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Repowering of wind power plants: Assessing future impacts and needs, exemplified for Austria

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Supervisor: Univ.-Prof. i.R. Dipl.-Ing. Dr.techn. Reinhard Haas

by

Lukas Pickerle BSc
0226267

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Abstract

The expansion of wind power is crucial for meeting climate targets and achieving a more independent energy supply in Austria. When suitable land becomes scarce, repowering provides an opportunity to receive significantly higher yields with the same land use.

This thesis investigates how repowering can contribute to national wind energy targets by assessing future technological and economic developments in Austria.

The method consists of layered models that integrate a wind park database, simulated and real-world capacity factors, technological trends and an economic sensitivity analysis. Based on this, several repowering scenarios were developed, incorporating regional differences, turbine trends and different installation densities for new developments in Austria.

In most scenarios, repowering at least doubles the current energy yield from existing wind park areas by 2050. Modern turbines already produce, on average, three times more than those from 2010 and up to seven times more by 2050. The economic analysis shows that repowering projects are economically viable under a wide range of market conditions, often with payback periods well below the turbine lifetime.

The results show that repowering makes a valuable contribution to both the economic and ecological performance of wind energy. It significantly boosts the efficiency of existing wind sites, but meeting Austria's energy targets can only be done through a combination of repowering and the development of new wind power areas.

Contents

1. Introduction

Wind energy plays an important role in our energy transition by reducing the need for imported fossil fuels and strengthening domestic energy production. Achieving climate targets also remains out of reach without the expansion of wind power. To make this possible, it is important not only to open up new areas for wind energy, but also to use existing sites as efficiently as possible.

In Austria, wind power plants have been increasingly deployed over the past decades, contributing significantly to our electricity generation. However, many of the existing wind turbines are approaching the end of their economic and technical lifespan, and this presents an opportunity for repowering: the replacement of existing wind turbines with modern, more powerful and efficient versions.

As this thesis will show, key wind turbine parameters such as rotor diameter and rated power have increased significantly in a linear trend over time. This development offers several advantages for repowering, such as increased energy yield, more efficient land use and better grid integration. Assessing the future impacts of repowering is essential for optimizing Austria's wind energy potential.

According to the „Innovative Energietechnologien in Österreich – Marktentwicklung 2023"[1], the development of Austria's wind sector, combined with an assumed turbine lifetime of around 20–25 years[2], means that, due to the strong expansion since 2011, several wind parks are now reaching the end of their operational life and offer the possibility for repowering. Those increasing numbers of aging wind turbines present both challenges and opportunities.

[1] Biermayr et al., 2024, p. 284.
[2] Schaffarczyk, 2022, p. 267.

There are studies that confirm the previously mentioned yield increases from repowering, as well as the enlargement of individual wind park elements.[3] [4] This study[5], shows that repowering is also an economically viable model for modernizing wind power in Germany. However, regulatory uncertainties, approval processes and tender procedures are critical factors for further expansion. It is also shown that clear and reliable planning frameworks with well-defined support mechanisms are essential to encourage investments in new wind turbines.[6]

In Austria, however, it has also become evident that, in response to the rising electricity prices in recent years, a large share of wind park operators have opted out of public support schemes in order to take economic advantage of the high market prices and now sell their electricity independently.[7]

For the economic evaluation of wind turbines, the Net Present Value (NPV) is frequently used according to relevant literature[8] [9], as it provides insights into the long-term profitability of an investment. For Austria, this means that a solid data basis is needed for various costs related to the construction, operation and electricity sales of wind turbines. Also in order to allocate energy yields, highlight regional differences or create repowering models, an even more extensive dataset on the technical configuration and size of individual wind parks in Austria is required.

While current national and regional developments in Austria are documented through figures on recent expansions and trends[10], there is a lack of detailed evaluations specifically related to repowering. Therefore, the core objective of this thesis is to evaluate the dynamic wind power potential in Austria including repowering in scenarios up to 2050 based on technological progress.

[3] Lacal-Arántegui, Uihlein, and Yusta, 2020.
[4] Biermayr et al., 2024.
[5] Fuchs, Kasten, and Vent, 2020.
[6] Fuchs, Kasten, and Vent, 2020, p. 13.
[7] Biermayr et al., 2024.
[8] Heier, 2022, p. 551.
[9] Hau, 2016, p. 551.
[10] Windkraft, 2024.

To meet these challenges, this thesis develops a data model to structure these parameters and an analytical model to calculate energy yields, based on simulated and real-world data, using the capacity factor. A forecast model extends the analysis into future trends, while a repowering factor model summarizes the technological development. Based on this, a sensitivity analysis of the net present value (NPV) evaluates the economic viability. Finally, a repowering scenario model assesses the repowering potential at national and regional levels, generating real-world yield scenarios under different conditions and allows future projections up to 2050 under various repowering scenarios as well as additional new installations.

The following chapter 2 provides a brief historical and technical overview of wind energy, wind turbines and the topic repowering. It then outlines the current situation of wind power in Austria. In the subsequent chapter 3, the data structure is described within the data model, followed by the analytical part, in which the previously mentioned detailed approaches are calculated and modeled. The graphical presentation in chapter 4 serves as the basis for a more in-depth analyses and interpretation of the individual models and economic assessments. Finally, the key findings of the different models, regarding trend developments, technological progress, economic viability and specific repowering scenarios are discussed in chapter 5.

2. State of the Art

This chapter begins with a brief review of historical developments and the fundamental physics of wind energy. The key aspects of repowering are then outlined, followed by a look at the current situation in Austria. Based on these findings, this thesis aims to develop a scenario model specific for Austria that contains results on repowering along with economic considerations.

2.1. Historical View on Wind Energy

Wind energy has been used for over 1,500 years, initially as a key driver of industrial and economic development when other energy sources were rare.
From 600 to 1890, classical windmills were widely used for mechanical purposes, with over 100,000 in Northwestern Europe, but their use declined after the invention of the steam engine. Between 1890 and 1930, wind turbines emerged for electricity generation, although they lost relevance because of cheaper oil. The first innovation phase (1930–1960) saw progress in aerodynamics, driven by rural electrification and wartime shortages, but it ended with the rise of inexpensive gas and oil. Since 1973, a second innovation phase has brought commercial success due to the energy crisis, environmental concerns, and technological advances, leading to large-scale electricity and hydrogen generation.[1]

[1] Schaffarczyk, 2022, pp. 1–2.

Windmills historically converted wind energy into mechanical power, but with the invention of electrical generators, they evolved into wind turbines for electricity generation. This transition gained momentum in the late 19th century and became a major economic success after the 1973 energy crisis.[2]

2.2. The Basics of Wind Energy

Wind energy arises from the movement of air caused by pressure differences in the Earth's atmosphere, primarily driven by solar radiation. The uneven heating of the Earth's surface creates high and low-pressure zones, leading to wind flow from high to low-pressure areas. Earth's rotation and surface characteristics further influence wind patterns, making the wind both intermittent and unpredictable.[3]

The potential of wind energy at any given site is determined by the average wind speed in meters per second, which varies due to geographical and topographical features. The wind power density, which depends on wind speed, is a crucial factor in determining the feasibility of wind park installations.[4]

The maximum theoretical wind power generation is governed by equation:

$$P = \frac{1}{2} A \rho v^3 \tag{2.1}$$

where:

- P the theoretical power $[W]$
- A is the rotor-swept area $[m^2]$
- ρ is the air density $[kg/m^3]$
- v is the wind velocity $[m/s]$

Since power is proportional to the cube of the wind speed, even small increases in wind velocity result in significant energy gains.

[2]Schaffarczyk, 2022, p. 2.
[3]Breeze, 2016, pp. 9–10.
[4]Breeze, 2016, pp. 11–13.

Notable in Equation 2.1 is also the linear relationship between the power and the harvested area, or rotor swept area. Since the rotor diameter appears in the term $\frac{d^2}{4} \cdot \pi$, it contributes quadratically to the power output. Such increases in rotor diameters and the resulting yields can also be found, for example, in the subsection 4.2.1 on future trends in wind energy in Austria.

The maximum theoretical efficiency of wind energy conversion is given by Betz's law, which states that no wind turbine can capture more than 59.3% of the kinetic energy in the wind.[5]

2.3. Components of Wind Turbines

Modern wind turbines however can achieve up to 80–90% of the Betz limit in practice.[6] The rotor captures kinetic wind energy from the rotor swept area and converts it into mechanical energy and for the different turbine designs, all are fundamentally limited by the Betz limit, result in the rotor types shown in Figure 2.1. The tip speed ratio („Schnelllaufzahl") used here is defined as the ratio between the blade tip speed and the wind speed. The power coefficient („Rotorleistungsbeiwert") refers to the aerodynamic efficiency for extracting energy from the wind.[7]

While more than three blades slightly increase efficiency, the gain usually does not justify the cost of an extra blade. However, fewer blades worsen the rotor's dynamic behavior, increase mechanical stress, noise and reduce visual smoothness. These factors have led to the dominance of a three bladed rotor in commercial turbines.[8]

This rotational energy is transferred via a gearbox to increase the rotor speed for standard sized generators, but gearboxes often fail due to mechanical stress and wind fluctuations. There are also direct drive systems eliminating the gearbox, improving

[5] Schaffarczyk, 2022, p. 133.
[6] Breeze, 2016, p. 13.
[7] Schaffarczyk, 2022, p. 150.
[8] Schaffarczyk, 2022, p. 151.

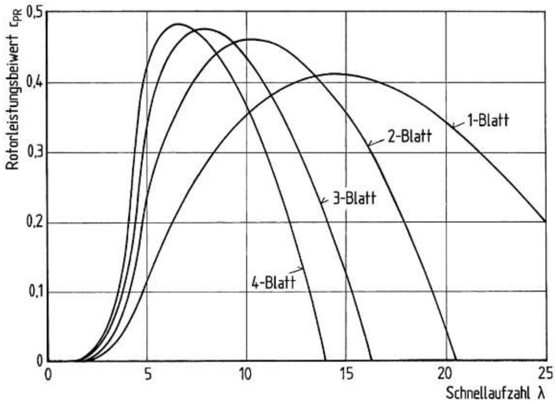


Figure 2.1.: Influence of the number of rotor blades on the shape of the power coefficient curve and the optimal tip speed ratio., Schaffarczyk (2022, p. 150)

reliability but requiring large, expensive low-speed generators.[9] Modern turbines often use doubly-fed induction generators or permanent magnet synchronous generators with power converters to enable variable-speed operation and better grid support.[10]

So the nacelle houses key components are the gearbox and the generator. It can also be rotated with motors to face the wind and is designed to be weatherproof, light and accessible for maintenance.[11] Finally the tower elevates the rotor to reduce turbulence and maximize energy capture. Standard tower heights range from 80 m to 150 m, built mainly from tubular steel, concrete, or hybrid designs.[12] Resonance risks in the tower require stiff designs to avoid damage and failure from rotor-induced vibrations. Also the foundations vary depending on soil conditions and mostly include a so-called gravity foundation, a large and heavy concrete base.[13]

[9] Breeze, 2016, pp. 42–43.
[10] Breeze, 2016, pp. 45–47.
[11] Breeze, 2016, p. 50.
[12] Breeze, 2016, pp. 53–55.
[13] Breeze, 2016, pp. 56–58.

2.4. Repowering, Lifetime and Layout of Wind Parks

This thesis focuses on full repowering, which refers to the dismantling of the old wind turbines and the construction of a new wind park on the same location using newer, more efficient models. Although older turbines may still work reliably, repowering can significantly increase energy output, often with fewer turbines, and is usually more economical than decommissioning the site, especially since new site permits are hard to obtain. Older turbines are sometimes resold and reused in other countries and therefore still represent an economic value.[14]

Data from Denmark shows that repowered turbines can generate up to nine times more energy compared to the old ones, with their capacity factor increasing by about 7%.[15] The study also highlights the clear trend toward significantly larger turbine parameters, with new models having three times the rotor diameter, nine times the swept area, and six times the nominal power.[16]

Beyond the scope of this thesis, a meta-analysis highlights the importance of a holistic approach to repowering, taking into account technical, economic, environmental, social, and political aspects. Single-factor analyses fall short in addressing the complexity and site-specific nature of repowering projects.[17]

At the end of the life of a wind turbine, most components like steel, copper and concrete can be dismantled and recycled. Often balancing out dismantling costs with the material resale value. A major exception is the rotor blades made of composite materials, which are difficult to recycle and currently require landfilling, though alternative recycling methods are under development.[18]

According to literature, the technical lifetime of wind turbines is typically around 20

[14]Breeze, 2016, pp. 64–65.
[15]Lacal-Arántegui, Uihlein, and Yusta, 2020, p. 669.
[16]Lacal-Arántegui, Uihlein, and Yusta, 2020, p. 660.
[17]Gil-Garcia et al., 2021.
[18]Hau, 2016, p. 956.

years.[19] [20] However, with industry designing components for longer use and assuming additional costs for replacing wear parts, a life of 25 to 30 years is also possible.[21]

The layout of a wind park affects its energy output and economics. Turbines placed too close together suffer from wake turbulences caused by nearby turbines, reducing efficiency. Since wind direction varies, spacing and orientation must be carefully planned.[22].

So the spacing ensures minimal wake losses and optimal electricity generation. This phenomenon is known as the wake effect, the rotor slows down the wind and extracts energy. Typical values for the spacing factors are:[23]

$$\begin{aligned} d_{\text{axial}} &= k_{\text{axial}} \cdot D \qquad & k_{\text{axial}} &= 5\text{–}7 \\ d_{\text{lateral}} &= k_{\text{lateral}} \cdot D \qquad & k_{\text{lateral}} &= 3\text{–}5 \end{aligned} \tag{2.2}$$

- D: Rotor diameter of the wind turbine [m]
- d_{axial}: Distance between turbines along the main wind direction [m]
- d_{lateral}: Distance between turbines perpendicular to the wind direction [m]

The information about spacing and lifetime will be relevant for the assumed wind turbine density and repowering cycles in the models presented in section 4.5.

2.5. Current State in Austria

2.5.1. Market Development

Austria has seen steady development in wind energy (see Figure 2.2), with significant expansions over the years. As of the end of 2023, a total of 1,426 wind turbines with

[19] Hau, 2016, p. 267.
[20] Breeze, 2016, p. 63.
[21] Hau, 2016, p. 955.
[22] Breeze, 2016, pp. 60–61.
[23] Hau, 2016, p. 804.

3,885 *MW* were installed, producing about 8 *TWh* annually, covering around 12% of the country's electricity demand.[24]

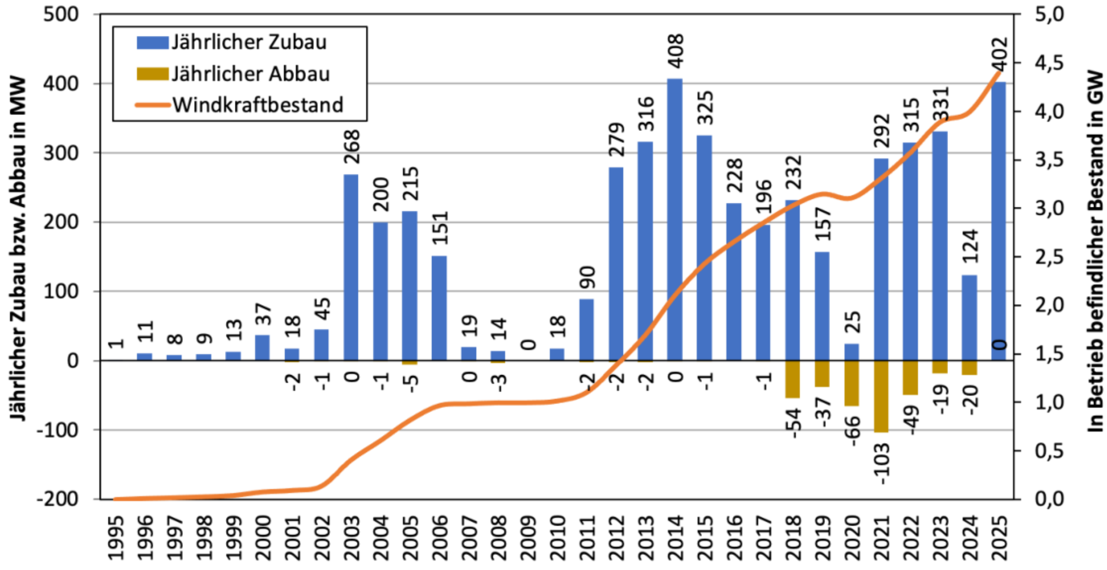


Figure 2.2.: Wind power market development in Austria up to 2023 and 2025 forecast, Biermayr et al. (2024, p. 284)

The main expansion regions are Lower Austria with 2,082 *MW* and Burgenland 1,411 *MW*, followed by Styria with 307 *MW*. Other federal states like Upper Austria and Carinthia remain below 50 *MW*, while some have no installed wind capacity at all. In the recent 2023 documented expansion primarily turbines with 4–6 *MW* rated power range were installed, highlighting the ongoing shift towards increasingly powerful turbines.[25]

With its current wind energy expansions, Austria positions itself as a mid-range contributor among EU countries in terms of new installations and ranks behind larger contributors like Germany, but continues its onshore growth with modest steady progress.[26]

[24] Biermayr et al., 2024, p. 284.
[25] Biermayr et al., 2024, pp. 287–289.
[26] WindEurope, 2024.

2.5.2. Policy Support Mechanisms

Austria's wind energy expansion has been supported by the 2002 Green Electricity Act (Ökostromgesetz) introduced fixed feed-in tariffs and sales guarantees, resulting in the first major wind buildout. After a stagnation phase, reforms in 2012 improved conditions, doubling wind capacity within four years (cf. Figure 2.2).[27]

In 2021, Austria introduced the Renewable Expansion Act (EAG), shifting from feed-in tariffs to a market-based floating Feed-in-Premium. Wind projects now receive a sliding market premium based on a reference value. This value is determined through competitive auctions. Wind project developers submit bids, and the awarded bid price becomes the individual floating Feed-in-Premium benchmark for that project.[28] To ensures that the wind park operator always receive a minimum payment for the electricity fed into the grid, as the difference is compensated when the market price falls below the awarded price. The current upper limit for bid submission is set at €0.096/kWh.[29]

IG Windkraft, an Austrian industry association, further emphasizes the need for accelerated permitting processes and stable funding conditions to achieve the expansion targets outlined in the next subsection.[30]

2.5.3. Expansion Targets

For Austria, Figure 2.3 from IG Windkraft are of particular interest, as they include different targets. For example, the Renewable Energy Expansion Act „Erneuerbaren-Ausbau-Gesetz“ sets a target of 17 TWh wind energy per year until 2030.

Achieving the more ambitious targets, 19 TWh as outlined in the National Energy and Climate Plan „Nationaler Energie und Klimaplan“ or even 25 TWh in the IGW „Interessensgemeinschaft Windkraft“ scenario by 2030, appears significantly more challenging,

[27] IG Windkraft, 2024a.
[28] EAG-Abwicklungsstelle, 2024.
[29] Ökostrom AG, 2025.
[30] Windkraft, 2024.

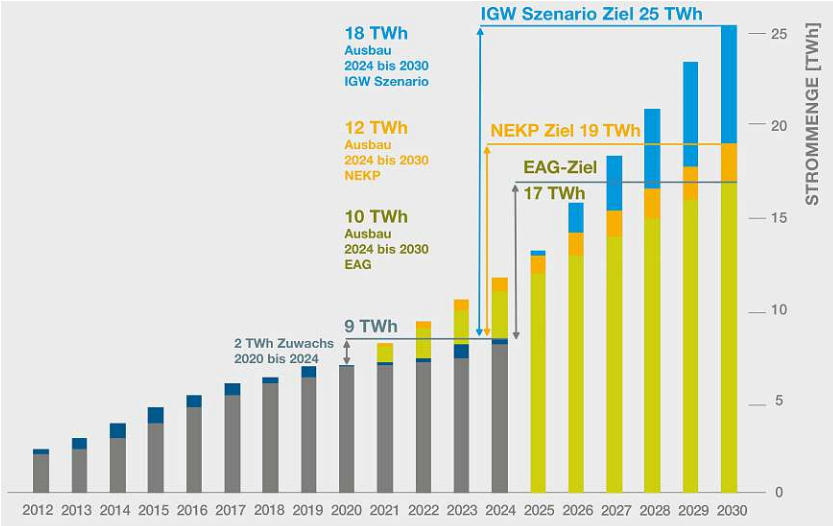


Figure 2.3.: 2030 target achievement pathway for wind energy in Austria, Windkraft (2024, p. 3)

given the current yield of only 8–9 *TWh*. WindEurope for example, formerly known as the European Wind Energy Association, projects an annual newly installed wind power capacity of 410–450 *MW* in Austria by 2030.[31]

For the scenarios up to 2050, there are three calculation models from the Environment Agency Austria „Umweltbundesamt" and the ENTSO-E (European Network of Transmission System Operators for Electricity), as shown in Figure 2.3.

These trends also form the basis for later comparisons from the results presented in chapter 4.

[31] WindEurope, 2024.

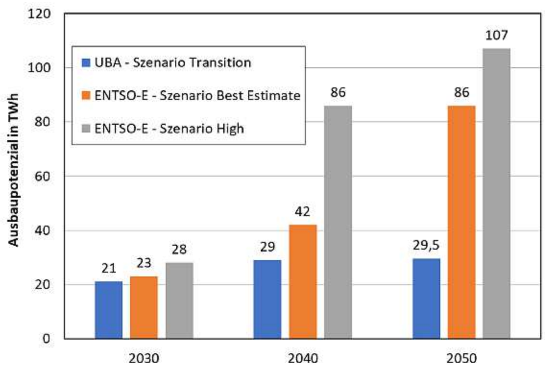


Figure 2.4.: Different expansion scenarios for wind power in Austria, Biermayr et al. (2024, p. 308)

3. Method of Approach and Data

For a comprehensive assessment of wind energy in Austria and, more importantly, to conduct meaningful analyses, it is essential to have detailed knowledge of all wind turbines and their technical specifications. Additionally, for further economic calculations, fluctuating electricity prices and the volatile real production data must be considered. When analyzing the entire lifecycle of a wind turbine in more detail, investment costs, operation and maintenance (O&M) costs, as well as capital interest rates, must also be taken into account. For this reason, this section begins with the development of a data model that incorporates the aforementioned aspects.

To construct the analytical model, this section starts with the calculation of the energy yield for each turbine using the so-called capacity factor. Based on this, along with the previously mentioned data, a sensitivity analysis of the net present value (NPV) can be conducted to assess the economic viability of such installations.
To make future projections, this diploma thesis utilizes a forecast model, which is also based on the developed data model. In order to provide a holistic statement on the technological development of wind energy in Austria, these projections are consolidated into a repowering factor.
Finally, a repowering scenario model is developed to assess repowering potential at the national and regional levels. This model generates real-world yield scenarios under various scenario-based conditions, enabling a more detailed evaluation of future wind energy deployment in Austria.

To perform the individual calculations and graphical representations, the integrated development environment PyCharm was used together with Python version 3.12. Within PyCharm, the GitHub Copilot plugin supported the process and was used as a debugging tool for workflows and data-related errors. All code implementations and decisions were critically reviewed and developed independently. The Python libraries NumPy (for basic numerical computations), pandas (for Excel files and data preprocessing), matplotlib (for graphical visualization) and sklearn (for the linear regression) were utilized.

3.1. Data

The development of the data model posed a significant challenge. In a competitive market, obtaining production data of wind parks is not easy. Ensuring the completeness of wind turbine data also remains difficult, despite the presence of IG Windkraft, an Austrian advocacy group for wind energy operators and promoters. The following subsections outline how these challenges were addressed.

3.1.1. Development of the Wind Park Database

The existing information and databases on Austrian wind parks and turbines are far from complete. Therefore, multiple sources were utilized and merged for this part of the thesis. Additionally, technical details (e.g. turbine type, hub height, etc.) were supplemented through extensive online research.

The foundation for the wind park database, which includes 328 wind parks, is based on the following sources: The Wind Power (2024), IG Windkraft (2024b), ImWind (2024), WEB (2024), Windkraft Simonsfeld (2024), EVN (2024), Wikipedia Windkraftanlagen in Niederösterreich (2024).

The database contains key attributes relevant to this thesis, including precise location and federal state, turbine type, rotor diameter, hub height, rated power, number of turbines, and year of commissioning. Decommissioned wind turbines have been removed, while repowered installations remain included.

The figure Figure 3.1 provides a visual overview of wind parks, turbines and average turbine size installed per year in Austria based on the wind park database.

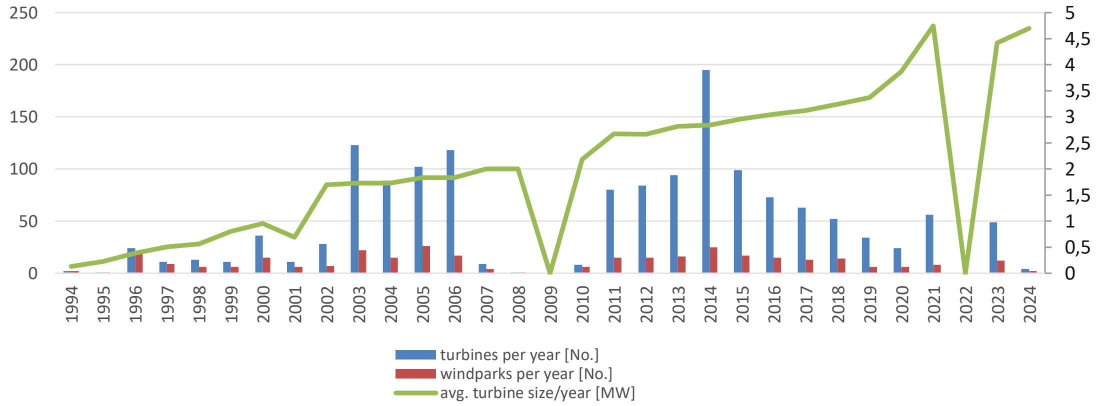


Figure 3.1.: Installed turbines/parks [No.] and average turbine size [MW] per year in Austria based on own wind park database

3.1.2. Real-World Power Output Data and Simulated Capacity Factors

To determine the power output of wind parks in Austria, data from 32 turbines across six wind parks were obtained through two interviews with wind energy companies[1] [2]. These wind parks are evenly distributed across Austria and the dataset covers the period from 2021 to 2023.

One company provided 10-minute average power data per turbine, measured in kilowatts [kW] for each interval, which is essential for the subsequent economic analysis as shown in subsection 3.2.4. The remaining measurement data was provided as monthly energy yields, which were later used to calibrate the simulated capacity factors. The capacity factor (*CF*) is defined as the ratio of the actual energy output to the maximum possible energy output if the turbine is operating at full capacity constantly.

[1]Expert Operations Manager, Imwind, 2025.
[2]Expert Project Planner, WEB, 2025.

$$CF = \frac{E_{\text{actual}}}{P_{\text{rated}} \times T} \tag{3.1}$$

- CF: Capacity factor
- E_{actual}: Actual energy generated over the period [MWh]
- P_{rated}: Rated power of the turbine [MW]
- T: Time period [h]

consequently there is a direct correlation between the capacity factor and a wind turbine's energy yield in relation to its rated power.

To obtain the remaining production data for the years 2021-2023, the Renewable.ninja[3] platform was utilized to receive the simulated capacity factor for each wind turbine in the database (see subsection 3.1.1). The key parameters from the database are formatted according to the naming conventions used by Renewable.ninja and then retrieved via the Python program code using the NinjaClient[4] (see section A.1).

Renewable.ninja is an online platform that simulates wind and solar power generation using historical meteorological data. For wind energy, it relies on datasets such as NASA's MERRA-2, which models wind speeds at different altitudes and combines them with turbine characteristics. As a result, capacity factors and wind speeds are obtained based on the input parameters.

For example, the exact location, year, capacity, hub height, and turbine model can be specified. Based on the corresponding historical weather data, combined with the performance characteristics of the selected wind turbine at its hub height, a capacity factor for the given installation is calculated.

3.1.3. Investment Costs

To accurately calculate the economic analysis in later chapters, it is important to understand what is meant by investment costs. They include all expenses that occur

[3] Renewable.ninja, 2024.
[4] Balestrieri, 2024.

before the plant is commissioned. This covers the purchase of the wind turbine itself, as well as additional technical components depending on how the system will operate. Costs may also increase due to specific safety requirements, additional expenses on road construction or network connection costs. Also, site-dependent costs must be included. These cover transport of components to the site, foundation work, cabling, and connection to the power grid. Such ancillary expenses typically amount to 15–30% of the core equipment costs.[5] [6]

For estimating current investment costs in Austria, a certain range is necessary, as these costs depend on the above-mentioned factors. As a result, locations that require extensive new grid infrastructure or the construction of complex access roads can have significantly higher investment costs compared to sites where these conditions are already in place. This leads to a substantial location-dependent variability in investment costs.

This could present an advantage for repowering, as existing access roads and grid connections can be reused. However, even in this case, the investment requirements vary, since the existing grid connection is often insufficient for the increased power output of new installations. As a result, new and sometimes multiple grid connections need to be established. Additionally, when constructing a new wind park, new foundations for the turbines are required due to changes in structural design and spacing.[7]

For these reasons, the investment cost assumptions used in this thesis are determined identically to the following sources. For example a recent study from Germany estimates these costs to be in the range of 1300–1900 €/kW[8] and for Austria, a major wind energy operator estimates investment costs at 1400–1900 €/kW[9].

Consequently, this thesis assumes investment costs of 1300–1900 €/kW of installed rated power for the economic feasibility calculations presented in chapter 3.2.4.

[5]Heier, 2022, p. 544.
[6]Expert Project Planner, WEB, 2025.
[7]Expert Project Planner, WEB, 2025.
[8]Kost et al., 2024, p. 12.
[9]Expert Project Planner, WEB, 2025.

3.1.4. Operation and Maintenance Costs

At first, it is again important to define what is meant by operation and maintenance costs in wind energy. Operating costs and maintenance refer to all expenses during the plant's operational lifetime. These include maintenance and repair, insurance, land lease fees, remote monitoring, and other ongoing services.[10]

There are different approaches in the literature regarding how the annual costs for maintenance and operation are specified:

- as a percentage of the installed capacity,
- as a percentage of the produced energy,
- or a mix of fixed and variable costs depending on capacity and yield.

Although some literature[11] assumes significantly lower operating costs for plants over 1.5 MW, the operating costs of wind power plants today seem to be higher. As the previously mentioned recent report[12] shows, variable costs are estimated at 0.007 €/kWh, and fixed costs at 32 €/kW per installed nominal capacity. However, practical figures from Austria currently suggest increased grid connection costs, resulting in total costs of 0.02 to 0.03 €/kWh[13].

As current wind energy project planning[14] indicates that grid connection costs are becoming an increasingly important factor and scale with the amount of energy to be transmitted, the further use of O&M costs in subsection 3.2.4 is based on variable costs, which are incorporated into the analysis at a range of 2 to 3 cents per kWh.

[10]Heier, 2022, pp. 544–545.
[11]Heier, 2022, p. 545.
[12]Kost et al., 2024, p. 13.
[13]Expert Project Planner, WEB, 2025.
[14]Expert Project Planner, WEB, 2025.

3.1.5. Electricity Prices

Since average electricity prices in 2023 were slightly above[15] and in 2024 slightly below[16] the current maximum bid limit of 0.096 €/kWh[17] in the EAG auction scheme lies exactly in between. Therefore, this thesis aims to analyze the model under the current market situation, excluding subsidies (see subsection 2.5.2). For the purposes of the following calculations, it is important to have time-specific electricity prices. The so-called day-ahead price refers to the rate at which electricity is bought or sold for the next day. It is determined through an auction process in which market participants submit hourly bids for the upcoming day. This mechanism, known as a market-clearing auction, matches supply and demand. The resulting price, the so-called market-clearing price, is defined by the intersection of aggregated supply and demand curves, ensuring a balanced market.[18]

Austria's transmission system operator, APG, publishes these prices for the years 2023 and 2024 on its official website[19], and they have been used in this thesis accordingly. To provide a clearer picture, a sample daily price profile from April 2024 is presented below, showing values in €/MWh for 15-minute intervals.

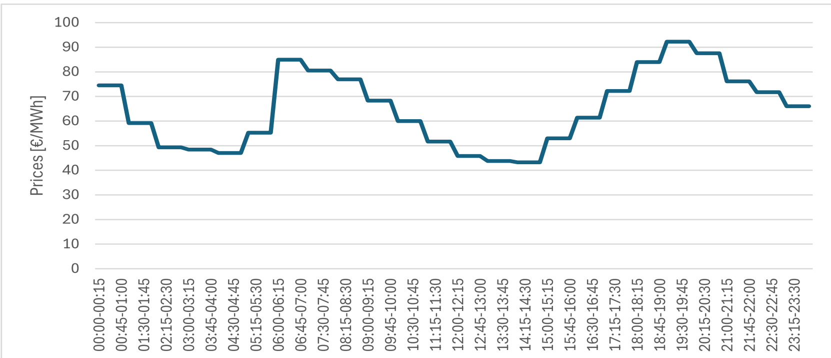


Figure 3.2.: APG Day-Ahead-Prices 19.04.2024, Austrian Power Grid AG, 2024

[15] Austrian Power Grid AG, 2024.
[16] Austrian Power Grid AG, 2024.
[17] Ökostrom AG, 2025.
[18] *EPEX Spot Dayahead Auktion* n.d.
[19] Austrian Power Grid AG, 2024.

3.2. Analytical Model

At first, this section outlines the specific methods used to calculate the capacity factors of wind parks and to forecast relevant wind park parameters based on the database (see subsection 3.1.1). Using these parameters and the available data, a model is developed to estimate the potential increase in electricity yield from wind power plants in Austria. Based on the information in subsection 3.2.2 an economic analysis is conducted to assess the profitability of wind energy systems (see subsection 3.2.4). Finally, a model is presented to estimate Austria's repowering potential through to the year 2050.

3.2.1. Calculation and Verification of Capacity Factors

Calculation Model

To calculate realistic capacity factors for each wind park in the database, the simulated values presented in subsection 3.1.2 are scaled using actual measurement data. The data obtained through the previously mentioned interviews[20] [21] is used to calculate the capacity factor, following Equation 3.1, for the corresponding wind parks in the database. The majority of the remaining unknown factors are estimated using a linear regression[22] through the origin.

A simple linear regression through the origin is a linear model that fits a line to data through the origin. The model assumes that the dependent variable is directly proportional to the independent variable. The regression line is forced to pass through the origin $(0,0)$, and the model is represented as:

[20]Expert Operations Manager, Imwind, 2025.
[21]Expert Project Planner, WEB, 2025.
[22]Pedregosa et al., 2025, cf. module linear_model.

$$y = \beta x \tag{3.2}$$

- y: real world data (response)
- x: simulated data (predictor)
- β: the regression coefficient (slope)

The use of a regression through the origin is easily justified: if hypothetically no wind is present, both the simulated and the measured values should consistently be zero. To achieve a more robust scaling across multiple years, the capacity factors used for further analysis are calculated as the average of the values from 2021, 2022, and 2023. This makes sense, as wind conditions are subject to different fluctuations each year.

As already mentioned above, this capacity factor is initially derived from simulated values, which depend on the site location and the wind turbine model, including its rated power, rotor diameter and hub height, as well as the specific years. Using the model described above and averaging over three years, a reference capacity factor is then determined for each wind park in the database (see Figure 3.3). This factor serves as the basis for all subsequent yield calculations in the upcoming models. The corresponding Python code can be found in section A.2, and the graphs for the years 2021 to 2023 are provided in Figure 3.4, Figure 3.5, Figure 3.6.

Verification

The energy yield of a wind park from database is calculated according to Equation 3.1, using the averaged reference capacity factors derived in subsubsection 3.2.1, the rated power, the number of turbines, and the number of hours per year ($24 \cdot 365$). Subsequently, the energy yields of all wind parks commissioned in the same year or earlier must be summed. This results in the Equation 3.3:

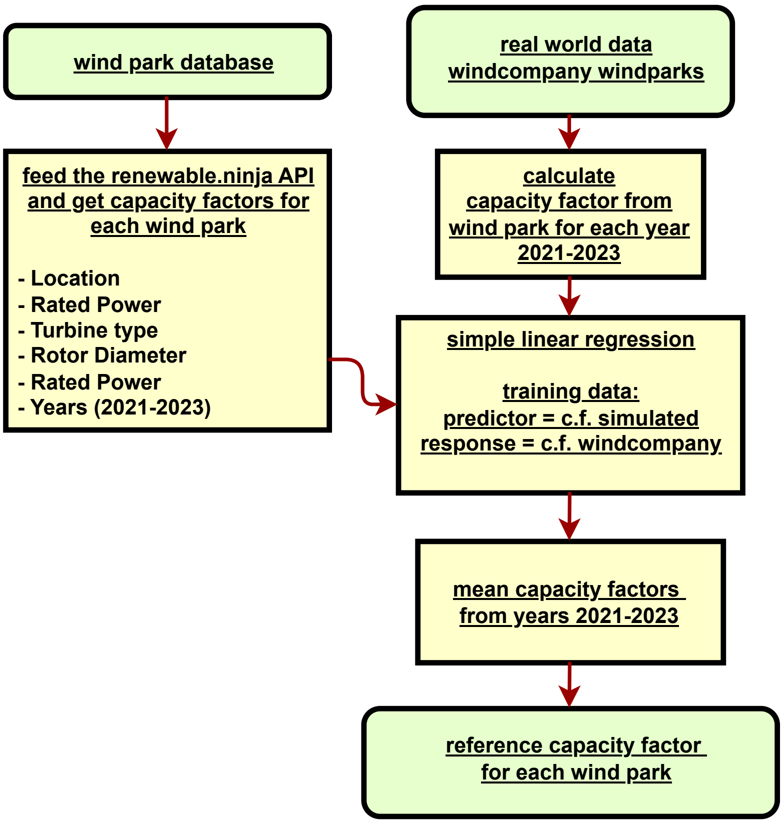


Figure 3.3.: Flowchart of the development of the reference capacity factor for each wind park of the database, Own figure

$$E_{\text{total}} = \frac{1}{10^9} \sum_{j=1998}^{J} \sum_{i=1}^{n_j} P_{\text{turbine},i,j} \cdot C_{\text{mean},i,j} \cdot N_{i,j} \cdot 24 \cdot 365 \tag{3.3}$$

- E_{total}: Total energy of all wind parks commissioned up to the year J [TWh]
- J: Target year for the energy calculation
- n_j: Number of wind parks commissioned in year j
- $N_{i,j}$: Number of turbines in wind park i in year j
- $P_{\text{turbine},i,j}$: Rated power per turbine of wind park i in year j [kW]
- $C_{\text{mean},i,j}$: Capacity factor of wind park i in year j

The corresponding Python code can be found in section A.3.

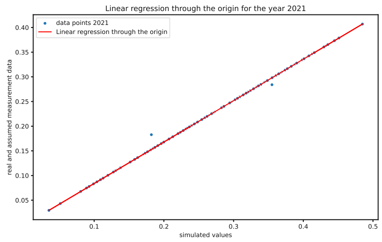


Figure 3.4.: Capacity factors 2021, Own analysis

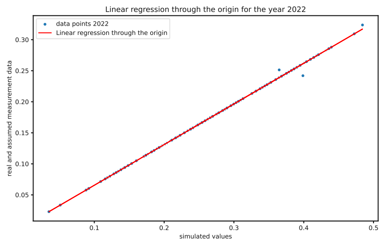


Figure 3.5.: Capacity factors 2022, Own analysis

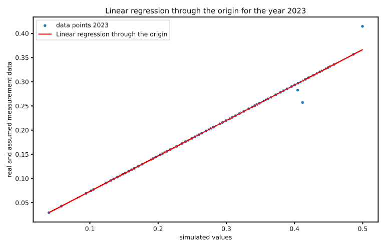


Figure 3.6.: Capacity factors 2023, Own analysis

3.2.2. Forecast Modeling

An analysis of the individual wind park parameters from the database over time reveals an approximately linear trend over time (see results section 4.2). To estimate future developments of key wind turbine parameters in Austria, a linear regression model under the assumption of a linear development was applied. The input data was received from the database with the wind park parameters including the capacity factor. The data was grouped by commissioning year, and annual average values for each parameter were computed. The electricity generation per turbine was calculated using Equation 3.1.

The following **annual average** parameters were modeled over time:

- average power output per turbine
- Rotor diameter
- Mean capacity factor
- Hub height
- Rated power per turbine

To predict those future values from 2025 to 2050, a MultiOutputRegressor[23] around a LinearRegression[24] was used, enabling simultaneous prediction of multiple target variables. The model was trained using historical average values from the database per commissioning year.

The general form of this regression model applied to each parameter y is given by:

$$y_j = \beta_0 + \beta_1 \cdot j \tag{3.4}$$

- y_j: Predicted parameter in year j
- β_0, β_1: Regression coefficients
- j: Commissioning year

The exact code for the above concept can be found in section A.4

3.2.3. The Repowering Factor

To better understand how much more profitable modern or future wind turbines in Austria are, this section introduces the so-called repowering factor Re based on the

[23] Pedregosa et al., 2025, module multioutput.
[24] Pedregosa et al., 2025, module linear_model.

projected trends. Especially in the context of repowering, this factor helps estimate past and future increases in energy yield in a meaningful way. The following equation is used

$$E_{\text{new}} = \text{Re}\left[CF\left(W(D,\ P),\ L,\ H,\ T\right),\ Y\right] \cdot E_{\text{ref}} \tag{3.5}$$

- E_{new}: Average future electricity generation [MWh/yr]
- E_{ref}: Average electricity generation from the reference year [MWh/yr]
- Re[...]: Repowering function based on:
  - $CF(W(D,\ P),\ L,\ H,\ T)$: Capacity factor as a function of:
    - $W(D,\ P)$: Wind turbine model with:
      - D: Rotor diameter [m]
      - P: Rated power per turbine [MW]
    - L: Location
    - H: Hub height [m]
    - T: year
  - Y: Year difference (reference year – commissioning year)

to show the rate of increase. The repowering factor reflects technological improvements in Austria based on the wind turbine parameters discussed above. It can also be expressed in a simplified form as:

$$Re = \frac{E_{\text{new}}}{\text{E}_{\text{ref}}} \tag{3.6}$$

The Python script shown in section A.6 is used to calculate those factors. It combines historical and future data from subsection 3.1.1 and subsection 3.2.2 and shows the yield over time, and plots the results along with trendlines.

In detail for a range of comparative years (every 5 years from 2000 to 2050), a repowering factor Re is calculated, as the ratio between a turbine's production in a given reference year and the average production of turbines installed in the comparative year.

The results are stored in a dataset (results) where each column represents a comparative year, and each row represents a commissioning year. Missing values are linearly interpolated[25] to fill gaps in years where no wind parks were installed. Afterwards a line plot with the numpy.polyfit[26] function was created showing how the repowering factor changes over time for each comparative year.

3.2.4. Economic Sensitivity Analysis of Wind Parks

Common methods used in dynamic economic evaluations of wind turbines are based on the net present value (NPV) approach. This method considers that cash flows, meaning revenues and costs, occur at different points in time. To make them comparable, all cash flows are discounted to a common reference date. The value of a cash flow at that date is called its present value, and the sum of all present values is referred to as the net present value. By comparing the discounted cash inflows with the initial investment, it is possible to assess the economic viability of a project.[27]

$$\mathrm{NPV} = -I_0 + \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t} \tag{3.7}$$

- I_0: Initial investment cost [€]
- CF_t: Cash flow in year [t]
- r: Discount rate
- T: Total project lifetime in years

So the NPV can be calculated for each point in the project's operational lifetime. In the beginning, the NPV is negative due to the initial investment. Over time, as revenues accumulate, the NPV becomes positive. A project is considered economically viable if the total NPV over its lifetime is positive.[28]

[25] team, 2020.
[26] NumPy Developers, 2024.
[27] Hau, 2016, p. 944.
[28] Hau, 2016, p. 944.

To account for the initial investment costs as well as the ongoing cash flow, consisting of O&M costs and energy yields, the NPV can be calculated in this model using the following formula:

$$\mathrm{NPV} = -I_0 + \sum_{t=1}^{T} \frac{(P_t \cdot E_t - C_{\mathrm{O\&M},t})}{(1+r)^t} \tag{3.8}$$

- I_0: Initial investment costs [€]
- P_t: Electricity price in year t [€$/MWh$]
- E_t: Electricity generated in year t [MWh]
- $C_{\mathrm{O\&M},t}$: Operating and maintenance costs in year t [€]
- r: Discount rate
- T: Project duration in years

In the subsection 3.1.3, the investment costs were given as a range in €/kW, the production yields as the average power output in kW over a 10-minute interval (see subsection 3.1.1), the prices as 15-minute values in €/MWh (see subsection 3.1.2), and the operation & maintenance costs as yield-dependent costs in €/kWh (see subsection 3.1.4). Therefore, an accurate calculation requires a minute-by-minute matching of energy output and electricity prices. As part of the data preprocessing, timestamp gaps are filled using the last known value (forward fill). Additionally, February 29 is removed from the dataset to enable better year-over-year comparisons. The model also assumes an ideal shutdown during periods of negative spot market electricity prices, which are therefore excluded from the analysis. In detail, the minute-level calculation can be expressed as:

$$\mathrm{NPV} = -(P_{\mathrm{inst}} \cdot C_{\mathrm{inv}}) + \sum_{t=1}^{T} \frac{\sum_{m=1}^{M} \left[\frac{C_{t,m}}{1000} \cdot \frac{1}{60} \cdot P_{t,m} - C_{\mathrm{O\&M},t} \cdot \frac{1}{60} \cdot P_{t,m} \right]}{(1+r)^t} \tag{3.9}$$

- P_{inst}: Installed capacity $[kW]$
- C_{inv}: Specific investment cost $[€/kW]$
- $C_{t,m}$: Electricity price in minute m of year t $[€/MWh]$
- $P_{t,m}$: average power generated per minute m of year t $[kW]$
- $C_{\mathrm{O\&M},t}$: Operating and maintenance costs in year t $[€/kWh]$
- r: Discount rate
- T: Project duration in years
- M: Number of minutes per year = 525600 $[min]$

To visualize it, a sensitivity analysis is carried out. For this purpose, the parameters specific investment cost and O&M cost are defined within a given range. Additionally, due to the uncertain development of electricity prices, an annual price "increase rate range" is assumed. In the Python script, this is implemented such that a separate loop is run for each parameter range, followed by the calculation according to Equation 3.9. The detailed implementation is shown in section A.5.

In addition to the NPV, the payback period is also an important indicator of economic performance. It is the point in time when the cumulative difference between revenues and costs equals the initial investment. In other words, the payback period is reached when the NPV becomes zero.[29] In the graphical evaluation, highlighting the zero line is therefore important and must be taken into account in the following chapters.

3.2.5. Model of Repowering Scenarios

To represent the repowering potential for Austria and its federal states, a model is required that is based on certain parameters, which serve as the foundation for creating repowering scenarios. As already described in section 2.4, the average operational lifetime of wind turbines is around 20–25 years. After this period, they are typically

[29] Hau, 2016, p. 945.

dismantled, repowered or sometimes continue operation if conditions allow. In this model, however, we define the scenario parameter "repower age", which enforces repowering once this age is reached.

To account for dismantling and construction time, a one-year buffer is included before the new wind park becomes operational. The new turbines are assigned updated parameters based on the projections from subsection 3.2.2, including rated power, hub height, rotor diameter, capacity factor, recalculated turbine number, and the new commissioning year.

The model assumes that repowering is possible on the same area as before. The minimum spacing between wind turbines in a wind park is typically defined as a multiple of the rotor diameter D, both in axial and lateral direction as previously described in Equation 2.2. So turbine spacing and layout depend on wind direction and to simplify this, the model assumes an average spacing of four times the rotor diameter based on the theoretical values discussed in section 2.2.

However, as stated during the interview[30], due to limited space at already designated high-potential wind sites, these distance rules are often relaxed further. This flexibility is governed by the model parameter "distance rule", as defined in the equation below, which is applied in the model.

$$4 \cdot D_{\text{old}} \cdot N_{\text{old}} >= d_{\text{rule}} \cdot D_{\text{new}} \cdot N_{\text{new}} \tag{3.10}$$

- D_{old}: Rotor diameter of the existing turbines $[m]$
- N_{old}: Number of existing turbines
- D_{new}: Rotor diameter of the repowered turbines $[m]$
- N_{new}: Number of repowered turbines
- $d_{\text{rule}} = [3, 4]$: Model parameter "distance rule"

Moreover, not all existing turbines are eligible for repowering. Legal restrictions vary and must be taken into account. As also visible in the database, many single turbines

[30]Expert Project Planner, WEB, 2025.

were installed before the year 2000 with comparatively low rated power from today's perspective. Many of these would no longer comply with current distance regulations (e.g., to residential areas), making repowering unfeasible. For this reason, stand-alone turbines with a rated power below $1MW$ are excluded from this model.

To account for the total electricity production from wind, the annual additions based on newly developed areas with the installed power in $[MW]$ must also be included. As previously mentioned, the production is calculated using Equation 3.3. In addition, the predicted capacity factor for each respective year was also used for the annually added capacity.

As a result of these considerations, the exact Python code for this calculation is provided in section A.7, and for better understanding, the process is additionally illustrated in the flow diagram Figure 3.7.

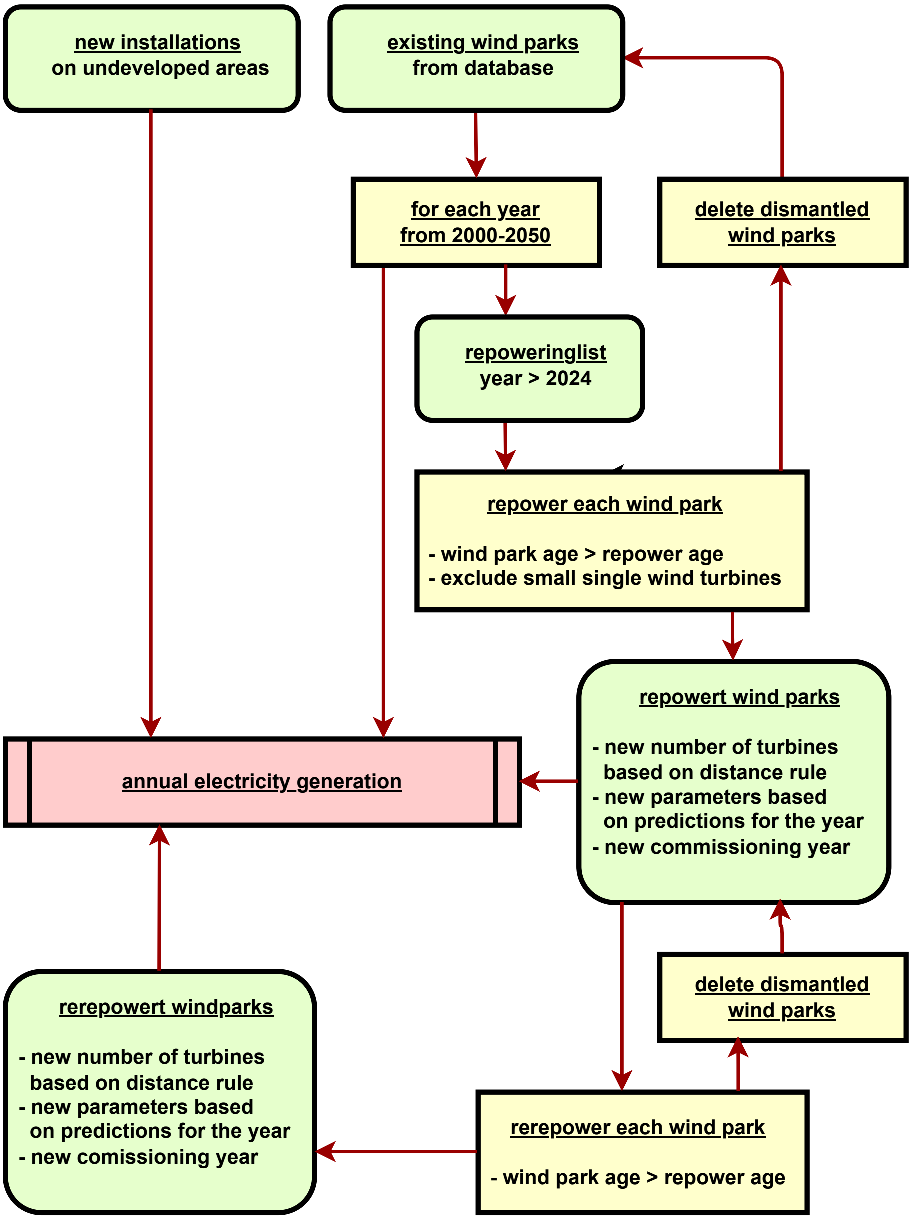


Figure 3.7.: Repowering scenario – flow diagram, Own figure

4. Results of the Analysis

This chapter presents and synthesizes the results derived from the previously defined methods. The foundation for all subsequent analyses is the capacity factor, calculated for each wind park in the database. As described in the corresponding methodology sections, this factor is based on a combination of simulation data and real measurement data. Accordingly, the first subsection focuses on the evaluation and validation of these data.

Building on this, the development of key turbine parameters over time is analyzed, both for Austria as a whole and for selected key regions. This assessment is based on historical data from existing wind turbines and aims to identify regional differences and national trends.

In the next step, the growth rate of wind turbine performance over the years is examined in the form of the repowering factor. Again, results are differentiated by region to reflect spatial variations.

For the economic analysis of wind power in Austria, and to identify meaningful points in time for potential repowering, section 4.3 evaluates a sensitivity analysis of three selected wind parks located in Lower Austria, Burgenland, and Styria. By combining various input parameters with high-resolution real-world data, this analysis provides deeper insights into the economic viability of repowering strategies.

Finally, the results of the repowering scenarios are synthesized for both Austria and the most relevant regions. This synthesis enables a conclusive response to the research question and allows for a data-driven outlook on the future development of wind energy in Austria through 2050.

4.1. Evaluation and Validation of Capacity Factors

To assess the reliability of the capacity factors obtained in subsection 3.2.1, they are compared against actual wind power feed-in data for Austria. The previously described script (see section A.3) provides the total energy yields of all wind turbines installed up to the respective year. The corresponding graphical analysis is shown in Figure 4.1.

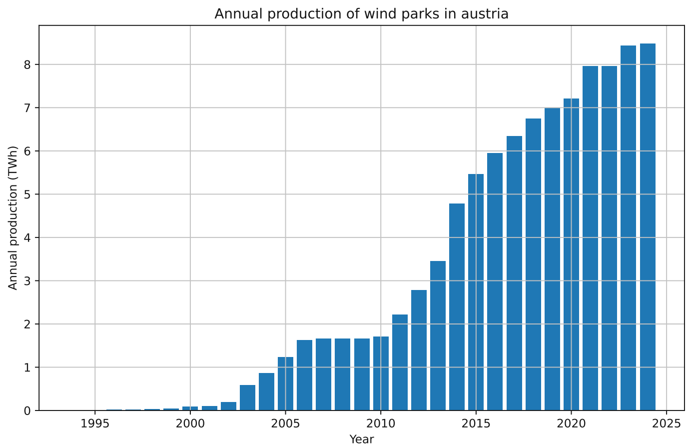


Figure 4.1.: Aggregated energy yields of wind parks up to the respective year, Source: Own calculation

In comparison, it can be seen in Figure 4.2 that the actual wind power fed into the grid from 2005 to 2024 generally follows the model. Naturally, there are years with stronger or weaker wind conditions, which lead to variations in annual wind energy yields in Austria.

For example, the years 2018 and 2010 show a decline that cannot be explained by the installation figures presented in section 3.1. However, looking at the most recent data, the modeled yields of over 8 TWh align quite closely with the actual values. This is further supported by a second data source (see Figure 4.3), which shows a very similar trend, although slightly below the reported values.

It should also be noted that the commissioning years in the database and in reality may vary slightly and could fall into the previous or following year in the model, which

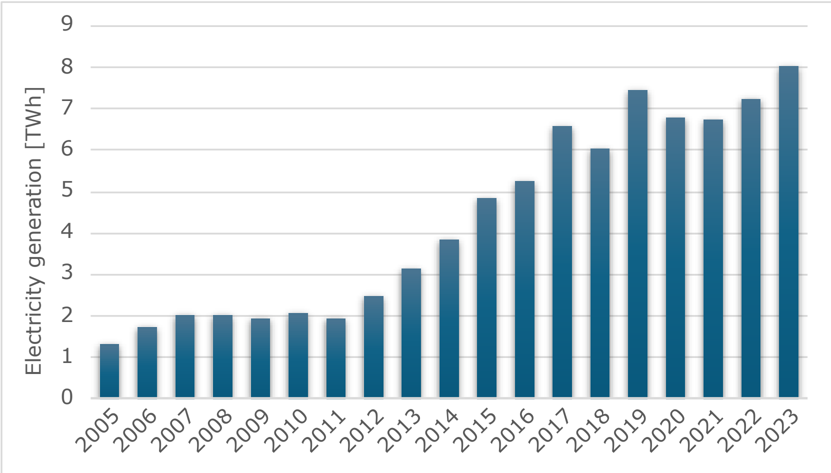


Figure 4.2.: Development of wind electricity generation in Austria based on data from Statistik Austria, Source: Austria (2024, p. 282)

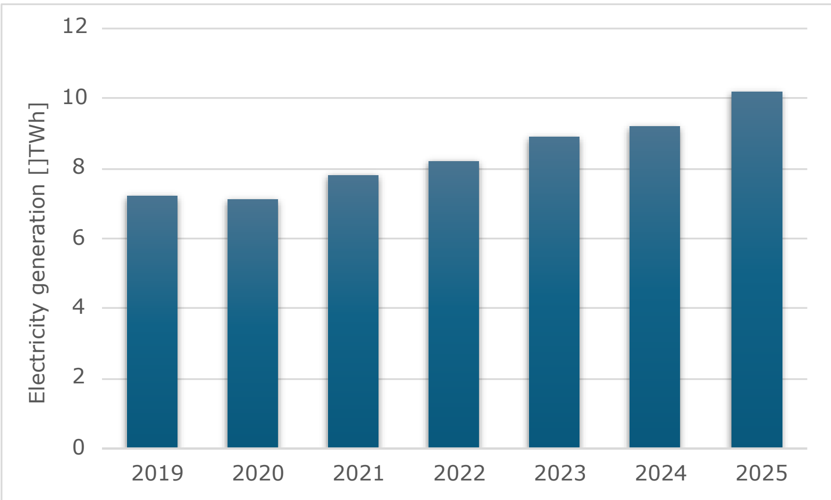


Figure 4.3.: Development of wind electricity generation in Austria based on data from IG Windkraft, Source: Windkraft (2024, p. 4)

may cause some minor distortions in the annual yield figures.

4.2. Trends in Wind Turbine Technology

Using the MultiOutput regression described in subsection 3.2.2, the parameters of the wind parks were modeled and additionally filtered by federal state.

4.2.1. Austria-wide Trends

The results for Austria as a whole are shown in Figure 4.4 and according to this model, Austria would experience a significant increase in average power output by 2050. On average, a single wind turbine would continuously feed around 2.4 MW into the grid. In addition, there would be a slight increase in the capacity factor, and rotor diameters would also grow considerably. Average rotor diameters of around 250 m are conceivable. In contrast, the increase in hub height would be relatively moderate.

4.2.2. Regional Differentiation

Since only Styria, Lower Austria, and Burgenland show a consistent expansion over the years or contribute a relevant share of wind energy generation, only these federal states will be discussed in detail.

Burgenland

For Burgenland (see Figure 4.5), as an important wind energy region, the forecasts are even more promising compared to the Austrian average. A continuous output of around 2.7 MW per turbine and average rated capacities of 8.7 MW are expected. Slightly larger rotor diameters and hub heights are also anticipated.

In addition to the already higher yields observed today, the region's geographical location and flat landscape could prove advantageous for the development of wind

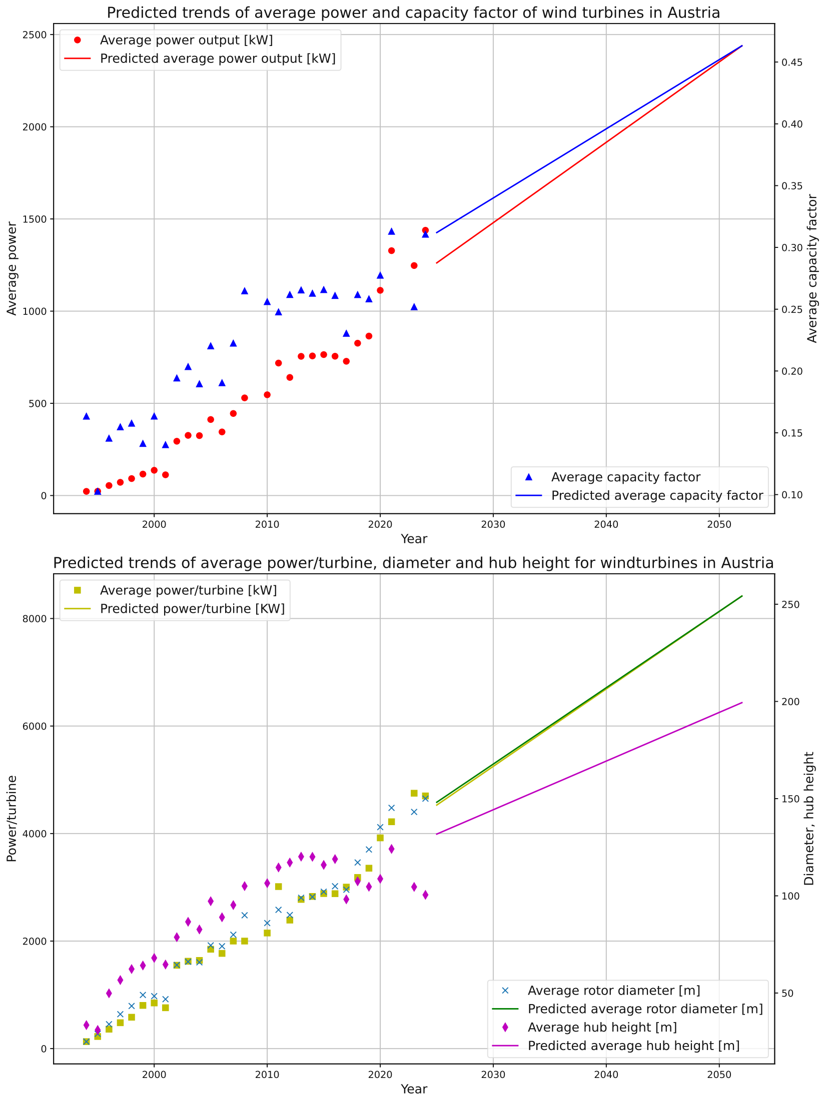


Figure 4.4.: Predicted trends of average production, capacity factor, power/turbine, diameter and hub height for wind turbines in Austria, Source: Own calculation

parks. For instance, transporting large rotor blades already poses significant logistical challenges.[1]

[1]Expert Project Planner, WEB, 2025.

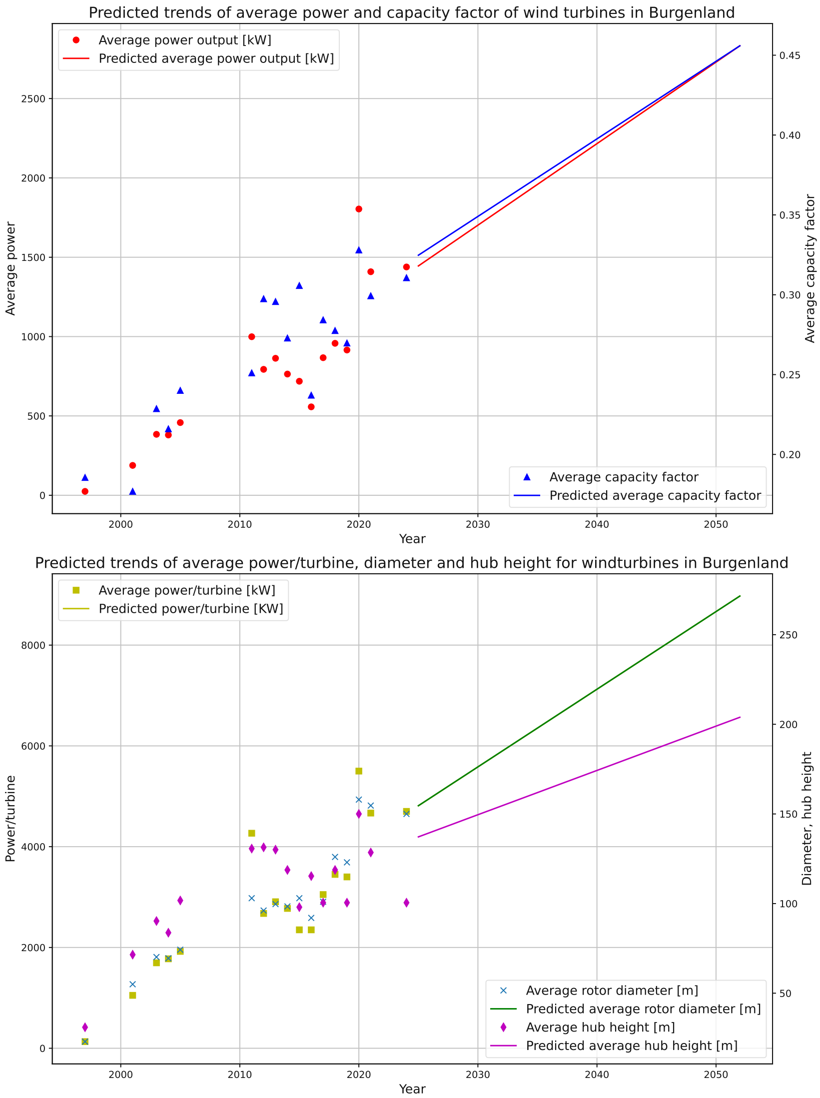


Figure 4.5.: Predicted trends of average production, capacity factor, power/turbine, diameter and hub height for wind turbines in Burgenland, Source: Own calculation

Lower Austria

The projected values for Lower Austria (see Figure 4.6) are roughly in line with the national trend. Here too, a significant increase of around 70% in both average power output and rated capacity is expected by 2050. Only the capacity factor and hub height are anticipated to show a moderate increase.

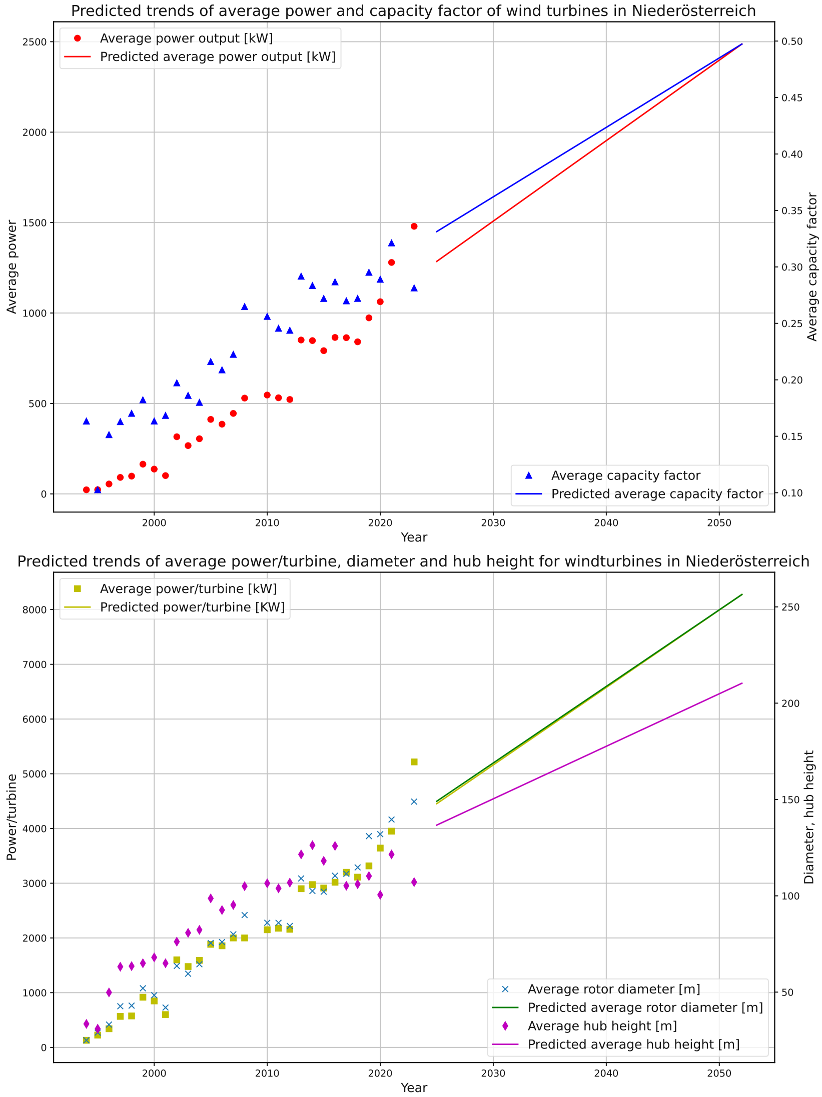


Figure 4.6.: Predicted trends of average production, capacity factor, power/turbine, diameter and hub height for wind turbines in Lower Austria, Source: Own calculation

Styria

Styria presents a different picture. The starting point is already distinct, with current average power outputs at around 0.7 MW and a capacity factor of approximately 20%. According to the projections, these two parameters will only reach today's national average by 2050. Nevertheless, rated capacities are expected to increase significantly to 7.5 MW, and rotor diameters are projected to reach 225 m. In terms of hub height, Styria also remains below the expected trends observed for Burgenland and Lower Austria.

It should also be noted that the previously mentioned geographical location may play a significant role. While the mountainous landscape can offer favorable wind conditions, it also poses greater challenges during construction. For example, winding mountain roads can hinder the transport of large rotor blades or hub components.

4.3. Analysis of the Repowering Factor

The Repowering Factor, defined in subsection 3.2.3, represents the expected increase in energy yield from new wind turbines compared to older ones, based on a specific reference or comparative year.

4.3.1. Throughout Austria

In Figure 4.8, the data points represent the ratios of new to old yields, with colors indicating the respective reference or comparative year. The colored line illustrates the trend for each comparative year, using five-year intervals.

This allows to observe, for example, that turbines from 2005 produce only about one-eighth of the yield expected from turbines in 2050, and that even current turbines from 2025 deliver nearly four times the output.

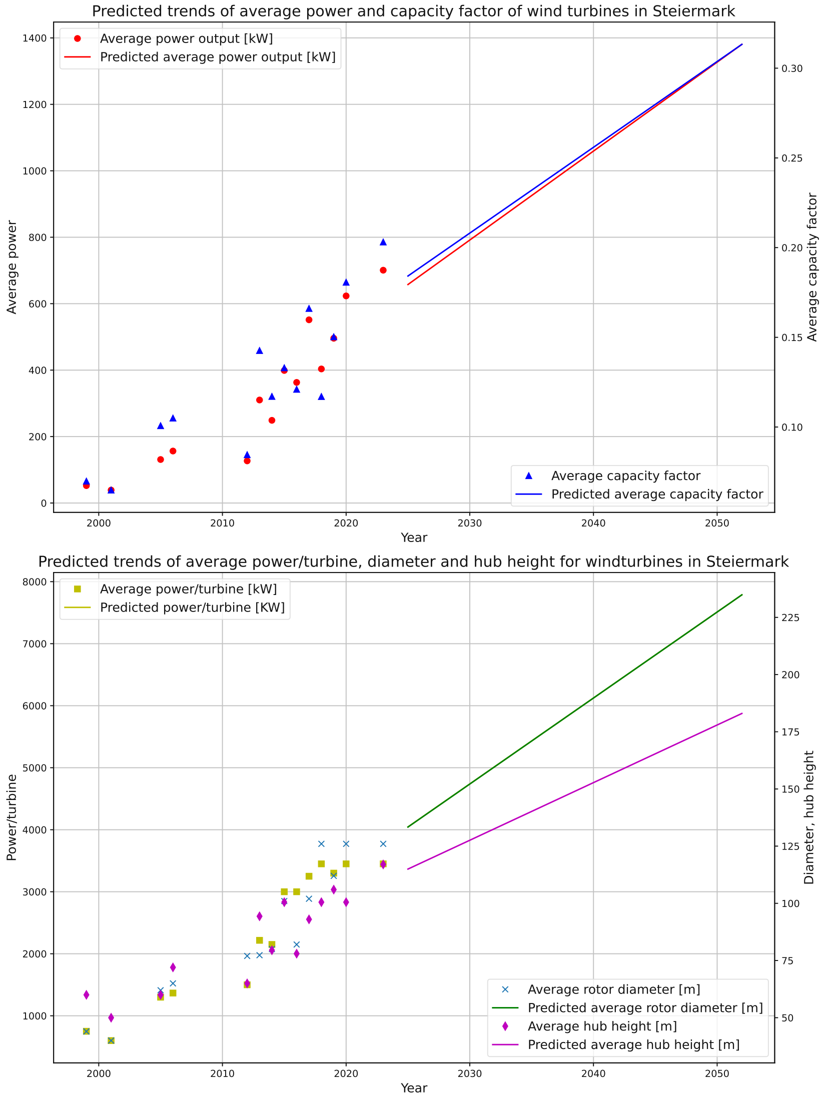


Figure 4.7.: Predicted trends of average production, capacity factor, power/turbine, diameter and hub height for wind turbines in Styria, Source: Own calculation

The Repowering Factor is particularly relevant for the years following 2011. As there was a significant expansion of wind power starting in 2011 (see Figure 3.1), many of these turbines are now approaching the end of their operational lifetime and are therefore of interest for repowering today. A glance at the table shows that an increase

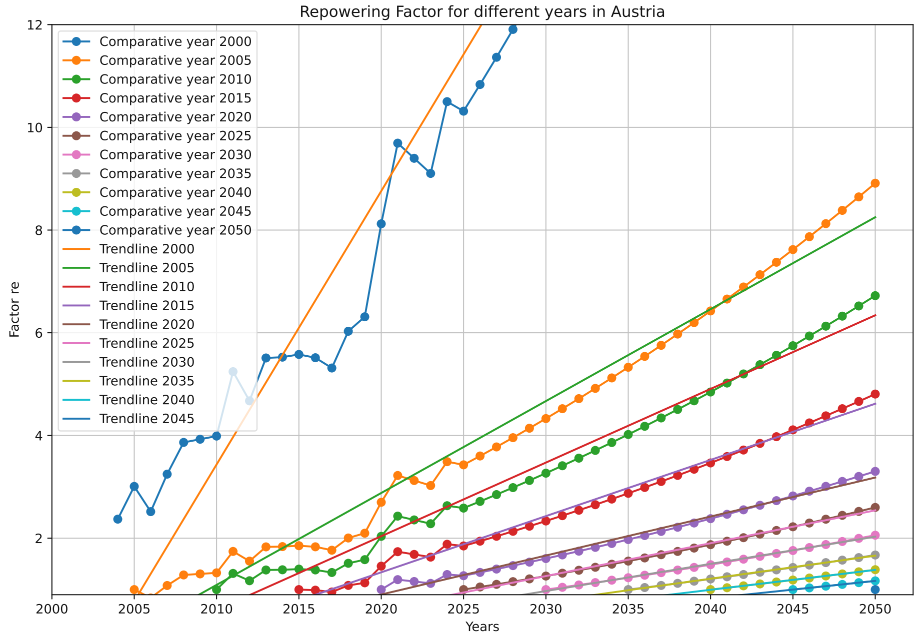


Figure 4.8.: Repowering Factor for different years in Austria, Source: Own calculation

in yield by a factor of 2 to 3 per turbine can be expected.

It is also evident that, although repowering continues to result in considerable yield improvements, its effect decreases with the increasing commissioning year of the replaced turbines when compared to earlier installations. This is particularly apparent in the steep trend line for the year 2000, which reflects the replacement of the first, still very small wind turbines.

It should also be noted that this model only considers the yield increase per turbine. However, since larger rotor diameters require greater spacing between turbines, the overall land area needed also increases. This aspect will be addressed in section 4.5.

4.3.2. Regional Perspective

When limited to the federal states, the Repowering Factor in Burgenland and Lower Austria shows values comparable to the national trend.

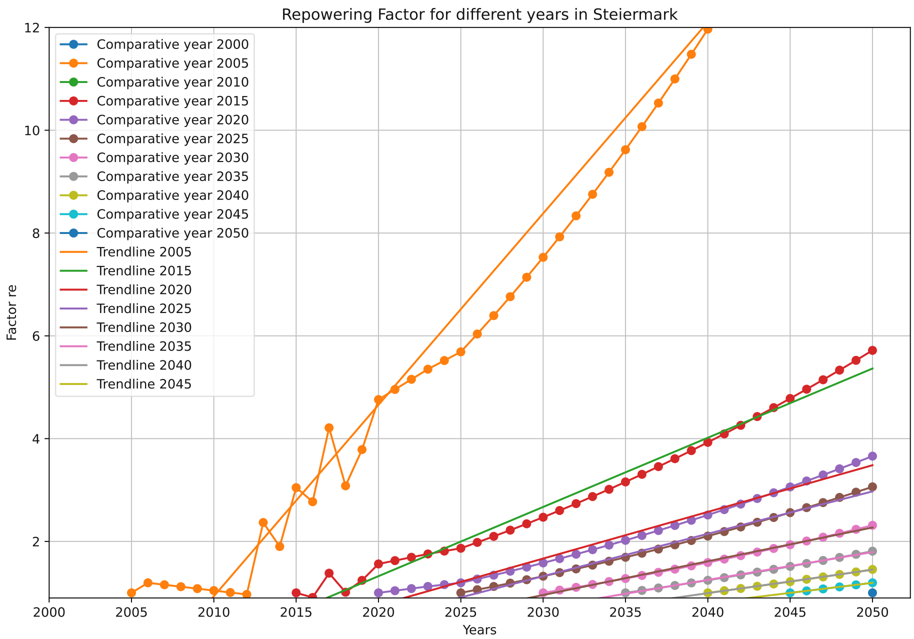


Figure 4.9.: Repowering Factor for different years in Styria, Source: Own calculation

In Styria, however, a slightly higher increase is expected. As shown in Figure 4.9, for example, 20-year-old turbines in this region are expected to at least double their yield by today's standards, and to increase by a factor of 5.5 by 2050. This could be due to the comparatively smaller existing installations in Styria compared to Lower Austria or Burgenland, resulting in significantly higher yields with modern turbines. The missing years in the graph are due to a lack of available data or the absence of installations in the respective reference years.

4.4. Economic Assessment and Sensitivity Analysis

As described in subsection 3.2.4, the Net Present Value (NPV) was used for the economic analysis. To better assess the impact of different input variables, a sensitivity analysis was carried out. The underlying Equation 3.9 ensures a minute accuracy resolution and the following parameter ranges were defined[2] for the analysis:

- **Investment cost range:** 1300–1900 [€/kW]
- **O&M cost range:** 0.02–0.03 [€/kWh]
- **Discount rate:** 6 %
- **Electricity price increase rate:** 1–2 % annually
- **Electricity prices:** from 2023 and 2024

Subject to availability and data recency, day-ahead electricity prices from 2023 (see Figure 4.10) and 2024 (see Figure 4.11) were selected as the basis for the NPV sensitivity analyses.

The distribution of the individual wind parks provides a good representation of Austria as a whole, as WP1 is located in Styria, WP2 in Burgenland, and WP3 in Lower Austria.

Overall, it can be observed that each scenario results in a positive NPV, even under the most conservative parameter assumptions. This indicates that the projects are economically viable and robust.

Furthermore, the NPV curves clearly show a strong dependence on investment costs. At high investment levels of around 1900 €/kW, the break-even point shifts significantly towards later years, indicating that controlling investment costs is crucial for the profitability of wind projects.

Due to higher electricity prices, the year 2023 offers a more favorable starting position. Consequently, it becomes evident that the electricity market price is a highly influential yet difficult-to-predict factor affecting the NPV. Fluctuations in revenue from

[2]See subsection 3.2.4

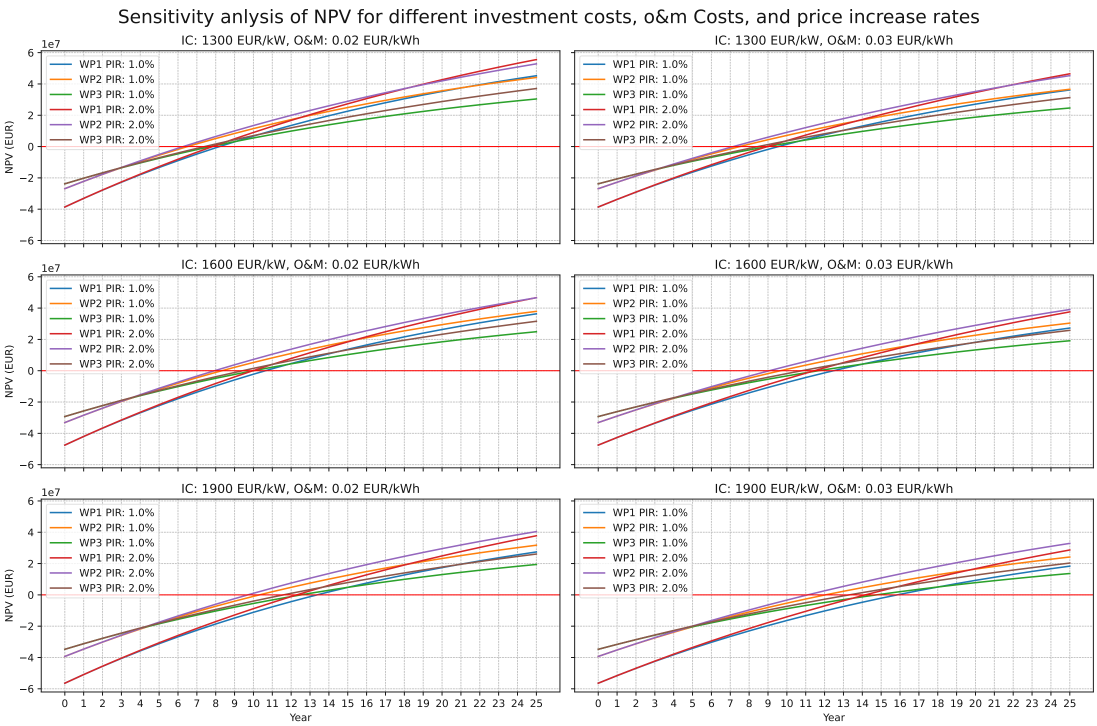


Figure 4.10.: NPV sensitivity analysis based on day-ahead electricity prices from 2023, Source: Own calculation

electricity sales can therefore only be economically managed through targeted support mechanisms, as discussed in subsection 2.5.2.

The influence of O&M costs is noticeable but not dominant. Higher operating costs of 0.03 €/kWh visibly reduce the NPV but do not lead to unprofitability as long as investment costs remain moderate.

It is also worth noting that moderat electricity price increases have only a minor impact on overall profitability. This highlights that actual cost efficiency, such as through lower investment costs, is a more significant factor than future price forecasts.

Furthermore, the location-specific differences between wind turbine sites in Austria appear to be relatively small. This suggests that, under comparable technology and

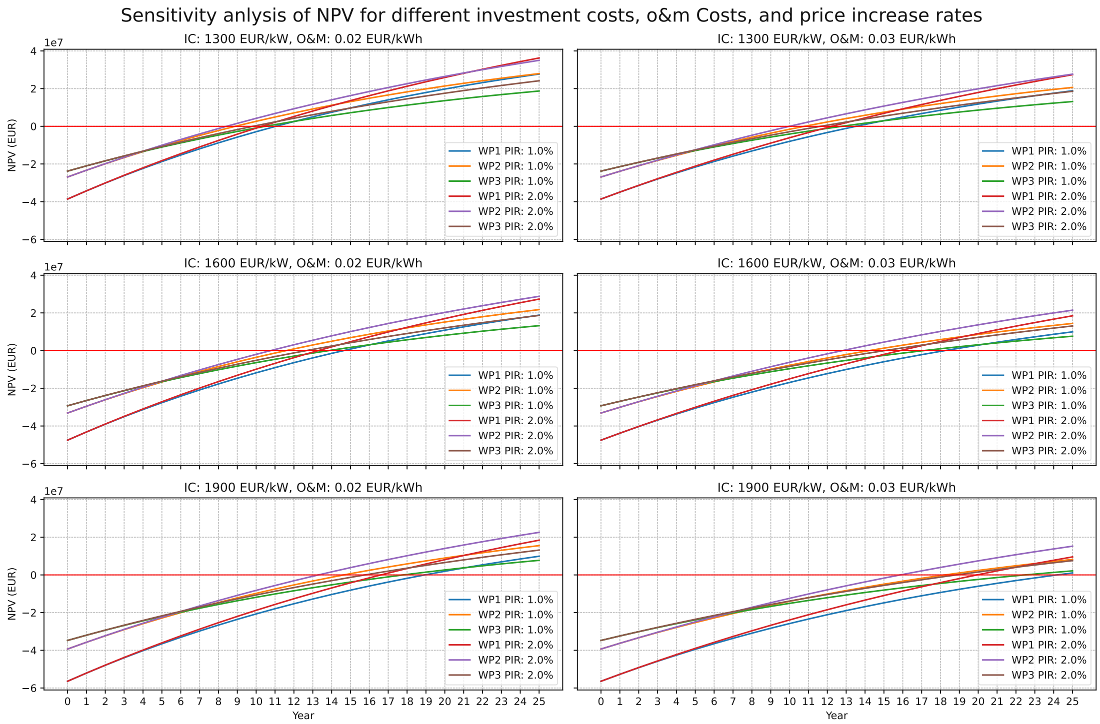


Figure 4.11.: NPV sensitivity analysis based on day-ahead electricity prices from 2024, Source: Own calculation

market conditions, the regional location has little impact on economic performance.

The economic break-even point occurs, for example, between 8 and 18 years for medium investment costs and both price years. On average, this corresponds to nearly half of the assumed project lifetime of 25 years (approximately 13 years). This leaves considerable time for positive capital returns, which increases investment security.

At an investment cost level of 1300 €/kW, almost all scenarios, regardless of O&M costs and price escalation, show a consistently positive net present value (NPV) early in the project lifecycle (cf. Figure 4.10). This indicates a very robust economic performance and highly favorable project conditions.

4.5. Repowering Scenarios

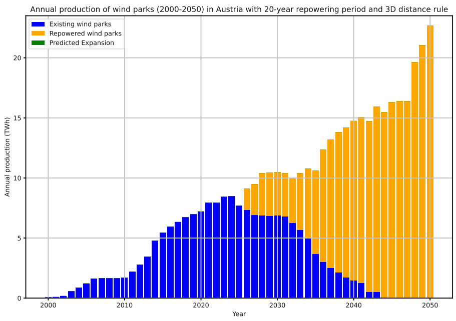
For all repowering scenarios (as defined in subsection 3.2.5), the following key conditions apply: each wind park must not exceed the previously required area as defined in Equation 3.10, and the exclusion criteria outlined in the same section must also be observed. In the following, '4D' and '3D' refer to four and three times the rotor diameter, respectively. Additionally, it is assumed that a complete repowering of all turbines takes place, and a one-year interval is included before the newly commissioned wind park starts producing.

4.5.1. Austria

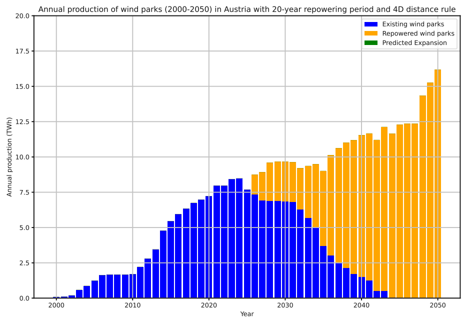
Assuming consistent continued use of the land area currently occupied by wind energy, different scenarios emerge for all of Austria as shown in Figure 4.12. Notably, even with similar turbine spacing (according to the 4D spacing rule), electricity yields increase by approximately 60–100% until 2050. With even more intensive land use (the 3D spacing rule), this model suggests that around 17 to 23 TWh per year could be generated from the existing areas.

In the case of a 20-year repowering cycle, a second repowering phase occurs, resulting in a significant increase in energy yields over time, as the model can take advantage of improved wind power technology at an earlier stage. In general, it can be stated that in all scenarios, except for those involving late repowering and restrictive spacing rules between turbines, at least a doubling of energy yields from the existing land use can be achieved.

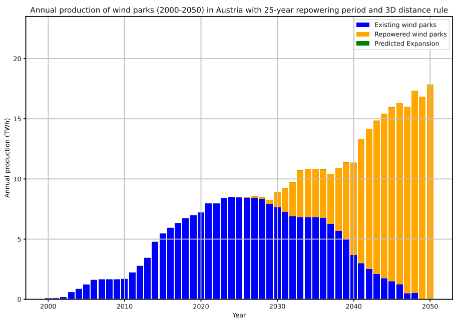
It can also be observed that earlier repowering and denser turbine spacing result in similar high increases in output. However, in this model, the negative effects of increased wake losses from closer spacing have been neglected.



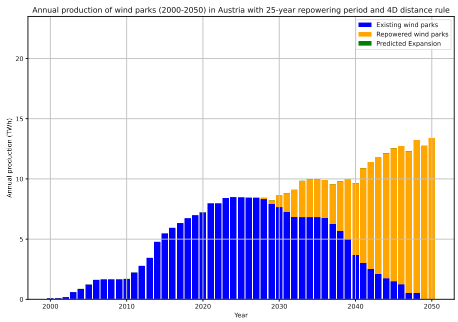
(a) Scenario: 20 years lifetime, 3D distance rule



(b) Scenario: 20 years lifetime, 4D distance rule

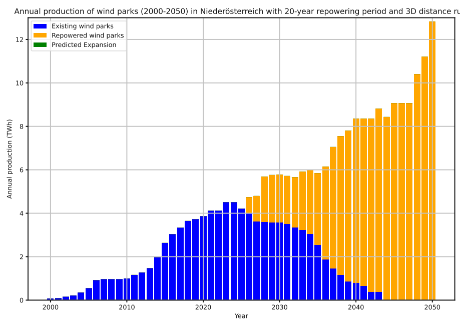


(c) Scenario: 25 years lifetime, 3D distance rule

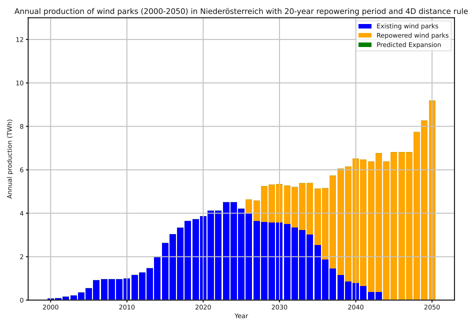


(d) Scenario: 25 years lifetime, 4D distance rule

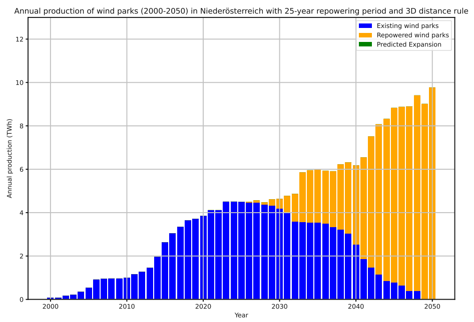
Figure 4.12.: Annual production of wind parks (2000–2050) in Austria with different (20/25 years) repowering period and (3D / 4D) distance rule. Source: Own calculation



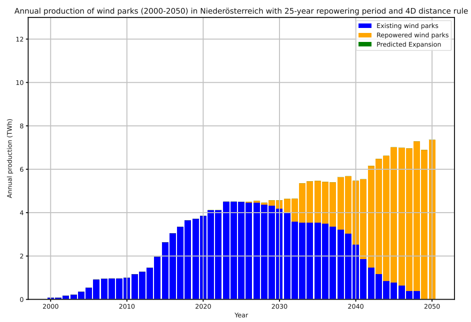
(a) Scenario: 20 years lifetime, 3D distance rule



(b) Scenario: 20 years lifetime, 4D distance rule



(c) Scenario: 25 years lifetime, 3D distance rule



(d) Scenario: 25 years lifetime, 4D distance rule

Figure 4.13.: Annual production of wind parks (2000–2050) in Lower Austria with different (20/25 years) repowering period and (3D / 4D) distance rule. Source: Own calculation

4.5.2. Lower Austria

As shown in Figure 4.13, a similar pattern emerges for Lower Austria. Doublings of energy yield are observed in the 20/25-year scenarios with 4D/3D spacing rules. In the case of dense turbine placement combined with a 20-year repowering cycle, a near tripling of output is even possible.

The model data is far from meeting the targets 2030 set by the EAG and IG Wind for Lower Austria.[3] This highlights that opening up new areas for development is essential.

4.5.3. Burgenland

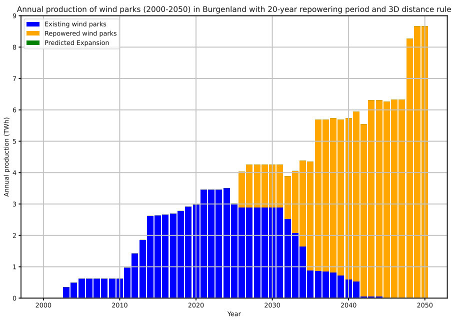
Overall, the expected increases in energy yield are lower in Burgenland (see Figure 4.14) compared to Austria as a whole (see Figure 4.12) and to Lower Austria(see Figure 4.13). A doubling of output is not quite achieved in the two intermediate scenarios; only the most optimistic scenario exceeds this threshold.

One possible explanation is the already above-average development of wind power infrastructure in Burgenland compared to the rest of Austria (see subsubsection 4.2.2). Moreover, Burgenland already meets the current requirements of the Renewable Expansion Act (EAG), although the target set by IG Wind of 6 TWh by 2030 is not yet reached by this scenario.[4]

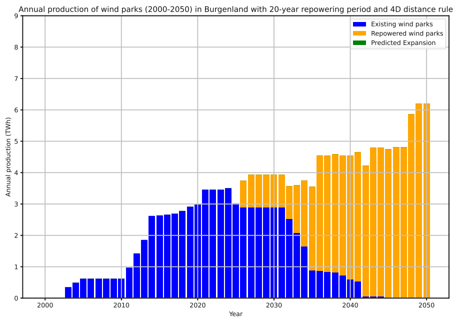
4.5.4. Styria

The model for Styria shown in Figure 4.15 also anticipates similar strong yield increases as in Lower Austria.

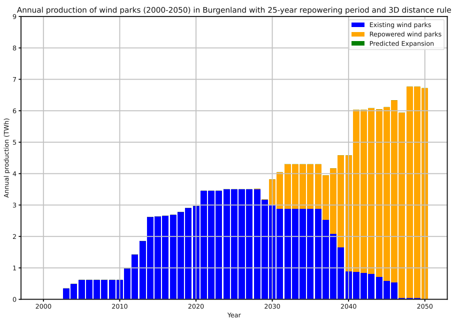
[3] Windkraft, 2024, p. 7.
[4] Windkraft, 2024, p. 7.



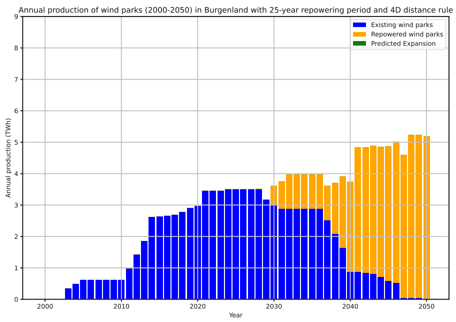
(a) Scenario: 20 years lifetime, 3D distance rule



(b) Scenario: 20 years lifetime, 4D distance rule



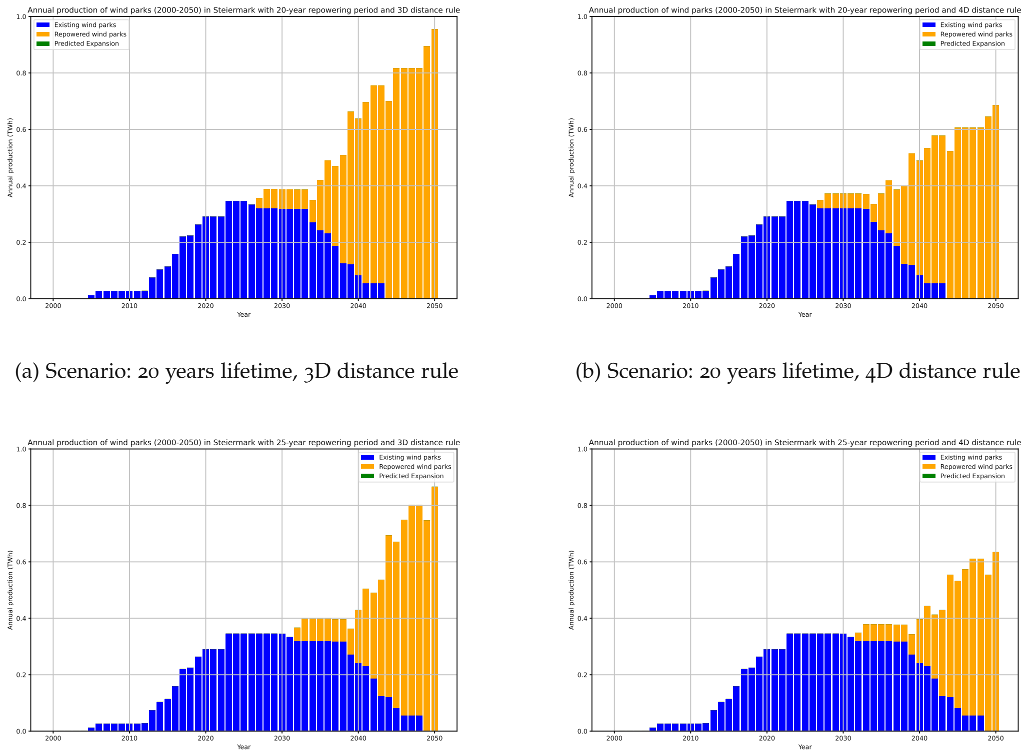
(c) Scenario: 25 years lifetime, 3D distance rule



(d) Scenario: 25 years lifetime, 4D distance rule

Figure 4.14.: Annual production of wind parks (2000–2050) in Burgenland with different (20/25 years) repowering period and (3D / 4D) distance rule. Source: Own calculation

However, it should be noted that overall installed capacity in Styria remains very low. The EAG and IG Wind targets of 2.4 TWh and 4.5 TWh respectively remain far out of reach by 2030, even with intensive repowering.[5]



(a) Scenario: 20 years lifetime, 3D distance rule

(b) Scenario: 20 years lifetime, 4D distance rule

(c) Scenario: 25 years lifetime, 3D distance rule

(d) Scenario: 25 years lifetime, 4D distance rule

Figure 4.15.: Annual production of wind parks (2000–2050) in Styria with different (20/25 years) repowering period and (3D / 4D) distance rule. Source: Own calculation

4.5.5. Targets for New Installations under Repowering

To meet its climate targets and achieve energy independence, Austria has set a number of specific goals (see subsection 2.5.3). One is the 2030 target defined in the Renewable

[5]Windkraft, 2024, p. 8.

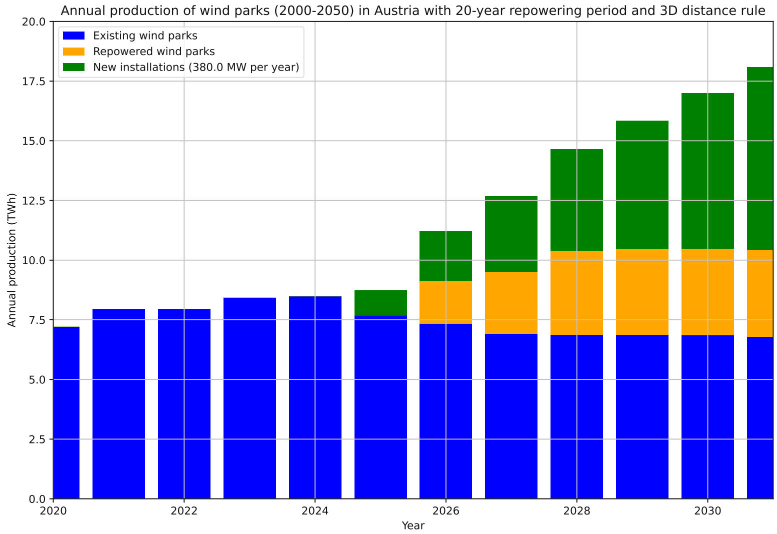
Energy Expansion Act (EAG), which aims to generate 17 TWh of wind energy annually by 2030.

Based on the analysis in subsection 4.5.1, each scenario results in a different required annual wind power capacity expansion (in MW). To meet the 2030 target, the outcome shown in Figure 4.16 and Figure 4.17 applies. This corresponds to an additional installed capacity on new land of approximately 380–490 MW per year.

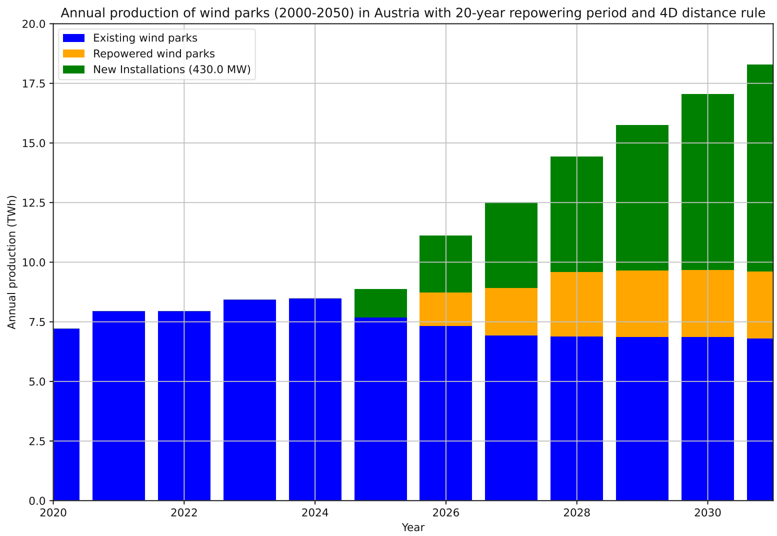
Another minimum target (see subsection 2.5.3) for the year 2040 is the recommendation by the Austrian Environment Agency of 29 TWh. A similar trend is evident here as well (see Figure 4.18 and Figure 4.19). An additional capacity expansion of approximately 380–490 MW per year is required.

It is worth noting that similar annual installation levels have only been achieved in Austria's wind power history in 2014, when more than 400 MW of new installations were realized.[6] However, it should be noted that achieving these targets would require maintaining this high expansion rate annually, and that the already repowered capacity in this year has not been taken into account.

[6] Biermayr et al., 2024, p. 284.

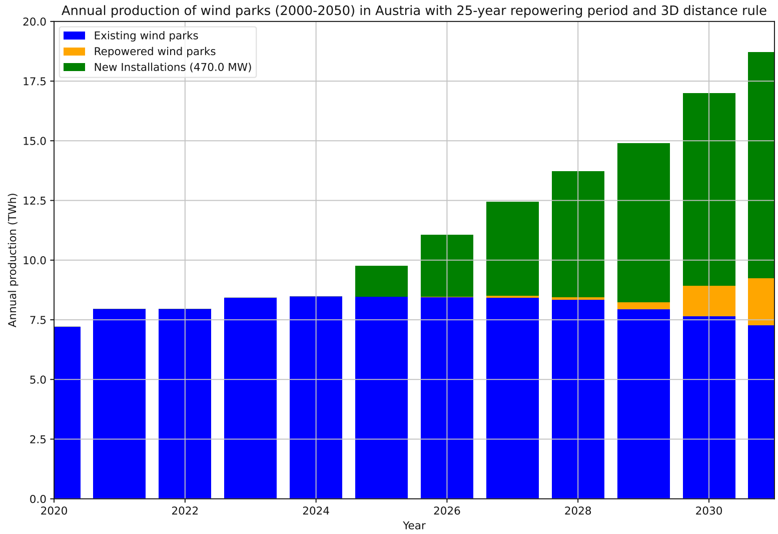


(a) Scenario: 20 years lifetime, 3D distance rule, 380 MW new installations

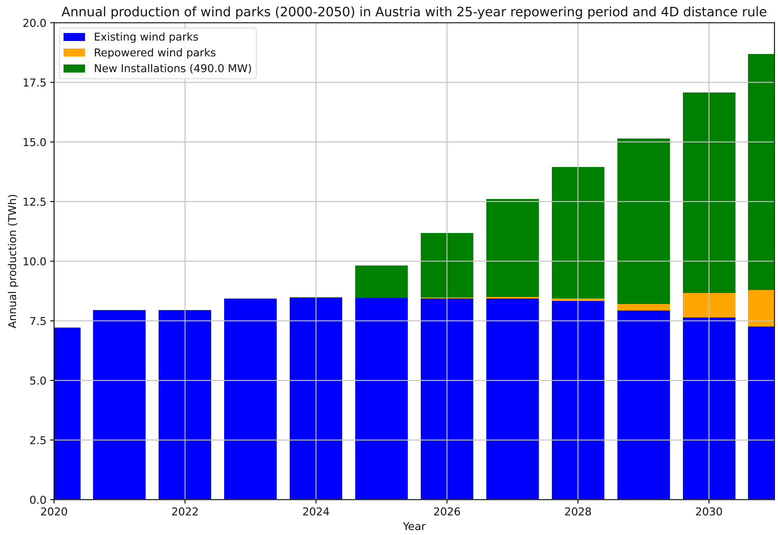


(b) Scenario: 20 years lifetime, 4D distance rule, 430 MW new installations

Figure 4.16.: Annual production of wind parks in Austria – scenarios with 20 years repowering period (2030 EAG goal). Source: Own calculation

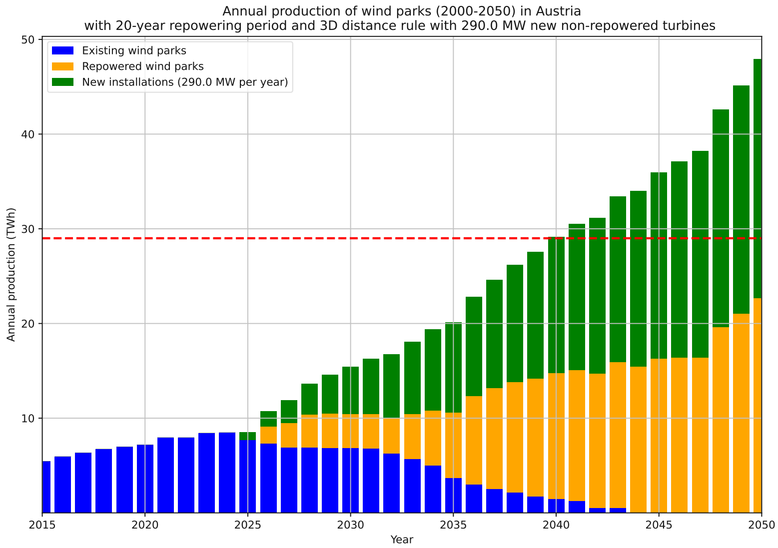


(a) Scenario: 25 years lifetime, 3D distance rule, 470 MW new installations

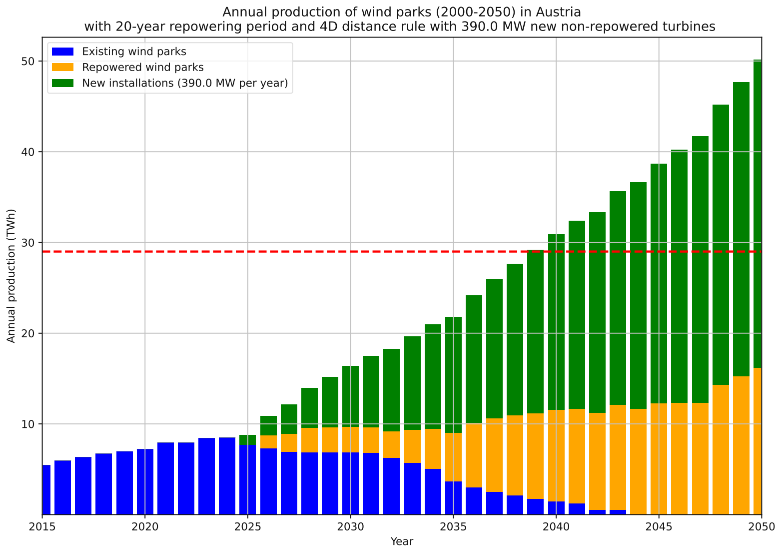


(b) Scenario: 25 years lifetime, 4D distance rule, 490 MW new installations

Figure 4.17.: Annual production of wind parks in Austria – scenarios with 25 years repowering period (2030 EAG goal). Source: Own calculation

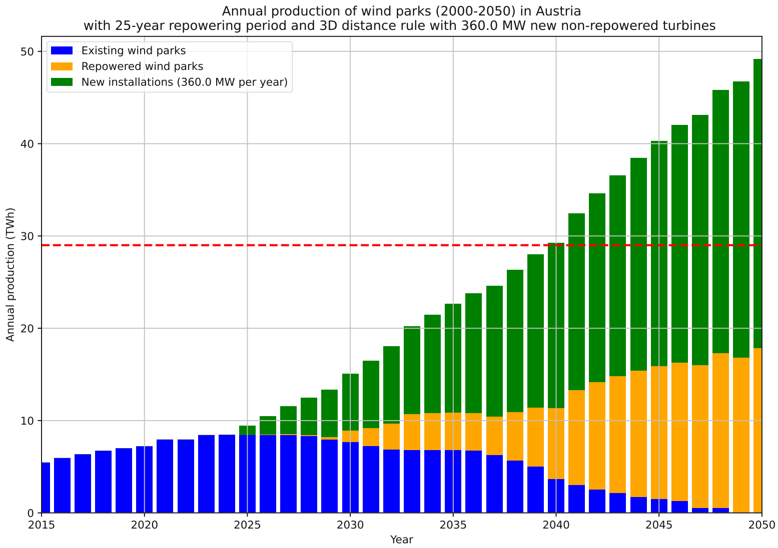


(a) Scenario: 20 years lifetime, 3D distance rule, 380 MW new installations

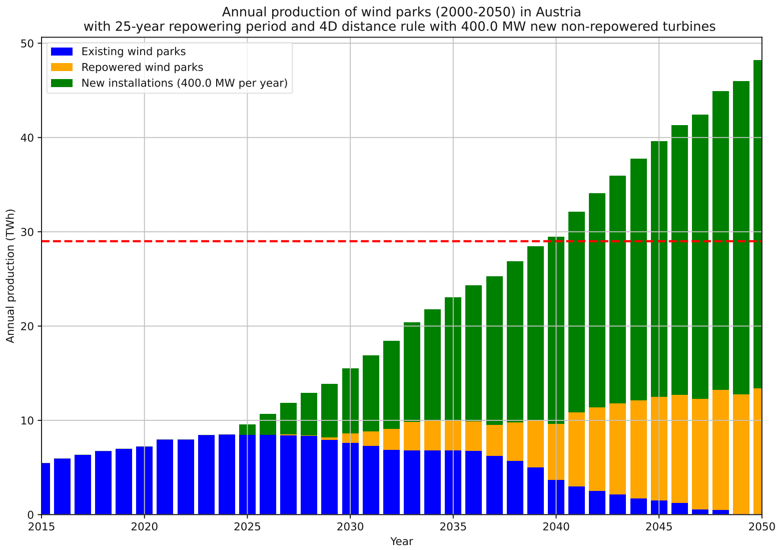


(b) Scenario: 20 years lifetime, 4D distance rule, 430 MW new installations

Figure 4.18.: Annual production of wind parks in Austria – scenarios with 20 years repowering period. Source: Own calculation



(a) Scenario: 25 years lifetime, 3D distance rule, 470 MW new installations



(b) Scenario: 25 years lifetime, 4D distance rule, 490 MW new installations

Figure 4.19.: Annual production of wind parks in Austria – scenarios with 25 years repowering period. Source: Own calculation

5. Conclusion and Outlook

The method of this thesis is based on an extensive dataset combined with a forecast model. The integration of simulated and real data allowed accurate and validated calculations of current and past production levels for Austria. Based on this, the economic analysis and scenario model provide valuable information on current and future factors affecting wind power in Austria. This step-by-step approach, using data models, forecasting, repowering factor determination, economic analysis and scenario simulation, was able to provide a comprehensive picture of Austria's dynamic wind power potential, including repowering.

Consistent repowering of existing wind parks is necessary to fully take advantage of the higher electricity yields on the same area. It has been shown that by replacing old turbines with modern ones, electricity generation can be increased significantly. Model calculations have even indicated that up to three times more output can be achieved on the same land by 2050. However, it also becomes clear that repowering alone will not be enough to meet Austria's ambitious expansion targets. Additional new installations are necessary to achieve the national climate goals, meaning that the expansion needs to exceed what has been built in recent years.

Through a forecast model of turbine parameters (see section 4.2), the thesis shows the linear growth trends in wind turbine technology and their performance. This highlights the development that future energy yield enhancements will be dominated by larger rotor diameters and efficient wind turbines, rather than taller towers. The technological progress enables the doubling of turbine power and average feed-in power by 2050, offering wind park operators the opportunity to strategically benefit from these advancements through repowering.

The idea behind the Repowering Factor concept is to estimate how much more energy a new turbine can produce compared to an older one. Wind turbines built today can deliver three times the output (see section 4.3) of a turbine from 2010. This is particularly important because, starting around 2012, Austria saw a significant expansion of wind power installations, many of which are now reaching the age where repowering should be considered. However, it should also be noted that while there was a dramatic increase in output from 2000 to 2020, the yield increases from 2020 to 2050 through repowering are comparatively smaller per turbine. This suggests that future repowering projects will continue to deliver higher outputs, but not at the same scale as those replacing the first generation of wind parks.

The economic analysis, based on a sensitivity analysis of the Net Present Value (NPV) (see section 4.4), showed that wind turbine projects in Austria are economically viable under a wide range of realistic assumptions. High electricity market prices and technological efficiency gains contribute to make wind projects profitable. However, it must also be noted that the results are sensitive to high investment costs, low energy prices and high operation & maintenance costs. The distance regulation simulated in the model shows that a tighter wind park layout results in significant yield increases, leading to economic advantages. Regulatory and planning decisions determine the success of repowering. Therefore, it is crucial to establish suitable funding mechanisms and regulatory frameworks so that operators can plan for the future and carry out profitable repowering projects.

The analysis also shows that regionally different strategies are necessary. In federal states with early wind power expansion (e.g., Lower Austria, Burgenland), many turbines are approaching the end of their operational life and offer significant repowering potential. Regions like Styria, which were developed later or more cautiously, present a different picture, with lower growth through repowering. For balanced progress in Austria, it is advisable to expand grid capacities in areas where a large number of old turbines could be replaced in the near future, while at the same time promoting new installations more actively in regions that currently contribute little or nothing to the national wind power supply.

In summary, consistent repowering of existing wind energy areas leads to significant increases in energy yield in Austria, but must be accompanied by the development of new sites in order to meet expansion targets. The combined approach of trends, energy yield models and economic evaluation provides a holistic view of Austria's wind power potential considering repowering.

Although this thesis has addressed many aspects, there are still several questions for future research. The estimation of the capacity factor in future scenarios could be improved, as well as the consideration of wake effects (see section 2.4) in repowering projects. Additionally, topics such as the interaction between wind power expansion and grid infrastructure, or environmental and social acceptance, play a major role in the further development of wind energy.

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Annex

Annex A.

Python Code

A.1. Simulate Data

```
# used libraries: ninjaclient, openpyxl
# this script fetches simulated wind power and wind speed from
    renewable.ninja for each turbine from database

# initialize renewable.ninja API client
ninja_client = NinjaClient(web_token='renewable.ninja_token')

# load turbine data (location, type, height, capacity) from Excel
    file
wb = load_workbook("simulation.xlsx")
ws = wb['simulation']

# loop over turbines and get renewable.ninja data
for row in range(2, 329):
    lat = ws[f"A{row}"].value
    lon = ws[f"B{row}"].value
    turbine = ws[f"C{row}"].value
    height = ws[f"D{row}"].value
    capacity = ws[f"E{row}"].value

    # get wind generation data from renewable.ninja
```

```
    df_wind, meta = ninja_client.get_wind_dataframe(
        lat, lon,
        date_from='202x-01-01',
        date_to='202x-12-31',
        dataset='merra2',
        capacity=capacity,
        height=height,
        turbine=turbine,
        interpolate=True,
        raw=True
    )

    # write average electricity output and wind speed back to
       Excel
    ws.cell(row=row, column=12, value=df_wind['electricity'].mean
       ())
    ws.cell(row=row, column=13, value=df_wind['wind_speed'].mean()
       )

wb.save('simulation.xlsx')
```

A.2. Capacity Factors

```
# used libraries: pandas, numpy, sklearn
# this script scales simulated renewable.ninja capacity factors
   using real measurement data

# capacity factor data loaded into dataframe (df) with columns
   simulated values 'CpFk year' and measurements 'MCpFk year'

# simulated years with available real measurement data
years = ['2021', '2022', '2023']

for year in years:
```

```
    simulation_column = f'CpFk {year}'
    measurement_column = f'MCpFk {year}'

    # preparing data for linear regression
    simulations = df[simulation_column].values.reshape(-1, 1)
    measurements = df[measurement_column].values

    # find indices of real measurement values
    valid_indices = np.where(~np.isnan(measurements))[0]

    # columns for linear regression
    x = simulations[valid_indices]
    y = measurements[valid_indices]

    # linear regression through the origin
    model = LinearRegression(fit_intercept=False)
    model.fit(x, y)

    # predict missing values and fill them in
    predictions = model.predict(simulations)

    # all missing values are filled with the predicted values
    df[measurement_column] = np.where(np.isnan(measurements),
       predictions, measurements)
```

A.3. Full Annual Electricity Generation

```
# used libraries: pandas
# this script calculates the yearly cumulative electricity
    generation of wind energy for each windpark

# calculate annual production
df['AnnualProduction'] = (df['Power/Turbine'] * df['Mean CpFkt'] *
    df['Number of turbines']) * 24 * 365
```

```
# set range, limit to 2024
years = range(2005, 2024 + 1)

# calculate annual production for each year for each windpark
production = []
for year in years:
    production.append(df[df['Commissioning year'] <= year]['
        AnnualProduction'].sum())

# convert in TWh
production = [prod / 1e9 for prod in production]
```

A.4. Future Trends of Wind Park Parameters in Austria

```
# used libraries: pandas, numpy, sklearn
# this script predicts the future parameters of wind turbines
    based on past data

# wind turbine data loaded into dataframe (df)

# calculate average power per turbine
df['Average power'] = df['Mean CpFkt'] * df['Power/Turbine']

# convert df/excel data into numeric values
numeric_df = df.apply(pd.to_numeric, errors='coerce')
numeric_df['Commissioning year'] = df['Commissioning year']

# calculate mean per commissioning year
yearly_mean = numeric_df.groupby('Commissioning year').mean().
    reset_index()

# set input years and target variables
x = yearly_mean[['Commissioning year']]
```

```
y = yearly_mean[['Average power', 'Diameter', 'Mean CpFkt', 'Hub
    height', 'Power/Turbine']]

# train multi-output regression
model = MultiOutputRegressor(LinearRegression()).fit(x, y)

# df for future years to predict
future_data = pd.DataFrame({'Commissioning year': np.arange(2025,
    2053)})

# predict future turbine characteristics based on years
future_predictions = model.predict(future_data[['Commissioning
    year']])
future_data['Average power'] = future_predictions[:, 0]
future_data['Diameter'] = future_predictions[:, 1]
future_data['Mean CpFkt'] = future_predictions[:, 2]
future_data['Hub height'] = future_predictions[:, 3]
future_data['Power/Turbine'] = future_predictions[:, 4]
```

A.5. The Repowering Factor

```
# used libraries: pandas, numpy
# this script calculates a repowering factor for wind turbines in
    Austria

# past and predicted turbine data loaded into dataframe (df)

# calculate average power per turbine
df['Average power'] = df['Mean CpFkt'] * df['Power/Turbine']

# define years range and comparative points
years = np.arange(2004, 2051)
comparative_years = np.arange(2000, 2051, 5)
```

```
# result dataframe for repowering factor
results = pd.DataFrame(index=years, columns=comparative_years)

# calculate the repowering factor for each comparative year
for comparative_year in comparative_years:
    df['Years_since_Commissioning'] = comparative_year - df['Commissioning year']

    # yearly mean of average power by commissioning year
    yearly_mean = df.groupby('Commissioning year')['Average power'].mean().reset_index()

    # mean average power of the reference year
    reference_average_power = df[df['Commissioning year'] == comparative_year]['Average power'].mean()

    # calculate repowering factor re
    yearly_mean['re'] = yearly_mean['Average power'] / reference_average_power

    # insert into results
    for year in years:
        if year >= comparative_year and year in yearly_mean['Commissioning year'].values:
            re_value = yearly_mean[yearly_mean['Commissioning year'] == year]['re'].values[0]
            if re_value >= 0:
                results.at[year, comparative_year] = re_value

# convert columns to numeric and interpolate missing values
results = results.apply(pd.to_numeric, errors='coerce')
results.interpolate(method='linear', inplace=True)
```

A.6. Economic Sensitivity Analysis

```
# used libraries: pandas, numpy
# this script performs a sensitivity analysis of the net present
    value (npv) with varying investment costs, o&m costs and
    electricity price increase rates

# input data are day-ahead prices in [EUR/MWh] and average power
    per turbine in [kW]

installations = {'WP1': ...}  # define number of turbines per site
installed_capacity = {'WP1': ...}  # define installed capacities
    per site in kW

# annual revenues and electricity generation per site
revenues = {}
total_productions = {}

for sheet in sheets:  # each sheet represents a wind park
    df_data = ...  # electricity generation and price data with
        one-minute timestamps

    # filter out negative values of prices and generation
    df_data = df_data[(df_data['Preis[EUR/MWh]'] >= 0) & (df_data[
        'AvgPower'] >= 0)]

    # calculate revenue in eur
    df_data['Revenue'] = (df_data['Preis[EUR/MWh]'] / 1000) *
        df_data['AvgPower'] * (1 / 60)
    revenue = df_data['Revenue'].sum() * installations[sheet]

    # calculate electricity generation in kwh
    production = df_data['AvgPower'].sum() / 60 * installations[
        sheet]
```

```
    revenues[sheet] = revenue
    total_productions[sheet] = production

# parameters for sensitivity analysis
investment_costs_range = np.arange(1300, 1901, 300)  # EUR/kW
om_cost_kwh_range = np.arange(0.02, 0.031, 0.01)  # EUR/kW
price_increase_rate_range = np.arange(0.01, 0.021, 0.01)
discount_rate = 0.06
years = 25
fixed_om_cost_kw = 0

# npv calculation for each parameter combination
results = []
for investment_cost_kW in investment_costs_range:
    for om_cost_kwh in om_cost_kwh_range:
        for price_increase_rate in price_increase_rate_range:
            npvs = {}
            for sheet in sheets:  # loop over wind parks
                annual_revenue = revenues[sheet]
                total_production = total_productions[sheet]
                investment_cost = investment_cost_kW *
                   installed_capacity[sheet]
                fixed_om_cost = fixed_om_cost_kw *
                   installed_capacity[sheet]
                variable_om_cost = om_cost_kwh * total_production
                npv_values = [-investment_cost]  # initial
                   investment in year 0
                for year in range(1, years + 1):
                    if year > 1:  # apply price increase from year
                        2
                        annual_revenue *= (1 + price_increase_rate
                           )
                    total_om_cost = variable_om_cost +
                       fixed_om_cost
                    cash_flow = annual_revenue - total_om_cost
```

```
                    discounted_cash_flow = cash_flow / ((1 +
                        discount_rate) ** year)
                    npv_values.append(npv_values[-1] +
                        discounted_cash_flow)
                npvs[sheet] = npv_values
            results.append((investment_cost_kW, om_cost_kwh,
                price_increase_rate, npvs))
```

A.7. Repowering Scenarios

```
# used libraries: pandas, numpy
# this script simulates the cumulative wind energy generation of
    Austria between 2000 and 2050 containing repowering, repowering
     of previous repowered wind parks and annual additions of new
    turbines

# scenario parameters
repowering_period = ...  # 20 or 25 years
distance_rule = ...  # 4 or 3
round_function = np.floor # round down to fit the distance rule
predicted_expansion = ...  # kw per year
location = 'Austria' # Austria or Bundesland

# wind park data (df) and future projections (future_df) are
    loaded and filtered by location

# define simulation years
years = np.arange(2000, 2051)
# cumulative electricity generation/production lists
cumulative_production = [0] * len(years)
cumulative_repowered_production = [0] * len(years)
cumulative_predicted_production = [0] * len(years)
# initialize wind park lists for tracking
new_windparks = []
```

```
old_windparks = []

for i, year in enumerate(years):
    # filter wind parks in operation
    operational = df[(df['Commissioning year'] <= year) & (year - df['Commissioning year'] <= 30)].copy()
    # calculate annual electricity generation for operational wind parks
    operational['AnnualProduction'] = operational['Power/Turbine'] * operational['Mean CpFkt'] * operational['Number of turbines'] * 24 * 365
    cumulative_production[i] = operational['AnnualProduction'].sum()

    # repowering for old wind parks
    if year >= 2024:
        # filter wind parks that are older than the repowering period and have Power/Turbine >= 1000
        repower_candidates = operational[(year - operational['Commissioning year'] >= repowering_period) & (operational['Power/Turbine'] >= 1000)]
        for _, wp in repower_candidates.iterrows():
            # get new wind park data with one year inbetween
            new_windpark_data = future_df[future_df['Commissioning year'] == (year + 2)]
            if not new_windpark_data.empty:
                new_windpark = new_windpark_data.iloc[0].copy()
                # calculate number of turbines for and set new commissioning year
                new_windpark['Number of turbines'] = max(1, round_function((4 * wp['Number of turbines'] * wp['Diameter']) / (distance_rule * new_windpark['Diameter'])))
                new_windpark['Commissioning year'] = year + 2
```

```
                # calculate annual electricity generation of new
                    wind park
                new_windpark['AnnualProduction'] = new_windpark['
                    Power/Turbine'] * new_windpark['Mean CpFkt'] *
                    new_windpark['Number of turbines'] * 24 * 365
                # add wind park to the list
                new_windparks.append(new_windpark[['Power/Turbine'
                    , 'Diameter', 'Hub height', 'Mean CpFkt', '
                    Number of turbines', 'Commissioning year', '
                    AnnualProduction']])
                old_windparks.append(wp[['Power/Turbine', '
                    Diameter', 'Hub height', 'Mean CpFkt', 'Number
                    of turbines', 'Commissioning year']])
                # remove old wind parks
                df = df[df.index != wp.name]

    # add new repowered wind parks starting this year
    new_this_year = [wp for wp in new_windparks if wp['
        Commissioning year'] == year]
    for wp in new_this_year:
        cumulative_repowered_production[i] += wp['AnnualProduction
            ']
    if i > 0:
        cumulative_repowered_production[i] +=
            cumulative_repowered_production[i - 1]

    # repowering of previous repowered wind parks
    rerepower_candidates = [wp for wp in new_windparks if (year -
        wp['Commissioning year'] >= repowering_period)]
    for wp in rerepower_candidates:
        new_windpark_data = future_df[future_df['Commissioning
            year'] == (year + 2)]
        if not new_windpark_data.empty:
            new_windpark = new_windpark_data.iloc[0].copy()
```

```
                new_windpark['Number of turbines'] = max(1,
                    round_function((4 * wp['Number of turbines'] * wp['
                    Diameter']) / (distance_rule * new_windpark['
                    Diameter'])))
                new_windpark['Commissioning year'] = year + 2
                new_windpark['AnnualProduction'] = new_windpark['Power
                    /Turbine'] * new_windpark['Mean CpFkt'] *
                    new_windpark['Number of turbines'] * 24 * 365
                # add new wind park to the list
                new_windparks.append(new_windpark[['Power/Turbine', '
                    Diameter', 'Hub height', 'Mean CpFkt', 'Number of
                    turbines', 'Commissioning year', 'AnnualProduction'
                    ]])
                new_windparks.remove(wp)

        # handle predicted extension electricity generation for the
            current year,
        if year >= 2025 and not future_df[future_df['Commissioning
            year'] == year].empty:
            # calculate predicted annual electricity generation of new
                wind park
            mean_cp_fkt = future_df[future_df['Commissioning year'] ==
                year]['Mean CpFkt'].values[0]
            predicted_production = predicted_expansion * mean_cp_fkt *
                24 * 365
            # add to cumulative predicted production
            if i > 0:
                cumulative_predicted_production[i] =
                    cumulative_predicted_production[i - 1] +
                    predicted_production
            else:
                cumulative_predicted_production[i] =
                    predicted_production

# convert production to TWh
```

```
cumulative_production = [p / 1e9 for p in cumulative_production]
cumulative_repowered_production = [p / 1e9 for p in
    cumulative_repowered_production]
cumulative_predicted_production = [p / 1e9 for p in
    cumulative_predicted_production]
```