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Estimation of Norwegian wind farm degradation using a performance index accounting for local wind resources

Estimering av norske vindparkers degradering ved bruk av en ytelsesindeks som tar hensyn til lokale vindressurser

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Declaration statement

Artificial Intelligence is used in this thesis according to the guidelines from REALTEK at NMBU listed at site with url: `https://www.nmbu.no/en/faculties/faculty-science-and-technology/kunstig-intelligens-ved-realtek`. This tool has exclusively been used for linguistic improvements such as for grammar and spelling checks, as well as to improve phrase structures. It has not been used for gathering information or for producing results.

Abstract

Wind power is expected to be an increasingly important part of the development in the Norwegian energy sector. Knowing how the wind farms perform over their lifetime and how this affects the power system as a whole, is important knowledge when considering further investments. An important aspect in this regard is the degradation of wind turbines. This thesis will therefore study the lifetime development of a wind farm´s performance.

The study consists of 15 wind farms spread across Norway. To find the rate of degradation, the expected power production is calculated using ERA5 weather data and publicly available information on the wind farms. This is then compared with actual production data to find a "performance index". The changes in this index provides the basis for a yearly degradation rate.

The average yearly degradation was found to be $-1.00 \pm 0.22\%$. This implies that after 20 years the wind farms will produce about 82% of their original capacity. Furthermore, this degradation will lead to an increase in the LCOE of 6,8 %, which in turn could affect electricity prices. These results call for a change in assumptions for future wind farm projects, as this is significantly higher than what is assumed in the industry today.

To find potential factors affecting the degradation rates, three sub-studies were performed. In the first test the wind farms were divided into three groups according to location to find out if local climate would affect the results. The second test was performed to find whether there were differences in degradation between turbines according to their age. Lastly, the degradation was divided in four seasons to assess whether these effects varied according to weather conditions. It was concluded that there were no significant differences between the groups.

The degradation rate found in the thesis is higher than what is found in Sweden, but lower than what was found in the UK. This may suggest that wind turbines degrade faster in coastal climates than in inland climates. Factors such as high average wind speeds, high precipitation and exposure to salt therefore seems to be more important causes of degradation than low temperatures and icing.

Sammendrag

Vindkraft er forventet å være en viktig del av utviklingen i den norske energisektoren. Det er viktig å vite hvordan vindparkene presterer i løpet av sin levetid, og hvordan dette påvirker kraftsystemet som helhet. Et viktig aspekt i denne sammenheng er hvordan vindturbiner degraderer. Denne oppgaven vil derfor ta for seg hvordan en vindturbins ytelse minker i løpet av levetiden.

Studien består av 15 vindparker spredt over hele Norge. Først beregnes forventet kraftproduksjon ved hjelp av ERA5-værdata og offentlig tilgjengelig informasjon om vindparkene. Denne sammenlignes deretter med faktiske produksjonsdata for å finne en "ytelsesindeks" (performance index). Endringene i denne indeksen danner grunnlaget for en årlig degraderingsrate.

Den gjennomsnittlige årlige degraderingen ble funnet til å være $-1,00 \pm 0,22\%$. Dette innebærer at vindparkene etter 20 år vil produsere omtrent 82% av sin opprinnelige kapasitet. Videre vil denne degraderingen føre til en økning i LCOE på 6,8 %, noe som vider vil kunne påvirke strømprisene. Disse resultatene krever en endring i forutsetningene for fremtidige vindparkprosjekter, ettersom dette er betydelig høyere enn det som antas i bransjen i dag.

For å finne potensielle faktorer som påvirker degraderingsratene, ble det utført tre delstudier. I den første testen ble vindparkene delt inn i tre grupper etter beliggenhet for å finne ut om det lokale klimaet ville påvirke resultatene. Den andre testen ble utført for å finne ut om det var forskjeller i degradering mellom turbinene avhengig av alder. Til slutt ble degraderingen delt inn i fire kvartal for å vurdere om disse effektene varierte med værforholdene. Det ble konkludert med at det ikke var signifikante forskjeller mellom gruppene.

Degraderingen som ble funnet i oppgaven, er høyere enn i Sverige, men lavere enn i Storbritannia. Dette kan tyde på at vindturbiner degraderes raskere i kystklima enn i innlandsklima. Faktorer som høy gjennomsnittlig vindhastighet, mye nedbør og eksponering for salt ser derfor ut til å påvirke degraderingsraten i større grad enn lave temperaturer og ising.

Contents

List of Figures

List of Tables

Abbrevations

NVE	The Norwegian Energy Regulatory Authority (Norges Vassdrags- og Energidirektorat)
WT	Wind Turbine
CF	Capacity Factor
PI	Performance Index
LCOE	Levelised Cost Of Energy
RANSAC	Random Sample Consensus
ARIMA	Autoregressive Integrated Moving Average
ECMWF	European Center for Medium-range Weather Forecasts
ERA5	ECMWF´s Reanalysis v5
CRISP-DM	Cross-Industry Standard Process for Data Mining
OB17	Study on Swedish wind farm degradation (Olauson, Bergkvist, Edström, & Carlstedt, 2017)
SG14	Study on British wind farm degradation (Staffel & Green, 2014)
ED24	Study on degradation of selected Norwegian wind farms (Drengsrud, 2024)
SH19	Master thesis on Windpowerlib (Haas, 2019)
pp/y	Percentage points per year
NMBU	Norwegian University of Life Sciences

1 Introduction

The substantial expansion of wind power in Norway over the past two decades has allowed for greater access to renewable energy. However, several challenges has been encountered with this development, leading to considerable debate about the future direction of wind power development (Nowell, Krange, Bakkestuen, & Ruud, 2020). One area that has received limited attention in the research literature is the extent to which wind turbines degrade over time, and the potential impact of this on factors such as the levelised cost of energy (LCOE) and electricity prices.

Like most other machines with moving parts, wind turbines will experience some degradation in performance over their lifetime (Staffel & Green, 2014). Although this is known, the degradation rate considered when building a wind farm varies. As this can have a significant impact on the lifetime performance and consequently the financial viability of a wind farm project, a more thorough understanding of the causes and effects of degradation would be valuable.

Two other important papers from other countries have been published on this subject. A study of British wind farms calculated an average annual degradation of 1,6% per year, which is significantly higher than what is normally expected in the industry (Staffel & Green, 2014). A study from Sweden in 2017 found a much smaller degradation, of around 0.50 % per year (Olauson et al., 2017). The total loss in lifetime production was found to be 12% in the UK study and 6% in the Swedish study. In Norway, a previous Master's thesis at NMBU looked at capacity factor losses for Norwegian wind farms. This study showed an annual capacity factor degradation of 1,3 % per year (Drengsrud, 2024).

The method used by Drengsrud does not consider variations in the wind resources, and therefore this study has some clear limitations. The studies by Olauson et al. and Staffel and Green do account for variations in wind resource, but still studies changes in the capacity factor (CF) of wind farms. The aim of this thesis was therefore to study the degradation of Norwegian wind farms, accounting for variations in wind resource. Also, an alternative method of calculating the power loss in wind turbines, where weather variations are systematically accounted for, will be proposed.

To provide a better basis for comparison between different production years than capacity factors allow, a method using the wind farm's *performance index* is introduced. This index compares the simulated output of a wind farm based on weather data from the region, with publicly available production data to see how the wind farm is performing compared to what is expected.

The model will study the same wind farms as the previous NMBU master's thesis on wind farm degradation (Drengsrud, 2024). This is done to compare how the model performs compared to a simpler approach of comparing capacity factors. In addition to providing a fair basis for comparison, correcting for variations in wind resource may also allow a deeper understanding of how different factors affect wind power degradation.

1.1 Problem statement

The aim of this thesis is to find out how the performance of Norwegian wind farms decline with age. The method of using the performance index will also be a central part of the discussion, as this method is relatively new and untested. An additional goal for the thesis will be to find potential risk factors that increase the rate of degradation. The implications of the results, such as how degradation impacts the total lifetime energy production and the calculated LCOE of wind power in Norway, will also be discussed. This leads to the following research questions:

- How does the performance of Norwegian wind farms decline with age?
- Is the performance index a good indicator of wind farm performance?
- Which factors impacts the degradation of wind turbines?
- What are the limitations of the model?

1.2 Limitations

During the work with this thesis, we were faced with several limiting factors, such as time constraints, limited resources and being restricted to using publicly available data. This will restrict both the scope of the thesis, as well as affecting the validity of the results. The model is a simplification of reality, which allows for potential error sources impacting the results. The scope of the thesis is also limited to the degradation of Norwegian wind farms. A specific selection of these has been made, so the results should be understood as an average of the selected wind farms. This will correlate with Norwegian wind power as a whole, although there may be some deviations from the national average.

1.3 Background

Norway's wind power sector represents approximately 12% of the country's annual energy production. This makes wind the second most significant source of energy, trailing only behind hydro power. The wind energy industry has experienced a remarkable expansion over the past two decades, with Norwegian wind farms generating 70 times more energy in 2022 than in 2003. Wind farms are now dispersed all across Norway. The majority of wind farms are situated in coastal areas, where wind speeds are typically higher and more stable. Consequently, the western, middle and northern regions of Norway account for the largest shares of wind power production.(NVE, 2023c)

The development of wind power has received broad political support, although there has been increasing criticism recently, mainly due to rising electricity prices and the siting of wind farms in controversial areas. The intermittency of wind is also a challenge in increasing the amount of wind power in the grid. It should be combined with other energy sources that are easier to regulate, such as hydropower or fossil fuel power plants, to ensure stable energy production. (NVE, 2023b)

Despite these challenges, wind power is seen as an important part of the move towards a more sustainable energy market. With the potential for hydropower reaching its limits, wind and solar are expected to be the fastest growing energy sources in the coming years. As wind energy is both emission-free and one of the cheapest energy sources available, combined with suitable weather conditions in Norway, most signs point to a continued emphasis on wind farms in the future.(NVE, 2023c)

2 Literature

The degradation of wind power has gained relatively little attention in academic milieus, although it has gained some interest in the later years, as some major studies have been conducted on this topic. The earliest major paper is a study of wind farms in Denmark and UK, by Gordon Hughes (Hughes, 2012). The two largest studies of wind farm degradation are SG14, where the degradation of British wind farms were studied, and OB17, which focuses on Swedish wind farm degradation (Staffel & Green, 2014) (Olauson et al., 2017). In Norway, one Master´s thesis on this topic have been published in 2024 at NMBU, where the degradation of a selection of Norwegian wind farms were studied (Drengsrud, 2024). A master thesis from Germany written by Sabine Haas, describes the implementation and usage of Windpowerlib as a tool for simulating wind power, which is a Python library made for simulating power output of wind turbines in virtual wind farms. These studies provide the background and foundation for this thesis.

2.1 Hughes

The study by Gordon Hughes on Danish and British wind farms in 2012 is one of the first attempts to systematically analyse wind farm degradation. Hughes uses production data from onshore wind farms in Britain and Denmark, as well as some offshore wind farms in Denmark. Changes in capacity factors, i.e. the actual production in a defined period of time, compared to the theoretical maximum production, were used to determine the loss in performance. Capacity factors is in the paper referred to as load factors. (Hughes, 2012)

Among the central findings is that British wind farms capacity factor deteriorate with a rate of -0,9 pp/y, or -2,8% per year. This is a substantial loss of performance compared to what is normally assumed, equating a loss of capacity factor from 24% to 11% from year 1 to year 15. The equivalent findings for onshore wind farms in Denmark were lower, showing a capacity factor loss from 24% to 18% in the same time span. Danish offshore wind farms showed the largest decline in capacity factor, from 39% in year 0, to 15% in year 15. (Hughes, 2012)

Since this study is quite old, a lot of the results are somewhat outdated. Later studies have shown a significantly lower decline in capacity factor for wind power. Still, it is interesting as an early attempt to find decline in wind farm performance. The study also seems to indicate that more mature technologies perform better when comparing degradation rates. Offshore wind energy was quite new at the time, and is expected to have improved since.(Hughes, 2012)

2.2 SG14

The study of British wind farms by Staffel and Green in 2014 was inspired by Hughes´paper from 2012. It is however conducted with a more systematic approach that accounted for other factors influencing the results. The study also included a much bigger data sample. These improvements, combined with a slightly more mature industry, yields these results much more relevant for modern day applications.(Staffel & Green, 2014)

The study uses free, available production data from 283 British wind farms in the period 2002-2012. As in Hughes´ paper, Staffel & Green analyses changes in capacity factors to find their loss in performance. It also accounts for variances in wind resource through the period. Through linear regression the authors found an average decline in the capacity factors of 1,6%, or 0,43 pp/year.(Staffel & Green, 2014)

The most notable improvement on Hughes´ study is the corrections of capacity factor based on wind resources. The study uses weather reanalyis data from the MERRA dataset to find average monthly wind speeds. This is combined with the power curves of the wind turbines at each wind farm to simulate expected power output. This information is used to find a weather adjusted capacity factor, which is better suited for comparing year-to-year energy production.

Although the degradation found in this study is small compared to what is seen in Hughes´paper, it is substantially larger than what is assumed in the industry. Accounting for this degradation, the LCOE of wind energy increases by 9%, which could impact the financial viability of future wind farm projects.(Staffel & Green, 2014)

2.3 OB17

A study of Swedish wind farms in 2017, which was a collaboration between the University of Uppsala, Sweco and Vindforsk, looked at the decline in performance for a selection of Swedish wind farms in the period between 1990-2015.(Olauson et al., 2017)

Using three different methods for linear regression, this paper improved on the method used in Staffel and Greens research. The use of hourly production data also allowed the researchers to identify downtime due to technical issues. This was found to increase as the wind farms aged, and was found to account for roughly 1/3 of the decline in performance.(Olauson et al., 2017)

The wind resource was adjusted for by using three different weather reanalysis models, namely ERA-Interim, MERRA and ConWx. As with SG14, these were used to adjust the capacity factors accordingly.

This study showed an average decline in yearly performance of 0,10-0,20 pp/y, which corresponds to a percentagewise loss of 0,30-0,60 %. The study also showed that the trend is steeper as the wind farms age. Also, wind farms with higher capacity factors showed a greater decline than average. The suggestion from these results is to assume a degradation in the upper end of this range, especially for wind farms with high capacity factors. (Olauson et al., 2017)

A yearly degradation of 0,10-0,20 pp/y corresponds to a total energy loss over a wind farm´s lifetime of 2,4%-6,3%, depending on initial capacity factors. This is significantly lower than what is found in SG14, but higher than what is normally assumed in the wind industry.(Olauson et al., 2017)

2.4 ED24

A Master´s thesis on the topic of degradation of Norwegian wind farms was published earlier in 2024, by Erik Drengsrud at NMBU. The thesis analyses production data from 16 Norwegian wind farms, looking at how the capacity factors has declined over the wind farms lifetime.(Drengsrud, 2024)

The thesis uses linear regression, like what is used in SG14 and OB17. It is however not adjusted for variations in wind resource. Instead this study uses a moving average to account for some of these variances. As the time period of the analysis is quite short for some of the wind farms, the variances in weather may have quite a large impact on the results, which is a potential weakness of the study. This thesis also has a smaller sample size compared to the larger studies from Sweden and Britain, but the results gives a good indication of how Norwegian wind farms performs compared to what is found previously in other countries.(Drengsrud, 2024)

Drengsrud finds an average decline in capacity factor of 0,43 pp/y, or 1,3% per year, weighted according to the size of the wind farms. The largest wind farms in the study also has the largest degradation, and will as such represent a big part of the overall degradation.(Drengsrud, 2024)

2.5 SH19

Sabine Haas wrote a Master´s thesis describing implementation and validation of the Windpowerlib model in 2019. The thesis was written published by *Technische Universitat Berlin*. (Haas, 2019)

The thesis describes the implementation of Windpowerlib in Python. Firstly, it presents functionalities for correcting climate related matter such as wind speed height correction and density. It also includes functionalities for simulating wind power, such as power output calculations, power curve smoothing, aggregated power curves and functionalities for handling wake loss. (Haas, 2019)

After implementation of Windpowerlib the model was validated using measured feed-in time series of several wind farms. Wind farms in Schleswig-Holstein serves as validation of coastal region and Brandenburg serves as validation of the inland region in Germany. The validation was carried out in 2015 and 2016. (Haas, 2019)

The clmate data sets MERRA-2 and FRED were used for validation. This showed an annual deviation of 4.7 % in inland wind farms and a deviation of 3.4 % in coastal regions from the actual energy output. The study showed that the wind farm feed-in simulation is overestimation when using the FRED weather data. The deviations turned out to be even higher when using MERRA-2 weather data. The deviation in the inland region was

26 percentage points higher and the deviation at the coastal region was ten percentage points higher. There is however as strong correlation between measured time series and the simulated time series when looking at Pearson correlation coefficients. The coefficient was calculated to be about 0.7 to 0.9. The study showed that the MERRA-2 data returns a slightly higher correlation compared to the open FRED data. (Haas, 2019)

3 Theory

3.1 Wind resource

Wind is regarded as a secondary form of energy, as the sun heats the earth unevenly, which leads to differences in pressure and density in the air. These temperature differences arises partly due to the various materials and terrains that is heated, such as water and soil. This leads to coastal areas typically being more exposed to wind than inland areas. The wind direction depends to a large degree on the rotation of the earth, as well as local topography. This may lead to tops of hills and mountains, as well as valleys being exposed to wind, depending on how the topography of the area coincides with wind directions. (Letcher, 2017)

3.1.1 Global wind effects

As the solar radiation is absorbed in the ground, it heats up the surrounding air. The hot air expands, and rises above the cold air. This effect is particularly strong near the equator. Conversely, the air sinks near the poles. This produces looped convection currents in the lower atmosphere (15 km). These convection currents are split in three cells in each hemisphere. This picture is further complicated by the rotation of the earth, which combined with the convection currents produces "trade winds" around the equator, "Westerlies" in the mid-latitudes, and "Polar easterlies" around the poles. (Twidell, 2021)

The areas with the strongest average winds are in the oceans in the region between 30 and 60 degrees both north and south, as can be seen in Figure 3.1. These areas coincides with densely populated areas in the northern hemisphere such as northern Europe and Scandinavia, as well as Northern USA and Canada. In the southern strong-wind regions there is generally less population, and therefore less suitable for large wind power installments. (Twidell, 2021)

As can be seen in Figure 3.1, the average wind speeds in the north generally are highest in the winter, peaking in January. Conversely, the wind speeds decreases in summer time. Norway is therefore well suited for wind power production due to its location in these high-wind speed areas, combined with a long coastline. The average wind speeds and temperatures in the regions defined in this thesis can be seen in Table A.

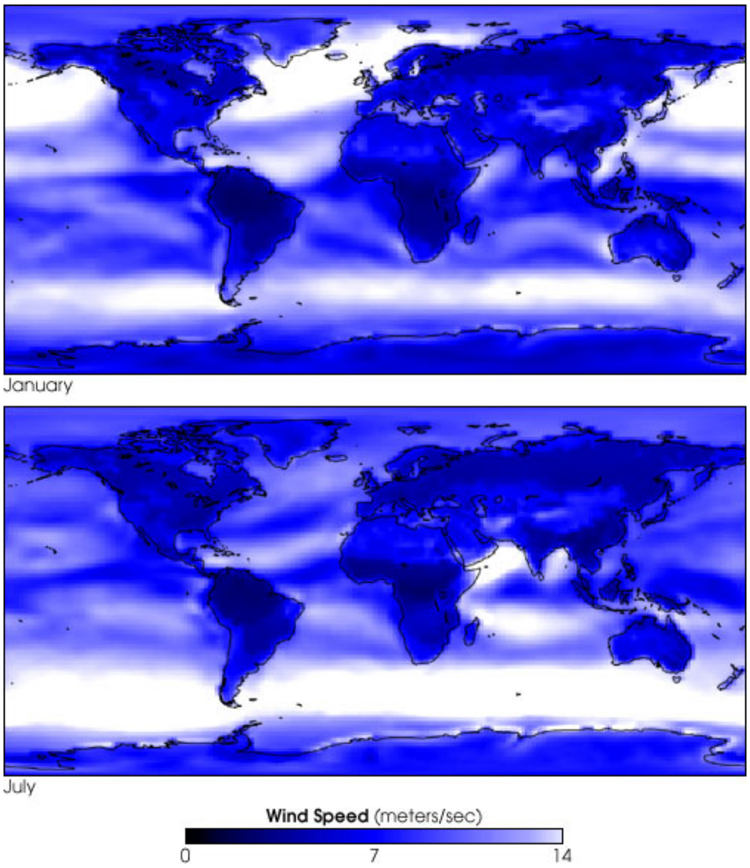


Figure 3.1: Global winds in January and July. Picture retrieved from https://earthobservatory.nasa.gov/images/1824/global-wind-speed

3.1.2 Energy in wind

The available power of the wind passing a wind turbine, $P_{available}$, depends on the wind speed, air density and the cross sectional area of the turbine, as given by the Equation 3.1:

$$P_{available} = 0,5 \times \rho \times A \times \nu^3 \tag{3.1}$$

where ρ is the air density in k/m^3, A is the cross-sectional area of the wind in m^2, and ν is the velocity of the wind in m/s. (Letcher, 2017)

3.1.3 Turbulence

Turbulence is the change of both wind speed and direction in the vertical and horizontal direction. All wind turbines is placed in the lowest part of the atmosphere, in what is known as the *planetary boundary.* In this part of the atmosphere, the wind is heavily influenced by terrain and obstacles, which produces turbulence. (Twidell, 2021)

The turbulence may be given as a non-dimensional factor, known as *turbulence intensity (l)*, which is the standard deviation of the instantaneous wind speed, divided by the average wind speed. (Twidell, 2021)

3.2 Wind modelling

3.2.1 Weather reanalysis and ERA5

Reanalysis is a process that combines observations from different sources, such as weather stations, satellites, and ocean buoys, with a weather model to create a consistent record of weather conditions over time. (Hersbach et al., 2023)

ERA5 is a weather reanalysis model that include weather data in Europe from 1940 to 2023, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset includes global climate variables at high spatial and temporal resolutions. It covers the period from 1940 to present and is updated regularly. Variables included in ERA5 data are temperature, humidity, wind speed, precipitation, sea level pressure, and many others. (Hersbach et al., 2023)

Due to ERA5 data being publicly available and of relatively high quality, it is widely used in climate research, weather forecasting, environmental monitoring, and various other applications. It is a significant improvement over its predecessor, ERA-Interim, as it has better spatial resolution, a larger database and better representation of various atmospheric processes. (Hersbach et al., 2023)

In ERA5, the weather data provided within a grid cell represents values for the entire area rather than a specific point within it. Each grid cell in the dataset contains gridded data representing an average value over the spatial extent of that cell. The size of the grid cells in ERA5 varies depending on the variable and the chosen spatial resolution, but they typically range from about 0.25 degrees to 1 degree in latitude and longitude. (Hersbach et al., 2023)

The size of the grid cells is important to consider when using the data for analyses that require high spatial precision, such as analysing wind power generation. The wind speeds at the actual site may therefore differ from the values provided by ERA5, as the wind speeds varies according to topology and other factors. In sites where no recordings of wind data exists, ERA5 data is a good alternative for predicting wind power production. It must however be kept in mind that the data may be inaccurate at some sites with specific topologies, as well as in shorter time periods, such as in hourly time-series. When using longer time series, these inaccuracies tend to average out. Some sites may have a more consistent difference in wind speeds and directions, which may lead to more systematic errors. (Hersbach et al., 2023)

3.2.2 Wind speed and height

The wind generally increases with the height above flat ground. Near the ground the wind is affected by local obstructions, and will therefore vary considerably. Above this region, the wind speed will be more predictable, and may be estimated through a height to wind speed relation described in Equation 3.2. (Twidell, 2021)

$$v_z = v_g \times (\frac{z}{z_g})^{\alpha} \tag{3.2}$$

where v_z is the wind speed at height z, v_g is the wind speed at a baseline height z_g (typically 10 or 100 meters), and α is an exponential coefficient, which varies according to the surrounding terrain.

3.2.3 Wind speed distribution

The wind speed at a location does not strictly adhere to a normal distribution. All wind speeds are non-negative and the distribution is skewed to the right, as lower wind speeds generally are more likely than higher wind speeds. There is no clear consensus on which distribution that best describes this data, although the Weibull distribution seems to be the most widely used. (Yu, 2020)

The shape of this distribution depends on the chosen parameters. These are estimated based on recordings of wind speeds at site, and can then be used to forecast wind speeds. How the specific parameters are determined is explained in detail in "Data science for wind energy" (Yu, 2020), but will not be described further here.

3.2.4 Wind direction and change points

The main direction of the wind at a location will prevail over a certain time period, before it changes at a point. These fluctuations are often hard to predict, and the length of each of these periods vary significantly. The point in time where the main wind direction changes is called a *change point*. A study referred to in "Data science for wind energy" found 119 change points across one year at location, with the average time period of one main direction being 3,04 days. The longest period where one direction prevailed was 15,5 days, and the shortest period being 6 hours. This implies that wind direction and speed will be autocorrelated. These periods do not follow arbitrarily selected calendar periods, so adjusting based on dates and time of year will not be helpful. This makes it challenging to control for wind direction in a data model. (Yu, 2020)

3.3 Wind turbine technologies

3.3.1 Basic principles of a wind turbine

A wind turbine converts the kinetic energy in the wind to rotational energy. This is further used to produce electrical energy through a generator. (Letcher, 2017)

When wind encounters the blades of a wind turbine, it exerts a force on them. This force is a result of the air molecules colliding with the surface of the blades. The shape and angle of the blades are designed to efficiently capture this force. They are shaped to create a pressure difference between the top and bottom surfaces as air flows over them. This pressure difference generates *lift forces*, F_L, which is the force that causes the blades to move. In addition, a *drag force* F_D is acting against the direction of motion. The net force the blades experience is the *rotational force* F_{rotate}, which equals F_L - F_D. The blades are further attached to the rotor hub, also known as the *nacelle*. This is further connected to a main shaft that transfers the rotational motion to the generator. (Twidell, 2021)

To optimize energy capture, wind turbines often have mechanisms to adjust the pitch, or angle, of the blades. This allows the turbine to respond to changes in wind speed and direction. When wind speeds are too high or too low, adjusting the blade pitch maintains optimal rotational speed to prevent damages and to ensure stable energy production. (Twidell, 2021)

Wind turbines also have yaw control systems that allow them to turn and face into the wind. This ensures that the blades are always positioned to capture the maximum amount of wind energy, regardless of wind direction. This can be done in many different ways. Some WTs are passively steered towards the wind with a fan tail. Others uses active steering through side rotors or motors inside the nacelle. (Twidell, 2021)

3.3.2 Generator

The rotating shaft is connected to a generator, where the rotational energy is converted to electrical energy. The generator consists of two main parts, a *rotor* and a *stator*. As the rotor revolves around the stator, a voltage is induced. (Wildi, 2021)

A synchronous generator requires the frequency of the generator to match the frequency of the grid. This means that the rotational speed of the rotor, and consequently the rotation of the WT must be held constant. However, one may couple this with an inverter, which allows the generator to rotate independently of the grid frequency. (Twidell, 2021)

An asynchronous generator does not require the generator to be synchronised to the grid frequency. These generators are therefore the most frequently used for wind turbine applications. (Twidell, 2021)

3.3.3 Dimensions of wind turbines

The *hub height* of a WT refers to the height of the rotor hub above ground level. The height of turbines varies, and has tended to increase from year to year. Offshore turbines are generally taller than onshore turbines. (Letcher, 2017)

The *rotor diameter* of a WT refers to the diameter of the cross-sectional area swept by the blades. This tends to be related to the maximum power output of the turbine, as the greater area swept, the more energy it may capture from the wind. (Letcher, 2017)

According to data from NVE, the average hub height of Norwegian grid-connected onshore wind turbines is 88 meters, while the average rotor diameter is 108 meters. An overview of the dimensions of the wind turbines selected for this study can be found in Section 4.

3.3.4 Geared and directly driven wind turbines

Wind turbines can be split into two categories, namely *geared* and *directly driven* turbines. A directly driven turbine drives the generator directly, where the rotational speed of the generator will vary according to wind speeds. A geared wind turbine includes a gearbox between the rotor and the generator that ensures an optimal rotational speed in the generator. (Twidell, 2021)

A geared turbine offers an advantage as it will be more efficient in a greater range of wind speeds. However, a directly driven turbine is a simpler construction, with fewer moving parts, and may as such be less vulnerable to wear and tear in the machinery. (Twidell, 2021)

3.3.5 Tip-speed ratio

The tip-speed ratio λ is the ratio between the wind speed and the speed of the tip of the blade, and follows Equation 3.3:

$$\lambda = \frac{v_{tip}}{v_{wind}} \tag{3.3}$$

where v_{tip} is the speed of the tip of the blade and v_{wind} is the wind speed.

The optimal tip-speed ratio varies between different types of turbines. For the ordinary 3-bladed turbine the maximum efficiency is at $\lambda \approx 4$. This is a result of more advanced calculations that is not further discussed here.(Twidell, 2021)

3.3.6 Power coefficient and the Betz limit

A wind turbine cannot utilize all the energy in the wind, as the wind must continue past the turbine to keep the turbine moving. The power coefficient Cp is a measure of how much energy a wind turbine produces, relative to how much energy the wind contains. It is given by the following Equation:

$$Cp = \frac{P}{P_{Available}} \tag{3.4}$$

, where P is the power output of a WT, and $P_{Available}$ is the available energy in the wind as calculated in Equation 3.1. (Twidell, 2021)

The theoretical maximum Cp of a WT is at 59,3%, which is known as the Betz limit. This is a simplification of the more advanced Glauert-criterion, which states that the optimal tip-speed is at the speed of sound, 353 m/s. This criterion converges with the Betz limit at high values of λ. (Twidell, 2021)

3.3.7 Wake loss

As the wind passes through a wind turbine, some of the kinetic energy will be lost. This will affect the area behind the turbine, in the turbine´s wake, and is therefore known as wake loss. This effect must be considered when designing a wind farm. The spacing between wind turbines must be large enough to minimize this effect. This contradicts the need for utilizing the natural areas effectively. The spacing of turbines must therefore meet a compromise between these opposing factors. Calculating the wake losses in a wind farm is complicated, but may be a significant factor affecting its performance. When simulating the power production of a wind farm, the wake loss is estimated based on recordings at the site, where the wind speed is reduced to account for the observed wake loss. (Twidell, 2021)

3.3.8 Rated wind speed

A wind turbine is designed to produce power within a specified range of wind speeds. The *cut-in speed* is the lowest wind speed where the wind turbine produces power, which is typically at between 2-4 m/s. As the wind speed increases, the power output will also gradually increase towards its rated power output, which it reaches at its rated wind speed, typically in the range of 10-14 m/s. When exceeding this limit, the turbine will adjust its blades to limit the output to prevent damages to the equipment. The *cut-off speed* is the highest wind speed where the turbine produces power. If the wind speeds exceeds this limit, the turbine is shut down. (Letcher, 2017)

3.3.9 Maximum power output and yearly energy production

A wind turbine is constructed to produce a certain power output, known as rated power output, which it reaches at rated wind speed. This is normally given in MW, where most onshore Norwegian wind turbines have a power output in the range 1-5 MW. The average yearly production is given in MWh or GWh, and is based on actual production data at the site. In addition to depending on the power output of the turbines, this also depends on the wind resource at the site and other factors.(NVE, 2023c)

3.4 Wind turbine performance

3.4.1 Power curve and power coefficient curve

The output of a wind turbine is characterized by its power curve. This is a plot of the WTs energy output at varying wind speeds. An example of this can be seen in Figure 3.2, where the power curve of a Vestas wind turbine is shown (blue curve). This shows how the WT starts power production at a specified cut-in speed. From this point the output increases as the wind speed increases, until it reaches it rated output at rated wind speed. As the wind speed increases further, the output is held more or less constant, until it reaches cut-off speed, where the WT is shut down. These curves can be used together with wind speed data at the site to estimate the power production of the turbine. (Twidell, 2021)

The power coefficient curve plots the power coefficient, Cp, at varying wind speeds. This can be seen in Figure 3.2 (red curve). As can be seen in the plot, the efficiency rises rapidly up to a certain point, slightly before the WT´s rated wind speed. From this point, the C_p decreases to maintain a constant power output.

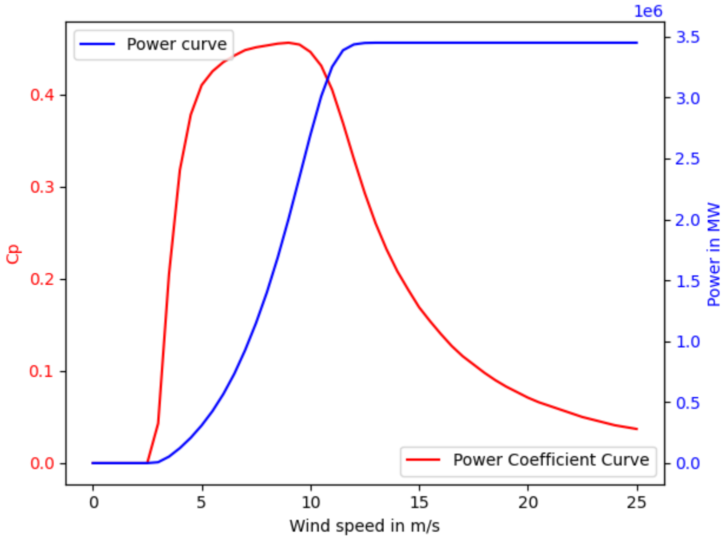


Figure 3.2: Power curve and power coefficient curve of V112-3.45 MW turbines used in Hamnefjell wind farm.

3.4.2 Capacity factor

Capacity factor (CF), also known as load factor, is a regular measure of the performance of power generators, such as a wind turbine. For wind energy, this is defined as the actual production of a wind farm, divided by the theoretical maximum output. It typically averages in the region of 20-40% over one year, depending on technology and weather conditions.(NVE, 2023c)

3.4.3 Full load hours

Full load hours is the amount of hours a wind farm must produce at maximum capacity to account for the total production in a year. It can also be the basis of calculating CF, as CF can be defined as Full load hours divided by the total number of hours in a year (8760 hours). (NVE, 2023c)

3.4.4 Availability

Availability is a measure of the amount of time a wind farm is available for production. This is given in percentage, and is estimated based on the number of hours the wind farm produced energy, divided by the total number of hours the wind speeds were in a range that allowed operation. (NVE, 2023c)

Downtime is the period of time where a wind farm is unavailable. A wind farm is in the model presented in this thesis defined as unavailable if the power output has been zero over a period of at least three hours. This is done to account for any inaccuracies in the weather data that may arise due to challenges described in Section 3.2.1.

3.4.5 Performance index

The performance index (PI) shows how much energy a wind farm produces, relative to what one would expect based on the available resources. This is a more complicated calculation than capacity factor, as it makes use of both production data, weather data and the specifications of the specified wind farm. The performance index follows the relation described in 3.5.

$$PI = \frac{E_{produced}}{E_{expected}} \tag{3.5}$$

where PI is the performance index, $E_{produced}$ is the amount of energy produced in a period of time in kWh, and $E_{expected}$ is the amount of energy the wind farm is expected to produce based on the wind resource in kWh.

A performance index of 1 implies that the wind farm produces energy as expected based on the wind speed at the site. Values greater than 1 indicate that the wind farm produces more than expected. Conversely, values less than 1 indicate that it produces less than expected.

Since this index accounts for changes in weather, it is a more accurate measure of the performance of a wind farm than capacity factor. It is however a more complicated approach, it may be harder for the industry to adopt this method, and the use of capacity factors may be sufficient for most purposes. As this also introduces some potential error sources, specifically due to inaccuracies in the weather data, it may in some cases be less accurate. How these calculations are made and how sources of error are handled is described in depth in methodology.

NVE uses the term "production index" to describe the same relation between expected and actual production. This number is however only given for all Norwegian wind farms as a whole, and is based on comparisons to observations in previous years rather than simulations based on weather data.(NVE, 2023c)

3.4.6 Degradation and performance loss

A wind turbine will experience a loss in performance over its lifetime, due to wear and tear in the components. The amount of degradation can be found by analysing changes in the performance of the turbine over time. This is typically done through linear regression, and thus finding an average yearly degradation. The usual way of doing this is by analysing the capacity factor, which is the main method used in the available literature on this topic, such as in OB17 and SG14 (Staffel & Green, 2014) (Olauson et al., 2017). However, one may also make use of other measures of performance to find this trend.

The causes of degradation has not been studied to a large degree, but it is however known that exposure to salt, such as in coastal areas may cause corrosion, and thereby loss in performance (Olauson et al., 2017). Also the effects of icing and snow is known causes of downtime of Norwegian wind farms, as can be seen in NordPool´s maintenance logs (*Nord Pool - Market Messages*, n.d.).

In OB17, two significant factors affecting degradation are found. The age of the turbine was found to be significant, as older WTs degrades faster than newer ones. Also, WTs placed in forests degraded slower compared to those placed in more open environments. No conclusion is drawn as to why this is the case, but it is discussed whether the exposure to higher wind speeds and salt spray (WTs in the open typically are located on the coast) may be a contributing factor in increasing degradation. (Olauson et al., 2017)

3.4.7 Windpowerlib

By combining weather data and information on the wind turbines in a wind farm, it is possible to simulate the performance of the wind farm. Windpowerlib is a Python library with information on a wide range of wind turbines. With information on how many of a certain type of turbine a wind farm consists of, combined with weather data at the site, one is able to predict the expected power output. This method has some limitations, and it is necessary to do some simplifications, as the dynamics of wind are quite complicated. The model will be increasingly accurate as one gather more accurate weather data and information of the site, such as wake loss, distribution of the turbines and surrounding terrain. Publicly available data can be quite limited regarding information on this, which is a clear limitation that must be considered when utilizing this tool.(Haas, 2019)

3.4.8 Power output data

NVE publishes a public dataset containing hourly energy production at all Norwegian wind farms. There is no public access to the individual power output of each WT. This is a challenge when modelling wind power, as the individual performances of WTs may vary within a wind farm. Production data containing hourly-time series could hide relevant information, as the power output will vary over this time period. A study of a 30-minute time-series weather model shows that about 50% of instances of zero production is hidden. This number is probably higher in an hourly time-series. This will not have great impact on a study such as this, but could be significant for energy systems relying on the constant energy production of a wind turbine. (Ward, Bamisile, Ejiyi, & Staffel, 2023)

3.5 Financial considerations of wind power

3.5.1 LCOE

LCOE stands for Levelized Cost Of Energy, and is a measure of the average cost of producing one energy unit. In Norway this is typically measured in øre/kWh. The calculation takes into account both investments costs and operational and maintenance costs, divided by the average energy output over a year. It is described by the following relation:

$$LCOE = \frac{I_0 + \sum_{t=1}^{n} \frac{A_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{M_{t,el}}{(1+r)^t}} \tag{3.6}$$

where I_0 is total investment costs, A_t is annual operational and maintenance costs,$M_{t,el}$ is the amount of energy produced in kWh per year, r is the interest rate, n is the expected lifetime of the installation and t is the number of years it has operated.(NVE, 2023a)

LCOE is useful when comparing the costs of various power producing technologies, as it gives a fair estimate of the average cost of an installment over its lifetime. Renewable energy alternatives such as wind, hydro and solar are typically characterized by relatively large initial investment costs, which can be a barrier for investing in these technologies. However, low annual costs due to no need for fueling and little need for maintenance, makes renewable technologies among the cheapest alternatives available.(NVE, 2023a)

3.5.2 How wind power affects electricity prices

LCOE does not translate into low electricity prices directly, as there are several factors affecting this. The main issue with wind power is the intermittency of wind, which makes the reliability of the power generation relatively low. A power system that depends to a large degree on wind power may experience large fluctuations in electricity prices. To even out such variances, it may be necessary to have backup systems, which in turn will increase the total costs in the power system. Studies from other countries, such as Australia and Denmark, indicate that larger shares of wind power contributes to lower electricity prices in general, but also increases the fluctuations in prices (Mwampashi, Nikitopoulos, Konstandatos, & Rai, 2021). In Norway, similar studies have indicated a positive relation between share of wind power in the power system and electricity price volatility (Gjerland & Gjerde, 2020). This is however a topic of much debate, and the effects will likely vary between countries.

3.6 Linear regression

In linear regression, it is assumed that there exists a linear relationship between the independent variables (X_i) and the dependent variable (Y). This relationship can be represented as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon$$

where: Y is the dependent variable. X_i are the independent variables. β_i are the parameters of the model. ε represents the error term, which captures the difference between the observed and predicted values of Y. (Wackerly & Schaeffer, 2008)

3.6.1 Least squares estimation

The goal in linear regression is to estimate the parameters that minimize the difference between the observed values of the dependent variable Y and the values predicted by the model. This is typically done using the method of least squares. Mathematically, this can be expressed as:

$$\text{minimize} \sum_{i=1}^{n} (Y_i - (\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik}))^2$$

where n is the number of observations.(Wackerly & Schaeffer, 2008)

After the parameters are estimated, they must be understood in the context of the problem. For example, β_1 represents the change in the expected value of Y for a one-unit change in X_1, holding all other variables constant.(Wackerly & Schaeffer, 2008)

3.6.2 Assumptions

Linear regression relies on several assumptions, including linearity, independence, homoscedasticity and normality of errors. (Wackerly & Schaeffer, 2008)

Linearity

The relationship between the independent variables (X_i) and the dependent variable (Y) is assumed to be linear. This means that the effect of a one-unit change in any independent variable on the dependent variable is constant, regardless of the values of the other independent variables.(Wackerly & Schaeffer, 2008)

Independency

The observations used to estimate the regression model should be independent of each other. The value of one observation should therefore not be influenced by the values of other observations. Independence ensures that each observation contributes new information to the model estimation process and prevents bias in parameter estimates.(Wackerly & Schaeffer, 2008)

Homoscedasticity

The variance of the errors (ε) should be constant across all the independent variables. This means that the spread of the residuals should be approximately the same across the range of predicted values. If the variance of the errors is not constant, the model's predictions may be unreliable, especially for extreme values of the predictors.(Wackerly & Schaeffer, 2008)

Normality of Errors

The errors (ε) are assumed to be normally distributed with a mean of zero. This assumption is important for hypothesis testing and constructing confidence intervals for the regression coefficients. The normality assumption is less critical for large sample sizes, but violations of normality can affect the precision and accuracy of statistical inference.(Wackerly & Schaeffer, 2008)

3.6.3 Evaluation of the model

After fitting the linear regression model, it is important to evaluate its fit and consider whether the model captures the relationship between the variables. This can involve examining diagnostic plots, such as residual plots, and performing hypothesis tests, such as testing the significance of the coefficients. Confidence interval is also used to evaluate the result. (Wackerly & Schaeffer, 2008)

3.6.4 p-value

The p-value in statistics is the probability of obtaining at least as extreme values as the observed values in a hypothesis test. This assumes that the null hypothesis is correct. A p-value less than the significant level would result in rejecting the null hypothesis. (Beers, 2024)

3.6.5 Confidence interval

A confidence interval is an interval which is estimated to cover the true parameter with a pre-determined significance level α. A significance level α is interpreted as the probability that the interval covers the true parameter. When the statistical parameter θ is unknown, a T-critical value and standard error to θ is used instead of a Z-critical value and the standard deviation to the parameter. The calculation is conducted on a given data set, where the upper limit are estimated by adding a term consisting of a T-critical value times the estimated standard error to the parameter that the confidence interval are estimated for. The lower limit are calculating by subtracting this term. (*Confidence Intervals*, 1997) This is shown in Equation 3.7:

$$\hat{\theta} \pm t_{\alpha/2,n-2} * SE(\hat{\theta}) \tag{3.7}$$

, where $\hat{\theta}$ is the estimated parameter to which the interval is constructed for. $t_{\alpha/2,n-2}$ is the T critical value and $SE(\hat{\theta})$ are the estimated standard error to the estimated parameter. (*Confidence Intervals*, 1997) The standard error are estimated using Equation 3.8:

$$SE(\hat{\theta}) = \frac{\sigma}{\sqrt{n}} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \times \frac{1}{\sqrt{n}} \tag{3.8}$$

, where n is number of observation, y_i is true observation $\hat{y_i}$ is the predicted observation. x_i independent variable of the observation and $\bar{x_i}$ is the average over all observations. (*Variance, Standard Deviation and Standard Error*, 2024)

The pooled standard error is used to calculated the confidence interval to the final result in this thesis. A measurement is an weighted average of the standard error to multiple groups. More weight are given to groups with larger samples sizes. In this thesis, the two groups compared have equal sample size, resulting in an equal weight. (*Pooled Standard Deviation: Formula, Definition, Example*, n.d.) This is calculated by Equation 3.9:

$$SE_{pooled} = \sqrt{\frac{(n_1 - 1) * SE_1^2 + (n_2 - 1) * SE_2^2}{n_1 + n_2 - 2}} \tag{3.9}$$

, where n_1 and $n_2 - 1$ are the samples to respectively group 1 and group 2. SE_1 and SE_2 are the estimated standard error to group 1 and 2. Degrees of freedom are also included in the expression and are represented by: $n_1 + n_2 - 2$. (*Pooled Standard Deviation: Formula, Definition, Example*, n.d.)

3.7 Regression with Seasonal ARIMA errors

In order to be able to utilise linear regression with autocorrelated residuals, ARIMA or seasonal ARIMA is used. By modeling residual error from the linear regression with the ARIMA model, the autocorrelation is corrected. (Date, u.d.)

The ARIMA model comprises seven components. *The auto-regressive* component is a linear combination of past values from the time series, with a specific number of lags, p, permitted. The equation for this parameter is illustrated in Equation 3.10. (Date, u.d.)

$$y_i = \widehat{\phi}_1 y_{i-1} + \widehat{\phi}_2 y_{i-2} + \cdots + \widehat{\phi}_p y_{i-p} + \epsilon_i \tag{3.10}$$

, where y_i is observed value at time step i. ϕ_i are the fitted regression models coefficients. ϵ_i represents the residual error of the model at time step i. The order p is determined by applying a combination of rules. The rules for establishing the parameter can be further read in *Forecasting: Principles and Practice* written by Rob J Hyndman and George Athanasopoulos. This is not part of the scope in this thesis. Date (u.d.)

The second component to the ARIMA model is the *The moving Average*. This is a linear combination of the past model´s past errors up to a p number of lags. The errors are calculated by subtracting the past prediction from the actual values. The expression for this component are visualized in 3.11 Date (u.d.):

$$y_i = -\widehat{\theta 1} \epsilon_{i-1} - \widehat{\theta}_2 \epsilon_{i-2} - \cdots - \widehat{\epsilon}_p y_{i-q} + \epsilon_i \tag{3.11}$$

, where y_i is the observed value at time step i. $\widehat{\theta}_i$ are coefficient from the fitted regression model. ϵ_i is the residual error of the regression at time step i. q is the order of the moving average component. Date (u.d.)

By combining these two components, the expression looks like:

$$y_i = \widehat{\phi}_1 y_{i-1} + \widehat{\phi}_2 y_{i-2} + \cdots + \widehat{\phi}_p y_{i-p} - \widehat{\theta 1} \epsilon_{i-1} - \widehat{\theta}_2 \epsilon_{i-2} - \cdots - \widehat{\epsilon}_p y_{i-q} + \epsilon_i \tag{3.12}$$

If the time series has a trend, the ARMA model expressed in figure 3.12 cannot be used. If the dataset demonstrates a trend such as a linear, quadratic and exponential or logarithmic trend, a number of differencing is applied to remove the trend. The first order is used to remove a linear trend. Second order and higher order remove polynomial trends. The order is denoted by the parameter d. Differencing is applied before the AR and the MA operation are applied. (Date, u.d.)

The ARIMA or Seasonal ARIMA model is an extension of the components above. A *Seasonal AR* (SAR) of order P, a *Seasonal MA (SMA* of order Q, and a *Seasonal Difference* of order D are implemented. A seasonal period m is the final parameter. The rules for establishing the values for P, D, Q and m can be further read in *Forecasting: Principles and Practice* written by Rob J Hyndman and George Athanasopoulos. This is not part of the scope in this thesis. (Date, u.d.)

If (p,d,q),(P,D,Q) and m are chosen correctly, the residual errors of the model would be expected to be independent, identically distributed (i.i.d.) random variable with zero mean and some constant variance. The residual errors would also be expected to not be auto-correlated.(Date, u.d.)

By modeling residuals in a linear regression model with the ARIMA model the auto-correlated is properly handled. The final model is called *Regression with Seasonal ARIMA errors (ARIMA).* (Date, u.d.)

4 Methodology

The methodology used in the thesis is mainly based on parts of the framework *Cross-Industry Standard Process for Data Mining*, or CRISP-DM. Data understanding and collection are important parts of the methodology. These parts of the framework lead to the data preparation, modelling and evaluation of the results (Chapman, Clinton, Kerper, Khabaza, & Shearer, 2000) The workflow is shown in Figure 4.1. The data used in the thesis, as well as the model used is further discussed.

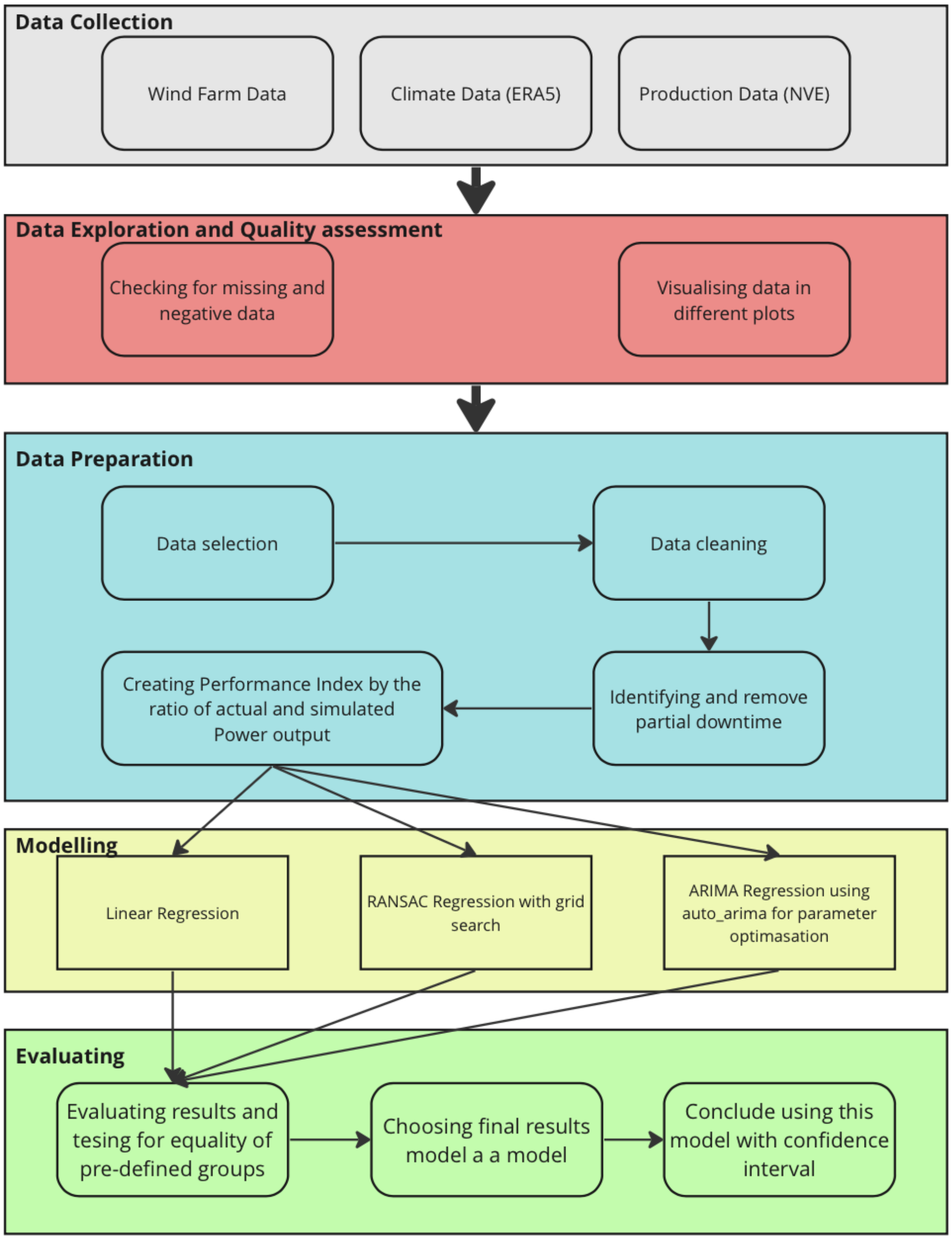


Figure 4.1: The workflow is shown in the figure using parts of the CRISP-DM framework.

4.1 Business understanding

The first phase of CRISP-DM is *Business Understanding.* This will lay the foundation for the rest of the project. In this phase it is determined what data will be collected and how the data will be managed. This is an important step in creating a model that is appropriate to achieve the objectives of the project. (Chapman et al., 2000)

As previously mentioned, this thesis builds on the work of another master thesis written at NMBU, ED24. Correcting for local wind resources in the modeling of the degradation rate is the main objective as low capacity factor can make the degradation rate look larger than it is.

The overall objective of the thesis is to estimate the degradation of Norwegian wind farms using a constructed performance index (PI). Calculating this index requires production data from the selected wind farms, as well as local weather data and information on the technical specifications of the wind farms. This includes turbine types, number of turbines and hub heights. PI is as mentioned the ratio between actual production and simulated production and will be the foundation to the estimation of degradation rate through a linear regression model.

It is also of interest to identify factors that contribute to an increase in the degradation rate. A geographical analysis of degradation will therefore be conducted to check whether there is a significant difference in degradation across the country. Moreover, it would be of interest to conduct an analysis to find whether the decline in performance is influenced by the different seasons of the year. Whether degradation rates are impacted by technological differences are also studied. Lastly, the degradation of newer and older wind turbines will be compared.

4.2 Data Understanding

The subsequent phase in the framework after *Business understanding* is *Data Understanding.* This includes collecting the required data as well as examining it. The understanding of the data used in the model is important. This include getting an understanding of the structure and quality in the data. This is essential to be able to process and construct it to fit the desired model. If the criteria are not met, new or more data should be collected. (Chapman et al., 2000)

4.2.1 Data Collection

Collecting data of good quality is fundamental to making a good model. As mentioned, different data sources will be used when modelling the degradation. The data sources used is:

- Production data from NVE
- ERA5 data set
- Data regarding different wind farms

Production data

Firstly, production data is retrieved from The Norwegian Water Resources and Energy Directorate (NVE). This is public production data in a hourly time-series format from 2002 to 2022. This data is retrieved from NVE´s website in an Excel file where each column correspond to one wind farm. The columns of wind farms installed in later years contain empty cells in years before installation. Statistics regarding all Norwegian wind farms are listed in Table 4.1.

Table 4.1: Statistics for modelling data

Description of production data	
Wind farms	65
Turbines	1392
Rated power output	5083 MW
Temporal resolution	Hourly
Wind farm capacity	0.225 - 400.0 MW
Average Wind farm capacity	78.2 MW
Median Wind farm capacity	54 MW
Commissioning period	1998- 2023

ERA5 Reanalysis

The climate data used in the simulation of power production are retrieved from Copernicus. The data is named ERA5 as this is the fifth generation ECMWF reanalysis. The dataset consist of data from 1940 till present time. A summary of the data properties are listed in Table 4.2. (Hersbach et al., 2023)

Data description	
Data Type	Gridded
Projection	Regular latitude-longitude grid
Horizontal Coverage	Global
Horizontal Resolution	Reanalysis: 0.25°x 0.25°
Temporal Coverage	1940 to present
Temporal Resolution	Hourly
File format	NETCDF (experimental)
Update frequency	Daily

Table 4.2: Description of ERA5 data

As mention in Theory, reanalysis data combines observations with model data creating a consistent worldwide dataset. ERA5 provides a hourly estimates on many different quantities. In this thesis five different measurements; *100m u-component wind, 100m v-component wind, Instantaneous 10m wind gust, Surface pressure, 2m temperature and Forecast surface roughness*, are retrieved from the ERA5 dataset.(Hersbach et al., 2023)

<u>100m u- and v-component of wind</u>

This parameter is the measurement of horizontal wind speed. 100m u-component is the measurement of air flowing towards east and 100m v-component is the measurement of air flowing north. The wind speed is measured in metres per second [m/s] at a height of 100 metres above the surface. Care should be taken when comparing model parameters with real observations as observations are bound to a specific geographical point at a specific time whereas the model parameter is an average over a model grid box. The u and v component are used to derive wind speed in a specific direction.(Hersbach et al., 2023)

<u>2m temperature</u>

2m temperature is the measurement of the temperature in the air. This is measured at a height of 2m above the surface, and the quantity is measured in Kelvin [K]. This parameter is calculated by interpolating between the lower model level and the surface of the Earth. The atmospheric conditions are also taking into account. (Hersbach et al., 2023)

<u>Forecast surface roughness</u>

Forecast surface roughness is the aerodynamic roughness length. This is a measurement of the surface resistance measured in metres [m]. This measurement is used to determine the air to surface transfer of momentum. Higher surface roughness cause a slower near-surface wind speed at determined atmospheric conditions. Surface roughness over land is determined from the vegetation type and snow cover at a specific site. (Hersbach et al., 2023)

Instantaneous 10m wind gust

At time t, this parameter refers to the maximum wind gust at that t. This is measured at a height of 10 m above the surface. Since the WMO definition of wind gust is shorter than the model time step, ECMWF extracts the magnitude of a gust within each hour from the averaged surface stress, surface friction, wind shear and stability. As a result, care should be taken when comparing model parameters with observations. Local observations is often specific to a specific geographic point and time. In other words, this does not represent an average over model grid boxes. (Hersbach et al., 2023)

Surface pressure

Surface pressure include the pressure of the atmosphere at the surface of land, sea and inland water. This is the vertical measurement of the weight of air at a specific point on the surface of the Earth. The unit used for surface pressure is Pascal [Pa]. (Hersbach et al., 2023)

ERA5 data is retrieved from `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form`. Several parameters must be defined when downloading data, including the geographical area and the time period of the request. All reanalysis data were downloaded with the chosen weather parameters mentioned above. However, during the thesis, *Instantaneous 10m wind gust*, was found irrelevant to the scope of this project. This parameter was therefore not used in the modeling.

The geographical area from which the data is to be downloaded must also be determined. For this project, the weather data at the location of each wind farm were downloaded separately. As the resolution of ERA5 data is 0.25°x 0.25°, the geographical area chosen was the rounding of the wind farm´s coordinates to nearest 0.1 in both directions. A more accurate geographical area was deemed unnecessary as the resolution of the data is worse than this rounding.

The time period and time resolution of the data must also be chosen. To get the best possible resolution, hourly data were downloaded. As there is a download limit of 120 000 data points per request, files consisting of two years of climate data at each area are downloaded separately. To limit the amount of data, only weather data for the operational years at each wind farm are downloaded.

When downloading data from Copernicus, a download request is sent to the database and in-queued. Whenever the request is first in line, the process of retrieving the data from the database starts. After a certain time the data are ready to be downloaded. A total number of 104 NETCDF files were downloaded containing the relevant climate data. These files were stitched together using Python to a total of 15 files, one for each wind farm.

Wind farm data

To be able to model different wind farms data regarding its position, the number of turbines and their hub heights are relevant. Wind farm data are imported from `https://pvexpect.com/Vind/Vindturbine_portfolio_2.csv`. This is a csv-file made by Jesper Frausig containing information about all wind farms in Norway and are based on information by NVE. Relevant data from the file was kept, and some data were added or updated.

Other data regarding wind farms is collected from each wind farm´s individual websites from NVE. This includes information such as first production year, number of turbines, maximum power output etc. As part of the quality check, the data from the mentioned csv-file was checked against the information from NVE.

Power curves are essential to model the power output in Windpowerlib. The library contains a set of different wind turbines with corresponding power curves. However, some turbines were not implemented in Windpowerlib and were missing a power curve. Turbines with missing power curve were:

- SWT-9.3-2300
- SWT-8.2-2300
- SWT-10.1-3000
- V27/225
- NM48/750

The power curves of the mentioned wind turbines were constructed manually in Excel by making a table of wind speeds with corresponding power output. The data has a resolution of 0.5 m/s. Power curves are gathered from `https://www.thewindpower.net/turbines_manufacturers_2_en.php`. Other relevant information regarding the turbine types were also retrieved from the same site. The construction of power curves was exported a csv-file which is then imported into Google Colab. Power coefficient curves were also constructed in the same spreadsheet using the power curve. The power coefficient is defined in Equation 3.4.

When modeling one wind farm, the model uses power curves from Windpowerlib. Whenever the model analyses one wind farm it checks whether the wind turbine is present in Windpowerlib or not. Whenever the object is not present, it constructs a turbine object with external information regarding hub height and rated power output. The power curve is constructed at standard air density using the `create_power_curve` -method with imported power curve data.

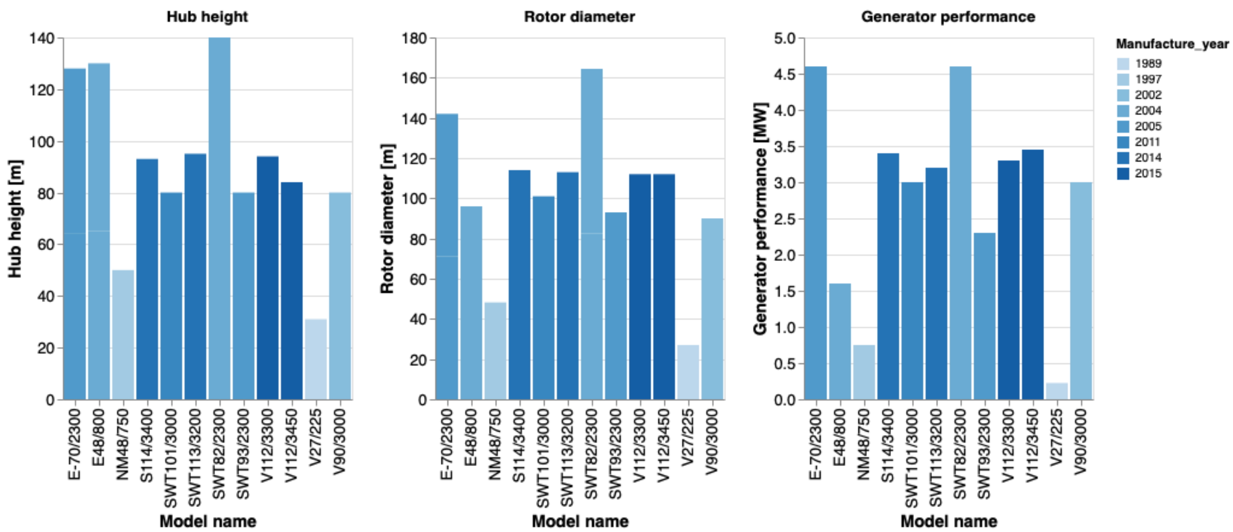


Figure 4.2: Bar plot showing the different dimensions of turbine types found in the selected wind farms.

There are multiple types of wind turbines found in the selected wind farms. These have different turbine dimensions. Figure 4.2 shows the different dimensions of the different turbine types.

Downtime can have great influence on the degradation rate wind farms. Classifying the downtime of the wind farms are of interest to be able to adjust for the downtime when analysing degradation. Nord Pool have published some maintenance reports with information regarding maintenance and therefore downtime. These reports have been downloaded for a manual inspection to try to match with registered downtime periods in the model. The maintenance logs includes an explanation of the downtime and whether the event was intentional or not. The duration of the downtime period is also registered here, as well as specifications on how much of the power output that was unavailable. Out of the selected wind farms only two had available maintenance reports, namely Egersund and Tellenes. These will be studied as examples to find information on typical downtime periods in Norway.

4.2.2 Data Exploration and Quality assessment

To ensure good modelling results, data of good quality is necessary. When all data is collected, the data must be visualized. A quality assessment of the data is also necessary to ensure that the data are complete without any missing values. An assessment of the correctness of data must then be committed. This showed that Valsneset wind farm included data out of range, as it included negative values. Some production data were also found to be greater than their rated power. If the data consist of errors decisions regarding the treatment of errors must also be made. (Chapman et al., 2000)

4.3 Data Preparation

All activities necessary to feed the final dataset into the model is covered by the *Data Preparation* phase. This phase can be redone multiple times and include table, record and selecting data. Cleaning and transforming data into a final format is also included in this phase. (Chapman et al., 2000)

4.3.1 Select data

One should decide on what data subset is to be used in the model. Data should be selected based on objectives, quality and technical constraints. This includes limitations to data access and volumes, which in turn may affect the results. (Chapman et al., 2000) Specific Norwegian wind farms have also been chosen to narrow the scope of the project, which were chosen based on the previous master thesis, ED24, to get a basis for comparison.

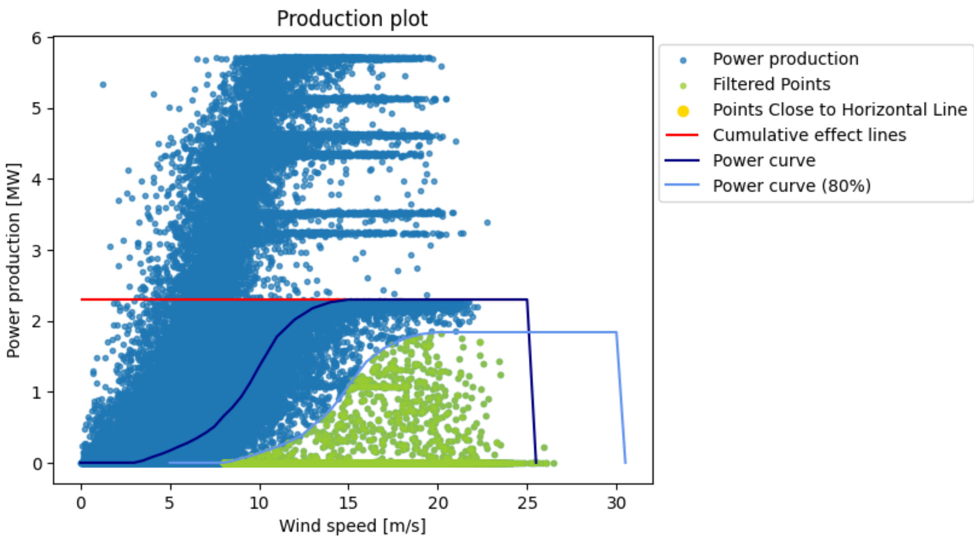


Figure 4.3: The production plot show that Karmøy Hywind produces more than its rated power as many production points are above the red line.

The main requirement for the selected wind farms was that they only had one installation. Including wind farms with several installations would be a challenge when modelling degradation, as their production would not be comparable over their lifetime. With only one installation, all the turbine have the same age. Having the same turbine type is also an advantage when modelling degradation.

Karmøy Hywind was removed from the selection of wind farms as this was found to be an offshore wind farm. In a dataset published by NVE, it was registered with coordinates on land. The production data was also discovered to be incorrect as the production in later years were higher than its rated power. This can be seen in Figure 4.3. It was discovered that the numbers of turbines was wrong in NVE´s database as Karmøy Hywind consists of two turbines, as a new turbine was installed in 2021 in that area by Shell. (Rustad, 2021) After removing wind farms that did not fit the criteria, 15 wind farms are selected for further study. These are listed in appendix A.

The locations of the selected wind farms are displayed in Figure 4.4. As can be seen here, the wind farms are all located near the coast of Norway. There are mainly three clusters, one in south-west Norway, one in mid Norway and one north in Norway. These belong to respectively price zones NO2, NO3 and NO4. These areas will further be used to study the impact of the local climate.

As the production data from NVE have records from 2002 and onwards, a subset of the

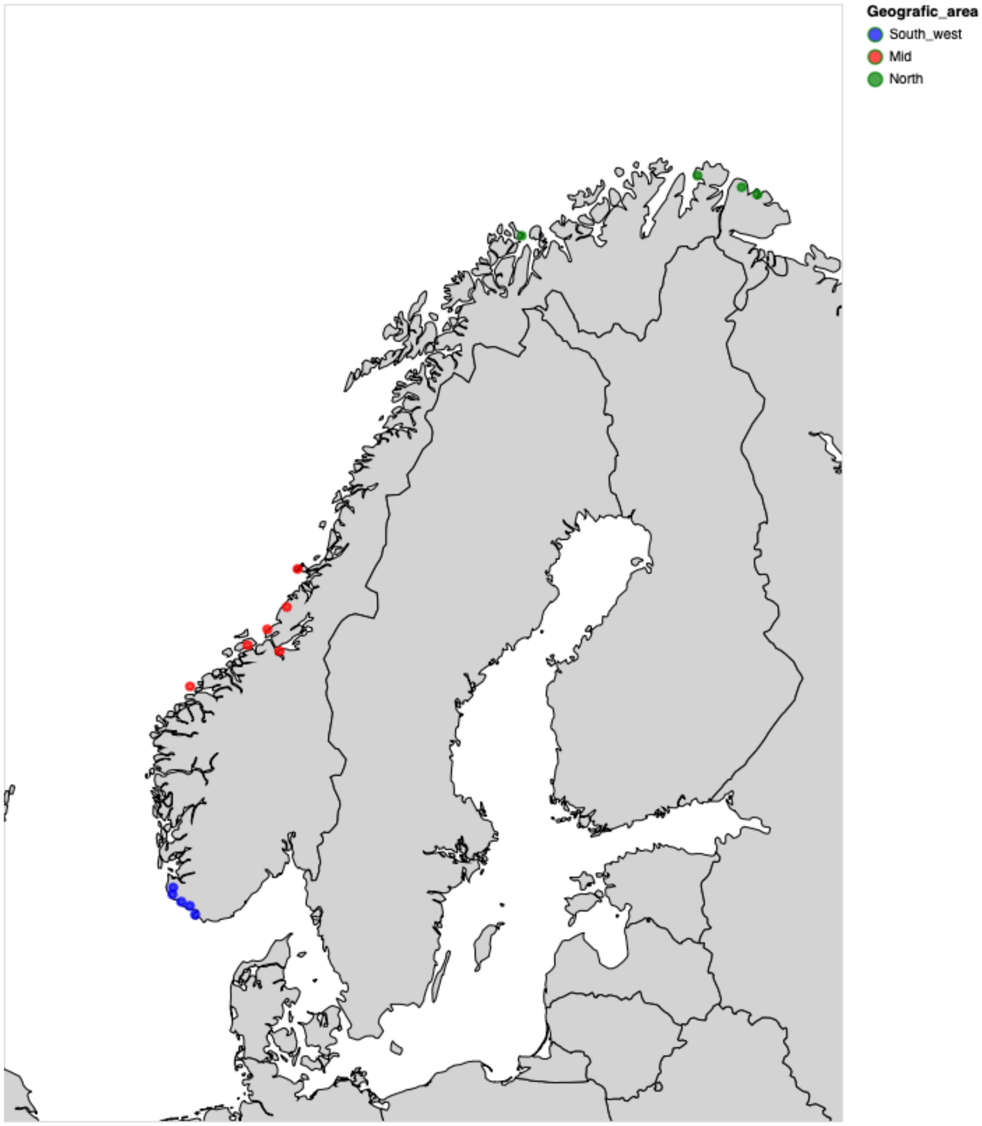


Figure 4.4: Map showing the location of selected wind farms in Norway. The wind farms are color coded showing the different geografic clusters. Blue, green and red colors represent respectively south-west, mid and north clusters.(Frausig, 2023)

climate data are also chosen from 2002. This means that the first production years at Sandøy are not in the data set.

4.3.2 Data cleaning

Data cleaning is an essential part of the data management. Missing entries or data out of range may be a concern and can lead to inaccurate results (Chapman et al., 2000). The non-selected wind farms are removed from the production data set to make the model more efficient. The data should be at a certain level of quality to be able to trust results from the model. This may include choosing a subset of clean data, insertion of suitable defaults, and techniques for estimating missing data. (Chapman et al., 2000)

Furthermore, the timestamps containing null before first production hour are removed from the time series. This ensures that the first timestamp at each wind farm corresponds to the first production hour. From the constructed downtime plots, it can be seen that the wind farms have quite significant downtime the first production year. This may have a large impact on the resulting degradation. The first production year is hence removed to ensure a more robust result, only using data from normal production years. This was also done in SG14, whereas OB17 only removed the first four month of production. (Olauson et al., 2017)

There were also discovered some irregularities in the data. Valsneset was the only wind farm affected by missing values. A total of 1104 hours had missing values since the commissioning year and onwards. Missing values in the time series were replaced by the average of the predecessor and successor of that timestamp. This was also the only wind farm containing negative production values. There were 334 cases of negative production values. These values were replaced by zero. Some of these production hours are considered downtime. All of the selected wind farms are affected by zero values. Production over rated power output are also occurring. These values are replaced by the maximum possible production for that hour. Further detail regarding the data statistics can be found in Appendix I.

4.3.3 Data construction

Construction of data include production of derived attributes or creating new records. Transforming values for existing attributes are also included in this task. This may include converting the data to the right format and/or concatenating different sets into a common dataset(Chapman et al., 2000)

The climate data are downloaded as netCDF files. This is a multidimensional data structure where wind speed in u- and v-component are kept separate. These components are used to calculate the magnitude of the wind speed in the specific direction. This is calculated by:

$$|\overrightarrow{V}| = \sqrt{u^2 + v^2} \tag{4.1}$$

, where $|\overrightarrow{V}|$ is magnitude of the wind speed, u is the wind speed in u- direction and v is the wind speed in v direction (*ERA5 - Documentation and user guides*, 2024).

To include the wind speed at each site, the objective is to include this parameter when constructing the regression model. The performance index is calculated by dividing actual production by simulated power output. This way the local wind resources are taken into account. The performance index gives an indication of how the wind farms performs.

4.3.4 Integrate data and formatting data

Combining information by merging multiple tables or creating new records or values may also be relevant before modeling. Formatting refers mainly to syntactic adjustment. This does not change the meaning of the data, but may be a requirement of the model. (Chapman et al., 2000) Windpowerlib requires the input data to have specific attributes and column names before simulating power output. A dataframe consisting of wind speed, temperature, pressure and surface roughness is required for the simulation. Figure 4.5 shows the format of datasets feed into Windpowerlib. Wind speed and temperature is also adjusted to the height specified in the ERA5 dataset. Wind speed are adjusted to 100 m above surface and the temperature are adjusted to 2 m above surface. The treated data are further to be used for modelling. This is also shown as a second header in the figure.

```
                     wind_speed temperature      pressure roughness_length
                            100           2             0                0
timestamp
2003-01-01 00:00:00   11.910254  275.244995  99773.328125         0.282934
2003-01-01 01:00:00   11.180261  275.018250  99758.476562         0.282808
2003-01-01 02:00:00   10.414387  274.884186  99696.031250         0.282669
2003-01-01 03:00:00    9.003632  274.677979  99646.765625         0.282486
2003-01-01 04:00:00    7.668620  274.779297  99579.882812         0.282225
...                         ...         ...           ...              ...
2022-12-31 19:00:00   11.575238  274.532867  98617.367188         0.282282
2022-12-31 20:00:00   10.949593  274.355011  98746.281250         0.282197
2022-12-31 21:00:00   10.749646  274.407074  98848.976562         0.281942
2022-12-31 22:00:00   10.836248  275.082123  98929.187500         0.278437
2022-12-31 23:00:00   10.247234  274.982361  99072.257812         0.279208
```

Figure 4.5: Screenshot of a dataset used to feed into Windpowerlib.

The data used in modeling have different properties. These are listed in Table 4.3. While there is some missing and negative values, are there quite many values that are zero or above the rated power. These are further treated. Properties regarding the selected wind farms are also listed in this table.

Table 4.3: Statistics and diagnostics for selected treated data.

Description of selected and treated production data	
Valid observations	1393761
Zero production [Count / [% of total observations]]	141464 / 10.15%
Negative production [Count / [% of total observations]	334/0.024%
Missing values [Count / [% of total observations]	1104/0.079%
Production over capacity [Count / [% of total observations]	14623/ 1.05%
Temporal resolution	Monthly/Weekly
Wind farms	15
Turbines	240
Total capacity	660.325 MW
Average Wind farm capacity	44 MW
Median Wind farm capacity	39.1 MW
Wind farm capacity	0.225 - 160 MW
Commissioning period	1999- 2017

4.4 Modelling

4.4.1 Selection of modeling technique

Selecting the modeling technique is the first step of modeling (Chapman et al., 2000). As discussed, linear regression was used for calculating degradation rates in the British and Swedish papers. As these assume a linear degradation, this is also assumed in this thesis. The recently written master thesis regarding the degradation of wind turbines at NMBU also used linear regression as the main model for estimating the degradation. Whereas the British and Swedish studies have taken the wind resources into account by using simulated wind as an expected power output, this is still yet to be done with Norwegian wind farms. The aim of this thesis is hence to include a simulated power output to correct the variation in wind speeds.

Linear regression is the main modeling technique used in this thesis. There are mainly four assumption when using a linear model. These are:

- Linearity
- Independence
- Homoscedasticity
- Normality

According to the first assumptions, there should be a relationship between the predictor variable (x) and the response variable (y). The residual should also be independent. This is especially important when working with time series data such as in this thesis. Any pattern in the residuals is unwanted. The assumption regarding homoscedasticity, tells that residuals should have a constant variance at every level of x. If this is not the case, the residuals are affected by heteroscedasticity. The results are not to be trusted when this assumption is not met, as the variance of the regression coefficient is too large. This may result in a model making statistically significant results when they are not. The fourth assumption tells that the residual should be normally distributed. (Bobbitt, 2020)

4.4.2 Sklearn Linear regression

A linear regression model from Sklearn is used to model in this thesis. This algorithm uses *Ordinary least squares*. `LinearRegression`-function fits a model by minimizing the residual sum of squares between the observations and the target predicted by the linear approximation. (scikit learn, n.d.)

4.4.3 RANSAC- algorithm

Results from the ordinary linear regression were impacted by outliers. An outlier is a data point/observation that lies an undesirable long distance from the majority of observations.

As a result, outliers have great leverage and impact on the results of the regression model. (*Statistical Methods: Process Monitoring Charts*, n.d.)

There are multiple statistical tests and ways to detect and treat outliers, which leaves the analyst to make a subjective decision on these matters. To classify an observation as an outlier, the normal observation has to be characterized first. In this thesis an algorithm called RANSAC is used in the attempt of automatically detecting outliers.

Random Sample Consensus (RANSAC) is a method for addressing and treating outliers when conducting regression analysis. Rather than removing outliers, the algorithm selects a subset of the dataset, which are then classified as inliers. These observations serve as the complement to outliers. (Raschka & Mirjalili, 2017)

The algorithm initially selects a random number of samples to be inliers. Subsequently, the model is fitted with the selected observations. The remaining observations are then compared with the fitted model. Those that are within a user-defined distance to the model are then classified as inliers. The model is then fitted again using all observations classified as inliers. An estimation of the error between the fitted model and inliers is then calculated. The algorithm runs through all steps until it meets a specified criteria by the analyst or if it reaches a specified number of iterations. (Raschka & Mirjalili, 2017)

The algorithm has several hyperparameters to be optimized. The minimum number of observations to be used for fitting is determined by the parameter `min_samples`. The parameter `max_trials` restricts the algorithm in the way that it terminates the algorithm if it reaches a certain number of iterations. Those observations that are closer to the fitted model than the `residual_threshold` hyperparameter are classified as inliers. The `loss` hyperparameter is used to measure the residuals or loss. (Raschka & Mirjalili, 2017)

Selecting an appropriate value for the various hyperparameters can be a challenging task, as it my depend on the specific case in question. In this thesis a method known as *grid search* is used in order to optimise the performance of the model. This method is used to identify optimal combinations of values for hyperparameters. Grid search is a relatively straightforward method, as it runs through a model multiple times with a set of different values for each hyperparameter. Upon completion of the model, it will return the optimal value for each chosen hyperparameter. This approach is however computationally demanding and time consuming, but can result in a higly performing model. (Raschka & Mirjalili, 2017)

In this thesis, grid search are utilized to optimise `min_samples`, `max_trials` and `residual_threshold`. With a set of different values the model has attempted to return an optimal combination these. However, to prevent the model from becoming too simple, a certain amount of samples and trials are needed to prevent underfitting. During the optimisation process, a number of the lower values very removed as the model choose hyperparameters that made the model too simple. This returned worse outcome when the entire model was fitted with the selected hyperparameters. (Raschka & Mirjalili, 2017)

4.4.4 Linear Regression with ARIMA errors

Due to dependent residuals in the data, a Linear regression model with ARIMA residual was also used in the thesis. An ordinary least squares -model, `OLS`, from statsmodel was used to fit the original model. (*statsmodels.regression.linear_ model.OLS*, 2023) This library works quite well when analyzing autocorrelated data as this python-package also has functions for making autocorrelation plots and ARIMA models. A plot was used to visualize the autocorrelation between residuals. This was done by using the `plot_acf`-function. (*Time Series Plots — statsmodels*, 2023)

To account for the variability in data to different wind farms, an auto-ARIMA model was used. This model is fitted several times with different values to the mentioned parameters (p, d, q)x(P, D, Q, S) to ensure the best possible output. An `auto_arima` model from the Python package pmdarima is used in this thesis. This model discovers the optimal order for an ARIMA model automatically. This is achieved by testing many combinations of the mentioned parameters. The identified optimal parameters are used in a final fitted ARIMA model. (Smith, n.d.)

`Auto_arima` determines the optimal differencing (d) by conducting different tests. Kwiatkowski–Phillips–Schmidt–Shin, Augmented Dickey-Fuller, or Phillips–Perron are some tests that are conducted. To limit the search for optimal parameters model parameters are set before fitting the model. `start_p`, `max_p`, `start_q`, `max_q` are set making ranges of 1-3 for both parameters p and q.(Smith, n.d.)

The `seasonal`-parameter is set to `True` as the Production Index is affected by seasonal patterns. Seasonal differencing is found by conducting a Canova-Hansen test. Furthermore the model seeks to find optimal P and Q-parameters by by testing with different values. (Smith, n.d.)

There are multiple criterias to use when optimizing the model. In this thesis, an information criterion called *Akaike Information Criterion* is used (AIC). The model returns the ARIMA parameters that minimize the AIC value. (Smith, n.d.)

4.4.5 Generate test design

A method for measuring the quality and validity of the model is important before making the model. Since linear regression is a supervised model where the target value is known, the data is split into two datasets; training and test set. The model is fitted or modelled on training data and the test data is used to make an estimation of the models quality. It is important to keep the test set unseen to the model until the quality assessment of the model. (Raschka & Mirjalili, 2017)

Residual plots are also used to discover non-linearity and outliers. They are also used to check if errors are randomly distributed. Since, a model realistically never would make a perfect prediction, observation is not align with the zero-line. However, if the residual are randomly scattered around the line, it would indicate randomly distributed residuals. This would fulfill the assumption $e \sim N(0, \sigma^2)$. A pattern in the residual plot would however indicate that some of the variance within the data are not captured by the regression model. Outliers can also be observed in residual plot if single data points are observed with a great distance from the centerline. (Raschka & Mirjalili, 2017)

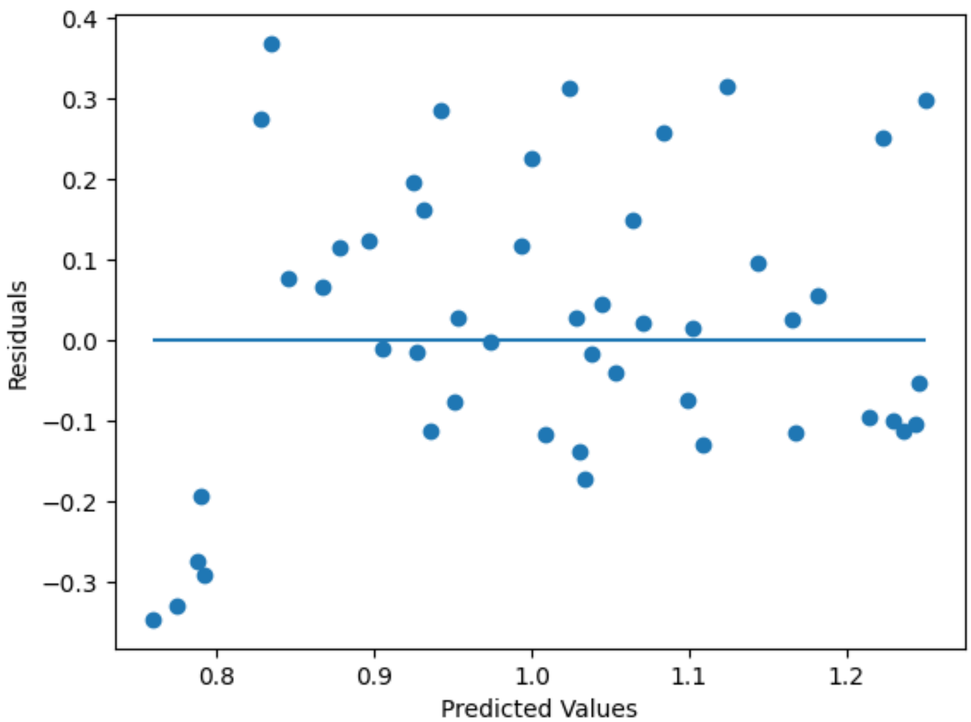


Figure 4.6: Residualplot showing the variance within the residuals.

In figure 4.6 the residuals are not properly aligned around the zero line. The residuals are mostly random, but there are some points that seem to belong to a separate cluster.

Mean Squared Error (MSE) is a useful method for measuring performance in a quantitative way. This is the averaged value of Sum of Squares Error (SSE). SSE is the error that are minimized when fitting a linear regression model. (Raschka & Mirjalili, 2017)

Confidence interval are calculated to the slope of the main regression model. The interval is calculated with a confidence of 95% using the t-statistic and the pooled standard error of an average result and a weighted average result. This means that it is 95% confident that the interval covers the true value of the degradation rate.

$$\hat{\beta}_1 \pm t_{\alpha/2,n-2} * SE(\hat{\beta}_1) \tag{4.2}$$

, where $\hat{\beta}_1$ is the estimated slope, $t_{\alpha/2,n-2}$ is the t-critical value and $SE(\hat{\beta}_1)$ are the estimated standard error to the estimated slope.

Validation of regression model

To evaluate evaluate the model and test whether a linear model is suitable in this project, several statistical tests are conducted.

To check whether the observations contain autocorrelation, a Ljungbox test was conducted. This is a statistical test used to test the lack of fit in a time series model. It is applied to the residuals to test the correlation between them. When the autocorrelation is small, the model does not show significant lack of fit.(of Standards & Technology, n.d.) The hypothesis test are formulated as:
H_0 - model does *not* show lack of fit.
H_a - model does show lack of fit. (of Standards & Technology, n.d.)

The output of the Ljung-box test is a test-statistic and a p-value. As this p -value was less than the significance level at 0.05, it means that the time series are dependent. The residuals are suffering from autocorrelation. An autocorrelation plot also indicate that the data are dependent as multiple point exceed the confidence interval visualized in the Figure 4.7. The first point is the correlation with itself and the correlation is consequently 1.

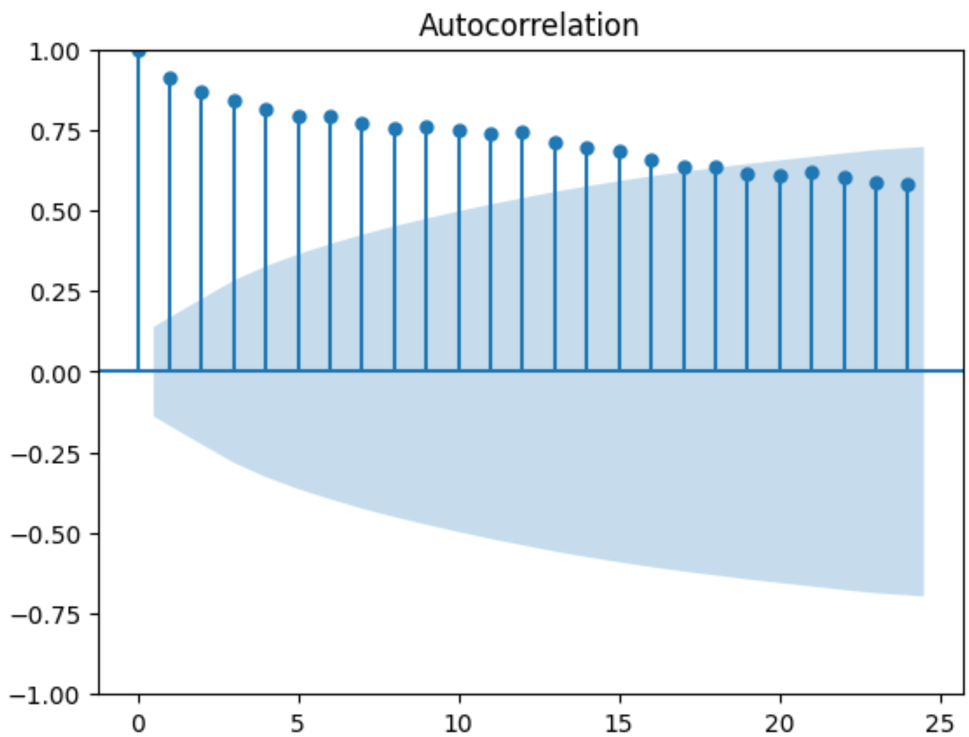


Figure 4.7: Autocorrelation plot of the monthly data points showing that the production data suffers from autocorrelation.

A diagnostic plot to the ARIMA model are plotted in Figure 4.8. The residual plot indicate that the residuals to the model are placed around zero, but skewed a little in positive direction. However, there are also abnormal residuals indicated by the peaks of the plot. The histogram indicate that the residuals are close to normal distribution, but there exist some deviation. The plot of theoretical quantiles implies that the distribution are not significantly skewed. There are however, some deviation are present in the residuals. The correleum indicate that the model have removed the autocorrelation between the residuals.

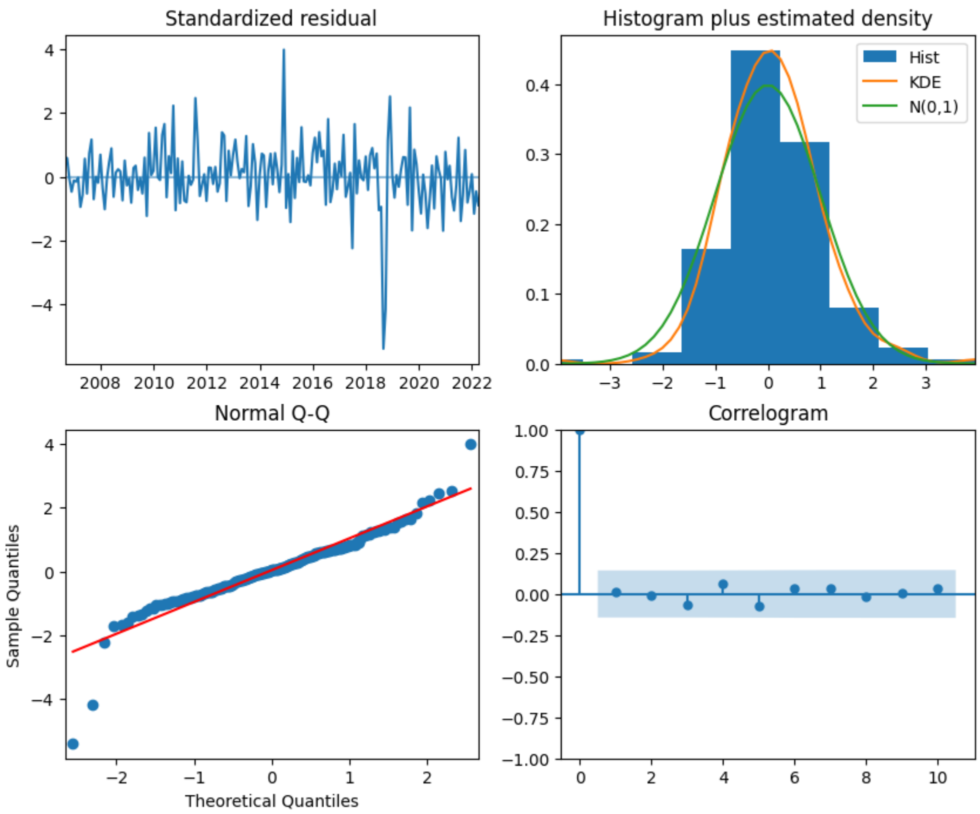


Figure 4.8: Diagnostic plot showing that the ARIMA improved some of the linear assumptions.

Dividing the data into several component is a strategy to highlight different patterns in time series data. Performance index data are divided into three main components; Trend, Seasonal and Residuals. Trend refers to a long-term increase or decrease in the data. This can either be linear or non-linear. In figure 4.9 there is naturally a decrease in the data. When seasonal patterns are present in the data, the data varies in a fixed and known frequency. From the mentioned plot, there is a seasonal pattern in the data with a yearly frequency. The last subplot in Figure 4.9 shows the residuals of the data. This plot shows the unsystematic variation in the data. The data points are modestly random meaning that there are not any clear pattern explained by the residuals. (Hyndman &

Athanasopoulos, 2021)

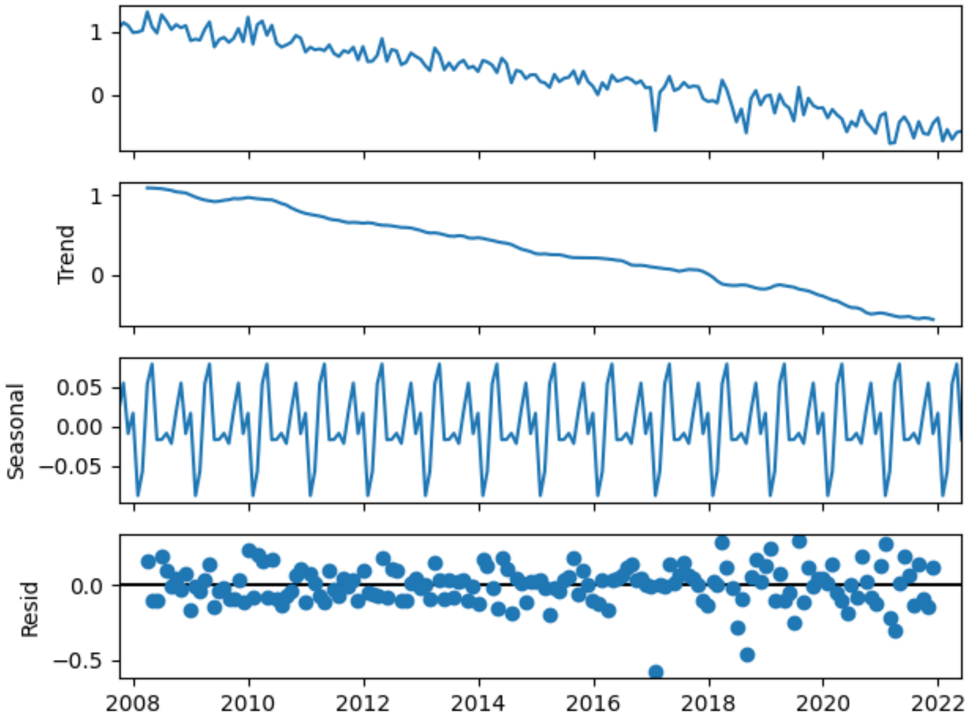


Figure 4.9: Decomposition of the performance index showing that it has a linear trend and a seasonal pattern. The residual are mostly random meaning that it does not contain any model information.

A Goldfeld Quandt Test is used to test homoscedasticity of a regression model. The test compares two subgroups of the data, one set with low values and one with high. If the variances between the sets are significantly different, the null hypothesis is rejected meaning that the variance is not constant. The test returns a p-value. (StatisticsHowTo, n.d.) The hypothesis test is formulated as:

H_0 - homoscedasticity is present in the residuals

H_a - heteroscedasticity is present in the residuals (StatisticsHowTo, n.d.)

Since the p-value is greater than the significance level, the null hypothesis can not be rejected. This indicate that homoscedasticity is present in the residuals.

The normality assumption was tested using a statistical test called Shapiro-Wilk test. This test assess whether a sample is likely to originate from a normal distribution. (Malato, 2023) The hypothesis test are formulated as:

H_0 - the sample originates from a normal distribution

H_a - the sample does *not* originate from a normal distribution. (Malato, 2023)

Shapiro-Wilk returns a test-statistic and a p-value. Since this p-value are close to zero, the null hypothesis is rejected. This means that the data are is not normally distributed.

4.4.6 Build model

After choosing of model, and determining the method of assessing the quality, the model itself should be created. (Chapman et al., 2000)

In order to create the performance index to be used in the model, it is necessary to carry out a simulated production output. In this thesis a Python library called `Windpowerlib` is utilised. This package provides a set of functionalities to calculate the power output to wind turbines by creating virtual wind farms. The library has been constructed in such way that it can be readily adapted to construct real wind farms. The Windpowerlib library takes climate data as input data to simulate power output. (Haas et al., 2023)

Input to the Windpowerlib model
The primary input to the Windpowerlib is climate data in a hourly time series format. The data will be used to estimate the power output of a pre-determined wind farm.

In this thesis, the selected wind farms are constructed in Python based on different parameters, including turbine types, the number of wind turbines, and hub height. Furthermore, the time series weather data can be employed to simulate the power output of the constructed wind farm. The output from Windpowerlib will be employed in several regression models. (Haas et al., 2023)

The processed data should further be used in a model to achieve the objective introduced in the introduction. `Windpowerlib` contains a set of different functions and classes that enable the user to simulate the power output from a virtual wind farm. This is achieved by feeding weather data in a time series format into the model. (Haas et al., 2023)

The most essential modules will be introduced below as these are essential to achieve the objective of identifying the degradation of different wind farms. The `wind_turbine` module contains of the `WindTurbine` class, which represents a wind turbine with additional functions. The output is a power curve or power coefficient-curve. The module also contains various of the most common wind turbines. (Haas, 2019)

The `wind_farm` module contains the `WindFarm` class, which is used to model wind farms.

The module also contains functions for calculating the mean hub height and installed power. Power curves are an important feature to export simulated power curves (Haas, 2019). The other mentioned modules are described in the Windpowerlib´s documentation.

The `WindTurbineCluster` class is part of the `wind_turbine_cluster` module. This class represents a cluster of different wind farms, which will have the same reference when considering the weather data. All the calculations regarding wind turbine specifications are also the same. (Haas, 2019)

The modules (`wind_speed`, `temperature` and `density`), regarding the weather, include functions for making sure the respective values are correct at hub height to the wind turbine. (Haas, 2019)

The `power_output` and the `power_curves` modules contain functions for calculating the power output and the power curve. `Tools` provide tools for the different functionalities of the Windpowerlib. (Haas, 2019)

4.4.7 Wake losses

Windpowerlib provides two options for implementing wake losses in a wind farm; reduction of wind speeds and wind farm efficiency (reduction of power in power curves). The first option provides wind efficiency curves that determine the average reduction of wind speeds within a wind farm induced by wake losses, which varies depending on the wind speed. The second option is to consider wake losses, is to apply them to the power curves, thereby reducing the power output. This is achieved by applying a constant or a wind speed depending on the efficiency of the wind farm. One advantage of using this method is that it allows for the use of aggregated power curves in order to obtain turbine cluster curves. (Haas et al., 2023)

4.4.8 Partial downtime

It is important to ensure that wind turbines are adequately maintained in order to prevent them from suddenly failing and to ensure their continued operational efficiency. Whenever a wind farm is not operative due to planned maintenance or due to failure, this is defined as a downtime period. The primary objective in regard to downtime is to exclude downtime hours from the model when estimating the degradation rate.

Furthermore, an overview of the development of downtime is of interest as this affects the number of production hours. While Nord Pool contains service logs for some of wind farms, it does not contain such records for all the selected farms. Despite the effort to map downtime using Nord Pool data, the result were not entirely consistent. However, maintenance logs for two of the selected wind farms were available. Egersund and Tellenes had public available maintenance logs. The information were retrieved from Nord Pool at:`https://umm.nordpoolgroup.com/#/messages`.

Egersund experiences periods of downtime due to a combination of planned and unplanned incidents. The wind farm had foreseen maintenance due to transformer outage and planned grid outage. Furthermore, Egersund also experienced downtime due to unplanned incidents such as Fault on overhead lines (OHL). (*Nord Pool - Market Messages*, n.d.)

According to the maintenance logs at Nord Pool, Tellenes experienced a greater degree of downtime compared to Egersund. Tellenes experienced a period of downtime due to unplanned grid outage and other grid failures. As a result of grid outage, it also had foreseen maintenance with turbines in 24 h dry out after planned grid outage. Additionally, it underwent scheduled maintenance due to repair of switch gear in the 132 kV station and work on the 132 kV bus bar. Planned maintenance on the internal grid and substations was also causes of planned downtime. Furthermore, ice on turbine blades was identified as a contributing factor to downtime. (*Nord Pool - Market Messages*, n.d.)

In order to get an comprehensive understanding of downtime, a project-specific definition of downtime has been developed to identify downtime in the selected wind farms. This definition aligns somewhat with the definition of downtime in OB17. (Olauson et al., 2017) A wind farm is considered to be in a state of downtime whenever it does not produce for three hours in a row despite the wind speed being within operational production interval, between the cut-in and cut-off speed.

The production data from various wind farms showed a clear horizontal pattern when plotting the production data against the wind speed. The addition of horizontal cumulative effect lines to the plot, resulted in the horizontal production pattern aligning with the lines. Figure 4.10 illustrates the production at Sandøy against its corresponding wind speed. The navy blue line is the power curve for the entire wind farm. The red lines represents the cumulative maximum effect of the wind turbines in the farm. A separate power curve is plotted with 80% of the original curve´s magnitude. The aforementioned curve is also shifted to the right. The objective is to identify and mark abnormal production point that lie beneath the original power curve. By detecting all points beneath the 80% curve this objective somewhat achieved. Furthermore, a horizontal pattern is identified among the green production points. These are marked by a yellow color. One possible explanation for this phenomenon is that some wind turbines are not operational at these times. In this thesis these points are considered to be instances of downtime. Consequently, these points are excluded from the analysis, along with all production points with zero production for three consecutive hours.

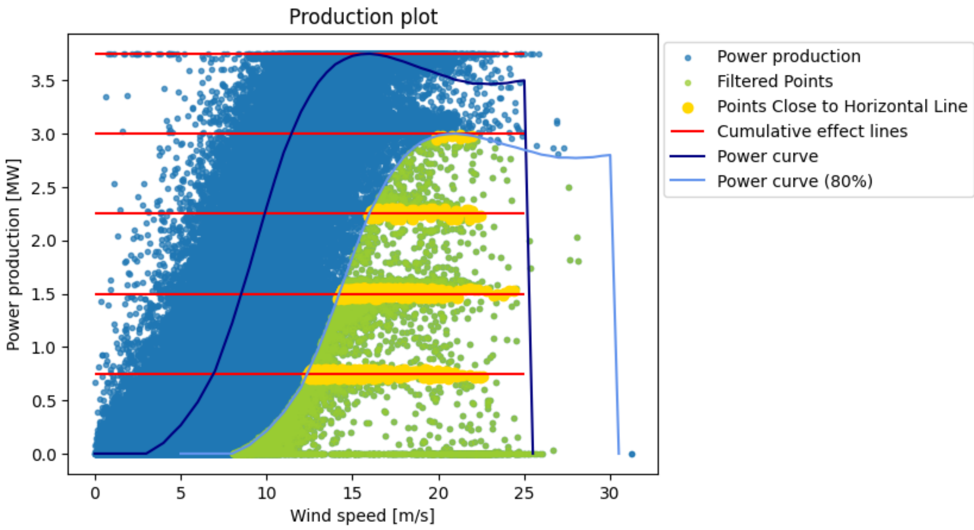


Figure 4.10: Production plot of Sandøy showing how partial downtime are identified near the cumulative effect lines.

4.4.9 Potential factors contributing to wind farm degradation

One aspect of this study is to identify potential contributing factors to the deterioration of wind turbines. The first case is to study whether the geographical location impacts the degradation of turbines. As discussed when selecting wind farms, there are mainly three clusters of wind farms. A significant difference in degradation between these clusters may indicate that the local climate impacts the degradation to the clusters differently. The three clusters are as visualized in Table 4.4. The clusters are quite balanced, but small sample sizes may result in unreliable results.

Region	Wind farm	Climate properties
South West	Egersund Karmøy Hywind Lista Røyrmyra Tellenes Åsen II	Avg. temp: 8.69 °C Avg. wind speed: 8.20 m/s
Mid	Hitra Rye Vind Sandøy Skomakerfjellet Valsneset Ytre Vikna	Avg. temp: 6.77 °C Avg. wind speed: 7.06 m/s
North	Fakken Kjøllefjord Raggovidda Hamnefjell	Avg. temp: 1.94 °C Avg. wind speed: 6.61 m/s

Table 4.4: Wind farms divided into three clusters with yearly average temperatures and wind speeds.

It is also of interest to investigate the improvement of wind turbine technology. The second case therefore involves the study of the five first years of each wind farm. This will ensure equal basis of comparison and a significant difference in degradation can indicate an improvement or worsening of wind power technology. Old and new turbines are grouped into cluster where turbines newer than 2011 are classified as new turbines and turbines older are classified as Old. This distinction also ensures that there are an approximately equal number of wind farms in each group. The groups are listed in table 4.5.

Categories	Wind farm	Manufacture year
New turbines	Egersund	2014
	Hamnefjell	2015
	Raggovidda	2011
	Skomakerfjellet	2015
	Tellenes	2014
Old Turbines	Fakken	2002
	Hitra	2004
	Kjøllefjord	2004
	Lista	2005
	Rye Vind	1989
	Røyrmyra	2004
	Sandøy	1997
	Valsneset	2005
	Ytre Vikna	2005
	Åsen II	2004

Table 4.5: Wind farms divided into three clusters together with manufacture year.

A third case is to check how different seasons impacts degradation. A regression model is conducted on four quarters:

- Q1: January, February, March
- Q2: April, May, June
- Q3: July, August,September,
- Q4: October, November, December

Firstly, an average degradation is calculated for each quarter to each wind farm. Then an average and weighted average is calculated to get the final result for each cluster. The regression with ARIMA errors is not fitted with the data as there are too few data points in each yearly quarter. The objective of dividing into each quarter is however, to test if there is a significant difference between the cluster. The grouping are made on the basis of assumed somewhat equal production rates. These data will consequently not suffer significantly from seasonal pattern.

To test whether there is a significant difference between these groups, a Mann-Whitney U-test is conducted. The test checks whether two sampled groups are likely to derive from the same population This is an alternative test to a standard students t-test where the data does not need to be normally distributed. This test does also work on groups with smaller sample sizes. (McClenaghan, 2022) The hypothesis is formulated as:

H_0 - the two groups are equal.

H_a - the two groups are *not* equal. (McClenaghan, 2022)

The regression models fails on three of the four tests. Firstly, the Ljungbox test fails, meaning that there exists autocorrelation in the residuals. Furthermore, the Rainbow test fails. This means that the null hypothesis saying that the data are linear also fails. The Shapiro-Wilk test also fails, which means that the data is not normally distributed. The fact that confidence intervals cannot be trusted is the main impact from the violation of the normality and independence assumptions. (Olauson et al., 2017) Knief and Forstmeier found that linear models are robust to violation of the normality assumtion. (Knief & Forstmeier, 2021) The main focus of this thesis is to estimate long-term degradation rate, resulting in this not being a too serious issue. The implementation of regression with ARIMA error also results in a violation of the assumptions of normality and linearity. However, the ARIMA model passes the test for independence. Through the regression with ARIMA error, seasonal patterns are introduced into the model as an attempt of handling this issue. Linear regression, RANSAC regression and regression with ARIMA errors is conducted and evaluated to find the most reliable model.

5 Results

Multiple regression models have been made to estimate degradation of Norwegian wind farms. Chosen models in this thesis has been a ordinary least square, a RANSAC model using ordinary least square and a linear regression using ARIMA errors. Degradation has been estimated for each wind farm individually based on the slope of the regression line. Furthermore, downtime has also been excluded to check whether it influences the results.

5.1 General results

When analysing the degradation to wind farm using linear regression, the objective is to determine the slope of the regression model. Regression plot of Rye Vind are plotted in Figure 5.1. The training set contains the green and yellow points. The blue points are the training set. The model have classified many of the data points in training set to be outliers. This have made the RANSAC regression line, marked in light blue, decrease compared to the navy blue line representing an ordinary linear regression. This model is fitted based on classified inliers.

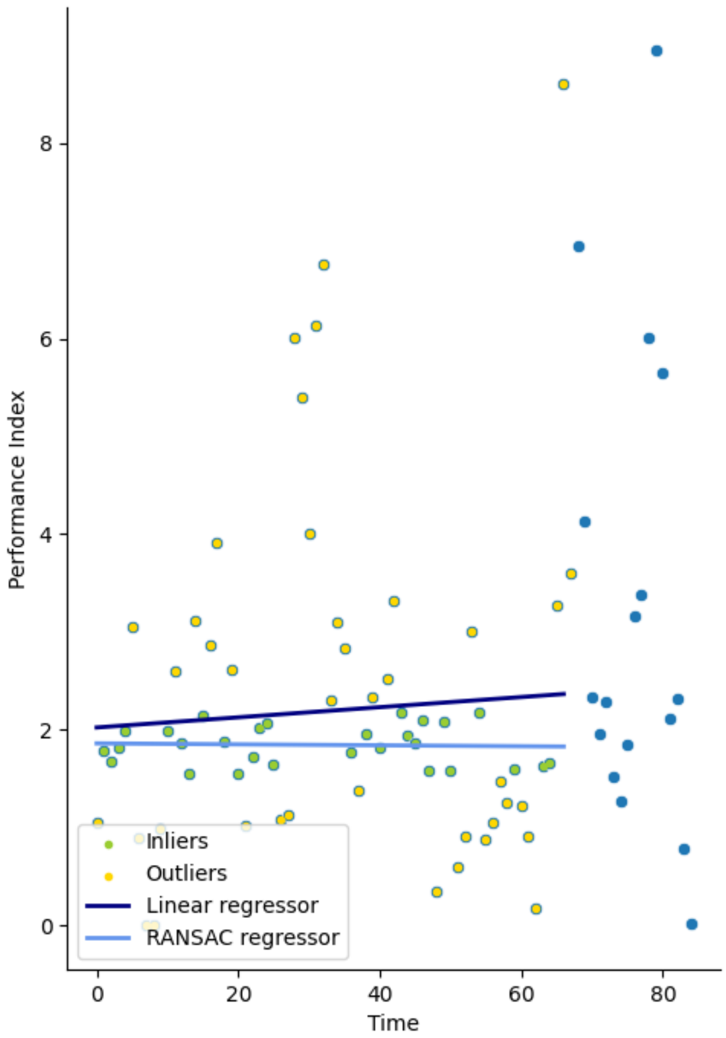


Figure 5.1: Regression plot from model, both linear and RANSAC model.

The monthly performance index is used in the regression models when modelling general degradation. This means that the slope, β_1 is the average monthly degradation rate. Hence, the yearly degradation rate is the slope (β_1) * 12, as the degradation rate is assumed to be linear. The individual results can be found in Appendix B. Results from the regression models are showed in Table 5.1. The table consists of average results using all data points from linear, RANSAC and ARIMA model. It is clear that removing partial downtime from the data makes the estimated degradation rate smaller. Additionally, it consists of results without partial downtime. The degradation values without downtime is shown in the main results, but not in the later sub-studies. A weighted average was also calculated with respect to each wind farms´ rated capacity.

The result from the linear regression and RANSAC-regression gave results within the same order of magnitude. Generally, the degradation rate is estimated to be higher when using

Table 5.1: General results from regression models using all data.

	With Downtime	Without Downtime
Linear Average degradation	-0.0089	-0.0035
Linear Weighted average degradation	-0.0169	-0.0148
RANSAC Average degradation	-0.0108	-0.0082
RANSAC Weighted average degradation	-0.0138	-0.0118
ARIMA Average degradation	-0.1179	-0.0653
ARIMA Weighted average degradation	-0.0255	-0.0710

weighted average compared to normal average. This is mainly because of Tellenes wind farm, which accounts for approximately 24 % of the total installed capacity. Removing partial downtime decreases the estimated degradation rate, which indicates an increase in downtime over the period. The degradation rate estimated by the regression model with ARIMA-error is significantly larger than the other two models. The histogram in Figure 5.4a shows that the model returns a greater variation in degradation rates compared to the linear and RANSAC model. There is especially one calculated degradation rate estimated at Røyrmyra that influences the total results from the model. Since regression with ARIMA errors return results with greater variations with respect to a linear degradation rate, the model is excluded from the rest of the result. It also contains more predictor variables than the other models and hence does not return a reliable degradation rate. A regression model with ARIMA errors does however return better forecast predictions compared to the other models. The model will be further discussed in section 6.

The degradation rate is plotted for each individual wind farm. Figure 5.2 shows the results from the linear regression model. Figure 5.3 shows the results from the RANSAC model. Both figures show ordinary degradation rates, as well as weighted degradation rates. The plots are colored according to their location, as is described in the figure. The RANSAC model tends to return a larger degradation rate compared to the linear model. The result from Rye Vind has changed from positive to negative when comparing the models. The regression plot, figure 5.1, shows that this wind farm have several points where the performance index is unusually high. This can be due to errors in the power prediction or reported energy production. RANSAC has classified many of these points to be outliers, resulting in a negative degradation rate.

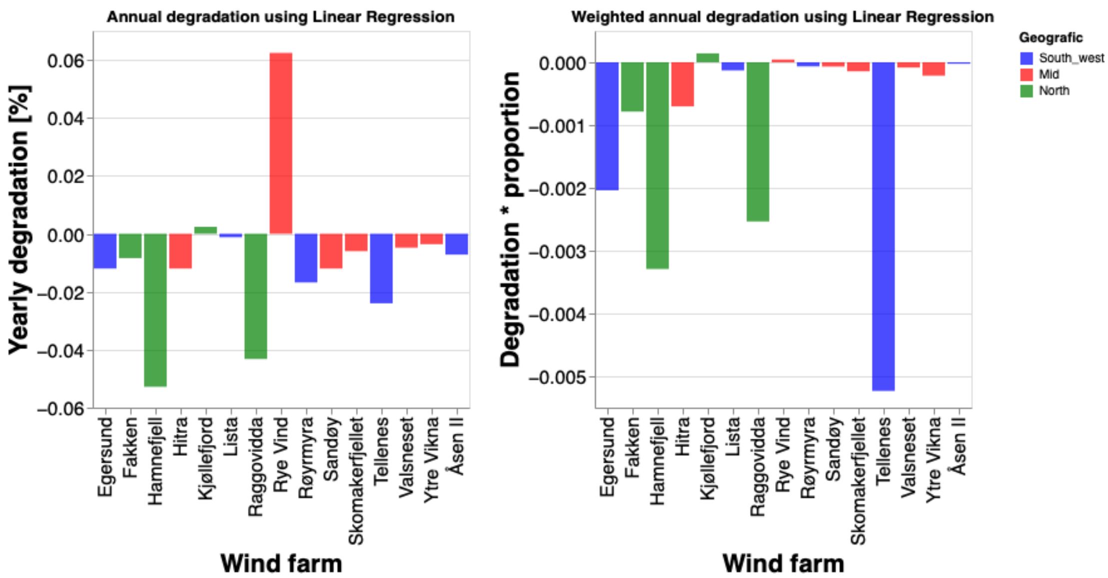


Figure 5.2: Individual degradation rates to each wind farm estimated by the linear regression model. The left plot visualizes degradation rates and the right plot visualizes the weighted degradation rates. Wind farms are marked to a color specifying which region the wind farm belong to.

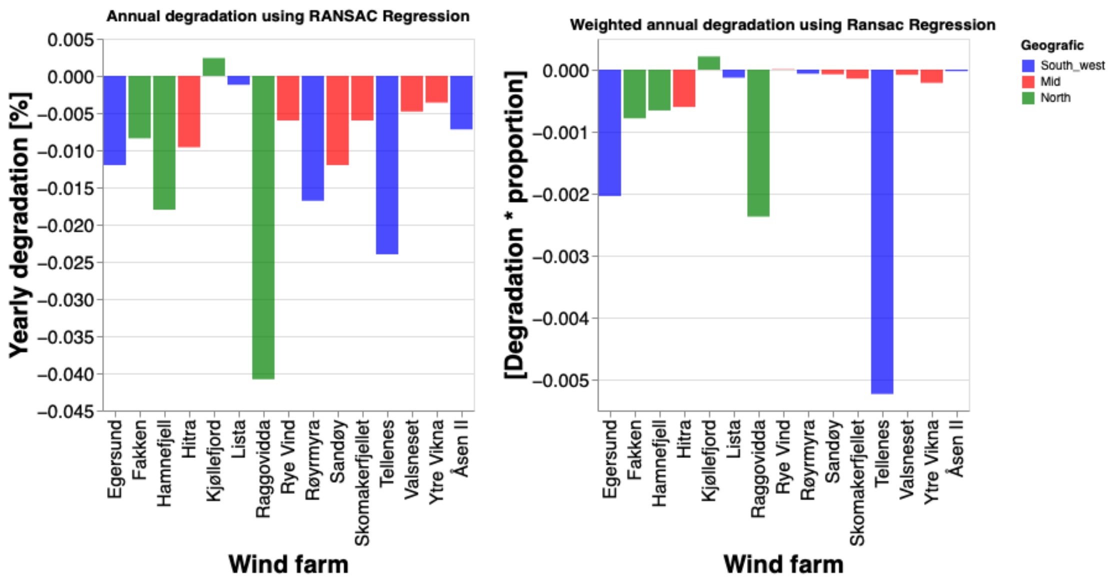
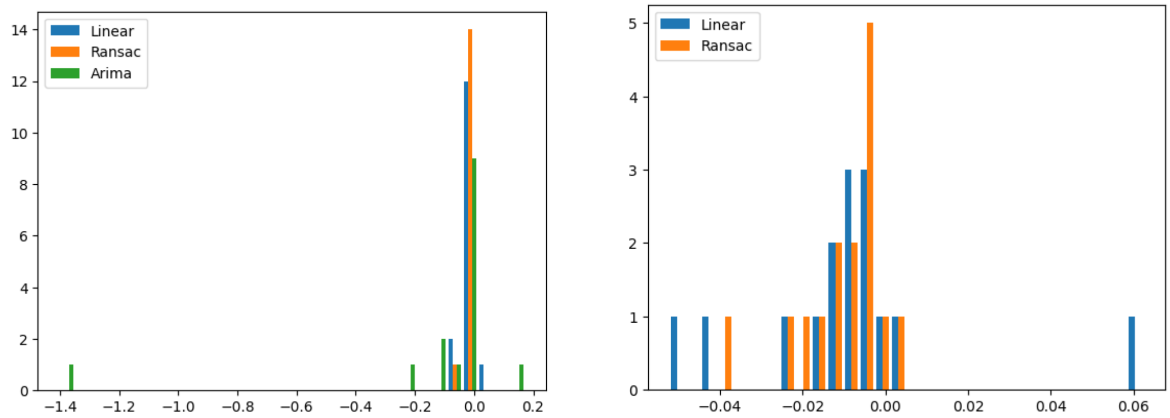


Figure 5.3: Individual degradation rates to each wind farm estimated by the RANSAC regression model. The left plot visualizes degradation rates and the right plot visualizes the weighted degradation rates. Wind farms are marked to a color specifying which region the wind farm belong to.

A histogram containing the distribution of the degradation rate is plotted in Figure 5.4. In Subfigure 5.4a it is shown that the regression with ARIMA errors have estimated degradation rates with larger spread compared to the linear and RANSAC model. Subfigure 5.4b shows that the linear and RANSAC have quite similar distributions, but the distribution to RANSAC regression is even more compact.



(a) Degradation rates from Linear-, RANSAC- and ARIMA models.

(b) Degradation rates from Linear- and RANSAC model.

Figure 5.4: Histograms show the distribution of calculated degradation rates. 5.4a show all models whereas 5.4b show the linear and RANSAC model.

Each regression model has accompanying metrics tables containing various error measurements in the model. This table can be found in Appendix F. The metrics are used to select the best regression model. As can be seen here, the linear and RANSAC regression models return quite similar metrics.

5.2 Partial Downtime

As mentioned in Section 4.4.8, downtime is present at all production sites. Ideally, all these downtime hours should be removed when estimating degradation rates. As this is quite challenging considering the data quality and the scope of the data, partial downtime is estimated in this thesis. Partial downtime is defined in Section 4.4.8, which states that if the power output is zero for three consecutive hours while the wind is within the range of operation, it is defined as downtime. Data points close to "capacity lines" are also considered downtime. These correspond to the cumulative rated power of n numbers of turbines in that wind farm. This is defined as downtime as this is interpreted as n number of turbines being shut down for a period of time. Data points considered downtime are removed in some regression models to get a more accurate result.

Figure 5.5 shows a plot of the partial downtime based on the definitions in this thesis. The downtime is plotted on a quarterly basis where all instances of downtime is counted. The partial downtime peaks during the summer quarters, where Egersund makes the majority of downtime in this plot.

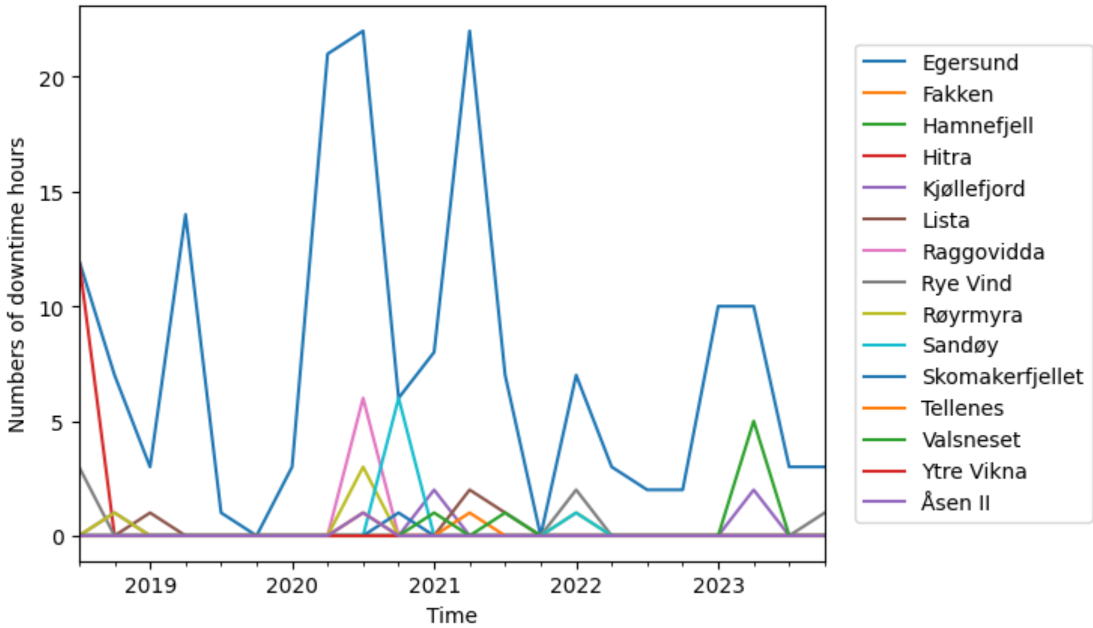


Figure 5.5: Quarterly partial downtime to all wind farms in the last five years.

The number of annual downtime hours are plotted in Figure 5.6. There are generally more downtime at the second half of the measurement period, than in the first, which implies an increase in downtime across the wind farms´ lifetime.

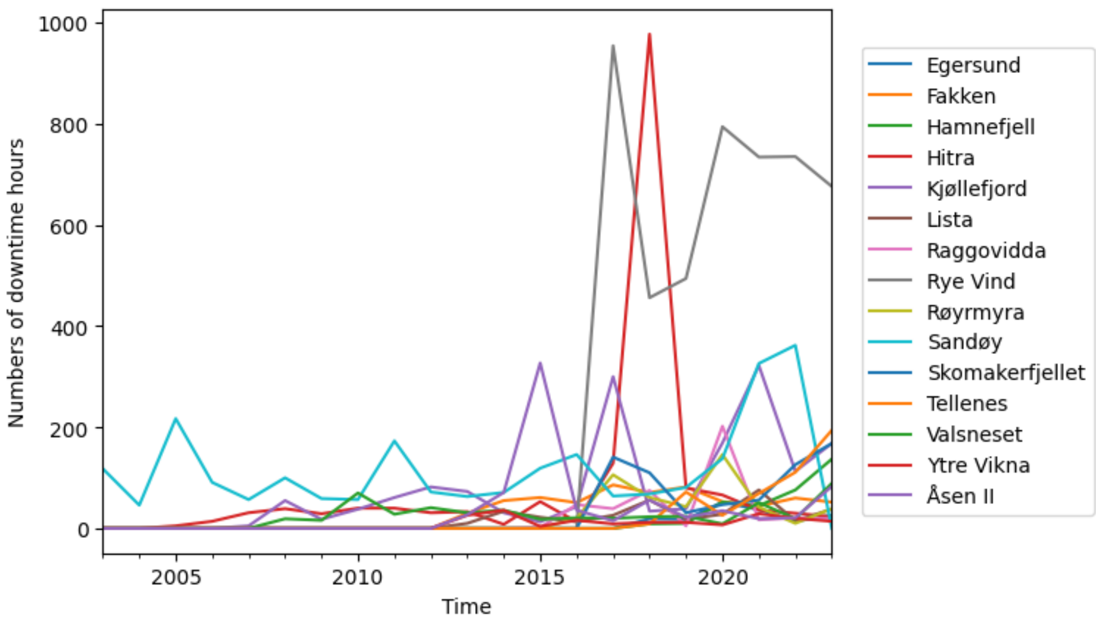


Figure 5.6: Annual partial downtime over the entire production period to the individual wind farms.

The total annual downtime is also calculated and plotted in Figure 5.7. This plot shows that there is an increase in annual downtime at the selected wind farms. Each point corresponds to annual downtime in percent. Only operating wind farms are taken into account when estimating the annual downtime, meaning that there are less wind farms at year 0 compared to year 22. The annual downtime ranges between 0.30 % and 1.80 %. The average annual increase is estimated to be 0.04 pp/y. This increase is estimated using a linear regression model.

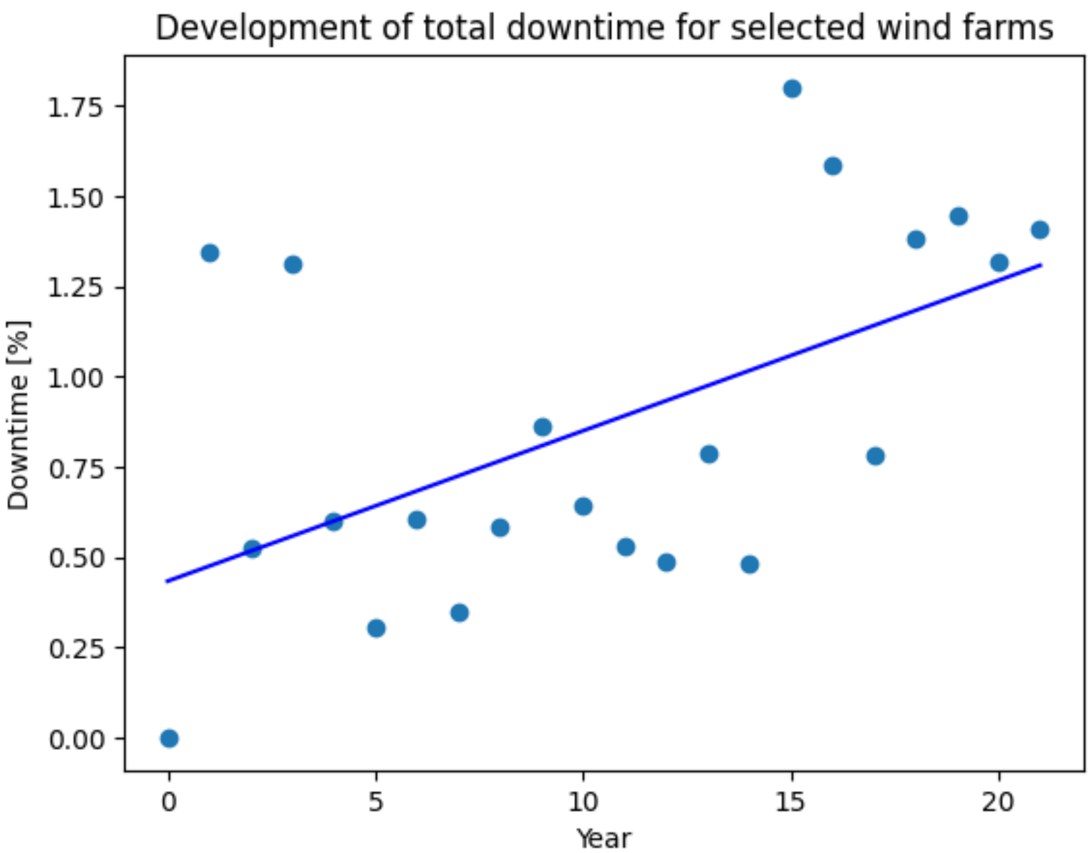


Figure 5.7: Regression model shows that there is an increasing partial downtime during the lifetime of selected wind farms.

5.3 Geographical factors

To assess whether the local climate has a significant impact on wind turbines degradation rate in Norway, the selected wind farm are grouped into three clusters, which are compared to each other. The results from the linear regression model are showed in table 5.2.

Table 5.2: Estimated degradation rates on data clustered into geographical locations.

Region	Regression model	Degradation rate
South West	Linear Average Degradation	-0.0047
	RANSAC Average degradation	-0.0047
	RANSAC Weighted average degradation	-0.0054
Mid	Linear Average degradation	0.0137
	Linear Weighted average degradation	-0.0021
	RANSAC Average degradation	-0.0168
	RANSAC Weighted average degradation	-0.0020
North	Linear Average degradation	-0.023
	Linear Weighted average degradation	-0.0068
	RANSAC Average degradation	-0.015
	RANSAC Weighted average degradation	-0.0040

The Mann-Whitney u-test gave a p-value above 5% for all regions, and consequently the null hypothesis, namely that the groups are similar, is not rejected. This means that there are no significant differences between the groups. Although there are some differences between the regions, these are not large enough to imply that geographical factors have significant impacts on degradation based on the study sample. The test result is listed in Table 5.3.

Table 5.3: Results from the Mann-Whitney U-test on the regression model fitted on the different geographical location.

		Linear Regression		RANSAC Regression	
Test Group 1	**Test Group 2**	**Test Statistic**	**p-value**	**Test Statistic**	**p-value**
South_west	Mid	7.0	0.18	7.0	0.17
South_west	North	12.0	0.73	11.0	0.90
Mid	North	18.0	0.26	17.0	0.34

5.4 Technological factors

To study whether there are differences in degradation between new and old wind turbine technologies, the wind farms are grouped into two groups: Wind farms constructed before 2011 are classified as old, while wind farms constructed from 2011 and onwards are classified as new. A degradation rate based on the first five years is calculated to get a common basis of comparison. The monthly production index is used as the predictor variable in the analysis. The regression model output results can be found in Table 5.4.

Table 5.4: Average Degradation

Linear regression	**Old Turbines**	**New Turbines**
Average Degradation	-0.0297	-0.012
Weighted Average Degradation	0.008	-0.0098
RANSAC regression	**Old Turbines**	**New Turbines**
Average Degradation	-0.0173	-0.016
Weighted Average Degradation	0.0078	-0.011
ARIMA regression	**Old Turbines**	**New Turbines**
Average Degradation	0.0013	-0.0183
Weighted Average Degradation	0.001999	-0.0109

The results from the Mann-Whitney u-test is listed in Table 5.5. The p-value indicate that the null hypothesis should not be rejected, as there is no sign of significant difference between the groups.

Table 5.5: Results from the Mann-Whitney U-test on the regression model fitted on the first five production years.

Regression type	**Test Group 1**	**Test Group 2**	**Test Statistic**	**p-value**
Linear model	Old Turbines	New turbines	31.0	0.69
RANSAC model	Old Turbines	New turbines	35.0	0.39

5.5 Seasonal variations

In order to assess the impact of different seasons, regression models are fitted with quarterly data (Q1-Q4). The results of the calculated degradation at each quarter are presented in Appendix E. Each row corresponds to an average degradation across all production years for the specific wind farm. The average degradation and weighted average degradation are calculated based on the data presented in the table and the results are plotted in Table 5.6. The table includes results from both ordinary linear regression and the RANSAC regression.

The Mann-Whitney U-test was conducted on all combinations of the four groups and the results are listed in Table 5.7. The majority of tests show no significant difference between the test groups, except the groups Q1 and Q4, which are shown to be significantly different.

Table 5.6: Estimated degradation rates on seasonal data using Linear and RANSAC models.

Linear regression	**Q1**	**Q2**	**Q3**	**Q4**
Average Degradation	0.0016	-0.0023	-0.0292	-0.0128
Weighted Average Degradation	-0.0060	0.0003	-0.0161	-0.0008
RANSAC regression	**Q1**	**Q2**	**Q3**	**Q4**
Average Degradation	0.0017	-0.0024	-0.0292	-0.012764
Weighted Average Degradation	-0.0029	0.0024	-0.0262	-0.0043

Table 5.7: Results from the MannWhitney U-test on seasonal regression model.

		Linear Regression		RANSAC Regression	
Test Group 1	**Test Group 2**	**Test Statistic**	**p-value**	**Test Statistic**	**p-value**
Q1	Q2	132.0	0.43	122.0	0.71
Q1	Q3	149.0	0.14	160.0	0.05
Q1	Q4	140.0	0.26	163.0	0.04
Q2	Q3	131.0	0.46	143.0	0.21
Q2	Q4	111.0	0.97	139.0	0.28
Q3	Q4	95.0	0.48	109.0	0.91

5.6 Summary of the results

The results from the RANSAC regression model without downtime turns out to be the most robust and are therefore used as the main results. In order to balance the impact between wind farms with large installed effect and wind farms with low installed effect, the average between the average and the weighted average are calculated. The linear and weighted annual degradation rates were estimated to be -0.82% and -1.19%, respectively. This gives an average degradation rate of -1.00%. Pooled standard error is estimated to approximately 0.22% This leads to a final result of $-1.00 \pm 0.22\%$ In general, there is no significant difference between the tested groups defined in Section 4.4.9. The p-value from the test between Q1 and Q4 in the RANSAC model is lower than 5%, resulting in a rejection of the null hypothesis. This indicates that there could be a significant difference in degradation rate between these two groups. The other tests do not indicate significant differences based on the three factors of location, seasonality or technological improvements.

6 Discussion

6.1 Limitations

As there are many complicated factors impacting wind power production and degradation, it is necessary to make several assumptions. How this affects the results obtained from the model is not known. A detailed description of the choices and assumptions made in the model is described in Section 4, and an estimation of how this affects the validity of the results is further discussed.

The model should be viewed as a simplification of reality. Although it involves relatively complex calculations, it still simplifies a lot of factors impacting the performance and degradation of a wind turbine. A large limiting factor has been a restriction to use publicly available data. This will undeniably lead to increasing the uncertainty of the results. Time limitations have also contributed to reducing the accuracy of the model, as well as forcing some factors and potentially interesting topics to remain unexplored. As several problems were encountered along the way, multiple functions and adjustments have been implemented to make the model more accurate.

6.1.1 Weather data

The use of ERA5 data allows the model to use relatively precise measurements everywhere in Norway to model wind power output. However, this dataset has some limitations that may affect the results. The main issue with ERA5 is that the grid size is 0.25 degrees in both longitude and latitude, where the wind speeds are average values across the spatial extent of the grid cell. This means that there may be some disparity between dataset values and actual wind speeds at the site. How this affects the results depend on whether these errors occur more randomly as noise, or more systematically.

If the ERA5 data have a random error relative to actual recordings at site, it would have little impact on the findings in this study. This could have an effect on single data points in an hourly time-series, but would be expected to average out over longer time periods to produce results that would be satisfactory.

A more systematic error could occur if the wind speeds at the wind farm site is consistently higher or lower than the average of the surrounding area. Wind speeds may vary a lot over short distances, especially in hilly terrain, where the wind speeds increase over hill tops and through valleys. As manufacturers will want to maximize energy production, it is probable that many wind farms are placed where the average wind speeds are most favourable. This will lead the model to underestimate the energy production, which in turn will increase the calculated performance index.

The use of hourly time-series also presents an issue. As wind speeds may vary significantly within an hour, variations within each hour may be hidden, which may affect wind power production. This will not necessary be of great importance, but could affect the data when the wind speeds are near cut-in- or cut-off speed. This could affect the model to assume stable power production across one hour, where in fact the WT were cut off at a large proportion of the time period.

In the model it is also assumed that the wind farms stands at the average height of the grid cell. The 100-meter above ground wind component is compared to the hub height of the turbine, and the difference in height is adjusted for, according to the relation between wind speed and height above ground described in Equation 3.2. This assumption is hard to verify, and could be a source of error in the study.

Although these inaccuracies is likely to affect the performance index, it does not necessarily have the same impact on calculations on degradation. As long as the differences between ERA5-data and actual wind speeds are stable and comparable from year to year, the degradation rates should be accurate over longer time periods. This implies that results on average yearly degradation will be little affected. However, the results that are based on shorter time periods, such as seasonal variances and especially downtime, which is based on hourly data, may be subject to greater impacts due to such discrepancies.

6.1.2 Improving weather data quality

There are multiple ways to improve the wind speed data. In Wind energy engineering (Letcher, 2017), the authors suggests a method called "measure-correlate-predict". This involves making measurements of the wind speeds at the wind farm, and then see how this correlates with ERA5 data. This may then be used to more accurately predict wind speeds at the site, without continuous measurements at the wind farms. These measurements should be done over a time period of at least some months, and ideally over a whole year as the patterns might change according to seasonal variances. This method was not feasible for our study due to limitations in both resources and time, but may be a way to improve on the model.

Weather reanalysis methods have become better over the last years, and ERA5 offers much better spatial resolution than its predecessor, ERA-Interim (Hersbach et al., 2023). If this development continues, weather reanalysis might become more suitable for wind energy purposes in the future.

More accurate data could of course be attained with access to weather data at the site of the wind farm. There is however not publicly available data on this, and obtaining this would require considerable effort and resources. In addition, a goal for this thesis was to make a model that could be applied for future studies on wind power degradation. If it is possible to use ERA5 data for this purpose, this method could be applied in other European countries.

6.1.3 Wind farm data from NVE

The wind power production data is gathered from public available data published by NVE. In addition, all information about the wind farms, such as the number of wind turbines, wind turbine models and locations of the farms are gathered there. This information is mostly assumed to be correct, except where the data were abnormal. The wind farm "Karmøy Hywind" is one such case that was present in our model, but had to be removed as the information in the dataset was flawed. Both the coordinates of the wind farm and the number of turbines was found to be incorrect.

6.1.4 Wake loss and turbulence

The wake loss at a wind farm provides a challenge for calculating the output. Finding how wake loss impacts each individual wind farm is a challenging task, as these effects are highly complicated, and will vary according to factors such as wind direction, wind turbine placements and the topography of the surrounding terrain. There were limited amounts of such data available online, so simulations including these factors was not possible. Simulating the effects of wake loss would also demand advanced data models, accounting for the complicated dynamics of wind.

A potential method for estimating how the wind farms are affected by wake loss with respect to wind direction was attempted to be included in the model. The idea was to look at how the average power output varies in each wind direction, which then could be adjusted for in the model. This would however further complicate the model, and it was also unclear to what extent this would improve on the results. It was therefore decided not to include this in the model.

There is a functionality in Windpowerlib for including wake loss in the simulation. This seems to lower the wind speed at the turbine with a given factor, such that a wake loss coefficient of 0,1 will lower the wind speed with 10% in the model. This seems like a gross oversimplification, as the wake loss will affect wind turbines in a wind farm differently. This will also vary according to wind direction and other factors, and it was therefore decided not to correct for this factor.

6.1.5 Distance

In Appendix H, the coordinates of the wind farms are presented alongside the weather coordinates. The values of the weather coordinates represents the middle point of the grid cell. From this the distance from the grid cell center point to the wind farm is calculated. In general, one may assume that the center point is closer to the average values in the grid cell, although this is not necessarily true. This means that larger distances between these coordinates will on average imply a greater uncertainty, and this information may be used as a guideline to investigate the uncertainties of each wind farm.

6.2 Evaluating the model

6.2.1 Wind farm selection

The study consists of 15 wind farms, spread across Norway in three clusters. These were partly chosen as the results could then be compared to ED24, which studied the same wind farms with a simpler model. In addition, these wind farms adhered to some criteria that made them suitable for this study, namely that:

- Relevant information was publicly available. This includes production data and specifications of the wind farms, such as wind turbine model, number of wind turbines, hub height and location.

- The wind farm was built as one installation, with no new expansions after the first year in production. This makes it easier to compare production data from year to year.
- The wind farm consisted of only one wind turbine type. This allows a much simpler modelling process.
- The wind farm was in operation in the time period 2017-2023. This allows comparable results between the wind farms, as well as a minimum of data points. There is one exception to this requirement, namely Sandøy, which was rebuilt in 2023, and therefore only production data up to 2022 is used. This is however one of the oldest wind farms in Norway, being in production in more than 20 years.

These requirements were all made to make the model both simple enough to handle, as well as comparative across the time period.

The study sample has a cumulative power output of 660,3 MW from 240 wind turbines. Their total yearly production is on average 2,1 TWh, about 20% of the total wind power production in Norway.

The average wind farm in the dataset consists of 16 wind turbines and a maximum power output of 44 MW. The average of all Norwegian wind farms is 22 wind turbines with an output of 75 MW. Also, the average starting year for the wind farms in the dataset is 2011, compared to 2014 for all Norwegian wind farms. This means that the wind farms selected are smaller and older than the Norwegian average. This is likely to be a consequence of the requirements set when selecting wind farms. The minimum requirement of 6 years in production causes newer wind farms to be excluded. The additional requirement that the wind farm was built during a single installation period, with only one turbine type, may also have excluded larger wind farms, as these are more likely to have been expanded during their lifetime.

Despite these factors, the dataset is a good representation of the Norwegian wind power industry. Geographically, it represents a balanced number of wind farms within the regions where wind power is most prominent. Also, it includes wind turbines from the three largest manufacturers in the market, as well as wind farms built across a 18 year period, from 1999 to 2017.

It should be noted that the degradation rate is specific for the dataset studied, and may not be completely representative for all Norwegian wind farms. As the wind farms selected is on average slightly older compared to the industry as a whole, technological advancements since could have made modern wind turbines less exposed to degradation. The literature studied may indicate such developments, as degradation rates seems to have dropped from the older studies to the more recent. Nevertheless, the wind farms studied in this case represent such a large part of the industry that they are at least indicative of what can be expected.

6.2.2 Performance index as a measurement of wind turbine performance

The use of a performance index for measuring wind power performance has its clear benefits compared to using their capacity factor. Adjusting for wind resource is a clear benefit, that allows for comparisons between seasons and years with varying weather.

If one were able to adjust for all disturbing factors perfectly, with information on exact weather conditions, downtimes and wake losses, the model should be able to predict production exactly, thus making the performance index 1. Since it is impossible to adjust for all the aforementioned factors exactly, the results do show considerable spread, as can be seen in Figure 6.1. The largest contributing factor to this is the weather data, which as discussed previously is a large source of uncertainty. This makes the model quite poor at predicting power output over shorter time periods. Over longer time periods this spread averages out across a mean, which makes it more reliable for long term predictions.

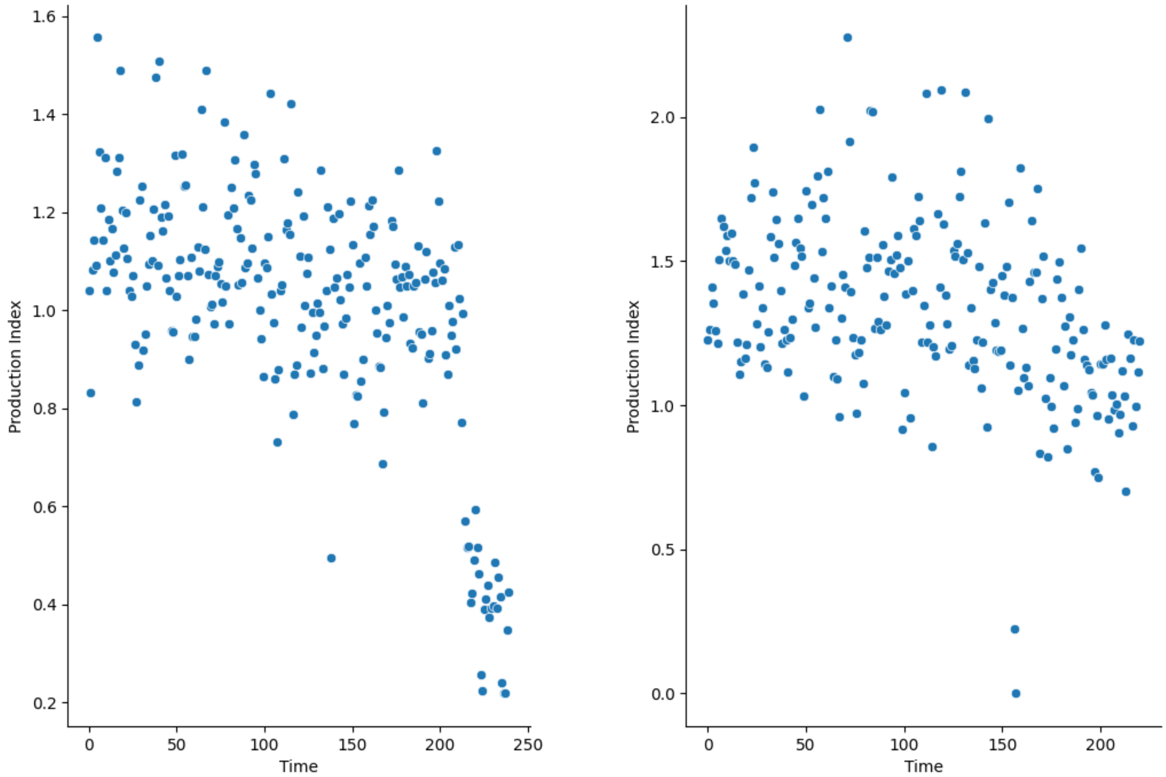
Some of the wind farms also show an average performance index above 1, while others have a performance index under 1. This points at more systematic errors in the model. For wind farms with performance indices consistently above 1, the model underestimates the power production. This may indicate that the wind resource at the site is greater than in the surrounding area . For under-performing wind farms with performance indexs below 1, the opposite may be the case, namely that the wind resource at the site is less than the data indicates. These wind farms may also be influenced by wake losses, which as mentioned are not adjusted for by the model. Both under- and over-performing wind farms are however subject to systematic errors that leads to the model wrongly predicting power output.

Although the issues of large spread and systematic errors constitutes a challenge for the model, they do not necessarily render the results useless. As the study of degradation involves analysing trends, the key is whether one time period is comparable to the next. As there is a clear relation between predicted and actual production, this assumption still holds true.

However, as an unproven method, that does come with its limitations and sources of error. Optimizing it further, through acquiring better weather data and expanding the sample size would improve on the reliability of the model, as well as allowing for studying more aspects on this topic.

6.2.3 Linearity

The method of linear regression relies on the assumption that the data follows a linear pattern. From what is seen in the trends from the various wind farms, this assumption does not always hold true. The older wind farms (pre 2015), seems to show a linear pattern for the first years, but the trend worsens as the wind farms age. An example of this can be seen at Sandøy wind farm in Figure 6.1a, where the trend is linear for the first 16 years, but significantly worsens the 4 last years of production. One point that is worth noting is that Sandøy invested in new turbines the year after the cut-off of this analysis. These results may therefore be affected by this project, for example due to partially turning off turbines. Figure 6.1 show a comparison of the development in performance index to Sandøy and Hitra. The plot shows that the PI to Hitra is more linear than the PI to Sandøy. Hitra is also quite old with 20 years of production. This may indicate that the results seen at Sandøy are more site-specific, and therefore not necessary applicable for other wind farms.



(a) Plot of PI at Sandøy.

(b) Plot of PI at Hitra.

Figure 6.1: Plot showing the development of Performance Index over time. Subfig. 6.1a PI to Sandøy and fig. 6.4 show the PI to Hitra. This show a more linear trend compared to Sandøy.

6.2.4 Linear degradation with or without RANSAC

Ordinary least squares (OLS) and RANSAC regression behave in similar ways. Many results when comparing wind farms are exactly the same. This is natural as RANSAC is a linear regression model, but removes potential outliers. When looking at different regression plots it is clear that many wind farms do not have abnormal Production Index points. The treatment of outliers is however an important consideration when doing statistical analysis. When doing regression analysis, abnormal data points have great impact on the results. Although outliers in the regression models not necessarily are wrongful, they may have great impact on the result. The right lower cluster in Figure 6.1a have a great impact on the regression line. RANSAC identifies and removes abnormal data points for some wind farms when fitting the model.

6.2.5 Regression with ARIMA errors

The regression model with ARIMA errors treats the data good according to the diagnostic tests and plots. Data used in the model are not suffering from autocorrelated residuals, and the residuals are more or less randomly distributed around zero. This is visualized in Figure 6.3. The model does however not perform much better when comparing metrics to the other models.

Regression with ARIMA is a more complicated model than ordinary least squares and RANSAC. The model performs better than the other models when comparing statistical tests and when looking at predictions. Figure 6.2 summarises the results of an ARIMA model from Hitra wind farm. The Ljungbox test returns a p-value of 0.88, meaning that the null hypothesis is not rejected. The p-value of heteroscedasticity is calculated to be 0.00 meaning that the null hypothesis of having heteroscedasticity in the residuals is rejected.

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                  y   No. Observations:                  200
Model:             SARIMAX(1, 0, 0)x(0, 1, [1], 12)   Log Likelihood                  62.053
Date:                            Thu, 25 Apr 2024   AIC                           -116.105
Time:                                    08:16:18   BIC                           -103.160
Sample:                                08-31-2005   HQIC                          -110.860
                                     - 03-31-2022
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Time          -0.0011      0.000     -3.230      0.001      -0.002      -0.000
ar.L1          0.3315      0.044      7.522      0.000       0.245       0.418
ma.S.L12      -0.8826      0.058    -15.188      0.000      -0.996      -0.769
sigma2         0.0275      0.002     15.935      0.000       0.024       0.031
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):               306.75
Prob(Q):                              0.88   Prob(JB):                         0.00
Heteroskedasticity (H):               2.56   Skew:                            -0.71
Prob(H) (two-sided):                  0.00   Kurtosis:                         9.09
===================================================================================
```

Figure 6.2: Screenshot of results from a ARIMA model fitted on Hitra data.

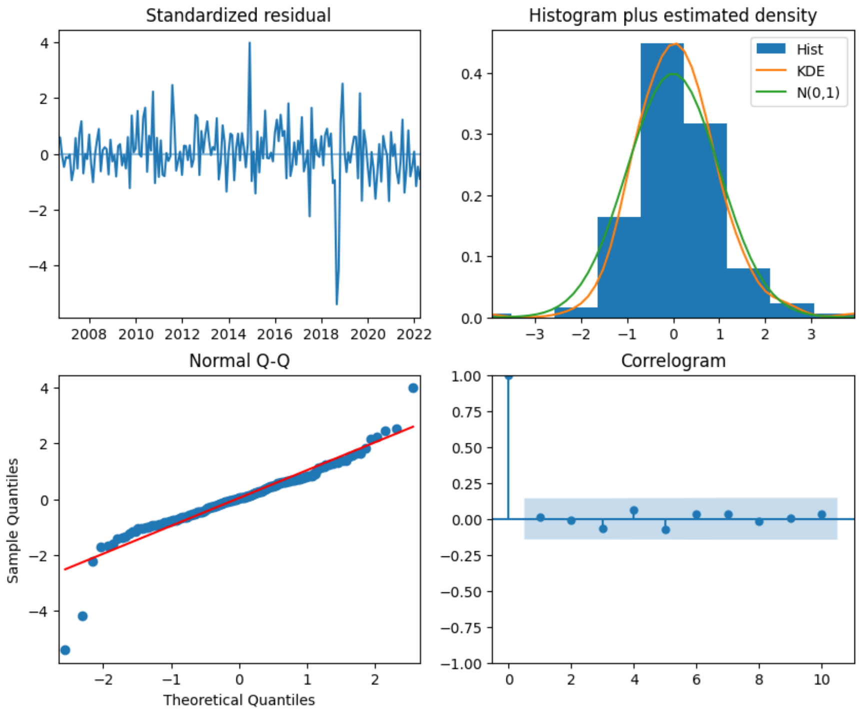


Figure 6.3: Diagnostic plot of the ARIMA model used on Hitra data.

Figure 6.4 shows that the predicted performance index are quite close to the actual Production Index.

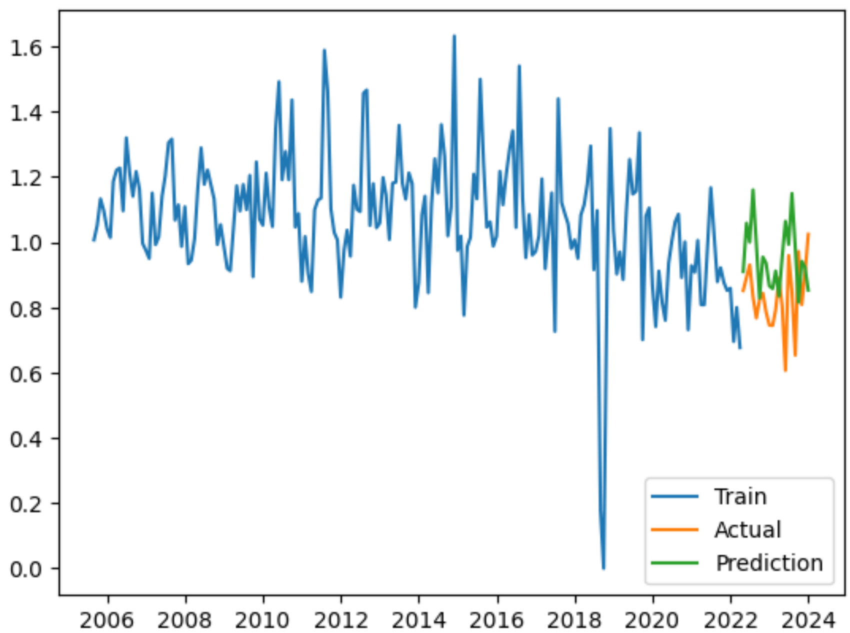


Figure 6.4: Production plot of Hitra with prediction from the ARIMA model.

From the plot in Figure 6.3 the residuals are quite centered around zero with the same magnitude. There are still some abnormal residuals. Jarque-Bera is a test to test the normality of the residuals. The null hypothesis is rejected as the test returns a low p-value. The plot of the distribution and the Quantile-Quantile the figure in indicate that the data are not far from being normally distribution, but there are deviations from a Gauss distribution. Even though the statistical test returns better result, it does however, return quite unrealistic degradation rates. The rate are calculated based on the slope of the *time*-component as done with the other models. Since Regression with ARIMA error is more complex model it additionally have other components regarding the AR and MA terms. It is a multivariate regression model making it dependent of more variables. This makes the model unsuitable for calculating the degradation rate.

6.2.6 Statistical tests

The Ljungbox-test failed when modelling with a simple linear regression and when using RANSAC-regression. Complete results are listed in Appendix F. Since the result are close to zero for all wind farms the null hypothesis assuming independent residuals is rejected. This corresponds naturally well with this ED24 as the same wind farms were studied (Drengsrud, 2024). However, this result shows that the correcting of wind resources do not entirely correct the autocorrelated residuals. The p-value is however larger in this study compared to ED24. This implies that correcting for wind resource has had a positive impact on the autocorrelation between the residuals. The study of autocorrelation also match the result found in OB17. In that study an extra term was added to the regression model to take autocorrelation into account. (Olauson et al., 2017) Autocorrelation in the constructed Production Index may be natural as this index is constructed using actual production data. One can clearly see that the actual production has a seasonal pattern meaning that one production point will be closely related the the point before in time. As the wind resources at a specific time also are related to the the wind resources before that time stamp, the simulated data are also containing autocorrelation. By adding an ARIMA term to the residuals, the autocorrelated residuals are corrected. This is shown in the visualized result for Hitra wind farm in Figure 6.2.

According to Shapiro Wilk test, the production index data are not normally distributed. The null hypothesis is rejected as the p-value are close to zero far from a significance level at 0.5. Regression with ARIMA errors does not correct the distribution either. The most serious consequence of a failing normality is that the confidence interval and p-value not being trustworthy. (Kilde) The objective of this thesis is to determine a long-term trend in production index.

The linearity test conducted are also failing. Ideally this should be linear with the models that is implemented. The Production Index is created to see how much a wind farm produces versus how much it is expected to produce. Ideally a decreasing production index is only caused by degradation as production is corrected for wind. By implementing a simulated production into the production index, more uncertainty are introduced to the model. There is a linear trend in the Production index plot even though there is large variance. It may be natural that the model implemented in this thesis fail on the rainbow-test compared to the model in ED24 which is exclusively based on production data and capacity factor of low uncertainty compared to the uncertainty in the ERA5 climate data.

6.2.7 Weighted and normal degradation

Both average and weighted average degradation rates are calculated from each windfarms´ estimated degradation rate. The weighting is done with respect to the total installed effect in each wind farm. There are pros and cons of both, and it may not be clear which measure to use. In Appendix A the installed effect to each wind farm as well as the the proportion to the total effect are plotted. One can see that Egersund and Tellenes account for around 41% of the installed effect. By using weighted average degradation these wind farms have a great impact on the total result. The two wind farms are quite new compared the majority of the selected wind farms. Egersund does also have a long downtime periods by the definitions specified in the thesis. As many of the wind farms lose their impact on the total calculated degradation rate when using weighted average. Average degradation rate on the other hand result in Rye Vind having an equal impact on the total degradation rate even though it only have approximately 0.14% of the installed effect compared to Tellenes. It would not make sense letting Rye Vind have the same impact as Tellenes. SG14 combines results from the different models to get an average of all the models. (Staffel & Green, 2014) To decrease the impact of Tellenes and Egersund in the weighted model and decrease the impact of small wind farms such as Rye vind in the average measurement, an average of the two results are used as the final result.

6.3 Comparisons to previous studies

6.3.1 Comparing the model

Although similar studies have been conducted previously, the method used in this thesis differs substantially from previous studies. In the former study on degradation of Norwegian wind farms, the capacity factor of the wind farms were studied without correcting for wind resource (Drengsrud, 2024). This allows for the results to be influenced by variations in wind, which could be a large source of error. Improvements on this study was therefore necessary to get a more robust result.

In SG14, the authors clearly states how variances in weather is accounted for. Although how this is done differs significantly from this thesis, their method relies on many of the same basic principles. The power output is calculated based on the weather reanalysis dataset MERRA, combined with the power curves of the turbines at each site. As the temporal and spatial resolution in this dataset is low, the weather for all of Great Britain was assumed to be similar and was analysed with a monthly time-series. The model in other words uses the average wind speed over a month in Great Britain to estimate wind power production. This does not account for losses due to turbulence, wake losses, downtime and loss due to technological inefficiencies. This, combined with a low spatial and temporal resolution, makes it quite inaccurate in predicting power output. (Staffel & Green, 2014)

The use of ERA5-data in this thesis allowed for much more accurate power prediction, providing access to weather data of the area of each wind farm. As power production data also is available as hourly time-series from each wind farm, predicted power output could be compared to actual production more directly than in SG14, where the estimated power production is used to adjust capacity factors. The use of performance index is therefore a more direct use of the predicted power output, which necessitates more accurate weather data than SG14 had access to.

In OB17, Olauson et al. also states that wind resource is accounted for. Three different weather reanalysis datasets are used, including MERRA and ERA-interim, the predecessor of ERA5. It also uses several statistical methods to account for disturbing effects, such as seasonal variances. It has clear similarities with SG14, as this was the inspiration of their analysis, although several improvements were made. As in SG14, the simulated power output was used to adjust capacity factors. OB17 therefore is a further development of the methodology used in studying wind power degradation.

The clear weakness of this thesis compared to OB17 and SG14 is the sample size. These studies have access to far more data, and as such the results are more robust. Still, seeing how Norwegian wind farms compare to other countries provides additional knowledge to the field.

6.3.2 Comparing results

As the results in the other papers is presented as the change in percentage points per year (pp/y), they are converted to changes in percentage to be comparable to the results in this thesis. Their results is therefore divided by the average CF of the study sample to find the result in terms of percentage.

This study showed a yearly degradation rate of -1.00%. The most natural basis for comparison is the study by Drengsrud (2024), as it looked largely at the same wind farms. Here, a yearly degradation of $-1,3\%$ per year is found. As can be seen, this is a slightly larger degradation rate, with about a 30% increase compared to this study. These results are however relatively similar, which is to be expected when comparing two studies of a similar sample. These similarities can be seen as providing further credibility to the study.

SG14 found a yearly decline in wind turbine performance of -1,6 ± 0,2% (Staffel & Green, 2014). This is a 60% increase compared to the results of this thesis. The causes of this discrepancy is not obvious, but as this study was conducted 10 years ago, the technological developments since may be a cause for the improvements. The weather in Great Britain is also similar to coastal regions in Norway, so the results is otherwise expected to be relatively similar.

OB17 found a degradation rate lower than the other studies. The annual degradation is here estimated to be 0,50% (Olauson et al., 2017), which is about half of the degradation found in this thesis. The study also indicated that new turbines have less decline in performance compared to older turbines. This effect was also studied in this thesis, without any significant result. Due to the larger sample size in OB17, it is probable that turbine age is a significant factor on degradation, and it would be interesting to see whether this is shown in a larger scale study on Norwegian wind farms.

Comparing the results with the other studies gives additional credibility to the results in the thesis. Although there are variations in the degradation rates found in the studies, the results in this thesis is in the same order of magnitude as what is seen elsewhere.

6.3.3 How different climates affects degradation

Olauson et al. (2017) argued that harsher climate with stronger wind speeds and more salt spray may be the reason why the UK experienced a larger degradation rate. Still, this is unlikely to account for the whole difference. Sweden has on the other hand a colder climate compared to UK, which should result in more icing, potentially increasing degradation rates (Olauson et al., 2017).

The climate in Norway is interesting in this regard, as it can be seen as a combination of the climate in Sweden and the UK. Figure 4.4 shows that all the selected wind farms are located at the coastal line of Norway. These regions are characterised by high average wind speeds, a lot of precipitation, as well as exposing the to salt spray. This will be similar to typical climate in the UK. At the same time wind turbines in Norway experience a colder climate, which may result in icing, like what is seen in Sweden.

Norway seems to be more similar to UK than Sweden in terms of wind turbine degradation. An interesting point that this seem to indicate, is that exposure to salt and harsh wind conditions are far more important factors on degradation rates than cold climate and icing. This point will be discussed further as this is seen together with the rest of the results.

6.4 Downtime

The model showed a significant increase in downtime, with an average of 0.04 pp/y increase per year. This correspond well with ED24, which found and increase of 0.06 pp/y. (Drengsrud, 2024) This may indicate that the increase in downtime is in the right order of magnitude. The annual downtime is estimated in this thesis to be in the range approximately 0.30 % and 1.80 %. This is lower than the downtime found in ED24 which ranges from approximately 10 % to 17 %. OB17 states that the annual downtime ranges from 1% - 6%. (Olauson et al., 2017) SG14 suggests a downtime of 4-7%. (Staffel & Green, 2014). There is large spread in suggested downtime in the mentioned studies, and it is challenging to assess the reliability of the results found in this thesis. However, it is likely that the real downtime is higher than what is estimated. ED24 might have overestimated the downtime as the study has defined all production points equal to zero as downtime. This excludes the downtime affecting only parts of the wind farms. At the same time, production hours outside of the production interval are defined as downtime.All studies mentioned, conclude that an increasing downtime is natural over the lifetime of wind turbines.

An increasing amount of downtime is a large contributing factor to the overall degradation. The results show that excluding downtime from the results reduces the total annual degradation by approximately 0.2 - 0.5 %. This difference is calculated by taking the difference between the degradation with partial downtime and the degradation without partial downtime. The difference is however varying depending on which model is used to estimate the degradation.

Egersund and Tellenes both had publicly available maintenance logs through NordPool. By the definition of partial downtime in the thesis, Egersund has by far the most downtime of the selected wind farms. Detected downtime was compared with the log from NordPool to find if these correspond. However, little correspondence is seen between NordPool logs and the defined partial downtime. There may be several reasons for this. Firstly, the downtime in the model relies on a definition in that may be inaccurate. In addition, some of the downtime might not be reported into this register, so one would not expect these to line up exactly. The downtime peaks during the summer and this is especially clear when looking at the detected downtime at Egersund. This makes sense when comparing to NordPool data, as downtime lasting for more than one day often takes place in June. The maintenance logs indicate that this is often due to foreseen maintenance work, and rarely unforeseen events.

Another reason for downtime may be periods with negative prices, where wind farms may be shut down. Such events may disturb the results, and not all registered downtime should therefore be interpreted as due to maintenance or operational issues. This is still a quite uncommon occurrence in Norway, with most wind farms operating at their maximum throughout the year. However, this phenomenon has been seen more frequently in recent years, and is expected to rise with the increase of intermittent energy sources such as solar and wind. (*Avoiding Negative Electricity Prices: What Measures Should TSOs Take?*, 2019)

6.5 Factors affecting degradation

6.5.1 Geographical factors

The test for whether location affected the degradation of the wind farms showed that there were no significant differences between the three defined regions. As the climate in the coastal regions in Norway are pretty similar, characterized by high wind speeds, a lot of downfall as well as exposure to salt, the wind farms seems to operate similarly in the selected regions. However, the northern region do experience more days below the freezing point and as such involves a higher risk of icing. This was hypothesized to lead to an increase in downtime, but such a correlation was not shown. As the study consists of a relatively small sample size of only 4-6 wind farms in each group, other factors than location may have affected the degradation. Still, it is interesting to see that the degradation is relatively similar in each region, which may point to the fact that icing and colder climates do not play as large a role on degradation as what was hypothesized. Another study with a larger sample size would however be needed to conclude on whether such factors play a significant role.

6.5.2 Technological factors

To see whether there are significant differences between newer and older wind turbines, the wind farms were grouped into two groups listed in Table 4.5. A Mann-Whitney u-test was conducted to test if there was a significant difference between the groups. To get an equal basis for comparison when studying the technology, the estimated degradation rate for the first five year was used in the test. Based on the p-value in the test, no significant difference between the groups were found. This means that the null hypothesis is not rejected and the groups are considered equal. This indicate that there are no significant differences in degradation rates when comparing new and old turbines.

According to the study by Staffel and Green, wind farms built before 2003 have a greater average decline rate than wind farms built after 2003. As the Norwegian wind power industry is much less mature, the dataset in this thesis only included three wind farms built before 2003. Due to this, such a divide was not feasible. OB17 found that new turbines does not behave significantly different from older units the first five year of production. (Olauson et al., 2017). This matches the result found in this thesis. The small sample size in this thesis makes the result hard to confirm, but as this aligns with the results in OB17, it is probable that the effects of turbine age are relatively small.

6.5.3 Seasonal variances

A test was also conducted to find whether there were significant differences between seasons. Initially, the wind farms were divided into four seasons: winter (December-February), spring (March-May), summer (June-August) and autumn (September-November). However, this proved challenging, as this divide lead the winter season to span two years. Consequently, the seasons were divided into quarters to avoid this issue.

The u-test of the RANSAC model did show a significant differences between Q1 and Q4, although it is unclear what caused this. As with the other tests the relatively small sample size may lead to individual factors at each wind farm being more significant than more general factors.

This test was proposed to see how weather conditions affected degradation, where one theory would be that icing in winter times would lead to higher degradation. The way this test was conducted may have lead to the results being affected by several other factors however. For example, maintenance is often conducted in summer, as the electricity prices generally are lower. In addition, the average wind speed is higher in autumn and winter, and it is unclear as to how this have influenced the results. A better way to test how weather influences degradation would be necessary to conclude on this topic, where one would need to adjust for other factors influencing the results.

6.5.4 Causes of degradation

Although no conclusions can be drawn purely from the results of these tests alone, they do point to some interesting discoveries. The fact that no significant difference was found, between geographically divided groups, may imply that colder temperatures, snow and icing has little effect on degradation. This aligns well with a finding in OB17, where the study showed that turbines placed in forests had a lower degradation rate than turbines placed in open land. Turbines in forests are typically placed inland, while wind turbines in the open are often located in coastal regions. This also coincides with the fact that the degradation of Norwegian wind farms is more similar to British than Swedish wind farms. This seems to imply that exposure to salt and more precipitation, as well as more extreme wind conditions affects degradation to a larger degree than exposure to temperatures below freezing and consequently icing.

Early in the process of this thesis, it was planned to compare inland WTs to coastal WTs, but as too few wind farms inland fit the criteria for the study, this was not possible. If a study is done in a few years, as more data can be gained from inland wind farms, such a study would be possible. It would then be interesting to see whether this pattern is shown in Norway as well, where based on the results mentioned, it is hypothesized that coastal WTs degrade faster than inland WTs.

Whether this effect also applies to offshore WTs is not known. It should be expected that they are subject to a lot of the same weather conditions as WTs on the coast, with high wind speeds and exposure to salt. Only one of the studies in the literature included offshore wind, namely the study of Danish and Britsh wind farms in 2012 (Hughes, 2012). This study showed that Danish offshore wind turbines degraded from a capacity factor of 39% at year 0, to 15% at year 15, which equals a degradation rate of 6% each year. As the offshore wind industry still was quite immature at this stage, as well as including a small sample of offshore WTs, these results probably are not representative for modern offshore wind power. A separate study on the degradation of offshore wind turbines would be necessary to find how these are affected by their surrounding climate.

6.6 Total lifetime energy loss

A degradation rate of 1,0 % corresponds to a yearly loss of 220 GWh from year to year for all Norwegian wind farms. Over their expected lifetime of 20 years this will lead to a loss in energy production of 9,8 %, or 21,6 TWh.

These results also indicate that the wind farms are expected to produce 82% of the wind energy at the end of their lifetime compared to today´s level. According to NVEs assumptions of 0,1% yearly degradation, one would expect a performance of 98% at year 20 compared to year 1 (NVE, 2023a). This means that the current wind farms in Norway will produce 1,3 TWh less in 20 years than NVE assumes. This gap needs to be covered with further investments in energy production.

6.7 LCOE

The loss in yearly production will have effects on the calculated LCOE of the wind farms. Using similar assumptions as NVE, with an interest rate of 6%, this will contribute to an increase in LCOE of 6,8 %, or an additional 4 øre/kWh compared to NVEs calculations.

If these results are indicative of the performance loss of all Norwegian wind farms, it calls for a change in the underlying assumptions for the future development of the industry. An increase in LCOE of 6,8% compared to NVEs calculations is substantial, and could be decisive when assessing the financial viability of a wind power project. These results do not take into account an increase in maintenance costs, which also would be expected to increase along with greater degradation and increasing downtimes.

6.8 Industry applications

A degradation rate of 1,0%, as was found in this study, is significantly larger than what is assumed in the industry. It is also similar to results in the literature, where all point to the fact that degradation rates are higher than expected.

In LCOE calculations, NVE have used a degradation rate of 0.1% (NVE, 2023a). This will likely have resulted in overestimating the profitability of wind turbines, as this is significantly lower than what is estimated in this thesis, as well as in other studies. Even though this model is a simplification of reality, it will together with the other studies give a better estimate of the decline in performance compared to the rate that has been used so far when estimating the profitability. Using a degradation rate of 1,0% is proposed to get a more realistic picture of the effects of degradation. This could potentially be the difference between a profitable and unprofitable project.

As both the literature and results from this study imply, exposure to salt and high wind speeds, such as is found in coastal regions in Norway, lead to a higher degradation rate. This means that higher degradation rates should be assumed when building wind farms in coastal regions, than inland regions. Although no inland WTs are studied in this thesis, one may expect the loss in performance to be more similar to what is seen in Sweden. Based on this a degradation rate of 1,0% could be assumed in coastal regions. If one assumes that degradation rates inland is similar to what is seen in Sweden, a rate of 0,5% might be assumed inland. This might in turn have an impact on decisions in the wind power industry in Norway, where most wind farms currently are built along the coast. The results could suggest that there should be a larger emphasis on developing inland wind farms in Norway.

The model could also be suitable for industry applications, although improvements would be necessary as previously discussed. It is likely that a wind farm operator have access to better weather data at the site, as well as more detailed information of the turbines, wake loss, et cetera, which would allow for a more precise prediction of power production.

As discussed, the weather data was a large source of uncertainty. Furthermore, obtaining all relevant information of the wind farms proved difficult at times. NVEs database on Norwegian wind farms both lacked important data, as well as containing incorrect information. Establishing a better system for sharing information between wind farm operators would therefore be valuable, both for academic and industrial purposes.

7 Conclusion

The model shows a yearly degradation rate of $-1.00 \pm 0.22\%$. Comparing these results with another study on an almost identical sample, ED24, shows a relatively similar degradation rate. This is significantly higher than what is found in Sweden, presented in the article OB17, but lower than what was found in Britain, in SG14.

If this rate is applicable to all Norwegian wind farms, it calls for a change in assumptions of degradation of wind farms. In NVE´s LCOE-calculations, a degradation rate of 0,10% is used. The results found in this study indicates that this should be increased. This should also be considered when developing new wind farm projects,

The use of ERA5 data as the basis for modelling wind farms was a significant error source. Specifically the large grid cell sizes made the wind data somewhat inaccurate, causing a large spread in the results. Inaccuracies related to height and wake loss, as well as the use of hourly time-series data also contributed to increasing the uncertainty of the model.

Linear regression model was utilised for estimating the degradation rate. To check whether the model satisfied the necessary requirements, several statistical tests were conducted. Two of these tests failed, but the model was still deemed useful. The unreliability of the confidence intervals is the most serious consequence due to the test failures. Even though the linearity test failed, scatter plots show a long-term linear trend to the majority wind farms, although it showed considerable variance. The objective is to find a long-term trend in the data, meaning that a regression model can give a good estimation of degradation rate despite failing tests.

The study also included tests to find potential risk factors for increased degradation, grouping the wind farms by age and location, as well as studying their performance in four seasons. None of these tests showed any significant differences between the selected groups, which could be affected by the small sample size of the study. If a large-scale study is done on the same topic in the future, it would be interesting to see whether these factors have significant impacts.

One interesting point that these results may point to, is that cold climate and icing have relatively small effects on degradation. Comparing the results to other studies, the degradation of Norwegian wind farms are relatively similar to what is found in the UK. However, these rates are considerably higher than in Sweden. As the climate along the coasts of Norway is quite similar to the climate Great Britain, this may imply that being exposed to a coastal climate causes higher degradation rates. This may be due to factors such as high precipitation, large average wind speeds and exposure to salt.

The model was created so that it could be implemented in future studies on similar topics. Using this as a framework, one may expect to get a better performing model if improvements as discussed is made. The use of publicly available resources throughout also allows for similar usage in future studies, and therefore could be replicated in all areas with publicly available production data.

7.1 Future research

The two greatest limiting factors in this study were the sample size and inaccurate weather data. Due to both time restrictions and lacking information on several wind farms, a study with a greater sample size was not feasible. The data model grew quite large, so a study on a greater number of wind farms with a similar model would need to be more effectively designed. It would however be interesting to see a bigger study on a more representative number of wind farms, similar to what has been done in Sweden and Great Britain. This could also provide a better basis for studying the underlying risk factors for performance loss, thus providing a better understanding of this phenomenon.

Secondly, better weather data would be a significant improvement of the study. If the technology of weather reanalysis improves, it could be more suitable for such usage. The most accurate solution would be to have access to wind speeds data at the site of the wind farm. If a collaboration study with firms in the wind industry had been done, this could have allowed collection of better data.

The study suggests that WTs in coastal regions are more vulnerable to degradation than inland WTs. This seems to be a more important factor for degradation than exposure to low temperatures and icing. A more thorough understanding of these phenomena would be interesting, as well as a separate study in Norway looking at these two groups. How offshore wind farms are affected by degradation would also be an interesting topic for further studies. The results imply that these could be more vulnerable to degradation, so further research on this would be valuable.

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Appendices

This section contains different data such as wind farm and turbine information. Furhermore, it also contains selected results from the different regression models to individual wind farms. Selected metrics and residuals to different models are also included in this section.

A Selected Wind farms

An overview of the selected wind farms with supplied specification are listed in Table A.1.

Table A.1: Chosen wind farms with associated information

Wind farm	Turbine type	First production year	Manufacture year	Maximum effect	Proportion of selected farms
Egersund	3.4M114	2017	2014	112.200	0.17
Fakken	V90-3.0	2012	2002	54.000	0.08
Hamnefjell	V112-3.45	2017	2015	51.750	0.08
Hitra	SWT-2.3-CS	2009	2004	55.200	0.08
Kjøllefjord	SWT-2.3-82VS	2006	2004	39.100	0.06
Lista	SWT-2.3-93	2012	2005	71.300	0.11
Raggovidda	SWT-3.0-101	2014	2011	45.000	0.07
Rye Vind	V27/225	2015	1989	0.225	0.0003
Røyrmyra	E-48	2015	2004	2.400	0.004
Sandøy	NM48/750	1999	1997	3.750	0.006
Skomakerfjellet	V112-3.3	2015	2015	13.200	0.02
Tellenes	SWT-3.2-113	2017	2014	160.000	0.24
Valsneset	E-70	2006	2005	11.500	0.02
Ytre Vikna	E-70	2012	2005	39.100	0.059
Åsen II	E-48	2012	2004	1.600	0.002

B General results

Individual wind farm results of all production years are listed in Table B.1. This tables presents results from the three main models.

Table B.1: Estimated degradation Rates for wind farms using all data.

Wind Farm	Linear Degradation	Ransac Degradation	Arima Degradation
Egersund	-0.0119	-0.0119	-0.0075
Fakken	-0.0087	-0.0089	0.0053
Hamnefjell	-0.0522	-0.0182	-0.0436
Hitra	-0.0083	-0.0058	-0.0130
Kjøllefjord	0.0022	0.0022	-0.0456
Lista	-0.0011	-0.0011	-0.0012
Raggovidda	-0.0433	-0.0407	-0.0243
Rye Vind	0.0622	-0.0058	0.1716
Røyrmyra	-0.0164	-0.0164	-1.3002
Sandøy	-0.0109	-0.0105	-0.3258
Skomakerfjellet	-0.0056	-0.0056	-0.0079
Tellenes	-0.0243	-0.0243	-0.0254
Valsneset	-0.0050	-0.0050	-0.1405
Ytre Vikna	-0.0034	-0.0034	-0.0065
Åsen II	-0.0067	-0.0067	-0.0043

C General results without downtime

Results to individual wind farm without downtime are listed in Table C.1. This tables presents results from the three main models.

Table C.1: Estimated degradation rates for all wind farms using data without partial downtime.

Wind Farm	Linear Degradation	Ransac Degradation	Arima Degradation
Egersund	-0.0120	-0.0120	-0.2620
Fakken	-0.0091	-0.0093	0.0049
Hamnefjell	-0.0422	-0.0080	-0.0393
Hitra	-0.0056	-0.0046	-0.0118
Kjøllefjord	0.0029	0.0039	-0.0436
Lista	-0.0010	-0.0010	-0.0781
Raggovidda	-0.0378	-0.0352	-0.0218
Rye Vind	0.1282	0.0190	0.1489
Røyrmyra	-0.0185	-0.0185	0.0841
Sandøy	-0.0112	-0.0108	-0.4063
Skomakerfjellet	-0.0074	-0.0074	-0.0071
Tellenes	-0.0214	-0.0214	-0.0204
Valsneset	-0.0053	-0.0053	-0.1405
Ytre Vikna	-0.0035	-0.0035	-0.0066
Åsen II	-0.0092	-0.0092	-0.1806

D Degradation the first five years

The estimated degradation rates to individual wind farm for the first years are presented in Table D.1. This tables presents results from the three main models.

Table D.1: Estimated degradation rates for all wind farms using data from the first five years.

Wind Farm	Linear Degradation	RANSAC Degradation	ARIMA Degradation
Egersund	-0.0066	-0.0066	0.0000
Fakken	0.1025	0.1025	0.0289
Hamnefjell	-0.0375	-0.0505	-0.0289
Hitra	0.0238	0.0238	0.0124
Kjøllefjord	0.0011	0.0011	-0.0076
Lista	-0.0061	-0.0061	-0.0001
Raggovidda	-0.0313	-0.0328	-0.0486
Rye Vind	-0.3232	-0.2112	-0.0000
Røyrmyra	-0.0497	-0.0497	-0.0280
Sandøy	-0.0104	-0.0104	-0.0028
Skomakerfjellet	0.0023	-0.0067	-0.0203
Tellenes	-0.0241	-0.0241	-0.0247
Valsneset	0.0020	0.0020	0.0073
Ytre Vikna	0.0045	0.0045	0.0009
Åsen II	0.0092	0.0092	0.0122

E Seasonal degradation

The estimated seasonal degradation rates to individual wind farms are presented in this section. The first table (E.1) shows the degradation rate estimated by ordinary least squares. Table E.2 shows the degradation rates estimated by RANSAC regression.

Table E.1: Quarterly Linear Rates for Wind Farms

Wind Farm	Q1	Q2	Q3	Q4
Egersund	-0.0076	-0.0020	-0.0040	0.0020
Fakken	-0.0355	-0.0438	-0.0332	0.0348
Hamnefjell	0.0087	0.0579	-0.0785	-0.0136
Hitra	0.0050	0.0123	-0.0296	-0.0139
Kjøllefjord	0.0056	-0.0229	-0.0071	-0.0046
Lista	0.0005	0.0002	0.0018	-0.0021
Raggovidda	0.0143	0.0791	-0.1324	-0.0527
Rye Vind	0.0420	-1.2677	-0.8087	1.7155
Røyrmyra	-0.0018	0.0107	0.0083	-0.0035
Sandøy	-0.0012	0.0180	-0.0057	-0.0002
Skomakerfjellet	0.0146	-0.0027	0.0088	-0.0080
Tellenes	-0.0188	-0.0195	0.0203	0.0071
Valsneset	0.0081	-0.0108	0.0016	0.0028
Ytre Vikna	-0.0025	-0.0023	0.0050	0.0048
Åsen II	0.0056	-0.0024	-0.0007	-0.0075

Table E.2: Quarterly Degradation Rates Ransac for Wind Farms

Wind Farm	Q1	Q2	Q3	Q4
Egersund	-0.0076	-0.0020	-0.0040	0.0020
Fakken	-0.0355	-0.0438	-0.0332	0.0348
Hamnefjell	0.0087	0.05	-0.0785	-0.0136
Hitra	0.0050	0.0123	-0.0296	-0.0139
Kjøllefjord	0.0056	-0.0229	-0.0071	-0.0046
Lista	0.0005	0.0002	0.0018	-0.0021
Raggovidda	0.0143	0.0791	-0.1324	-0.0527
Rye Vind	0.0420	-1.2677	-0.8087	1.7155
Røyrmyra	-0.0018	0.0107	0.0083	-0.0035
Sandøy	-0.0012	0.0180	-0.0057	-0.0002
Skomakerfjellet	0.0146	-0.0027	0.0088	-0.0080
Tellenes	-0.0188	-0.0195	0.0203	0.0071
Valsneset	0.0081	-0.0108	0.0016	0.0028
Ytre Vikna	-0.0025	-0.0023	0.0050	0.0048
Åsen II	0.0056	-0.0024	-0.0007	-0.0075

F Metrics

Metrics to the individual wind farms are included in this section. Table F.1 show the metrics from to the general results presented in Table B.1. Metrics to RANSAC-model and ARIMA-model results are presented in Tables respectively F.2 and F.3.

Table F.1: Metrics to the Linear Regression model used on all data.

Wind Farm	R2	MSE	MAE
Egersund	0.042	0.0019	0.039
Fakken	-0.187	0.513	0.499
Hamnefjell	-0.153	0.091	0.219
Hitra	0.138	0.043	0.147
Kjøllefjord	0.042	0.022	0.113
Lista	-0.072	0.002	0.038
Raggovidda	-0.106	0.231	0.426
Rye Vind	-0.465	1.645	1.042
Røyrmyra	-0.169	0.032	0.136
Sandøy	0.473	0.031	0.140
Skomakerfjellet	0.017	0.009	0.075
Tellenes	0.150	0.007	0.070
Valsneset	-0.040	0.007	0.066
Ytre Vikna	-0.034	0.005	0.056
Åsen II	0.013	0.012	0.087

Table F.2: Metrics to the RANSAC Regression model used on all data.

Wind Farm	R2	MSE	MAE
Egersund	0.042	0.001	0.038
Fakken	-0.288	0.556	0.523
Hamnefjell	-0.084	0.085	0.210
Hitra	0.137	0.044	0.146
Kjøllefjord	0.045	0.022	0.111
Lista	-0.073	0.0024	0.038
Raggovidda	-0.077	0.226	0.398
Rye Vind	-0.045	1.173	0.863
Røyrmyra	-0.169	0.032	0.136
Sandøy	0.473	0.030	0.140
Skomakerfjellet	0.018	0.009	0.075
Tellenes	0.150	0.007	0.070
Valsneset	-0.048	0.007	0.068
Ytre Vikna	-0.034	0.005	0.056
Åsen II	0.013	0.012	0.087

Table F.3: Calculated Mean Squared Error (MSE) and Mean Absolute Error (MAE) from the ARIMA model

Wind Farm	MSE	MAE
Egersund	0.002	0.039
Fakken	0.257	0.408
Hamnefjell	0.060	0.181
Hitra	0.053	0.196
Kjøllefjord	0.089	0.265
Lista	0.004	0.052
Raggovidda	0.104	0.279
Rye Vind	5.162	1.563
Røyrmyra	0.019	0.072
Sandøy	0.366	0.590
Skomakerfjellet	0.032	0.149
Tellenes	0.008	0.068
Valsneset	0.045	0.139
Ytre Vikna	0.006	0.069
Åsen II	0.014	0.089

G Statistical tests

Results from statistical tests used to test the linear assumptions are listed in this section. Table G.1 shows the results from the test made on the linear model, and Table G.2 presents the test results from the RANSAC-model.

Table G.1: Statistical Tests from Linear regression used on all data

Wind Farm	Ljungbox Test	Rainbow Test	Shapiro-Wilk Test	Goldfeld Quandt
Egersund	7.99e-02	8.89e-05	2.55e-13	0.25
Fakken	1.78e-01	1.26e-03	1.04e-18	0.82
Hamnefjell	5.90e-01	4.48e-05	2.31e-13	0.14
Hitra	9.65e-02	1.46e-12	9.74e-25	0.69
Kjøllefjord	1.51e-01	2.18e-12	2.20e-23	0.02
Lista	3.30e-02	6.30e-08	9.28e-19	0.04
Raggovidda	3.95e-01	3.78e-04	8.11e-17	0.37
Rye Vind	1.20e-02	3.52e-01	1.05e-14	0.14
Røyrmyra	6.97e-01	2.43e-04	1.55e-15	0.004
Sandøy	1.88e-42	5.94e-12	1.08e-25	1.00
Skomakerfjellet	3.26e-02	2.38e-05	3.02e-15	0.53
Tellenes	4.58e-01	6.11e-04	2.07e-13	0.12
Valsneset	1.39e-03	2.54e-08	2.51e-23	0.03
Ytre Vikna	5.38e-01	9.56e-09	6.58e-19	0.94
Åsen II	8.64e-01	3.26e-12	4.06e-19	0.07

Table G.2: Statistical from RANSAC regression used on all data

Wind Farm	**Ljungbox Test**	**Rainbow Test**	**Shapiro-Wilk Test**	**Goldfeld Quandt**
Egersund	7.99e-02	8.89e-05	2.54e-13	0.25
Fakken	1.78e-01	1.26e-03	1.04e-18	0.82
Hamnefjell	6.10e-01	4.48e-05	2.31e-13	0.14
Hitra	7.99e-02	1.46e-12	9.74e-25	0.70
Kjøllefjord	1.51e-01	2.18e-12	2.20e-23	0.02
Lista	3.30e-02	6.29e-08	9.28e-19	0.04
Raggovidda	3.93e-01	3.78e-04	8.11e-17	0.37
Rye Vind	1.17e-02	3.52e-01	1.05e-14	0.14
Røyrmyra	6.97e-01	2.43e-04	1.55e-15	0.01
Sandøy	1.70e-42	5.94e-12	1.08e-25	0.99
Skomakerfjellet	3.26e-02	2.38e-05	3.02e-15	0.53
Tellenes	4.58-01	6.11e-04	2.07e-13	0.12
Valsneset	1.39e-03	2.54e-08	2.52e-23	0.03
Ytre Vikna	5.38e-01	9.56e-09	6.58e-19	0.94
Åsen II	8.64e-01	3.26e-12	4.06e-19	0.07

H Distances

The distance between from given point in the climate data and the wind farms are listed in Table H.1. The distance are measured in kilometres and are calculated from the respectively coordinates using a Python library `geopy.distance`.

Table H.1: Wind Farm Coordinates and Distances

Wind Farm	Weather Coordinate	Windfarm Coordinate	Distance [km]
Egersund	(58.4, 6.0)	(58.4330, 6.0855)	6.198248
Fakken	(70.0, 20.0)	(70.0980, 20.0502)	11.100324
Hamnefjell	(70.6, 29.7)	(70.6673, 29.7191)	7.543222
Hitra	(63.5, 8.8)	(63.5256, 8.8042)	2.862820
Karmøy Hywind	(59.2, 5.2)	(59.2924, 5.2846)	11.371548
Kjøllefjord	(70.9, 27.2)	(70.9222, 27.2667)	3.478261
Lista	(58.1, 6.6)	(58.1556, 6.6562)	7.025415
Raggovidda	(70.7, 29.0)	(70.7649, 29.0835)	7.866564
Rye Vind	(63.4, 10.1)	(63.4181, 10.1181)	2.210809
Røyrmyra	(58.5, 5.7)	(58.5906, 5.7275)	10.217946
Sandøy	(62.7, 6.4)	(62.7631, 6.4464)	7.422359
Skomakerfjellet	(64.2, 10.4)	(64.2156, 10.4167)	1.919253
Tellenes	(58.3, 6.3)	(58.3439, 6.4356)	9.330275
Valsneset	(63.8, 9.6)	(63.8164, 9.6183)	2.038473
Ytre Vikna	(64.8, 10.8)	(64.8875, 10.8622)	10.191766
Åsen II	(58.7, 5.7)	(58.7369, 5.7519)	5.092905

I Data diagnostics

Table I.1 shows the diagnostics of the production data retrieved from NVE. Data cleaning and construction prepared the data for modelling.

Table I.1: Data diagnostic before cleaning and construction

Location	Observations	Missing Value	Negative Values	Zero Values	Production o/ capacity
Egersund	47270	0	0	3544	0
Fakken	92030	0	0	9440	0
Hamnefjell	47857	0	0	3681	1
Hitra	161081	0	0	17114	317
Kjøllefjord	142609	0	0	13354	39
Lista	90683	0	0	5338	0
Raggovidda	74004	0	0	5570	1068
Rye Vind	61368	0	0	25590	9
Røyrmyra	63481	0	0	2598	4020
Sandøy	175320	0	0	26406	4942
Skomakerfjellet	61094	0	0	7016	0
Tellenes	47864	0	0	3916	205
Valsneset	142105	1104	334	9069	2182
Ytre Vikna	92099	0	0	3784	0
Åsen II	94896	0	0	5044	1840

J Code used in analysis

The code used to estimate the degradation can be found at url: `https://github.com/olavfg/Masterthesis2024_Degradation_of_Norwegian_wind_farms` or by scanning the QR-code beneath. Only a selected part of the result are included in this thesis and in the script. It is however, possible to extract more result from the different models in the attached script.

Figure J.1: The code used to estimate the degradation rate can be found using the QR-code

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