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The investment potential of offshore wind in Germany
An investigation of the world's first zero-subsidy offshore wind farm

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Abstract

In April 2017, Danish utility Ørsted won the right to develop an offshore wind project in the German North Sea with a zero-subsidy bid, which marked the first time in the history of offshore wind. Numerous factors where essential in bringing down the cost of electricity, including the potential of larger turbines becoming available, increased capacity and extended operational lifetime.

In this thesis, we wish to analyse the profitability of this subsidy-free project and how it is affected by the availability of the three cost reducing options mentioned above. We will base our analysis on an in-depth investigation of the financial and technical aspects of the project, the theory that substantiates these aspects and how they affect the performance of the project.

Based on historical data, we will construct stochastic models for simulating relevant inputs for the investigation, such as the wind flow, production and spot price. We will then use the Monte Carlo method to forecast the future revenue of the project.

The costs of the wind farm have been estimated using a regression analysis of existing German offshore wind projects. We find a decreasing relationship between Total Capex per MW and total capacity, which confirms the existence of economies of scale in offshore wind power. Furthermore, an investigation of the dependency of total Capex per MW on turbine size has been conducted. We find that increasing turbine size decreases Total Capex per MW and also Opex, resulting from fewer turbine positions.

Using the traditional NPV valuation approach, we find that the project in the case where none of the mentioned factors are available, the base case, is unprofitable and should not be pursued by Ørsted. Analysing the sensitivity of the project to changes in the underlying drivers reveals that the forecasted trend in the spot price of electricity and the estimate of Total Capex are the most influential determinants of the profitability of the project.

Following the preliminary valuation, we investigate the value of the three options that may become available to the project with a real option approach. We find that all three has a positive effect on the value of the project, but that none of them, when exercised separately, delivers a return above the required return. If however all three become available, exercising all of them creates a combination effect and delivers both value and a somewhat satisfactory return, which would justify the zero-subsidy bid.

In the last section, we construct a stochastic model for the technological development of large scale electricity storage as a function of investment in research and development. We use this to develop a framework suited for analysing the option to invest in this technology. Although we believe the method could be useful in the future, the lack of data and research on the effect and cost of the technology makes it hard to extract meaningful insights from applying the method today.

Contents

1 Introduction

The offshore wind industry has undergone tremendous progress since the first offshore wind farm was built in 1991. In 2016, investment in offshore wind had a record year where new investment reached \$30 billion (€25 billion[1], a 41% improvement compared to the year before and total installed capacity increased by nearly 2,2 GW to 14,4 GW [71][41]. An important driver of this increase in investment and capacity has been that the costs have fallen significantly since 2012, where the levelised cost of electricity (LCOE) of offshore wind peaked. In 2017, the global average LCOE had fallen 44% from its peak in 2012, driven by improvements in both technology, operational efficiency and financing terms [72].

Although being on an impressive trajectory of growth and cost reductions, offshore wind power is still a relatively new technology and has long been reliant on government support to be profitable and to attract investment. However, for offshore wind power to be a viable long-term technology, it must prove to be profitability on its own without the support of government subsidies. Fortunately, subsidies *have* decreased significantly over the last couple of years as many regimes have switched from guaranteed prices, called feed-in-tariffs (FITs), to allocating project sites via auctions. This has forced developers to compete for allocations and outbid each other, which has driven the subsidy price down and resulted in improved cost competitiveness [72].

In April 2017, a significant milestone was reached for the offshore wind industry. Danish utility Ørsted was one of two developers who won the right to build offshore wind projects in the German North Sea with bids of €0 per MWh in subsidy. This is the first time this has happened and has led industry participants and policy makers to speculate whether the offshore wind industry is closing in on becoming so cost competitive that subsidies are no longer required for investment in the industry to be profitable.

Motivated by this, in this thesis we wish to investigate the profitability and investment potential of offshore wind in Germany in the near future. We will do so through a case study of the two German projects won by Ørsted with zero-subsidy bids in 2017. In the following, we will give an introduction to these projects and the case of them combined as one project, which we henceforth will term the Project.

1.1 Introduction to the Project

Ørsted won the right to develop the Project, consisting of the two projects Borkum Riffgrund West 2 and OWP West, each with a capacity of 240 MW and thus with combined capacity of 480 MW, in the first round of the German offshore wind tender in 2017. The projects are located in the

[1] See global parameters in Appendix A.25 for use throughout this thesis

German North Sea off the coast of Borkum and to the north west of Ørsted's existing wind farms Borkum Riffgrund 1 & 2 [86].

Several factors helped deliver an expected cost-of-electricity below Ørsted's forecasted wholesale electricity price. First, in Germany, developers do not have to pay for connection to the electrical grid that transports the electricity production to shore and onwards, as developers in different countries do. This is in effect is a financial support mechanism, although it comes in a different form than a FIT [64].

Second, Ørsted will leverage economies of scale achieved partly through combining the two neighbouring projects and partly through the fact that they also own and operate Borkum Riffgrund 1 & 2 and therefore can achieve synergies in operation and maintenance (O&M). Furthermore, at the time of the auction, Ørsted hoped to be able to increase the capacity of the Project in the second round of the offshore wind tender in 2018. When deciding on the scope of this thesis, this tender was still not concluded, however, it was concluded on the 27th of April and Ørsted won the right to this capacity extension that involves the 420 MW project Borkum Riffgrund West 1, located directly in between the two projects making up the Project [85]. We will consider the result of this auction as unknown and analyse the impact of winning this extra capacity from this perspective.

Third, the Project is not to be commissioned until 2024, and therefore Ørsted expects turbines to reach 13-15 MW capacity before the Project is constructed. This would improve the business case as the same capacity can be installed with fewer turbine location, which would reduce the costs of constructing and operating the Project [84].

Fourth, the location of the Project in the German part of the North Sea benefits from a very attractive wind resource with measured average wind speed above 10 m/s, the highest measured average wind speed across all of Ørsted's offshore wind portfolio [84].

Finally, German authorities are open to the possibility of extending the operational lifetime of the Project from 25 to 30 years [84].

The Final Investment Decision (FID) on the Project will be taken in 2021. If the above mentioned initiatives do not develop according to expectations and Ørsted decide to cancel the Project, they will face a penalty of €59 million [86].

In our investigation, we will analyse the profitability of the Project in different scenarios regarding which of the above mentioned cost reduction drivers that will be available. In the most conservative scenario, which we will term as our base case scenario, we assume a 13 MW turbine will be available in the market and deployed in the wind farm. We assume the operational lifetime will only be 25 years and also that the Project will not be extended in the 2018 auction. That leaves an upside potential of a 15 MW turbine becoming available, the operational life being extended to

30 years and the total capacity of the Project to be increased. We will analyse the value of these three possible upsides in the theoretical framework of real options and determine how this might affect the overall profitability of the Project.

Driven by its relevance and our own interest in the matter, we will include a theoretical analysis of the impact that the development of large scale electrical storage would have on the Project and how this might be investigated once the technology reaches a more mature state.

1.2 Research questions

Now that we have given an introduction to what the objective of this thesis is and the motivation for it, we present the research questions we have formulated to guide and structure our investigation around.

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i. What financial and technical characteristics determine the profitability of an offshore wind farm in Germany?

ii. How is the profitability of an offshore wind farm determined and how can this be applied to the Project and with what result? Does the result justify the zero-subsidy bid made for it?

iii. How can real options be used to analyse the profitability of the Project and how do they affect the results found in question ii.?

iv. How would electrical storage affect wind farm profitability if developed and how could this be analysed using a stochastic model for technological development?

Question (i) will establish the necessary theoretical foundation for understanding and valuing an offshore wind farm. It will focus on all the inputs necessary to find the cash flows of an offshore wind farm, such as wind speed and direction, availability, the spot price of electricity, the capital expenditure (Capex) and operational expenditure (Opex). Since the wind farm is not operational, cash flows are derived from future realisations of the spot price of electricity, the future wind flow at the site and the costs of constructing and operating the wind farm, and therefore we need to estimate these. For the price and wind flow, we will do so by constructing an appropriate stochastic model for each of them and then use the Monte Carlo method to predict the future movements. For the costs, we will rely on a regression analysis of the cost of existing German wind farms, other research and market expectations.

Question (ii) will consist of valuation of the base case scenario and an assessment of the profitability and stability of the Project. We will do so by introducing the financial theory, models and methods most commonly used in practice today, such as the CAPM, NPV valuation, IRR and sensitivity analysis.

Question (iii) will seek to value of the potential upsides available to the Project as real options in order to give a more holistic view of the value. We will discuss how this value corresponds to the one found under question (ii) and what implications this has for the classical valuation methods so broadly applied in the professional world of finance.

In question (iv) we will explore what implications large scale electrical storage would have on the profitability of offshore wind projects if developed. Since the technology is in a very early stage, not a lot of data is available on the exact effects of storage and so our investigation will be of a more theoretical and methodical character. We will construct a stochastic model for technological development as a function of investments in research and development and analyse how this could potentially be applied to the Project had there been reliable data available.

1.3 Delimitations

We do not intend on making our investigation of technical nature as we are students of mathematical economics and finance, but will only to the extent we find necessary include technical aspects in our analysis. Given that offshore wind is rather technical in its essence, however, we will introduce some of the necessary theory behind technical and physical aspects of the industry when we feel it is necessary in order to understand the workings of the industry and drivers of financial performance.

We have decided not to go into detail with breakdowns and failure rates of wind turbines, although these do have a significant impact on the financial performance of an offshore wind farm. We do not feel that our analysis suffers great losses of generality from the way we have decided to work around these and believe an investigation of these aspects would have been too technical to fit the financial profile of this thesis.

Since the offshore industry is very competitive, a lot of data is not available to the public and therefore some of our analysis could have been materially improved if data had been available. This is for instance the case for our analysis of the costs of offshore wind, where our analysis of economies of scale could have been supported by an analysis of the price of turbines and other components as well as for construction work and O&M. These data are however very sensitive for competition reasons and therefore, we have relied on cost data on an aggregate level as well as industry research reports and academic research papers.

2 Wind flow simulations

In this section, we will analyse the wind resource available to the Project, which we will need in order to compute the power production of the Project.

A wind turbine generates energy by capturing the kinetic energy in the wind and converting it to electrical energy via a generator. The wind drives the propeller-like blades around a rotor which is connected to the main shaft. The main shaft spins a generator which creates electricity by converting the mechanical energy of the movement driven by the shaft into electrical energy via electromagnetic induction [97].

Obviously, the main driver of the production of a wind farm is the incoming wind flow. The two main drivers of the wind in relation to prioduction is wind speed and the wind direction. At an individual turbine level, the most important characteristic is the wind speed as higher wind speeds will drive the blades around the rotor faster and thereby generate more power. The direction is not as important to the single turbine, as all wind turbines are equipped with a yaw component which can turn the nacelle so it is always facing the current wind direction. However, at a park level the wind direction matters a lot due to the presence of the so-called wake effect, which is caused by obstacles standing in the proximity of the turbines creating an obstruction of the wind flow and lowering the wind speed and therefore the output of the turbines. This effect can be caused by external object in the general topography but also by internal object such as the other turbines in the same park. This means that all turbines standing downwind of other turbines will experience a lower production. As a result, to maximise the production of a wind farm, it is extremely important to place the turbines such that these wake losses are minimised [4].

Although this is important, we will not in this thesis try to optimise wind farm design, but rather just assume that Ørsted will consider this and place the turbines optimally among each other. This seems a sensible assumption to make as a sloppy wind farm design could potentially cause significant losses and make a project much less profitable.

In order to simulate the Project's cash flows, we will analyse historical data of the wind resource in the German North Sea and fit a statistical model that can be used to simulate the future wind flows.

2.1 Wind data from the FINO1 meteorological mast

We have established that the on-site wind conditions are some of the main drivers of the production of a wind farm and therefore knowledge of wind conditions is of paramount importance in evaluating a location for an offshore wind farm. In order to analyse the wind conditions for the Project, we need reliable, historical data from the area.

Normally, the developer of an offshore wind farm will conduct their own wind measurement campaign on the site. This requires an onsite installation of a meteorological mast equipped with devices that can measure the wind speed, called anemometers, and wind direction, called wind vanes. This is obviously not a possibility for us. Furthermore, offshore wind turbines are typically also equipped with anemometers and wind vanes, so the wind resource reaching each turbine can be measured. However, as the Project is yet to be built, no such devices are in place to measure the wind exactly at the site yet. Therefore, we cannot get data on the wind climate *exactly* at the site, but we can get data from the nearby FINO1 meteorological mast.

FINO1 research platform has been build to gather information of the ambient conditions in the North Sea and analyse the impact of offshore wind on the environment with the purpose of promoting the deployment of offshore wind in Germany. The platform has been established as a joint project between the Bundesministerium für Wirtschaft und Energie, BMWi (the Federal Ministry for Economic Affairs and Energy) in Germany together with Projektträger Jülich (The project executing organisation). The platform has been in operation since primo 2004 and is located approx. 45 km north of Borkum and only about 25 km east of the Project, so it provides high-quality, long-term historical data of the wind resource available in close proximity of the Project [88]. This data is available free of charge to all scientific institutions in the EU and therefore we have an opportunity to analyse the wind resource ourselves.

The FINO1 meteorological mast is equipped with anemometers at different heights and thus measures the wind speed and wind direction at 33 m, 40 m, 50 m, 60 m, 70 m, 80 m and 90 m. According to the wind shear profile, which represents the relationship between wind speed and altitude, wind speeds are increasing with altitude [4]. Therefore, it would be expected that the average wind speed measured at 90 m would be higher than that measured at 33 m. Thus it is relevant to use the data for the height closest to the hub height of the turbines deployed in the specific wind farm. We do not yet know what the hub height will be of the turbines to be deployed in the Project as these turbines have not yet been developed, but we do know that it will be above 90 m. For instance, the MHI Vestas 8 MW turbine used at the Burbo Bank Extension wind farm in the UK, which went into operation in 2017, has a hub height of 105 m. The Project will utilise the next generation of turbines which obviously will be higher as the rated power increases with the rotor swept area which increases with longer rotor blades [10]. More on this later in Section 3 where power curves will be introduced. We will use the measurements from 90 m as this is the highest we can get and thus the data that will resemble the actual wind speed at hub height of the next generation turbines the most.

The data from the FINO1 meteorological mast is measured in 10 minute intervals from 01/01/2004 to 30/09/2017. Below are summary statistics of the wind speed data:

Table 2.1: Summary statistics of the FINO1 wind data

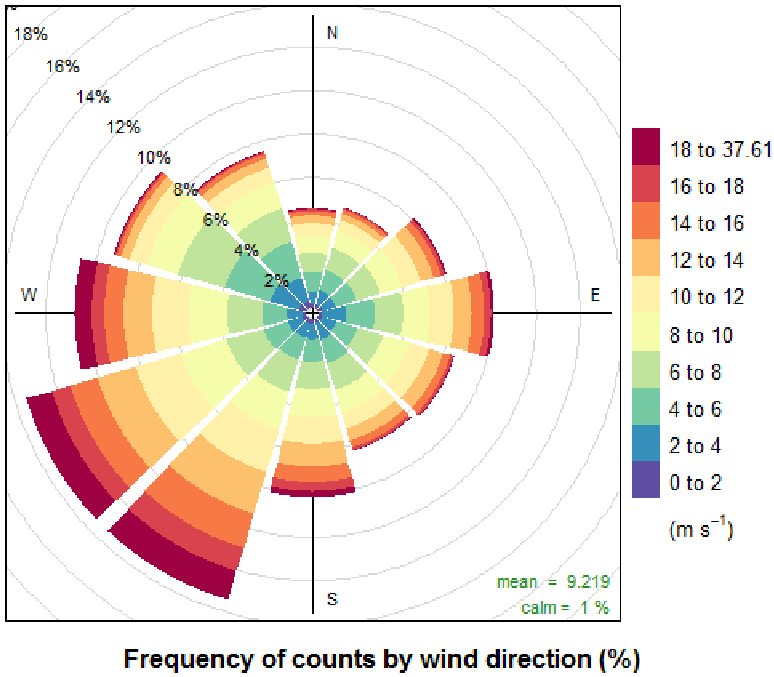
	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Wind speed at 90 m	0	5.73	8.69	9.22	12.17	37.61
Wind speed at 33 m	0	5.42	8.02	8.44	11	36.62

A few points can be made here. First, the original dataset contained entries of -999 m/s, which makes no sense as wind speed cannot be negative. These entries corresponds to periods where data is not available for some reason. All the enntries with value equal to -999 m/s were corrected to reflect that data was not available at that given time. Therefore, we see that the minimum is zero and we have no negative values. Second, the maximum is within what we would expect to be realistic. A turbine typically has a so-called survival wind speed, which is the minimum wind speed it is designed to withstand safely, and this is typically around 50-60 m/s, thus the maximum wind speed measured at both heights are below what turbines in general are designed to withstand [87]. Third, the mean and median are not that far from each other which shows that after removing the extreme negative outliers, the dataset does not have other significant outliers, as these would have biased the mean more than the median and thus driving a larger difference between the two. Lastly, we can see the wind shear profile holds, as the data show that wind speeds measured at 90 m are higher than those measured at 33 m.

In Figure 2.1 we have computed a graphical representation of the data called a wind rose. It conveys all the relevant characteristics regarding wind speeds and directions in an intuitive and complete way.

The wind rose is split into 12 sections, all expressed in degrees, whose length indicates the frequency of winds blowing from that given direction. It also indicates, for each of the 12 directions, the distribution of wind speeds distinguished by color. It is obvious from the wind rose of the historical wind data that the wind most often blows from W, WSW and SSW and that the winds from these directions are also the strongest compared to the other directions. Therefore, we would expect Ørsted to design the Project in such a way that the aggregate wake loss is minimised and power production is maximised when winds are blowing from these south-western directions. The data is kept at a 10 minute interval as wind speeds are so volatile that in order to correctly analyse the variations in wind speed, we need to simulate them for as precise intervals as possible. Aggregating them to hourly averages would significantly reduce the variance, thus bias the data towards being more stable and less volatile.

Figure 2.1: *Wind rose for the FINO1 wind data*



2.2 Modelling wind flow

To model the wind flow at the site, we need to model both the speed and the direction of the wind. We will model the direction by randomising which direction the wind is blowing from using the frequency of the wind directions found in the wind rose of the historical data. For instance the wind can be seen to blow from direction East approximately 8% of the time. We need to do this, as the production of the wind farm will depend on which direction the wind is blowing from, as the wake effect will be different depending on the wind direction. We will discuss this more detailed in Section 3.2.1 in power production. To model the wind speed, we need to consider the distribution of wind speed. This is important as the distribution of the wind speed combined with the power curve of the turbine determine the energy production of the Project [4].

The Weibull distribution

The two-factor Weibull distribution is a mathematical expression that generally has been shown to present good approximations for distrubutions of wind speeds [4][7][10]. The Weibull distribution has the following density function which states the probability of wind speed being v during any time interval:

$$f(v) = \frac{k}{\alpha}\left(\frac{v}{\alpha}\right)^{(k-1)} \exp\left[-\left(\frac{v}{\alpha}\right)^{k}\right] \tag{2.1}$$

and the corresponding distribution function

$$F(v) = 1 - \exp\left[-\left(\frac{v}{\alpha}\right)^k\right] \tag{2.2}$$

Where α is called the scale parameter and k is called the shape parameter.

The shape parameter k naturally determines the shape of the curve. A shape parameter equal to one is in fact the exponential distribution, while a shape parameter of two gives a Rayleigh distribution. With a shape parameter of three and above the Weibull distribution approaches the normal distribution with the well known bell shape. A graphical representation of these density functions with fixed scale parameters and shape parameter $k = 1, 2, 3$ can be found in Appendix A.1. The scale parameter α shifts the distribution to the right which indicates more days with higher wind speed. The higher the α, the more number of days with high winds. A graphical representation of density functions with different scale parameters and fixed shape parameter can be found in Appendix A.2

I fact most wind sites have a wind speed approximately equal to the Rayleigh distribution which is seen when comparing historical wind speeds with the distribution. Thus many decides only to use a one factor model, because the Reyleigh distribution is a more simple and still accurate enough representation of the wind speed. The only parameter to estimate will then be the scale parameter[10]. However, we still prefer the two-factor model which requires estimation of both the scale and shape parameter. The wind speed has a key role in our valuation of the Project and we prefer to make the wind predictions as accurate as possible.

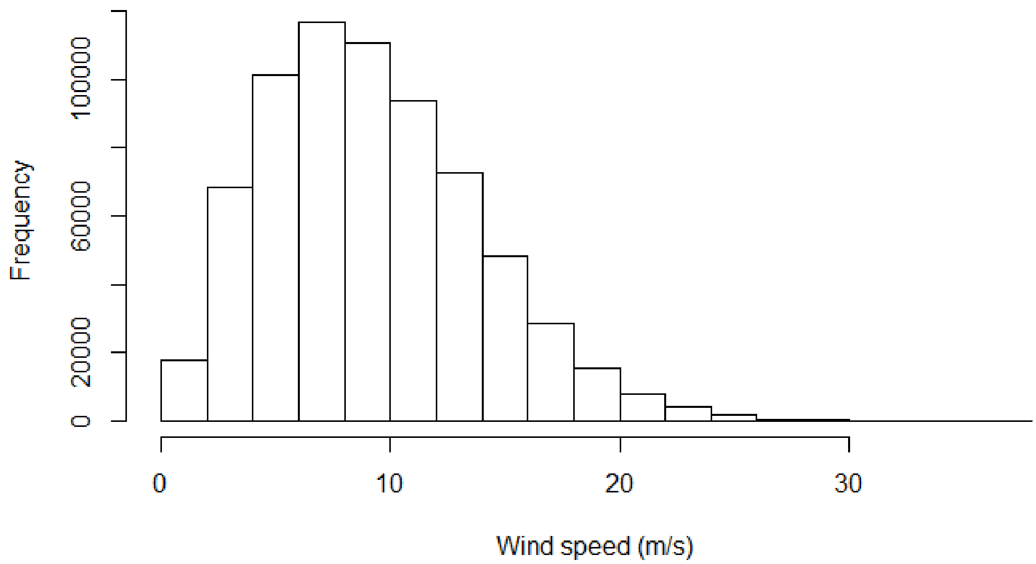
A histogram of the historical wind speeds from FINO1 is shown in Figure 2.2. The data clearly shows significantly similarities with the Weibull distribution. The shape of the historical data looks similar to the shape of the Weibull curve in Appendix A.1 with $k = 2$ and thus aligns with the expectations of the Rayleigh distribution as a sensible one-factor approximation. Interestingly enough the interval with wind speeds at 7-8 m/s can be seen to have the largest frequency, even though the average mean speed lies above 9 m/s. But as we can see the small frequencies of large wind speed pulls the average value up to an average value on 9,22 m/s.

2.2.1 Estimation of the scale and shape parameters for the Weibull distribution

The selected two-factor Weibull distribution model for wind speeds requires estimation of both the shape and scale parameter. There are several estimation methods available for this, but the most common are Least Square Method, Maximum Likelihood, Moment Method and Density Power Method[36].

We will use the Maximum Likelihood Estimation (MLE) method on the historical data to

Figure 2.2: *Histogram of historical wind speed distribution*



estimate these parameters, in order to predict the future wind flow from the Weibull distribution, in a similar way to previous studies[13][17][36]. MLE is chosen because it is commonly acknowledge in the industry to be a reliable estimator. Most of the studies investigated used this method to estimate the parameters, and therefore we will follow that manner because it has shown good result in the reviewed studies.

The likelihood function of a random sample with size n is the joint density of the n random observations, which are assumed to be independent and identically distributed. The likelihood will then be a function of the observations and the unknown parameters in the density function the sample is drawn from. In this case the Weibull distribution. Applying the likelihood function to the probability density function given in equation (2.1) gives the likelihood function for the Weibull distribution, as a function of the shape parameter k and scale parameter α. This can be seen in equation (2.3) below:

$$L(v_1, v_2, ..., v_n, k, \alpha) = \prod_{i=1}^{n} \frac{k}{\alpha} \left(\frac{v_i}{\alpha}\right)^{(k-1)} \exp\left[-\left(\frac{v_i}{\alpha}\right)^k\right] \tag{2.3}$$

We want to estimate the parameters so they maximise the likelihood that the process described by the model produced the data actually observed. From basic math we know that we can find the optimum of a function by differentiating and setting equal to zero. Before doing so, we take the logarithm to the likelihood function. This gives the log likelihood function, which is much more simple to differentiate. Thus taking the logarithm to equation (2.3) and differentiating with respect to k an α results in the following equations

$$\frac{\partial lnL}{\partial k} = \frac{n}{k} + \sum_{i=1}^{n} ln(v_i) - \frac{1}{\alpha}\sum_{i=1}^{n} v_i^k ln(v_i) = 0 \tag{2.4}$$

$$\frac{\partial lnL}{\partial \alpha} = -\frac{n}{\alpha} + \frac{1}{\alpha^2}\sum_{i=1}^{n} v_i^k = 0 \tag{2.5}$$

which can be recognised as two equations with two unknowns parameters. Starting with k, we solve equation (2.5) for α and insert this expression in equation(2.4) to obtained the following reduced form of k:

$$\frac{1}{k} = \frac{\sum_{i=1}^{n} v_i^k ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{1}{n}\sum_{i=1}^{n} ln(v_i) \tag{2.6}$$

This formula can be solved with the use of Newton-Raphsons method, a method that given a starting point k_0 uses an iterative process to find the solution. When equation (2.6) has been solved for a solution k, this solution can be used to estimated α this

$$\alpha = \frac{\sum_{i=1}^{n} v_i^k}{n} \tag{2.7}$$

Because MLE is such a popular method for estimating parameters in different distributions, most statistical tools have a function build into the software. This is also the case in the statistical program R and we will use this build-in function to estimate the parameters with MLE insted of performing all the calculations our self.

From the wind rose plot of historical data in Figure 2.1 we observed that the direction of the wind has a huge influence on the wind speed. To make our wind forecast as precise as possible we therefore decide to predict the wind speed from all twelve directions in the wind rose instead of just one total prediction of wind speed. Thus we have to estimate shape and scale parameters for all twelve directions in the wind rose. This is done by separating the historical data into the 12 directions and using MLE to estimate the parameters for each direction. We use the historical observed frequency of the directions to apply each direction with a probability of wind blowing from that direction. The results is printed in Table 2.2 together with the historical observed average and maximum speed of each direction

From Table 2.2 we see that the shape parameter is close to the Rayleigh value of $k = 2$ as expected. However, there is still some difference to detect from the Rayleigh value to the

Table 2.2: Direction probabilities, estimated shape and scale parameters, average wind speed and maximum wind speed

Wind Direction	Probability	Shape	Scale	Average m/s	Max m/s
N	4.62%	2.15	8.94	7.91	25.92
NNE	4.84%	2.17	8.52	7.54	22.54
ENE	6.22%	2.25	9.59	8.49	22.24
E	8.17%	2.13	9.74	8.62	23.67
ESE	6.62%	2.34	9.45	8.39	20.66
SSE	6.64%	2.22	9.06	8.02	23.29
S	8.27%	2.25	10.84	9.6	28.87
SSW	13.59%	2.48	12.98	11.52	31.14
WSW	13.58%	2.37	12.42	11.01	34.15
W	10.77%	2.25	11.7	10.36	37.61
WNW	9.35%	2.16	7.95	7.03	29.8
NNW	7.58%	2.12	8.16	7.22	27.51

estimated shape parameters. The estimates show that the directions with the highest probability and historical wind speed also has the largest shape parameters. This confirms the choice of using a two factor Weibull distribution instead of the Rayleigh distribution, because a scale parameter above two secures a higher wind speed, as already discussed in the introduction of the Weibull distribution. The table also shoes a larger scale parameter when the wind is blowing from the directions with high average wind speed, which aligns with our expectations of more days with high wind speeds in those directions. So our estimates shows the discussed characteristics of the FINO1 data and the the Weibull distribution.

2.2.2 Seasonality in wind data

A time series plot of the historic FINO1 data, which can be found in Appendix A.3, clearly exhibit a strong annual seasonal pattern. This is due to the fact that Northern Europe experience stronger winds during winter than summer. When the effect of the seasonal pattern is this obvious, we have decided to include a seasonal component in our wind model. This seasonal component has to adjust the simulated wind data from the Weibull distribution according to the seasonal time of the year. We will include a seasonal component in the same way as previous studies has done for the spot price [1][22]. As we will see later on in Section 4, the spot price also tends to be higher during winter than summer. Because the seasonal patterns are similar to each other, we have decided to use the method suggested by the mentioned studies to model the seasonality in wind speeds. The seasonal component will be included in such a way that wind speed will be determined by the following model:

$$w_t = [1 + \theta cos(2\pi\beta t)] \cdot Weibull(\alpha_i, k_i) \quad (2.8)$$

where the +1 element is included to offset the cosinus curve to avoid negative numbers, because wind speed cannot be negative. The seasonal component will work as an scaling factor for the wind speed drawn from the Weibull distribution. During winter the seasonal component will be above 1 and below 1 during summer. This secures a seasonal effect in the data because winter speed is increased and summer speeds decreased.

The parameters in the model has the following functionality

- α_i: Scale parameter of wind from direction i, i=1,2,...,12
- k_i: Shape parameter of wind from direction i, i=1,2,...,12
- θ: Controls the effect of the seasonal component on the wind speed
- β: Controls the timing of the cosinus curve

The cosinus curve is preferred because it starts at its highest level. This is exactly what we need as we will start modelling from first of January, where we expect the seasonal effect to be at it highest. Because we are constructing a yearly seasonal component, beta has to ensure the correct timing of the cosinus curve when modelling 10-minute intervals of the wind speed. This is done by setting equal to:

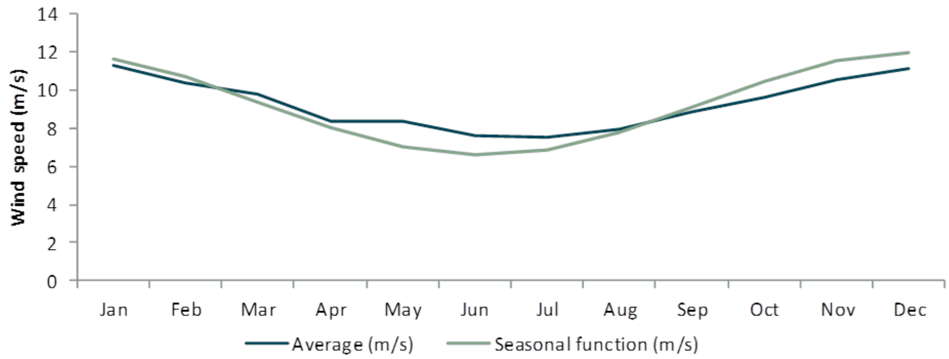
$$\beta = \frac{1}{6 \cdot 24 \cdot 365} = \frac{1}{52.560} \quad (2.9)$$

where 6 is the number of observations in one hour. Thus the nominator in β gives the number of observations in one year

To get an idea of the estimate of θ we compute the monthly averages of wind speeds in the historic FINO1 data. These averages are shown in the table to the left in Figure 2.3 together with an illustration of them to the right. This plot clearly illustrates the seasonal pattern in the wind data, with significantly higher average wind speeds during winter months. Another takeaway from the illustration is the smoothness of the averages, which aligns very well with our choice of function for the seasonal component - the cosinus function.

Based on the monthly averages we define summer as April to September (the lowest monthly averages) and winter as October to March (the highest monthly averages. From this categorisation of summer and winter we can calculate their respectively average and use these averages to estimate the percentage difference between summer and winter. This percentage difference will serve as our estimate of θ:

Figure 2.3: *Left: List of historic monthly average wind speed and the historic summer and winter average. Right: Plot of the historic monthly average and the constructed seasonal component*



Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Summer	Winter
Average (m/s)	11.28	10.33	9.75	8.39	8.32	7.57	7.54	7.94	8.82	9.60	10.51	11.14	**8.09**	**10.43**

Source: Own construction based on FINO1 data [88]

$$\theta = \frac{10,43 - 8,09}{8,09} \cdot 100\% = 28,88\% \tag{2.10}$$

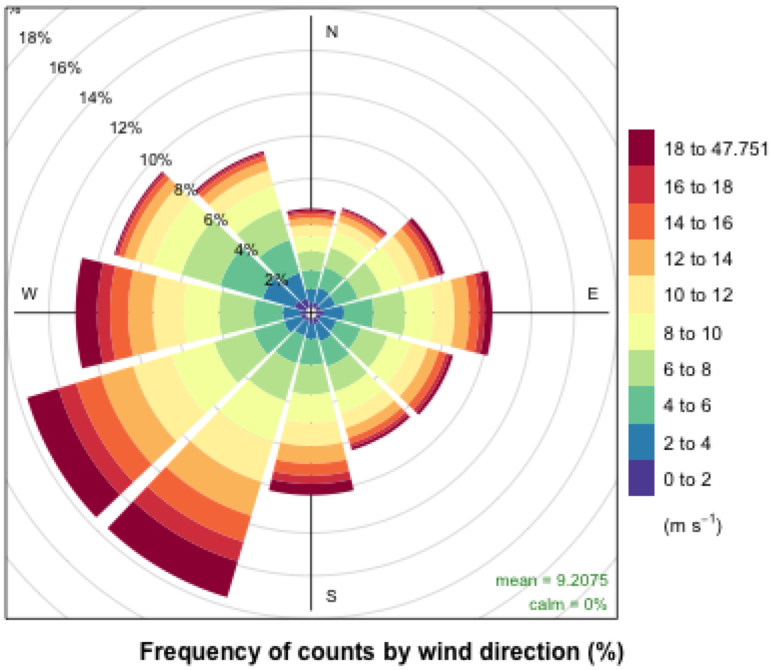
In the illustration of the monthly wind speed averages in Figure 2.3 we have also added the constructed seasonal component with the estimates of θ and β to see how well the constructed seasonal component captures the observed seasonal pattern in the historic FINO1 data. It penalizes the summer a little to hard and lies a little above in the last months of the year, but we are quite satisfied with the constructed component and the way it aligns with the actual historic season pattern. Including this component to our model of wind speeds will definitely make it more realistic and in accordance with the historic FINO1 data.

2.3 Simulation of wind

We have now addressed all the necessary aspects to simulate the future wind data for the Project. For each observation the directions will be drawn from a random sample with frequencies according to Table 2.2 and corresponding wind speeds will be estimated with the model presented in equation (2.8). The direction controls the shape and scale parameters for the model. We simulate 10-minute wind speeds and wind directions for the lifetime of the Project, which is 25 years. This means one single simulation will consist of 1.314.000 wind observations. The wind rose for a single Monte Carlo simulation is presented in Figure 2.4 with the same interpretation as the wind rose described in Figure 2.1.

The two wind roses looks very much alike, indicating that the simulated wind data provides

Figure 2.4: *Wind rose of simulated wind data*



a good fit for the historical data. The simulated data shows the same signs of frequencies and wind speed from the different directions. This is a confirmation of the accuracy of the model, the estimated parameters and the inclusion of the seasonal component in the model.

In table 2.3 we have printed a summary of the wind directions, probabilies and average wind speeds resulting from averaging across 1000 Monte Carlo simulations.

Comparing the values in the simulated Table 2.3 to the values in Table 2.2 we see that even though we have simulated almost twice the number of historical observations, both the probabilities for each direction and the corresponding average wind speeds are almost identical in the two tables. This works as another indicator of a successful construction of wind data.

A last investigation of the model is a further check of the shape and scale parameters estimated with MLE. In Appendix A.4 can be found a plot for each direction, containing a histogram for historical wind speeds plotted with the estimated Weibull distribution. They can be used to get an idea of the accuracy of the estimated parameters for each direction. For all directions the estimated Weibull distribution aligns very well with the historical data, thus the MLE estimation seems very successful.

As we can see in Table 2.1 the average wind speed at FINO1 in 90 m height is $9,2$ m/s. As alerady mentioned in the introduction, when Ørsted won the rights to the Project, some details about the Project was released. One of these details was that the average wind speed at the Project

Table 2.3: Direction, speed and frequency of the simulated wind data

Wind Direction	Probability	Average m/s
N	4.61%	7.92
NNE	4.84%	7.53
ENE	6.19%	8.49
E	8.18%	8.66
ESE	6.63%	8.39
SSE	6.40%	8.02
S	8.24%	9.58
SSW	13.58%	11.51
WSW	13.60%	11
W	10.76%	10.37
WNW	9.35%	7.04
NNW	7.62%	7.23

lies above 10 m/s [84][86]. This is of course very important to the valuation of the project because an increased average wind speed will also result in a higher production of the Project. Because we have estimated our wind model based on the historical FINO1 data, our simulated wind data also has an average wind speed around $9,2$ m/s. Later on we will correct the data for the increased hub height of the larger turbines, accordingly to the wind shear profile. After correcting the data we need to examine if this correction has been sufficient to increase the average wind speed above 10 m/s. More on this in Section 3.

To summarise we have succeeded in modelling the future wind flow for the Project based on the FINO1 historical data. Our estimate of future wind flow is almost identical to the historical wind flow because we do not expect any environmental changes that might affect the future wind flow at the site. One could choose to investigate the effect of global warming on the expected future wind flow, to see if the seasonality effect will increase or decrease or we will expect a higher or lower average wind speed in the future. However, this is out of the scope for this thesis and therefore not taken into consideration when modelling future wind flow.

3 Power production

In this chapter, we will aim to determine the energy production of the Project, as this is a direct driver of its revenue. To do so, we first need to introduce the necessary theory behind the production of energy from wind and then apply this to the simulated wind speeds and directions from the previous section.

3.1 Wind turbine power curve

A power curve is a model of how much electricity a turbine produces as a function of the wind speeds at hub height available at the site. The power curve describes the relationship between a turbine and the extraction of energy from the wind. It can be used to understand the performance of a wind turbine and also to predict the energy output of a turbine based on forecasts of wind speeds. Wind farm developers may also use them to choose which turbine to use at a specific site according to how its specifications match the wind regime at the site, to monitor and troubleshoot the performance of operational turbines and to predict component failures or other types of failures causing downtime [52]. For all these reasons, it is evident that modelling of the power curve of a turbine can be very useful and can help optimise the energy production of the turbine. In our case, we will primarily use the power curve to convert our wind forecasts from the previous section into actual power production.

Three key concepts are essential when modelling the power curve of a wind turbine, namely the cut-in speed, the rated speed and the cut-out speed. The cut-in speed is the minimum speed at which the turbine delivers useful power, so when the wind speed is below this, either the torque exerted on the blades is too weak to overcome frictions or the power produced is simply not enough to cover internal consumption and power losses. For most commercial wind turbines the cut-in speed is in the range of 3-5 m/s. The rated speed is the wind speed at which the turbine first start to produce energy at the rated capacity which is the maximum permissible power output of the turbine, typically limited by the generator. This output level is typically reached at a wind speed between 12-17 m/s. Lastly, the cut-out speed is the speed at which the wind turbine is turned off in order to protect the rotor from potential damages caused by the rising forces working on the turbine structure. This is typically around 25 m/s [131]. Figure 3.1 shows a typical power curve of a wind turbine.

The theoretical power captured by the rotor of a turbine is given by

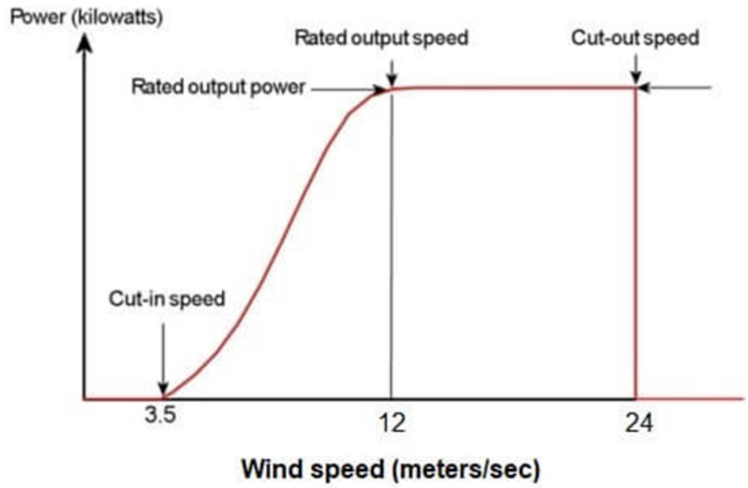
$$P = 0,5\rho A C_p w^3 \tag{3.1}$$

where ρ is the air density, A is the rotor swept area, w is the wind speed and C_p is a turbine-specific power coefficient reflecting the aerodynamic, transmission and mechanical-electrical efficiencies of the turbine [7]. We will look at all these parameters in the following sections.

3.1.1 Power coefficient

According to German physicist Albert Betz, no turbine can have a power coefficient higher than 0,593 and thus cannot convert more than 59,3% of the kinetic energy of an undisturbed wind

Figure 3.1: *A typical power curve of a wind turbine*



Source: www.windpowerengineering.com

flow into mechanical energy, implying that there is a natural limit to the efficiency of a turbine, regardless of future technological developments. This is called the Betz Limit, however, it is a theoretical result based on a frictionless setup with no losses and therefore real-world turbines can never reach this level of efficiency no matter how well designed they are or were to be. Once you account for factors such as the aerodynamic, transmission and mechanical-electrical efficiencies of the turbine this limit is commonly in the range of 35-45% [114].

3.1.2 Rotor swept area

The rotor swept area is given by the formula for the area of a circle, which we know to be

$$A = \pi r^2 = \frac{1}{4}\pi d^2 \tag{3.2}$$

Where r is the radius of the rotor, i.e. the length of one blade and d is the diameter of the swept area.

From equation (3.1) we see that produced energy of the turbine increases linearly with the rotor swept area, implying that turbines with larger rotors produce more energy. While this conjecture is correct, it will not change the rated capacity of the turbine as this is limited by the generator. Therefore, an increase in the rotor swept area implies a gain in energy yield only if there is a simultaneous increase in the rated generator power. However, it is still a valid argument for increasing rotor size to improve wind power production as the production at wind speeds lower than the rated wind speed is still increased. Even when assuming the rated generator power increases when rotor sewpt area increases, some technical restrictions are still present prohibiting the blades from increasing in size indefinitely. As they get longer, they also get heavier, which makes them more expensive, so the material used to build them need to both have the right stiffness-to-mass ratio and be cost effective in order for the gain in power production to not be exactly or more than offset by the increased costs [99].

3.1.3 Air density

The density of the air is given by the following relationship

$$\rho = \frac{P}{R \cdot T} \tag{3.3}$$

Where P is the air pressure, R is the gas constant, which reflects the humidity of the air and T is the temperature [98].

We will not go into detail with the factors that determine the air density as we feel it is out of the scope of this thesis and also because air density generally does not affect the power production significantly. We will however briefly discuss the effect changes in air density has on power production. It is instructional to note that just like air pressure, air density is decreasing with increasing altitude [124]. From equation (3.1) we see that power production increases linearly with increasing air density and therefore if we look at the isolated effect of changes in air density, increasing the hub height of a wind turbine will have a negative impact on power production. However, this effect is more than offset by the increasing mean wind speeds in higher altitudes, which we will discuss next.

3.1.4 Hub height

Although hub height is not included in the formula for power production, it has a significant effect on power production as wind speeds are increasing with increasing altitudes, like mentioned in Section 2. This follows from the wind profile power law, which is a relationship between the wind speeds at one height and another. It is given by the formula

$$w = w_r \left(\frac{h}{h_r} \right)^{\alpha} \tag{3.4}$$

Where w is wind speed, h is height, w_r and h_r are the wind speed and height of a reference height where the wind speed is known and α is the Hellmann exponent, a coefficient accounting for the roughness of the terrain and the stability of the air [125].

Therefore, the modest negative effect on power production from decreasing air density with increased hub height is more than offset by the fact that mean wind speed gets higher with altitude. This is the main argument for building increasingly higher turbines to improve power production and combined with a larger rotor there is significant potential for improved production. This has been known in the industry for a while and as a result, turbines have gotten increasingly large since the first wind farm was commissioned in 1991 as can be seen in the figure in Appendix A.5. However, there are drawbacks to building increasingly large turbines as well. Higher towers costs more in materials and, more importantly, the foundations need to be bigger and stronger to support the higher towers and bigger rotors on the turbine. As we will see in Section 7.1, foundations account for a significant amount of the total capital expenditures of a wind farm. As a result of this, a point is likely to be reached where returns to scale of turbines will be decreasing as the marginal increase in power production and thus revenue will be offset by higher costs.

3.2 Loss factors

Until now, we have been focusing on the factors driving production up and so in this section, we will focus on the factors driving production down. There are several loss factors to consider when analysing the production of an offshore wind farm, too many for us to deal with them all in details, so we will strive to give the reader an overview of the most important ones.

When analysing the loss of production of an offshore wind farm, the starting point is the gross energy production, which is the production of the wind farm entirely without losses. It can be interpreted as the hypothetical production one gets when matching the wind speeds at hub height with the power curve of the turbines. From here, the losses are withdrawn one by one to ultimately yield the net energy production of the wind farm [4].

The most significant loss factors affecting an offshore wind farm include wake loss, availability and electrical efficiency. In the following, we will look at these three in turn, and in the end we will look at some other typical loss factors, besides those three mentioned, that affects an offshore wind farm.

3.2.1 Wake loss

Wake losses results from obstacles prohibiting the wind from flowing freely and thereby slowing down the wind and creating turbulence which lowers the electricity output below the theoretical gross output. It can be caused by all sorts of different objects standing upstream from a turbine or from the general topography of the surroundings. It is generally classified into two categories, namely internal or external wake loss.

Internal wake loss is the wake loss resulting from wind turbines in the same wind farm standing upwind of each other and thus slowing down the wind and creating turbulence which results in a loss of production for the other turbines. This happens as the rotor extracts some of the kinetic energy from the wind, resulting in a lower speed and less energy available in the wind stream after passing through a rotor. Therefore the turbines downwind will have less energy to extract from the wind and thus production will be lowered.

External wake loss is the wake loss caused by objects other than the turbines in the same wind farm. Onshore objects such as hills, trees and buildings and the topography of the terrain in general have an effect on the production of onshore wind farm. Depending on the location of the wind farm and the mast used to measure the wind resource at the site, this effect might already be reflected in the wind measurements and thus already be reflected in the theoretical gross energy production. Also, the wake effect dies out after some distance when the wind recovers. Therefore, the wake effect from the topography of the onshore terrain and objects such as buildings does not affect most offshore wind farms, being as they are placed on the water some distance from shore. This is also the case for the Project.

However, the external wake effect caused by neighbouring offshore wind farms can be substantial for offshore wind farms. When constructing an offshore wind farm near existing ones, the new wind farm will likely experience wake loss caused by the existing ones when the wind is blowing from the direction of the these neighbouring farms and this need to be taken into account when evaluating a project. However, the existing wind farm will likely also experience wake effect caused by the new. This is neither optimal or fair for the existing wind farms as their business case most likely did not include this wake loss when the decision to build was made. As a result, new wind farms may have to compensate the neighbouring wind farms for the loss of production caused by the project if it is built.

As evident from the above discussion, it is very important to consider the spacing and placing of the turbines in a wind farm both in relation to the terrain, other wind farms and the other turbines in the same farm in order to minimise wake losses. However, this cannot be done solely based on a mathematical optimisation model as there are technical, legal and environmental aspects to consider as well. For instance, a turbine's location will depend on the seabed condition and therefore an unexpected dent in the sea bed may make it necessary to locate the turbine sub-optimally relative to the neighbouring turbines as the foundation will otherwise need to be undesirably high.

3.2.2 Availability

Another loss factor affecting the electricity production of an offshore wind farm is availability, which can be defined as the percentage of time that a wind farm is available to generate electricity expressed as a percentage of the theoretical maximum [4]. A more mathematical term has been defoned by the International Electrotechnical Commission,

$$Availability = 1 - \frac{Unavailable\ time}{Available\ time + Unavailable\ time} \tag{3.5}$$

The total availability of a wind farm captures all the following categories of availability:

- *Turbine Availability:* the expected average turbine availability of the wind farm over the lifetime of the project
- *Balance of Plant (BOP) Availability:* the expected availability of turbine transformers, on-site electrical infrastructure and the substation infrastructure up to the point of connection to the grid
- *Grid Availability:* the expected availability of the electrical grid needed to export the electricity produced

Breakdowns and failures are crucial factors in determining the availability of a wind farm and have not only one but two negative effects on a project. First, there is the costs associated with maintenance and reparations of the park, Opex, which will be discussed in Section 7.2. Secondly, there is an effect on the production. When a wind turbine experiences a breakdown it cannot produce electricity until the breakdown is fixed. The length of the breakdown, called the downtime, can vary from hours to days depending on the complexity of the breakdown. In the meantime the production of the wind farm will be lower than expected.

The turbine has the largest impact on total availability and therefore most studies has directed the focus towards this. To estimate the turbine availability, an investigation of failure rates of the different components in the turbine and the resulting downtime can be done. However, data for existing wind parks on breakdowns, downtime and availability is very limited due to confidentiality in the industry about this. Turbine manufacturers and owners of a wind park do not want to advertise how many breakdowns that occurs to the public, policy makers or investors. Secondly, the business is very competitive, so most information about technology and production is kept very secret in order to prevent competitors from gaining knowledge that can be leveraged to improve their own products or leaked to relevant stakeholders when deemed profitable for the competitor.

In the following section, we will briefly highlight some of the findings from different studies in relation to failure rates and downtime's in order to give the reader an overview of the current industry consensus regarding total wind farm availability. We will use this in our discussion of the availability for the Project later in this section.

The failure rate of a wind turbine is expected to follow a so-called bathtub curve. In Appendix A.6 is an illustration of such a curve. A bathtub curve indicates a higher failure rate in the beginning and end of the lifetime for the turbine, and a lower steady-state failure rate. The curve is divided into three periods, beginning with a high but decreasing failure rate called Infant Mortalit. This is primarily driven by failed preliminary work that is quickly fixed, resulting in the decreasing failure rate. It then reaches the steady-state level, called Normal Life, where failures occur, but at a lower and more steady rate. In the end of the turbine's lifetime it reaches the the End of Life Wear-Out stage where the failure rate increases again [40][75].

It is very important to distinguish between investigations for onshore and offshore projects because offshore projects tends to have a lower availability for several reasons. One is that the downtime usually is significant higher for offshore parks, primarily due to the longer transportation time for engineers to reach the park before they can start fixing the problem [21][43]. Secondly, the offshore industry is relatively new and immature compared to the more mature onshore industry and therefore uses a less mature technology. The technology has therefore not been optimised as much, resulting in higher failure rates for offshore wind farms.

Two studies have investigated the failure rates and average downtime of specific components in the turbine with data from offshore wind parks in Germany. In Appendix A.7 is an overview of the results from the two studies[40][43]. As seen from the figures, there are many different components that can break down in a wind turbine. The electrical systems and electronic control have the highest failure rates in both studies, but luckily for wind farm owners, also some of the smallest downtime estimates. On the other hand we have the drive train, generator and gearbox, all of which have a very long downtime of approximately six days, however, the failure rate of these components is very low implying a break down every 20 years for the drive train, while the generator and gearbox experience a break down every 10 years.

Most studies include the Balance of Plant availability in their analysis, but leave out the grid availability and assume it to be available at all times. The grid availability is out of control for the owners of the wind parks in Germany, and thus an external factor, but it still needs to be taken into account when valuating the Project. Interestingly enough, in Germany there has been some troubles with delayed grid connection resulting in total unavailability of the grid for some time, giving rise to large losses in revenue [64]. This happened as a result of the way grid operation was handled in Germany, where the offshore connections are constructed, owned and operated by TSO. Prior to 2013, TSOs were legally obligated to guarantee grid connection to all projects, which resulted in many projects not getting connected to the grid as planned, becuase TSO could not keep up with the demand for grid connestions. This sparked a change of regulation and grid connection is no longer guaranteed, but allocated to developers in a way that allows for transmission assets to be shared across wind farms[64].

3.2.3 Electrical efficiency

The last loss factor we will discuss is the electrical efficiency. In all electrical systems, there are losses arising when transporting electricity from one place to another and this is also the case for offshore wind farms. A small part of the electricity production will be lost due to electrical inefficiency in the cables linking turbines to the onshore substation. As a result there will be a small discrepancy between the energy production measured at the turbines and the energy production measured at the point of connection to the electrical grid from where the electricity is exported. Also another small part of production is lost due to own consumption from the wind farm. The electrical equipment of the wind farm consumes electricity and when in operation this electricity is taken from the energy produced, which results in a loss of production. Moreover, the electrical equipment of a wind farm will also use electricity even though the wind farm is not operational which can be because of a breakdown or because the wind speed is below cut-in speed or above cut-out speed. Energy is needed to keep electrical equipment such as anemometers, wind vanes or even lights used for signalling a wind farms location to aeroplanes. This energy is supplied from the grid, which is then subtracted from the production later [4].

Several studies of the electrical efficiency of wind farms have been carried out and the total loss resulting from this is generally measured to be in the range of 2-3% of annual electricity production [24][28].

As an interesting perspective, the fact that wind farms need power whether operational or not when they have finished construction makes the timing of the connection to the grid important. If grid connection is not possible when a wind farm finishes construction, not only can the wind farm operator not export its power and sell it, resulting in lost revenues like we discussed in the above section, but it can neither get electricity needed for own consumption which in some cases can lead to damages to the turbines. Therefore, wind farm operators will in this case likely have to supply electricity to its own wind farm using large batteries or diesel powered generators resulting in extra costs. So not only will delayed grid connection cost the project operator in terms of lost revenue, but it will also cost in terms of extra expenses. Therefore, we reiterate that attention needs to be paid to the regulatory frame work surrounding late grid connection.

3.2.4 Other losses

Other loss factors include turbine performance, environmental factors and curtailment. Turbine performance relates to power curve adjustments and high-wind hysteresis. Losses arise if the turbines do not perform as promised, but typically the risk of this is mitigated in the Turbine

Supply Agreement, TSA, where the turbine manufacturer provides a power curve warranty. This warrenty requires them to pay compensation if the realised power curve is not as good as promised. Losses from hysteresis occur when turbines are intentionally slowed down in high winds close to the cut-out speed, to prevent repeated start-up and shut down of turbines, which can cause significant fatigue loading [4].

Environmental loss factors are related to the weather conditions at the site and includes losses due to blade degradation, accumulation of dirt or ice on the blades, which can reduce aerodynamics of a blade and high temperature shut downs to prevent overheating [4].

Curtailment is the loss incurred in certain instances of supply and demand imbalances where there is a excess supply of electricity after demand has been met. This can be related to different things, typically as a consequence of constraints in distribution and transmission networks and as a precautionary measure to secure stability of the system when there is a high risk of extreme weather or grid faults. This is widely discussed in academia today as the deployment of renewables has introduced this phenomenon to electrical grids and the continued penetration of these technologies are expected increase curtailment in the future [15]. This happens as a result of the higher volatility and less predictability of renewable power generation, which makes capacity planning hard for grid operators. Although this is an interesting and very relevant field of study in relation to both wind power and other renewable technologies, we will not go further into detail with it in our analysis, but will simply include it in our estimate of other losses.

3.3 Constructing the power curve

Now that we have introduced all the necessary theory about power production, we can start modelling the power curve we will use to convert the forecasted wind speeds and directions into actual power production. As the Project in our base case is expecting to use 13 MW turbines not on the market yet, this will be based on a range of assumptions of how the future turbines will perform. As power curves are some of the most secret elements of the offshore wind industry, we have not been able to get much information about the expectations and as such the model we develop will rely on scarce information and to a wide extent on our own intuition and logic.

The power curve will be constructed based on the theoretical power captured by a turbine given in equation (3.1). Therefore, we need to estimate all the necessary parameters for the turbine expected to be used in the Project.

3.3.1 Turbine characteristics

General Electric has announced that they are developing a 12 MW turbine which they expect to have ready for deployment in 2021. They expect the turbine to have hub height of 150 m and carry a rotor on 220 m in diameter [113]. Compared to one of the largest turbines available today, the Vestas V164 turbine of 8 MW rated capacity, which sits at 113 m hub height and carries a 164 m rotor, this 12 MW turbine is going to be a giant and the reality of such enormous turbines does not appear to be very far out in the future.

In June 2017, Wind Europe, the former European Wind Energy Association, published a report in collaboration with BVG Associates, a technical and economics consultancy with expertise in wind energy, in which Europe's offshore wind potential towards 2030 is analysed. In their analysis, they include a case study of future offshore wind farms in scenarios where wind turbines of 13 MW and 15 MW, respectively, have become available. They make detailed assumptions on the characteristics of these turbines and combined with the characteristics of General Electric's 12 MW turbine, we can use this to make estimates of our own on the characteristics of the turbines to be used in the Project. In Table 3.1, we present the characteristics of General Electric's 12 MW turbine, Wind Europe's 13 MW and 15 MW turbines and our estimated 13 MW and 15 MW turbines [77].

Table 3.1: *Turbine characteristics*

Turbine (MW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Hub height (m)	Rotor diameter (m)	Rotor swept area (m^2)	Air density (kg/m^3)	Power constant (%)
GE 12	n.a.	n.a.	n.a.	150	220	38,013	n.a.	n.a.
WindEU 13	n.a.	n.a.	n.a.	128	212	35,299	n.a.	n.a.
WindEU 15	n.a.	n.a.	n.a.	136	228	40,828	n.a.	n.a.
Model 13	4	10.63	25	155	225	39,761	1.21	45%
Model 15	4	10.83	25	160	235	43,374	1.21	45%

As we can see in the table, General Electric's 12 MW turbine has a bigger rotor than Wind Europe's hypothetical 13 MW turbine. Since General Electric's turbine is an actual turbine currently being developed, we believe it presents a more accurate estimate of the turbine size. Since our turbines have higher ratings, we set the rotor of our 13 MW to be a little bigger and the 15 MW a little bigger again. Rotor swept area can then be calculated using equation (3.2).

The height of a turbine needs to follow the rotor size, at least to the extent that the rotor is not too close to sea level. So in order to use a larger rotor, hub height needs to be larger as well. From the tip of the blade pointing straight down to the ground of the General Electric turbine there are 40 m, and for the Wind Europe turbines there are 22 m, calculated simply by subtracting half the rotor diameter from the hub height. Again, we have decided to rely more on

General Electric's actual turbine and have set the hub height of our turbines so the distance from the rotor to sea level is 42,5 m.

We calculate the air density with equation (3.3), using a standard air pressure (P=10^5 Pa), dry air (R=287,058 $J/(Kg \cdot K)$) and a constant temperature of 15 °C (T=288,15 K) [98]. The power coefficient, we choose to set to 45% as this is the top of the typical range for modern turbines as we established earlier, which we believe is a fair assumption to make given that the new turbines represent a newer technology that has been improved and therefore will likely, at least have as good a power coefficient as the best turbines available today. Investigating the capacity factor later on will shows is this estimate ensurer a capacity factor aligned with expectations in the industry.

For simplicity, we set the cut-in speed of both turbines to be 4 m/s and the cut-out speed to be 25 m/s, the same as the Vestas V164-8MW turbine and generally in line with industry standards [132]. Now we can calculate the rated speed by rearranging equation (3.1) to get

$$w = \sqrt[3]{\frac{P}{0,5\rho A C_p}} \tag{3.6}$$

Using the inputs established above, we get a rated speed of 10,63 m/s and 10,83 m/s for the 13 MW and 15 MW turbine, respectively. Note that the increased rotor size for the 15 MW turbine is not enough to compensate for the increased power. Thus the rated speed will be larger for the 15 MW turbine which might result in a slightly lower production compared to the 15 MW turbine on a park level. It seems fair to assume this if the 15 MW turbine develops in time, they will not have had the chance to optimize every aspect of the turbine yet. To lower the rated power of the 15 MW turbine they could increase the size of the rotor even further or work on an increase in the power constant. Both would lower the rated speed according to equation (3.1). The rated speed of the Vestas V164-8MW is 13 m/s, which implies that our modelled turbines reach their rated capacity at lower wind speeds.

3.3.2 Increased hub height

As we have discussed, wind speeds are increasing with altitude and therefore using a turbine with a hub height of 155-160 m needs to be accounted for in our model. In Section 2, we used data from an anemometer located 90 m above sea level and made our simulations according to this height, so we need to extrapolate our wind simulations to the increased wind speeds reached at higher hub height.

We will use the wind profile power law presented in equation (3.4) and to do so, we need to estimate the Hellmann exponent. This is often assumed to be $1/7 \approx 0,14$ for flat terrains, but as we will see, this does not fit our data very well [14]. Wind Europe use a Hellman coefficient of 0,12 in WindEurope (2007) [77], but again this does not fit our data well. Instead, we will estimate it from the actual wind speed data.

We have data on the wind speed at the FINO1 site for seven different heights ranging between 33 m and 90 m. Taking the average wind speed at each of these heights and using the data from 90 m as the reference height, we can estimate the Hellmann coefficient by minimising the sum of squared errors between the observed average wind speeds and the ones estimated with equation (3.4). Mathematically, this can be stated as

$$\min_{\alpha} \sum_{i=1}^{7} \epsilon_i^2 \tag{3.7}$$

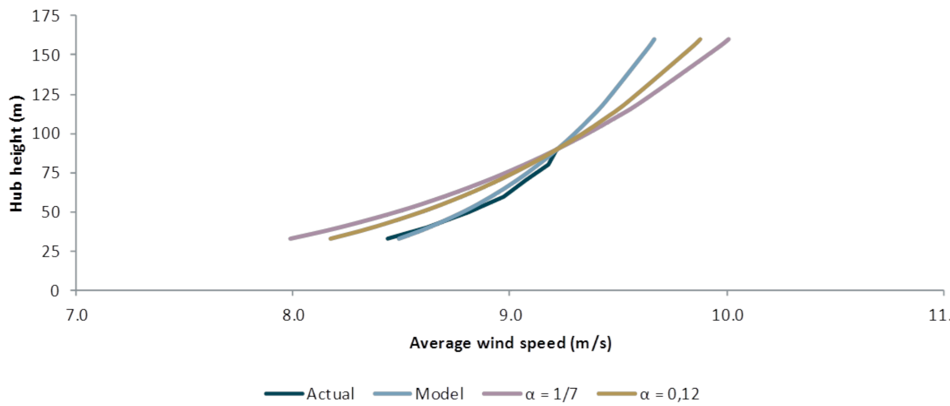
$$\text{with } \epsilon_i = w_i^{actual} - w_7 \left(\frac{h_i}{h_7}\right)^{\alpha} \tag{3.8}$$

Where $i = 1$ corresponds to 33 m, $i = 2$ to 40 m, $i = 3$ to 50 m and so on up to $i = 7$ corresponding to 90 m height. Doing so yields a Hellmann coefficient of $\alpha = 0,0823$, which provides a nice fit to the observed data as can be seen in Figure 3.2.

Now we can use the estimated Hellmann coefficient to find the average wind speed at the hub height of each turbine. Doing so yields an average wind speed of 9,64 m/s and 9,67 m/s for the 13 MW and 15 MW turbine, respectively, compared to the 9,22 m/s average wind speed at 90 m. This implies that wind speeds *on average* are 4,6% and 4,9% higher at 155 m and 160 m compared to at 90 m and we will use these factors to extrapolate our wind speed simulations from 90 m to the hub height of the respectively turbines. In Figure 3.2, the extrapolation of the mean wind speed using our estimated Hellmann coefficient, the $\alpha = 1/7$ and the $\alpha = 0,12$ can be seen. It is obvious that the two other models provide worse fit to the historical data than our model. They both overestimate the mean wind speed at the increased hub height and using one of these rather than our model would lead to significantly higher wind speeds which in turn would result in significantly higher production and revenue. Therefore, we see that the method used to extrapolate the wind speed to the actual height of the turbines is important.

Now we have corrected the wind speed to reflect the increased hub height, but the average wind speeds of 9,64 m/s and 9,67 m/s we have found are still too low compared to what Ørsted announced when they won the Project. As we discussed in the introduction, one of the factors that enabled the zero-subsidy bid was the very attractive wind resource at the site, with measured mean wind speed above 10 m/s and among the highest measured across Ørsted's entire offshore wind portfolio. This discrepancy can most likely be explained by the fact that we use data from the FINO1 mast located some 25 km from the Project site, whereas Ørsted surely has conducted a thorough wind measurement campaign directly at the site prior to bidding without subsidy. They

Figure 3.2: *Extrapolation of mean wind speed from 90-160 m hub height based on historical data*



Source: Own construction

surely invest quite some time and resources in this and therefore their measured mean wind speed is surely more accurate for the site than the data from the FINO1 mast. As we discussed above, wake from the surroundings can vary from site to site so a discrepancy between the mean wind speed at the site and 25 km away is not unlikely. We therefore feel it is necessary to correct our wind speed simulations to reflect the higher mean wind speed stated by Ørsted in order to get a realistic impression of the Project.

We will do this by correcting the wind speed first to reflect the increased hub height as explained and then by a factor of 6% *on average* to reflect the discrepancy between measurements from the FINO1 mast and the wind speed measured by Ørsted at the site. Doing so, we get a mean wind speed of 10,22 m/s and 10,25 m/s, for the 13 MW and 15 MW turbine respectively. After consulting industry professionals from Ørsted, we have confirmed that this correction is adequate and strictly necessary to reflect the true conditions at the site more precisely. The 6% is chosen only to take the average wind speed a little above 10 m/s and thus there is no deeper thoughts behind this exact estimate.

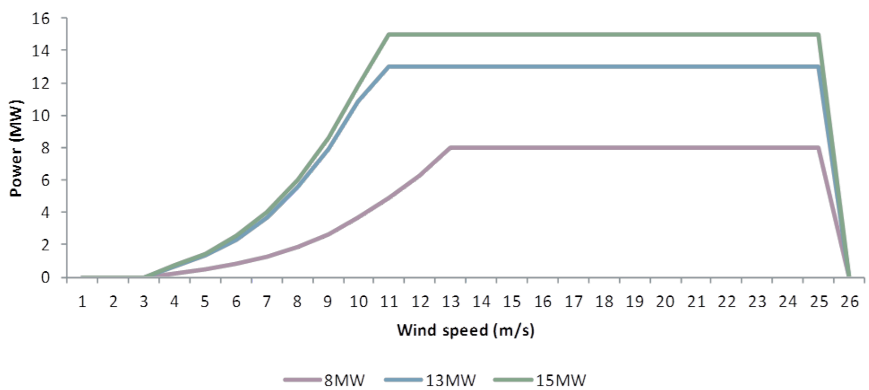
3.3.3 The power curve

We now have all the necessary inputs and can compute the power curves of our turbines using the equation

$$P(w) = \begin{cases} 0 & , for\ w < w_{\text{cut-in}} \\ 0 & , for\ w > w_{\text{cut-out}} \\ \min(\frac{\rho}{2} A C_p w^3; w_r) & else \end{cases} \tag{3.9}$$

Using the notation of equation (3.1) and w_r as the rated speed of the turbine. The resulting power curves are seen in Figure 3.3. For comparison, the power curve of the Vestas V164-8MW can also be seen, calculated in the same way as the others and based on the numbers stated in [132]. The power curve for the 13 MW and 15 MW turbine can be seen to have significantly lower rated speed than the 8 MW turbine, which is a result of the increased rotor swept area and our assumption of the relatively high capacity factor, due to technological development.

Figure 3.3: *Comparison of power curves of 8 MW, 13 MW and 15 MW turbines*



Source: Own construction

These constructed power curves ignore losses altogether and are therefore called the free WTG (Wind Turbine Generator) power curve. This can be a good benchmark power curve to use when comparing different turbines or different wind farms, but for finding the actual production of a turbine adjustments need to be made to account for the loss factors discussed above.

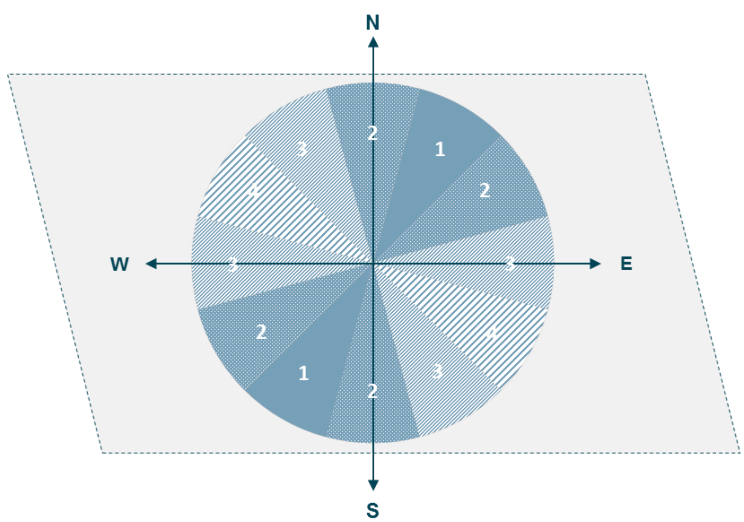
3.3.4 Applying wake loss

Wake loss is the largest of the discussed loss factors, and thus it will seem reasonable to assume that wind farms are designed in such a way that the wake loss is minimised. A previous study has estimated the wake loss of the Danish wind farm Horns Rev I, a farm consisting of 80 turbines with a hub height of 70 m, to be around 11% [62]. Investigating the design of Horns Rev I reveals that this wind farm is designed as a parallelogram [86], a design we will use as a reference for a wind park that minimises a wake loss. For simplicity we will assume a design of Project which allows us to implement wake losses to the Project in an easy way. Based on the design of Horns Rev I we assume that Ørsted will construct the Project with a design very similar to Horns Rev I.

In relations to this we assume that, excluding the possibility for other factors affecting the design, that Ørsted will design the wind farm in such a way that wake losses are minimised when the wind is blowing from the direction that is both most frequent and have the strongest winds and assign this direction the lowest percentage of wake losses. From there, the remaining directions will be assigned higher percentages of wake losses according to how close to the optimum direction they are.

In Section 2, we established that the direction with highest frequency and wind speed was SSW. When wind is blowing from the exact opposite direction, that is NNE, the turbines are able to turn 180 degrees and the design of the wind farm will be so, that the wake loss experienced from this direction is the same as from SSW. We will call this the wake loss zone 1 and apply a 5% decrease in power production due to wake losses when the wind is blowing from a direction in this zone. Now, the directions immediately next to wake loss zone 1 directions will be termed wake loss zone 2, those next to these wake loss zone 3 and finally those next to wake loss zone 3 will be termed wake loss zone 4. A graphical representation of this can be seen in Figure 3.4. We will apply 8%, 12% and 15% for directions in wake loss zone 2, 3 and 4, respectively. Taking a probability weighted average of the resulting wake loss yields an overall wake loss of 10,1%, which corresponds with the wake loss seen in [62] for a park with the same design as the one we have assumed.

Figure 3.4: *Wake loss zones combined with parallelogram representing the design of the park*



Source: Own construction

However, we realise that these assumptions are rather strong and will not necessarily hold for the Project when it is constructed, but as we shall see, the overall annual wake loss of the wind farm resembles levels found in other studies [62]. Furthermore, after consulting industry insiders from Ørsted, we have confirmed that this way of modelling wake loss makes sense and is technically viable. Consequently, we will keep in mind that our assumptions regarding the wind farm design are rather strong, but as it will not have a material effect on the investigation as a whole, we will accept them and apply the described methodology in our model.

3.3.5 Applying availability

We estimate the total availability of the Project, including both turbine, Balance of Plant and electrical efficiency availability using the currently prevailing consensus among researchers of 90-96%.

Some studies have shown a negative correlation between availability and the turbine size [40][43]. Given that we expect the turbine size to increase up to 13-15 MW for the Project, we might need to adjust current estimates of availability in a negative direction. On the other hand, the offshore wind industry will be a more mature industry at the time of FOD, which will lead to a higher availability because the technology has been further developed. This has also been the case for the onshore industry, where the technology has developed through the years and achieved a current availability of up to 97-98% even though the turbine size also has increased in the onshore industry [43][92]. The offshore industry will have developed around 30 years when the Project will commence operation in 2024, and this development will of course have affected the the availability in a positive direction, even though there exists a negative correlation between failure rate and size of the turbine.

In their financial reports, Ørsted states their total availability, which was 93% in 2017 and 94 % in the first quarter of 2018 [82][83]. Because Ørsted's portfolio of wind production only consists of offshore wind farms, these estimates are probably some of the most accurate and reliable once available to the public. One thing about the availability stated in the financial report is of course to make sure what it actually covers. It is stated in the appendix of the report how Ørsted defines the availability: "*Total availability is weighted on the basis of the size of the individual wind farms. Availability is adjusted for breakdowns if compensation is received from the transmission owner*"[82]. This highlights another aspect related to the availability, the fact the contracts on availability between owner and manufacture of wind turbines etc. are a common thing in the industry. Thus the actual availability of Ørsted's wind farms might be lower than what is stated in the report, but compensation from the manufactures adjusts the availability upwards to a more real availability, seen from a financial point of view.

Motivated by the points made in the discussion above about bigger turbines and newer technology, and with the current availability of 94% stated by Ørsted, we will set the availability of the Project to 96%. The small increase in availability of two percentage points comes from the fact that the current availability estimate contains all Ørsted's wind farms, including some of the old once where the technology was very young. We expect these to have a negative impact on the stated availability, and therefore correct the stated availability upwards. The increase is also motivated by the more mature technology at 2024, but also the fact that the turbine size has increased, which is why we will not increase the availability by more than 2 percentage points, even though onshore availability has reached up to 98% availability.

3.3.6 Applying electrical efficiency and other losses

As mentioned above, electrical efficiency is typically in the range of 2-3% and we will set the losses due to electrical inefficiencies to the bottom of the range, at 2%. We decided to do so as the technology behind electrical grids are not likely to be much improved as grids for the transportation of electricity are no new technology and therefore the potential for efficiency improvements is low. In the absence of a big technological development happening that eliminates electrical inefficiencies completely, we only see minor improvements happen and therefore the bottom of the current range seems a fair approximation.

The remaining losses we need to include are power curve efficiency, environmental factors and curtailment, which we will bundle together as "Other losses". In their annual Monitoring Report, the Bundesnetzagentur find that curtailment for renewable energy in Germany in 2016 can be estimated to 2,3% [19]. For power curve efficiency and environmental factors it has been difficult to find a useful study, probably because these factors are relatively small compared to the other factors. (EWEA, 2009)[4] finds that total losses of gross production are estimated to be in the range of 10-20%, implicating that we already are in the high end of this spectrum. We will then assume little impact by environmental factors and estimate other losses to be 3%, mostly driven by curtailment.

3.4 Power generation results

Now we will turn to how we are going to implement the power curves to get the wind farm production.

In Figure 3.1, we saw the free WTG power curves for an 8 MW Vestas turbine and for our modelled 13 MW and 15 MW turbines. However, in order to be able to match our simulated wind speed and directions with a power curve, we need to have the power curve given in units of *energy*. It is important to distinguish between power and energy and the power curves in Figure 3.1 are given in units of power. Energy is the capacity needed to perform work whereas power is the *rate* at which energy is produced or used. Power can therefore be measured at any given time whereas energy can only be measured over a given period of time. So in order for us to determine the energy production, we need to convert the power curves from a measure of power to a measure of energy, from MW to MWh. If a turbine operates at a rate of 13 MW for an hour, it has produced 13 MWh and if a wind farm consists of 37 turbines, like the Project does in the base-case, and all of these are operating at 13 MW for an hour, it produces $13 \cdot 37 = 481$ MWh.

Since our wind data and subsequently our wind simulations are given in 10 minute intervals, we will construct the power curves accordingly so the wind speed of a 10 minute interval can be converted into energy production. Therefore we need to adjust the hourly energy production by a factor of 1/6 and thus if all 37 turbines are operating at maximum capacity for 10 minutes, the wind farm will produce $481/6 = 80$ MWh.

The production resulting from matching the wind simulations and the constructed free WTG power curve yields the gross energy production, that is, the hypothetical production in a world without losses. To get the net energy production, the described losses need to be subtracted.

To implement the described wake loss scheme, we need to make separate power curves for each wake loss zone. This is easily done by multiplying the gross energy production at any given wind speed by the wake loss percentage corresponding to the wake loss zone:

$$\hat{P}_i(w_i, d_i) = \begin{cases} P(w_i)/6 \cdot (1 - \psi_1) & , for\ d_i \in \text{wake loss zone 1} \\ P(w_i)/6 \cdot (1 - \psi_2) & , for\ d_i \in \text{wake loss zone 2} \\ P(w_i)/6 \cdot (1 - \psi_3) & , for\ d_i \in \text{wake loss zone 3} \\ P(w_i)/6 \cdot (1 - \psi_4) & , for\ d_i \in \text{wake loss zone 4} \end{cases} \tag{3.10}$$

Where i is an index of 10 minute time intervals, P is the gross power curve given by equation (3.9), ψ_k is the percentage wake loss of wake loss zone k.

Doing so, we get the power curves of energy production for each wake loss zones, which can be seen in Appendix A.8. Matching these with the wind speed and direction from our wind simulation yields an energy production close to net energy production, but availability, electrical efficiency and other losses still needs to be subtracted. This is simply done by multiplying with the 96% availability and subtracting the electrical efficiency loss of 2% and other losses of 3%.

Now we arrive at the net energy production over every 10 min interval, which can then be accumulated to daily, yearly and lifetime production for the wind farm. For our base-case scenario, we get the following result:

In Table 3.2 we have included the capacity factor which is a widely used measure of wind farm productivity. It is calculated as the ratio between the hypothetical energy production of a wind farm if it were operating at rated capacity at all times during its operational lifetime. The capacity factor is then the ratio of the actual production to this hypothetical rated production. A capacity factor on 48,7% aligns very well with the capacity factors of other German offshore wind

Table 3.2: *Energy production resulting from 1.000 MC simulations of wind speed and direction matched with constructed power curve*

Base case			
Production (MWh)	**Gross production**	**Net of wake loss**	**Net production**
Lifetime production	60,212,564	54,520,392	49,613,556
Mean yearly production	2,408,503	2,180,816	2,049,967
Mean yearly capacity factor	**57.2%**	**51.8%**	**48.7%**
Lifetime loss factor		**9.5%**	**17.6%**

farms, according to Energynumbers.info. In Germany capacity factors up to 48,6% are observed and capacity factors of 50,0% are also observed in Danish offshore wind farms [95]. With this level of capacity factor already present in the market, we are very confident in our estimates, both regarding the power curves but also the applied loss factors.

Furthermore, we see that the actual wake loss is 9,5%, which is slightly below the probability weighted average of 10,1% we found earlier. As the production is derived from our stochastic wind model, it is not unthinkable that we get a result slightly different from what we theoretically would expect. Had we simulated the production more than 1.000 times, we would expect the actual wake loss estimated in the model to converge to the theoretical, probability weighted average.

Ultimately, we arrive at a total loss of 17,6% from gross production to net production. This is somewhat below the 19,1% we would have expected, that is 10,1% wake loss, 96,0% availability implying a 4% loss from availability, 2,0% electrical loss and 3,0% other losses. Like with wake loss, this deviation may be due to variations in the distribution of wind directions resulting from the simulations. Had we simulated the wind more times than 1.000, we would expect the loss to converge towards 19,1%, but due to computational limitations, we decided to only do 1.000 simulations.

4 Spot Price

An investigation of the spot price is essential to the valuation of the project. The spot price is the price at which the electricity generated by the wind farm is sold, and therefore significant for the future revenue of the project.

4.1 Spot Price Characteristics

Like everything else, spot prices follows the classic economic theory of price equals the equilibrium between supply and demand. Electricity is a commodity, but the electricity market is very different from any other commodity markets due to the fact that electricity is continuously generated and consumed but the lack of storage results in a highly volatile market. In electricity market *daily* volatility up to 30% is common. To compare, the international stock markets have a volatility around 20% - on a *yearly* basis [5]. For a commodity that can be transported at a very high speed, electricity also tends to be very localized, mainly because of capacity constraints on the transmissions lines combined with the lack of storage [1]. When we have to model the spot price, we can decompose the high volatility into some sub parts which each explains some of the volatility.

First we try to break down the effect from limited transportation possibilities and the lack of storage, meaning all produced electricity has to be consumed immediately. This gives rise to very low prices when production is extremely high and demand is low, referring to the classic supply-demand theory. It can even be the case that prices will go as low as negative for a short time period. Because we consider daily averages of spot prices we will not expect this to occur very often, but nevertheless it is a possibility that we might have to consider in the model Sia Partners (2013) [111] investigates this phenomenon a little further and explains that we have experienced days with more than ten hours of negative prices, because energy producers are willing to pay to sell their electricity when the production is way above the demand, instead of shutting down their production. The same goes for the other case, in which an extraordinary high demand can be caused by some extreme weather situations. This results in a very high spot prices, especially if the supply at the same time is low. This could be the case if the weather became to extreme, so wind farms had to shut down because the wind speed exceeded the cut-out limit. These suddenly increase and drop in the spot price can be characterised as a price spike or jump, and is something our model need to account for.

Secondly, another important characteristic of power prices is the seasonal pattern, which is very unique in the sense that power prices faces a yearly, weekly and daily effect. The yearly effect can to some extent be explained by the extra need for warm and light during winter compared to the summer, if the market is placed in a country with cold winters. A country in a more tropical climate would most likely observe a high price during the summer from electricity required for air conditioning compared to the mild winters, like Germany. The weekly effect comes from lower price in the weekends, because most industrial production and business offices mainly operate Monday to Friday. The daily effect follows from a higher requirement of electricity during day and evening and a lower demand in the night. Because we will use an average daily spot price, the daily effect will not be present in out model. But if we had to model an hourly spot price model, we definitively had to consider this daily effect, because it is significantly present and shown in many studies of spot price [1][38].

4.1.1 Mean reversion

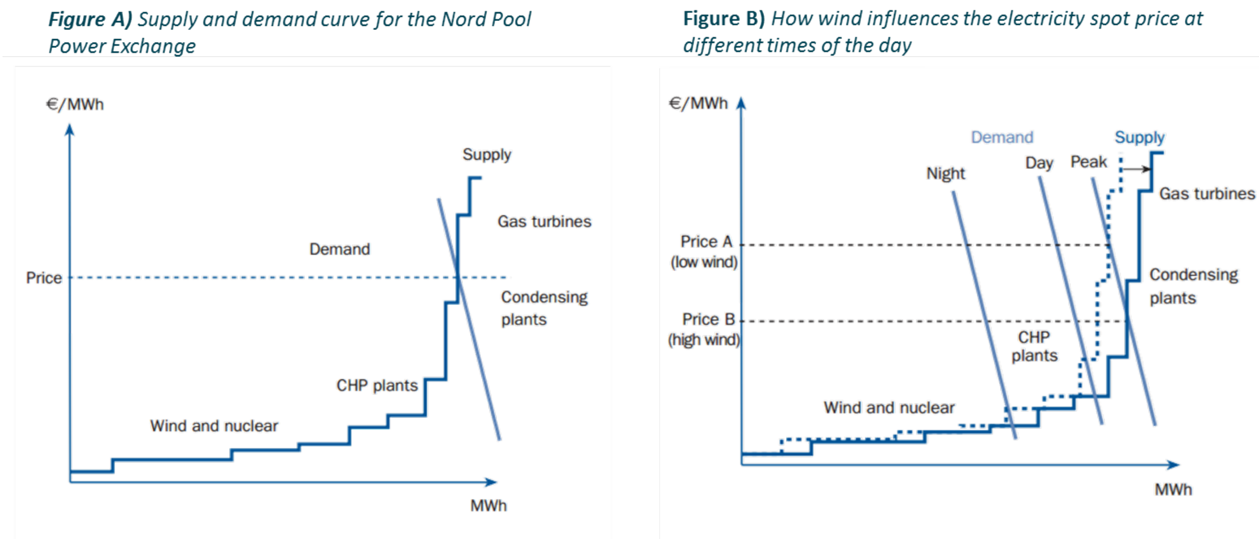
The introduced jumps in the spot price is almost immediately followed by a jump in the other direction. This jump takes the spot price back to the level it had before the jump occurred. The same goes for periods without jumps, the volatility is still high and prices moves up and down within a certain range of the steady state level of the spot price. This is also known as mean reversion, and a very important characteristic for spot prices. In general it is natural to consider mean reversion when modeling commodity prices [8]. One will not experience a spot price that acts as a random walk, so even though we will use a stochastic process to model the spot price, we need to make sure that the model will include a mean reverting component, such that the price won't explode in a positive or negative direction.

4.1.2 The Merit Order Effect

Electricity has a very inelastic demand curve, meaning that despite changes in the price the demand curve will almost remain unchanged. The community still needs electricity for everything, which results in an almost vertical demand curve. This means changes in supply will have a large immediately impact on the price, as already discussed. The supply curve in the electricity market consists of all the different energy sources available; Wind, nuclear, solar, hydro, coal, gas, etc. Some argue that competition does not exists in the electricity market, but with all these different suppliers, competition definitely exists. In a market with quasi-perfect competition, a product is sold at price equal to marginal cost. The merit order curve incorporates the supply of the energy sources and stack them according to their respectively marginal costs, as shown in Figure 4.1 below.

The graph to the left in Figure 4.1 shows the merit order curve for electricity, including renewable energy such as wind, solar etc. Renewable energy has the lowest marginal costs of all the energy sources currently available. This is because the production of renawable energy almost entirely rely on weather conditions. This is a contrast to the other energy sources which requires some kind of fuel in order to produce electricity, increasing the marginal costs. The introduction of renewable energy to the electricity market has shifted the supply curve to the right in the past years. To the same demand this gives a lower spot price compared to an electricity market without renewable energy. Increasing the supply from renewable energy in the market will again shift the supply curve to the right and reduce the spot price even further as seen in the graph to the right in Figure 4.1 where the dashed line is the supply before the increase in renewable production. The price of electricity before the increase in renewable production is determined by *Price A* - the intercept between supply and demand, which in this case is at a peak level - and the price after increase in renewable supply is lowered to the new intercept *Price B* [38]. It can also been seen

Figure 4.1: Merit order curve for electricity and the influence of a peak in wind supply

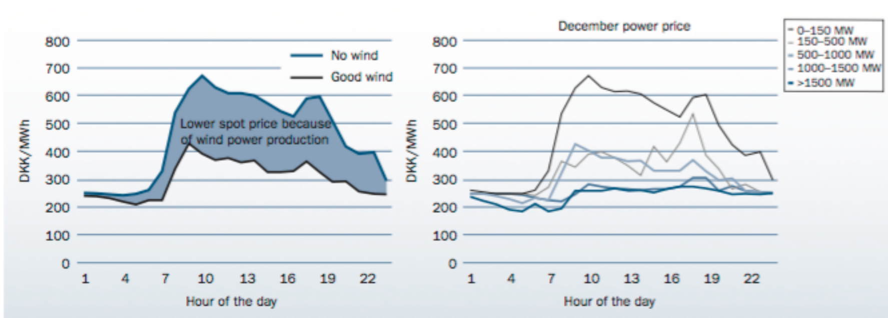


Source: *https://www.ewea.org*

how the demand shifts during the day as discussed earlier on, with a high demand during the day and a lower demand in the night.

The European Wind Energy Association has publish a report in which they study the effect of wind energy on the spot price. An illustration of this from the report is printed below in Figure 4.2. This Figure summaries some of the characteristics already discussed. During the day the wind tens to be stronger, generating a higher supply of wind energy and a larger impact on the spot price. This effect is illustrated to the left in the figure below. It also shows the effect of higher demand during day time which result in the higher price. To the right is a graph that shows five levels of wind power production and their respective spot price, on an hourly level. We see that increasing the wind power supply lowers the spot price significantly during the day, and it reduces most of the daily effect on the spot price. Thus we see a lower, but less volatile spot price [38]. This is something we will come back to later on when discussing the technological developments in the future, more precisely storage. However, when the supply of wind is at a minimum we will still experience a high volatility because the price has to jump to the marginal costs of some of the other energy sources. When increased penetration of wind in the market has lowered the spot price, this jump up to the next marginal cost will be a bigger jump, resulting in a higher volatility of the spot price.

Figure 4.2: Impact of wind energy on the spot price in Denmark, 2005.



Source: *https://www.ewea.org*

4.1.3 Intermittency

Wind energy falls into the category as an intermittent energy source, which is an energy source that is not continuously available for electricity generation. When the intermittenct energy source is unavailable other sources has to produce electricity, which accordingly to the merit order curve will be at a higher price. Thus it comes as no surprise that the average daily price received by an intermittent renewable, as wind energy, will be lower than the total average daily price due to the hourly price fluctuations in response to intermittent spikes during the day [120].

In the future, more production is expected to come from these sources: wind, solar and wave which will result in a more reliable production from intermittent energy sources. The increase of intermittent energy sources will have two major impacts on the electricity price. First, as already discussed, it results in a lower electricity price due to the merit order effect. Secondly, it will increase the volatility of the price due to the higher volatility in supply from intermittent energy sources [48]. The volatility of the intermittent energy sources is of course affected by the weather, and an increase in the production from these will result in a more volatile price because the periods with high and low production will be more extreme.

A Danish NGO called Danish Energy (*Danskenergi.dk*) has published a report of their expectations about the spot price in the future. This report of course focuses on Denmark, but it also includes expectations about the German and Nordic power market because they influence the Danish power market. In a recent study they find that the intermittency effect in Germany over the past years has been 10-15% [25]. In Appendix A.9 can be found a figure from the report in which the relative price pressure on wind from from 2009 to 2016 is illustrated. For Germany this varies between 6-14%, meaning that the average price received by wind is below the average spot price with this percentage.

In generel Germany has the highest relative price pressure for wind. There are several reasons for this, but one of the interesting is that the wind production in Germany is very unstable because of a high amount of onshore wind combined the fact that they have limited possibilities to balance the production with other cheap sources such as hydropower [25].

Over the last years the Germany coal power plants has developed their capability to reduce and increase the production during the day, so they can vary the production from 20% to 100%. The fact that the coal power plants can withdraw some of their production when the wind is blowing ensures a higher price for the wind, because the supply is lowered. This reduces the intermittency effect on the wind price [25].

Another important thing to address is the difference between offshore and onshore wind and their relation to the spot price. The onshore wind production will generally experience a higher intermittency effect due to the fact that the wind is more unstable compared to offshore wind. The wind flow also tends to be higher during the day, resulting in most of the production from the onshore wind farms falls during the day with high price pressure from solar energy as well. The offshore wind farms delivers a more stable production because the wind is more consistent over the sea, and thus they do not only produce during peak times. The total installed wind capacity in Germany at the end of 2017 was 55,6 GW with offshore wind accounting for 5,2 GW. This means the offshore wind industry only generated around 9,4% of the total wind production at the end of 2017. This indicates that the relative price estimated to 6-14% by Danish Energy reflects the price pressure of onshore wind because it accounts for such a large part of the total wind production in Germany [25]. Because of the more stable offshore wind flow we expect the intermittency effect to be lower than in the onshore case.

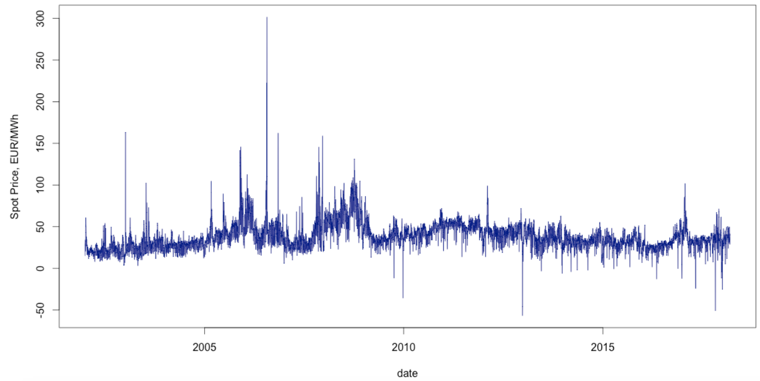
4.2 Constructing the model

We have chosen to construct a stochastic model for the spot price based on the historical observed spot price and combining this with our expectations about the future spot price. One could also have chosen to focus on the main drivers of the spot price, such as coal marginals and try to estimate these in the future to see how the spot price will develop. Because these future expectation are very difficult to predict, we have chosen to go with a stochastic model of the historical spot price, focusing on the price process and not the actual drivers behind the process. However, these drivers will still be discussed in Section 4.2.4 when we have to discuss the trend of the future spot price.

The model will be estimated from historical daily spot prices in the German Electricity market. The data period runs from January 1th 2002 to March 13th 2018 which gives a data set of 5.916 observations. Data has been downloaded from *Energinet* and is shown in Figure 4.3.

The graph shows many of the discussed characteristics about spot price, e.g. large volatility, price jumps, mean reversion and a declining trend in the end due to the merit order effect of

Figure 4.3: Historical daily electricity price in Germany



Source: *https://energinet.dk*

increased renewables in the market.

4.2.1 Stationary mean reversion

The very first step of the model is to find a stochastic process which we can develop the model from. A process called Geometric Brownian Motion (GBM) is well known for its easy implementation into financial models, and we will also use this model as our basic stochastic model. If we denote the spot price S_t at any given day t, it will satisfy the equation

$$S_t = S_{t-1} + \mu_S dt + \sigma_S dW_t \tag{4.1}$$

where μ_S captures the drift/mean of the process, σ_S is the volatility and W_t is a standard wiener process which has the following characteristics[8]:

- $W(0) = 0$
- W_t is normally distributed
- W_t has independent increments
- W_t is continuous

The GBM process will estimate the next step in the process by the current state plus a drift parameter and a stochastic element ensuring the daily volatility in the spot prices.

A mean reverting process can be incorporated to the GBM process in equation (4.1) in a similar way to previous studies by adjusting the drift parameter which gives the model in equation (4.2) [8][50].

$$S_t = S_{t-1} + \kappa(\mu_S - S_{t-1})dt + \sigma_S dW_t \tag{4.2}$$

This model is also known as an Ornstein-Uhlenbeck (OU) process and we can see that the drift parameter has changed. If the price is above its expected long term level, μ_S, the drift will become negative and pull the price towards its mean level. The same goes for the case where the price is below the long term level, the drift will then be positive, driving the price up towards the mean level. κ measures the speed of the reversion, a large estimated of κ will ensure the process quickly returns to mean level whenever it differs from this level.

4.2.2 Seasonality

Even though it is not clear from the historical data in Figure 4.3 that the spot price in Germany is influenced by a yearly seasonal component, several studies suggest to include a seasonal component in a spot price model [1][22][50]. The reason we cannot see the seasonal effect in the graph is due to the large data period that has to be fit into on relatively small graph, thus making it very difficult to identify summer and winter months. The weekly effect is also something to take into consideration, and several studies also includes this effect in the model.

Lucia and Schwartz gives two suggestions on how to incorporate a cyclical component for seasonality. One way is to include dummy variables and model both a weekend effect with a dummy and a yearly effect with 12 monthly dummies. In their second suggestion they still use the dummy for the weekly effect, but uses a sinusoidal function to model the yearly effect [50].

Cartea and Figueroa suggest to remove the weekly effect from the data preliminary to estimating the model. The yearly effect is then incorporated to the model with the use of a Fourier fit to the monthly averages [22].

Barlow also acknowledge the seasonal effect and incorporates the yearly effect with a sinusoidal function and suggest to use this approach for daily and weekly effect as well, if it is necessary to include in the model [1].

We will use a sinusodial function to incorporate the seasonal component into the model, in a similar way as Barlov (2002)[1] and Lucia (2002)[50]. This method is good when you expect a higher and a lower phase in the yearly effect, as we do with higher prices in the winter and lower prices during the summer. Because of the very long data period and our wish to create a generic and easy applying model, we prefer to avoid including dummy variables to our model. Thus we will also leave out the weekly effect from the model, because it cannot be implemented with a sinusoidal function.

We need consider the timing of the seasonality effect as well. The estimation will run from 1th of January, which is in the middle of the winter, meaning we have to make sure our seasonal component starts at a high level. To do so, we decide the use *cosinus* as our sinusoidal function, because $cos(0) = 1$, indicating that it starts at the highest possible level. The seasonal component will be added to the mean reverting model in the following way, which the reader might recognise as the same way we implemented a yearly effect to the wind model.

$$S_t = S_{t-1} + \kappa(\mu_S - S_{t-1})dt + \sigma_S dW_t + \cos(2\pi\beta t)\theta \tag{4.3}$$

with the two new parameters θ and β defined as below
β - Controls the timing of the cosinus curve, here one year, hence $\beta = 1/365$.
θ - Controls the effect of the seasonal component on the spot price.

4.2.3 Price jumps

The historical data in Figure 4.3 clearly shows the price jumps are a common phenomenon in the spot price. It also shows that the price spikes returns to the their steady state level very quickly.

We will implement the jump process in a similar manner to previous studies where the jump component is incorporated into model with use of the Poisson process as shown below [5][22]:

$$S_t = S_{t-1} + \kappa(\mu_S - S_{t-1})dt + \sigma_S dW_{1,t} + \cos(2\pi\beta t)\theta + \rho[S_{t-1}(\mu_j + \sigma_j W_{2,t})] \tag{4.4}$$

where the new parameters is defined as
ρ_t - Binary variable following a Poisson process with λ as the process' intensity.
μ_j - The mean estimate of price jumps
σ_j - The volatility estimate of price jumps
$W_{1,t}, W_{2,t}$ - Standard Brownian Motion identical to W_t in equation (4.1)

The Poisson process generates a binary variable that turns on the jump component, which increases/decreases the spot price with $\mu_j + \sigma_j W_{2,t}$. Based on the historical data we have chosen to allow for negative price jumps, even though we are considering daily spot prices. One could have imposed a minimum restriction to the jump process, with zero as the other option, so the daily price would reach zero when the jump process generated a negative price jump. However, we want our model to reflect the historical data, as well as our future expectations and we expect the negative price jumps to continue in the future. More on this later in this section.

The mean reversion component is not strong enough to bring the process back to the steady state level within a short time period. In order to bring the process back to its steady state level after a price jump, we implement a regime switching model. Such a model allows for more than more price process depending on the situation, which is exactly what we need. We will have two price stages - a general one that will model the spot price most of the time and a post-jump state in which we secure the price process to return to steady state right after a jump is observed. The general model will be the one already described in equation (4.4). The post-jump model will only be used the day after a jump has occurred, and it will follow the model below:

$$S_t = S_{t-1} + \kappa(\mu_S - S_{t-1})dt + \sigma_S dW_{1,t} + \cos(2\pi\beta t)\theta - \rho[S_{t-2}(\mu_j + \sigma_j W_{2,t-1})]\gamma \tag{4.5}$$

which tells us that the size of the jump at time t will be included in the post-jump stage with an opposite direction. The parameter γ controls how much the effect of the jump at time t will influence the spot price at time $t+1$

4.2.4 Trend

The last thing we need to consider when constructing a model for the spot price is if it has to include a trend. The discussion of this will be based on what the historical data suggest and what expectations we have about the development of the spot price in the future.

Several studies we have read suggest to include a positive trend when modelling the spot prices [1][22][50]. The way they incorporate trend naturally differs, some of them estimate the trend from historical data while others uses an industry estimate of the expected trend. It follows from the basic economic theory that inflation causes prices to increase in the future. This is probably one of the best arguments for including inflation in the model. Even though we might expect the industry to be more efficient in the future, we would also expect higher prices on labor and goods as a consequence of inflation. As a consequence the production will be more expensive which results in a higher marginal costs, and thus a higher price according to the merit order curve. It is important to realize that deciding only to include a inflation in the model as trend actually means including a zero growth, because the price will only follow the general economic. Including an actual trend means we expect prices to grow above the inflation rate.

Looking at the historical data in Figure 4.3 does not at first sight support any expectations of trend. The data period is more than 15 years which should be sufficient to detect a trend. However, one could argue that dividing the period into two sub periods reveals a small trend for each sub period. From 2002 until 2010 we can see a small positive trend in data and from 2010 to present this positive trend no longer exists. Actually one could argue it had been replaced by a small negative trend. There might be several reasons for this, but one explanation is the effect of renewable energy sources on the merit order curve, explained in Section 4.1.2.

In the future we expect renewable energy sources to increase even further due to ambitious political targets regarding installation of renewable energy sources [71]. Thus we expect a negative effect from this on the future trend of spot price. This is also confirmed by a study performed by Pöyry for EWEA [38], which states that an increased penetration of wind power will reduce the wholesale spot price. The negative trend from increased renewable energy production is very difficult to predict and the question is how long this trend will continue in the future. At some point the spot price will reach a steady state level for the renewable effect on the spot price.

As mentioned earlier on, it is important to identify the main drivers of the price if you want to understand the price and how it will develop in the future. *Energinet* has developed a detailed report about the influences of the spot price with help from *DanskEnergi*. Focusing on supply minus renewable production gives the production needed from power plants in order to balance the supply and demand in the electricity market. In Germany this production primarily comes from coal power plants, and thus the marginal cost of coal production plays a key role in determination of the spot price. This can also be seen in Appendix A.10 where the German spot price, wind price and marginal cost of coal have been illustrated together. Especially the relationship between the wind price and the coal marginal is very interesting, because it determines that the wind price in recent years has been driven by the coal marginal. Another interesting takeaway from the study is the intermittency effect illustrated as the gab between the spot price and the wind price, which fluctuates around 10% over the period [25].

Based on the strong correlation between wind price and the coal marginal it is relevant to consider the expectations about the coal marginal in the future. This marginal is driven by two factors; the price of coal and the quota price for CO_2 [25]. The price of coal is mostly driven by China who accounts for half of the yearly coal consumption. In 2016 China decided to cut 10% of their domestic coal production, which opened up for a larger import and thus a higher demand for coal. This price increase in not visible in the figure in Appendix A.10 because the price is an average yearly price. However, the price of coal was as low as 0,11 DKK/kWh (14,74 €/MWh) in febuary 2016 and doubled over the year to a price on 0,22 DKK/kWh (29,48 €/MWh), which is why we cannot see the very low price in the Figure [25]. The decrease in the coal price from 2010 and until 2016 aligns very well with the observed negative trend in the spot price. Thus the negative trend might not only be a result of increased penetration of renewables in the energy market, but also an effect from a decreasing coal price in the same period.

The quota price of CO_2 is the other driver of the marginal cost of coal, and this is highly interesting when focusing on the future. The political decisions associated with the quota is of highly relevance to the coal marginal. In Europe the quota price is determined by EU. One might expect these quota prices to increase in the future because EU is expected to be one of the main drives behind green energy. However, there are several ways to back the renewable transformation from the politicians side. They can either do it by subsidies, which has been the case so far, or with political decisions to increase the quota of coal, resulting in a higher spot price which generates higher revenue for renewable energy [25].

The German Federal Environmental Agency (UBA) has publish a report in which they state that the best way to achieve the national environmental targets is to reduce the coal production and start a process of eliminating coal production from the Germany energy market. In 2009 the German government set ambitious environmental targets with the aim of cutting greenhouse gas emissions with 40% by 2020 and 95% by 2050, compared to the 1990 levels [123]. Germany are a little behind its ambitious targets in the moment and UBA states that the best way to catch up on these targets are to start phasing out coal production in the electricity market. In fact Germany has already decided on changing 2,7 GW of brown coal plants form utility to capacity reserve [123]. Phasing out the coal production would increase the spot price because the next supplier of energy is gas, which has a higher marginal cost as seen in the merit order curve in Figure 4.1 and Appendix A.10.

General forecasts of the future spot price like the once from Energinet [37] andEnergistyrelsen [34] are available to the public. These forecasts take all things stated in the discussion above into account, such as increased penetration of renewables and the future expectations of the coal marginal. Both the mentioned forecasts expect the spot price in Germany to show a positive growth in the future. In Appendix A.11 is an illustration of the forecast from Energinet for the electricity price in various countries. Remember that Energinet was our source for the historical spot price data in Germany. They expect a little decrease in the spot price until 2020, but from there on they expect the spot price to increase significantly over the following 20 years, resulting in a yearly growth in the spot price until 2040 around $4,73\%$, which to us sounds extremely high.

Danish Energy Agency have also published a forecast and an illustration of this can be found in Appendix A.12. They expect the spot price to grow with a steady level until 2030. The yearly growth in the price from 2017 to 2030 is $5,19\%$. So both of them forecast a significantly growth rate of spot price.

We have decided to include the general economic trend in our model without questions. All the observed publications include a positive trend beyond the inflation, meaning no one question if there will be an inflation in the price, and neither will we. In general it is also a normal approach to include an inflation term in revenues and costs which of course has to be the same, because it sort of equals out the effect when we increase costs and revenue with the same factor, and thus the relative estimate of the inflation rate is not that significant to the results.

When including the inflation rate as the trend in our model, we have to use the daily inflation given from the estimated yearly inflation. The daily inflation is calculated as

$i = i_{daily} = (1 + i_{yearly})^{\frac{1}{365}} - 1$, and the daily inflation is then added to the model in the following way for the normal stage

$$S_t = S_{t-1} \cdot (1+i) + \kappa(\mu_S \cdot (1+i)^t - S_{t-1})dt + \sigma_S dW_{1,t} + \cos(2\pi\beta t)\theta + \rho[S_{t-1}(\mu_j + \sigma_j W_{2,t})] \quad (4.6)$$

and for the post jump stage

$$S_t = S_{t-1} \cdot (1+i) + \kappa(\mu_S \cdot (1+i)^t - S_{t-1})dt + \sigma_S dW_{1,t} + \cos(2\pi\beta t)\theta - \rho[S_{t-2}(\mu_j + \sigma_j W_{2,t-1})]\gamma \quad (4.7)$$

where one has to notice that the steady state price of the mean reverting component changes with the introduction of inflation to the model. This is because the long run mean of electricity prices will be affected by inflation, which implies that it has to be adjusted every time with the current inflation effect on the mean level, such that our mean reverting process will revert the process to the true mean of the process and not the constant estimated historical mean.

The model of the spot price now includes all the discussed characteristics and expectations for the future spot price in the Germany electricity market and we can continue with the estimation process.

4.3 Estimation of parameters

Final step in constructing the model is naturally estimating the parameters present in the final spot price model in equation (4.6) constructed above. The model include a lot of parameters with different estimation methods, which will be explained below. To give the reader a quick overview of this, we have printed the information in Table 4.1 shown later in this section.

The mean μ_s and standard deviation σ_s of the spot price is of course based on the historical data. One important issue to address regarding these parameters is the price spikes and their effect on these parameters. The price spikes is sudden chocks to the supply/demand and thus considered as outliers for the normal price process. Thus we need to identify these outliers and filter them out, before estimating mean and standard deviation. We will account for these outliers with our jump component, which is also why it will be wrong to have the jump effect included in the standard deviation of the normal price. The mean is a little more neutral to these price spikes because they occur as both positive and negative spikes in the historical data.

Usually one would use the standard deviation to define what might be considered as jumps and not just normal volatility of the process. One example is the use of two or three standard deviations, saying that everything that falls outside this range are considered jumps. However it is the standard deviation we are trying to estimate, so we will use an iterative process to reach the true standard deviation of the spot price. To start the process we take the standard deviation of the unfiltered data and decide on jumps in the price being prices outside the area of three times this standard deviations. The jumps are filtered out of the data, and we estimation a new standard deviation on the filtered data. This process continue until the standard deviation no longer changes, indicating that we have reached a steady state level for the standard deviation $\hat{\sigma_s}$. The mean can then be estimated on the filtered data with three times $\hat{\sigma_s}$ as the filter, resulting in the average historical price without jumps.

There is two commonly used ways of estimating κ, one is with Ordinary Least Square (OLS) and the other one is MLE. We have choosen to use OLS to estimate κ because it has a simple implementation. The estimation of κ with OLS is based on previous studies that have estimated the speed of mean reversion with use of OLS [16][65].

The stochastic difference equation for a standard mean reverting Ornstein-Uhlenbeck process is given by

$$dS_t = \kappa(\mu - S_{t-1})dt + \sigma dW_t \tag{4.8}$$

which can be written as a simple linear regression of the form $y = ax + b + \epsilon$ where $a = \kappa dt$, $b = \kappa\mu dt$ and $\epsilon = \sigma dW_t$. The parameters in the linear regression is estimated with OLS and from there estimates we can calculate our way back to an estimate of κ.

Because we are modeling the exact values of the spot price, not the returns, we are interested in the solution to the difference equation. This solution is gives by

$$S_{t+1} = S_t e^{-\kappa\delta} + \mu(1 - e^{-\kappa\delta}) + \sigma\sqrt{\frac{1 - e^{-2\kappa\delta}}{2\kappa}}W \tag{4.9}$$

Even though this formula looks complex, we can still write on the simple linear regression form with

$$a = e^{-\kappa\delta} \tag{4.10}$$

$$b = \mu(1 - e^{-\kappa\delta}) \tag{4.11}$$

$$\epsilon = \sigma\sqrt{\frac{1 - e^{-2\kappa\delta}}{2\kappa}}W \tag{4.12}$$

This means an estimation of κ can be done by regressing S_{t+1} against S_t and from the estimate of a defined as in equation (4.10) we can isolate κ as the only unknown parameter, $\kappa = -\frac{ln(a)}{\delta} = 276$

β ensures the right timing of the cosinus curve, which has to reflect the yearly pattern. The distance between peaks in a sinusoidal curve is 2π, and with daily observations we easily ensures the right timing by setting $\beta = 1/365$.

The seasonal effect on the spot price, θ is naturally considered in a manner similar to the one in the wind section when we estimated the same effect on the wind speed. We used the relative difference in wind speed between summer and winter to get the estimate of the seasonal component. As mentioned we can't see the seasonal effect in Figure 4.3 and applying the same approach as in the wind section leaves us with an insignificant estimate of θ. In Section 4.2.2 we discussed that we still expects a seasonal effect on the spot price and therefore decide to use the same estimate as the seasonal effect on the wind speed, on the spot price.

μ_J and σ_J represent the mean and standard deviation of the prices defined as jump. Because the jumps are implemented to the model in such way that they describe a the movement in the price, we need to estimate these parameters on returns. We will repeat the iterative process used to determine μ_s and σ_s but this time on returns instead. We can then determine the mean and standard deviation of the jumps identified as outliers.

The probability of a price jump at any given day λ, is a simple probability estimate calculated from historical data. We count how many jumps, positive and negative, that has occurred in the data and relate it to the total number of observations.

ρ is the parameter that controls the effect of the post jump stage revering parameter. This has been estimated with a trial and error method, which basically is to try out different value and see what gives the best model. Here it is an easy approach because we will expect the value of rho to lie in the area $[0-1]$ due to the fact that we only expect the process to return to its steady state level after a jump.

A summary of the above can be seen in Table 4.1 which includes a description, estimation method and the estimate of all the parameters.

Table 4.1: Estimate and method of parameters included in the spot price model

Parameter	Function	Method	Estimate
μ_s	Steady State level	Iterative average	38.92
σ_s	Volatility	Iterative standard deviation	7.52
κ	Speed of mean reversion	OLS	275.75
β	Timing of the seasonality	-	1/365
θ	Seasonal effect on price	Assumption from Figure 2.3	28.90%
μ_J	Average size of jumps	Iterative average	88.40%
σ_J	Jump volatility	Iterative standard deviation	66.20%
λ	Probability of daily jumps	Frequency	1.97%
ρ	Post jump effect	Trial and error	0.8

4.3.1 Applying trend to the model

First of all we decided to include the inflation rate in our spot price model, as discussed in Section 4.2.4. The historical yearly inflation rate in Germany from 1997 to 2017 is shown in Appendix A.13 where we can see that the inflation rate has fluctuated from 0,5% to 2,5% during the past 21 years. Instead of applying a 2% inflation rate, which is a commonly used approximation of the inflation rate, we have calculated the observed average yearly inflation rate in the following way

$$Return = 100 \cdot ((1 + i_{1997}) \cdot (1 + i_{1998}) \cdot ... \cdot (1 + i_{2017})) \tag{4.13}$$

$$i_{yearly} = \left(\frac{Return - 100}{100} \right)^{1/21} \tag{4.14}$$

This approach gives a yearly inflation rate on 1.4% and the daily inflation calculated from this yearly rate will be applied to the model described in equation (4.6).

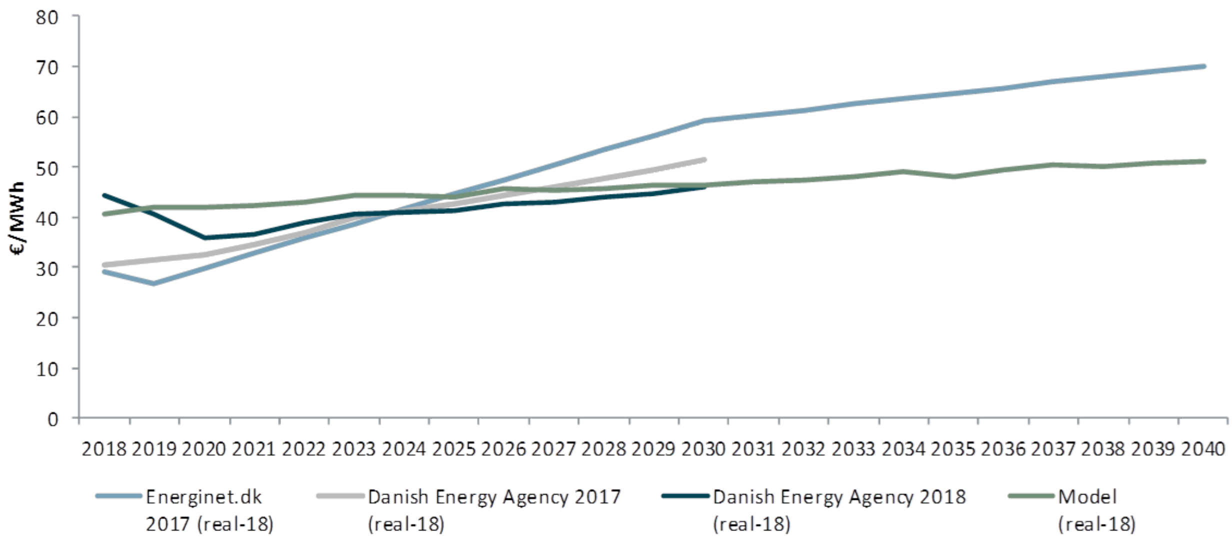
Even though we have identified and discussed that the merit order effect of lower marginal costs from renewable energy on the spot price results in a negative trend, we have chosen to incorporate a positive growth rate in the spot price because that's the general expectation in all the publications we have read. However, we acknowledge the negative trend following increased penetration of renewables in the energy market and thus we include a positive trend significantly less than the one suggested from Danish Energy Agency [34] and Energinet [37].

The Danish Energy Agency has recently published their 2018 expectations of the spot price, and they have drastically lowered their expectation of the spot price compared to the result from the 2017 report. Instead of an expected yearly increase on $5,19\%$ in 2017, they now expect the spot price to increase with approximately 1,32% per year [35]. This is of course beyond the general inflation increase in the spot price. We can see that they have lowered their expectations to the yearly increase in the spot price with more than three percentage points. This just works as an example on how difficult it is to predict the future, and also tells a story about some of the more uncertain parts of the industry. As we will see later on, the price trend plays a key role in the valuation of the Project, thus it is an estimate where companies tends to deviate a little depending on their interests.

As we do not have any preferences regarding final valuation of the Project we decide to include a more conservative estimate of the trend, which we will assume to be a 1,00% yearly growth in price. This estimate is slightly below the most recent update from Danish Energy Agency on 1,32%, because we prefer the more conservative estimate due to acknowledgement of the declining trend from increased penetration of renewables.

Figure 4.4 contains the 3 different forecasts mentioned plotted together with the growth rate assumed in the model. As we can see the forecasts from 2017 starts at a lower level but develops quickly due to their large growth rates. The 2018 forecast from Danish Energy Agency decrease in the first years and then starts to increase slowly from 2020. We will not use the simulated price before 2024 when the projects starts operating, thus we do not need to worry that much about the decrease in the first years. As we can see the different price trends lies within the same area at this time.

Figure 4.4: *Forecasts of the electricity price from Danish Energy Agency and Energinet*



Source: Own construction based on [37] [34] and [35].

4.3.2 Applying Intermittency effect

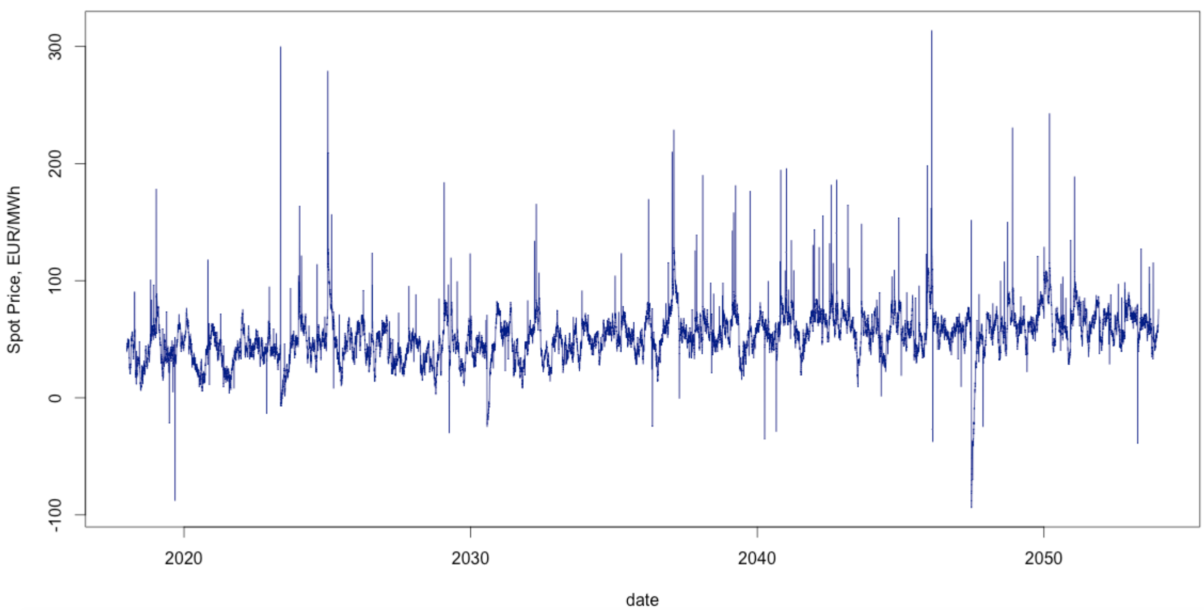
As discussed in Section 4.1.3, the intermittency effect is extremely important to consider when modelling the average daily spot price and not the exact price received for wind production. Because the effect has been shown to be very significant over the past years, we have chosen to include this effect in our valuation of the Project. The effect has been estimated to lie within 10-15% for wind production in Germany [25]. Based on this and the fact that this is almost entirely based on onshore wind which tends to have a higher intermittency effect, we have chosen to include a 10% daily intermittency effect on the spot price. This is of course an assumption and not an accurate estimate, but nevertheless we will include it in the valuation and leave it open for others to estimate the future offshore intermittency effect in Germany, and the effect of this on the valuation of the Project.

This intermittency effect is applied by simulating the future spot price as described above. This price will be the actual daily spot price observed in the market. However, the Project will not be able to sell the produced electricity to this price, but at a price assumed to be 10% below. Therefore, before multiplying the production with the price, we will adjust the simulated price for the intermittency effect by subtracting 10% from the simulated spot price.

4.4 Price simulation results

We have now estimated all the parameters needed for the regime switching spot price model in equation (4.6). Next step is then to simulate the model 1.000 times to get 1.000 spot price paths. In Figure 4.5 is the illustration of one of those simulations. Because of the inflation we start simulating the price path from 2018 and onward, even though we do not need the price before 2024 when the Project is estimated to start producing.

Figure 4.5: *Simulated path for the future spot price*



From a graphical point of view the simulated price path do not correspond exactly to the historical spot price in Figure 4.3. But we still see many of the discussed characteristics of spot price in the simulated price path.

The first thing you notice is of course the jumps in the price, which comes as both positive and negative jumps. As discussed we expect both positive and negative jumps in the future, so we are quite happy with these. One thing we still need to address in relation to these negative jumps is of course that a negative price for the production of an entire day is not realistic. We have seen up to half a day of negative prices, but also shorter time periods with large negative prices can cause the average price of a day to be negative. However, when using the Monte Carlo method to simulate the price path 1000 times, these negative prices will be eliminated.

In relation to the jumps we also see the successful implementation of the regime switching model. Immediately after a jump has occurred the process reverts to its steady state level. The same goes for the more general OU mean reverting process, which is still very significant in the simulated path. When focusing on the main price process, meaning trying to exclude the jumps, we definitely see that the price fluctuates around its steady state level.

We can also see the effect of the small positive trend in the price process, and the successful implementation of this in the model, especially to the steady state level of the mean reverting process. The last and most important thing is of course the high volatility of the price path. This is what makes the electricity price so unique compared to many other commodities, and what makes the entire business of electricity so difficult. This high volatility is still present in the simulated price path.

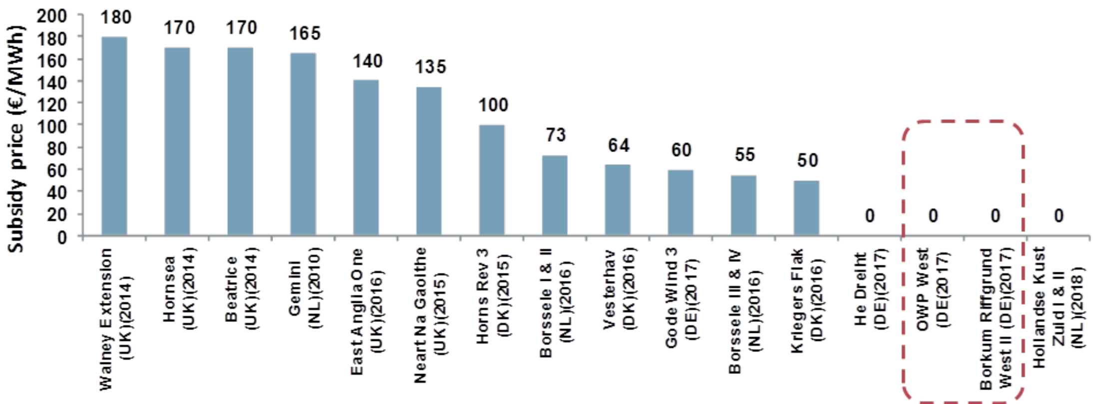
In Appendix A.14 is a figure of the historical data plotted with a price path from our model, simulated with the same number of observations, 5916. This figure illustrates the successful implementation of the price jumps and the size and frequency of the simulated jumps also seems to be consistent with the historical data. A minor deviation between the model and the historical price is that the randomness of the model generating the daily volatility is not as characteristic as the one we see in the historical spot price.

Combining the 1000 Monte Carlo simulations of the price with the 1000 Monte Carlo simulations of wind flow and resulting power production gives us the revenue of the Project.

5 Subsidies

As briefly touched upon in the introduction, offshore wind and other renewable technologies have long been reliant on government subsidies to underpin returns and limit risk and thereby attracting investment to the sector. There are severeal different ways to provide producers of renewable energy subsidies and every country's government has its own specific way. In the US, subsidies are structured around tax credits that provide producers with either a production tax credit or an investment tax credit that effectively reduce their corporate tax. These credits can either be applied directly by the producer or be passed on to investors in return of so-called tax-equity financing [133]. In Europe, the most commonly used subsidy regime has historically taken the form of a feed-in tariff (FIT) where producers receive a set price per MWh produced, that price typically being well above the wholesale price of electricity. However, over the last few years auctions have taken over as the most common way for the European governments to allocate capacity. In these auctions, developers bid against each other for capacity by bidding the price per MWh they require in FIT [3]. The use of such auction-based subsidy regimes has helped deliver significant cost reductions in the industry as developers are pressuring each other to constantly find new ways of reducing costs to facilitate lower bids and thus securing capacity. As can be seen in Figure 6.2, the bid prices for offshore wind projects have dropped dramatically over recent years, leading down to the three zero-subsidy bids, two of which comprise the Project.

Figure 5.1: *Winning auction bid prices for offshore wind projects since 2010*



Source: Own construction based on Frost & Sullivan [41] and 4C Offshore [86]

It is important to note that the figure contains projects from across different countries. As different countries have different support schemes and scopes, it can be difficult to compare the auction prices one-to-one, but they can serve as an indicator of the general movement in the industry. The projects in the UK are not as cost competitive as the rest, which can be attributed to a difference in scope of the subsidy regime between the UK and for instance Germany.

As said in the introduction, in Germany, the onshore transmission assets are constructed, owned and operated by the TSOs, meaning the developers of wind farms only have responsibility of the offshore transmission substations [64]. The cost of the transmission of electricity to shore is passed on to consumers as a part of the public support scheme. In the UK, developers can choose to either construct transmission assets themselves and later sell them or let an Offshore Transmission Network Owner (OFTO), but regardless of what they choose they pay for the connection to the grid and thus for transporting electricity to shore and onwards [106]. In Denmark and the Netherlands, developers own neither onshore nor offshore transmission assets and do not pay for grid connection, which in effect makes construction of offshore wind farms cheaper for developers in these countries compared to Germany and even more so when compared to the UK.

Therefore, it is logical that the UK projects in Figure 5.1 are lacking behind the rest as the scope in the UK is less favourable to developers, which in turn makes the need for subsidies in the more traditional, monetary sense. The German system on the other hand is somewhere in between the UK on one side and Denmark and the Netherlands on the other when it comes to the cost of grid connection and transmission assets. This cost differential was a determining factor enabling Ørsted to make the zero-subsidy bid for the Project and consequently, had the Project been located in a different country with a different regulatory setup, it probably would not have been possible to bid without subsidy.

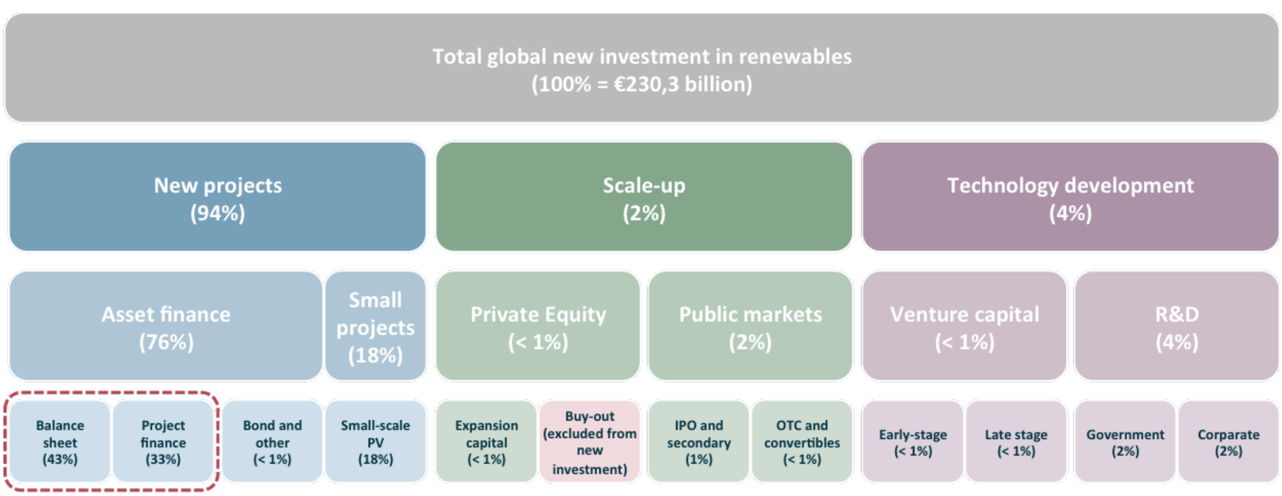
Now, as we stated in the introduction, the fact that German developers do not pay for grid connection is a government support scheme and as such is in effect a subsidy, although not directly monetary. Consequently, when we state that the Project is subsidy-free, we mean only that it is not receiving a FIT on top of the wholesale price of electricity.

Since the Project we investigate is being developed without subsidy we do not model a subsidy into our valuation model. However, in Section 8.2, we will analyse the effect of a subsidy on the Project.

6 Financing

Offshore wind farms are large infrastructure assets and like other types of infrastructure assets such as bridges, toll roads and airports, they require significant amounts of financing. The vast majority of the investment has to be made up front as it is primarily needed for the initial construction of the asset and therefore only investors with large capital bases are present in the space.

Figure 6.1: *Categorisation of new investment in renewables*



Source: Own construction based on [72] (Percentages may not add up due to rounding)

Total global new investment in renewables amounted to $279,8 billion (€230,3 billion) in 2017 and is split according to Figure 6.1. Using this framework, the financing of the Project is classified as asset finance, as it has capacity above 1 MW, which is the threshold separating asset finance and small projects. In 2017, 76,1% of total new investment went into asset finance [2], which seems rather natural as this category includes all new sizable projects being built. Wind power and solar are by far the two leading technologies and together account for 97% of asset finance. Especially investment in offshore wind has increased significantly in recent years, doubling in dollar-value from 2014 to 2016, and in 2016 accounted for 16% of asset finance [71][72].

Asset finance is split into two subcategories; balance sheet finance and non-recourse project finance which are both frequently used to finance offshore wind projects. Balance sheet finance usually comes directly from the balance sheets of the utility or energy company developing the project, whereas non-recourse project finance comes from multilateral financial institutions, export credit agencies and commercial banks and is supplied in packages of debt and equity linked to the project vehicles rather than the corporate entities developing the projects.

Ørsted, the developer of the Project, is financed with both debt, equity and hybrid capital, resembling common equity, but only at the corporate level. At the project level, all financing comes in the form of equity and thus directly from the balance sheet. When financing offshore wind projects, Ørsted's Wind Power division uses a special partnership model where they "farm down" their ownership stake by selling a significant stake, typically around 50%, primarily to financial and institutional investors. These buyers may then use non-recourse project finance to fund their investment in the project [81].

The farm-down will typically be completed 12-24 months after the Final Investment Decision (FID) as the project has then been granted all the necessary permits and consents and procurement of key components and early stage construction has commenced. Thereby, the project has been de-risked significantly and Ørsted can get outside financing to help finance the costly construction phase. It is done in one of two ways, either following the "EPC Wrap Model" or the "Shared Risk Model", which cater to two different types of investors and risk appetites.

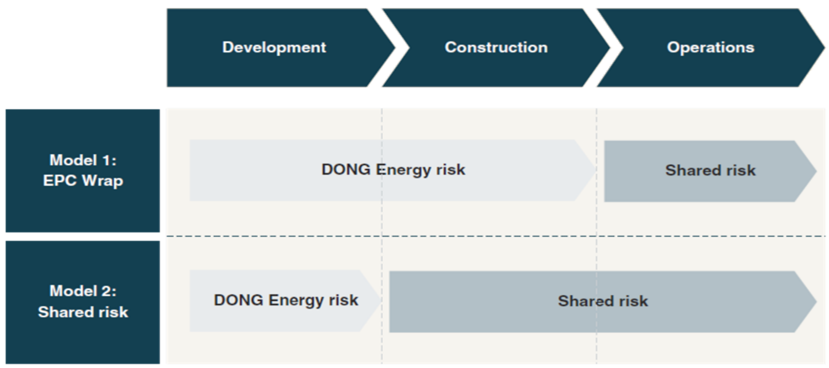
In the Shared Risk model, the investor will take part in the majority of risks associated with the construction of the project and therefore caters to investors with interest in exposure to construction risk. In the EPC Wrap model, which is the most commonly used of the two, Ørsted retains nearly all risks associated with procurement, construction, cost overruns and delays and, as such, investing in the project then resembles investing in an operating asset. This model primarily caters to investors with little experience with or appetite for taking construction risk, but can to a large extent be tailored to fit the risk appetite of the investor in the way the construction

[2] Corrected for re-invested equity

agreement is constructed. In this model, Ørsted retains more risk than their ownership interests imply, which makes Ørsted's Wind Power business in general more risky than the rest of the firm's operations [81].

By utilising these partnership models, Ørsted can use the proceeds from selling stakes to finance new projects which gives them financial flexibility, improves the speed at which they can expand their portfolio and helps spread risk across a larger portfolio.

Figure 6.2: *Ørsted's partnership models*



Source: Dong Energy Offering Circular [81]

We will assume Ørsted will finance the Project on their balance sheet like they have done historically. However, since Ørsted is financed with both equity and leverage at the corporate level and the equity invested in the Project in reality flows from the corporate level down to the Project, the required return of the Project will have to account for both the cost of equity and the cost of debt of Ørsted. In the following we will seek to estimate the required return Ørsted needs to apply in the Project, which we will use in the valuation of the Project.

6.1 Estimating the cost of capital

An important input to our valuation model is the cost of capital used to discount future cash flows to reflect the time value of money. In this section, we will estimate the Weighted Average Cost of Capital, the WACC, which basically is a measure of investors' opportunity cost related to investing their funds in one project instead of others with similar risk [6]. The well known formula is printed below for the reader's convenience and in order to introduce the notation:

$$\mathrm{WACC} = r_e \cdot \frac{E}{V} + r_d \cdot (1 - T_c) \cdot \frac{D}{V} \tag{6.1}$$

Where r_e is the cost of equity, r_d the pre-tax cost of debt, T_c the corporate tax rate and E, D and V are the long-term targeted market values of equity, debt and total firm value, respectively. As the formula shows, the WACC weighs the cost of equity and after-tax cost of debt according to the long-term ratio of equity and debt in the firm. Evidently, it consists of three elements, the cost of equity, the after-tax cost of debt and the capital structure, all of which will be estimated in the following.

6.1.1 Capital structure

Theoretically, the WACC should include a weighing of all types of capital in the firm. Ørsted has something called Hybrid Capital, and if the risk of this capital is different from that of the equity and debt, theoretically, the weighted cost of this should also be included in the WACC. However, Ørsted themselves characterises it as a type of equity capital, so for the sake of simplicity, we will consider it as part of the equity capital.

Furthermore, the WACC should be weighed with the long-term targeted *market values* of equity and debt, which for a public company like Ørsted isn't that difficult to find. The problem for us is that Ørsted was not listed on the Copenhagen Stock Exchange until June 2016, so the estimate of the long-term target would be based on data over a very short period of time if we did this. Instead, the accounting values of equity and debt can be used as proxies [12], although this is not an optimal approach. Taking the reported total equity and dividing by the sum of reported total equity and the reported total debt of Ørsted for the last six financial periods yields an average equity ratio of 60%. Obviously, the debt ratio is then the remaining 40%. We will use these values as proxies for the targeted long-term ratios.

6.1.2 Cost of debt

Next, we need to find the cost of debt and we do so by adding the risk premium on debt to the risk-free rate that we found ealier. Aswath Damodaran, profesor of corporate finance and valuation at the Stern School of Business at New York University, publishes a table that matches a firms credit rating with the corresponding default spreads, available on his website [91]. He has estimated this using all rated companies in the US and data on a selection of traded bonds. Ørsted currently has a credit rating of BBB+/Baa1 from the three largest credit agencies, Moody's, Fitch and S&P and has had this rating or higher since 2009 [78][134]. Also, it is Ørsted's long-term target to maintain these credit ratings [81]. Using the table, we find Ørsted's default spread to be 1,27%. Adding this to the risk-free rate yields a pre-tax cost of debt of 4,13% for Ørsted. As equation (6.1) shows, we get the after-tax cost of debt by multiplying with 1 minus the corporate tax rate. For Ørsted, the tax rate to use would be the Danish of 22%, but since the Project is located in Germany and will pay German taxes, we need to use the German tax rate, which is currently 30% [105]. Doing so yields an after-tax cost of debt of 2,89%.

6.1.3 Cost of equity

Estimating the cost of equity can be done using a number of different models, such as the Capital Asset Pricing Model, CAPM, the Fama-French three-factor model and the Arbtrage Pricing Theory, APT, to name a few [2]. The CAPM is the most generally used of the three and for that reasons we have chosen to use that. We have chosen not to focus on the other models, because the scope of this thesis is not to evaluate analyse the difference between different models for cost of equity.

$$r_e = r_f + \beta(r_m - r_f) \tag{6.2}$$

Where r_f is the risk-free rate, β the levered β that measures idiosyncratic risk and r_m the return of the market. $(r_m - r_f)$ is also referred to as the market risk premium. All these parameters need to be estimated, as the "true values" are not observable.

Risk-free rate

To estimate the risk-free rate, we have used the yield of a 30-year US Treasury bond index with ticker symbol "I05230Y Index". We found the yield of this index on Bloomberg as the mid price on the 29^{th} March 2018 where it was 2,86%.

Market risk premium

To estimate the expected market return, usually historical data is used, although this might not be a very good predictor of future return as future events affecting the risk premium are independent of past events. If you construct a prediction model based on historical data, it will to a large extent follow the pattern of the historical data and won't be able to foresee events that has not happened in the time frame of the historical data. Moreover, there is also the question of which market to use as a proxy for the entire market; do we use the German, as the Project is in Germany, do we use the US market as this is the largest, most mature and most diversified market or do we use a global index?

As the focus of this thesis lies elsewhere, we will not estimate this ourselves, but rather rely on estimates made by Aswath Damodaran, profesor of corporate finance and valuation at the Stern School of Business at New York University, available on his website [91]. These estimates are widely accepted as industry standards and used by corporate finance professionals around the world. In Ross (2002)[12], Aswath Damodaran's estimates are referred to as "actual industry-level" estimates. He currently estimates the market risk premium of a mature market to be 5,08%. Germany has a Aaa sovereign rating and therefore no country-specific risk premium needs to be added [90].

Industry β

The β measures the risk of a firm relative to the market and as such can be interpreted as a measure of a firms co-movement with the market. High-beta firms are thus highly cyclical stocks that rise and fall with the market and the opposite holds for low-beta firms [2].

The β can be estimated by regressing the historical return of the firm on the historical market return, then the β will then be the slope of the resulting regression line. Doing so gives rise to four estimation issues as outlined in Damodaran (2012)[2]; i) the length of the estimation period, ii) the return interval, iii) which market index to use and iv) if the estimate should be adjusted to reflect the likelihood of estimation errors.

According to McKinsey et al. (2005)[6], the estimation period should be no less than 60 data points, as this leads to too large standard errors. Furthermore, the return interval should be at least monthly, as intra-daily, daily and weekly leads to systematic biases. Combined, this adds up to using no less than five years of monthly data. This recommendation makes estimating the β of Ørsted impossible for us to do, as return data is only available for the little under 2 years the firm has been listed.

Instead, an *industry* β constructed from regression analysis of the return of comparable listed firms with return data for a longer period of time available can be used. This way of estimating β, is broadly used to estimate the β of non-public companies and fortunately for us, estimates are available on Damodaran's website [91]. He publishes estimates of the industry β for 94 industries estimated using comparable firms from around the world and we have chosen the "Green and Renewable Energy" industry to be the most fitting for Ørsted. We will use the estimate of the industry's *unlevered* β, as we can then releverage it with the targeted long-term debt-to-equity ratio we determined for Ørsted above. By doing so we are using a more firm-specific debt-to-equity ratio and not relying on the average ratio of the industry.

This industry has an unlevered β of 0,73 and then we releverage that using the formula

$$\beta_L = \beta_U(1 + (1 - T_c)\frac{D}{E} \tag{6.3}$$

We then get $\beta_L = 1,06$. Using all the estimates found in this section, we can now find Ørsted's

WACC by using equation (6.1). This yields a WACC of 6,14%[3]. As a sanity check, we can compare this to the average WACC estimated by brokers covering Ørsted, which we find to be 6,48%[4] and we see that it corresponds well with broker estimates.

Corrections

Some important points need to be made here. First of all, the β of a company can only be used to value projects undertaken by the company if the risk of the project resembles the risk of the company's *current* projects. And second of all, the risk of a company or an industry will likely change over time as the company or the industry's business change. We need to take both of these points into account and therefore we need to make the following corrections;

i) the β needs to be adjusted for the higher risk of the Wind Power division,

ii) the β needs to be adjusted for the electricity price exposure of the Project

iii) the β needs to fall over time as the renewable energy industry matures

Ad i): As discussed earlier in this chapter, the risk of Ørsted's Wind Power division is higher than the rest of Ørsted's operations due to the higher construction risk compared to ownership interests the partnership model implies. This risk premium has to be added and we will do that by raising the β enough to add 50 basis points to the final WACC. To do so, we raise the β to 1,23 and get a Wind Power WACC of 6,64%[5].

Ad ii): The Project is the first project in Ørsted's portfolio to be exposed to wholesale electricity price fluctuations during the entire project lifetime which makes the Proect's risk fundamentally different. All prior projects have had some kind of government subsidy during the first 10-20 years, depending on the country and subsidy regime, to underpin returns, so the complete exposure to price risk increases the overall riskyness of the project. This needs to be reflected in the cost of capital applied, as investors will require a higher return to compensate them for the higher inherent risk of the Project. Samuel Leupold, the CEO of Wind Power at Ørsted, said in the press release [84]: "*We are of course reflecting the project's exposure to market risk in the cost of capital applied*. However, Ørsted will likely try to eliminate most of this risk by entering into corporate Power Purchase Agreements, PPAs, where large corporations agree to pay a set price for their power in order for them to lock in the price and thereby hedge out the price risk. It is however unlikely Ørsted will manage to hedge out all price risk with PPAs and therefore the cost of capital still needs to be adjusted [56].

[3]For calculation see Appendix A.24

[4]For calculation and sources see appendix A.23

[5]For calculation see Appendix A.24

We estimate that the electricity price exposure warrants a risk premium of 25 basis points and will account for this by raising the β to 1,31 and thus we arrive at a WACC of 6,89%[6].

As a side note, we see that our initial WACC estimate of 6,14% was a bit lower than the broker average for Ørsted, but correcting for the Wind Power division and electricity price risk puts us above the broker average which matches well with our intention to increase the WACC to account for the increased risk.

Ad iii): The risk of an industry is always higher for industries in their early stages and then falls as the industry matures. The renewable energy industry is still rather young and one could argue that with the technological advances and cost reductions expected in the not-too-distant future, the industry risk is likely to be significantly lowered over the lifetime of the Project. Therefore, we have chosen to implement a decreasing estimate of the industry's β over time to reflect the falling risk.

We will model this decreasing risk by assuming that the risk of the renewable energy industry at the end of the Project's lifetime in 2049 will resemble that of a general utility today. We believe this is a fair assumption based on the argumentation above.

Therefore, at time $t = 0$, the beginning of the Project's lifetime, we use the estimate from above, $\beta_0 = 1,31$ and at time $t = T$, the end of the Project's lifetime, we use the β corresponding to the "General Utility" industry. Damodaran estimates the unlevered β of this industry to be 0,50 [91] and using equation (6.3), we get a levered estimate of $\beta_T = 0,73$. We then model the β over the lifetime of the Project as the linear interpolation between these two estimates with the formula:

$$\beta_t = \beta_0 - \left(\frac{\beta_0 - \beta_T}{T}\right) t, \quad \text{for } t = \{0, 1, \cdots, T\} \tag{6.4}$$

This yields a WACC that drops linearly from 6,89% in year 0 to 5,12% in year T. This dynamic WACC will be used when discounting cash flows for valuation purposes.

7 Costs

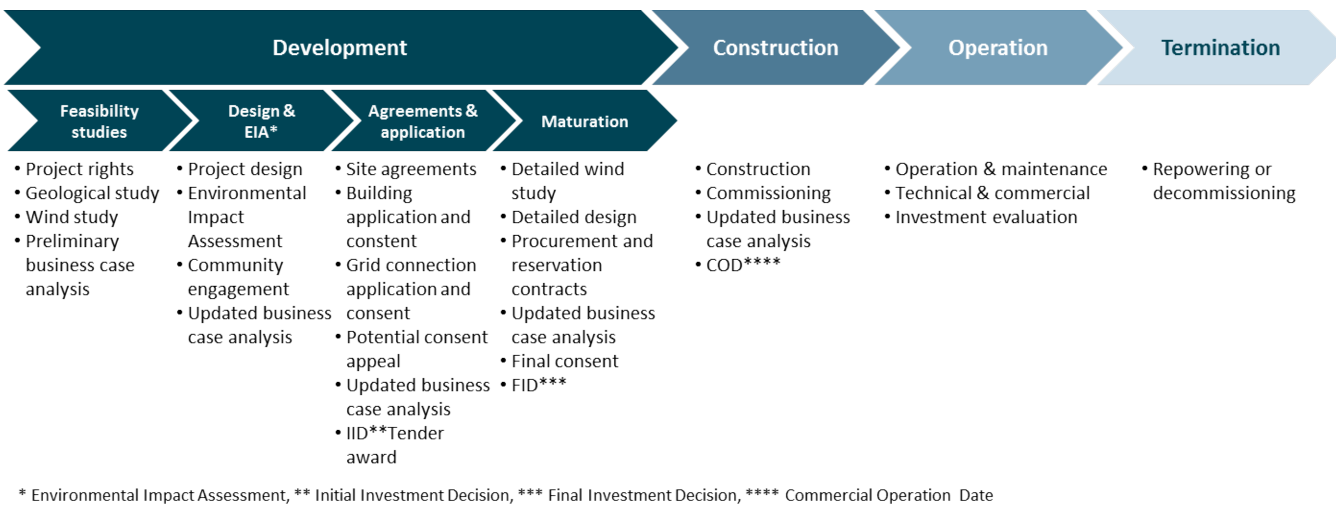
In the previous sections, we have been determining the different components making up the revenue earned by the Project. In this section, we will look at the other side of the coin, the costs

[6] For calculation see Appendix A.24

of offshore wind. We will give an overview of the most important cost categories and what these typically consist of in the offshore wind industry. This will provide us with the insight and inputs necessary for us to estimate the cost of the Project. This is in nature very uncertain as all the actual costs have been neither incurred nor planned and therefore our analysis will to a large extent depend on data available on other projects and industry benchmarks at an aggregate level. However, it is essential to include in our analysis as it will help us understand the drivers of the cost and through that the profitability of the Project.

In order to analyse the costs of an offshore wind project, it is instructional to understand the different phases it goes through over its lifetime. In Figure 7.1, the typical phases of an offshore wind farm's lifetime can be seen together with an overview of some of the typical work streams going on in each phase.

Figure 7.1: *Typical phases and work streams of an offshore wind project's lifetime and the cost category associated with each phase*



Source: own construction based on [27]

Offshore wind projects are typically split into four phases, namely, development, construction, operation and termination. The development phase relates to bringing the project to Final Investment Decision (FID) and thus to facilitate the start of construction. It includes general feasibility studies, such as analysis of the site and its wind resource, design and environmental impact assessment as well as all work related to applying for and acquiring various permits and consents [77]. Throughout the development phase, the general business case is developed which forms the foundation for taking the decision to construct the project or not.

Once FID has been taken, construction of the project can start. Construction costs include all costs related to acquiring turbines, building foundations, installing turbines and all electrical wiring and cables. This is a significant part of the total costs of a project and requires a lot of upfront capital to complete, why a lot of effort goes into analysing the business case prior to taking FID.

The operational phase is the longest part of a project's lifetime and will typically be 20-30 years [4]. It commences once construction is done and the project is commissioned and it is during this phase the project generates power and thereby revenue. It runs until the project is either repowered or decommissioned, which depends on the economic outlook of continuing operation and the possible expiration of central agreements and permits. This phase is called the termination and includes the cost of either repowering or decommissioning the wind farm.

The costs of offshore wind farms are classified according to which phase of the project's lifetime they are incurred in and are generally classified as either Development Expenditure, called Devex for short, Capital Expenditure, Capex, Operational Expenditure, Opex, or Abandonment Expenditure, Abex. Devex includes costs related to the development phase, Capex those related to the construction phase, Opex those related to the operational phase and Abex those related to the termination phase.

Devex, Capex and Abex are all capital expenditures and are therefore often considered in conjunction, which is why we will term the combination of the three as the Total Capex. Using this terminology, we can calculate the total lifetime cost of a project as

$$C = \sum_{t=0}^{T} I_t + M_t \tag{7.1}$$

Where I_t is the Total Capex in year t and M_t is the Opex in year t.

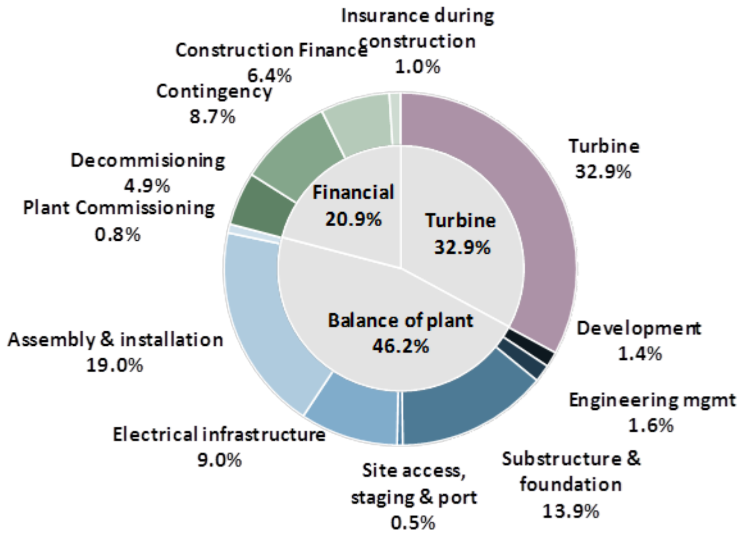
In the following, we will look at what each of these two cost categories consist of and determine the inputs necessary for simulating the costs of the Project.

7.1 Total Capital Expenditure, Total Capex

A typical split of the Total Capex of an offshore wind farm can be seen in Figure 7.2. As we can see, the costs associated with turbines is the biggest single item accounting for 33% of the total, however when all supporting components and auxiliary systems are bundled together as the Balance of Plant (BOP), this accounts for a larger share of 46%.

As we mentioned in the introduction, Ørsted expects certain costs reductions for the Project.

Figure 7.2: *Typical split of Total Capex items for an offshore wind farm*



Source: Own construction based on [68]

For Total Capex, cost reductions are primarily expected to be driven by increased turbine size and economies of scale. Larger turbines enable a wind farm developer to build the same total capacity using fewer turbines, which implies cost savings per MW on for instance foundations, installation and cables. Economies of scale from building larger wind farms reduce costs since fixed costs, such as development and engineering management, are unaffected by increased project size and quantity-proportional costs, such as materials and components, can be lowered per unit through negotiation of quantity discounts. Time-dependent costs, such as labour costs and daily installation vessel cost, are the only costs that increase linearly with the size of a project as larger projects take longer time to construct. Construction teams are typically paid per day they are engaged, so if the day rate of these teams can be negotiated or lowered through a bidding process with several construction teams bidding to win the job, these time-dependent costs could potentially be lowered as well [66].

Economies of scale in offshore wind power is being claimed as one of the cost reduction levers with highest potential in the offshore industry today, but not much academic research has been conducted on the field. Junginger et al. (2004)([47] find that for orders above 100 turbines, there is a 30% reduction in list price per unit, implying economies of scale in procurement. Snyder and Kaiser (2008)[66] infer from a multiple regression analysis that even though capital costs increase with the size of a project, they are unlikely to scale linearly. However, Dismukes and Upton (2015)[30] find evidence of constant returns to scale and thus actually reject economies of scale in offshore wind, based on a multiple regression analysis of 41 European offshore wind farms constructed between 1991 and 2012. One reason for this could be that the projects examined were all completed before 2012 and there was an increasing trend in the cost of offshore wind from 2009 to 2012, driven primarily by the move into deeper waters [72]. However, they do correct for water depth in their specification so we cannot attribute the lack of economies of scale to increased water depth. Another reason could be that they examine projects over a time period of 20 years and the cost of offshore can vary significantly over time.

7.1.1 Estimating Total Capex

In this section we will estimate the Total Capex of the Project using an approach with three steps. First, we analyse the relationship between the cost and capacity of offshore wind farms by regression analysis. Second, we do not include turbine size in the specification of the regression model, we manually adjust the estimate resulting from the regression to reflect the lower cost of using larger and fewer turbines. And finally, we critically assess the resulting estimate and use a comparative analysis to adjust the cost estimate to reflect current market expectations of the cost of offshore wind in the near future.

Step 1: Regression analysis

As the objective of this thesis is not to empirically determine whether or not economies of scale exists in the construction of offshore wind we primarily conduct the analysis to estimate the Total Capex required for the Project. For the analysis, it is important to compare apples with apples and therefore we cannot use data on all existing offshore wind projects with cost data available. There is a big difference in the level of Total Capex between countries arising from different support schemes, regulatory frame work and, as we discussed in Section 5, there are different scopes for what the developer has the responsibility for between countries. Ideally, we could have corrected for country fixed effects in a similar way to the one used by Dismukes and Upton (2015)[30], but we decided instead to only use data from German projects.

We have used data on cost and capacity of German offshore wind projects from 4C Offshore, a Brittish market research organisation devoted to the offshore wind industry [86]. They receive cost estimates for projects from industry insiders, identified with name and credentials, but people with knowledge of project costs may not want to contribute data if the project costs have been very high and therefore, the data may suffer from selection bias. Nonetheless, it is the best we could find, which is why we will use it anyway. We do need to keep this uncertainty in mind when interpreting the results though.

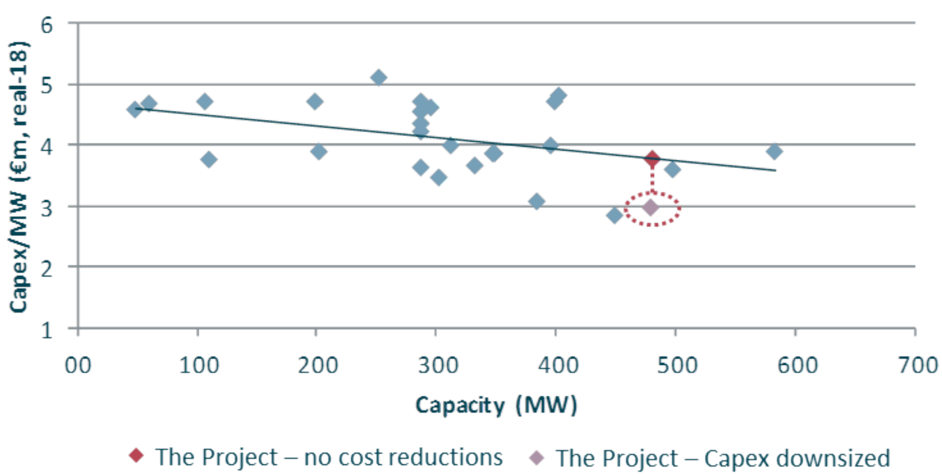
Since the offshore wind industry is still rather young and projects take a long time to construct, not that many projects have reached a state where costs could be estimated with some precision and even fewer have cost estimates available. Luckily, Germany is the country in the world with second most installed offshore wind capacity and so we have been able to get a decent data sample of 25 projects with cost estimates [41]. We have assumed the cost of each project to be stated in the prices corresponding to the year of commissioning, which may not be entirely correct, but it enables inflation correction, which enables the comparison of data collected over several years with no information on when it was collected. We present the data used in Appendix A.16.

Now, to analyse the relationship between cost and capacity, we regress the estimated Total Capex per MW in 2018 prices on the total capacity of each project according to the standard linear regression equation:

$$(\text{Total Capex/MW}_i) = \beta\,(\text{Capacity}_i) + \alpha + \epsilon_i \tag{7.2}$$

The resulting regression line can be seen in Figure 7.3 and the regression output in Appendix A.17.

Figure 7.3: *Regression analysis of historical Total Capex of German offshore wind farms*



Source: Own construction based on data from [86]

From the regression line, we see that the slope is negative, which supports our hypothesis regarding economies of scale. Building larger wind farms does seem to result in lower cost per MW, which also seems logical considering economic theory of economies of scale. In the regression output, we can see that both the slope and intercept parameters are statistically significant which confirms the downward sloping relationship.

Now, if we assume the cost of the Project can be described from the cost of the other German projects in in our data sample, we can estimate the Total Capex/MW from the regression. This yields a cost of €3,78 million per MW capacity, represented by the red dot in Figure 7.3.

Step 2: Scale-down due to fewer turbines

Blindly setting the Total Capex per MW of the Project to the estimate found above would be ignoring the cost reduction expected from deploying larger turbines. None of the projects in the sample employ above 8 MW turbines, but in our base-case scenario, the Project will deploy 13 MW turbines which without question will reduce costs. To model this, we scale down the cost items that we assess will be affected by fewer turbine position by a factor of 37/60. This is the number of turbine positions needed to build the Project when using 13 MW turbines in relation to when using 8 MW turbines, respectively. This assumes the projects used in the regression all uses a 8 MW turbines, which is not the case, but is set to this since the largest turbine used in the sample of projects is 8 MW. Hence, our estimate resulting from the scale-down will be conservative, since the scale factor would have been lower had we assumed a smaller turbine for the other projects.

Assuming the Total Capex of the sample projects can be split according to Figure 7.2, we can calculate the cost per MW of each category and then scale them down to the 13 MW scenario. In Table 7.1, we present the results of applying this procedure to the Project, together with the results for a 15 MW turbine which implies a scale factor of 32/60. The 15 MW result is for use later on when discussing the option of increase turbine size.

Table 7.1: *Breakdown of downsizing of Total Capex as a result of increased turbine capacity*

Capex item	8 MW (€m/MW)	13 MW (€m/MW)	15 MW (€m/MW)	Split 8 MW (%)	Split 13 MW (%)	Split 15 MW (%)
Turbine	**1.242**	**1.242**	**1.242**	**32.9%**	**42.3%**	**45.0%**
Development	**0.053**	**0.053**	**0.053**	**1.4%**	**1.8%**	**1.9%**
Engineering mgmt	**0.060**	**0.060**	**0.060**	**1.6%**	**2.1%**	**2.2%**
Substructure & foundation	0.525	0.324	0.280	13.9%	11.0%	10.1%
Site access, staging & port	0.019	0.012	0.010	0.5%	0.4%	0.4%
Electrical infrastructure	0.340	0.210	0.181	9.0%	7.1%	6.6%
Assembly & installation	0.717	0.442	0.383	19.0%	15.0%	13.9%
Plant Commissioning	0.030	0.019	0.016	0.8%	0.6%	0.6%
Decommisioning	0.185	0.114	0.099	4.9%	3.9%	3.6%
Contingency	0.327	0.201	0.174	8.7%	6.9%	6.3%
Construction Finance	**0.240**	**0.240**	**0.240**	**6.4%**	**8.2%**	**8.7%**
Insurance during construction	0.038	0.023	0.020	1.0%	0.8%	0.7%
Total	**3.78**	**2.94**	**2.76**	**100.0%**	**100.0%**	**100.0%**

The highlighted items are the items, for which we have assessed that the cost per MW will not change from fewer turbine positions. Most notable of these items is the turbine item. We have assessed that the per MW cost of turbines will not be affected even though fewer turbines will be needed, since the newer, larger turbines will be correspondingly more expensive per unit. However, turbine manufacturers are currently experiencing significant drops in prices of turbines due to price pressure, which could potentially also reduce prices per MW of turbines. For instance, General Electric experienced a 13% reduction in list prices of turbines in the first quarter of 2018 compared to the year before [89]. Nonetheless, we will assume the turbine item stays the same and analyse the effect of a price reduction in more details later.

The remaining items we have assessed to be unaffected by turbine positions are development, engineering management and construction finance. Development is related to site evaluation, agreements and applications for permits and consents, design and business case analysis, and since none of these tasks are related to the number of turbines, we keep it fixed. The same can be said of the last two items.

All other items are scaled down to account for the savings achieved from having fewer turbine locations. These include items that with fewer turbine locations either require less manual labour, such as installation, or less materials, such as foundations. Of these items, foundations and insurance need to be considered a little more closely. As we discussed in Section 3, when hub height increases, foundations need to be bigger to support the weight of the tower. Also, with a bigger rotor, a higher force is working on the structure and therefore, foundations need to be bigger [4]. However, we do not believe that the increased material cost per foundation will offset the savings from constructing fewer foundations and so we scale the cost of foundations down.

Insurance under construction is related to both the assets being built and potential accidents etc. during the construction. We have decided to scale this item down also since there are fewer assets to insure. Even though turbines are assumed to cost the same per MW, which implies the insurance of these will not be reduced either, insurance of all other assets, such as foundations and electrical infrastructure, will however be reduced as a result of fewer of positions.

Notice that the split of Total Capex changes depending on the turbine size, resulting from scaling down some and not all items. We have included graphical representations of this in Appendix A.18. Naturally, items that are not scaled down account for an increasing portion of Total Capex and vice versa for items that are scaled down. Therefore, the fact that turbines does not decrease in cost per MW, results in turbines accounting for a larger share of Total Capex.

As a result of the downsizing of cost items, we estimate a Total Capex of €2,94 million per MW. In Figure 7.3, this is represented by the purple dot, and it represents a 22% discount compared to the cost estimated from the regression, the red dot.

Step 3: Scale-down due to market expectations

When looking at the estimate from above, we notice that it is not an unprecedented Total Capex multiple as two other projects have similar Total Capex multiples, namely Borkum Riffgrund 2 and Arkona. Both are expected to be commissioned in 2019 and Borkum Riffgrund 2 will use 8 MW turbines and Arkona 6 MW turbines and we therefore find it odd to estimate the price of the Project in the same range as these. To put our estimate in perspective, we reviewed a report on the future cost of offshore wind made by BVG Associates on behalf of InnoEnergy published in 2017 [45].

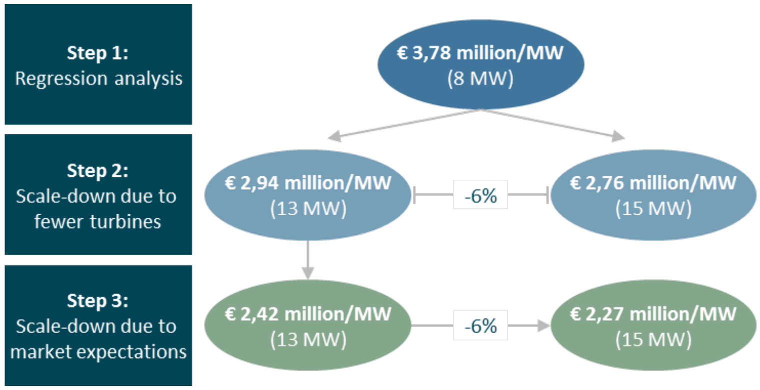
In this report, BVG Associates analyse a hypothetical future offshore wind farm that is highly comparable to the Project. They estimate the Total Capex per MW to €1,90 million per MW, more than €1 million less than what we have estimated. In Appendix A.19, we have included a table comparing the characteristics of hypothetical wind farm and our base case. As we can see, no assumption on what country the wind farm is constructed in is made, however, transmission assets are excluded, which is the most important factor differentiating the cost between countries. In Germany, developers do not own transmission assets and on this matter the Project and the hypothetical wind farm are comparable.

However, the hypothetical wind farm uses 12 MW turbines which in isolation would imply the Project should be cheaper, since it uses larger and fewer turbines. Furthermore, the Project is closer to shore, which also implies the Project should be cheaper, all else being equal.

Based on these considerations and combined with the fact that our estimate is not lower than Borkum Riffgrund 2 and Arkona, we will scale down our estimate further. We choose to scale it down by half the difference between our estimate of €2,94 million per MW and BVG Associates' estimate of €1,90 million per MW and therefore, we arrive at a final Total Capex estimate of €2,42 million per MW in 2018 prices. That we choose to scale down with half the difference may seem a bit arbitrary, but in Section 7.3 we will see that the total cost of the Project when we use the final estimate is in line with the expected future cost of electricity estimated by several energy organisations, such as the United Nations Energy Program, Bloomberg New Energy Finance and also BVG Associates. In Section 7.3, we will also analyse the impact of choosing a different estimate on the Project.

Now Total Capex per MW has been estimated and in Figure 7.4 we give an overview of the methodology just described to reach this estimate. We present the results for the 15 MW turbine also, as we will use this later on.

Figure 7.4: *Methhodology used to estimate Total Capex per MW of the Project*

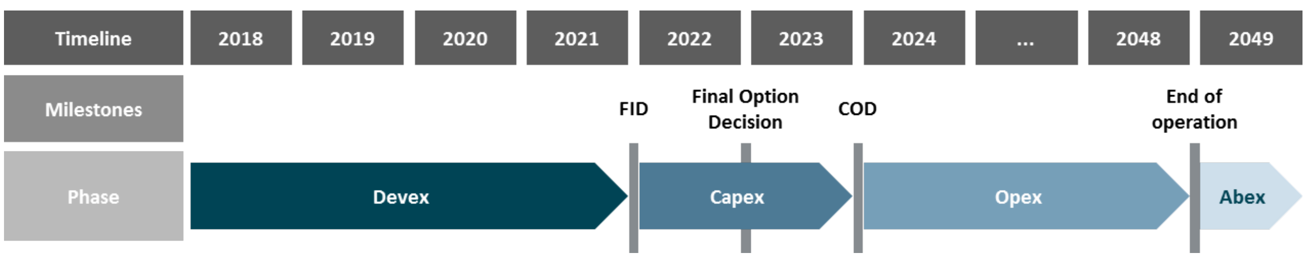


Source: Own construction

7.1.2 Timing of Capex

Because of the time-value of money, the spending profile of Total Capex is important to consider since later payment means less discounting and therefore cheaper in nominal terms. To consider the timing of the Total Capex, we first need to consider the overall timing of the Project. In Figure 7.5, we present the timing of the Project as we have assumed it to be.

Figure 7.5: *Timeline of the Project*



Source: Own construction based on [84]

From Ørsted's press release regarding the Project we know FID will be taken in 2021 [84]. For simplicity we decide this will be end of year 2021, so the development of the cost-reducing elements has time to materialise. Commercial Operation Date (COD) is expected in 2024 and we have assumed this will be beginning of year 2024, implying construction will be done in two years. In our base case, operational lifetime is 25 years and thus end of operation will be end of year 2048. We have assumed decommissioning will be done immediately after the end of operation and will take one year. The Final Option Decision, FOD, is our term for when the decision of whether or not to exercise the real options we will evaluate later is taken and we assume this to be end of year 2022. We have chosen to set it here so the developer has one year to install all foundations and turbines and finish electrical works, regardless of whether the options to expand the total capacity of the Project or to deploy 15 MW turbines are exercised. Again, we have chosen this to make the time for technological innovations to be developed while still leaving time for the construction.

To estimate the spending profile of Total Capex, we have taken point of departure in the split resulting from the downsizing seen in Table 7.1 and taken inspiration from the spending profile proposed by Wind Europe in [77], which we have included in Appendix A.20. In Table 7.2, we present our spend profile of Total Capex, in both real 2018 prices and in nominal prices growing with inflation.

Table 7.2: *Capex spend profile*

Item	Unit	Total	Devex				Capex		Abex
			2018	2019	2020	2021	2022	2023	2048
Capex profile	**%**	**100.0%**	1.0%	1.0%	2.0%	2.0%	14.0%	76.1%	3.9%
Capex, real-18	**€m**	**1,163.38**	11.63	11.63	23.27	23.27	163.42	885.00	45.15
Capex, nom.	**€m**	**1,261.45**	11.63	11.80	23.92	24.26	172.75	948.62	68.47

Wind Europe proposes to spend 6% in the first year, which we assume corresponds to the development phase of their hypothetical wind farm. We split these 6% out over the development phase of our project, that is from 2018 to 2021, with the cost in the first two years being lower than in the latter two to reflect the rising costs associated with intensified development work as the Project closes in on FID.

In Table 7.1, we can see that decommissioning accounts for 3,9% of Total Capex for the case with 13 MW turbines and so we set Abex to this. To ensure developers have the capital necessary to carry out the decommissioning of the site after the end of operation, German authorities require developers to post a bank guarantee when construction is commenced [31]. Developers typically build up a decommissioning provision on their balance sheet to meet this future obligation, but since this is mostly for accounting purposes and only has little effect on the Project from a financial point of view, we assume the cost of decommissioning is held when incurred.

The remaining part of Total Capex relates to the construction of the Project. Using Table 7.1, we identify the cost items that depend on the decision of which options to exercise and assume these costs are held in 2023 following FOD. These costs include turbines, substructure and foundations, electrical infrastructure, assembly and installation and plant commissioning, which combined account for 76,1% of Total Capex. The remaining 14,0% is then spent in the first year of construction, 2022.

Note that when we evaluate the three options discussed in the introduction later, we need to hold the costs held prior to FOD fixed, since changes in Total Capex resulting from exercising one or more options will only be known after the decision is taken at FOD.

7.2 Operational Expenditure, Opex

Operational expenditure is incurred during the operational lifetime of a project and includes costs related to the operation and maintenance of the wind farm, such as insurance, regular maintenance, repair, spare parts and administration [4]. Compared to conventional fossil fuel power generating technologies, these costs account for a much smaller part of total costs as there are no fuel costs related to generating power from wind energy.

Opex can be split into planned Opex and unplanned Opex. The planned Opex, including for instance insurance, regular maintenance and administration, is typically covered under contracts covering a considerable share of a wind farm's lifetime and are therefore rather predictable and stable. On the other hand, unplanned Opex, including spare parts and repairs of unexpected breakdowns, can be very hard to predict and will vary from year to year [92]. As we discussed in Section 3, breakdowns follow the bathtub curve. As a result, Opex is high in the beginning of a project's lifetime and then levels out as the project matures, however it is not necessarily the case that it rises towards the end of a project's lifetime. A wind farm developer may choose not to fix a breakdown if it happens late and costs more to repair than is lost in revenue in the remaining operational years if it is not repaired [4].

7.2.1 Estimating Opex

Since the offshore wind industry is still young and only one large scale project has lived out its operational phase entirely (Vindeby, 1991), very little data on Opex over the lifetime of a project is available. Furthermore, there is a large degree of commercial sensitivity surrounding the performance of different turbines and projects which has resulted in a lack of operational data publicly available [92]. Therefore estimating Opex for the Project is inevitably going to rely on benchmarks and other industry-wide estimates. A different approach could be to model breakdowns stochastically with a Poisson process, like we also commented on doing regarding availability in Section 3.2.2, which to a higher degree would account for the variability of Opex resulting from unexpected breakdowns. However, in order to do so the cost of all types of repair would need to be estimated, which would depend on a range of things, such as which component fails, the downtime, the cost of spare parts and the cost of the maintenance team's man hours and transportation, which depend on the distance to the maintenance hub and the weather at the time. This could be done, but would rely on assumptions regarding all the aforementioned determinants and so the increased level of detail would likely be drowned in estimation errors. Therefore, we have decided to simply model Opex as a percentage of total wind farm costs.

According to several studies, the Opex of an offshore wind farm is estimated to be in the range of 14%-33% of total costs [55][53][92]. According to BVG Associates, Opex could potentially fall 40% by 2030 driven by bigger turbines becoming available, projects increasing in size and from sharing of resources between projects [23]. These are some of the same drivers expected to reduce Opex for the Project as well. Like we discussed in the introduction, by the time the Project is commissioned, Ørsted will already have two operational offshore wind farms nearby and therefore we expect reductions in Opex since the existing O&M hub and maintenance crew can service both the two existing projects as well as the Project. Therefore we believe it is appropriate to estimate Opex to the bottom of the mentioned range, at 14% of total wind farm costs.

Given the estimated Total Capex found in the previous section, we get a total Opex of **€ 189,39 million** in real 2018 prices. We will not take the bathtub curve distribution of unplanned Opex into account, but simply split total Opex evenly across the operational lifetime of the Project. This leads to an annual Opex of € 7,58 million in 2018 prices.

We have now estimated the two major cost components and can therefore compute the total cost of the Project over its lifetime. We arrive at a total lifetime cost of the Project in the base case scenario of **€ 1.352,76 million** in 2018 prices. Table 7.3 below summarises the results:

Table 7.3: *Lifetime costs of the Project in the base case scenario*

Item	Unit	Real-2018	Split	Nominal	Split
Devex	€m	69.80	5%	71.61	5%
Capex	€m	1,048.43	78%	1,121.37	74%
Abex	€m	45.15	3%	68.47	5%
Total Capex	**€m**	**1,163.38**	**86%**	**1,261.45**	**84%**
Total Opex	**€m**	**189.39**	**14%**	**244.37**	**16%**
Total lifetime costs	**€m**	**1,352.76**	**100%**	**1,505.82**	**100%**

Note: split refers to the percentage of total lifetime costs

In order to critically assess the results of our cost analysis, in the following section we will introduce a common measure used to compare the cost of electricity among technologies and projects.

7.3 Levelised Cost of Electricity, LCOE

A common measure used to compare electricity generating technologies and projects is the Levelised Cost of Electricity, LCOE. It enables an apples-to-apples comparison of projects, which can help policy makers, utilities and investors when deciding which technology to support or which projects to invest in. It measures the discounted lifetime costs of a project compared to the discounted lifetime electricity generation and is expressed in monetary terms per megawatt-hour of electricity produced. It can be interpreted as the price of electricity required for a project to break even, including making the required return on invested capital [46]. Mathematically, it can be expressed as

$$LCOE = \frac{\sum_{t=0}^{T} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_t}{(1+r)^t}} \tag{7.3}$$

Where F_t is the fuel cost incurred in year t, E_t is the electricity generated in year t and r is the required return.

LCOE varies by technology, country and project depending on the energy resource, the efficiency of the technology, the financing costs and the operational efficiency. All these inputs go into the LCOE calculation and therefore it enables an apples-to-apples comparison of technologies and projects with significant structural differences.

In the Global Trend Report published annually by the United Nations Energy Program, the LCOE of a range of technologies is closely followed from year to year. In Appendix A.21, the evolution of LCOE for different electricity generation technologies are presented as they are estimated in this report. They estimate the global average LCOE of offshore wind to be $124 (€102) per MWh in 2017. The graph gives a good idea of the development of the LCOE of offshore wind, showing that the trend of the cost was increasing until the peak in 2012, driven by developers moving into deeper waters and, more importantly, it shows the drastic reductions since then. Only solar has experienced greater reductions, which is why solar, together with offshore wind, is one of the most promising technologies at present [72].

Furthermore, we see that offshore wind has been closing the gap to onshore wind rapidly, but is still lacking behind. This makes sense as offshore is a newer technology. Also, given the location is offshore, both construction and operation is more expensive because of higher transportation costs for construction and repair teams and lower accessibility due to weather. However, offshore location provides access to higher wind speeds as we have discussed already. Bloomberg New Energy Finance expects the LCOE of offshore to fall faster than onshore towards 2040, where they expect the LCOE of offshore will have fallen by 71% [18].

In Appendix A.22, the range of the global LCOE for seven different renewable technologies calculated by the International Renewable Energy Agency, IRENA, are presented, which provides a good insight to how the LCOE varies for each technology. We can see that the range of LCOE for solar varies significantly compared to the other technologies, whereas the range for offshore wind is much smaller. We see that the bottom of the range for offshore wind was around $95 (€78) per MWh in 2016.

LCOE does not serve well as an overall indicator of the profitability of offshore wind as it leaves out important variables such as taxes, depreciations, subsidies and the general economic environment, but it does serve well for comparing different technologies and different projects to each other. Below, we will compute the LCOE of the Project and use it to evaluate the estimated cost of the Project.

7.3.1 LCOE - results

In precious sections, we have estimated the components making up the total lifetime cost of the Project, the required return and the production, and so, we have all the inputs necessary to compute the LCOE of the Project using equation (7.3). In Table 7.4 below, we present the inputs and results. Notice that costs are stated in *nominal* values.

Table 7.4: *Calculation of LCOE for the Project in the base case scenario*

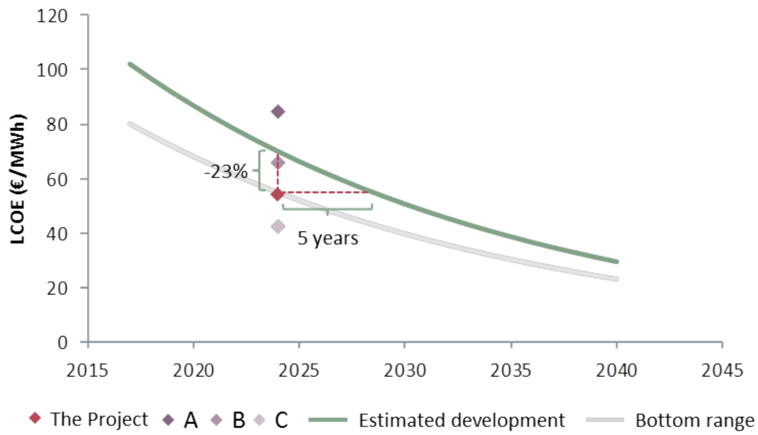
Item	Unit	Nominal
Total Capex	€m	1,261.45
Total Opex	€m	244.37
Lifetime costs	€m	1,505.82
Discounted lifetime costs	**€m**	**916.38**
Net lifetime production	MWh	49,613,556
Discounted lifetime production	**MWh**	**16,907,346**
LCOE	**€/MWh**	**54.20**

As evident, we arrive at an LCOE for the Project of **€ 54,20 per MWh**. Compared to the UN's global average in 2017 of € 102 per MWh, this may seem low, but we must keep in mind the Project is not commissioned until 2024.

If we assume the global average LCOE will fall by 71% by 2040 as estimated by Bloomberg New Energy Finance, the global average will drop from € 102 in 2017 to € 30 in 2040, which represents a compound annual growth rate of -5,2% [18]. Using this growth rate, we can visualise the expected development of LCOE as done in Figure 7.6. If we then use the same methodology on the the bottom range estimated by IRENA of € 78, which in 2017 prices is € 79, we can visualise a roughly estimated bottom range of the LCOE. We realise that assuming the bottom of the range will fall by as much as the average may be a stretch, but if taken as a rough estimate and no more, it can be useful in getting an idea of what range of LCOE future projects might have.

In Figure 7.6, we have plotted our LCOE estimate for the Project, the red dot. As we can see, the Project is approx. 23% cheaper than the expected trajectory of the global average LCOE, or said differently, 5 years ahead of its time. This is not completely unthinkable, since the Project, as we established by now, is far from an average project. Also, we see that it lies within the roughly estimated range which gives us some confidence that our estimate is not far off what is expected in the industry.

Figure 7.6: *LCOE of the Project compared to expected development*



Source: Own construction based on [18], [72] and [46]

Furthermore, we can use the estimated range of future LCOE to compare the cost of the Project using the current estimate with the cost of the Project if we had chosen a different estimate. In Section 7.1, we started by estimating the Total Capex per MW of the Project from a regression analysis of other German projects and found an estimate of €3,78 million per MW. Using this estimate would yield an LCOE of €85 per MWh, which is represented by the dot A in Figure 7.6. As we see, this estimate is too high compared to the expected development of the global average LCOE for offshore wind, which supports our decision to scale down the estimate.

Dot B represents the LCOE of the Project after we scaled down our Total Capex estimate to reflect the bigger turbines being used. It lies within the expected range of future LCOE and is very close to the estimated development of the global average LCOE. However, as we have discussed, the Project is not an average project, it is at the forefront of the industry with regard to technology and is being developed by the world's leading offshore wind developer that already has other projects in the area, from where they can transfer learnings and share O&M expenses. Furthermore, it is located in an area with an outstanding wind resource, in a country with a stable political environment and a favourable scope regarding transmission assets. We believe these considerations justify scaling down the Total Capex estimate further to the one presented in and thereby bringing down the LCOE to the one represented by the red dot.

But we cannot justify bringing it down even further. Had we applied the Total Capex multiple estimated by BVG Associates for the hypothetical, comparable wind farm in InnoEnergy (2017)[45], we would have gotten an LCOE of the Project of €42 per MWh, represented by dot C. As we can see, this does not lie in our roughly estimated range of future LCOE and therefore we believe it is too low. Indeed, BVG Associates does not find an LCOE that low for the hypothetical wind farm either. They estimate an LCOE of €54 per MWh for the hypothetical wind farm, *including* transmission assets, meaning that had transmission assets been partly excluded, like in the German scope, it would have been even lower. Now, since their Total Capex estimate is lower than ours, but their LCOE is aligned with ours, obviously they have estimated either other costs to be higher or they have estimated a lower production.

However, all in all, this analysis shows that our LCOE, and thereby our cost estimate, is well aligned with the current expectation in the industry. This also confirms that the estimates that have gone into the computation of the LCOE are in a range in line with or not far from the expectations to the industry going forward. We therefore feel confident about our model inputs which in the following sections will form the foundation of our valuation and profitability analysis of the Project.

8 Valuation

Now that we have introduced and estimated all the different drivers of offshore wind farm value, in this section we will determine the value of the Project and discuss whether this value justifies the zero-subsidy bid made for it. Before we do this, however, we will briefly introduce the theory behind the Net Present Value method used for valuation purposes.

8.1 The Net Present Value approach

The Net Present Value (NPV) approach to valuing an investment or project is the cornerstone of corporate valuation and capital budgeting and is simply an evaluation of the difference between cash inflows and cash outflows in present value terms. It is built on the premise that the value of an investment project is equal to the present value of all future expected net cash flows resulting from the project. A closely related term is the Discounted Cash Flow (DCF) model. In the DCF model, the NPV approach is used as a tool, and so the main difference between the two is that DCF is a valuation model and NPV is a valuation approach. The DCF model can be used to value investments with indefinite lifetime, such as a company or so-called going concern, which involves assumptions on the continuing value. The NPV can only be used to value investment projects with definite lifetime and is typically used to value investment projects within a firm, which is what we will be doing [11].

In capital budgeting, that is the process of choosing which investment projects to undertake, the NPV approach defines an extremely simple decision-making rule, the positive-NPV rule. This rule states, that in a world with unlimited capital, a profit maximising agent should undertake all projects with a positive NPV. In a more realistic setting with budget constraints, the projects with the highest, positive NPVs should be prioritised. When a project has a positive NPV, it indicates that the expected earnings exceeds the costs, including the cost of capital [11].

The NPV approach is praised for its simplicity and ease of use, but since the method in it self is uncomplicated, the inputs are conversely more important. Obviously, the NPV of a project is simply a reflection of the inputs and so if the inputs are flawed, so will the NPV be. The phrase "garbage in, garbage out" essentially captures this significant drawback of the method.

Another drawback is that it does not take potential flexibilities of a project into account, which could lead to underestimation of the value of the project. Later, we will look at a method that corrects this drawback.

The NPV of a project can in its simplest form be calculated with the formula [11]

$$NPV = \sum_{t=0}^{T} \frac{FCF_t}{(1+r)^t} \tag{8.1}$$

Where FCF_t is the expected free cash flow in year t and r is the required return, typically the WACC.

As we can see from the formula, really only two elements go into the calculation of the NPV, namely the expected free cash flow and the required return. The free cash flow of a project is the net cash flow available to all stakeholders with a claim on the cash generated by the project and can be found with the formula

$$FCF_t = EBIT_t(1 - T_c) + D\&A_t - Capex_t \tag{8.2}$$

Where $EBIT_t$ is the earnings before interest and taxes in year t, $D\&A_t$ is depreciation and amortisation in year t, and T_c is the corporate tax rate.

Since we assume Ørsted will finance the Project entirely with equity, no interest payments are made, which is why we can ignore this. In Germany, depreciable assets, such as turbines and foundations, are depreciated over a useful lifetime of 16 years using the straight-line method [61].

Although it is simple, any recommendation made strictly based on the positive-NPV rule does not provide much flexibility or maneuverability in the decision making. If, for instance, an investor has some flexibility in the cost of capital to be applied, that is, could potentially tolerate a slightly lower return on equity, a negative-NPV project might be undertaken anyway. A metric that provides some insight on this is the Internal Rate of Return (IRR). which we will analyse in the next section.

8.1.1 Internal Rate of Return

The IRR is a metric often used to evaluate the performance of an investment and is essentially the required return that makes the NPV of a project zero, that is, the rate of return that makes the present value of the profits and costs of a project break even. It is computed by setting the NPV equal to zero in equation (8.1) and solving for the required return. Accordingly, the higher the IRR of a project, the more desirable it is to undertake and so when deciding between projects, if based solely on IRR, the project with the highest IRR above the required return should be undertaken.

This metric gives a good insight for investors when evaluating a project. If, for instance, a project has a negative NPV, like our Project in the base case, the IRR can be used to see how much the investor's required return should be lowered for the project to break even. If the IRR is only slightly lower than the required return, the investor could consider whether this could be tolerated and the project might then be undertaken anyway. Since the IRR is forward looking, a project will not necessarily earn a return exactly equal to the IRR in reality. The IRR is just the most probable return, given the expectations for future cash flow generation [2].

Although a good metric for investment performance, the IRR has downsides as well and can be misleading if used alone. One caveat is that depending on the initial investment, a project may have a low IRR, but a high NPV, meaning that while the project is generating return at a low pace, it may add a lot of value. Another caveat of the metric is that it may be difficult to evaluate projects with different lifetimes. A project with a shorter lifetime may have a high IRR, making it appear to be a good investment, but may at the same time have a low NPV. Conversely, a longer project may have a low IRR, earning returns slowly, but may add a lot of value over time [2].

8.1.2 NPV valuation of the Project

Now that we have introduced the necessary theoretical framework, we can value the Project using equation (8.1).

First we have to determine the free cash flow, and using equation (8.2) and all the inputs we have estimated in the previous sections, we get the free cash flow of each year from 2018 to the last year of operation, 2048. In Table 8.1 we present this approach for an extract of the years of the Project and in Appendix A.26, we present the approach for the full lifetime of the Project. Using equation (8.1) and the WACC we estimated in Section 6.1, we find the NPV of the Project.

As we can see, the NPV is **€-82,08** million and thus negative, which in theory means that the Project should not be undertaken. The IRR of the Project is **5,13%**, but since we have a dynamic WACC, that drops linearly from 6,89% to 5,12% over the course of the Project's lifetime, it is not completely straight forward to compare to. To facilitate a comparison, we can solve for the static return that gives the same NPV as when using the dynamic WACC and use this as a

Table 8.1: *Valuation results*

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	...	2044	2045	2046	2047	2048
Revenue	**€m**	**2,934**	**0**	**0**	**0**	**0**	**0**	**0**	**88**	**89**	**93**	**94**	**...**	**140**	**144**	**145**	**148**	**154**
- Opex	€m	244	0	0	0	0	0	0	8	8	8	9	...	11	11	11	11	11
- Abex	€m	68	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	68
EBITDA	**€m**	**2,621**	**0**	**0**	**0**	**0**	**0**	**0**	**79**	**81**	**84**	**85**	**...**	**129**	**133**	**134**	**137**	**74**
- Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	...	0	0	0	0	0
EBIT	**€m**	**1,428**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**5**	**6**	**10**	**11**	**...**	**129**	**133**	**134**	**137**	**74**
- Tax	€m	428	0	0	0	-1	-1	-5	1	2	3	3	...	39	40	40	41	22
Profit after tax	**€m**	**999**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**3**	**4**	**7**	**7**	**...**	**91**	**93**	**94**	**96**	**52**
+ Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	...	0	0	0	0	0
- Capex additions	€m	1,193	12	12	24	24	173	949	0	0	0	0	...	0	0	0	0	0
Free cash flow, FCF	**€m**	**999**	**-12**	**-12**	**-23**	**-23**	**-171**	**-944**	**78**	**79**	**81**	**82**	**...**	**91**	**93**	**94**	**96**	**52**
													...					
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	...	5.00	5.27	5.55	5.84	6.14
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-124**	**-638**	**49**	**47**	**46**	**43**	**...**	**18**	**18**	**17**	**16**	**8**

NPV	**€m**	**-82.08**
IRR	**%**	**5.13%**

proxy for a static WACC. This yields a static WACC of 6,13% and so we can see that the IRR is a whole percentage point, or 100 basis points, lower. Whether Ørsted is prepared to accept a required return this much lower is hard to speculate about, but stand-alone this does not seem likely.

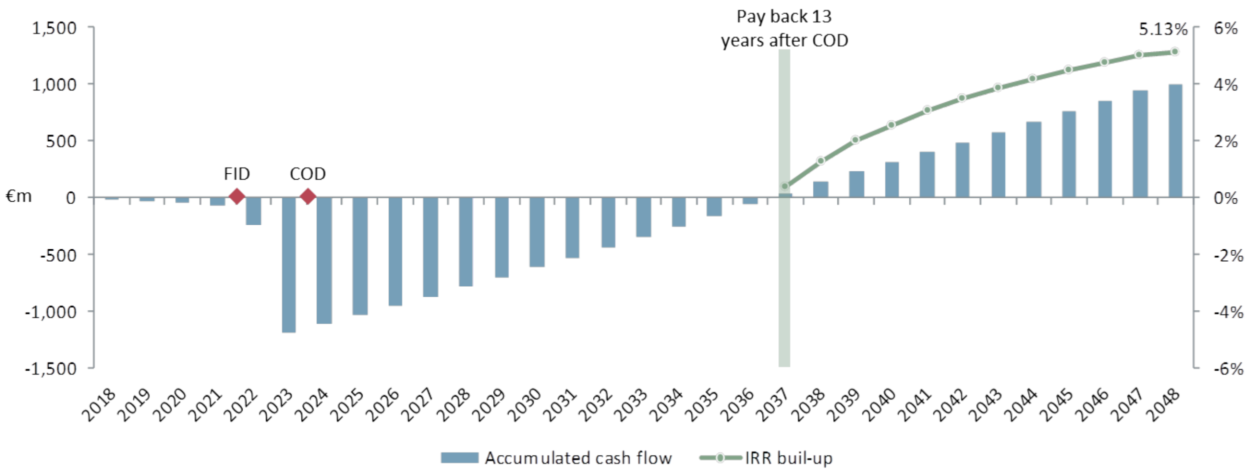
To compliment our analysis, in Figure 8.1 we present an overview of how the cash flow and IRR of the Project is built up over its lifetime. As we can see, total repayment of the investment in the Project occurs 13 years after COD and the IRR only then starts to accumulate. Had the Project been longer, we might expect that the IRR would continue up since the investment is completely paid back and all further profit goes straight to the bottom line.

Even though the Project seems to be unprofitable, there are some strategic aspects to consider before we can write it off completely.

First, like we have mentioned earlier, if Ørsted decides not to construct the Project, they face a penalty of €59 million, and hence, if the Project NPV were *less negative* than this, it would actually be more profitable to construct it than not, although it would not create additional value. However, as we can see, the NPV is lower than the penalty and thus based solely on the positive-NPV rule the Project should still not be undertaken.

Second, being the first to develop, own and operate an offshore wind farm without the need for public subsidies definitely carries a branding value and signals strength. It would confirm Ørsted's position as the market leader, which improves their ability to negotiate with suppliers and subcontractors and to attract talent and could potentially give them an edge to other developers in

Figure 8.1: *Accumulated cash flow and IRR build-up*



auctions for new projects. For this to be an argument, however, Ørsted has to be the sole owners of the Project and thus cannot use their partnership model, as a financial investor will not stand to benefit from these strategic benefits and will only value the monetary benefits of the Project. However, if they decide not to sell off a stake, they tie up a lot of capital that could otherwise have been allocated to other projects. Whether this strategic upside is enough to convince Ørsted to accept a return that is 100 basis points lower than their required return difficult to say, but we still believe it is unlikely.

8.2 The need for subsidy

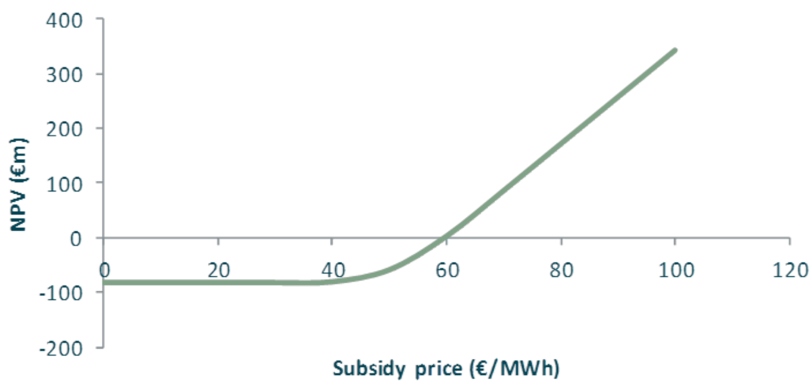
Judging from the NPV and IRR found above, the Project is not profitable in the base case. There are two ways this can be changed and that is to either lower costs or increase revenue. In the following sections, we will look at two initiatives that reduce costs and one that increase revenue and in this section we will look at a way revenues could have been higher: with the aid of public subsidies.

As we established in Section 5, German developers do not pay for grid connection, which is a form of subsidy, and so the Project already receives some indirect support. Nonetheless, it does not receive any direct, monetary subsidy, which in light of the unprofitable base case may seem a bit strange. We therefore decided to look at what subsidy Ørsted *should have bid* in order for the Project to be if not profitable, then at least not unprofitable.

We will do so by simply calculating the NPV for different FIT bids and determine which subsidy should have been bid to make the NPV equal to zero. In Germany, the FIT subsidy received is structured as a market premium paid when electricity prices are under the price awarded in the tender and is paid over a 20-year period from COD. That means, that if a developer s awarded a tender price of €100 per MWh, and the electricity price in a time period is below this, the government pays the difference. This way developers have limited downside, but unlimited upside with regard to the price of electricity.

When we implement this scheme into our valuation model, we get the results presented in Figure 8.2. In Appendix A.27, we present the same analysis, but for IRR rather than NPV. We have not included it here as it gives the same picture as for NPV.

Figure 8.2: *The value of the Project as a function of the subsidy price*



We notice a few things from the graph. First, we see that the NPV is unchanged for subsidy bids lower than €40 per MWh, which reflects that the realised electricity price after intermittency effect is not below €40 per MWh in our forecast.

Second, we see that the NPV increases linearly with subsidy prices above €40 per MWh. This makes sense as the higher price results in higher revenue which flows all the way down to the free cash flow.

Last but not least, we see that for the Project to break even and make the required return, that is have an NPV of 0, Ørsted should have bid €60 per MWh. Interestingly, this is the exact subsidy price Ørsted was awarded for the third project they won in the German auction in 2017, Gode Wind 3. From our analysis so far, it could be inferred that bidding this price for the Project would have improved the profitability of it to the point of a break-even. However, had they bid this price, they may not have gotten the award to connect the Project to the grid as other developers may have bid lower prices for other projects and so this is just conjectures of what could have been.

8.3 Sensitivity analysis

Until now, we have looked at the NPV and IRR in a static manner, assuming they are set in stone. However, as we started out by saying in this section, the NPV approach is highly dependent on the inputs you feed into the calculation and since IRR is basically just a rearrangement of the NPV equation, so is the IRR. Since all inputs are estimates of future realisations, they are estimated with uncertainty and it is therefore important to reflect on the stability of the results to changes in the inputs. In the following, we will analyse the sensitivity of the base case to key inputs and discuss the results.

8.3.1 Price trend sensitivity

As we discussed in Section 4, the trend in the spot price of electricity is a highly debated subject and different sources all find evidence for different price paths. We decided to set the price trend in our model to 1,0% which compared to other estimates we analysed is a conservative estimate. Nonetheless, the price is a significant driver of offshore wind farm profitability and therefore we need to analyse the sensitivity of changes to this estimate. In Table 8.2, we present the NPV and IRR of the Project using simulated price paths with different trends.

Table 8.2: *Spot price trend sensitivity*

	Price trend				
	0.0%	0.5%	1.0%	1.5%	2.0%
NPV	-176.48	-130.80	-82.08	-26.49	33.46
IRR	3.77%	4.46%	5.13%	5.84%	6.53%

NPV > 0 / IRR > 6%   Base case   NPV < 0 / IRR < 6%

As we can see, the Project is highly sensitive to changes of the trend in the spot price. If the trend is increased to 1,5%, the IRR increases by 70 basis points and if it is increased to 2,0%, an increase of just one percentage point from the base case, the NPV of the Project turns positive and the IRR increases to above 6%. Conversely, if the price does not realise any upwards trend in real terms, but only grows with inflation, the NPV drops almost €100 million and the Project should clearly not be undertaken.

This illustrates very well the importance of the price forecasts when evaluating the profitability of an offshore wind farm that is exposed to electricity prices. Also, it puts the forecasts made by Energinet and the Danish Energy Agency into perspective. In 2017, they forecast a compound annual growth rate of 4,73% and 5,19%, respectively, which would make the Project very profitable in the base case. However, their newest forecast from 2018 of 1,3% growth towards 2030 would also improve the profitability of the Project, but whether the Project should be undertaken or not would still be debatable.

8.3.2 Capex and Opex sensitivity

Another important driver of the value and profitability of the Project is the total costs. In Section 7, we analysed the total cost of the Project consisting of Total Capex and Opex. As we discussed, our estimate of Total Capex is subject to uncertainty and through that so is Opex. Even though we confirmed that the LCOE of the Project was well in line with the expectations in the industry, it is important to analyse the Project's sensitivity to changes in these estimates as their true values could potentially differ substantially from our estimates. In Table 8.3, we present the Project's sensitivity to changes in Capex and Opex.

Table 8.3: *Capex and Opex sensitivity*

		Total Capex				
		-20%	-10%	0%	+10%	+20%
Opex	-20%	62.62	-4.13	-70.88	-137.63	-204.38
	-10%	57.02	-9.73	-76.48	-143.23	-209.98
	0%	51.42	-15.33	-82.08	-148.83	-215.58
	+10%	45.82	-20.93	-87.68	-154.43	-221.18
	+20%	40.22	-26.53	-93.28	-160.03	-226.78

NPV > 0 Base case NPV < 0

		Total Capex				
		-20%	-10%	0%	+10%	+20%
Opex	-20%	7.07%	6.11%	5.28%	4.55%	3.91%
	-10%	6.99%	6.03%	5.21%	4.49%	3.85%
	0%	6.91%	5.96%	5.13%	4.42%	3.78%
	+10%	6.83%	5.88%	5.06%	4.35%	3.71%
	+20%	6.75%	5.81%	4.99%	4.28%	3.64%

IRR > 6% Base case IRR < 6%

As we can see, the Project is highly sensitive to changes in especially Total Capex. When lowering Capex by 10% while keeping Opex fixed, the NPV of the Project increases by close to €70 million, which implies that the project in theory should be undertaken rather than cancelled to avoid the penalty for cancelling. The IRR increases with 80 basis points to just under 6%, which is still not thrilling, but the increase is significant. A 10% reduction in Total Capex is a significant reduction and corresponds to a reduction of about €115 million. However, it is not unthinkable that a reduction like this could happen. For instance, if the price pressure on turbines currently experienced by turbine manufacturers continues and the cost of turbines drop by 20%, Total Capex is reduced by approximately €120 million. As we mentioned earlier, General Electric experienced a 13% decrease in turbine prices in first quarter of 2018, so a 20% reduction until 2023 when construction of the Project commences is not impossible to imagine.

Although it is not impossible that the Project might realise a 10% reduction in Capex, it is neither impossible that it conversely realises a 10% increase in costs. Cost overruns and delays in construction are common in infrastructure projects, including in the offshore wind industry, which only cements the importance of sensitivity analysis [109][110]. From the table, we see that a 10% and 20% increase would imply a reduction of NPV of approximately €65 million and €130 million, respectively. In both cases, it is clear that the Project should not be undertaken and this should feed into the Final Investment Decision.

In conclusion, if it were decided that the negative NPV in the base case could be outweighed by the strategic benefit of being first movers, it is now clear that this would be way too risky and should not be undertaken as even moderate increases in Total Capex makes the business case go south. And while it is possible that Total Capex could decrease, it needs to decrease by a lot just to have a non-negative NPV, whereas it does not even need to increase for the Project to be unprofitable, but if it does, it becomes very unprofitable, very fast.

Looking at Opex, we can see that the Project is less sensitive to Opex, which seems logical since it accounts for a smaller part of the total cost. A 10% change in Opex, whether positive or negative, causes NPV to change by about €5 million and so, by itself, moderate changes to Opex does not have material impact on the business case. This result will be used later on for discussion of the option to increase lifetime of the Project.

8.3.3 Loss factor sensitivity

In Section 3, we estimated the availability, electrical loss and other losses based on the results of other studies. These estimates are also subject to uncertainty and therefore we also perform a sensitivity analysis of these.

However, since we have modelled all three as a percentage loss of production, it does not make any difference whether we make a change to one or the other of these factors as the resulting change in NPV and IRR will be identical. Therefore we only present the results of the analysis of availability and refer to Appendix A.33 for the analysis of electrical loss and other losses. The sensitivity of availability is presented in Table 8.4 below:

Table 8.4: *Availability sensitivity*

	Availability				
	100%	98%	96%	94%	92%
NPV	-53.34	-67.71	-82.08	-96.45	-110.82
IRR	5.50%	5.32%	5.13%	4.95%	4.76%

NPV > 0 / IRR > 6%   Base case   NPV < 0 / IRR < 6%

We see that even if the availability were at 100%, which is close to impossible to achieve, the NPV of the Project would still be negative and the IRR below 6%. We see that a 2% change in availability, or any of the other loss factors for that matter, whether positive or negative, results in a change in NPV of about €14 million.

To summarise, we can see from the sensitivity analysis that the most influential drivers of the value and profitability of the Project are the trend in the spot price of electricity and Total Capex. Changes to either of these two input have a material impact on both the NPV and IRR of the Project and should therefore be attributed significant resources to estimate and seek to control. Since the spot price is out of the control of a developer, but is so influential, a lot of effort should go into analysing the future development of it before taking the final investment decision. Total Capex can be affected by the developer, who can contribute resources to identifying the most economical subcontractors and suppliers, negotiating prices, warranties and terms of all major component purchase agreements and controlling and keeping track of the construction process to ensure it progresses as planned and will be done in due time.

All in all, the sensitivity analysis has revealed that the Project in the base case should not be undertaken, as it is unprofitable and could potentially be very unprofitable if either the spot price or Total Capex change for the worse. Our estimated spot price trend is relatively conservative compared to other forecasts, but it could potentially be lower and even small changes have a material impact on the profitability of the Project. Total Capex also affects the business case significantly and cost overruns could potentially make the Project very unprofitable.

9 Real option valuation

Now that we have determined the value of the Project in the base case scenario, we will move on to evaluate the Project, if the flexibilities and potential improvements, that may become available are factored in as real options.

When evaluating an investment project in a traditional way, using for instance the NPV approach, investments are considered as a now-or-never decision, leaving no room for managerial flexibility. This ignores the potential value inherent in the possibility to alter the project over its lifetime, when information of previously uncertain issues becomes avilable [51]. This difference between the way of viewing decision making has been well defined by Mun (2006) [9]:

"Traditional approaches assume a static decision-making ability, while real options assume a dynamic series of future decision where management has the flexibility to adapt given changes in the business environment"

In the real world of business, decision-making is rarely static and there is almost always some kind of intrinsic flexibility and on-going process where opportunities arise and are assessed as the information about them becomes available. Therefore, when evaluating an investment project, where strategic options can arise, an NPV valuation may not be optimal as it does not take the value of any of these business opportunities and flexibilities into account.

The value of the Project we found in the previous section does not consider the value of any of the three options facing the Project, namely the option to increase turbine size, expand capacity and extend operational lifetime, which implies that the value of the Project potentially has been underestimated. To account for the value of these uncertain strategic options, and thereby get a more precise estimate of the potential profitability of the Project, we can use real option valuation (ROV).

Before we do this, we first briefly introduce the theory behind financial and real options.

9.1 Option theory

Generally speaking, a financial option represents the right, but not the obligation to acquire or sell a security or another financial asset within a certain amount of time. They are used primarily for hedging and speculation and the two most common option types are the call and the put. A call option gives the right, but not obligation to buy an asset, the *underlying asset*, at a specified price, the *strike price*, within a specified time, the *time to maturity*. The owner of a call may choose to exercise this right or not, and if exercised, the owner is entitled to all future cash flows generated by the asset. The put option goes the other way around, meaning it gives the right, but not the obligation to *sell* an asset at a specified price within a specified time [8].

A real option can be characterised as the right, but not the obligation to make a business decision. Some investment opportunities present flexibilities, that can be considered as options because investors are not forced to execute them if not profitable. An example could be the option to abandon a project at a later time if new information is revealed and the project is deemed unprofitable. In this case, the underlying asset is represented by the project's cash flows, the strike price by the investment cost and the volatility by the uncertainty of the project cash flows. Real options are valuable because they allow investors to react optimally to changes in market conditions, which can improve the upside and limit the downside of an investment project. The value of this extra flexibility could explain why companies sometimes invest in projects with a negative NPV, which according to the standard positive-NPV rule should be avoided [9].

In contrast to the relatively small amount of financial option types that exist, there are as many kinds of real options as there are business flexibilities. Some of the most common are presented below.

- *Option to expand:* the option to increase the size of the business in the future

- *Option to abandon:* the option to cease or sell a non-profitable project in the future

- *Option to delay:* the option to postpone a business decision to the future
- *Option to switch:* the option to shut down at some point in the future when conditions are bad and then resume when profitable conditions are back on track

Several methods are available to evaluate and price a real option. The three most common methods are closed form solutions, binomial lattices and Monte Carlo simulation [9].

Closed form solutions, such as the Black-Scholes formula, are models where difference equations exists and can be solved given a set of input variables. Closed form solutions tends to be very specific with limited modelling flexibility. For instance, the Black-Scholes formula gives exact solutions for European options, but only approximations for American options.

Binomial Lattices are flexible and easy to implement. All option types can be solved with use of binomial lattices, but they become impractical in projects with multiple uncertainty inputs. An important fact about binomial lattices is that they approach the closed form solution for large number of steps in the lattice.

Monte Carlo simulation allows for several sources of uncertainty to be accounted for relatively easy, however, because the accuracy of the method increases with the number of simulation, it can be computational heavy for complex cases [9].

To evaluate the three real options available to the project, we have chosen to use the Monte Carlo method as this enables us to include several sources of uncertainty, such as the uncertainty from the stochastic wind simulation model and the stochastic price simulation model. Closed form solutions are too inflexible to account for this and using a binomial lattice would be unnecessarily complex and include too many steps to be practical.

Using the terminology of real options, the cash flow of the Project if the option is exercised will serve as the underlying asset and the cash flow of the base case scenario will serve as the strike price, as this is the opportunity cost of exercising the options. This means that we will exercise the option if and only if the present value of the Project's cash flows with the option exceeds those in the base case scenario. Consequently, the value of any of the real options available to the Project can be found to be:

$$V = \max(NPV_{option} - NPV_{\text{base case}} \ ; \ 0) \tag{9.1}$$

9.2 Increased turbine size option

In this section we will analyse the option of deploying 15 MW turbines rather than 13 MW. Using larger turbines will have several postive effects on the Project. Most importantly the Total Capex will be lowered as fewer foundations need to be constructed and fewer turbines need to be installed and maintained. Jensen (2018)[103] states the effect of larger turbines in the following way:

"... utilities can save large costs by ordering larger wind turbines because at the same time they need to purchase fewer foundations, pull fewer cables and fly out to fewer turbines for maintenance. In offshore business, big is beautiful and the sky is still the limit."

From the sensitivity analysis in Section 8.3, we know that a reduction in Total Capex will will have a significant, positive influence on the Project, which is why we expect the value of the option to be positive.

This option can be characterised as an American call option as the decision to exercise it can be taken any time when the bigger turbine has been developed. As we discussed in Section 7.1, we have assumed the decision to exercise any of the real options has to be taken before FOD in the end of 2022 meaning the maturity of the options is at FOD.

For this option, we could in principle have set the date of maturity later, but this would require that we assumed turbines could be changed or updated from 13 MW to 15 MW any time during the lifetime of the Project. However, the main advantage of increased turbine size lies in the cost reductions from the need to construct and maintain fewer turbine positions, but changing already installed turbines would not reduce positions. It would increase the capacity of the Project and thus production. Projects are auctioned off in specific capacities and grid connection allocated according to this. Thus the Project would most likely not even have allocated grid connection for the increased production and so this change or update of turbine would not make sense from an economical perspective.

9.2.1 Option assumptions

To value the option of deploying 15 MW rather than 13 MW turbines, we need to estimate the cash flow of the Project using the larger turbine. To do so, we use the same methodology as we did for the base case, but with few key changes. In the following, we will give a brief overview of these key changes.

The two things affected by an increase in the turbine size are costs and production, which is why we need to consider these in order to find the value of the real option. In Section 3 we defined the characteristics of both the 13 MW and 15 MW turbine, which we presented in Table 3.1 and constructed power curves for both turbines. These can be seen in Figure 3.3, and we can conclude that they are close to identical in shape except for the obvious difference in rated power.

We use the power curve of the 15 MW turbine to convert simulated wind speeds and directions into power production. We then apply the same wake loss scheme as in the base case and assume the same availability (96%), electrical loss (2%) and other losses (3%.) In Appendix A.34, we present the resulting power production as well as the base case production to ease comparison. Notice that the production has actually fallen slightly from the base case. This can be attributed to the fact that in the base case, the Project is made up of 37, 13 MW turbines resulting in a total capacity of 481 MW, whereas with 15 MW turbines, it consists of 32 turbines resulting in a total capacity of 480 MW and thus there is a slightly higher capacity in the base case. Other than this, the production in the two cases resemble each other a lot.

The cost reductions from deploying larger and fewer turbines affect both Capex and Opex. In Section 7.1, we estimated the Total Capex per MW of the Project using 13 MW turbines and in Figure 7.4, we presented the methodology used and the results. As can be seen in the Figure, we find the final Total Capex estimate of the scenario with 15 MW turbines by applying the difference of 6% between the estimates found by scaling down due to fewer turbines to the final Total Capex estimate of the base case. This yields a Total Capex of **€ 2,27 million per MW**.

Since we have estimated Opex as a percentage of total cost, the reduction in Opex driven by the fewer turbine locations that need maintenance is already accounted for when we reduce Total Capex.

9.2.2 Increased turbine size option - results

Now that we have discussed the two main changes to the case when 15 MW turbines become available, we can simulate the remaining inputs following the same methodology as for the base case and determine the cash flow from the Project. Finally, we can find the NPV and calculate the value of the option using equation (9.1). In Appendix A.28, we present an extract of the valuation model and in Table 9.1 below, we present the results.

Table 9.1: *Results from increased turbine size option*

Case	Production (MWh)	Revenue (€m, real-18)	Costs (€m, real-18)		Total profit (€m, real-18)	LCOE (€/MWh)	NPV (€m)	IRR (%)	Option value (€m)
			Total Capex	Opex					
Base case	49,613,556	2,258.20	1,163.38	189.39	719.50	54.20	-82.08	5.13%	-
W/ option	48,780,788	2,220.99	1,089.20	177.31	748.62	51.77	-48.15	5.53%	33.93

As we can see, the slightly lower production results in slightly lower revenue, but improvements are made on the costs. Total Capex is around € 70 million lower than base case and Opex around € 15 million lower, which combined drive the LCOE down and makes the total profit higher, despite the slight decrease in revenue. Ultimately, this improves the Project, both the NPV and IRR are increased and we find the option value to be positive **€ 33,93 million**. Therefore, we can conclude, that exercising the option has a positive effect on the value and profitability of the Project and thus if a 15 MW turbine becomes available to the Project before FOD, it would be profitable to exercise the real option and deploy this turbine rather than a 13 MW turbine. This supports the general consensus in the industry that bigger turbines improves profitability of offshore wind farms through lowering the costs.

However, whether the Project will be undertaken at all is still not entirely clear. Even when including the value of the option to deploy larger turbines, the NPV is still negative and whether Ørsted would tolerate an IRR of **5,53%** is doubtful. This decision could in fact be viewed as a real option in it self, with the penalty for cancellation as strike price and we can find the value of this option is positive since the NPV of the Project using 15 MW turbines is slightly higher than the penalty. This could lead us to recommend the Project should be undertaken, however, as we saw in Section 7.1, the profitability of the Project is highly sensitive to changes in price trend and Total Capex. Therefore, it could be argued that the Project should not be undertaken, since the NPV could could potentially drop below the penalty if the Total Capex budget is exceeded even by a little bit. Also, there is a mismatch in timing since FID is taken in 2021 and FOD is not before the end of year 2022. If larger turbines actually improved the case enough to make Ørsted want to undertake it, they would need to know that the larger turbines would become available when they take FID, otherwise the Project should not be undertaken.

Consequently, we could say that by undertaking the Project, Ørsted would be taking a lot of risk without being sure to be compensated accordingly.

As an interesting perspective on the increase in turbine size, it remains a question if turbines can get infinitely bigger and still improve profitability. One could imagine that at some point, the upside of building bigger turbines will be offset by the costs of foundations and installation or that the size reaches some physical or logistical limit. With bigger turbines comes questions of whether installation vessels will be able to accommodate them and if transportation from the manufacturing plant to the assembly point can be done using existing equipment and infrastructure [58].

While these are relevant questions, we have not considered them in more detail since we believe the industry will work out solutions that will mitigate these concerns, at least in the medium term leading up to the construction of the Project. In the longer term, these logistical obstacles might pose constraints on the size of turbine, but initiatives are already being taken to mitigete the effect of this. For instance, using floating foundations could enable installation to take place on a dock, before towing the complete structure to its final location as seen in the Hywind floating offshore wind farm in Scotland [116]. This would eliminate the need for increaingly bigger installation vessels. Another option being pursued is to build turbine equipment in smaller pieces which would enable the bigger equipment to be transported and installed in ways similar to today, only with the final structure being made up of more pieces [58]. Whether any of these or other initiatives will succeed in enabling increasingly big turbines to be deployed is uncertain, but we have established that there is plenty incentive to try. As stated by Derek Barry, an engineer with the National Renewable Energy Laboratory in Colorado:

"Many people thought 100 feet (33 m) was the largest (blades) we were going to get, except we always find a way to get around it." Osbourne (2016)[58]

9.3 Capacity extension option

In this section we will analyse the option of increasing the total capacity of the Project. As we mentioned in the introduction to the Project, Ørsted recently won the right to develop the site Borkum Riffgrund West 1, which is located right in the middle of the two projects making up the Project. We will consider this case as if the auction was not concluded yet and value the real option of including the extra capacity in the Project.

9.3.1 Option assumptions

The extension consists of an additional capacity of 420 MW and thus represents close to a double in the total capacity of the Project. From our analysis in Section 7, we know that increased capacity will lower both Capex and Opex.

Ideally, to estimate the effect of increased capacity on Total Capex, an analysis of the price paid for turbines, foundations, construction etc. compared to the list price should be done. A regression analysis of the realised discount as a function of total wind farm capacity would provide insight into what the discount could be expected when increasing Project capacity from 480 MW to 900 MW. Unfortunately, price data is highly sensitive for competition reasons, which is why we have not been able to do so. Consequently, our estimate of the discount will rely on our own assessment and expectation, guided by our analysis of Total Capex.

In Section 7.1, we established a regression model explaining the Total Capex of German offshore wind farms from the total capacity. If we use this to predict the Total Capex of the Project with the capacity extension, we find a Total Capex of €2,98 million per MW, which represents a 21% discount to the multiple found for 480 MW capacity on €3,78 million per MW. Note that this is compared to the multiple in step 1 in Figure 7.4. However, since a 900 MW project is unprecedented in the sample of projects used in the regression, we are making an out-of-sample prediction which means there are no points of reference to use for validating the estimate found. If we instead predict the Total Capex multiple of the largest project in the data sample, Gode Wind 1 & 2 with a capacity of 582 MW, we find a multiple of €3,58 per MW, a 5% discount to the multiple for 480 MW.

Furthermore, we need to consider whether the relationship found in the regression from a logical and economical point of view holds for much larger projects as well. While we do believe Total Capex will be lowered by increased scale, we also expect the effect to be limited by physical and technical boundaries. For instance, Junginger et al. (2004) empirically found a negative correlation between the list price of turbines and order size, but assuming they will fall linearly with the order size would be wrong as the cost of materials and time used in making a turbine, the marginal cost, presents a technical limit to the discount that can be achieved. Also, the study is old and does not take the current market conditions into account. As we have seen, turbine prices are already low and under heavy pressure and therefore it is unlikely can be pressured indefinitely further down by ordering large quantities.

Based on these considerations, we believe that the discount achieved from the extension should be closer to the 5% estimated from the regression for a 582 MW project than the 21% discount estimated for a 900 MW and choose to set it to 7%. This discount represents only a slightly higher discount than if the extension would have increased capacity to only 582 MW, which implies rapidly decreasing returns to scale for larger projects. Therefore, we feel this estimate is conservative and that it is substantiated by both our previous analysis and a logical and economical assessment. Nonetheless, we realise that it is highly uncertain and therefore we will analyse the sensitivity of the option value to changes in this estimate.

Apart from affecting Total Capex, increased capacity also affects Opex. In fact, several sources, including Ørsted, attribute the greatest impact on cost reductions resulting from increased capacity to Opex [84][70][23][92]. Now, since Opex is modelled as a percentage of total costs, reducing Total Capex implicitly also lowers Opex, so we have already accounted for this.

9.3.2 Capacity extension option - results

Now that we have discussed the major assumptions needed to model the capacity extension, we can implement the changes and simulate the necessary inputs using the same methodology as for the base case, only now with 69, 13 MW turbines and thus a total capacity of 897 MW. In Appendix A.29, we present an extract of the valuation model and in Table 9.2 below, we present the results.

Production and revenue nearly scales with a factor equal to the capacity increase, 420/480 = 88%. As no changes to the wind model, power curve or loss factors are assumed, this makes sense. The reason they do not increase by *exactly* that factor is that our wind model is stochastic and so different simulations yield slightly different results.

Costs however, increase by less than this factor, which is expected given the cost reductions

Table 9.2: *Results of the capacity extension option*

Case	Production (MWh)	Revenue (€m, real-18)	Costs (€m, real-18)		Total profit (€m, real-18)	LCOE (€/MWh)	NPV (€m)	IRR (%)	Option value (€m)
			Total Capex	Opex					
Base case	49,613,556	2,258.20	1,163.38	189.39	719.50	54.20	-82.08	5.13%	-
W/ option	92,522,578	4,211.23	2,017.67	328.46	1,454.20	50.06	-47.88	5.81%	34.20

we have implemented. As a result of costs increasing less than revenue, the profits of the Project increase to more than the double. Consequently, the option affects the Project NPV positively and therefore, in this case, the option should be exercised if available. However, as we discussed above, the underlying assumption of the Total Capex discount is highly uncertain, which is why we need to conduct a sensitivity analysis with respect to this assumption. In Table 9.3, we present the results.

Table 9.3: *Sensitivity analysis of the capacity extension option*

Discount on Total Capex

	4%	5%	6%	7%	8%	9%	10%
NPV	-88.35	-74.86	-61.37	-47.88	-34.38	-20.89	-7.40
IRR	5.53%	5.62%	5.72%	5.81%	5.91%	6.00%	6.10%
Option value	-6.27	7.22	20.71	34.20	47.69	61.19	74.68

NPV > 0 / IRR > 6% / Option > 0 Model NPV < 0 / IRR < 6% / Option < 0

A number of things are interesting about these results. First, we see that the option value is rather sensitive to changes in the Total Capex discount and therefore the value of the capacity extension option could be stated as a range rather than a point to show a more accurate picture.

Second, we see that if the realised Total Capex reduction resulting from the extension is below 5%, the option value is actually negative, meaning that the Project NPV is less than in the base case and implying that the option should not be exercised. This is very interesting as we might expect the option to be positive when Total Capex is reduced, even if only by 4%, but this is not the case. Thinking about this, we realise that it makes sense that if a project is unprofitable and the capacity is increased with little or no realised cost reductions, the value of the project is simply worsened by increasing the scale. The value of increasing the capacity of a project arises solely from the cost reductions arising from economies of scale.

Now, as with the option to use larger turbines, it is not certain that the Project, even with the capacity extension, should be undertaken at all. The NPV is only just higher than the penalty for cancelling the Project, but as we see from the sensitivity table, if the Total Capex discount is overestimated at 7% and the realised discount from economies of scale is just 6%, the NPV is lower than the penalty and the Project should not be undertaken. It is highly unlikely that Ørsted would undertake a project with a business case this unstable. Furthermore, the Project is still exposed to changes in the other inputs, such as the price trend, and therefore not only the Total Capex discount can cause the Project to be unprofitable.

9.4 Lifetime extension option

In this section we will analyse the option of extending the operational lifetime of the Project from 25 to 30 years. Intuitively, this seems to have a high potential for adding value as the initial investment does not change, but five extra years of revenue is added, which can help cover costs and increase return.

In Figure 8.1, we presented the accumulated cash flow of the Project in base case and the build-up of IRR. We recall that the Project had a repayment period of 13 years, leaving 12 years for generating a positive return in the base case. That means that after 13 years, the investment has been paid back and therefore five more years of revenue simply go straight into delivering returns.

Considering the maturity of the option, one could argue that this option does not need to have maturity at FOD. The approval of the extension could be revealed later and still be exercised as no extra investment or new arrangements would need to be made. However, if this option turns out to be essential in making the Project profitable, Ørsted needs to have certainty that the lifetime extension will be available to the Project at FID, otherwise it is unlikely they will undertake the Project.

9.4.1 Option assumptions

Modelling the extension of operational lifetime is rather straight forward. We simply use the same methodology as we did in the base case, only now we simulate all inputs five years further into the future. Doing so yields the production and the revenue of the Project and so we only need to consider the costs in order to compute the expected free cash flows and value them using the NPV approach.

On the cost side, the Total Capex of the project is the same as for the base case as no new equipment is needed to extend the lifetime of the Project. The Abex is postponed further into the future meaning it will be discounted even more and therefore, in present value terms, it will be cheaper to decommission the Project. However, we do need to increase total Opex, as it would not make sense to assume annual Opex would be lower because of longer operational lifetime. An interesting perspective is whether annual Opex would actually rise in the years of extended lifetime as an effect of the wind farm's longer lifetime. This could potentially reduce or entirely offset the gain resulting from extended lifetime. Recalling that breakdowns follow the bathtub curve it would be a fair assumption to make that Opex would be higher in these extra five years of operation, but since we have not taken this into account until now, but rather applied a constant Opex over the lifetime of the Project, we leave this for others to study.

9.4.2 Lifetime extension option - results

We have established all necessary changes to the model and we can thus simulate inputs and calculate the value of the real option of extending the lifetime of the Project. In Appendix A.30, we present an extract of the valuation model and in Table 9.4 below, we present the results.

Table 9.4: *Results of lifetime extension option*

Case	Production (MWh)	Revenue (€m, real-18)	Costs (€m, real-18)		Total profit (€m, real-18)	LCOE (€/MWh)	NPV (€m)	IRR (%)	Option value (€m)
			Total Capex	Opex					
Base case	49,613,556	2,258.20	1,163.38	189.39	719.50	54.20	-82.08	5.13%	-
W/ option	59,543,786	2,777.13	1,163.38	227.26	1,056.24	50.42	-6.08	6.02%	75.99

We see that the option value is positive and almost enough to make the Project as a whole profitable. The NPV of the Project is still negative, but it is significantly higher than the penalty for cancelling the Project and therefore, the Project could potentially be undertaken if the option to extend operational lifetime is available. As we have said for the other options, this needs to be known at FID in order for the Project to be undertaken since the Project in the base case is not profitable and will likely not be undertaken.

9.5 Upside case option

Now that we have assessed the impact of all three real options separately, in this section we will analyse the effect of all three becoming available to the Project. This would mean that all the cost reduction initiatives expected by Ørsted will materialise and therefore, we will term this the upside case. As we have already introduced all the changes in assumptions and estimates related to each option, we will skip directly to the results.

9.5.1 Upside case option - results

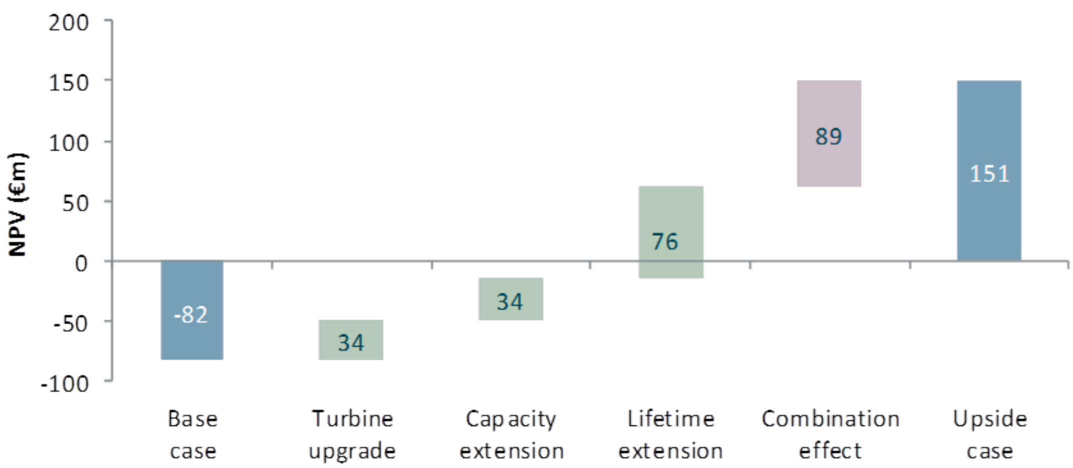
Applying the assumptions from all three options at the same time and simulating the necessary inputs, we can value the option of the upside case being available to the Project. In Appendix A.31, we present an extract of the valuation model and in Table 9.5 below, we present the results.

Table 9.5: *Results of upside case option*

Case	Production (MWh)	Revenue (€m, real-18)	Costs (€m, real-18)		Total profit (€m, real-18)	LCOE (€/MWh)	NPV (€m)	IRR (%)	Option value (€m)
			Total Capex	Opex					
Base case	49,613,556	2,258.20	1,163.38	189.39	719.50	54.20	-82.08	5.13%	-
W/ option	109,770,601	5,121.24	1,899.29	371.02	2,135.99	44.46	150.67	7.04%	232.74

As we can see, the value of the option to exercise all three real options is very positive and should be exercised if available. It presents a significant value uplift to the Project and the NPV of the Project is now positive and the IRR is just above 7%. This is well above the static WACC of Ørsted as well as above the actual WACC in the first year. In Figure 9.1, we illustrate how the three options affect the NPV of the Project separately and when combined.

Figure 9.1: *Effect of real options on Project value, separately and combined*



It is clear that separately, only the lifetime extension option adds enough value for the decision to undertake the Project to be debatable and this is still only because of the penalty if the Project is cancelled. However, the combination effect of exercising all three adds significant value and the project ends up actually creating value - even without a subsidy. It earns an IRR of just above 7% which is not outstanding, but considering the strategic value of being the first in the world to bid for and develop and offshore wind farm without any subsidy, it seems like a decent business opportunity.

10 Storage

In this section we will look a promising technology currently under development with a high potential of having a material effect on the profitability of offshore wind and other renewable, intermittent energy sources, namely large scale electrical storage. We will approach it from a theoretical angle and propose a methodology for analysing the impact of investing in research and development as a real option. We construct a stochastic model for the technological development of storage as a function of investments in R&D and apply it to the Project for illustration.

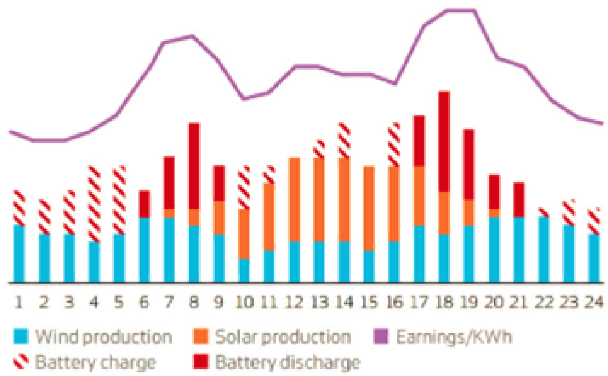
10.1 Impact of storage on the wind industry

The idea behind storage is to save excess production of electricity when supply exceeds demand and distribute the stored electricity when demand excess supply. In this way storage provides assistance to the grid operators in balancing the load on the grid. The effect of storage on a daily basis is illustrated in Figure 10.1 below. Wind and solar provides renewable electricity to the market and storage balances the supply with the demand in the market. During the night the demand for electricity is low, resulting in an excess electricity production. This production can be stored instead of being sold to low or negative prices. In the morning the demand tends to be higher than renewable production, yielding the need for additional electricity provided by other energy sources such as gas and coal. However, instead of using these sources, the renewable electricity stored during the night can be used. In the daytime electricity can be produced by both wind and solar which might result in an excess supply. Once again this excess supply can be stored for usage later in the day, where the demand usually peak again in the afternoon when people get home from work and the stored renewable electricity can be supplied to the grid once again to meet demand.

In relation to the discussion in Section 4.1.3 of an intermittent energy source and the problems related to this, development of storage has the potential to solve all these problems. Storage can secure a sustainable and secure delivery of renewable electricity to the grid, and thus reduce the current needs for additional energy sources. Something that will have a significantly positive environmental effect as well. Referring to the merit order curve in Figure 4.1, we see that the energy sources that will be drastically reduced from the electricity production will be those with highest marginal costs. This means the development of storage will decrease the large price spikes in the electricity price when other sources than renewable energy have to produce.

One storage solution currently being developed focuses on implementing a small storage solution locally in the turbine rather than externally setting up one storage solution. The project is run by KK Wind Solutions in collaboration with Vestas, PowerCon and Aalborg University and

Figure 10.1: *Daily effect of storage*



Source: https://www.vestas.com/en/about/hybrid

has investigated the relationship between storage and volatility of production. They find that a storage solution on 8% of a wind farm's capacity can eliminate almost 90% of the fluctuations in the production [104][112]. Reducing the volatility of the production will affect the capture price of wind because the intermittency effect will be reduced due to the less volatile production. The wind farm no longer needs to sell all production at a low price when supply exceeds demand. The wind farm can also benefit from the higher prices when demand excess supply and the battery starts discharging, all implying a lower intermittency effect when storage is added to the wind farm.

What causes a lot of discussion related to storage is the effect of storage on the wholesale spot price. As already described in Section 4.2.4, the current electricity price follows the coal marginal. If coal is drastically reduced from the market it no longer makes sense to assume that electricity price will follow the coal marginal, but what will then determine the electricity price?

Focusing only on the merit order curve, when reducing coal and gas from the curve and increasing the supply from renewable energy due to the development of storage, the price should decrease because renewable energy will have the potential to meet most of the demand. Of course this will require further investments in renewable energy, because even with the introduction of storage, the supply from renewable energy will not be enough to meet the demand. For renewable energy to be able to meet the demand it still requires heavy investments in increased capacity of renewables. However, as the technology develops, it will be fair to expect renewable energy to increase further in the future, even without support from governments. Especially if the development of storage becomes successful.

Last year, Tesla partnered with the Australian government to provide the batteries for a large scale storage solution with a capacity on 129 MWh. The project was installed in connection to the wind farm Hornsdale in South Australia and commissioned on 1th December, 2017 [107][118].

The battery is implemented in such a way that the grid operator controls some of the capacity, allowing for immediate balance of the grid with electricity from the battery.

The other part of the capacity is controlled by the electricity provider, and thus can be used in a way that maximises the revenue from the battery. It is especially the last part that affects Ørsted and there has been some interesting findings from the Australian project. The battery has been delivering remarkable profits due to the fact that it can charge at very low prices and sell the electricity at high prices, thus it provides a safe arbitrage opportunity for the owner of the battery. Investigations has shown that the battery have delivered profits up to 1m AU$ in only a few days when the wind production has been very unstable, giving the owner of the battery the possibility to charge the battery when wind production is high and sell the stored electricity when demand is high. This aspect of storage will of course primarily work as long as production from coal and gas is still needed in the market. This actually supports taking action in the development part og storage so one can enter the market as first mover and take advantage of this arbitrage opportunity [107][119].

Another study performed by Nyamdash and Denny (2012) has analysed the potential impact of storage on the Irish electricity market. They argue that the introduction of storage gives rise to a price increase of electricity. They find that a storage capacity on 200 MW and above will increase the price of electricity in the Irish market with approximately €2/MW [57].

To summarise, it can be difficult to predict the impact of storage on the future electricity price. There are arguments for an increase in price and arguments for a decrease. As a result we will not go any further into the effect on the wholesale electricity price. However, we will use the fact that 8% storage is found to reduce the volatility with 90% together with the result from the Tesla battery in Australia which allows renewable production to take advantage of high and low prices of electricity. We assume that combining these two effects will result in a decrease in the intermittency effect, allowing the capture price of wind to approach the wholesale spot price when storage is implemented.

10.2 Model for technological development of storage

In this section we will introduce a method for modelling the technological development of storage, run through the implementation of the model and use the Project as an example of how the method could be used in the future to evaluate the effect of storage.

10.2.1 Constructing a model for technological development

Our stochastic model of the technological development of storage will be anchored in a Poisson process, where draws from the Poisson distribution function will serve as indicators of a breakthrough in the technological development in a similar manner to [63]. The Poisson process is a statistic distribution for modelling the number of times an event occurs in an interval of time. In a similar manner to how we used it in Section 4, we can draw the number of breakthroughs during the development period from the Poisson distribution.

$$\rho_i \sim \text{Poisson}(\lambda) \tag{10.1}$$

with ρ_i being a binary variable that equals one if a technological shock has occurred at any given day i and zero otherwise. λ defines the arrival rate or frequency of the poisson process which Schegel estimates as a linear function of R&D investment [63]. However, we will assume a constant arrival rate for the shocks and let the R&D investment influence the size of the shock instead of the frequency of the shocks. One could argue that the possibility of a shock increases with the R&D investment, but it will be double-counting to let both frequency and size of shocks depend on the investment level, and we prefer to let size be the dependent part.

The size of each breakthrough will be determined by random draws from the normal distribution and the parameters of this will be determined by the investment level in R&D. This refers to the assumption that we expect a positive correlation between investment in R&D and technological development, thus the size of the breakthroughs will increase with the size of investment. The normal distribution provides the randomness to the size of the breakthroughs. This aspect is important because not all technological breakthroughs will be of the same size. Some breakthroughs are small, such as minor upgrades to existing technology, and others are large, representing the invention of an entirely new platform or subgroup of the technology.

This methodology can be stated in the following way:

$$\nu_i = \begin{cases} max(0; N(\mu, \sigma)) & , for\ \rho_i = 1 \\ 0 & , for\ \rho_i = 0 \end{cases} \tag{10.2}$$

where we have assumed that we cannot observe a negative shock to the technological development. The parameters of the normal distribution, μ and σ, will be dependent of the R&D investment, and therefore also the size of the breakthrough.

In the model, we define the cumulative sum of the simulated stochastic breakthroughs throughout the development period to be the final level of storage available to the Project at FOD.

$$s_i = \sum_{i=1}^{T} \nu_i \tag{10.3}$$

with T = 1.826 which is the number of days until FOD.

The R&D dependent parameter μ will be determined with a logistic function, which is commonly used as a tool for estimating a development curve for technology, also referred to as a learning curve or s-curve [115][127].

The s-surve illustrates the introduction, growth and maturation of innovations as well as the technological cycle most industries experience. In the early stages, large amounts of investment, effort and other resources are expended on the new technology but small performance improvements are observed. Then, as the knowledge about the technology accumulates, progress becomes more rapid. As soon as major problems are solved and the innovation reaches a certain adoption level, an exponential growth will take place. During this phase relatively small increments of effort and resources will result in large development gains. Finally, as the technology starts to approach its physical limit, further pushing of the development becomes more difficult [115].

The logistic function shows the same patterns as the stages in the learning curve, and therefore we use this to model a learning curve for development of storage. The logistic function for μ dependent on the investment level, x, is given by the following standard logistic function:

$$\mu(x) = \frac{L}{1 + e^{-k(x-x_0)}} \tag{10.4}$$

where x_0 is the average investment in R&D over the development period, L determines the maximum level of development the technology can achieve and k represents the steepness of the curve.

10.2.2 Estimation of parameters

For the estimation process it has been difficult to find any previous studies that could provide us with some insights about the parameters. Thus most of the estimation is anchored in some relatively harsh assumptions and our own best guesses. Especially regarding the relationship between the investment in R&D and the development of storage and also the link between storage and intermittency. However, we believe that the method used to construct the stochastic model for technological developments represents a sensible method that can be applied later on when more insights about the parameters become available. Thus, this method should be taken more as an investigation of a possible method to model the technological development of storage rather than a final model.

The frequency parameter λ for the Poisson process of a potential technological shock given in equation (10.1) is set to be a constant as mentioned earlier on. Because we are in the beginning of the technological lifetime of storage, we do not expect a lot of significant shocks to the industry. One important thing to notice is the negative correlation between number of shocks and size of the shocks. If we for instance want to reach a storage level around 8%, we can either do so by changing the number of shocks or the average size of the shocks. Thus the exact estimation of λ and μ does not affect the results from the model that much. We generally expect the number of shocks to approximately 1 per year, maybe a litte below this estimate. Thus we have decided on an average of 4 shocks during the development period, resulting in an frequency parameter for the Poisson process equal to

$$\hat{\lambda} = \frac{4}{1.826} = 0,00183 \tag{10.5}$$

with 1.826 being the number of days in the development period from 2018 to 2023.

First off when considering the logistic function is to determine the investment levels in R&D. The input parameter for the Poisson process μ depends on these levels, and the logistic function requires the average of these as an input. It is very common in the industry to create a joint venture between different actors in the value chain, as seen in previous cases where turbine manufacturers, grid operators, and electricity providers has joined forces, also when it comes to storage [94] [112]. This is a way to bring more capital and more knowledge across the value chain into the development project, which makes sense because storage is expected to affect the entire value chain of the wind energy industry. However, for the sake of simplicity we will only focus Ørsted like they were running a development project alone, but acknowledge that they most likely will join with other partners in different projects and other development projects in the industry will also influence the development process.

The level of investment in R&D will be anchored in the information published by Ørsted in their financial statement. In their annual report for 2017 they stated a total gross investment level of DKK 17,7 billion (€2,38 billion). Together with this they accounted for their strategic expected share of gross investment in the period 2018-2023. They expect to invest 85-90% in offshore wind, 5-10% in utility business and 0-10% in new growth initiatives [82]. Storage lies within new growth initiatives together with several other things such as:

- Continue the commercial development of our innovative Renescience technology for enzymatic waste treatment
- Mature the Energy-as-a-Service concept for our industrial and commercial customers
- Explore potential within other renewable energy technologies: Energy storage, Solar PV and Onshore wind

Based on the given information we assume that Ørsted invests 0,5% of their annual gross investment in development of storage each year in the development period. This is based on the percentages given for expected strategic investment together with the fact that Ørsted has mentioned a several growth initiatives besides storage. In 2017 they expected their gross investments to be in the range of 16-18 billion DKK (€2,15-2,42 billion), and these expectation are identical to their expectations to the gross investment in 2018. Unfortunately they have only stated their expectation for 2018 in the financial statement. Gross investments is primarily driven by constructing and operating wind farms, thus we could investigate the expected construction of new wind farms in the period and from this determine the gross investments each year. However, for sake of simplicity we will assume a constant gross investment on €2,28 billion in the development period, resulting in an annual investment in storage during the development period on €11,41 million. Over a 5 year development period this amounts to a total investment in development of storage of €57,05 million. Thus we will assume the midpoint of the investigated investment levels in R&D to lie within this area, and therefore we set $x_0 = €60$ million.

The maximum possible level of storage to achieve in the development period is assumed 16% storage capacity. This is based on the statement from KK Wind Solutions, saying 8% storage reduces production volatility with 90%. We have then simply doubled this percentage and chosen to use it as the maximum storage capacity, which may or may not be realistic, but in the absence of any reliable information to elaborate on it, we will use it for the sake of introducing the method.

For comparison, the storage project in Australia, has a storage capacity of 129 MWh which is equivalent to 2,4% of the average daily production of the Project of 5.433 MWh. Thus the technology will have to develop significantly to reach a 16% storage capacity.

The last parameter in the logistic function is k, the steepness of the curve. This estimate will be based on a trial an error approach to give a learning curve resembling that found in other studies [128][115]. By this method we find the steepness to be $k = 0,009$. However, this parameter is very sensitive to the investment levels so the best way to estimate this is by an trail and error approach, until the right shape of the s-curve occurs. In Table 10.1 is a print of the estimated parameters for the stochastic model.

Table 10.1: Estimated parameters for the stochastic model of technological development in storage

Parameter	λ	L	k	x_0
Estimate	0.02%	0.16	0.009	€ 60m

10.2.3 Results from the model

Applying the estimated parameters in Table 10.1 to the learning curve given by equation (10.4) yields the different estimates of the R&D dependent input parameter μ representing the size of the shocks. In Table 10.2 is a print of the investigated levels of R&D investments combined with the resulting estimate of μ and σ, where we have estimated σ to be half the value of μ.

Table 10.2: Parameter estimates for the stochastic R&D model

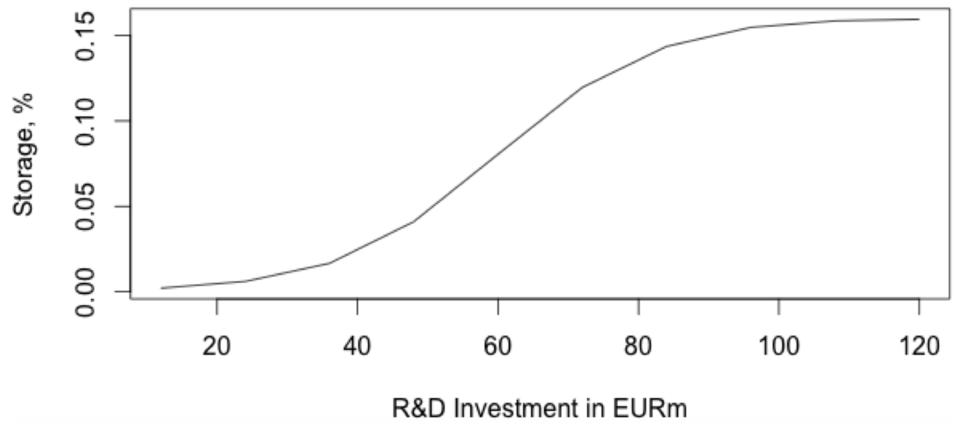
R&D (€)	μ	σ
12,000,000	0.07%	0.04%
24,000,000	0.19%	0.09%
36,000,000	0.48%	0.24%
88,000,000	1.08%	0.54%
60,000,000	2.00%	1.00%
72,000,000	2.92%	1.46%
84,000,000	3.52%	1.76%
96,000,000	3.81%	1.91%
108,000,000	3.93%	1.96%
120,000,000	3.97%	1.99%

The capital invested in R&D will be treated as a capital expenditure, and will be split equally over the years in the development period and depreciated in the same way as we did with Total Capex.

Figure 10.2 illustrates the the different levels of R&D and the effect on the technological development of storage. As mentioned earlier on, we wanted the development to be dependent of the investment level, and the dependence relationship was assumed to show the shape of a s-curve. The graph in Figure 10.2 clearly represent this and all the mentioned stages of the s-curve. The illustration also highlights the effect of the parameters in the logistic function. We can see that the curve approaches the estimate of $L = 16\%$, the maximum potential level assumed for development of storage. The estimate of $x_0 =$ €60m secures the midpoint of the s-curve, representing the steepest point on the curve.

Everything related to the stochastic model of the technological development of storage, represented by the Poisson process in equation (10.1) and the related size of the shocks drawn from the normal distribution as defined in equation (10.2) has now been identified and estimated. Thus we can start drawing the breakthroughs during the development period and find the total effect as the cummulative sum of the breakthroughs. A single realisation of the Poisson process for an investment level of €120 million is presented in Figure 10.3. In Appendix A.35 is 4 additional

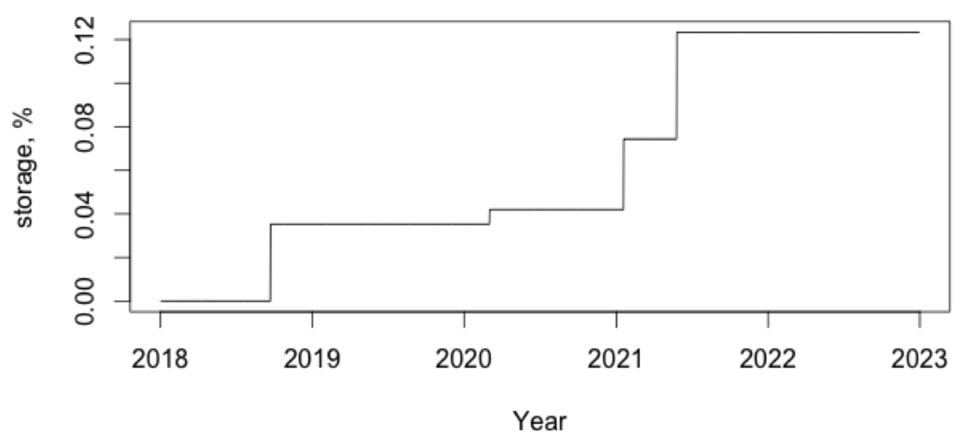
Figure 10.2: *Learning curve representing the relationship between the stochastic parameter R&D and the level of investment in R&D*



Source: Own construction based on parameters in Table 10.1

illustrations of a single representation from the stochastic model. All the illustrations shows the randomness and stochastic behavior expected from a the technological development. Both when and how many breakthroughs that occur during the development period is completely random, as well as the size of them. In the figure we can see that for this single realisation of the model the process will experience three major and one minor breakthroughs during the development period. The storage level available at FOD for this specific case will be approximately 12% of total capacity of the Project following an investment in R&D of €120 million.

Figure 10.3: *Illustration of the stochastic model for development of storage.*



Source: Own construction

Using 10.000 Monte Carlo simulations of the stochastic model for each investment level of R&D and taking the average of the total technological development over the period equation (10.3), gives us the accumulated storage capacity as a percentage of total capacity, for each investment level. The results are printed in Table 10.3 below, together with the level of intermittency, which will be explained en more details in the next section.

Table 10.3: Summary of storage model and the impact on intermittency

R&D (€)	Storage	Intermittency
12,000,000	0.29%	9.82%
24,000,000	0.76%	9.52%
36,000,000	1.91%	8.80%
48,000,000	4.34%	7.29%
60,000,000	8.06%	4.96%
72,000,000	11.73%	2.67%
84,000,000	14.21%	1.12%
96,000,000	15.29%	0.45%
108,000,000	15.85%	0.09%
120,000,000	15.94%	0.04%

10.3 Storage option assumptions

In Section 10.1 we discussed the impact of storage and found that storage will reduce the intermittency effect. Despite some studies and results from the Australian project have shown a more positive effect from storage, we will run with this more conservative assumption that the only effect of implementing storage will be a reduced intermittency effect. The reduction in the intermittency effect will be correlated to the developed capacity of storage. For simplicity we will assume that a developed storage percentage on 8% results in an intermittency effect of 5%, thus a 50% reduction in the effect compared to the 10% intermittency effect assumed in the base case. Again, this is pure speculation an cannot be substantiated by any previous studies or other sources, and is simply chosen to illustrate how the method *could be* used in the future, when the relationship between storage and intermittency has been studied in more detail.

We will use this dependency between storage and intermittency to calculate the intermittency effect for every investment level by assuming a linear dependence between storage and intermittency. Again, this is not substantiated, but the model can easily be modified once the relationship between storage and intermittency is more clearly established.

$$5\% = 8\% \cdot \alpha + 10\% \tag{10.6}$$

$$\alpha = \frac{5\%}{8\%} = 0,625 \tag{10.7}$$

where +10% comes from the base case with R&D=0 and 10% intermittency. Solving the equation for α gives us the slope of the linear dependency as seen in equation (10.7). Rewriting equation (10.6) to give intermittency as a function of storage gives us the following expression, which has been used to determine all the intermittency effects printed in Table 10.3.

$$Intermittency(R\&D) = 10 - \frac{5}{8} \cdot S(R\&D) \tag{10.8}$$

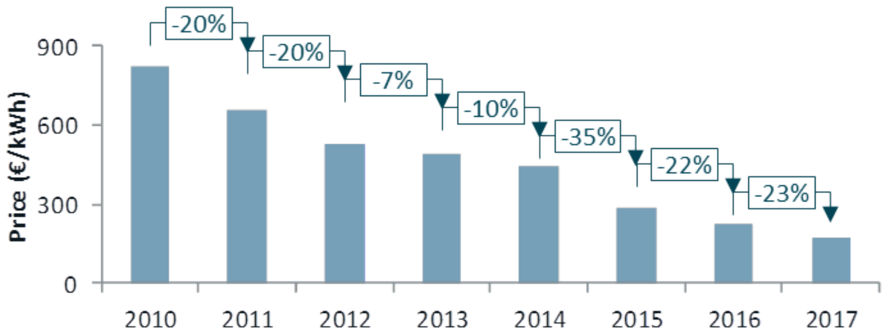
Where S(R&D) is the storage capacity as a function of investments in R&D. With the developed relation between R&D investment, storage and intermittency effect, we can now evaluate the investment in storage in relation to the Project.

Normally, one would not evaluate the total R&D investment in relation to a single project but insted to all current and future projects that might benefit from this technological development. However, when investing in R&D and in the process of developing the technology, it is quite common to use a specific project for testing and implementation purposes. For instance Ørsted currently operates a storage project at Burbo Bank offshore wind farm where a battery has been integrated with the wind farm [83]. However, the costs of development would then be carried at the corporate level, and therefore not affect the financial position of the Project.

On the other hand, it could be decided not to invest in the research and development of a solution in-house, but instead bet that a different company will develop it and sell the technology to others, such as Tesla did with the battery in Australia. To get an understanding of what the acquisition and implementation costs might be for a storage solution with a capacity on 8%, we will briefly present the current estimates in the industry. Note that a 8% daily storage for the Project results in a capacity of 435 MW, which is 8% of the the average daily production of 5.433 MWh.

Tan et al. (2012) and Paka et al. (2009) present a cost of storage for a battery solution in the range of 150-1200 \$/kWh (124-988 €/kWh) dependent on the quality of the battery [59][69]. However, these studies are rather old and may not reflect the current price of batteries. One of the battery solutions with the highest quality and potential is the Lithium-ion battery, and thus one of the most expensive solutions mentioned in the studies. Bloomberg New Energy Finance facilitates a price index for Lithium-ion batteries, where the development from 2010 to 2017 is presented in Figure 10.4

Figure 10.4: *Bloomberg New Energy Finance Lithium-ion battery price survey, 2010-2017 (€/kWh)*



Source: Own construction based on [49] and [122]

The Lithium-ion battery price was in the range of €528-823 per kWh in 2010-2012 and comparing these with the studies, we find that they actually compare to the more expensive end of the price interval. What is really interesting is the significant decrease in the price of Lithium-ion batteries, which amounted to a 79% decrease from 2010 to 2017. This will of course influence the development and profitability of storage in the coming years. Bloomberg explains the drastically decreasing price with technologic improvements, economies of scale from production, and an increased competition between the major manufactures in the industry. They specifically highlight electric vehicles and large scale storage solutions as two of the main drivers for the drastic price reduction [49][122].

Ørsted states in their financial report for Q1 2018 that they expect a 20% reduction in cost of storage by 2020, and a 40% reduction in cost of storage by 2025. Lithium-ion price is one of the main drivers for costs of battery storage, and a price reduction of 40% of the 2017 price yields a price on €105 per kWh. Bloomberg New Energy Finance also presents a forecast of the Lithium-ion price, which can be seen in Appendix A.36 [49]. This forecast aligns well with the expectation presented by Ørsted, yielding a price in 2023 on approximately 107,43 €/kWh. They even predict the price to decrease all the way down to €59,50 per kWh by 2030, indicating a huge potential for storage in the future.

These prices provides information regarding the minimum costs of implementing storage to the Project. Once again we focus on the 8% storage solution in 435 MW. From the price forecast by Bloomberg New Energy Finance in 2023 of €107,43 per kWh, we can calculate the price of the storage solution to be €0,107 /MWh $\cdot$ 435 MWh = €46,7 million. Using instead the 2017 price of €172,73 per kWh this would have resulted in a price of €75,1 million for an 8% storage solution. In our analysis, we estimated a development cost of an 8% storage solution of €60 million, and so our estimate is somewhat substantiated and in line with Bloomberg's forecasted battery prices.

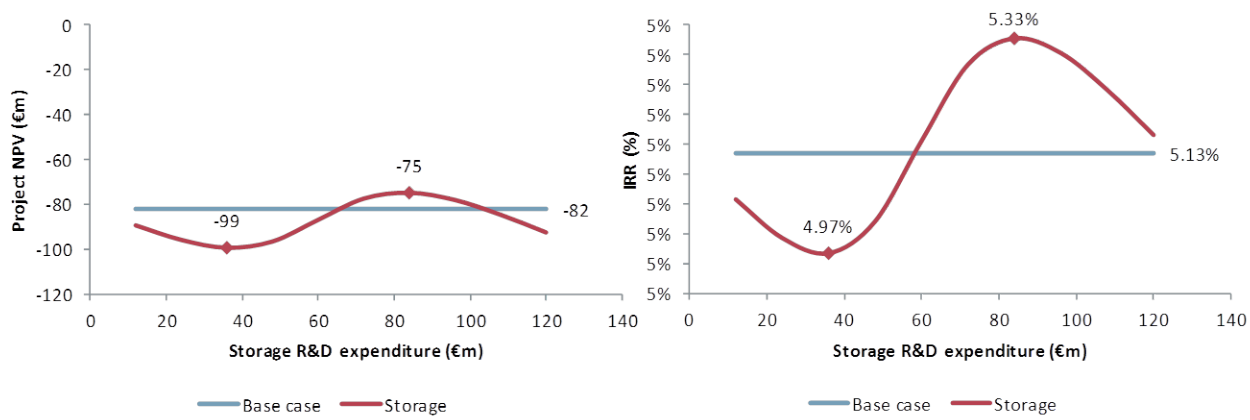
10.4 Storage option - results

Having constructed a stochastic model for the technological development of storage dependent on the investment level in R&D and combining this with a reduction in the intermittency effect as a result of introduction of storage, we are now ready to evaluate the profitability of storage in relation to the Project. This valuation will be based on the real option approach already used to value the options in Section 9.

We implement the reduction in the intermittency effect in the base case model for each investment level of R&D. The results are shown in Figure 10.5. Notice the NPV to the left and IRR to the right.

The figures reveals that investing in R&D with the purpose of developing storage actually results in a potential positive effect on the base case. For an R&D investment in the range of €72-96 million with a peak at €84 million, NPV of the Project will be improved. This corresponds to the top half of the steepest part of the logistic function, generating the relationship between R&D investment and storage and eventually also the intermittency.

Figure 10.5: *Effect of R&D investment in storage on NPV and IRR*



For the optimal investment level found in the figure above to be €84 million, we present the results of the real option valuation in Table 10.4.

Table 10.4: *Results of storage option*

Case	Production (MWh)	Revenue (€m, real-18)	Costs (€m, real-18)		Total profit (€m, real-18)	LCOE (€/MWh)	NPV (€m)	IRR (%)	Option value (€m)
			Total Capex	Opex					
Base case	49,613,556	2,258.20	1,163.38	189.39	719.50	54.20	-82.08	5.13%	-
W/ option	49,613,556	2,483.48	1,247.38	189.39	824.84	58.40	-74.86	5.33%	7.21

We see that the option to invest in R&D has a positive value equal to €7,21 million for the investment level of €84 million. The effect of the option can also be seen in the way that revenue increases without increase in production, meaning that this increase can only be a result of an increase in the price, resulting from less intermittency effect. Total Capex has also increased due to the investment in R&D.

In Appendix A.37 we present a graph identical to Figure 10.5 for the effect of storage on the upside case. The picture is almost the same, the optimal investment is still €84 million, but the investment range providing a positive effect to NPV is now wider at €60-120 million. The value of the option in the upside case is €36 million.

There are several important remarks to make about these results. First of all it relies on the expectation that development of storage will result in a reduction in the intermittency effect. How large this reduction will be is debatable, but there is no doubt that as the penetration of renewables *and* storage increase, the intermittency effect will decrease.

In summary, we have successfully constructed a model for the technological development of storage as a function of R&D investment and presented a methodology to implement and analyse the effect of such investment on the profitability of an offshore wind project. However, all results related to the analysis applied to the Project should only be viewed as illustration of the model and not be used to infer how this would effect a real-life project. The model is based on unsubstantiated assumptions and inputs, that were not possible to validate due to the limited amount of research in the still young technology.

11 Conclusion

Structured around our research questions, we have in this thesis studied a broad range of academic fields in order to illuminate the profitability and investment potential of an offshore wind farm in Germany in the near future. We have done so taking point of departure in a simulation of the actual offshore wind farm under development, which was won by Ørsted at a historical zero-subsidy bid price in 2017.

To perform this simulation, we have studied both the technical drivers of offshore wind farm profitability, such as wind flow, production and loss factors and also the financial drivers such as the spot price of electricity, the required return and the costs.

To model the wind flow at the site, we constructed a stochastic model based on historical data from the nearby FINO1 meteorological mast supplied by the BMWi (Bundesministerium fuer Wirtschaft und Energie). We fitted a Weibull distribution to the historical data using Maximum Likelihood Estimation and used this to model the future wind flow at the site. We confirmed that the model aligned very well with the historical data and that it therefore is well suited for predicting wind speed and direction for the future. Using the Monte Carlo method, we simulated the future wind flow at the site and thereby found the final wind flow used in the further analysis.

In order to convert the simulated wind flow into power production, we developed a power curve for a hypothetical 13 MW wind turbine. To do so, we first estimated the characteristics of the turbine based on information from a manufacturer and other studies. We then investigated the physical theory governing the extraction of the kinetic energy contained in a wind flow and used this to construct a free WTG power curve, i.e. without wake losses. To account for the increased hub height of the hypothetical wind turbine, we used the historical data and a least squares methodology to estimate the Hellmann exponent to be used in the wind power profile law.

After reviewing several other studies, we estimated the most important loss factors, including wake loss, availability and electrical losses and a bundled category termed other losses accounting for curtailment, environmental losses and power curve inefficiencies.

On the financial side, we investigated the theory of power prices and constructed a stochastic regime switching model based on the historical spot price of electricity in Germany. We implemented an Ornstein-Uhlenbeck process to model mean reversion and also modelled three other electricity price characteristics, namely price jumps, seasonality and trend. Of these, the trend is especially important as it directly affects the revenue generated by the Project and therefore it needs to be considered thoroughly. Many factors drive the trend of the spot price and after reviewing a number of reports on the subject, we estimated the trend to 1,0%. We then applied the

Monte Carlo method and found that the simulated spot price portrayed a pattern highly similar to the historical spot price.

Using the CAPM model, we estimated the cost of equity of Ørsted, which enabled us to find the required return, represented by the WACC. We modelled a decreasing cost of equity and thus WACC to reflect the maturing of the renewable energy industry as a whole.

To estimate the costs of the Project, we investigated the two major cost components of an offshore wind farm, Total Capex and Opex. We used a regression analysis to infer a relationship between Total Capex and total capacity and found a Total Capex per MW of €2,42 million. To determine Opex, we consulted several studies and estimated it to account for 14% of total costs. Combining the total cost of the Project with the power production, we computed the LCOE of the Project and found it to be in the low end of the range of industry expectations for future projects.

Using our simulated and estimated inputs we were able to calculate the NPV of the Project in the base, which we found to be €-82,08 million, and judging solely from this preliminary NPV result, we infered that this did not justify the zero-subsidy bid. For the Project to break even in the base case, we found that Ørsted should have bid a subsidy of €60 per MWh.

The base case realised an IRR of 5,13%, which we concluded would be too low to tolerate for Ørsted, regardless of potential strategic considerations of being the first developer in the world to construct a subsidy-free offshore wind farm. This was confirmed by the sensitivity analysis, where we found that the business case is highly sensitive to changes is Total Capex and the trend in spot price. We found that if Total Capex could be reduced by 20%, the Project would earn an IRR just under 6% and thereby almost breaking even, but that if it on the other hand increased by 10%, the Project would be highly unprofitable. Considering that cost overruns are frequent in infrastructure projects, we concluded that the risk associated with the Project would be too great compared to the limited upside potential and that Ørsted should not undertake it in its base case scenario.

Turning to the real option valuation of the Project, we defined three different real options, namely a turbine size increase option, a capacity extension option and a lifetime extension option. Of these, the lifetime extension option seemed to have the biggest stand-alone impact on the profitability of the Project, but that none of them, when exercised alone, would even make the Project break even at zero NPV. However, when all three were exercised in combination, there was a significant value uptake and the Project realised an NPV of €150,67 million and an IRR of 7,04%. This would require all three real options to become available to Ørsted in time for construction and for Ørsted to undertake the Project in the first place, they would need to have some level of certainty of the availability of the real options at FID.

From our analysis of of large scale electrical storage in renewable energy, we found that the main impact of this being developed would be a reduction in the intermittency effect and thus a higher capture price for offshore wind projects. To illustrate this, we developed a stochastic model for the technological development of storage as a function of investment in research and development. We then defined a real option valuation approach that an offshore wind farm owner could use to evaluate the option to invest in the development of a storage solution to be combined with the wind farm. For the sake of illustrating the method, we applied it to the Project using highly uncertain inputs and found that the optimal investment

In conclusion, our investigation has shed light on the technical and financial drivers of offshore wind farm profitability and has helped us understand the overall economics of the industry. Furthermore, we have identified the two factors with the biggest influence on the value of the Project, namely Total Capex and the price trend and since only Total Capex can be controlled by the developer, special effort should be attributed to bringing this down and limiting the risk of cost overruns going forward. Increasing turbine size is one specific area where this could be achieved and increasing project size is another, although both could potentially reach some point of decreasing returns to scale when a technical or physical limit is approached.

Another area that potentially could improve the business case of the Project is the development of electrical storage, however the technology is too young to say exactly how big an effect it would have and it would be contingent on a number of things such as the level of investment in research and development and how much intermittency could be reduced by and how big storage capacity this would take.

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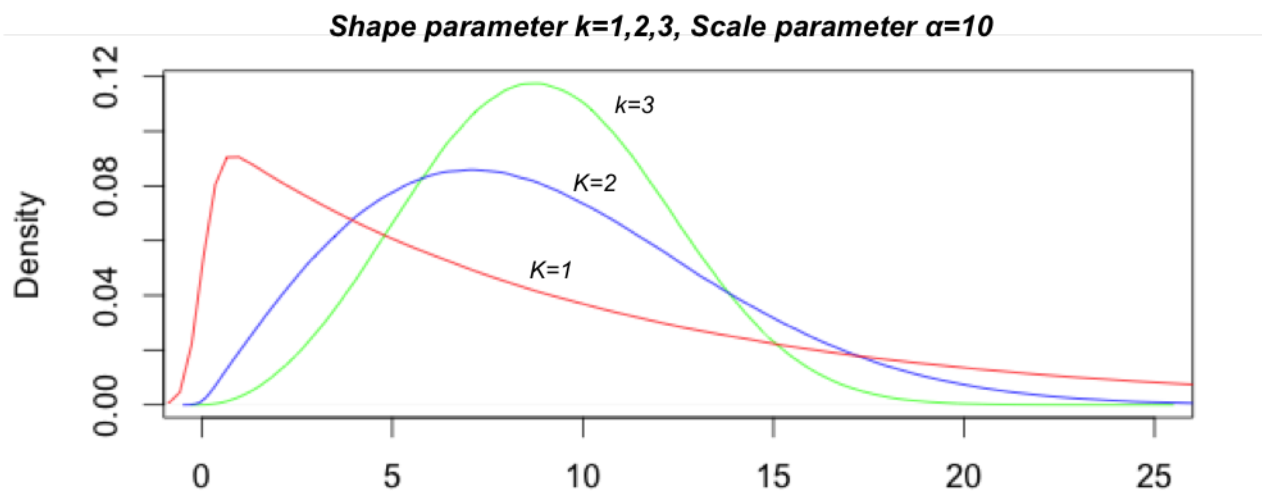
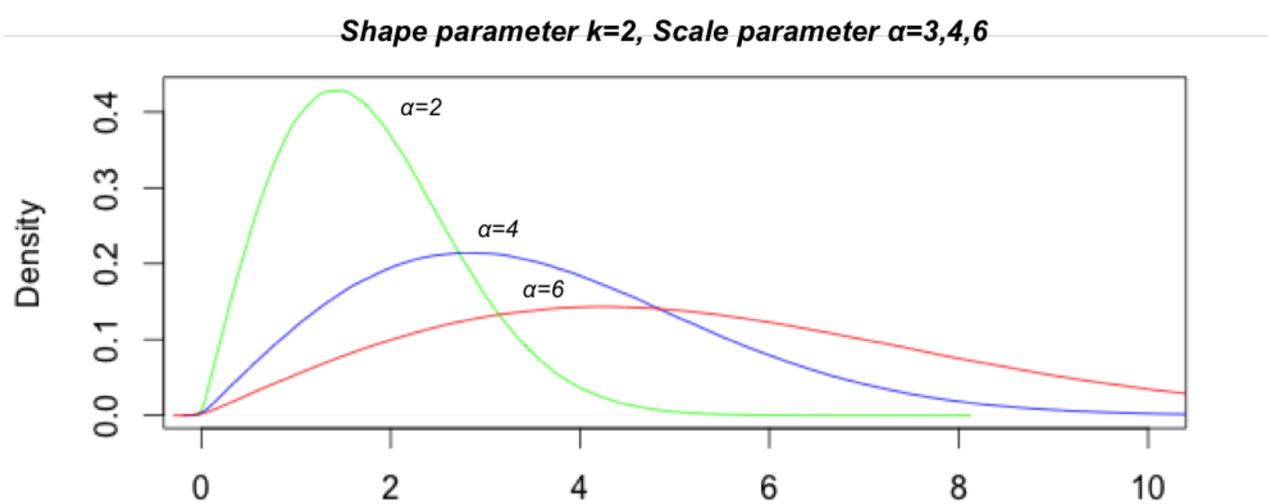
A Appendix

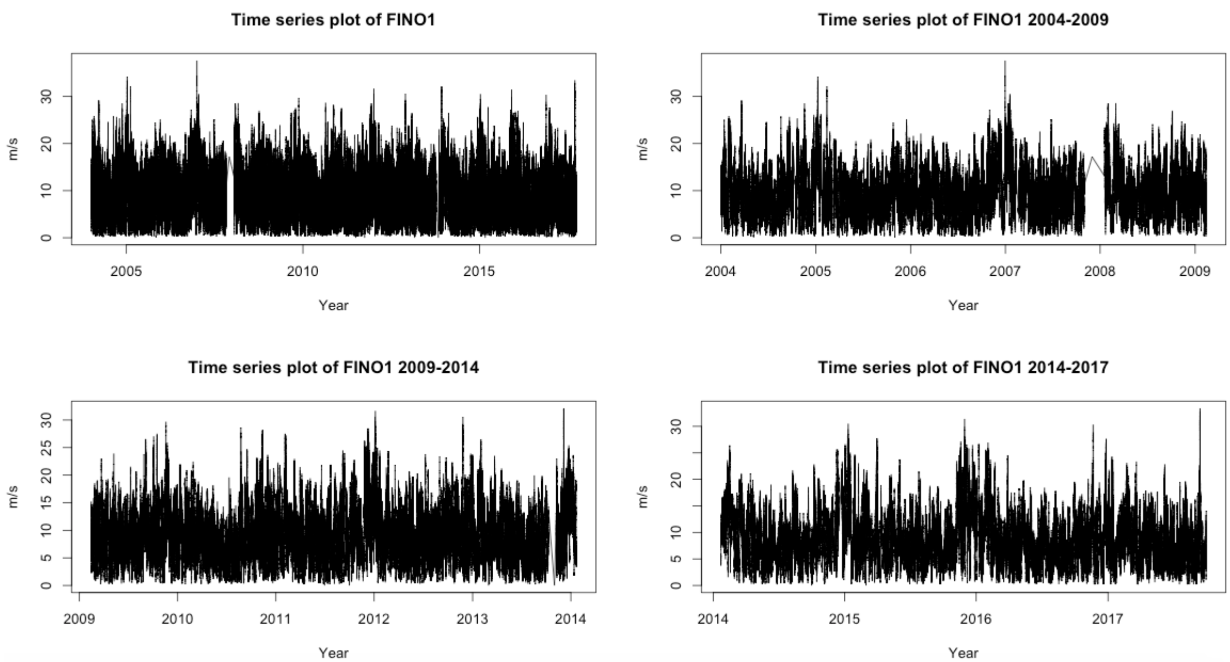
A.1 Weibull distribution functions for different shape parameters



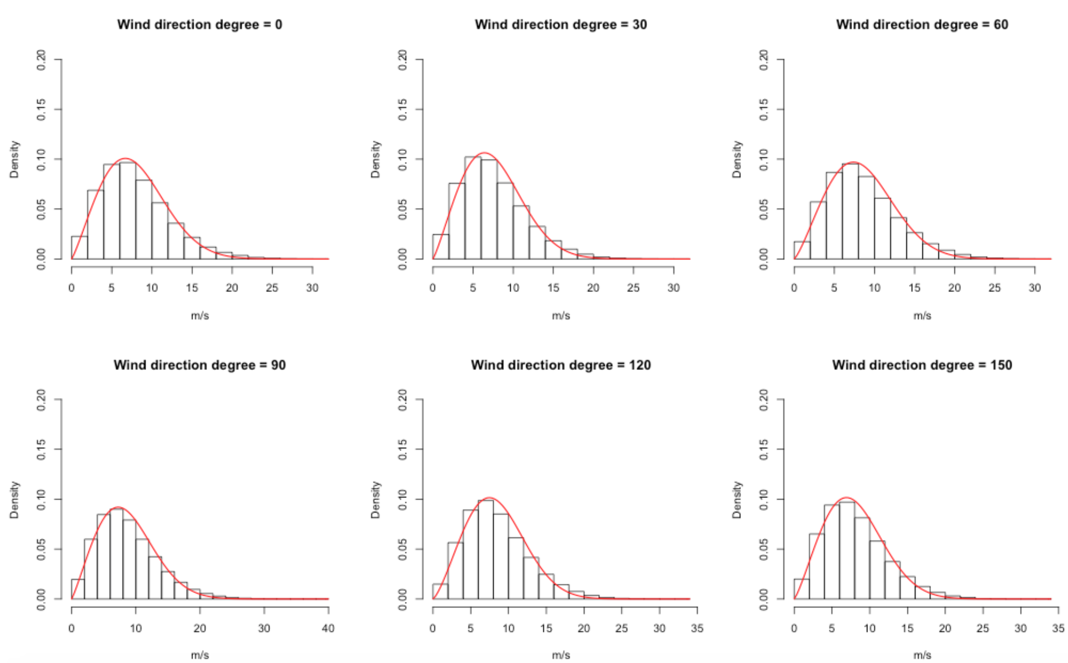
A.2 Weibull distribution functions for different scale parameters

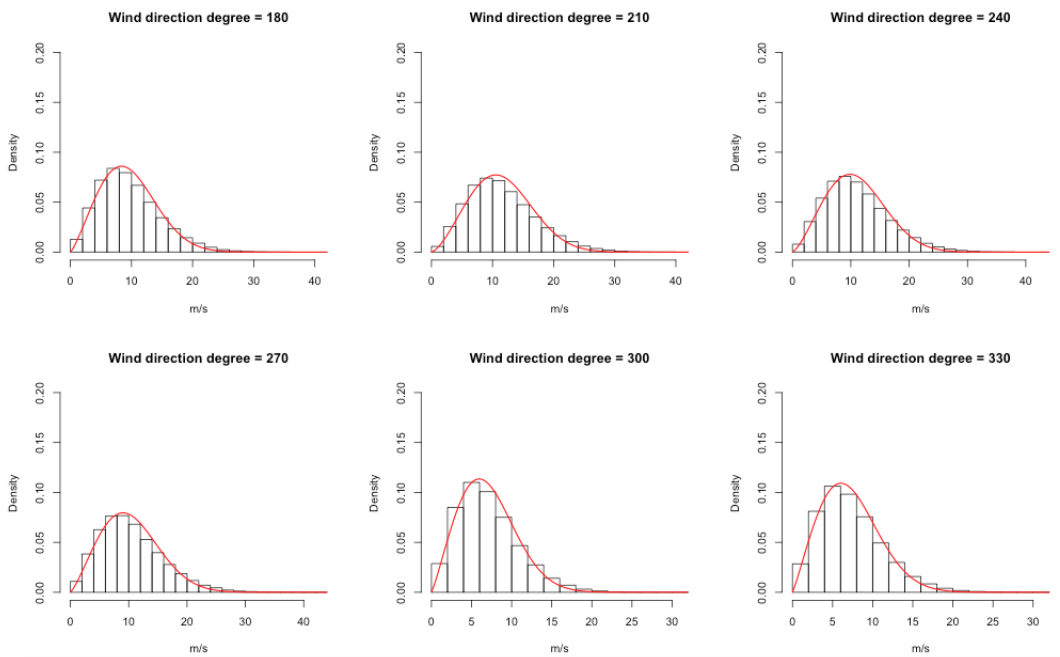


A.3 Time series plots of historic FINO1 data

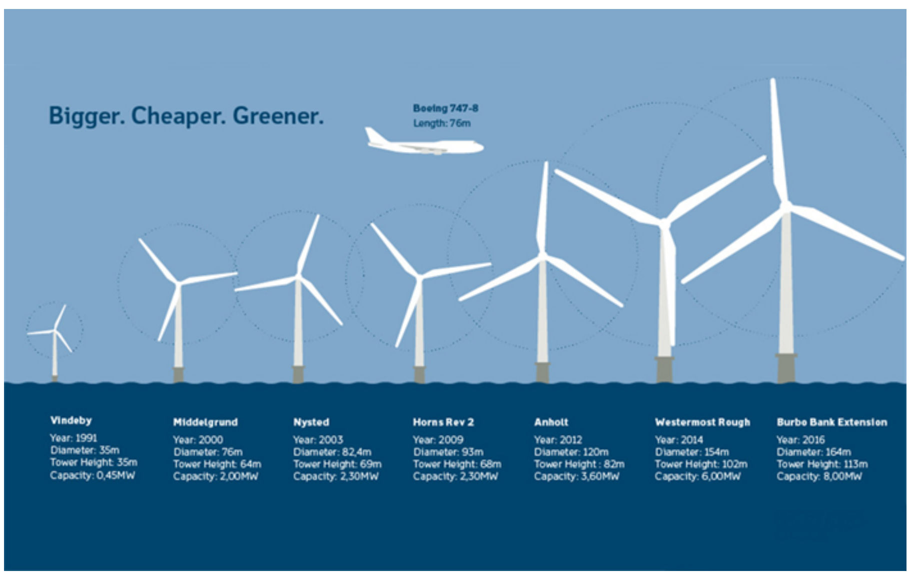


A.4 Histograms of wind speeds for every direction with estimated Weibull function





A.5 The evolution of the offshore wind turbine

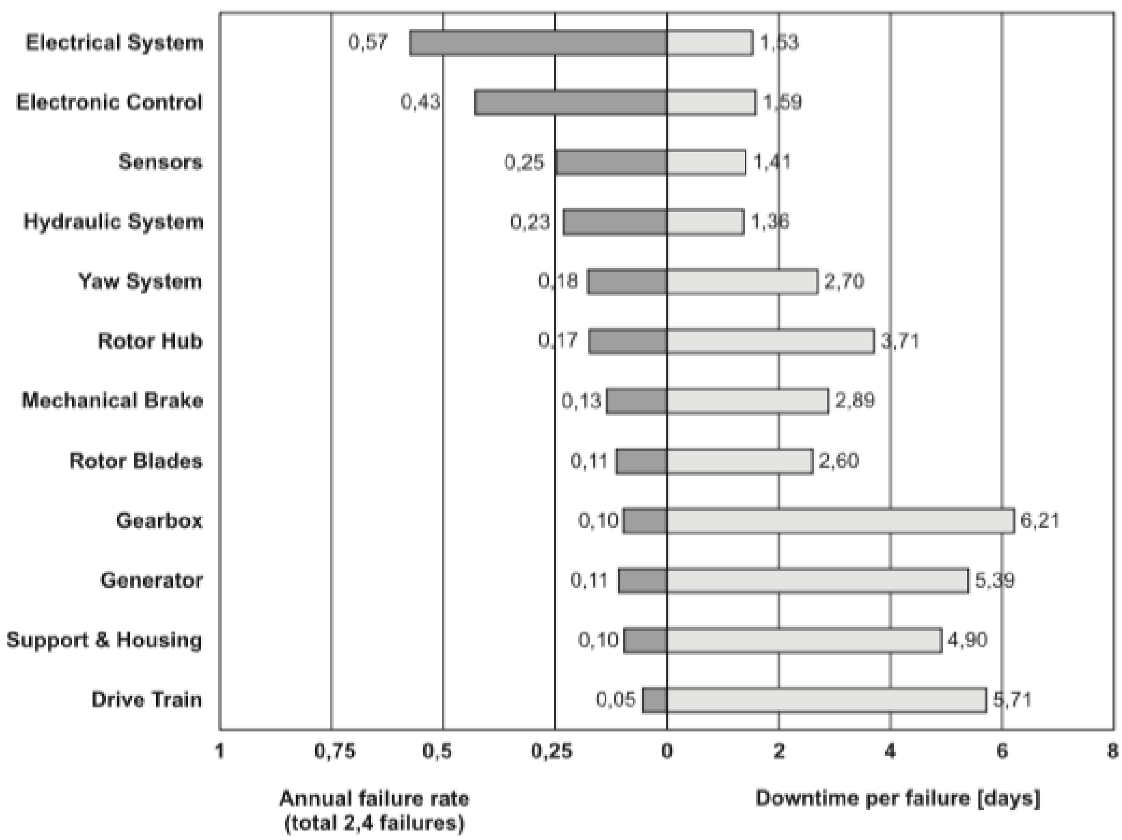


Source: Ørsted A/S

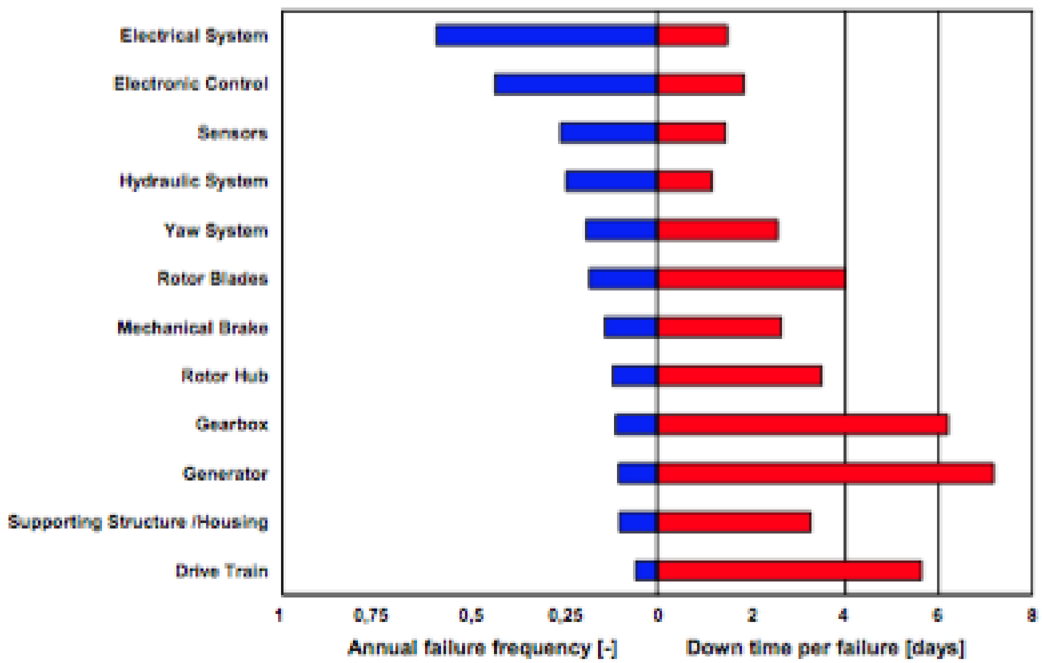
A.6 Bathtub curve for failure rate

Source: www.solarpowerworldonline.com

A.7 Failure Frequency and downtimes of components in a wind turbine

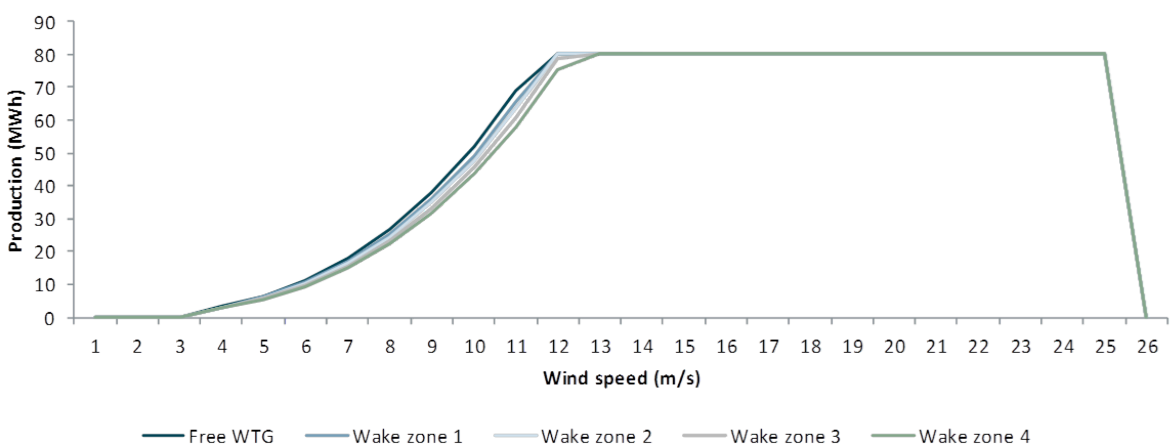


Source: Wind turbine downtime and its importance for offshore deployment [40].



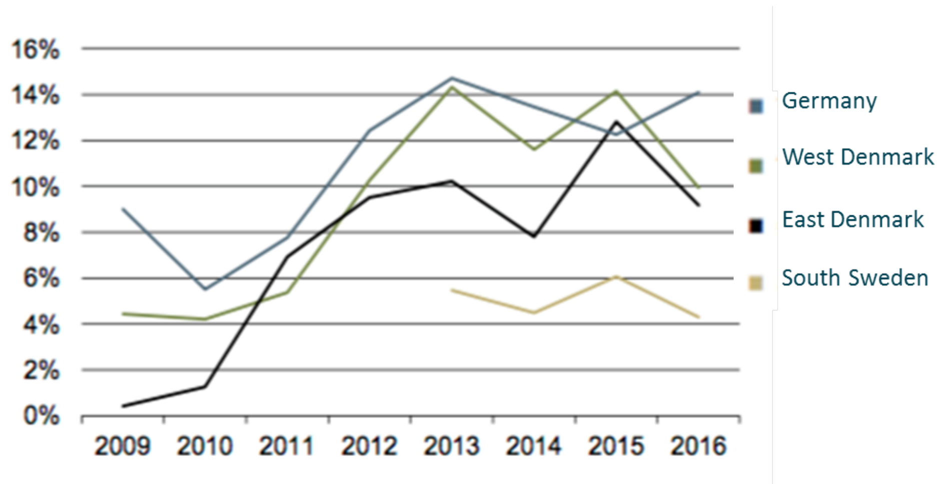
Source: Reliability of Wind Turbines [43].

A.8 Power curves for wind farm production per 10-min. interval



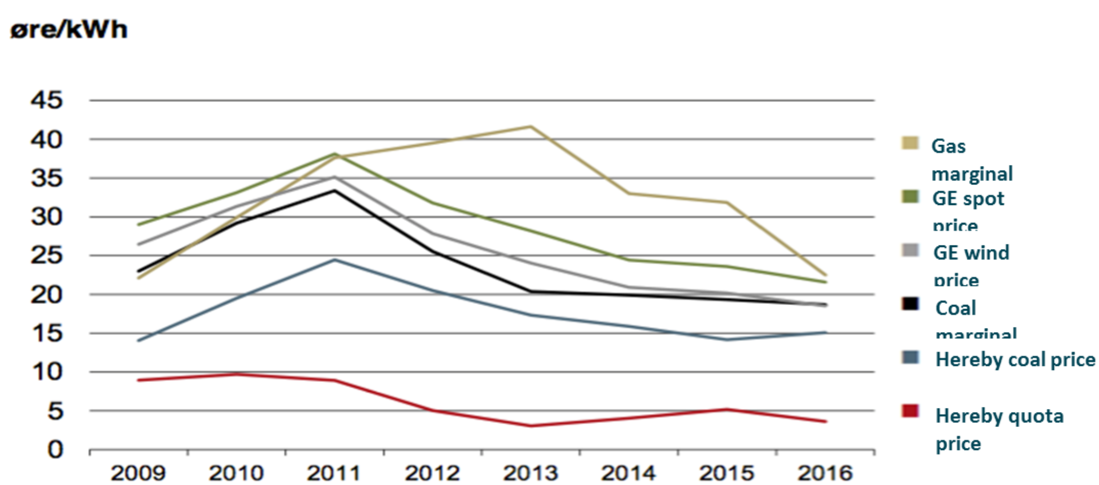
Source: Own construction

A.9 Relative price pressure for wind



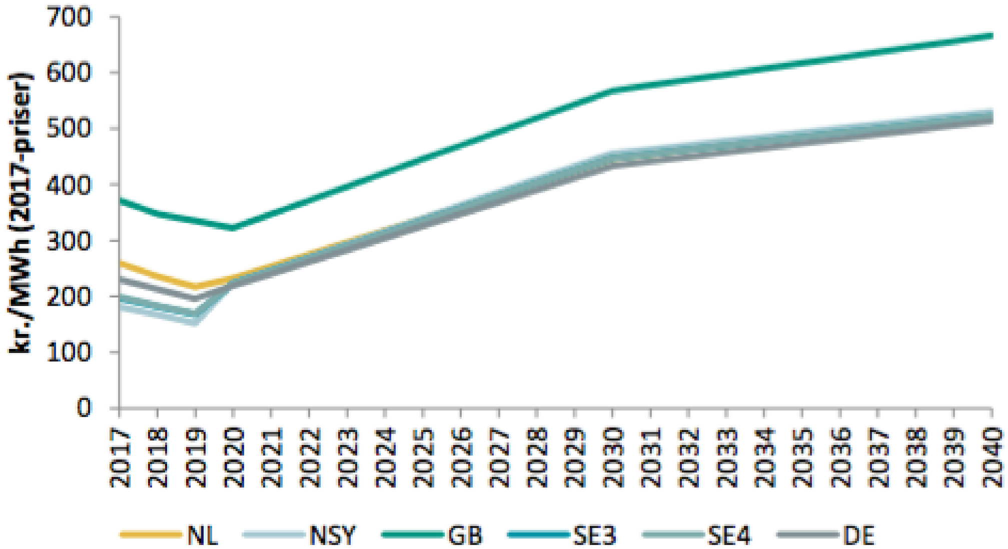
Source: https://danskenergi.dk [25]

A.10 German spot price, wind price and coal marginal



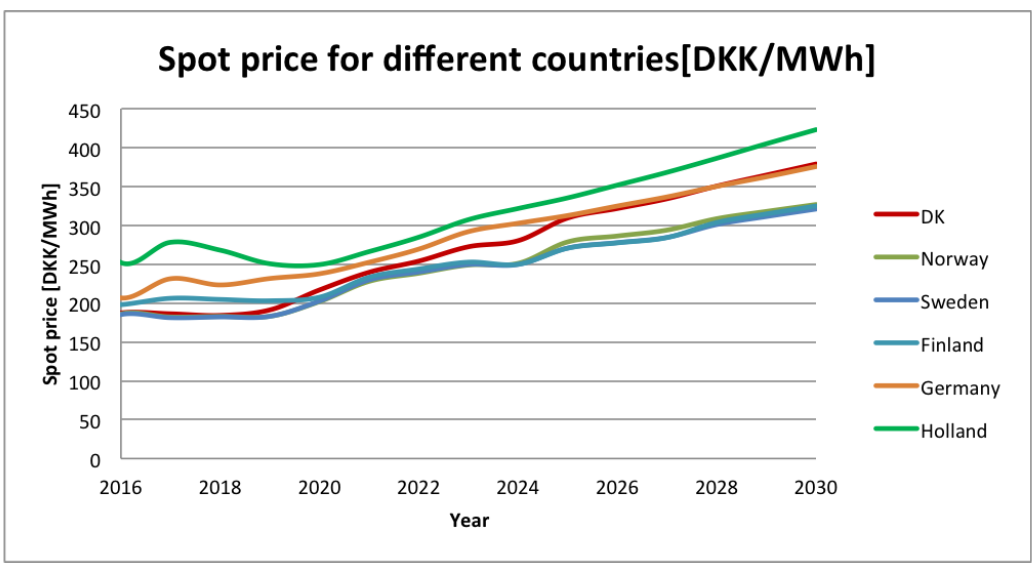
Source: https://danskenergi.dk [25]

A.11 Energinet's average yearly spot price forecasts for Northern Europe



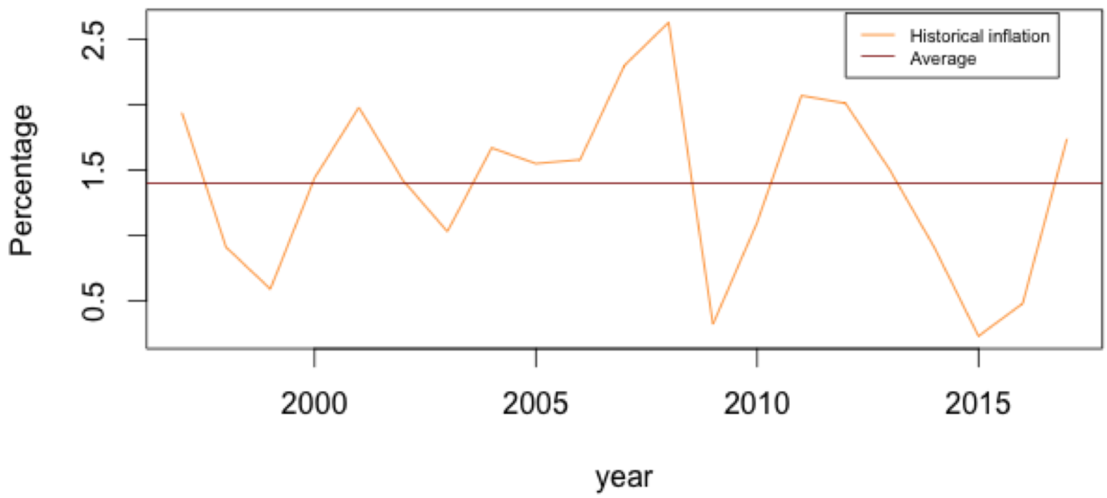
Source: [37]

A.12 Energistyrelsens average yearly spot price forecasts for Northern Europe



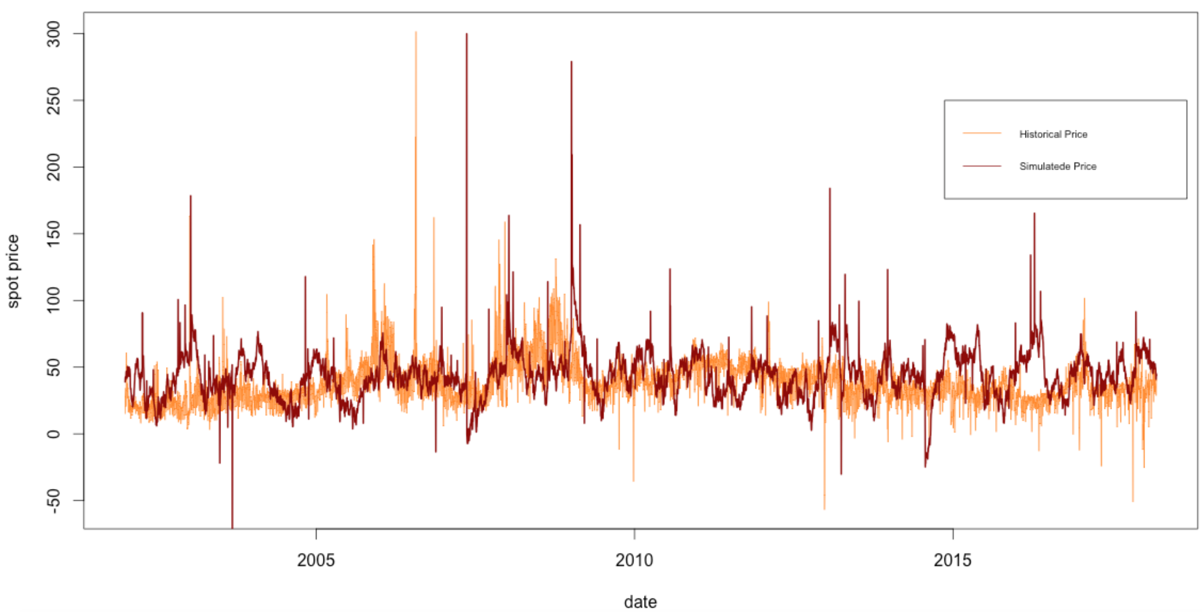
Source: [34]

A.13 Observed inflation rate in Germany 1997-2017



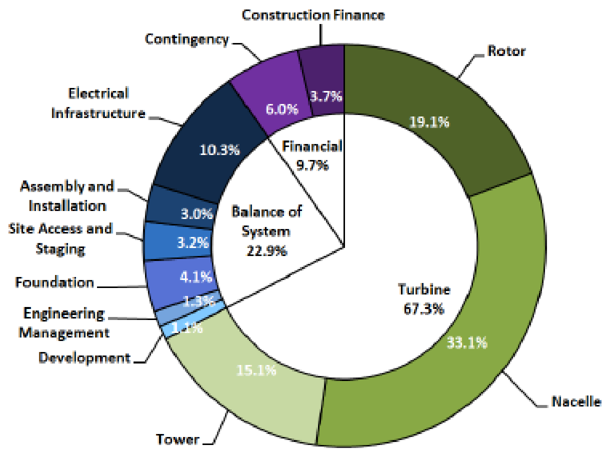
Source: https//:www.inflation.eu

A.14 Historical spot price data plotted with a simulated price path



Source: Historical spot price source: https://energinet.dk

A.15 Typical Capex split of an onshore wind farm



Source: [68]

A.16 Data used for Capex regression

Project	Commissioning year	Turbine size (MW)	Capacity (MW)	Capex (€m nom.)	Capex (€m real-18)	CAPEX/MW (€m real-18)
Alpha Ventus	2010	5.0	60	250	279	4.66
EnBW Baltic 1	2011	2.3	48	200	220	4.56
Riffgat	2014	3.6	108	480	507	4.70
Amrumbank West	2015	3.8	302	1,000	1,043	3.45
Borkum Riffgrund 1	2015	4.0	312	1,190	1,241	3.98
Butendiek	2015	3.6	288	1,300	1,355	4.71
DanTysk	2015	3.6	288	1,000	1,043	3.62
EnBW Baltic 2	2015	3.6	288	1,250	1,303	4.53
Global Tech 1	2015	5.0	400	1,800	1,877	4.69
Meerwind Süd/Ost	2015	3.6	288	1,200	1,251	4.34
Nordsee Ost	2015	6.2	295	1,300	1,355	4.59
Trianel	2015	5.0	200	900	938	4.69
Gode Wind 1 & 2	2016	6.0	582	2,200	2,262	3.89
Nordergründe	2017	6.2	111	410	416	3.76
Nordsee One	2017	6.2	332	1,200	1,217	3.66
Sandbank	2017	4.0	288	1,200	1,217	4.23
Veja Mate	2017	6.0	402	1,900	1,927	4.79
Wikinger	2018	6.0	350	1,350	1,350	3.86
Arkona	2019	6.4	385	1,200	1,183	3.07
Borkum Riffgrund 2	2019	8.0	450	1,300	1,282	2.85
Merkur	2019	6.0	396	1,600	1,578	3.98
Deutsche Bucht	2019	8.0	252	1,300	1,282	5.09
Hohe See	2019	7.0	497	1,800	1,775	3.57
Trianel Windpark Borkum II	2019	6.2	203	800	789	3.89
Arcadis Ost 1	2021	6.0	348	1,400	1,343	3.86

Source: 4C Offshore

A.17 Output for Capex regression

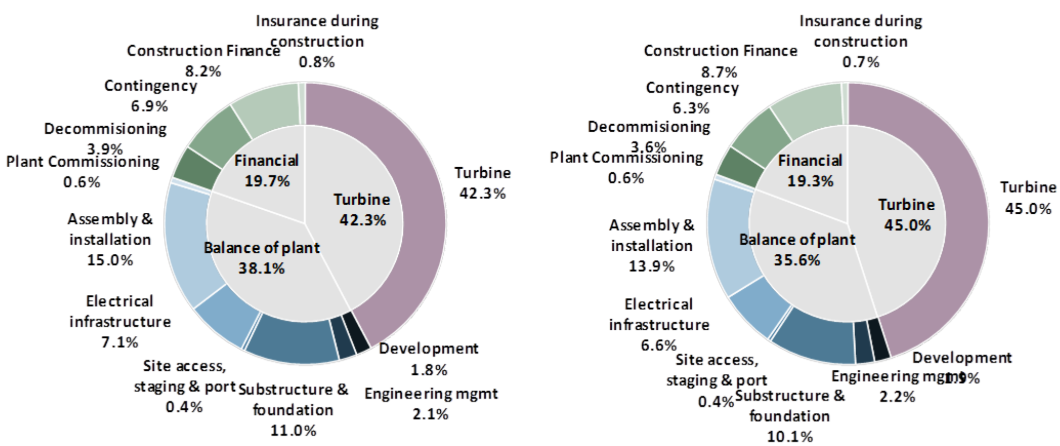
Regression Statistics	
Multiple R	0.425244
R Square	0.1808324
Adjusted R Square	0.1452164
Standard Error	0.5333034
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.444042804	1.4440428	5.0772832	0.034078513
Residual	23	6.541487444	0.2844125		
Total	24	7.985530248			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	4.6886113	0.273780806	17.12542	1.382E-14	4.122252589	5.2549701	4.122252589	5.254970084
X Variable 1	-0.0019006	0.000843502	-2.2532828	0.0340785	-0.003645564	-0.0001557	-0.003645564	-0.00015573

A.18 Capex split for 13 MW turbine, panel a), and 15 MW turbine, panel b)



Source: own construction

A.19 Comparison of characteristics between base case and BVG hypothetical wind farm

Item	Base case	BVG Associates
Turbine (MW)	13	12
FID	2021	2025
Country	Germany	None
Transmission assets	Offshore	None
Distance from shore (km)	65-80	125
Water depth (m)	30-35	35
Wind speed (m/s)	10	10
Farms size (MW)	480	500
Capex/MW (€m)	**2.94**	**1.90**

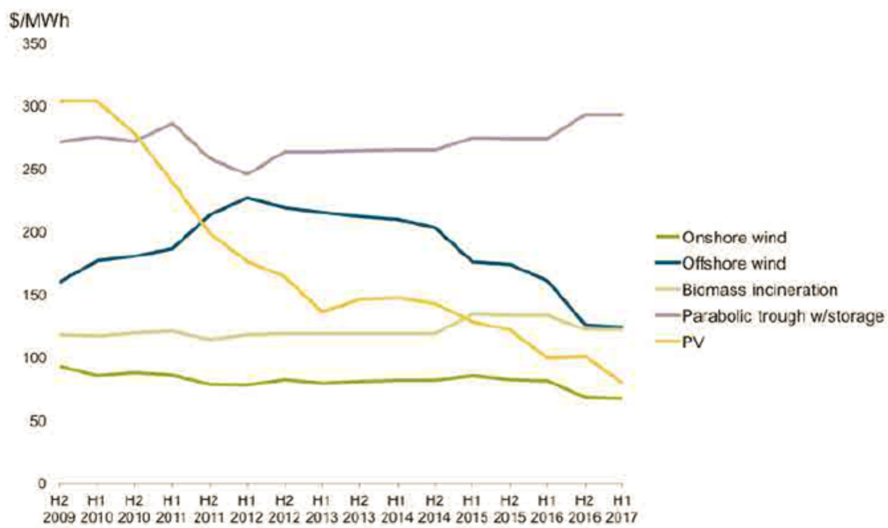
Source: own construction based on [86] and [45]

A.20 Capex spending profile proposed by Wind Europe

YEAR	-5	-4	-3	-2	-1	0
CAPEX SPEND			6%	10%	34%	50%

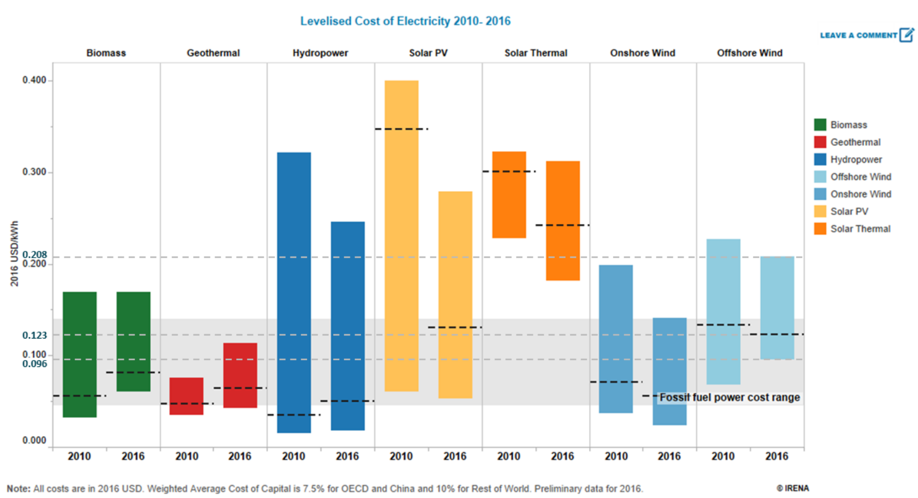
Source: [77]

A.21 Development of LCOE for different renewable technologies



Source: [72]

A.22 LCOE range for different renewable technologies



Source: [46]

A.23 Broker WACC estimates

Contributor	Date	Estimate
SEB	21-03-2018	6.00%
UBS	15-03-2018	6.70%
Morgan Stanley	07-03-2018	5.80%
Credit Suisse	28-02-2018	6.00%
Deutsche Bank	09-02-2018	7.00%
Jyske Bank	20-12-2017	7.40%
HSBC	05-10-2017	6.90%
Maquarie	18-09-2017	6.00%
Average		**6.48%**
Median		**6.35%**

Source of reports: Capital IQ, Thomson One

A.24 WACC calculation

Beta estimation	Metric	Comments	Source
Unlevered beta	0,73	*Green & Renewable Energy*	*A. Damodaran*
Target equity ratio	60%	*Long-term assumption*	*Assumption*
Target debt ratio	40%	*Long-term assumption*	*Assumption*
D/E, target	0,7x	*Implied*	*Implied*
Tax rate	30%	*German tax rate 2018*	*KPMG*
Ørsted beta	**1,06**	*Initial estimate*	
Wind Power beta	**1,23**	*Corrected for excess construction risk*	
Project beta	**1,31**	*Corrected for electricity price exposure*	

WACC estimation	Metric	Comments	Source
Risk-free rate	2,86%	*US 30-year Treasury bond yield*	*Bloomberg*
Risk premium on debt	1,27%	*Default spread*	*A. Damodaran*
Cost of debt (after tax)	**2,89%**		
Equity risk premium	5,08%	*Germany estimate*	*A. Damodaran*
Cost of equity, Ørsted	**8,26%**		
Cost of equity, Wind Power	**9,09%**		
Cost of equity, Project	**9,50%**		
Ørsted WACC	**6,14%**		
Risk premium of Wind Power	**0,50%**	*Estimate*	
Wind Power WACC	**6,64%**		
Risk premium of electricity price exposure	**0,25%**	*Estimate*	
Project WACC	**6,89%**	*To be used in valuation*	
Total risk premium	**0,75%**	*Implied*	

A.25 Global defined parameters used in the Thesis

Global parameters		
Parameter	Value	Source
EUR/USD	1.21484	Oanda.com
EUR/DKK	7.44771	Oanda.com
German inflation rate	1.40%	Inflation.eu (21-year average)
Depreciation (straight line)	16 years	PwC
German tax rate	30%	KPMG

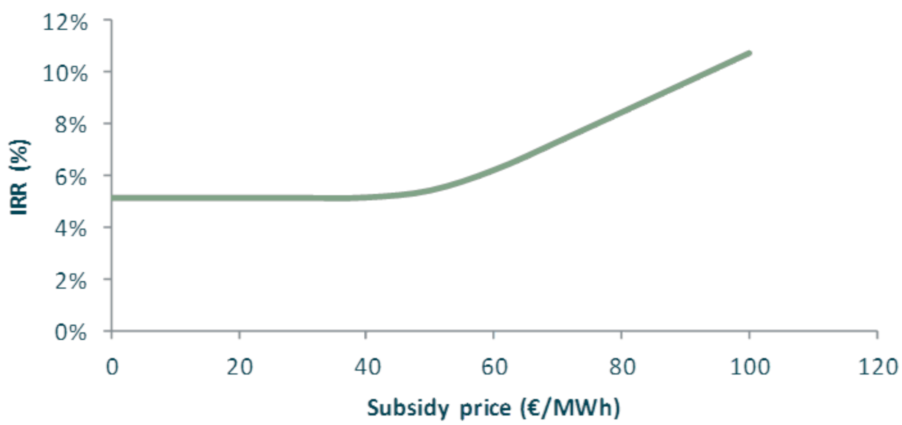
A.26 Full valuation results

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Revenue	**€m**	**2,934**	**0**	**0**	**0**	**0**	**0**	**0**	**88**	**89**	**93**	**94**	**97**	**98**	**99**
- Opex	€m	244	0	0	0	0	0	0	8	8	8	9	9	9	9
- Abex	€m	68	0	0	0	0	0	0	0	0	0	0	0	0	0
EBITDA	**€m**	**2,621**	**0**	**0**	**0**	**0**	**0**	**0**	**79**	**81**	**84**	**85**	**89**	**89**	**91**
- Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	75	75	75
EBIT	**€m**	**1,428**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**5**	**6**	**10**	**11**	**14**	**14**	**16**
- Tax	€m	428	0	0	0	-1	-1	-5	1	2	3	3	4	4	5
Profit after tax	**€m**	**999**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**3**	**4**	**7**	**7**	**10**	**10**	**11**
+ Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	75	75	75
- Capex additions	€m	1,193	12	12	24	24	173	949	0	0	0	0	0	0	0
Free cash flow, FCF	**€m**	**999**	**-12**	**-12**	**-23**	**-23**	**-171**	**-944**	**78**	**79**	**81**	**82**	**84**	**85**	**86**
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	2.02	2.15	2.28
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-124**	**-638**	**49**	**47**	**46**	**43**	**42**	**39**	**38**

	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048
Revenue	**102**	**105**	**107**	**110**	**114**	**116**	**118**	**120**	**123**	**128**	**130**	**134**	**136**	**140**	**144**	**145**	**148**	**154**
- Opex	9	9	9	9	10	10	10	10	10	10	10	11	11	11	11	11	11	11
- Abex	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68
EBITDA	**93**	**96**	**97**	**101**	**104**	**106**	**108**	**110**	**113**	**118**	**120**	**123**	**125**	**129**	**133**	**134**	**137**	**74**
- Depreciations	75	75	75	75	74	73	72	70	59	0	0	0	0	0	0	0	0	0
EBIT	**19**	**22**	**23**	**26**	**31**	**33**	**37**	**40**	**54**	**118**	**120**	**123**	**125**	**129**	**133**	**134**	**137**	**74**
- Tax	6	7	7	8	9	10	11	12	16	35	36	37	38	39	40	40	41	22
Profit after tax	**13**	**15**	**16**	**18**	**21**	**23**	**26**	**28**	**38**	**82**	**84**	**86**	**88**	**91**	**93**	**94**	**96**	**52**
+ Depreciations	75	75	75	75	74	73	72	70	59	0	0	0	0	0	0	0	0	0
- Capex additions	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Free cash flow, FCF	**88**	**90**	**91**	**93**	**95**	**96**	**97**	**98**	**97**	**82**	**84**	**86**	**88**	**91**	**93**	**94**	**96**	**52**
Discount factor	2.42	2.57	2.72	2.88	3.05	3.23	3.42	3.62	3.82	4.04	4.26	4.50	4.74	5.00	5.27	5.55	5.84	6.14
Discounted FCF	**36**	**35**	**33**	**32**	**31**	**30**	**28**	**27**	**25**	**20**	**20**	**19**	**18**	**18**	**18**	**17**	**16**	**8**

NPV	**€m**	**-82.08**
IRR	**%**	**5.13%**

A.27 IRR of the base case as a function of subsidy price



A.28 Turbine size option valuation results

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	...	2044	2045	2046	2047	2048
Revenue	**€m**	**2,885**	**0**	**0**	**0**	**0**	**0**	**0**	**86**	**88**	**91**	**92**	...	**138**	**142**	**143**	**146**	**151**
- Opex	€m	229	0	0	0	0	0	0	8	8	8	8	...	10	10	10	11	11
- Abex	€m	59	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	59
EBITDA	**€m**	**2,597**	**0**	**0**	**0**	**0**	**0**	**0**	**78**	**80**	**83**	**84**	...	**128**	**132**	**132**	**135**	**81**
- Depreciations	€m	1,120	0	1	1	3	4	15	70	70	70	70	...	0	0	0	0	0
EBIT	**€m**	**1,477**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**8**	**10**	**13**	**14**	...	**128**	**132**	**132**	**135**	**81**
- Tax	€m	443	0	0	0	-1	-1	-5	3	3	4	4	...	38	39	40	40	24
Profit after tax	**€m**	**1,034**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**6**	**7**	**9**	**10**	...	**89**	**92**	**93**	**94**	**57**
+ Depreciations	€m	1,120	0	1	1	3	4	15	70	70	70	70	...	0	0	0	0	0
- Capex additions	€m	1,120	12	12	24	24	175	874	0	0	0	0	...	0	0	0	0	0
Free cash flow, FCF	**€m**	**1,034**	**-12**	**-12**	**-23**	**-23**	**-173**	**-869**	**76**	**77**	**79**	**80**	...	**89**	**92**	**93**	**94**	**57**
													...					
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	...	5.00	5.27	5.55	5.84	6.14
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-125**	**-588**	**48**	**46**	**44**	**42**	...	**18**	**17**	**17**	**16**	**9**

NPV	**€m**	**-48.15**
IRR	**%**	**5.53%**

A.29 Capacity extension option valuation results

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	...	2044	2045	2046	2047	2048
Revenue	**€m**	**5,471**	**0**	**0**	**0**	**0**	**0**	**0**	**163**	**166**	**173**	**175**	...	**261**	**269**	**271**	**276**	**286**
- Opex	€m	424	0	0	0	0	0	0	14	14	15	15	...	19	19	19	20	20
- Abex	€m	119	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	119
EBITDA	**€m**	**4,928**	**0**	**0**	**0**	**0**	**0**	**0**	**149**	**152**	**158**	**160**	...	**243**	**250**	**252**	**256**	**148**
- Depreciations	€m	2,073	0	1	1	3	4	15	130	130	130	130	...	0	0	0	0	0
EBIT	**€m**	**2,855**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**19**	**22**	**29**	**30**	...	**243**	**250**	**252**	**256**	**148**
- Tax	€m	856	0	0	0	-1	-1	-5	6	7	9	9	...	73	75	75	77	44
Profit after tax	**€m**	**1,998**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**14**	**16**	**20**	**21**	...	**170**	**175**	**176**	**179**	**103**
+ Depreciations	€m	2,073	0	1	1	3	4	15	130	130	130	130	...	0	0	0	0	0
- Capex additions	€m	2,073	12	12	24	24	173	1,829	0	0	0	0	...	0	0	0	0	0
Free cash flow, FCF	**€m**	**1,998**	**-12**	**-12**	**-23**	**-23**	**-171**	**-1,824**	**143**	**145**	**150**	**151**	...	**170**	**175**	**176**	**179**	**103**
													...					
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	...	5.00	5.27	5.55	5.84	6.14
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-124**	**-1,233**	**91**	**87**	**84**	**79**	...	**34**	**33**	**32**	**31**	**17**

NPV	**€m**	**-47.88**
IRR	**%**	**5.81%**

A.30 Lifetime extension option valuation results

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	...	2044	2045	2046	2047	2048	2049	2050	2051	2052	2053
Revenue	**€m**	**2,934**	**0**	**0**	**0**	**0**	**0**	**0**	**88**	**89**	**93**	**94**	...	**140**	**144**	**145**	**148**	**154**	**156**	**160**	**165**	**168**	**172**
- Opex	€m	244	0	0	0	0	0	0	8	8	8	9	...	11	11	11	11	11	12	12	12	12	12
- Abex	€m	0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	73
EBITDA	**€m**	**2,689**	**0**	**0**	**0**	**0**	**0**	**0**	**79**	**81**	**84**	**85**	...	**129**	**133**	**134**	**137**	**142**	**144**	**148**	**153**	**156**	**86**
- Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	...	0	0	0	0	0	0	0	0	0	0
EBIT	**€m**	**1,496**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**5**	**6**	**10**	**11**	...	**129**	**133**	**134**	**137**	**142**	**144**	**148**	**153**	**156**	**86**
- Tax	€m	449	0	0	0	-1	-1	-5	1	2	3	3	...	39	40	40	41	43	43	44	46	47	26
Profit after tax	**€m**	**1,047**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**3**	**4**	**7**	**7**	...	**91**	**93**	**94**	**96**	**99**	**101**	**103**	**107**	**109**	**60**
+ Depreciations	€m	1,193	0	1	1	3	4	15	75	75	75	75	...	0	0	0	0	0	0	0	0	0	0
- Capex additions	€m	1,193	12	12	24	24	173	949	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Free cash flow, FCF	**€m**	**1,047**	**-12**	**-12**	**-23**	**-23**	**-171**	**-944**	**78**	**79**	**81**	**82**	...	**91**	**93**	**94**	**96**	**99**	**101**	**103**	**107**	**109**	**60**
													...										
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	...	5.00	5.27	5.55	5.84	6.14	6.45	6.78	7.13	7.49	7.88
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-124**	**-638**	**49**	**47**	**46**	**43**	...	**18**	**18**	**17**	**16**	**16**	**16**	**15**	**15**	**15**	**8**

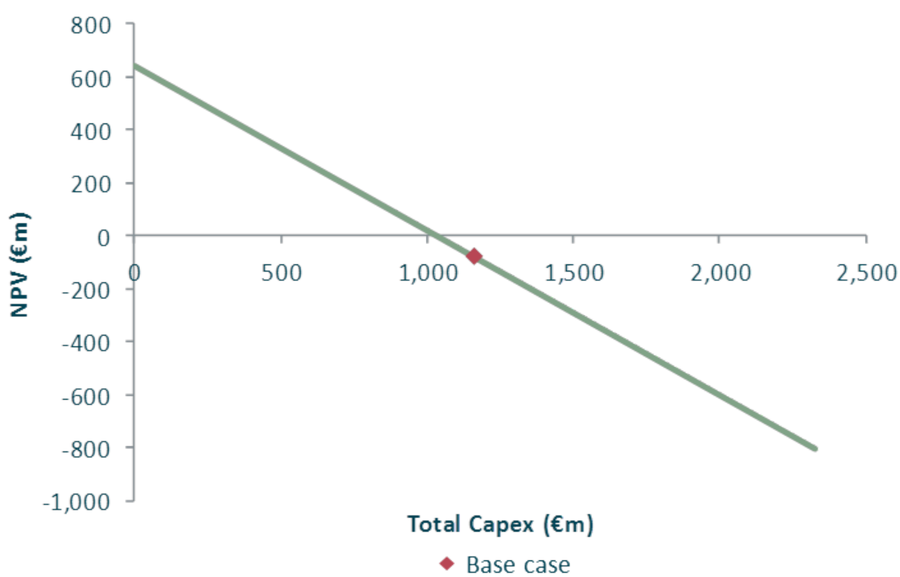
NPV	**€m**	**-6.08**
IRR	**%**	**6.02%**

A.31 Upside case valuation results

	Unit	Sum	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	...	2044	2045	2046	2047	2048	2049	2050	2051	2052	2053
Revenue	**€m**	**5,410**	**0**	**0**	**0**	**0**	**0**	**0**	**162**	**165**	**171**	**173**	...	**259**	**266**	**268**	**273**	**283**	**288**	**294**	**305**	**310**	**317**
- Opex	€m	399	0	0	0	0	0	0	13	14	14	14	...	18	18	18	18	19	19	19	20	20	20
- Abex	€m	0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	110
EBITDA	**€m**	**5,011**	**0**	**0**	**0**	**0**	**0**	**0**	**148**	**151**	**157**	**159**	...	**241**	**248**	**250**	**254**	**264**	**268**	**275**	**285**	**290**	**187**
- Depreciations	€m	1,957	0	1	1	3	4	15	122	122	122	122	...	0	0	0	0	0	0	0	0	0	0
EBIT	**€m**	**3,054**	**0**	**-1**	**-1**	**-3**	**-4**	**-15**	**26**	**29**	**35**	**37**	...	**241**	**248**	**250**	**254**	**264**	**268**	**275**	**285**	**290**	**187**
- Tax	€m	916	0	0	0	-1	-1	-5	8	9	10	11	...	72	74	75	76	79	81	83	86	87	56
Profit after tax	**€m**	**2,137**	**0**	**-1**	**-1**	**-2**	**-3**	**-11**	**18**	**20**	**24**	**26**	...	**169**	**174**	**175**	**178**	**185**	**188**	**193**	**200**	**203**	**131**
+ Depreciations	€m	1,957	0	1	1	3	4	15	122	122	122	122	...	0	0	0	0	0	0	0	0	0	0
- Capex additions	€m	1,957	12	12	24	24	175	1,711	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Free cash flow, FCF	**€m**	**2,137**	**-12**	**-12**	**-23**	**-23**	**-173**	**-1,706**	**140**	**142**	**147**	**148**	...	**169**	**174**	**175**	**178**	**185**	**188**	**193**	**200**	**203**	**131**
													...										
Discount factor	Factor		1.07	1.14	1.22	1.30	1.39	1.48	1.58	1.68	1.79	1.90	...	5.00	5.27	5.55	5.84	6.14	6.45	6.78	7.13	7.49	7.88
Discounted FCF	**€m**		**-11**	**-10**	**-19**	**-18**	**-125**	**-1,154**	**89**	**85**	**82**	**78**	...	**34**	**33**	**32**	**31**	**30**	**29**	**28**	**28**	**27**	**17**

NPV	**€m**	**150.67**
IRR	**%**	**7.04%**

A.32 Sensitivity to Total Capex



A.33 Sensitivity to changes in gridloss and other losses

a)

Electrical loss \ Other losses	1%	2%	3%	4%	5%
0%	-53.34	-60.52	-67.71	-74.89	-82.08
1%	-60.52	-67.71	-74.89	-82.08	-89.26
2%	-67.71	-74.89	-82.08	-89.26	-96.45
3%	-74.89	-82.08	-89.26	-96.45	-103.63
4%	-82.08	-89.26	-96.45	-103.63	-110.82

NPV > 0   Base case   NPV < 0

b)

Electrical loss \ Other losses	1%	2%	3%	4%	5%
0%	5.50%	5.41%	5.32%	5.23%	5.13%
1%	5.41%	5.32%	5.23%	5.13%	5.04%
2%	5.32%	5.23%	5.13%	5.04%	4.95%
3%	5.23%	5.13%	5.04%	4.95%	4.85%
4%	5.13%	5.04%	4.95%	4.85%	4.76%

IRR > 6%   Base case   IRR < 6%

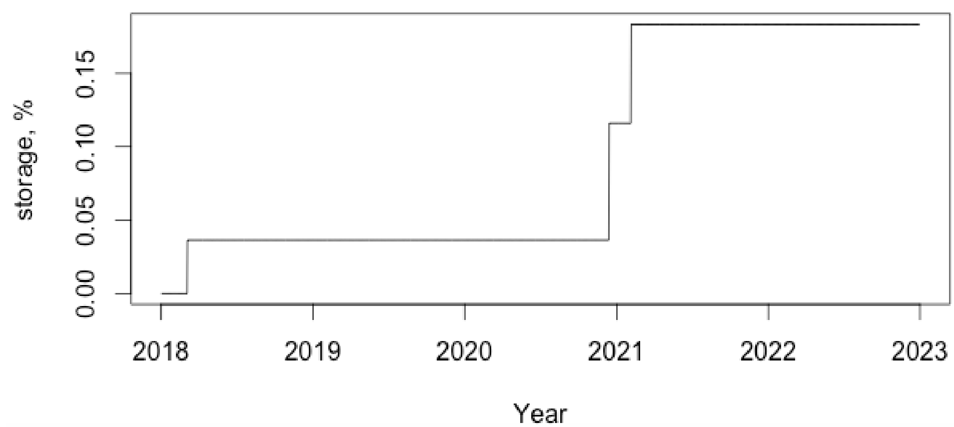
A.34 Production for increased turbine size option

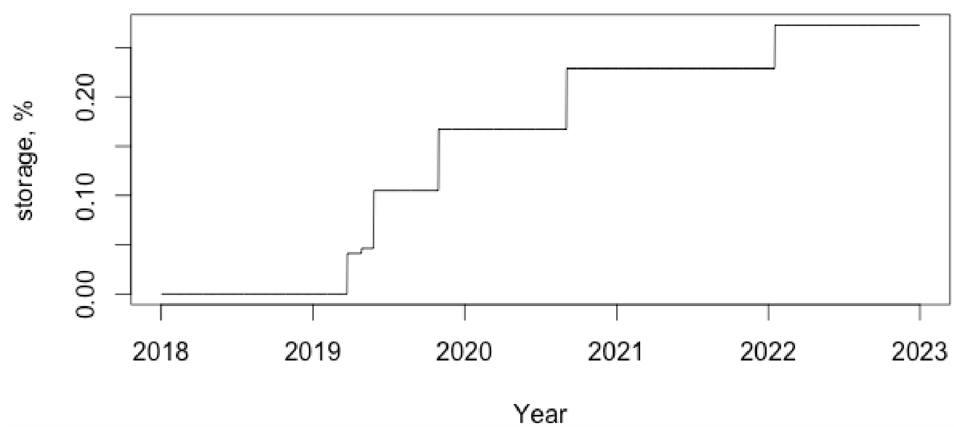
Base case			
Production (MWh)	**Gross production**	**Net of wake loss**	**Net production**
Lifetime production	60,212,564	54,520,392	49,613,556
Mean yearly production	2,408,503	2,180,816	2,049,967
Mean yearly capacity factor	**57.2%**	**51.8%**	**48.7%**
Lifetime loss factor		**9.5%**	**17.6%**

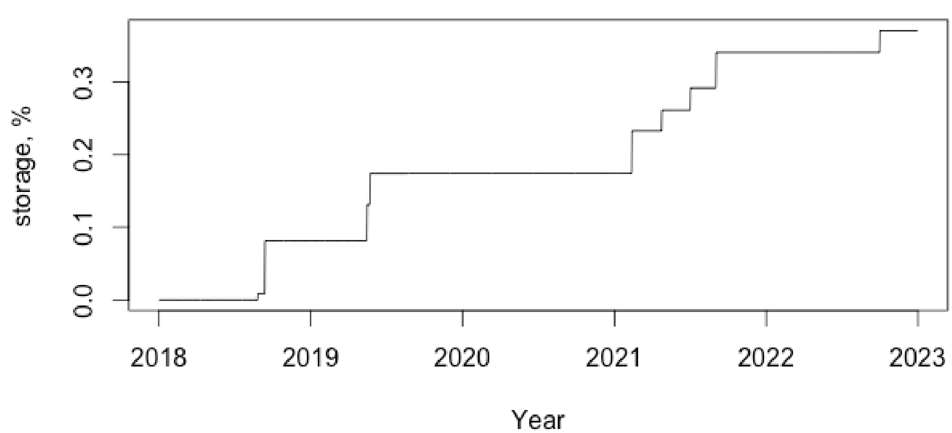
Increased turbine size (15 MW)			
Production (MWh)	**Gross production**	**Net of wake loss**	**Net production**
Total production	59,198,544	53,605,262	48,780,788
Mean yearly production	2,367,942	2,144,210	2,015,558
Mean yearly capacity factor	**56.3%**	**51.0%**	**47.9%**
Loss		**9.4%**	**17.6%**

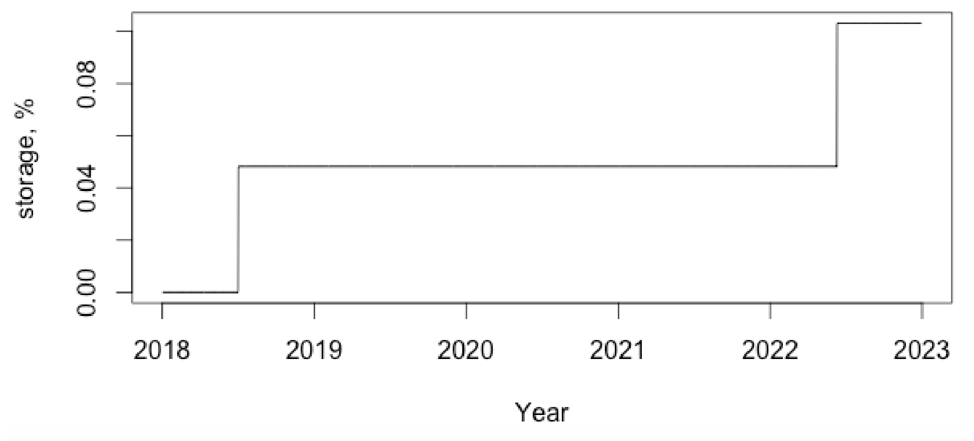
Resulting from 1.000 MC simulations of wind speed and direction matched with constructed power curve

A.35 Representations of storage development for R&D= 20m EUR

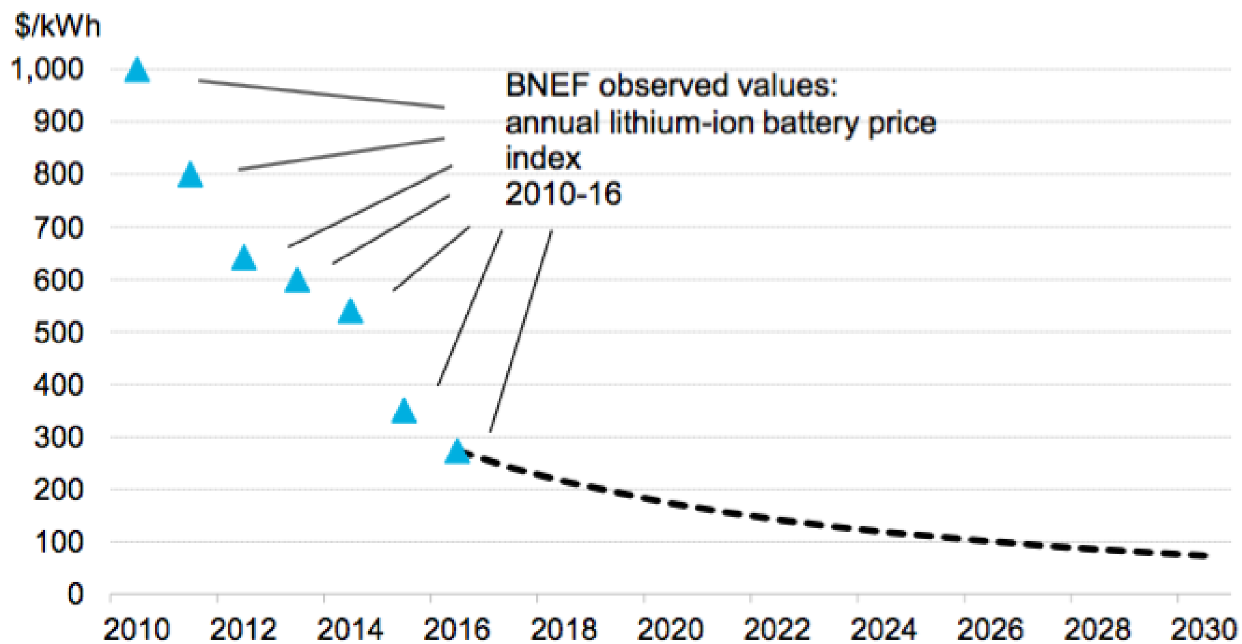








A.36 Bloomberg New Energy Finance forecast of lithium-ion battery price



A.37 Basecase+extension+15MW turbine+Totalcapacity+storage