing the wind power prediction. The model was able to follow the trend and APD variation bounds for flat surfaces and it was able to fairly estimate the wind power production within the APD variation bounds for complex terrains.

A sensitivity analysis was performed to analyze the variation in the production estimation based on the ‘roughness class’, ‘the distance between the wind farm and the measuring station’ and ‘roughness difference %’. There is no trend in the graphical representation of the production difference, which made it difficult to claim that the production difference increases or decreases in a trend when the ‘roughness class’ or ‘the distance between the wind farm and measuring station’ increases.

From these results, it is seen that the model works fine following the production trend and the variation bounds for flat surfaces (i.e. Gotland cases). Also, the model works fairly estimating the production within the APD variation bounds for elevated surfaces (i.e. mainland cases) considering the annual mean. The accuracy of the model is limited to predict the wind power on monthly averages. But the accuracy can be improved based on future work, to assess the $\alpha$ parameter for different terrain and validate the model for different time scales provided if the APD is available on different time scales.
Literature


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