Predicting Wind Turbine Performance

INST737 Milestone 1

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Introduction

In the field of renewable energy, wind power is essential to the global effort to generate electricity in a sustainable manner. A thorough understanding of wind turbine performance, installation costs, and maintenance needs is crucial for maximizing efficiency and lifespan. This study does an initial analysis that will be expanded upon using the United States Wind Turbine Database (USWTDB), a large repository holding significant data on both onshore and offshore wind turbines in the United States.

Our analysis looks for important insights that might guide strategic decision-making and spur innovation in the wind energy industry in an effort to add to the continuing conversation about renewable energy. Our objective is to create a path towards a future in energy that is more resilient and sustainable.

Research Questions

The burgeoning issue of climate change poses an unprecedented challenge to global stability, affecting ecosystems, economies, and communities worldwide. Among the myriad sources contributing to this environmental crisis, the generation of electricity through the combustion of fossil fuels stands out as a significant contributor to air pollution and the greenhouse effect, primarily due to the emission of CO_2 and other harmful pollutants. This reality has propelled a global shift towards more sustainable and less environmentally damaging sources of energy, with a particular focus on harnessing renewable resources.

Wind energy, harnessed through turbines, represents a cornerstone of this transition. Unlike traditional fossil fuel-based power generation, wind turbines offer a clean, inexhaustible solution for electricity generation, aligning with efforts to mitigate climate change impacts. As countries worldwide strive to increase their share of renewable energy in the power mix, the optimization of wind turbine efficiency emerges as a critical endeavor. The effectiveness of wind turbines is intrinsically linked to their design parameters, including model specifics, height, rotor diameter, and installation location, which directly influence their capacity to convert wind into electrical energy.

Given the urgency to optimize renewable energy sources for a sustainable future, this project aims to delve into the wind turbine performance through a predictive lens. The primary research question we seek to address is:

Can we predict wind turbine performance based on their model, height, rotor diameter, location (latitude, longitude) ?

In alignment with the course requirements, this project aims to address the aforementioned question by examining the relationship between wind turbine design parameters, turbine capacity, and geographic variables such as wind speed. Ultimately, the insights gained from this project could serve as a cornerstone for policy-making, strategic planning, and technological innovation in the renewable energy sector to achieve environmental sustainability and energy security.

State of the Art

The escalation in global temperature alongside drastic climate changes has intensified environmental apprehensions globally. In the United States, data from the US Energy Information Administration reveal that approximately 60% of electricity is produced through fossil fuels, while renewable energy sources such as wind, hydropower, and solar contribute about 21%. Specifically, wind turbines alone generate 10.3% of this electricity (Chehouri, A., et al., 2015; US Energy Information Administration).

In contrast to fossil fuels, renewable energy sources have an almost negligible impact on the environment, primarily due to their lack of direct CO2 or NOx emissions. Technologies ranging from solar panels to wind turbines are capable of converting ambient energy into electricity, with wind turbines being particularly prominent and accessible for this purpose (Charabi et al., 2019; Yang et al., 2018).

The United States has established a goal for 2030 to source at least 20% of its energy from onshore and offshore wind farms (Lindenberg et.al., 2008). Achieving this target requires wind energy to be cost-competitive with conventional fossil fuel sources. Consequently, it is crucial for wind turbine designers and manufacturers to identify optimal solutions that meet the objectives within specified design constraints. Over the past 30 years, the focus has shifted from maximizing the power coefficient to enhancing the annual energy production, with strategies such as minimizing blade mass and maximizing rotor thrust and torque being explored (Chehouri, A., et al., 2015).

To decrease the cost of energy, expressed in $/kWh, there has been a significant increase in the size of commercial wind turbines over the last three decades. This scale-up is economically beneficial because it allows for the exploitation of higher wind speeds due to wind shear, thereby reducing the number of turbines needed for wind farm setups and subsequently lowering operational costs. However, this increase in rotor size also presents greater challenges in terms of structural performance and durability, with the maximum achievable rotor diameter with current materials and manufacturing technologies still being an area of uncertainty (Grujicic et al., 2010).

Summary:

Maki, K., Sbragio, R., & Vlahopoulos, N. (2012). System design of a wind turbine using a multi-level optimization approach. Renewable Energy, 43, 101-110. https://doi.org/10.1016/j.renene.2011.11.027

This study focuses on the optimization of wind turbine design to minimize the cost of energy (COE), considering critical design variables such as rotor diameter, hub height, and blade characteristics (thickness, twist angle, chord distribution) to optimize turbine performance. Utilizing a multi-level optimization strategy and simulation tools developed by the National Renewable Energy Laboratory (NREL), this study emphasizes the importance of these design parameters in boosting annual energy production (AEP) and reducing blade-root bending moments, which directly influence the turbine's efficiency and operational costs. Also, scalar models have been developed to link the design feature with performance matrices, optimizing the main characteristics of the wind turbine. This approach allows for a comprehensive evaluation of the wind turbine system, considering the interactions among various performance metrics. Also, through sensitivity analysis, the research demonstrates how variations in design parameters can impact the overall performance of the turbine, providing insights into achieving an optimal balance between energy output and cost efficiency (Maki et al., 2012).

Yassine, C., & Abdul-Wahab, S. (2020). Wind Turbine performance analysis for energy cost minimization. Renewables; Wind, Water, and Solar, 7(1). https://doi.org/10.1186/s40807-020-00062-7

In their comprehensive analysis of wind turbine performance for minimizing energy costs, the researchers utilize HOMER Pro software to meticulously evaluate wind energy potential in Oman. The study intricately compares six different wind turbines, grounding its analysis on several critical factors. Firstly, it incorporates precise wind speed measurements to accurately represent local wind conditions. This involves leveraging the Weibull distribution method to statistically model wind speed probabilities, ensuring a detailed understanding of wind patterns across different regions of Oman.The researchers delve into the technical specifications of each wind turbine model, examining their design, power output capabilities, and suitability for specific wind conditions. This level of detail extends to evaluating the economic aspects of wind turbine deployment, including both capital and operational maintenance costs, to ascertain the overall financial feasibility.

Central to the analysis is the use of turbines' power curves, which are essential for predicting the energy output based on varying wind speeds. By comparing these curves alongside the economic data, the study identifies the most cost-effective wind turbines for both northern and southern regions of Oman, aiming for the optimal blend of high energy output and low cost of energy (COE).This methodical approach underscores the importance of a multifaceted analysis, combining technical performance with economic viability, to select the most suitable wind turbine models for specific locales.

Raciti Castelli, M., Englaro, A., & Benini, E. (2011). The Darrieus wind turbine: proposal for a new performance prediction model based on cfd. Energy, 36(8). https://doi.org/10.1016/j.energy.2011.05.036

This paper presents a Computational Fluid Dynamic (CFD) model for the evaluation of energy performance and aerodynamic forces acting on a straight-bladed vertical-axis Darrieus wind turbine. Standard wind performance prediction models are based on existing Blade Element Momentum BE-M models - mathematical formulas that break down wind turbines into smaller elements along the length of the rotor blade. BE-M models conduct element-level analysis of aerodynamic forces (e.g., lift, drag, momentum change) and then aggregate across the entire blade to most accurately calculate overall wind turbine performance including power output, thrust, and efficiency. These calculations are most accurate for laminar wind conditions and are not as effective at predicting performance when windflow is considered mixed or turbulent.

To address these limitations, the authors of this study presented a prediction model by transferring traditional BE-M principles into a CFD model by integrating Navier-Stokes equations to understand the motion of airflow. This allowed them to determine rotor power by correlating geometric flow characteristics with dynamic quantities (e.g., rotor torque, blade forces) even under non-laminar conditions. The main geometrical features of the model include rotor diameter, rotor height, number of blades, length of blade, and spoke-blade connection. Simulating this model, the authors analyzed distributions of torque coefficients at various tip speed ratios and found a significant relationship between torque, power extraction, and blade length. As a result, the model is proposed as an optimization tool for the development of new rotor designs.

Veena, R., Manuel, S. M., Mathew, S., & Petra, I. (2020). Parametric models for predicting the performance of wind turbines. Materials Today: Proceedings: Part 3, 24, 1795–1803. https://doi.org/10.1016/j.matpr.2020.03.604

This paper compares eight commonly used parametric models to predict the wind performance of four wind turbines in four different locations. By using actual performance data, the authors aimed to evaluate manufacturer-provided power curve models, compare accuracy of parametric models and real data, and lastly demonstrate how to use parametric models to develop power curves with limited data. The eight parametric models were the linear segmented model, quadratic model, cubic model, generalized polynomial model, WERA model, probabilistic model, and both four and five parameter logistic functions. Of the models, the WERA (Wind Energy Resource Analysis) model presented the lowest prediction errors and was used to predict the wind performance of a small wind turbine (1kW) with limited data.

Datasets

The United States Wind Turbine Database (USWTDB) is a resource that provides detailed information about the locations of land-based and offshore wind turbines in the United States, along with comprehensive wind project data and technical specifications for the turbines. The establishment of this database was made possible through joint funding from the U.S. Department of Energy (DOE) Wind Energy, Lawrence Berkeley National Laboratory (LBNL), the U.S. Geological Survey (USGS) Energy Resources Program, and the American Clean Power Association (ACP).

The collaborative development of the USWTDB commenced in 2016, bringing together USGS, LBNL, and the American Wind Energy Association (AWEA, now the American Clean Power Association, ACP). Their primary objective was to create a comprehensive and highly accurate database that surpassed the capabilities of individual wind turbine datasets. Federal agencies began using this consolidated data in April 2017, and in April 2018, the dataset was made accessible to the public through an online portal (Hoen et al., 2018).

The data set includes around 72731 wind turbines , of which approximately 71,085 of them have a full confidence level, indicating that the available image shows an installed turbine. On the other hand, approximately 1,646 turbines have a confidence level below 3, which corresponds to cases where either no turbine is shown in the image, the image contains clouds, or the imagery is older than the turbine's built date. Furthermore, a confidence level of 2 indicates that the image portrays a developed pad with a concrete base and/or turbine components on the ground. (Table 1)

Table 1: The Distribution of Wind Turbines by Level of Confidence

Row	Level of Confidence	Number of Turbines
1	1	1,508
2	2	138
3	3	71,085

Moreover, the dataset encompasses wind turbines installed across 43 states in the USA, including Guam (GU) and Puerto Rico (PR), covering installations from 1983 to 2023.

Through the analysis of the USWTDB, we aim to delve deeper into the distribution, capacity trends, and evaluation of wind energy turbines across the United States. This dataset empowers us to investigate the growth and evolution of wind energy infrastructure, pinpoint essential patterns, and identify areas of concentration and significance.

According to the dataset codebook, the variables present in the data frame are as follows:

- The dataset comprises four types of identifier codes: case_id, faa_ors, faa_asn, and usgs_pr_id.
- The geographical location of each turbine point is specified by state, county, fips (5-digit location code for each turbine), and latitude and longitude coordinates.
- Various time-related variables are defined, including the turbine's operational start date (p_year), partial retrofit year (retrofit_year), and the date (t_image_date) when the turbine's location was visually verified.
- Turbine attributes encompass the number of turbines, manufacturer, capacity (kW), hub height (m), rotor diameter (m), rotor swept area (m^2), height from the ground to its apex (m), and retrofit status.
- Confidence levels are assigned to both the location and attributes of the turbines.

To answer questions on energy generation, we reference publicly available annual data from the U.S. Energy Information Administration (EIA). This database tracks the amount of energy generated by all fifty states and the District of Columbia on an annual basis. It is important to note that this data aggregates different sources of energy including renewable and fossil fuels and the EIA does not disaggregate by source. Other commercial entities provide wind-specific generation data but data quality and rigor could be compromised. Instead, we opt to use verified governmental records and assume that the aggregate data could potentially skew any data interpretations. For the purposes of this assignment, we referenced available data from 2015 which included the following variables:

- Average retail price (cents/kWh) - sold to consumers by retail provider
- Net summer capacity (MW) - maximum amount of electricity that a state needs to produce under ideal conditions during the summer months (i.e., heavy demand)
- Net generation (MWh) - total amount of electricity generated by power plants in the state
- Total retail sales (MWh) - total amount of electricity sold to consumers by retail providers

Data Cleaning Efforts

To adapt the datasets to our needs, data cleaning was imperative, involving adjustments like adding standardized abbreviations to resolve discrepancies in state representation among datasets, alongside meticulous examination of variables and elimination of unnecessary fields.

For our analysis, we prioritized the 'case_id' while excluding other identifiers such as 'faa_ors', 'faa_asn', and 'usgs_pr_id'. Additionally, we removed 't_img_date' and 't_img_srce' since they are related to visual verification of turbine locations, which is not relevant to our objectives. To maintain data integrity, we meticulously checked the dataset for duplicates and performed a comprehensive examination of each variable's type and summary. This rigorous process was essential for ensuring the consistency and reliability of our data, laying a solid foundation for our analysis.

There were instances when we needed to modify data to make it work for our needs. Since we were working with two different datasets, creating a common field was necessary for the merger. Although the states under consideration were indicated in a field in both datasets, one dataset used state abbreviations, and the other utilized full state names. We discovered that adding a new column with the state abbreviations was required to address this disparity.

We made use of R's built-in function state. abb to get the state abbreviations. We now have a quick and easy method to obtain the state-specific standardized abbreviations thanks to this tool. Through the integration of the state. abb function into our data preprocessing pipeline, we were able to produce the necessary abbreviations with ease, which made the process of combining the two datasets easier.

There were no duplicates or outliers detected, though null values were present, which will be addressed later in the project if deemed necessary to do so.

Other Software Engineering Efforts

Apart from the previously mentioned packages, we also used a multitude of libraries for visualization efforts including: patchwork, ggplot2, cowplot, and gridExtra. Every one of these packages was essential to improving our attempts at data visualization.

- **patchwork**: This package makes it easier to combine several ggplot2 charts into one layout. It makes it easy to exhibit numerous visualizations simultaneously by allowing the creation of sophisticated layouts through the arrangement and alignment of multiple plots.
- **ggplot2**: This package is an R data visualization library with strong capabilities. It offers an adaptable and simple syntax for making many different kinds of plots, such as scatter, bar, and line graphs, among others. ggplot2 allows users to construct intricate representations layer by layer by adhering to the syntax of the graphics paradigm.
- **cowplot**: ggplot2's capabilities are expanded by this package, which offers more tools for building intricate layouts and annotations. It makes it simpler to create visualizations fit for publishing by providing tools for organizing numerous plots, adding annotations, and changing plot themes.
- **gridExtra**: This package provides functions for arranging multiple grid-based plots on a single page. It allows users to combine ggplot2 plots, lattice plots, and other grid-based graphics into a single layout.

Together, these packages offer a comprehensive set of tools for data visualization in R, enabling us to create, customize, and combine a wide range of plots to effectively communicate insights from the data.

Contributions

The contributions of each team member were evenly distributed among their respective skill sets and knowledge.

- Code:
  - READ_ME file: Nour
  - R file: All students contributed equally to the code portion of this project.
- Presentation:
  - All students contributed equally to the preparation and recording of the presentation.
- Report:
  - Introduction: Nour
  - Research Questions: Zahra
  - State of the Art: Kurubel (50%) & Zahra (50%)
  - Dataset : Zahra (50%) & Kurubel (50%)
  - Data Cleaning: Zahra (50%) & Nour (50%)
  - Other Software Engineering: Nour

Figures

	Min.	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Max.**
Energy Net Generation (MWh)	1,982,047	556,658,918	83,640,067	179,595,163	449,826,336	449,826,336
Turbine Capacity (kW)	50	1600	2000	2076	2500	6000
Rotor Swept Area (m^2)	141	5346	7854	8186	10568	20612
Rotor Diameter (m)	13.4	82.5	100	99.28	116	162
Turbine Tip Height (m)	30.4	121.3	130.1	132.1	150.0	205.4
Hub Height (m)	22.8	80	80	82.5	89	137

Table 2: Summary statistics of key turbine parameters and net energy generated

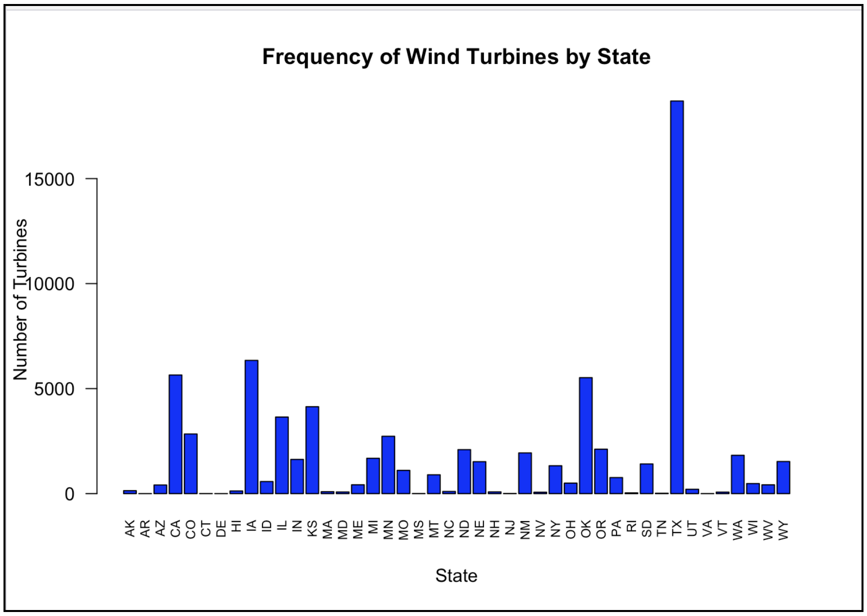

Figure 1: Frequency of wind turbines by state

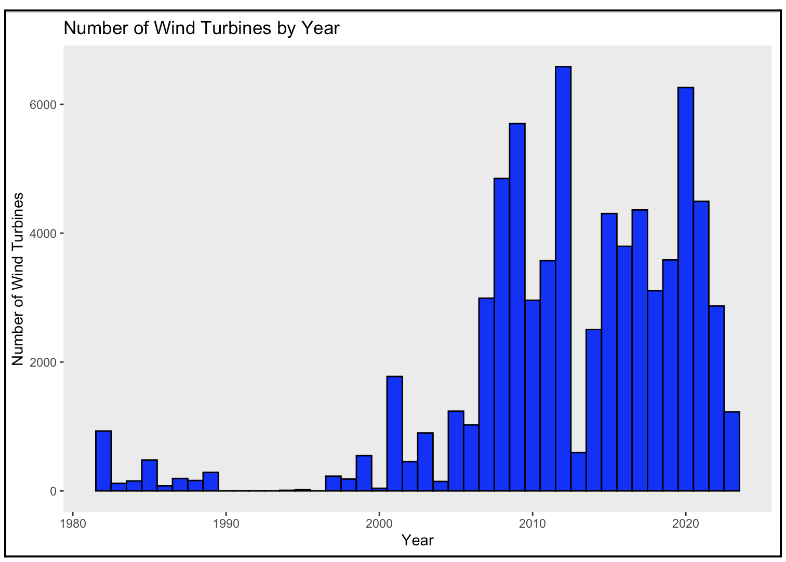

Figure 2: Number of wind turbines by year from 1983-2023

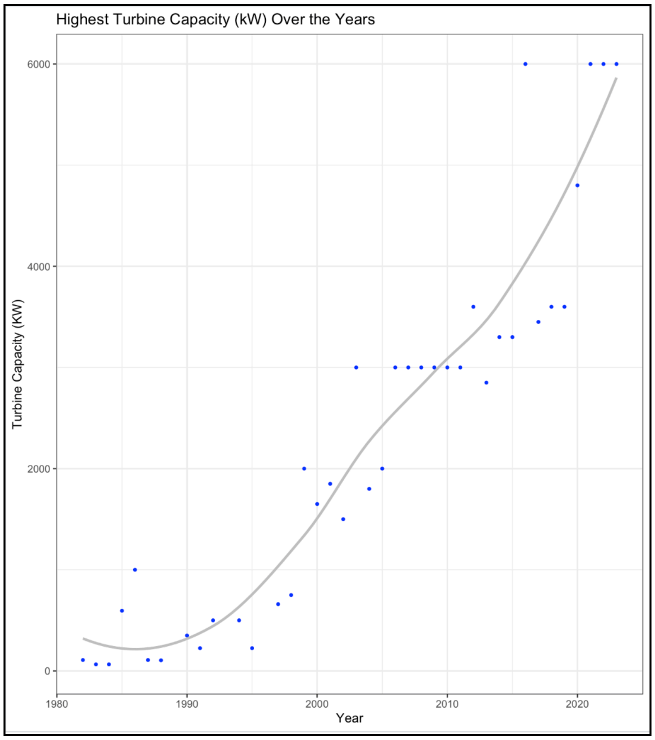

Figure 3: Growth of individual wind turbine capacity (kW) from 1983-2023

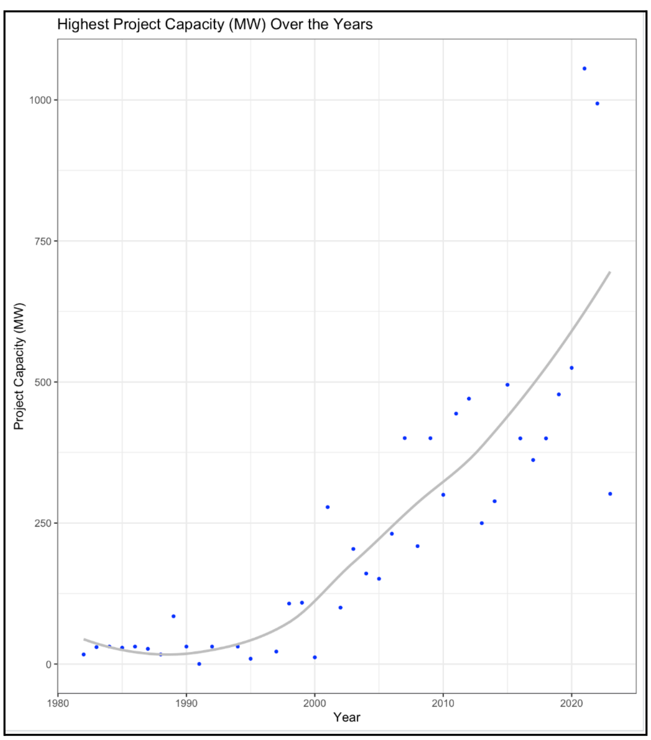

Figure 4: Growth of wind turbine project capacity (MW) from 1983-2023

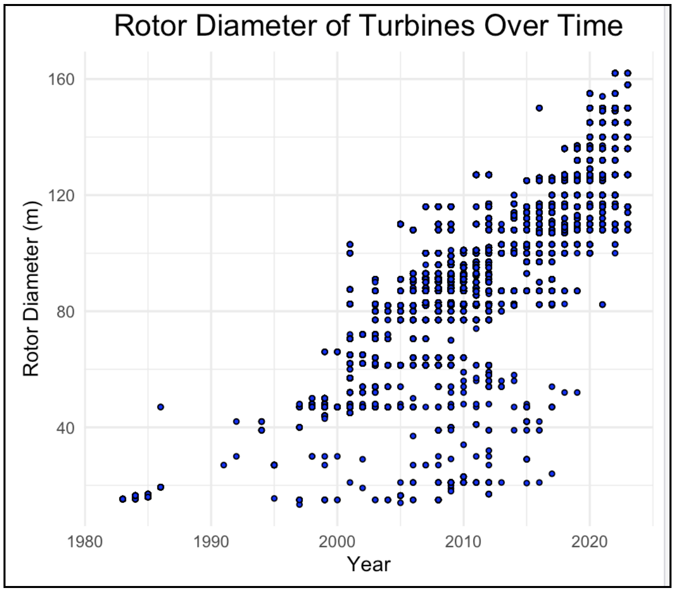

Figure 5: Growth of wind turbine rotor diameters (m) from 1983-2023

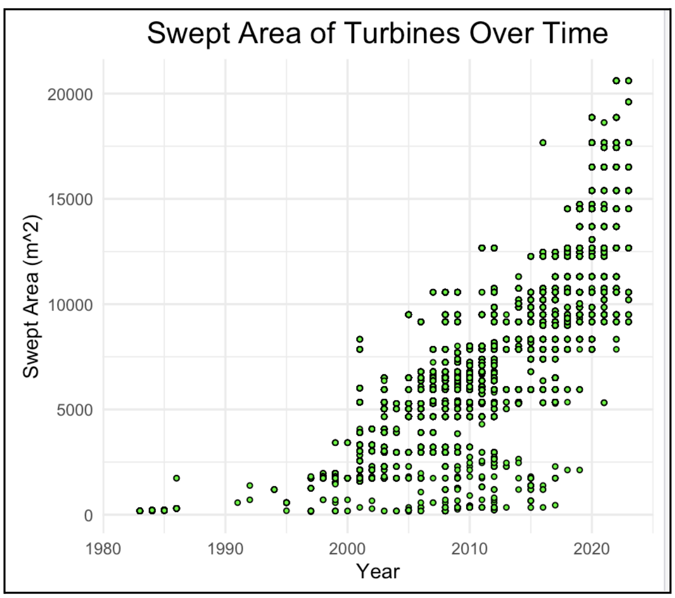

Figure 6: Growth of wind turbine swept area (m^2) from 1983-2023

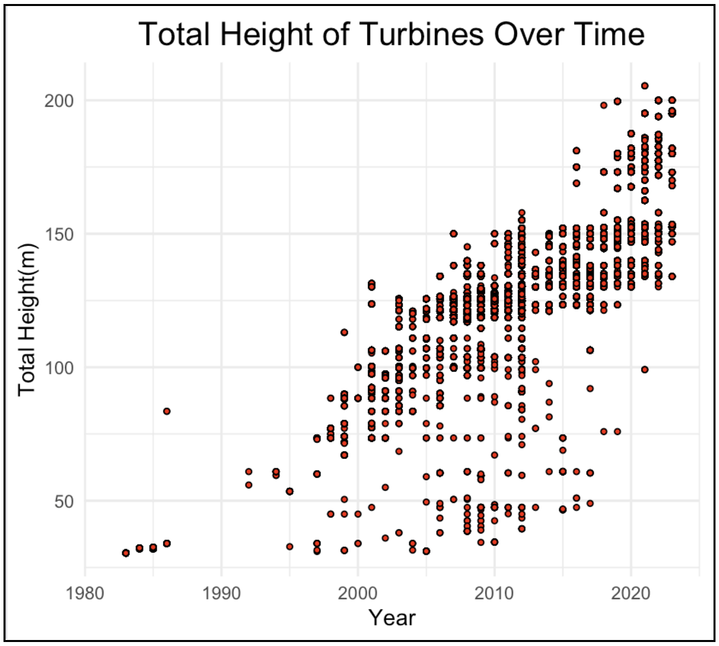

Figure 7: Growth of wind turbine height (m) from 1983-2023

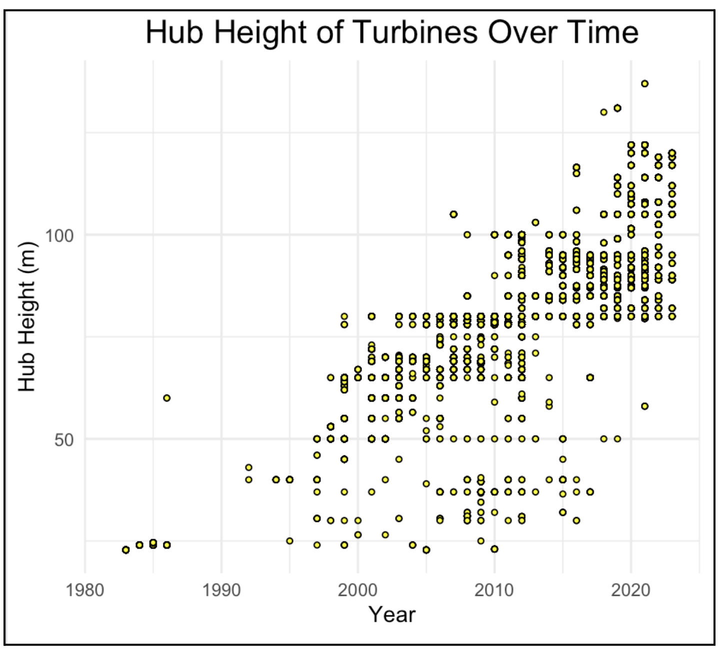

Figure 8: Growth of wind turbine hub height (m) from 1983-2023

Acknowledgement

I, Zahra Halimi, used StackOverflow, ChatGPT, RStudio help, and course materials for doing this assignment. ChatGPT also aided in grammatical editing.The links of the resources and relevant websites are shown as following.

- R for Data Science
- ChatGPT
- StackOverflow

References

Chehouri, A., Younes, R., Ilinca, A., & Perron, J. (2015). Review of performance optimization techniques applied to wind turbines. Applied Energy, 142, 361-388.

U.S. Energy Information Administration. (2023, October 20). What is U.S. electricity generation by energy source? Electric Power Annual. Retrieved from https://www.eia.gov/tools/faqs/faq.php?id=427&t=3

Charabi, Y., Al Hinai, A., Al-Yahyai, S., Al Awadhi, T., & Choudri, B. S. (2019). Offshore wind potential and wind atlas over the Oman Maritime Zone. Energy, Ecology and Environment, 4, 1-14

Yang, B., Yu, T., Shu, H., Dong, J., & Jiang, L. (2018). Robust sliding-mode control of wind energy conversion systems for optimal power extraction via nonlinear perturbation observers. Applied Energy, 210, 711-723.

Lindenberg, S., Smith, B., & O'Dell, K. (2008). 20% wind energy by 2030. National renewable energy laboratory (NREL), US department of energy, renewable energy consulting services, energetics incorporated.)

Grujicic, M., Arakere, G., Pandurangan, B., Sellappan, V., Vallejo, A., & Ozen, M. (2010). Multidisciplinary design optimization for glass-fiber epoxy-matrix composite 5 MW horizontal-axis wind-turbine blades. Journal of materials engineering and performance, 19, 1116-1127.

Maki, K., Sbragio, R., & Vlahopoulos, N. (2012). System design of a wind turbine using a multi-level optimization approach. Renewable Energy, 43, 101-110

Raciti Castelli, M., Englaro, A., & Benini, E. (2011). The Darrieus wind turbine: proposal for a new performance prediction model based on cfd. Energy, 36(8). https://doi.org/10.1016/j.energy.2011.05.036

Veena, R., Manuel, S. M., Mathew, S., & Petra, I. (2020). Parametric models for predicting the performance of wind turbines. Materials Today: Proceedings: Part 3, 24, 1795–1803. https://doi.org/10.1016/j.matpr.2020.03.604