Project documentation
"Wind farm potential analysis"

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1. Potential analysis as identifier for a business case

This document will show the potential analysis of the Wind farm plant DEMO. The asset is in the planning status and not built yet. These simulations will include P90, P75, P50, yearly, quarterly and monthly estimated energy generation data. The data will be shared in tables, figures and as dataset. Also, this simulation will mainly focus on Turbine Model X. In the report we will change this model and will simulate some other turbine types to get a better overview of the business case. Later in this document there is also a full chapter about the weather data including windspeeds and other features.

Described in chapter 4, we expect after the deep analysis of WP-DEMO, that the Wind farm can produce in the **P50 23.92 M. kWh** and **P75 23.02 M. kWh** and **P90 22.30 M. kWh per year**. This leads to a total production of (**P50**) **122,383,853.9 kWh per year**.

At hub height (172m) the mean wind speed is at **7,18 m/s**.

The following wind energy potential analysis is used to assess the possible energy potential of a specific area or region for the use of wind energy. It takes several factors into account to determine how much energy could be generated by wind turbines in an economically and environmentally viable way. The following are the key steps and factors in conducting a wind energy potential analysis.

Turbine Type	Yearly estimated energy production [kWh]	Hub height [m]
P50 Vestas V172-7.2 MW	**122,383,853.90 kWh**	172m
P75 Vestas V172-7.2 MW	**117,491,319.42 kWh**	172m
P90 Vestas V172-7.2 MW	**113,778,022.23 kWh**	172m
Alternative turbines:		
Vestas V172-7.2 MW	**127,588,573.77 kWh**	199m
Enercon E-175 EP5 6 MW	**113,222,567.70 kWh**	162m
Enercon E-175 EP5 7 MW	**122,135,203.54 kWh**	175m

Table 1: Executive summary

1.1. Wind resource analysis

- Wind speed and direction: The wind speed and direction are crucial for determining the wind potential. Higher wind speeds, especially above 5-6 m/s, are well suited for wind turbines.

- Wind data: Long-term wind data (NAECO Blue AI-Weather, 10+ years of historical information from different resources, matched for this specific location) that is as accurate as possible is analyzed to understand average wind conditions and seasonal fluctuations.

- Modeling and simulations: With the help of computer models and AI-Algorithms (e.g. NAECO Blue Digital Twin) wind conditions can be modeled in detail for specific locations, even if no measurements are taken on site.

1.2. Topography and terrain analysis

- Terrain shape: Mountains, hills or valleys have a significant influence on wind distribution. An open, flat terrain without obstacles (e.g. tall trees or buildings) favors stable wind conditions.

- Obstacles: Forests, buildings and other obstacles can reduce wind speed and create turbulence, which has a negative effect on the efficiency of wind turbines.

- Site conditions: Suitable site conditions include not only good wind conditions, but also access to infrastructure such as roads and power grids.

1.3. Land potential and legal framework conditions

- Land use planning: The areas that may be used for wind energy are often determined by regional planning and legislation. In Germany, for example, concentration zones are often designated for wind turbines.

- Protected areas and distance regulations: Protected areas (e.g. for nature conservation) or statutory distance regulations from residential areas and infrastructure often restrict the available land potential.

- Approval procedures: Local approval procedures must be observed, which include requirements for noise and shadow impact assessments as well as environmental impact assessments.

1.4. Technological potential

- Choice of wind turbine model: Different types of wind turbines have different requirements and performance potential. Modern turbines with larger rotors can also operate efficiently at lower wind speeds.

- Height potential: The height of the wind turbines is a decisive factor, as the wind speed increases with height. Towers with a hub height of 100 to 150 meters are generally ideal for exploiting higher wind speeds.

1.5. Economic factors

- Energy yield and profitability: The potential energy yield is calculated based on wind data, the site conditions and the selected turbines. This helps to assess the economic viability of the site.

- Investment and operating costs: Costs for the construction, operation and maintenance of the turbines must be compared with the expected energy yield.

- Subsidy programs and feed-in tariffs: Subsidies (e.g. EEG in Germany) and feed-in tariffs have a major influence on the profitability of projects.

1.6. Environmental and social factors

- Nature conservation and species protection: The impact on birds, bats and other animals is usually investigated and verified by expert reports.

- Noise and shadow impact: The potential noise and shadow impact of wind turbines on neighboring areas must be considered and possibly minimized through distance regulations.

- Public acceptance: The acceptance of the local population and a transparent planning process can have a strong influence on the success of wind projects.

2. Artificial intelligence at NAECO Blue

Achieving best results using NAECO Blue's AI for precise and location specific fore- and backcasts.

For AI model learning, after data analysis power data is then combined with multiple other relevant features to prepare data for model training. All those features are then correlated to find feature importance and feature consideration for model training.

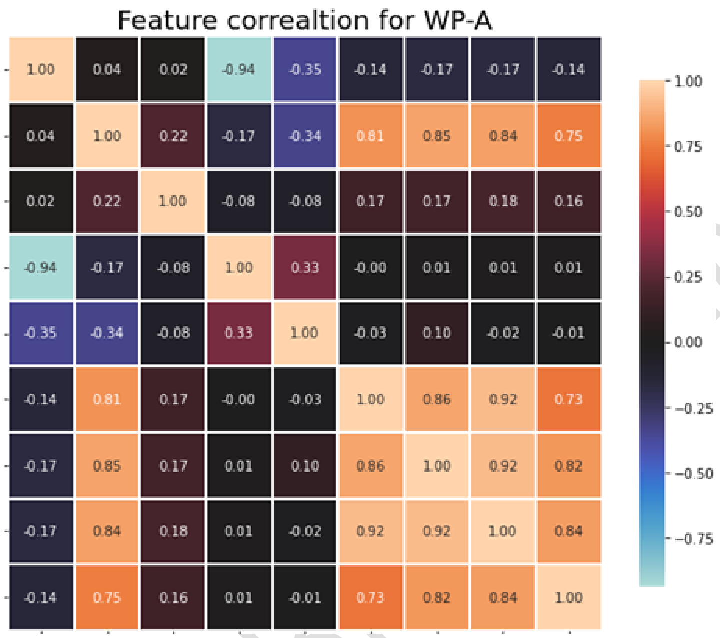

*Figure 1: Feature correlation for a usual Wind farmt**

*This correlation matrix is a demo. The correlation matrix of the desired Solar plant is shown later.

2.1. Model training

AI model training is the process of teaching an artificial intelligence system to make accurate predictions or decisions based on data. This involves feeding large datasets into machine learning algorithms, allowing the model to learn patterns, relationships, and insights from the data.

Key steps in AI Model Training:

1. **Data Collection**: Gathering relevant and high-quality data that the model will learn from.
2. **Data Preprocessing**: Cleaning and organizing the data to ensure it's in a usable format.
3. **Model Selection**: Choosing the appropriate algorithm or architecture for the task.
4. **Training**: Running the algorithm on the data to learn from it, often involving adjusting parameters to minimize errors.
5. **Evaluation**: Testing the model on unseen data to assess its accuracy and generalization.
6. **Optimization**: Fine-tuning the model to improve performance based on evaluation results.

Through iterative training and optimization, AI models become proficient at tasks such as image recognition, natural language processing, and predictive analytics, enabling transformative applications across industries.

After performing deep feature and data engineering, data is prepared and finalized to train a model. The model is then trained, tuned after initial results, retrained and optimized for best calculations in terms of minimum error and max performance. For error calculation many performance measures are considered like mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), explained variance, maximum error, deviation percentage and normalized root mean square error (NRMSE). Out of all key performance measure for better evaluation are MAE, RMSE and deviation percentage.

2.2. Model tuning

AI model tuning is the process of optimizing an already trained machine learning model to achieve the best possible performance. This involves fine-tuning hyperparameters, adjusting model architecture, and employing various techniques to enhance accuracy, efficiency, and generalization.

Key steps in AI model tuning:

1. **Hyperparameter Tuning**: Adjusting settings such as learning rate, batch size, and number of layers to find the optimal configuration.
2. **Cross-Validation**: Using techniques like k-fold cross-validation to assess model performance across different subsets of the data, ensuring robust evaluation.
3. **Regularization**: Applying methods like L1 or L2 regularization to prevent overfitting and improve model generalization.
4. **Feature Selection**: Identifying and utilizing the most relevant features to improve model efficiency and accuracy.
5. **Ensemble Methods**: Combining multiple models to leverage their strengths and achieve better overall performance.
6. **Learning Rate Schedules**: Dynamically adjusting the learning rate during training to fine-tune the model's learning process.

Through meticulous tuning, AI models can deliver superior results, making them more reliable and effective for real-world applications. This critical step transforms good models into exceptional ones, ensuring they perform optimally in diverse and dynamic environments.

2.3. Model optimization

Model optimization refers to the process of improving the performance, efficiency, or other desirable characteristics of a machine learning model. This process typically involves various techniques aimed at enhancing one or more aspects of the model, such as accuracy, speed, memory usage, or interpretability. Here are some common strategies for model optimization:

1. **Hyperparameter Optimization**: Adjusting the hyperparameters of the model to find the optimal configuration. This can be done manually or through automated techniques like grid search, random search, or Bayesian optimization.
2. **Feature Engineering**: Selecting, transforming, or creating new features from the raw data to improve model performance. Feature engineering can involve techniques like dimensionality reduction, feature scaling, or encoding categorical variables.
3. **Regularization**: Introducing penalties on model parameters to prevent overfitting and improve generalization. Common regularization techniques include L1 and L2 regularization, dropout, and early stopping.
4. **Model Selection**: Choosing the appropriate model architecture or algorithm for the given task. This may involve comparing different types of models (e.g., decision trees, neural networks, support vector machines) and selecting the one that best fits the data and requirements.

3. WP-DEMO asset investigation

3.1. Plant information

Figure 2: WP-DEMO planned area

Figure 3: WP-DEMO provided drawings

	Plant name	Windpark XXX
	Turbine Type	5 x Vestas V172-7.2
	Hub height	172m
	Blade diameter	172m
	Installed capacity (planned)	36 MW
	Construction date	In planning
	Data available from	
	Data available up to	
	Address	XXX, Germany
	Latitude, Longitude	51.5XX, 13.7XX

Table 2: WP-DEMO asset information

The expected and provided power curve by the manufacturer of a V172-7.2 MW is the following:

Vestas V172-7.2 MW PO7200 Mode Wind speed oscillating speed [m/s]	Air density [kg/m³] 1.225 Power in [kW]
0.0	0
0.5	0
1.0	0
1.5	0
2.0	0
2.5	0
3.0	32
3.5	129
4.0	288
4.5	481
5.0	715
5.5	99
6.0	1340
6.5	1739
7.0	2203
7.5	2729
8.0	3324
8.5	3986
9.0	4685
9.5	5314
10.0	5904
10.5	6441
11.0	6854

11.5	7078
12.0	7160
12.5	7195
13.0	7200
13.5	7200
14.0	7200
14.5	7200
15.0	7200
15.5	7200
16.0	7200
16.5	7200
17.0	7200
17.5	7194
18.0	7124
18.5	6959
19.0	6789
19.5	6630
20.0	6472
20.5	6262
21.0	5946
21.5	5538
22.0	5069
22.5	4597
23.0	4121
23.5	3636
24.0	3169
24.5	2718
25.0	2328

Table 3: Power curve Vestas V172-7.2 MW

3.2. Typical Meteorological Year

A Typical Meteorological Year (TMY), or typical meteorological year, is a dataset that represents the average weather of a particular location over a year. This dataset is compiled from several years of actual weather data and represents typical meteorological conditions that are particularly suitable for simulations and energy analyses. In wind energy and photovoltaics, the TMY is used to realistically and consistently simulate turbine performance and energy yield over the course of a year.

Features of the TMY:

- Selection of characteristic months: The TMY dataset typically contains data for 12 months selected from a much longer data series of 5 to 10 years. Each month in the TMY is representative of the average conditions for that month over the entire period.

- Key parameters: A TMY dataset typically includes meteorological parameters such as solar radiation, temperature, wind speed and direction, barometric pressure, humidity, and sometimes precipitation.

- Timescale: The data in TMY is arranged in hourly resolution, making it particularly valuable for energy simulations where a detailed history of weather conditions is required.

In this analysis, we calculated the yearly energy production of a single wind turbine in XXX by scenarios based on Typical Meteorological Year data. The TMY data was constructed from hourly weather dataset from 2016 to the most recent months of 2024, providing a representative long-term view of wind conditions at this location. For each scenario, the theoretical power output was calculated and aggregated to estimate annual production.

3.3. Weibull distribution by sections for the WP

This report presents a comprehensive wind energy potential assessment for * based on 5-20 years of wind data (NEW European Wind Atlas, several other weather Models and NAECO Blue Weather AI). The study includes:

- **Directional wind distribution** (wind rose)
- **Weibull statistical analysis** of wind speeds
- **Sector-wise Weibull parameters (k, c)** and frequency distributions

The analysis aims to:

1. Quantify wind speed distribution across 12 directional sectors (30° each)

2. Determine Weibull parameters (k, c) for each sector. Where the shape parameter (k) indicates wind speed variability. And the scale parameter (c) represents characteristic wind speed.
3. Assess sectoral dominance for wind turbine placement optimization

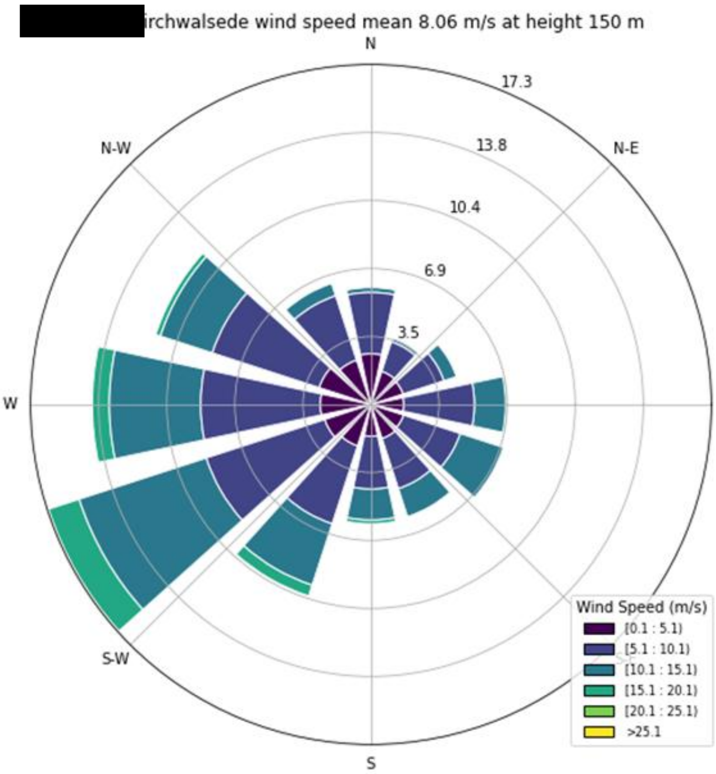

Figure 4: Windspeed mean WP X

3.3.1. Wind investigation per month

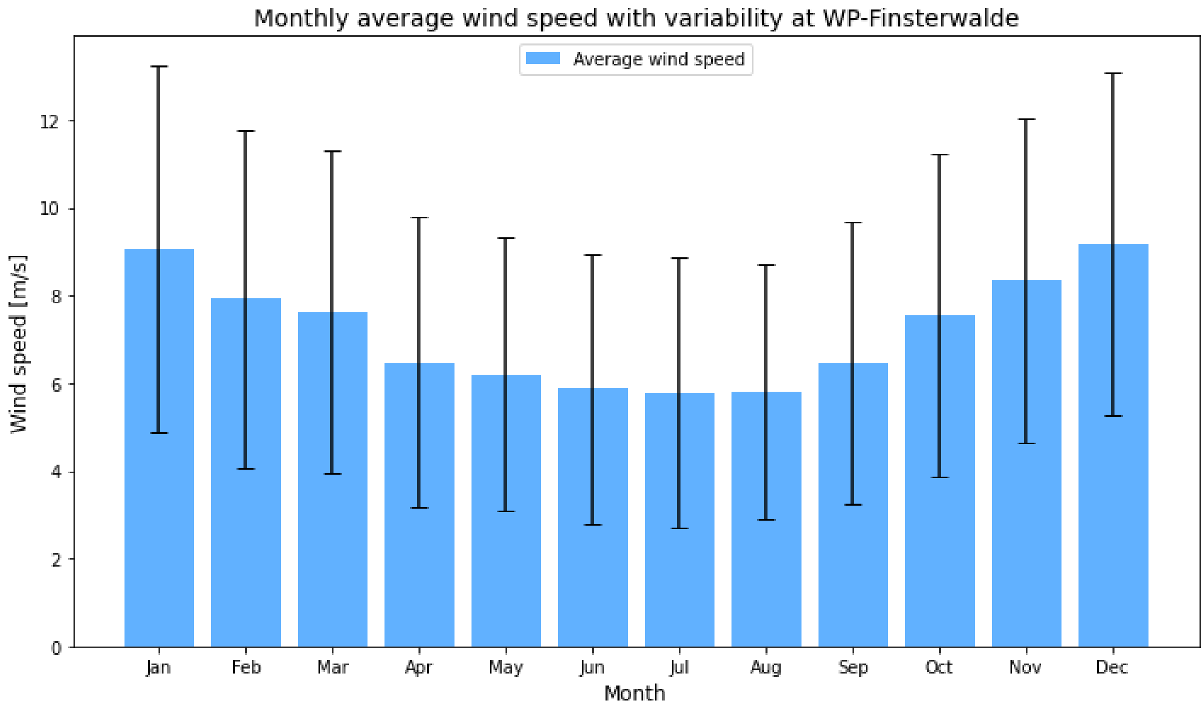

Figure 5: Monthly average wind speed WP-XXX

3.3.2. Windspeed investigations

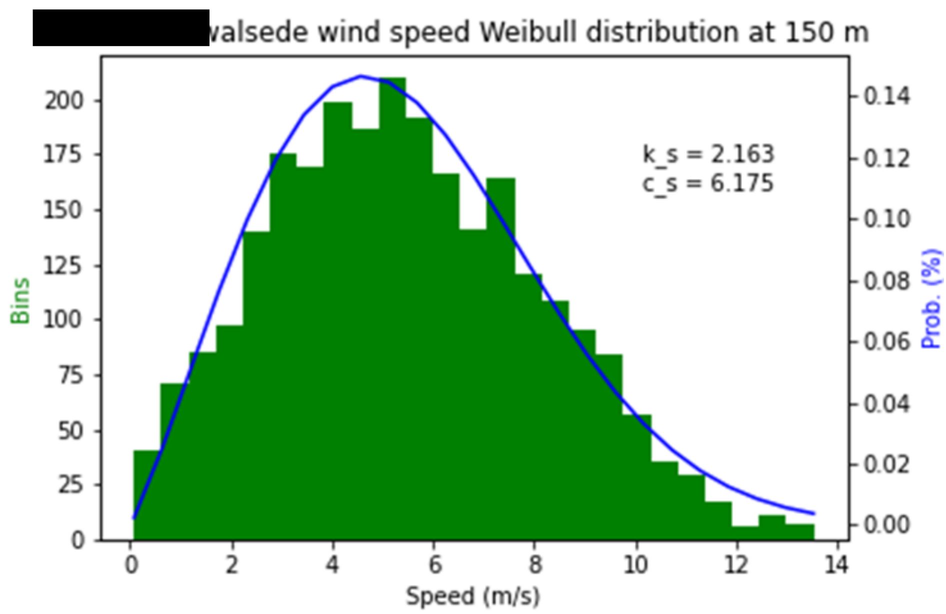

Figure 6: Wind speed Weibull Distribution 150m

From (deg)	To (deg)	Wind Speed mean (m/s)	k	a	Percentage section (%)
1	30	5.468174302	2.162906226	6.174518122	3.718913986

31	60	5.702135655	1.994814447	6.433860849	3.844398814
61	90	7.225817442	2.314765613	8.155709189	6.024697696
91	120	7.981014674	2.527469685	8.992598991	7.318047
121	150	7.553594574	2.30814224	8.525968657	6.875998175
151	180	7.544699379	2.110787606	8.518673808	5.802247319
181	210	8.180751544	2.171403274	9.237485593	7.955452886
211	240	9.503267263	2.499494451	10.71081029	14.24395391
241	270	9.623491917	2.537618935	10.84211447	17.64487794
271	300	8.204001273	2.256068966	9.262220841	11.55743783
301	330	7.190096015	2.368347384	8.112699449	10.15286334
331	360	5.72523842	2.175133678	6.464778528	4.861111111

Table 4: Weibull Distribution

3.4. Topography and terrain

The planned wind farm is located in the area of a small elevation and is planned with individual turbines on the eastern elevation in a wooded area. The forest extends over the entire planning area and can provide thermal effects here. The topographical survey shows that there is a region to the east of the site, which is on average 20-50 m above the area where the wind farm is to be built. This elevation can affect the wind flow in the NNE to SSE directions. In the west, there are individual smaller elevations, which are on average between 20-30m above the wind farm level. These can also have a small negative impact on individual wind directions, but the wind has sufficient alternative areas at this height to overcome these elevations. In addition, a slight depression runs from NOW-SSO through the planning area, which can cause channeling, especially in NW and W winds, and thus cause higher wind speeds than average at this location.

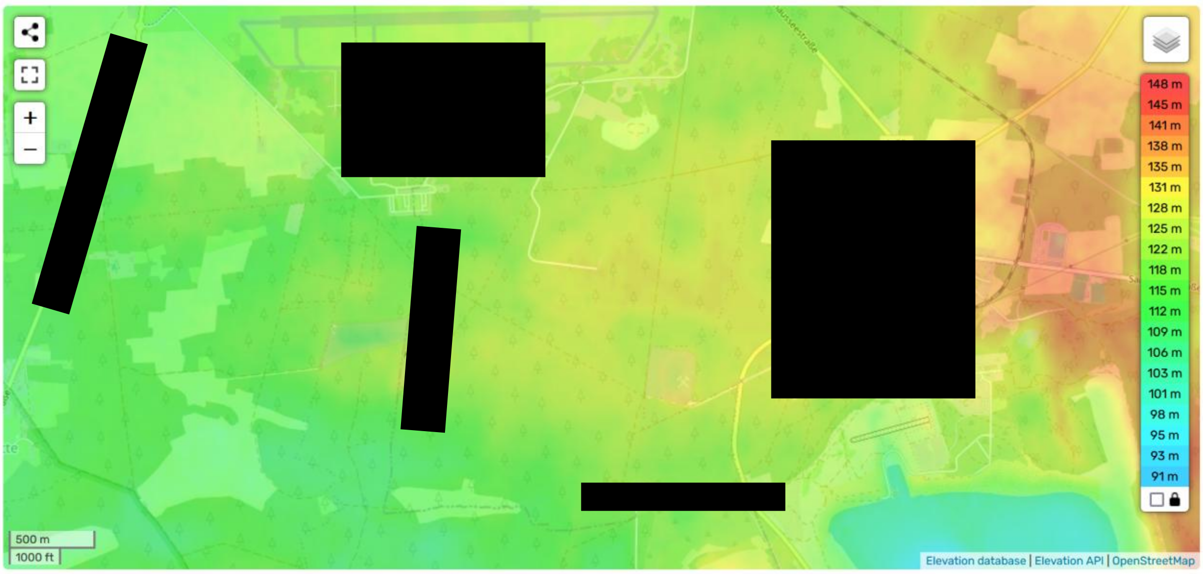

Figure 7: Topography XXX 500m scale

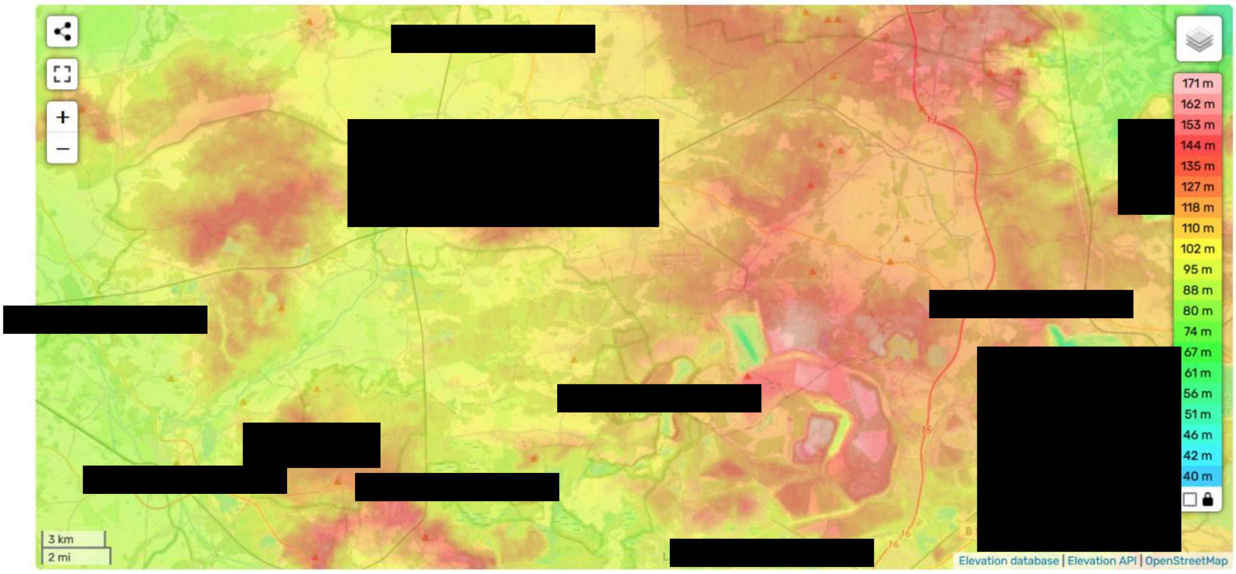

Figure 8: Topography XXX 3000m scale

3.5. Potential analysis approach

The potential analysis of NAECO Blue is divided into several steps. As in the previous chapter, the first step is to create the weather data for the specific location. In the next chapter, this data is applied to the planned wind farm. First, a conservative floor is developed so that the planner can be certain that this generation will occur on the basis of the weather data. In the next step, the weather phenomena and various other features as well as the behavior of the planned wind turbine are adjusted and taken into account. The terrain and the so-called wake effect are also calculated and integrated into the simulation. In the initial study, these factors are only used as a worse-case scenario.

In the following, we want to show alternatives to the selected turbine model and simulate the same wind farm with other turbine types. In particular, we change the tower height and diameter. Another very important factor is the power curve. Some turbines reach their full load earlier and are therefore particularly suitable for locations with slightly below-average wind speeds. This investigation of the other models is based on the same meteorological data and is simulated using the same procedure. The planned wind farm layout will not be changed.

The simulation is followed by the creation of the percentiles and the presentation of the estimated generation on an annual, quarterly and monthly basis for the wind farm. An estimate of possible uncertainties and losses is also provided.

3.5.1. Percentiles

A percentile (also called percentile rank) is a proportion of a distribution. The distribution is divided into 100 units of equal size. The percentile of a measured value provides information on what proportion of the distribution is above or below this measured value. If we look at the 95th percentile, for example, this means that 95% of the measured values are less than or equal to the measured value of the 95th percentile.

In the potential analysis, various percentiles are calculated in order to better estimate the expected generation. These include the percentiles P50(median), P75(quartile) and the P90(decile) simulated. For a better risk management, the percentiles are the base to obtain information for the risk management. In advance the percentiles are giving a detailed outlook for the estimated energy and the probability that this will happen.

In the world of financing a Solar plant and calculating a business case, the percentiles are interpreted like the following. A P90 percentile means, with a probability of 90% the yearly estimated production of, for example, 10 M. kWh will be happen. A P10 means, with a probability of 10% the generated energy will be higher than 90% of the possible reproducible energy, for example 20 M. kWh. So, the P90 kWh value is always smaller than the P75, P50 and P10 percentile. P1 would mean the most possible estimated energy will be generated with a probability of just 1%. Due to weather uncertainties and local losses, maintenance and other shutdown time the probability this will not happen is 99%.

3.5.2. Yearly, quarterly and monthly estimated energy production

The next step shows the estimated annual, quarterly and monthly generation in kWh. These are generally estimated to be higher in winter, as there is usually more wind than in the summer months. Accordingly, a curve with the maximum values at the beginning and end of the year with a minimum in the summer months is to be expected. This estimated generation is formed from the determined weather data, which is also resolved at least hourly and then simulated and mapped by the AI. The generated data is displayed in tabular form and in graphs.

3.5.3. Wake effects

The wake effect in a wind farm refers to the influence of the wind flow through the rotors of the wind turbines. When wind flows through a turbine, it extracts energy from the wind to generate electricity. The wind behind the turbine becomes slower, more turbulent and loses energy - this area is known as the “shadow” or wake.

Main features of the wake effect:

- Speed reduction: the wind is slower behind the turbine as the rotor blades draw energy from the wind.
- Turbulence: Turbulence and fluctuations occur in the wake, which can affect the efficiency and load of downstream wind turbines.
- Range: The wake can extend over several hundred meters and depends on factors such as wind speed, turbine height and weather conditions.
- Influencing efficiency: In a wind farm, the turbines that are in the slipstream of others can produce less energy as the wind brings less energy with it. This is known as the park effect.

Minimizing the wake effect:

To reduce the wake effect, wind farms are designed so that the turbines are placed at a sufficient distance from each other. Typically, this distance is around 7 to 10 times the rotor diameter in the wind direction. Software-supported layout planning and modern turbine technologies also help to reduce the negative effects.

3.5.4. Power curve

The power curve of a wind turbine describes the relationship between the wind speed and the electrical power generated by the turbine. It is a graphical representation that shows how much energy a wind turbine produces at different wind speeds. This curve is an essential tool for assessing the efficiency and energy yield of a turbine.

Features of the power curve:

- Start-up speed (cut-in wind speed): The minimum wind speed at which the wind turbine starts generating electricity. This is typically between 3 and 5 m/s.
- Rated Power: The maximum electrical output that the turbine can achieve. It is achieved at a certain rated wind speed, often in the range of 12 to 15 m/s. Above this speed, the power remains constant.
- Cut-out wind speed: At very high wind speeds (e.g. from 25 m/s), the turbine switches off for safety reasons to prevent damage. This is done by adjusting the rotor blades (pitch control).
- Power increase: Between the start-up speed and the nominal wind speed, the power generated increases exponentially with the wind speed, as the wind energy increases in proportion to the third power of the speed.
- Plateau of rated power: Once the rated power has been reached, it remains constant, as the turbine no longer generates energy

In the following chapters we generated for every turbine a dedicated power curve which includes the wake effect and other local weather effects.

4. Potential analysis of Vestas V172-7.2 MW Hub height: 172m

The following chapter is describing the deep potential analysis of WP-DEMO with the provided information and turbine model.

In Figure below it is shown that the plant is behaving over the meteorological reference year. So overall the performance of the plant is good, and as expected in this location.

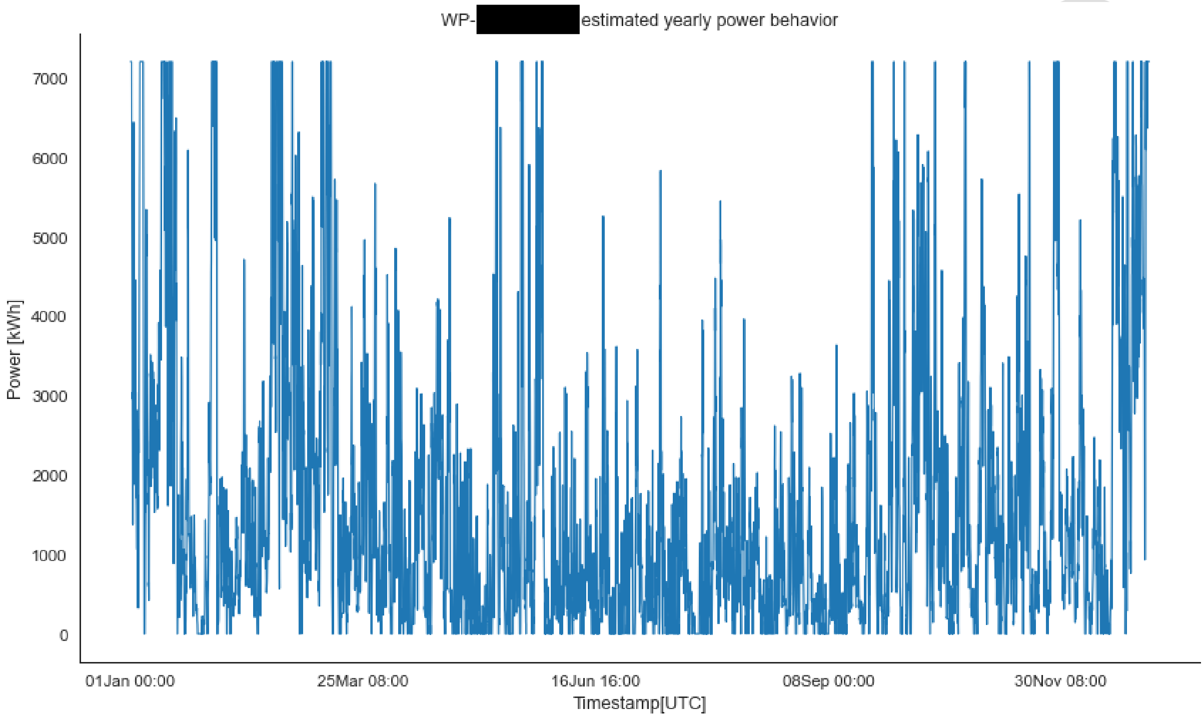

Figure 9: WP-XXX estimated yearly power behavior on a typical meteorological year P50 for WEA0

4.1. Correlation matrix for WP-XXX

The following figure shows the correlation between some of the used features to understand deeply the effects of weather features to the energy generation.

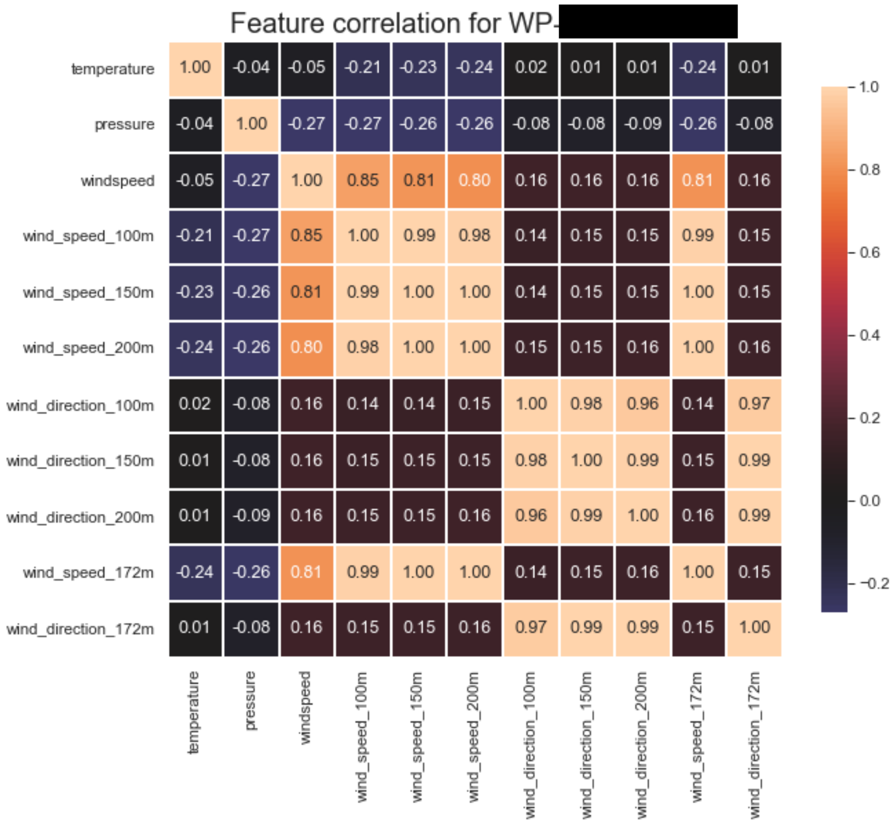

Figure 10: Correlation matrix WP-XXX

4.2. Wake effects WP-XXX

The wake effect shows how the weather effects and turbulences lead to different estimated generations within the wind park. Below the first figure shows the estimated production without including turbulence and weather effects due to the terrain. The second figure included weather and turbulence, and it is getting visible that the turbines in the northeast are producing less than the one in southwest.

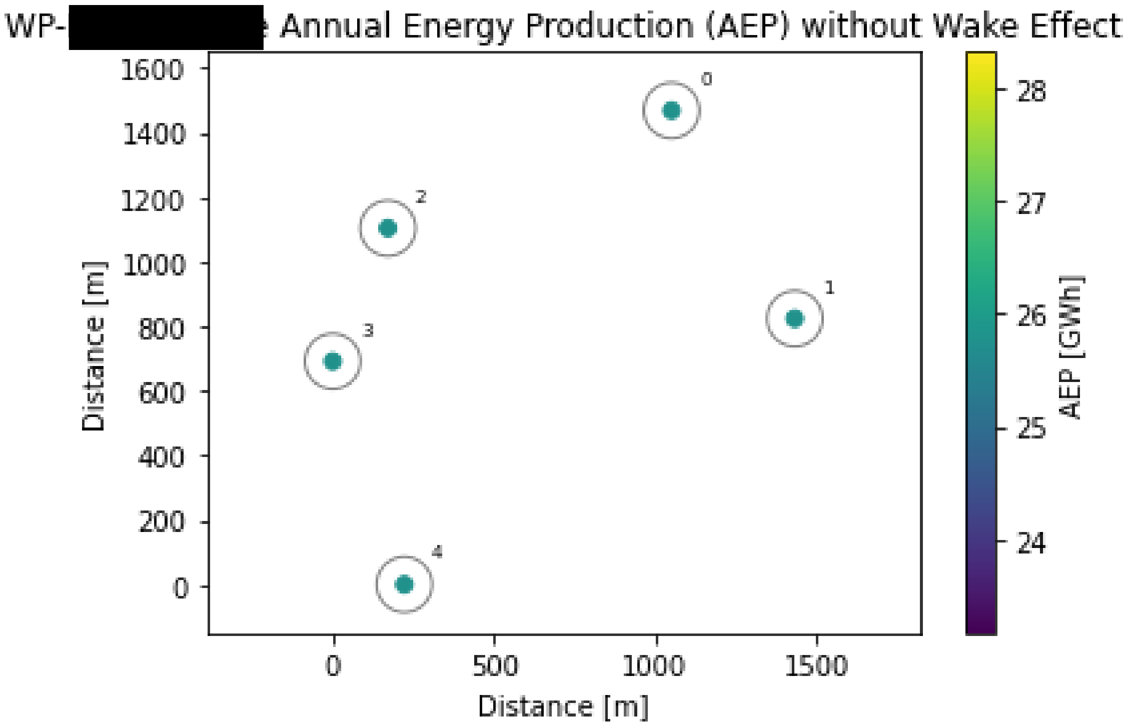

Figure 11: Annual estimated energy production without wake effect P50

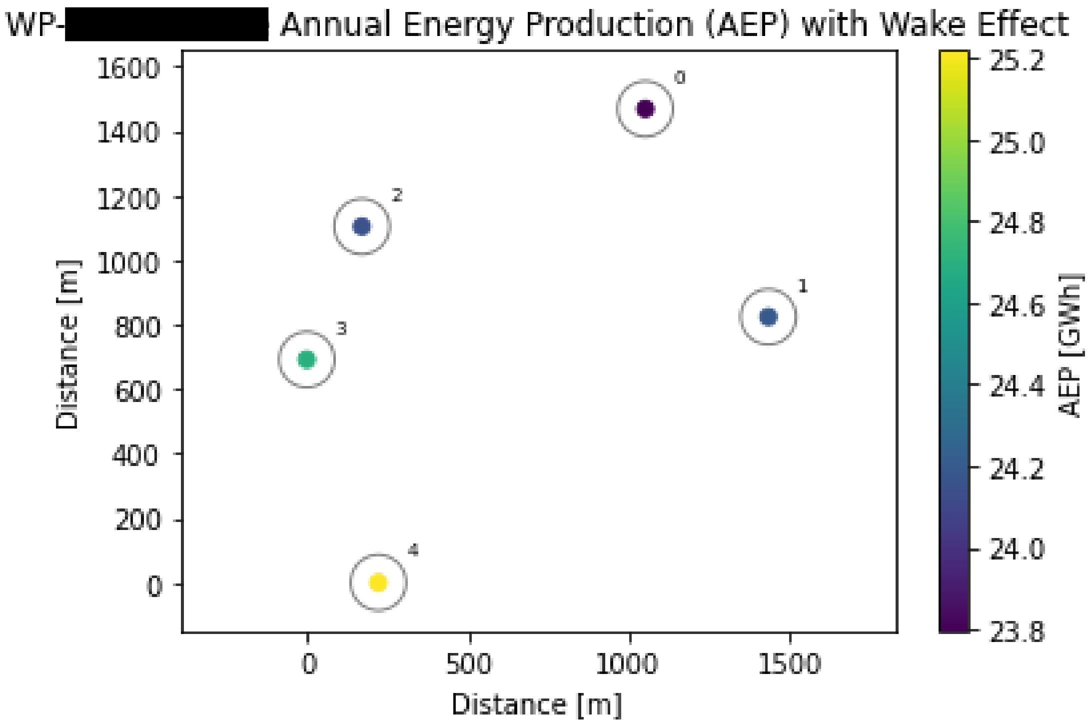

Figure 12: Annual estimated energy production with wake effect P50

Overview of different estimated yearly production levels for with and without taking the wake effect into account:

AEP	WEA0	WEA1	WEA2	WEA3	WEA4
No wake effect [GWh]	25,643,919.09	25,643,919.09	25,643,919.09	25,643,919.09	25,643,919.09
With wake effect [GWh]	23,918,012.92	23,964,633.84	24,623,855.48	24,695,890.83	25,181,460.86
Percentage [%]	6.7302746	6.5484735	3.97779921	3.69689305	1.80338358

Table 5: Power analysis WP-XXX annual estimated production (AEP) with and without the wake effect P50

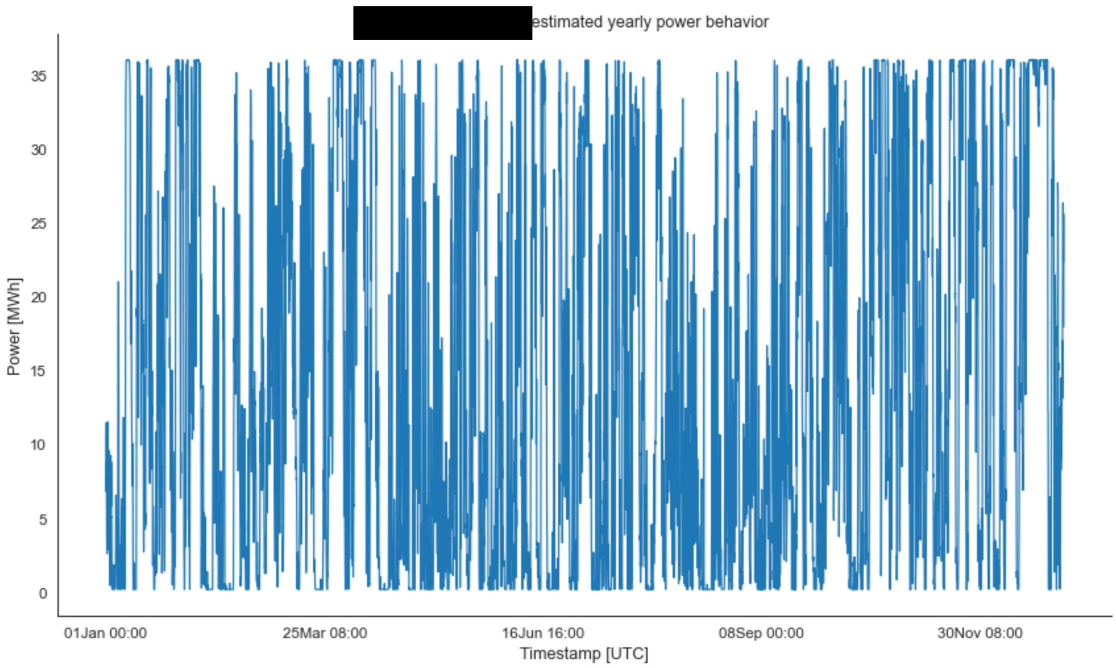

Figure 13: Yearly production behavior WP-XXX at plant level

4.3. Monthly, quarterly and yearly estimated production

Month	Sum of estimated power plant [kWh]	Sum of estimated power WEA0 [kWh]	Sum of estimated power WEA1 [kWh]	Sum of estimated power WEA2 [kWh]	Sum of estimated power WEA3 [kWh]	Sum of estimated power WEA4 [kWh]
Jan	11,141,944.9	2,239,302.3	2,245,368.82	2,166,587.25	2,207,473.18	2,283,213.38
Feb	7,021,523.23	1,441,582.72	1,397,159.46	1,421,171.99	1,372,725.27	1,388,883.80
Mar	12,325,232.29	2,422,166.78	2,332,109.84	2,511,197.76	2,525,795.68	2,533,962.23
Apr	9,882,234.05	2,049,007.70	1,893,761.31	1,982,758.11	1,957,399.35	1,999,307.58
May	7,416,353.15	1,378,532.51	1,488,798.54	1,501,007.48	1,494,780.93	1,553,233.69
Jun	8,258,090.59	1,583,422.44	1,566,126.77	1,693,510.92	1,703,980.54	1,711,049.92
Jul	10,546,361.71	2,080,442.54	1,983,232.99	2,140,488.31	2,178,231.82	2,163,966.06
Aug	5,650,926.613	1,052,416.69	1,069,167.23	1,143,697.52	1,188,288.33	1,197,356.85
Sep	7,396,366.184	1,505,758.04	1,468,191.41	1,497,567.00	1,410,320.15	1,514,529.58
Oct	13,371,304.95	2,512,543.33	2,728,708.78	2,686,433.56	2,638,103.76	2,805,515.51
Nov	13,187,673.7	2,503,174.46	2,592,995.02	2,621,763.05	2,727,078.71	2,742,662.46
Dec	16,185,842.53	3,149,663.41	3,199,013.70	3,257,672.53	3,291,713.10	3,287,779.79
Q1	30,488,700.46	6,103,051.80	5,974,638.12	6,098,956.99	6,105,994.13	6,206,059.42
Q2	25,556,677.79	5,010,962.65	4,948,686.62	5,177,276.51	5,156,160.82	5,263,591.18
Q3	23,593,654.51	4,638,617.27	4,520,591.62	4,781,752.83	4,776,840.30	4,875,852.49
Q4	42,744,821.18	8,165,381.20	8,520,717.49	8,565,869.14	8,656,895.57	8,835,957.78
Yearly						
P50	**122,383,853.90**	**23,918,012.92**	**23,964,633.84**	**24,623,855.48**	**24,695,890.83**	**25,181,460.86**
P75	**117,491,319.42**	**23,139,611.10**	**23,164,044.68**	**23,280,257.17**	**23,690,097.23**	**24,217,309.24**
P90	**113,778,022.23**	**22,132,199.85**	**22,519,821.48**	**22,645,096.27**	**22,997,095.22**	**23,483,809.41**

Table 6: Monthly, quarterly and yearly estimated production P50

All figures below are generated at plant level considering the sum of all turbines production.

The included losses are the turbine specific ones, the losses due to micro weather and terrain effects as well as the effects due to the chosen wind park layout and the wake effects. Some more losses on the engineering side and infeed side as well as the operational side can come up later.

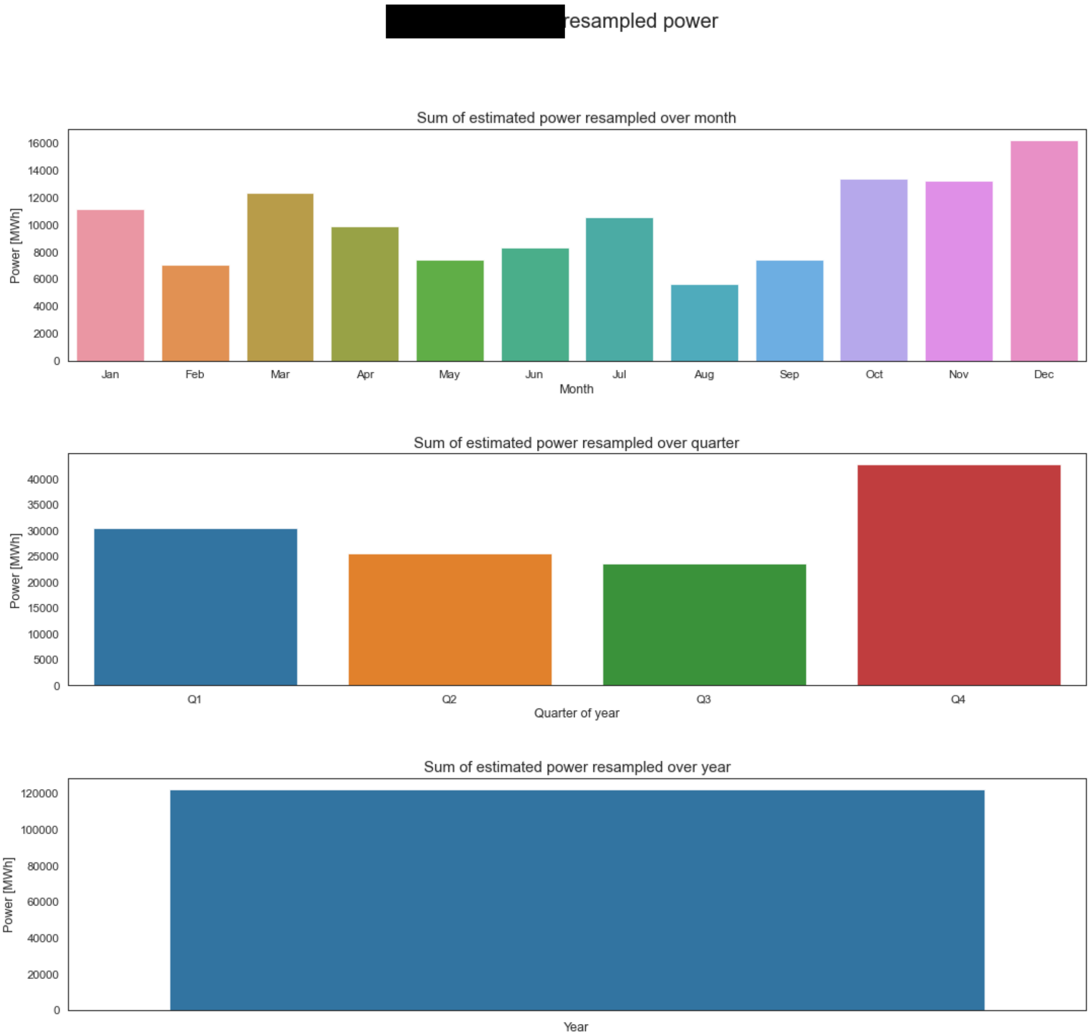

Figure 14: WP-XXX yearly, monthly and quarterly estimated production P50

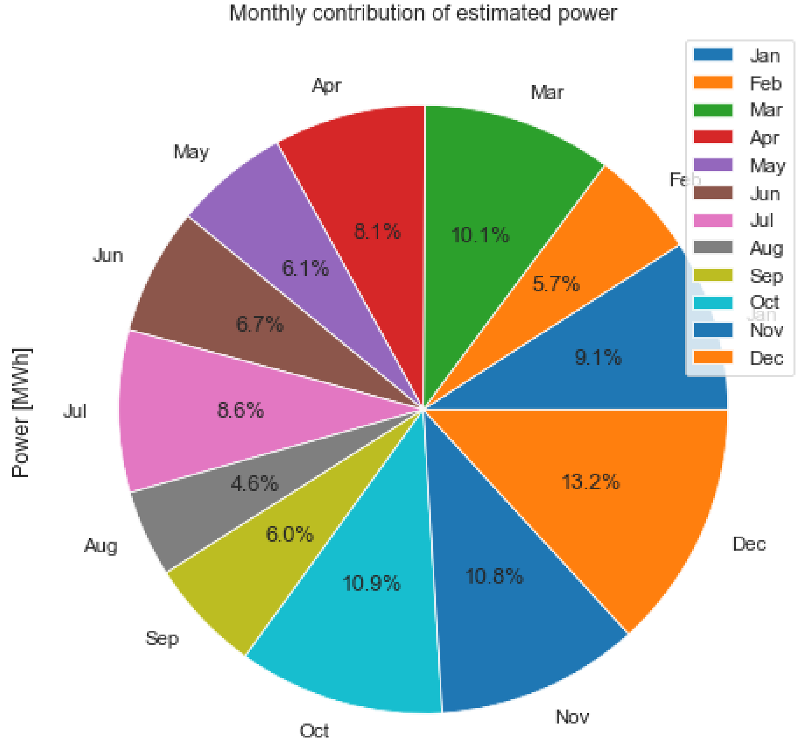

Figure 15: Monthly contribution of estimated power P50

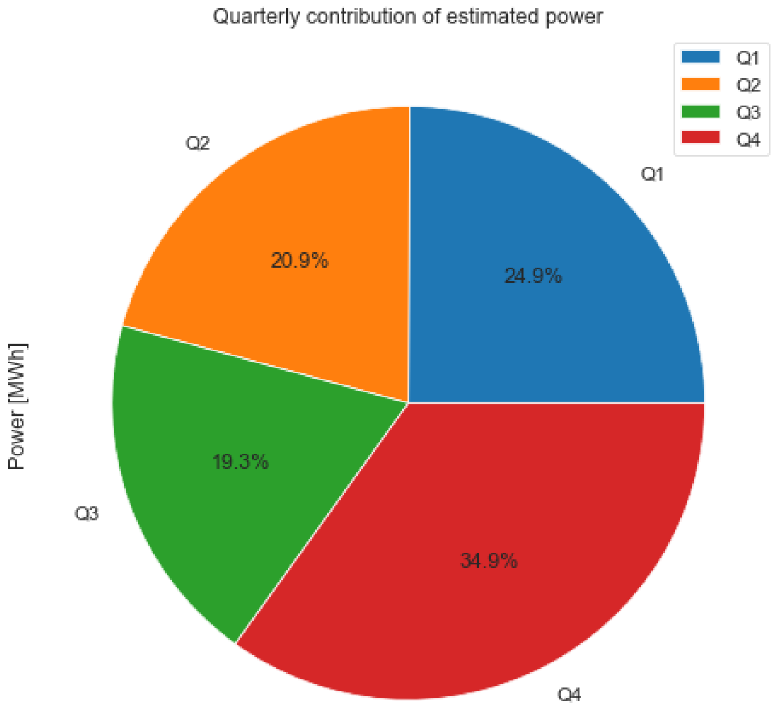

Figure 16: Quarterly contribution of estimated power P50

4.4. Percentiles Vestas V172-7.2 MW 172m

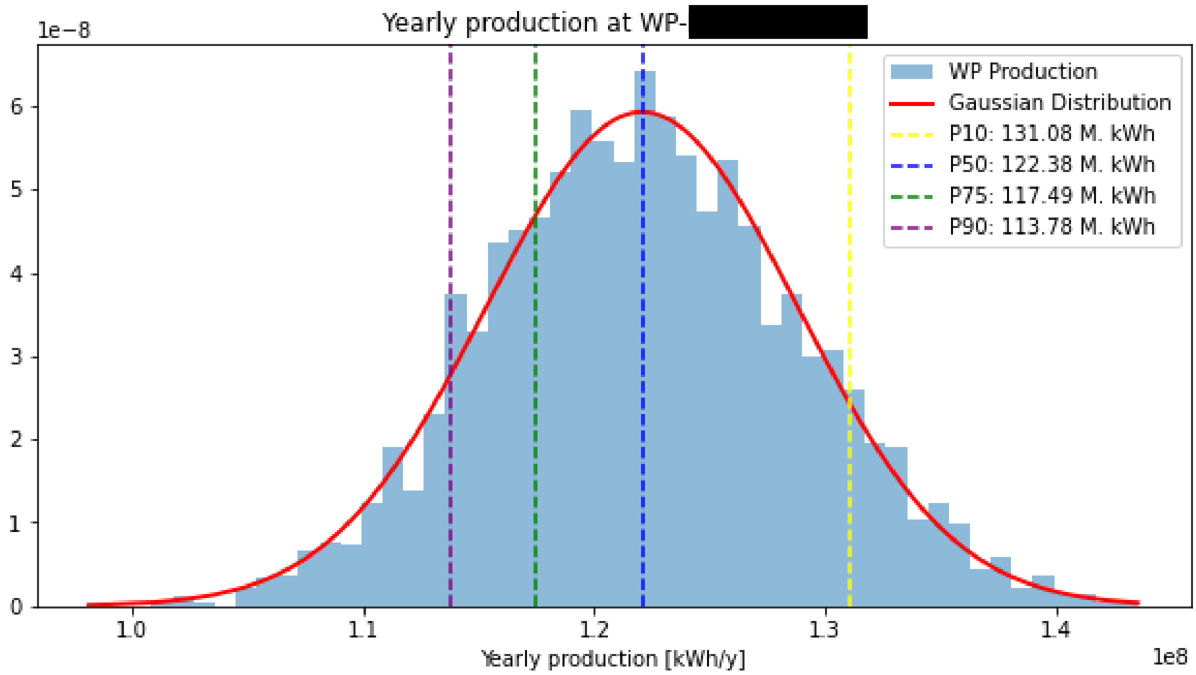

Figure 17: Percentiles WP-XXX Vestas V172-7.2 MW 172m, P10, P50, P75 and P90

4.5. Power curve including weather and wake effects

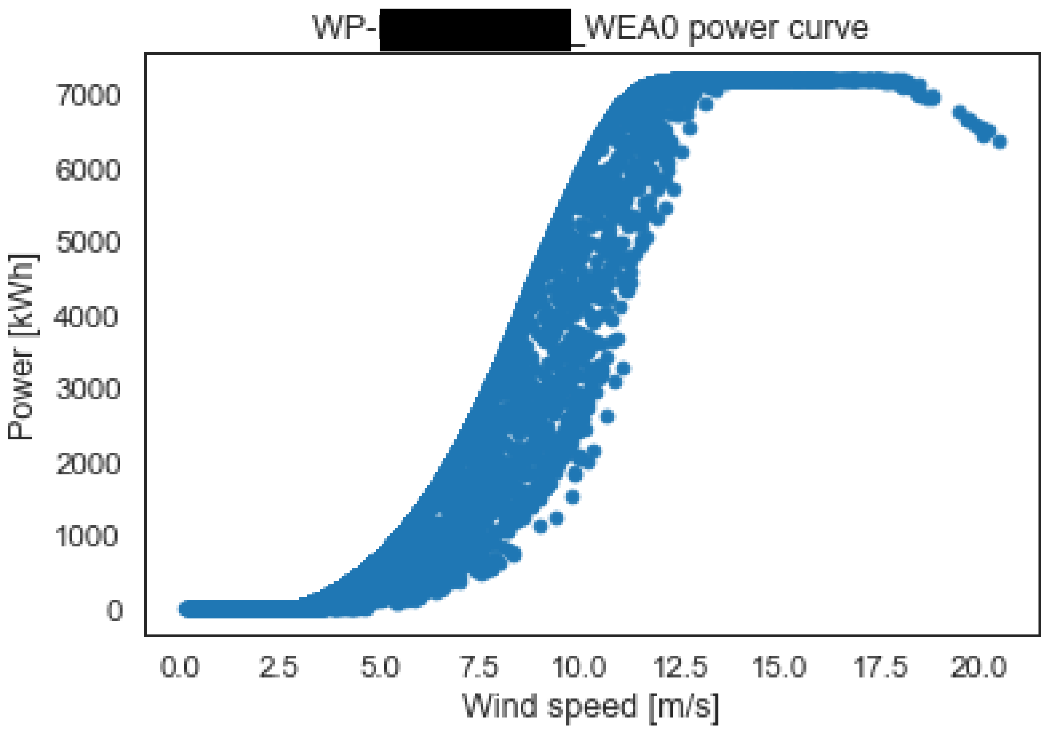

Figure 18: Power curve with wake effect WEA0

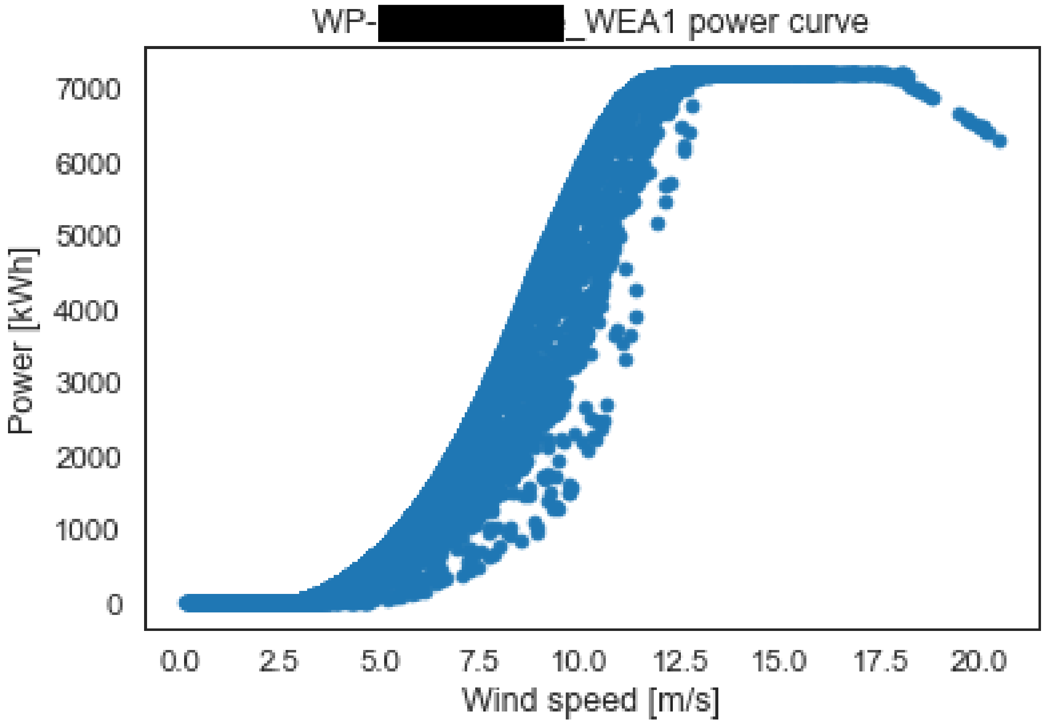

Figure 19: Power curve with wake effect WEA1

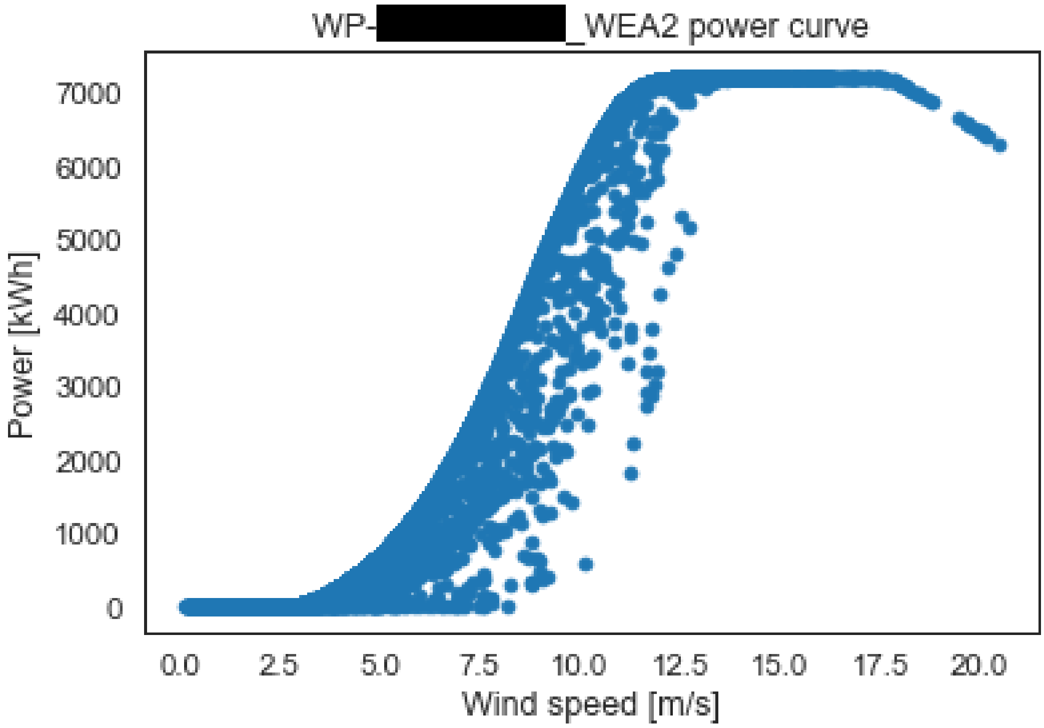

Figure 20: Power curve with wake effect WEA2

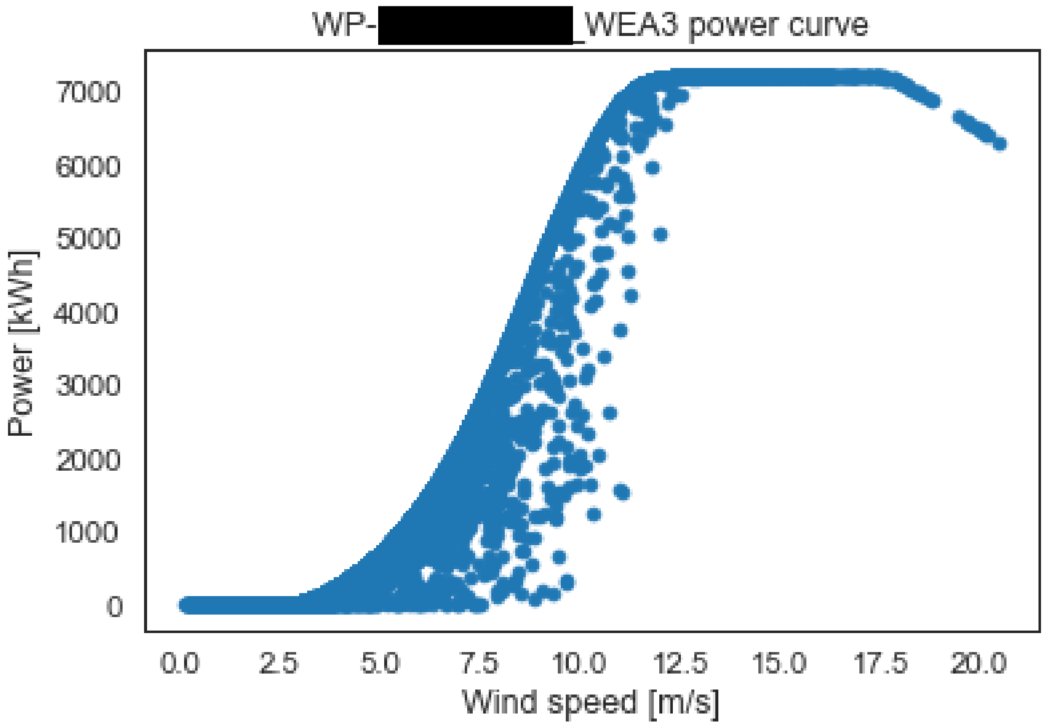

Figure 21: Power curve with wake effect WEA3

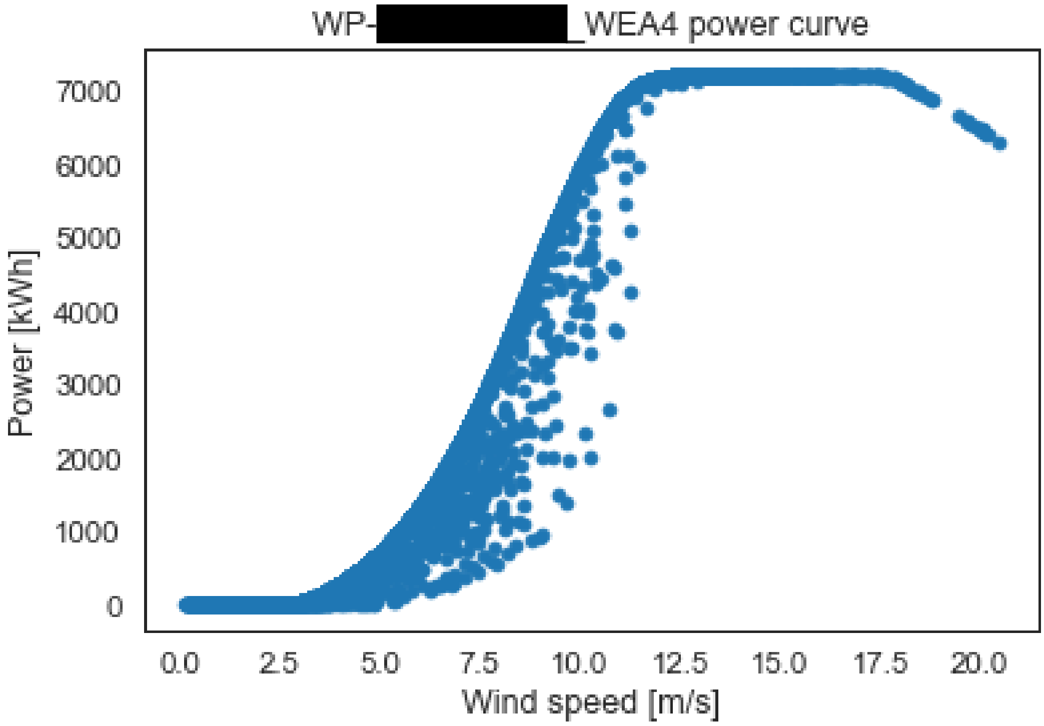

Figure 22: Power curve with wake effect WEA4

5. Potential analysis for other turbine types

For calculating the best possible business case, NAECO blue is always simulating also other turbines on the same location and layout to give the customer a comprehensive data resource for the finance calculation.

5.1. Enercon E-175 EP5 6 MW, Hub height: 162m

Enercon is one of the best-known manufacturers of wind turbines, especially for low wind speeds. The E-175 EP5 6 MW is one of the latest turbine types and available at different heights.

5.1.1. Power curve Enercon E-175 EP5 6 MW, 162m

Enercon E-175 EP5 6 MW OM-0-0 Mode Wind speed oscillating speed [m/s]	Air density [kg/m³] 1.225 Power [kW]
0.0	0
0.5	0
1.0	0
1.5	0
2.0	0
2.5	57
3.0	147
3.5	272
4.0	438
4.5	650
5.0	901
5.5	1205
6.0	1565
6.5	1986
7.0	2465
7.5	2992
8.0	3545
8.5	4093
9.0	4600
9.5	5032
10.0	5375
10.5	5624
11.0	5794
11.5	5901
12.0	5964
12.5	5999
13.0	6000
13.5	6000
14.0	6000

14.5	6000
15.0	6000
15.5	6000
16.0	6000
16.5	6000
17.0	6000
17.5	6000
18.0	6000
18.5	6000
19.0	6000
19.5	5992
20.0	5939
20.5	5853
21.0	5721
21.5	5534
22.0	5278
22.5	4951
23.0	4549
23.5	4080
24.0	3163
24.5	2548
25.0	2070

Table 7: Power curve Enercon E-175 6 MW

5.1.2. Percentiles Enercon E-175 EP5 6 MW, 162m

The following figure will describe the percentiles for the chosen turbine and hub height:

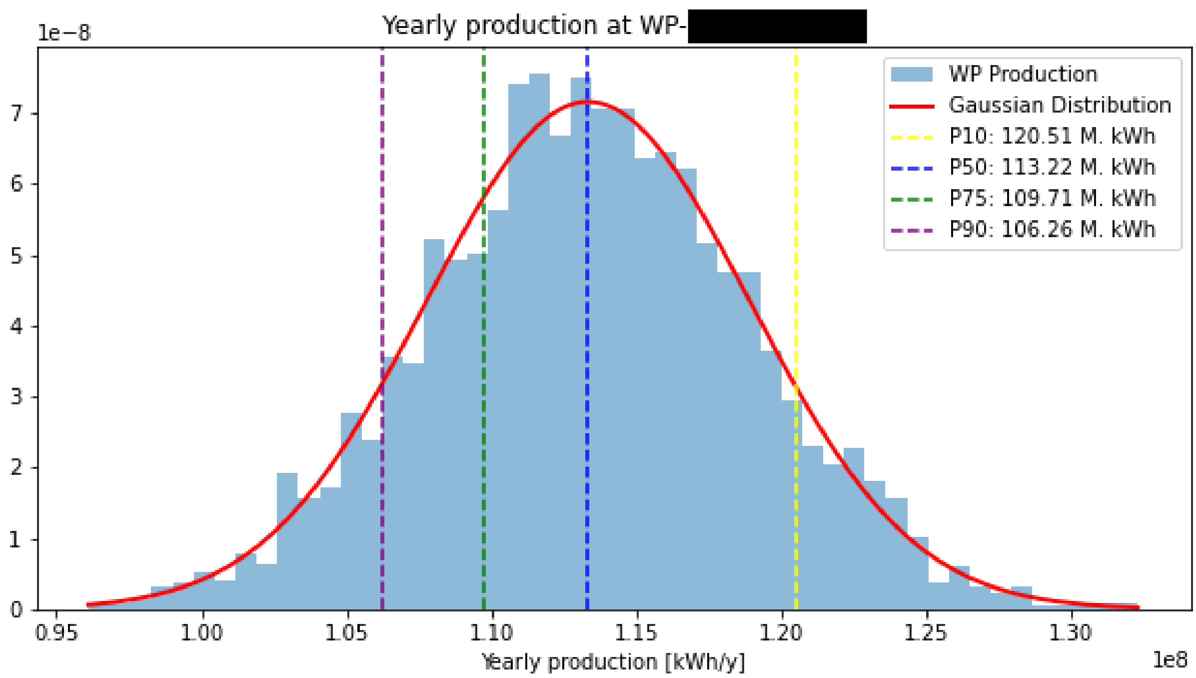

Figure 23: Percentiles Enercon E-175 EP5 6 MW, P10, P50, P75 and P90

5.1.3. Monthly, quarterly and yearly estimated production

The following table will describe the monthly, quarterly and yearly estimated power generation by the chosen hub height and turbine type:

Month	Sum of estimated power plant [kWh]	Sum of estimated power WEA0 [kWh]	Sum of estimated power WEA1 [kWh]	Sum of estimated power WEA2 [kWh]	Sum of estimated power WEA3 [kWh]	Sum of estimated power WEA4 [kWh]
Jan	11,773,332.06	2,339,159.94	2,344,346.28	2,304,598.93	2,370,657.49	2,414,569.43
Feb	12,011,593.67	2,387,679.27	2,358,297.89	2,366,696.53	2,447,417.10	2,451,502.89
Mar	10,540,230.82	2,158,992.13	2,126,603.22	2,091,852.05	2,012,815.62	2,149,967.80
Apr	7,866,406.80	1,548,394.06	1,637,202.60	1,515,629.62	1,533,767.33	1,631,413.19
May	7,260,859.14	1,367,546.52	1,455,234.67	1,465,498.94	1,459,456.03	1,513,122.98
Jun	6,495,208.86	1,303,508.68	1,269,670.30	1,298,724.90	1,289,926.91	1,333,378.07
Jul	7,752,763.60	1,434,797.69	1,529,144.63	1,558,841.54	1,611,959.64	1,618,020.10
Aug	5,312,819.16	1,067,182.32	1,037,394.10	1,032,549.95	1,064,927.10	1,110,765.68
Sep	7,563,305.39	1,478,379.00	1,437,986.13	1,481,042.45	1,577,494.21	1,588,403.60
Oct	11,293,246.29	2,245,982.00	2,174,241.46	2,256,676.10	2,309,746.38	2,306,600.36
Nov	13,195,253.52	2,536,488.58	2,636,113.66	2,583,987.48	2,701,507.10	2,737,156.70
Dec	12,157,548.40	2,417,969.71	2,390,358.47	2,425,640.02	2,464,234.30	2,459,345.91
Q1	34,325,156.55	6,885,831.34	6,829,247.39	6,763,147.51	6,830,890.20	6,206,059.42
Q2	21,622,474.80	4,219,449.26	4,362,107.57	4,279,853.46	4,283,150.27	5,263,591.18
Q3	20,628,888.14	3,980,359.01	4,004,524.87	4,072,433.95	4,254,380.95	4,875,852.49
Q4	36,646,048.22	7,200,440.29	7,200,713.59	7,266,303.59	7,475,487.77	8,835,957.78
Yearly						
P50	**113,222,567.70**	**22,286,079.90**	**22,396,593.42**	**22,381,738.51**	**22,843,909.19**	**23,314,246.70**
P75	**109,709,868.77**	**21,758,459.18**	**21,655,405.86**	**21,805,106.44**	**22,009,929.98**	**22,480,967.31**
P90	**106,257,390.78**	**21,040,401.45**	**20,971,964.90**	**21,186,739.63**	**21,298,291.29**	**21,759,993.50**

Table 8: Enercon E-175 EP5 6 MW monthly, quarterly and yearly estimated production P50

5.2. Vestas V172-7.2 MW, Hub height: 199m

Vestas is one of the best know manufacturers of wind turbines. The V172-7.2 MW turbine is the newest generation. In advance to the previous potential analysis with a hub height of 172m, this analysis represents the same turbine in 199m hub height.

5.2.1. Power curve Vestas V172-7.2 MW, 199m

Vestas V172-7.2 MW PO7200 Mode Wind speed oscillating speed [m/s]	Air density [kg/m³] 1.225 Power [kW]
0.0	0
0.5	0
1.0	0
1.5	0
2.0	0
2.5	0
3.0	32
3.5	129
4.0	288
4.5	481
5.0	715
5.5	99
6.0	1340
6.5	1739
7.0	2203
7.5	2729
8.0	3324
8.5	3986
9.0	4685
9.5	5314
10.0	5904
10.5	6441
11.0	6854
11.5	7078
12.0	7160
12.5	7195
13.0	7200
13.5	7200
14.0	7200
14.5	7200
15.0	7200
15.5	7200
16.0	7200
16.5	7200
17.0	7200
17.5	7194

18.0	7124
18.5	6959
19.0	6789
19.5	6630
20.0	6472
20.5	6262
21.0	5946
21.5	5538
22.0	5069
22.5	4597
23.0	4121
23.5	3636
24.0	3169
24.5	2718
25.0	2328

Table 9: Power curve Vestas V172-7.2 MW

5.2.2. Percentiles Vestas V172-7.2 MW, 199m

The following figure will describe the percentiles for the chosen turbine and hub height:

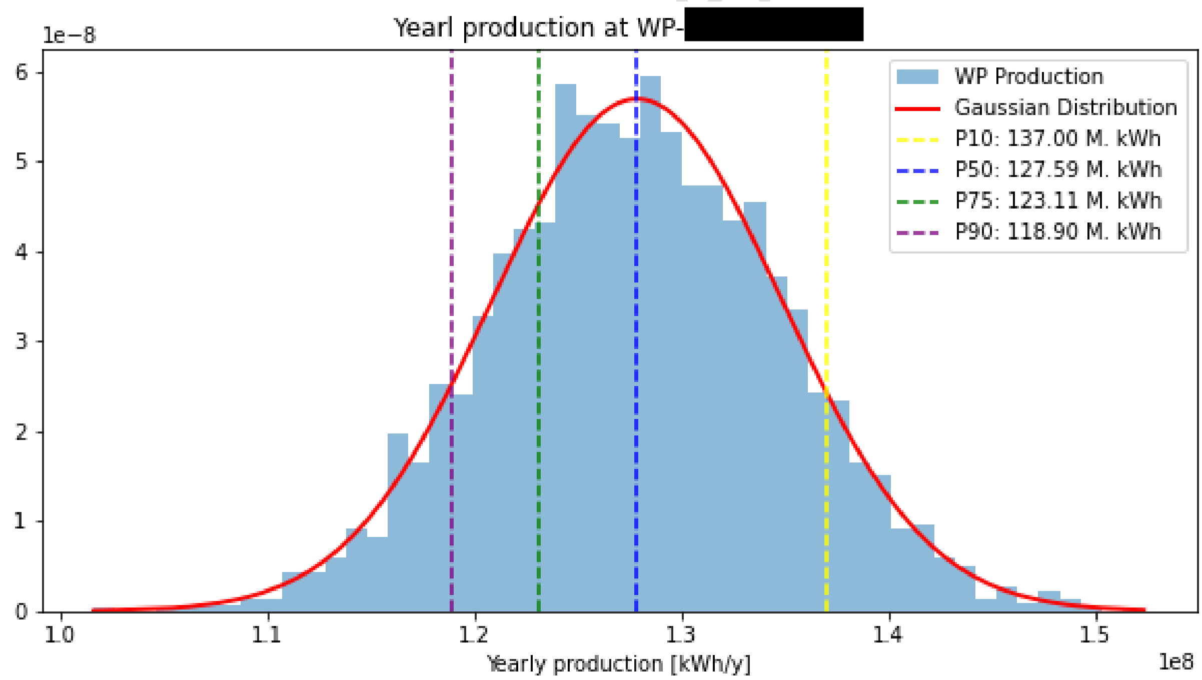

Figure 24: Percentiles Vestas V172-7.2 MW, P10, P50, P75 and P90

5.2.3. Monthly, quarterly and yearly estimated production

Month	Sum of estimated power plant [kWh]	Sum of estimated power WEA0 [kWh]	Sum of estimated power WEA1 [kWh]	Sum of estimated power WEA2 [kWh]	Sum of estimated power WEA3 [kWh]	Sum of estimated power WEA4 [kWh]
Jan	11,855,275.40	2,297,582.47	2,321,511.07	2,375,804.49	2,410,114.50	2,450,262.87
Feb	14,257,241.51	2,770,832.90	2,889,452.61	2,679,894.13	2,924,616.04	2,992,445.82
Mar	11,855,720.00	2,427,992.59	2,389,584.91	2,360,746.15	2,257,822.05	2,419,574.31
Apr	9,188,108.71	1,863,264.48	1,844,290.74	1,867,124.05	1,746,036.24	1,867,393.20
May	6,783,667.03	1,392,337.25	1,325,020.53	1,357,530.13	1,338,020.49	1,370,758.63
Jun	8,316,124.70	1,624,633.20	1,634,387.88	1,696,805.62	1,658,503.08	1,701,794.92
Jul	4,433,409.06	891,172.00	849,575.89	890,829.85	903,002.80	898,828.52
Aug	10,351,737.96	1,937,700.40	1,957,008.85	2,146,851.98	2,134,403.79	2,175,772.94
Sep	7,634,157.81	1,543,210.70	1,507,978.62	1,521,493.39	1,492,842.39	1,568,632.71
Oct	9,007,009.12	1,730,128.11	1,840,413.01	1,757,231.68	1,805,773.50	1,873,462.82
Nov	12,083,243.90	2,370,708.02	2,485,299.65	2,274,784.76	2,434,070.73	2,518,380.75
Dec	21,822,878.57	4,294,364.40	4,344,631.28	4,244,602.52	4,467,631.37	4,471,649.00
Q1	37,968,236.92	7,496,407.97	7,600,548.59	7,416,444.77	7,592,552.59	7,862,283.00
Q2	24,287,900.44	4,880,234.93	4,803,699.15	4,921,459.81	4,742,559.80	4,939,946.76
Q3	22,419,304.82	4,372,083.10	4,314,563.36	4,559,175.22	4,530,248.98	4,643,234.16
Q4	42,913,131.59	8,395,200.53	8,670,343.94	8,276,618.95	8,707,475.60	8,863,492.57
Yearly						
P50	**127,588,573.77**	**25,143,926.53**	**25,389,155.04**	**25,173,698.75**	**25,572,836.97**	**26,308,956.49**
P75	**123,107,236.73**	**24,320,475.57**	**24,164,601.75**	**24,436,439.03**	**24,914,186.26**	**25,271,534.13**
P90	**118,897,177.61**	**23,423,460.15**	**23,480,525.38**	**23,707,894.24**	**23,999,225.69**	**24,286,072.16**

Table 10: Vestas V172-7.2 MW monthly, quarterly and yearly estimated production P50

5.3. Enercon E-175 EP5 7 MW, Hub height: 175m

Enercon is one of the best know manufacturers of wind turbines, especially for low wind speeds. The E-175 EP5 7 MW is one of the latest turbine types and the next evolution of the 6MW Version and available at different heights.

5.3.1. Power curve Enercon E-175 EP5 7 MW, 175m

Enercon E-175 EP5 7 MW PO7200 Mode Wind speed oscillating speed [m/s]	Air density [kg/m³] 1.225 Power [kW]
0.0	0
0.5	0
1.0	0
1.5	0
2.0	0
2.5	60
3.0	165
3.5	287
4.0	444
4.5	644
5.0	885
5.5	1174
6.0	1515
6.5	1913
7.0	2373
7.5	2897
8.0	3478
8.5	4090
9.0	4684
9.5	5214
10.0	5665
10.5	6053
11.0	6392
11.5	6677
12.0	6892
12.5	6997
13.0	7000
13.5	7000
14.0	7000
14.5	7000
15.0	7000
15.5	7000
16.0	7000
16.5	7000
17.0	7000
17.5	7000

18.0	7000
18.5	7000
19.0	7000
19.5	7000
20.0	7000
20.5	7000
21.0	6936
21.5	6780
22.0	6519
22.5	6142
23.0	5636
23.5	4977
24.0	4137
24.5	3138
25.0	2371

Table 11: Power curve Enercon E-175 EP5 7 MW

5.3.2. Percentiles Enercon E-175 EP5 7 MW, 175m

The following figure will describe the percentiles for the chosen turbine and hub height:

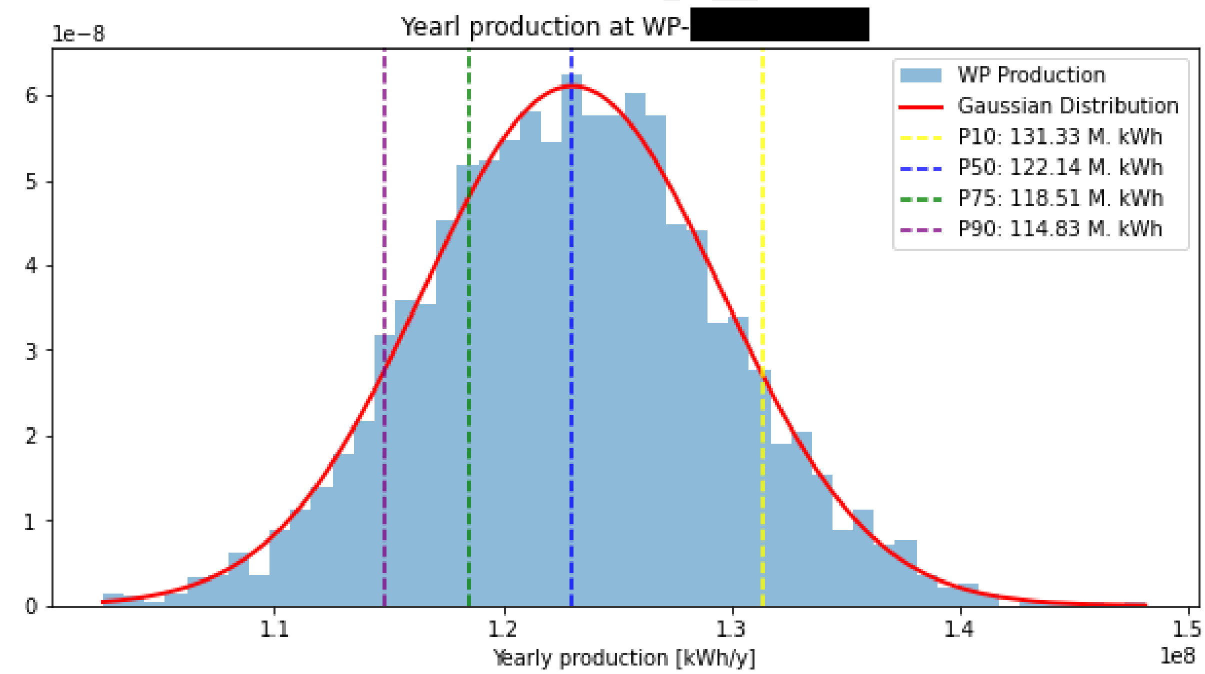

Figure 25: Percentiles Enercon E-175 EP5 7 MW, P10, P50, P75 and P90

5.3.3. Monthly, quarterly and yearly estimated production

Month	Sum of estimated power plant [kWh]	Sum of estimated power WEA0 [kWh]	Sum of estimated power WEA1 [kWh]	Sum of estimated power WEA2 [kWh]	Sum of estimated power WEA3 [kWh]	Sum of estimated power WEA4 [kWh]
Jan	11,196,662.11	2,257,149.61	2,248,736.35	2,182,384.89	2,218,438.71	2,289,952.55
Feb	11,757,852.60	2,308,134.60	2,370,111.53	2,352,007.58	2,385,463.47	2,342,135.42
Mar	12,339,095.80	2,350,929.96	2,428,352.44	2,509,833.65	2,519,801.44	2,530,178.32
Apr	8,852,233.89	1,769,391.52	1,790,499.31	1,795,255.07	1,690,795.19	1,806,292.81
May	6,725,408.20	1,313,853.70	1,376,029.12	1,344,134.91	1,325,212.69	1,366,177.78
Jun	7,502,516.31	1,439,453.68	1,492,045.67	1,537,971.01	1,503,907.87	1,529,138.08
Jul	7,548,177.36	1,435,334.55	1,466,608.37	1,520,482.68	1,561,833.88	1,563,917.89
Aug	6,829,153.41	1,284,170.34	1,276,023.32	1,402,588.24	1,420,270.39	1,446,101.14
Sep	7,951,829.95	1,505,187.74	1,556,665.61	1,561,923.96	1,657,386.41	1,670,666.23
Oct	15,754,874.86	3,052,834.10	3,061,069.37	3,154,295.99	3,238,760.82	3,247,914.58
Nov	12,339,746.46	2,463,452.43	2,448,047.80	2,398,862.60	2,504,509.32	2,524,874.31
Dec	13,337,652.58	2,610,347.60	2,662,281.50	2,658,902.59	2,711,638.64	2,694,482.25
Q1	35,293,610.50	6,916,214.16	7,047,200.32	7,044,226.11	7,123,703.63	7,162,266.28
Q2	23,080,158.41	4,522,698.90	4,658,574.10	4,677,360.99	4,519,915.74	4,701,608.67
Q3	22,329,160.73	4,224,692.62	4,299,297.30	4,484,994.87	4,639,490.67	4,680,685.26
Q4	41,432,273.91	8,126,634.12	8,171,398.68	8,212,061.18	8,454,908.78	8,467,271.15
Yearly						
P50	**122,135,203.54**	**23,790,239.81**	**24,176,470.39**	**24,418,643.16**	**24,738,018.82**	**25,011,831.36**
P75	**118,513,535.86**	**23,408,259.07**	**23,491,760.83**	**23,452,569.72**	**23,919,524.10**	**24,241,422.13**
P90	**114,833,337.74**	**22,725,178.20**	**22,814,727.40**	**22,663,840.02**	**23,023,602.80**	**23,605,989.32**

Table 12: Enercon E-175 EP5 7 MW monthly, quarterly and yearly estimated production P50

6. Conclusion

The estimated yearly energy production can change for the more advanced investigation. Not included in this number are shutdowns under licensing law, bat shutdowns, maintenance, wake effects and other small factors. These factors differ and need a deeper investigation which will be done in the next days.

The deep and intense investigation is delivering more detailed results than the initial investigation which shows more a worse-case simulation than a full simulation. The investigation of terrain and the mean wind speed at hub height showcases that the positioning of the windmill is very productive and even at the mean speed better than in the whole area. Due to the wind rose and the terrain we discovered some channel effects to the Solar plant. This results in good, estimated energy production. When we take the wake effects into account, the layout is chosen well because the wind is blowing mainly from south to west and most of the western wind turbines do not have a lot of loss due to turbulence.

After deep investigation and considering all effects, we expect a performance of WP-DEMO, that the Solar plant can produce in the **P50 23.92 M. kWh** and **P75 23.02 M. kWh** and **P90 22.30 M. kWh per year.** This leads to a total production of (**P50**) **122,383,853.9 kWh per year**.

At hub height (172m) the mean wind speed is at **7,18 m/s**.

The difference in wind speed and energy production between the two studies is due to the spatial resolution and number of models used. The study, incorporating eight models with a finer spatial resolution, captured local terrain and atmospheric variations, resulting in an average wind speed of *7.18 m/s*. Higher resolution and a broader model ensemble enable better identification of wind acceleration effects, microclimates, and localized energy potential, significantly improving the accuracy of wind resource assessments.

The distribution over the month is behaving as expected and does have the maximum within the wintertime and minimum in the summer. The named estimated production values include some losses specific to the turbine and the terrain as well as the wake effects. As mentioned before, losses caused by maintenance, shutdowns etc. can reduce the yearly production by a certain percentage.

In the analysis of different wind turbine types, we put the focus on other manufacturers and different power curves. With a mean wind speed between 7-8 m/s it could be more beneficial to take an Enercon model. Also, some models start earlier and reach the cutoff speed at different wind speed. Therefore, the team investigates and took different types of turbines with different capacities and a different hub height. From this investigation, the results for the whole plant are the following:

Turbine Type	Yearly estimated energy production [kWh]	Hub height [m]
P50 Vestas V172-7.2 MW	**122,383,853.90 kWh**	172m
P75 Vestas V172-7.2 MW	**117,491,319.42 kWh**	172m
P90 Vestas V172-7.2 MW	**113,778,022.23 kWh**	172m
Alternative turbines:		
Vestas V172-7.2 MW	**127,588,573.77 kWh**	199m
Enercon E-175 EP5 6 MW	**113,222,567.70 kWh**	162m
Enercon E-175 EP5 7 MW	**122,135,203.54 kWh**	175m

Table 13: Conclusion of all investigations P50

This table shows that there are differences between the turbine types and that the hub height, if possible, to build is directly connected with a higher estimated production per year. Depending on the financing case it is worth calculating not only one version of the Solar plant.

7. Disclaimer

NAECO Blue's forecasts also refer to external data sources such as weather data and historical generation data provided. NAECO Blue assumes no liability for the results of these forecasts and the resulting actions of the customer. We do not make any recommendations for action and are merely in an advisory role.

8. Contact

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