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**Name of thesis**

Offshore wind: Investment decision model

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## **Abstract**

Climate change-related concerns force nations to reduce greenhouse gas emissions using renewable energy sources. Wind power is one of the fastest-growing power generation sources worldwide. Over the past decade, offshore wind (OW) has reached a reasonable level of maturity, and the European market is comprised of a diverse pool of investors willing to find attractive projects. An integrated decision support system developed for potential Offshore wind investors is presented in this thesis. Using tools from decision analysis, the decision support system provides a step-by-step approach to assessing the present situation, identifying objectives and alternatives and making good decisions. Overall, the framework connects insightful information from literature with up-to-date datasets for selected parameters. In addition to it, a techno-economical model has been developed in python to provide calculations and get the results for specified parameters. A sensitivity analysis is performed within this thesis, to find the parameters that affect the decision (material parameters) to further conduct a probabilistic analysis with detailed results to help different investors with certain risk profiles adopt the good decision.

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## 1. Introduction

Among the biggest challenges of our day is climate change. Scientists believe that the primary cause of global warming is human activities, such as the burning of fossil fuels to generate energy. In response, global agreements like the Paris Agreement have enabled aggressive targets to be set to diminish fossil fuels. International Energy Agency (2019) states that fossil fuels provided most of the world's primary energy. Due to predicted future energy demand growth, it will be necessary to rely on a more significant portion of renewable energy (International Energy Agency, 2019).

Wind energy is the second-fastest-growing power source in the world, after solar power. Currently, onshore wind is the most common way to generate wind energy (International Energy Agency, 2019). Yet, the Government of Canada (2014) has expressed concerns about the sound and visual pollution that may result from this technology. Because they are placed far from the coast, offshore wind farms (OWF) overcome both of these issues. Due to the fact that most of the earth is covered in water, OWFs have access to a broader geographical area than equivalent onshore farms. Wind energy accounted for only 0.3 percent of the world's total electricity consumption in 2018. Meanwhile, offshore wind is expected to produce more than 420 000 TWh of electricity annually, surpassing global demands by 18 times.

A variety of investors have risen to take advantage of the market and supply chain growth of offshore wind turbines, including utility companies, original equipment manufacturers (OEMs), independent power producers, pension funds and banks, with more than 100 wind farms currently operational across Europe. Risk tolerance (technology readiness, track record, portfolio type, country, and asset phase), return expectation (Internal Rate of Return (IRR) and yield), holding period, and participation level can be used to group investors.

In addition to producing models to determine OW farm costs, several researchers have considered the technological and economic feasibility of OW farms. Schweitzer (2016) investigated the potential for OW farms in the Northern Adriatic Sea to evaluate the region's suitability for technology development, while Satir M, Murphy F, McDonnell K (2018) discussed a feasibility study of the Turkish coast. Another study, carried out by Mattar and Guzmán-Ibarra (2017), looked at the profitability of an OW energy investment in various locations in Chile. Kaiser and Snyder used data from European wind farms to build models for the installation and maintenance costs of offshore wind farms. A model introduced by Dicorato et al. (2011) is a generic tool for assessing the cost of OW farms before and after investment, and for selecting the best wind farm design. Gonzales-Rodriguez AG (2017) analyzed offshore wind cost components

using parametric statements and literature data, including the cost of wind farms, foundations, electricity, predevelopment expenses, and so on. The Schaffie et al. (2016) study has also developed a model that takes fewer inputs than other tools and which is intended to provide a comprehensive framework to evaluate the Levelized cost of electricity (LCOE) of offshore wind farms. Furthermore, the data were trained in order to produce expressions that estimated the cost of wind turbine materials and offshore substation construction costs. The LCOE was determined by sensitivity analysis based on the most influential model parameters.

Entrepreneurs and policymakers might find the decision-making helpful framework in determining the feasibility of investments and anticipating the profile of their returns. In addition, analyzing the capital expenditure (CAPEX) and the operational expenditure (OPEX) may help in determining the input parameters that affect the viability of the project the most.

Norwegian Minister of Petroleum and Energy Tina Bru said that the Norwegian Continental Shelf (NCS) opened to large offshore wind projects on June 12th, 2020 (Norwegian Minister of Petroleum and Energy Tina Bru, 2020). O&G platforms could be electrified using OWFs located near them. In response, major Norwegian oil and gas corporations focus on the offshore wind industry as a source of future development (Eik, 2020; Vassbotn, 2020). Although the study focuses on Norway, a country with considerable technological resources and a developed industry with substantial secondary sales revenue, the proposed technique may be implemented in other countries as well.



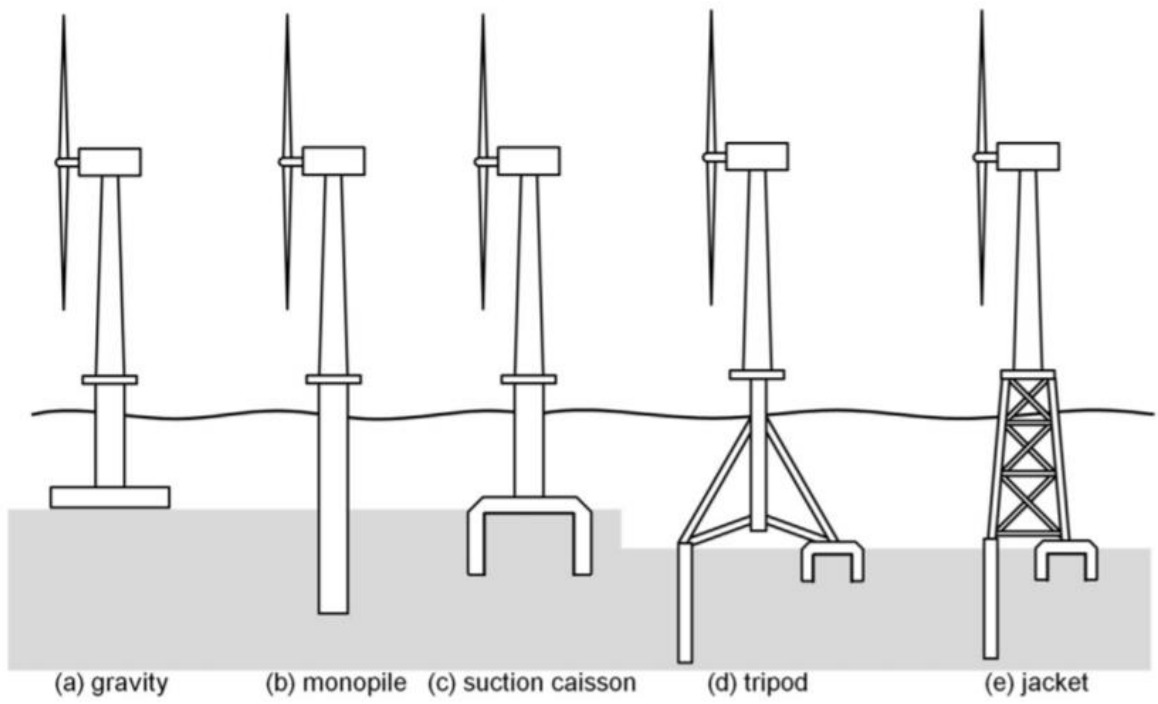
## 2. Brief overview of technology

Many energy sources are available to generate electricity, and fossil sources are being phased out due to increased greenhouse gas emissions. In replacing fossil fuels, renewable energy seems a viable option as it does not emit that much CO<sub>2</sub> emission as its counterpart. Among them, wind power is leading the way in this transition. Furthermore, offshore wind turbines are offshore, which means there is no noise and no visual pollution.

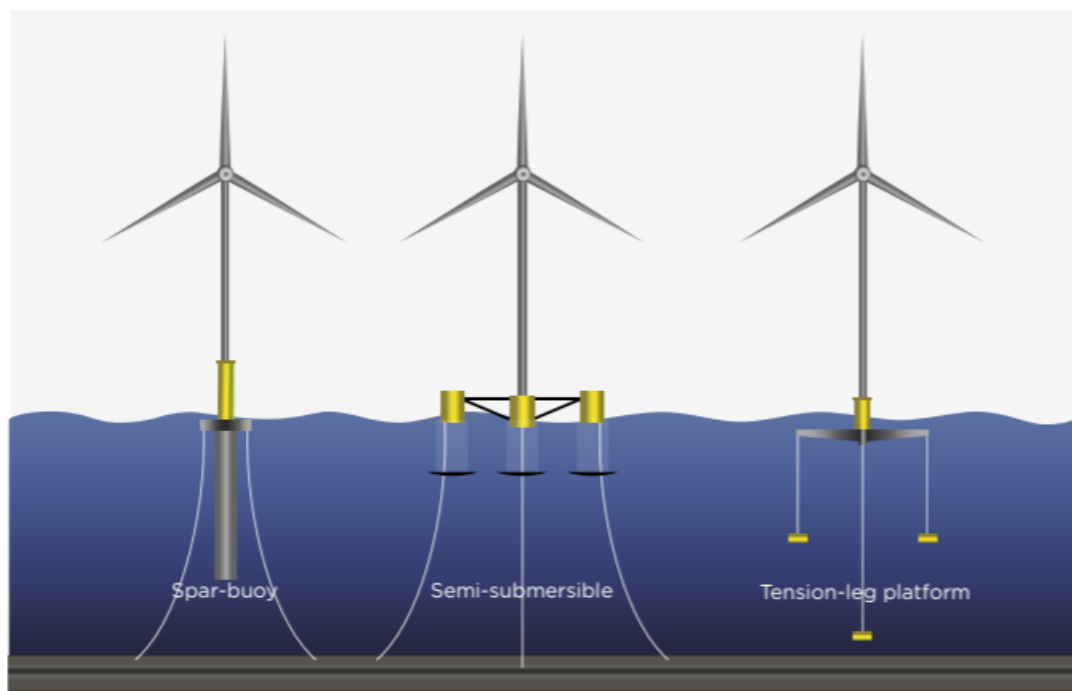
Despite the fact that onshore wind turbines are used in the majority of cases, offshore wind turbines are becoming increasingly attractive. In general, offshore wind turbines fall into two categories: fixed-bottom and floating. A fixed-bottom turbine uses foundations directly attached to the seabed, whereas floating turbines rely on moorings to connect to the seabed. Since substantial materials are needed to construct fixed-bottom turbines, their economic viability is not considered in depths over 60 m. This has led to an increased interest in floating wind turbines.

As shown in Figure 2.1, fixed-bottom turbines are classified based on their foundations: Gravity, monopile, suction caisson, tripod, and jacket. Monopiles, suction caissons, and gravity structures are suitable for shallow waters of no more than 30 m. However, for deeper waters, tripod and jacket, are used in order to reduce construction costs while maintaining stability and protecting against extreme weather conditions.

As shown in Figure 2.2. There are three main concepts of floating wind structures: spar-buoy, semi-submersible, and tension-leg platforms. The technology is still in its pre-commercial phase and will be further developed. Gravity and buoyancy are used to hold spar-buoy foundations and semi-submersible foundations stable, respectively, but tension-leg platforms rely on mooring systems by exerting tension.



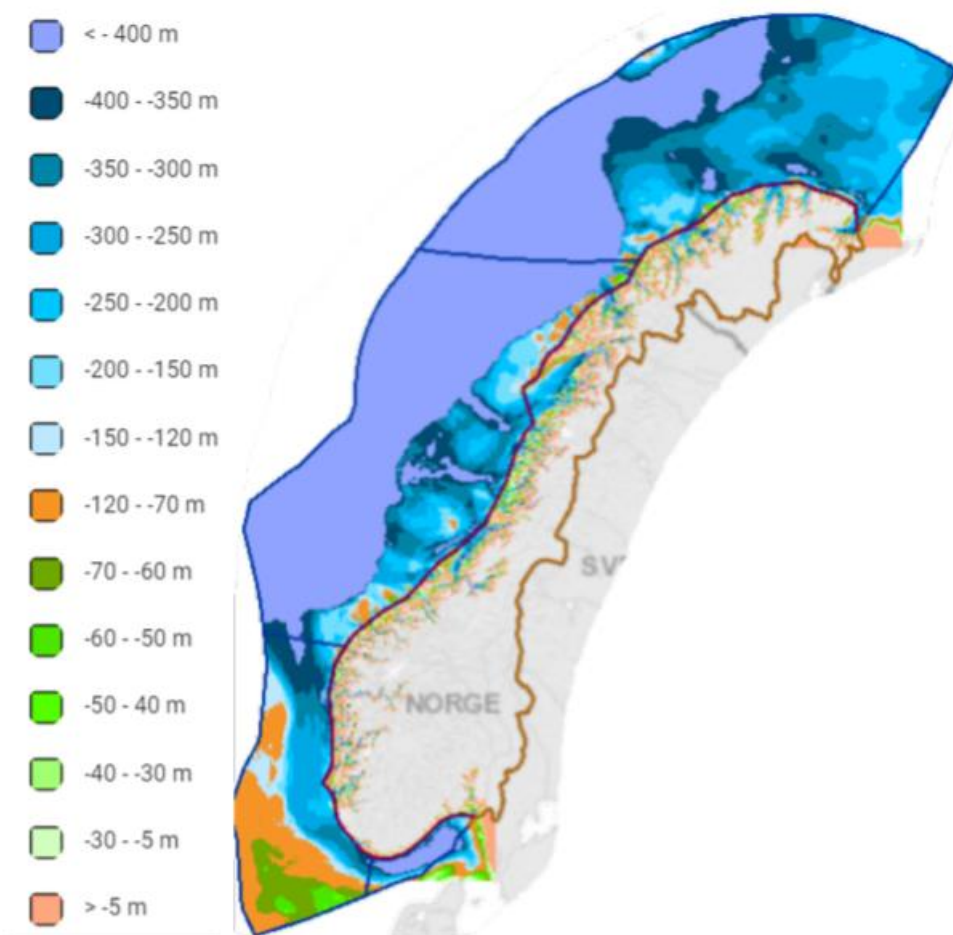
**Figure 2.1:** Foundation types for offshore wind turbines with fixed bottoms (Oh et al., 2018)



**Figure 2.2:** Floating foundations for offshore wind turbines (IRENA, 2016)

The Norwegian continental shelf has a total area of more than two million square kilometers (2 039 951 km<sup>2</sup>). This is approximately six times greater in area than Norway, Svalbard, and Jan Mayen combined. In addition, there is a Norwegian Economic Zone (NEZ) covering 968,700 km<sup>2</sup> of the NCS, with the rest mainly being fishing zones around Svalbard and Jan Mayen (Norwegian Ministry of Petroleum and Energy, 2016). Norway has sovereignty over all natural resources in the NEZ, despite not having sovereignty in the area, and therefore, Norway is permitted to develop offshore wind projects within the NEZ.

Norway also has a particular interest in floating offshore wind farms because a large portion of the NEZ consists of water about 60 meters deep, as shown in Figure 2.3.



**Figure 2.3:** The NEZ's sea depth in metres (Daniel Aghajani, 2020)

### **3. Decision-making framework**

A Decision-making framework is considered in this chapter that may be used to assess investing in Offshore wind farms on the NCS from a potential investor viewpoint. The framework is based on Clemen's (1996) decision-analysis process flowchart but includes decision analysis tools at each level to assist the decision-maker. Below, we'll go through each level of the structure and the tools that go with it.

#### **3.1 Decision analysis**

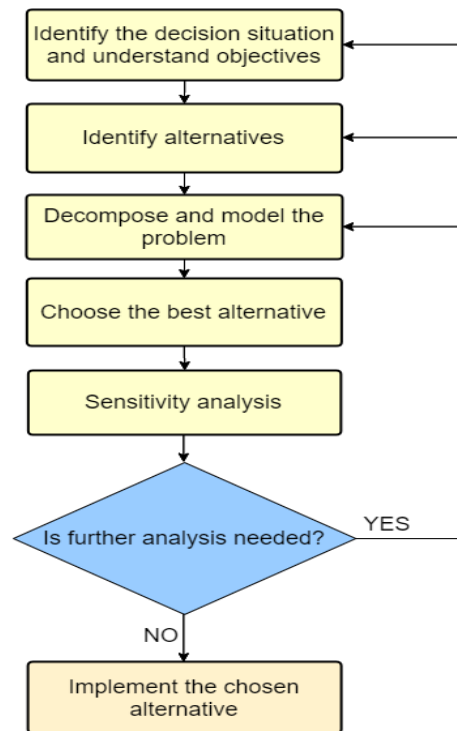
There are many challenges to making the best possible decisions when dealing with complex real-world problems. Using decision analysis, decision-makers will be afforded the tools and the framework to more transparently evaluate these complex problems (Bratvold and Begg, 2010).

According to Howard (1988): "a systematic procedure for transforming opaque decision problems into transparent decision problems by a sequence of transparent steps". A decision-making framework can be created by combining these steps. The development of decision-making frameworks simplifies the process of making decisions in complex situations. It is often difficult to measure and obtain the variables that are involved in problems with uncertainty and risk (Arsham, 2015). Multiple techniques and tools are available to simplify, build, breakdown, and evaluate the decision problem in a way that aids the decision-maker in arriving at the best solution (Bratvold and Begg, 2010).

#### **3.2 Decision-making framework**

Clemen (1996) developed the decision-analysis flowchart shown in Figure 4.2, which will serve as a basis for developing the decision-making framework. An initial problem needs to be addressed before any decision can be made. In order to effectively deal with a problem, a decision-maker must understand the relevant factors, the objectives, and the circumstances surrounding the issue. As soon as this is done, one may identify possible alternatives before breaking it into components and modeling it. As the steps are problem-specific, the flowchart of Clemen does not provide precise guidelines on how to execute them. The flowchart here is extended into a decision-making framework by adding steps that adapt the flowchart to the NCS for evaluation.

Comparatively to Clemen (1996), this paper presents a more comprehensive framework, which refers to several tools considered relevant to assist the decision-maker in the study.



**Figure 3.1:** Decision analysis flowchart

### 3.2.1 First step: Identifying the decision problem and evaluating goals

An essential first step is to recognize the decision problem and determine the objectives. As the decision-maker moves through this stage, one should familiarize themselves with the context of the decision problem. According to Bratvold & Begg (2010), "it is impossible to rationally choose the best course of action in any given situation without having a clear idea of what the decision is intended to achieve ". A decision-making framework should be developed to analyze the situation and determine the goals to achieve.

Decision-makers often rely on values as high-level allegations to guide them regarding important issues and factors. Based on the chosen values, the objectives are described as criteria. Creating alternatives is also influenced by objectives. In addition, attributes are used to measure objectives. An alternative's attributes measure the degree to which it meets the goals of the decision problem. Multiple objectives may lead to preference issues, so different attributes should be assigned weights in order to avoid the problem of preference (Bratvold and Begg, 2010).

### **3.2.2 Second step: Choosing objectives**

Next, select objectives for the framework. The decision-maker may be forced to narrow down the list of objectives in case if there are many of them. A decision problem with many objectives may be harder to analyze or compute. If multiple objectives represent the same value, then they may be redundant. It can be resolved by eliminating superfluous objectives, which illustrates non-orthogonality in dimensions. (G. James et al., 2013) calls this process dimensionality reduction. If excessive and non-quantifiable objectives are removed, the problem can be lowered in complexity (Doshi, 2020).

### **3.2.3 Third step: Identifying alternatives**

Thirdly, the framework identifies alternatives. Identifying the alternatives corresponds to determining the decision. As a result, each option should be possible and realistic. Several decision-makers in each industry are aware of the alternative solutions available. In some situations, these may not be relevant.

Consequently, the ultimate decision will have to be made by collecting and analyzing all relevant alternatives. This step is therefore named "Data collection and analysis". All options for the decision problem should be investigated and identified by the decision-maker. The decision-maker needs to identify and account for "the best" alternative in order to implement it.

### **3.2.4 Fourth step: Identifying parameters**

It is at this point that parameters are defined. In this stage, many parameters of the case might be introduced by the alternatives, making it a complicated, time-consuming process. The parameters that should be taken into consideration, as well as the suitable values, need to be identified

### **3.2.5 Fifth step: Creating a model for the decision problem**

Modeling the problem is the fifth step of the framework. As part of this framework, the information gathered in previous stages is utilized to calculate the best alternative. Different objectives can be resulted in different units. As a result, model-creating tools will not be able to compare numerical values being generated by different units. In order to resolve this problem, both

scaling and converting to a one unit can be done. Alternatively, it is possible to use normalization, which allows each alternative to be between zero and one for each objective. Additionally, preferences for objectives may differ between decision-makers (Bratvold and Begg, 2010).

### **3.2.6 Sixth step: Choosing the best alternative**

Sixth in the framework is identifying the best alternatives available. To accomplish this, it is necessary to solve the problem that was developed earlier. To analyze changes in the optimal decision when parameters are uncertain, sensitivity analysis is necessary. Identifying these parameters will help you make the best choice. A tornado sensitivity plot can be used for assessing the type of sensitivity of an objective value to different inputs, such as uncertain parameter values or value levers. It is essential to use reasonable lower and upper bounds for the uncertainties in Step 4 in order to produce tornado plots (Bratvold & Begg, 2010). These parameters are then plotted against the objectives. Using these plots, one can identify the parameters that have the most significant impact on the objectives. The uncertainty of a parameter value can be estimated if it has little impact on the objective of the tornado plot, and therefore may be neglected.

### **3.2.7 Making the decision**

As a final step, the decision-maker will get the decision with the chosen alternative. The decision-maker may, however, believe that a deeper examination is needed. Then they need to revisit a previous process node and update the values.

## **4. Case study**

This chapter is dedicated to the application of a previously described decision analysis framework to assess the investment decision in the hypothetical Offshore wind farm

### **4.1 Identify the decision situation and understand objectives**

As the first step of applying the framework, the decision situation and objectives have to be specified. This case study focuses on a potential investor deciding on whether to invest in an Offshore wind farm or not.

### **4.2 Choose objectives**

This step usually focuses on selecting the most relevant objectives in terms of a decision-making problem. Since a potential investor in this project is only driven by the profitability of the project, the following objective is considered plausible and suitable.

#### **Objective: Reach positive NPV**

Upon its introduction in the 1980s, the principle that corporations' primary objective is to maximize shareholder value has been firmly entrenched in the leading global markets (Lazonick, O'Sullivan 2010). Companies frequently utilize an NPV estimate to evaluate projects in order to choose the one that returns the most incredible value to shareholders.

Thus, a company's decision-making process needs to consider the net present value of a project. As the main metric for measuring value creation on the Norwegian Continental Shelf, the Norwegian Petroleum Directorate uses NPV (Norwegian Petroleum Directorate, 2018). Therefore, it is assumed that any potential investor is primarily interested in having a positive NPV of a project.

### **4.3 Identify alternatives**

Identifying relevant alternatives in the decision situation is the next step in the decision analysis framework. In terms of the objective presented in the previous section, two alternative options have been selected for this part of the decision-making process



## **Alternative 1: Invest in the project**

## **Alternative 2: Not invest in the project**

### **4.4 Identify parameters**

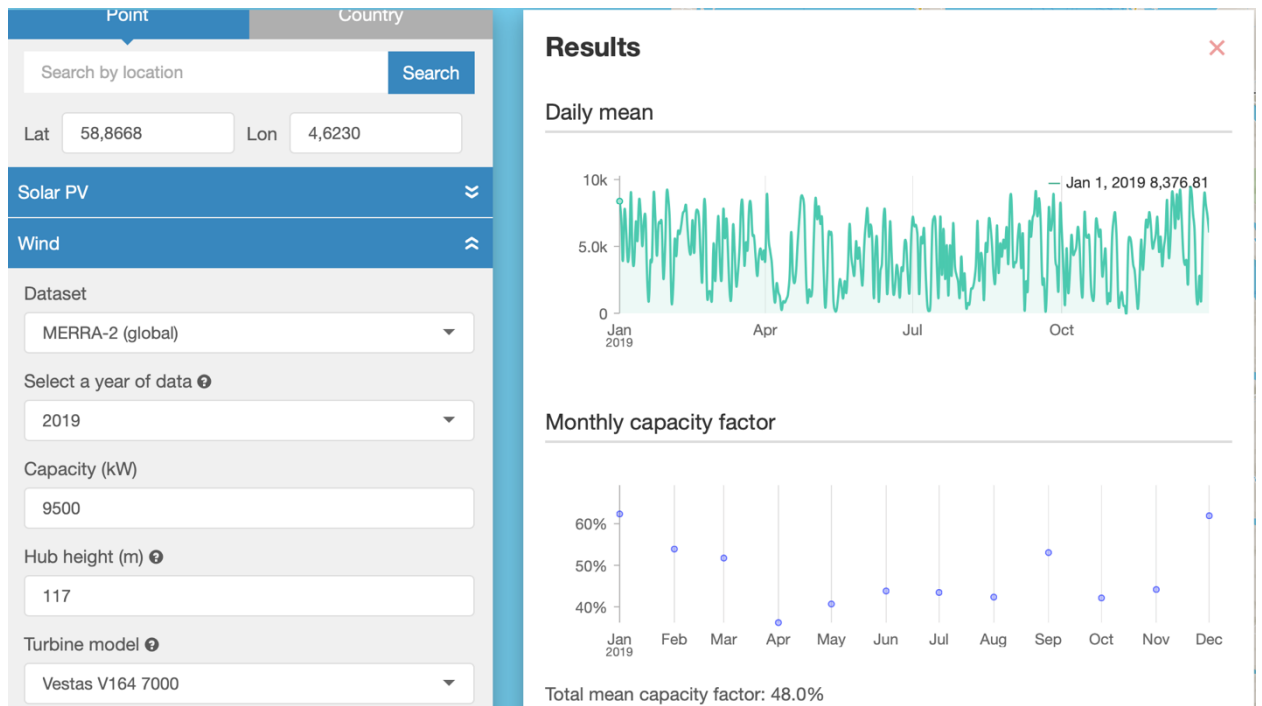
A description of the assumptions and characteristics of a potential offshore wind farm are provided in this section.

#### **Site related parameters**

The 693.5 MW wind farm is located in the NCS, 20 km from shore. A wind farm of specified capacity is considered to be a relevant choice, as it corresponds to recently commissioned wind farms like Borssele 1&2 and East Anglia One, both commissioned in 2020 with 752 MW and 714 MW respectively (Wikipedia). The capacity of the wind farm is obtained with 73 wind turbines 'MHI Vestas V164 9.5MW' with 9.5 MW capacity each. The specified turbines are installed at Borssele 3&4 site, commissioned in 2021. The pattern has to be predetermined considering such issues as wave effect to maximize the efficiency. The selected turbine has a rotor diameter of 164 m. A reasonable hub height for a turbine of this caliber is spread between 100 and 150 meters. Therefore a 117 m height is assumed. According to the International Electrotechnical Commission (2005) standard, wind turbines are built to maintain operational conditions for at least 20 years period. Despite this, many wind farms have operated past the 20-year mark due to maintenance methods that reduce stress (Ziegler et al., 2018). According to the new Ocean Energy Act regulation, licenses with a validity of up to 30 years mark are allowed to be assigned (Uggerud and Hermansen, 2020b). Therefore, a lifespan of a project is considered to be 25 years. Water depth is assumed to be equal to 26 m (A lifecycle techno-economic model of offshore wind energy for different entry and exit instances, 2018).

#### **Capacity factor**

Wind turbine capacity factor determines the actual production vs. the potential production, limiting output compared to wind energy. It is included in calculations to determine a realistic scenario of energy produced throughout to project lifetime. The data about capacity factor for a specified wind turbine in a specific location is withdrawn for Renewableninja.com website and is provided as following:



**Figure 4.1:** Capacity factor data for selected wind turbine

The coordinates correspond to the location within Norwegian Continental Shelf approximately 20 km away from shore. Therefore, capacity factor for a base case scenario is equal to 0.48.

### Cost related parameters

#### Cost of cables per unit

Array cables

AC unit price equals to 321 EUR/m [15]

Subsea cables

SC unit price equals to 690 EUR/m [15]

Onshore cables

OC unit price equals to 299.3 EUR/m [15]

#### Cost of cables installation per unit

Array cables

AC unit price inst equals to 135 EUR/m [15]

Subsea cables

SC unit price inst equals to 639 EUR/m [15]

Onshore cables

OC unit price inst equals to 687 EUR/m [15]

## **Revenue related parameters**

### **Discount rate**

According to the information obtained in the following report (THEMA-Report 2020-13 Offshore Wind – Opportunities for the Norwegian Industry), the discount rate (weighted average cost of capital) for a typical renewable energy utility in Europe lies at 6 percent real. Therefore, WACC is assumed to be equal to 6 percent in base case scenario.

### **Power purchase agreement**

In Norway, the majority of power produced and consumed is traded on the Nord Pool power exchange. Recent developments show that bilateral agreements, also known as Power Purchase Agreements (PPAs), are becoming increasingly popular both in the Nordic region and throughout Europe. The PPA allows electricity producers to sell generated power for a fixed price per MWh throughout the period of project exploitation. Unfortunately, the information about corporate Power Purchase Agreements in Norway has not been studied well yet. Therefore, in terms of this work, the correlation between the electricity spot price and PPA is utilized. The electricity price dataset for the Oslo region, which ranges from 1 January 2021 to 26 May 2021, is taken from the Nord Pool database. The mean value constitutes 479.56 NOK/MWh, which is approximately equal to 48 euro/MWh. Therefore, the PPA value is 48 EUR/MWh for the base case scenario.

## **5. Implementing the model**

The Techno-economical model, which was created in python, is used to calculate the NPV value of the project. The model uses previously specified parameters as an input and returns the NPV as an output. The model goes through the following steps:

### **5.1 Capital expenditures**

The CAPEX section comprises costs throughout four subsequent stages of OW farm lifetime, namely Development and consenting, Production and acquisition, installation and commissioning, Decommissioning, and disposal. Those stages are presented in the following subsections

#### **5.1.1 Development and consenting**

Project planning costs consist of expenditures that happen before the financial closure and therefore before the conditions have been met and the contract has been signed. Thus, legal authorization, project management, surveys and research, front-end engineering and design, as well as contingency costs are included in the category. The costs during project planning are a subject of many factors such as location, timeframe, strategical approach, etc. Therefore, they vary drastically across different sites. The literature provides the following values in a million pounds for 500 MW farms:

- 60, [8]
- 202.8, [4]
- 156.5, [9]

Since wind farm in our case is 693.5 MW, the assumption of 202.8 million EUR is taken for Development and consenting costs.

#### **5.1.2 Production and acquisition**

##### **Cost of turbine**

An integrated wind farm is one of the most expensive components due to the cost of purchasing a turbine with its full range of equipment. Turbine cost is typically expressed as functions of capacity, and different parametric equations have been produced to estimate them [2,3,15]. A cost

estimation has been made based on the following expression within the context of the reference case study[2]:

$$\text{Cost of turbine} = 1000 * (2.95 * 1000 * \ln(P_{WT}) - 375.2) , \text{ in EUR per turbine}$$

where  $P_{WT}$  is a capacity of wind turbine in MW.

### **Cost of foundation**

For the reference case study, it was assumed that a monopile configuration would be used due to its popularity, with 87% of all foundations installed in 2017 having monopiles [17]. It is important to note that foundation costs vary with site depth, seabed characteristics, and turbine capacity. To a lesser extent, it is dependent on wave and wind conditions [15]. Using a parametric equation [16], the cost of foundation is linked to a turbine geometry and capacity as follows:

$$\begin{aligned} \text{Cost of foundation} &= 320000 * P_{WT} * (1 + 0.02 * (WD - 8)) * \\ &* (1 + 8 * 10^{-7} * (h * ((\frac{d}{2})^2 - 100000))) , \quad \text{in EUR per foundation} \end{aligned}$$

where h is a hub height, d is a rotor diameter and WD is water depth

### **Cost of cables**

#### **Array cables**

Turbines are arranged in clusters by the array cables in different grid schemes, such as the radial design, through which turbines are linked together in a string of turbines to an offshore substation. The linear equation used in the model is based on the number of wind turbines  $n_{WT}$  and the diameter of the rotor  $d$  (in meters) as variables[18]:

$$\text{Cost of array cables} = 1000 * (1.25 * n_{WT} + 1.055 * d - 122.64) * AC \text{ unit price}, \text{ in EUR}$$

#### **Subsea cables**

Subsea cables connect the offshore substation and onshore substation. Therefore, the length of the cables is assumed to be equal to distance to shore. The cost is calculated as followed equation:

$$\text{Cost of subsea cables} = 1000 * \text{distance to shore} * SC \text{ unit price}, \text{ in EUR}$$

## **Onshore cables**

Onshore cables connect the onshore substation and the grid. The length of the cables is assumed to be 15 km.

*Cost of onshore cables* = 15000 \* *OC unit price*, in EUR

Thus, total cost of cables equals to

*Cost of cables* = *Cost of array cables* + *Cost of subsea cables* +  
*Cost of onshore cables*, in EUR

## **Cost of substations**

### **Offshore substation**

Electric power transmission through offshore substations is considered the most cost-effective means to reduce cable losses suitable for projects located more than 20 kilometers offshore [9].

The cost of substation is calculated through a parametric equation[15]

*Cost of offshore substation* = 539 \* 1000 \* ( $n_{WT} * P_{WT}$ )<sup>0.678</sup>, In EUR

### **Onshore substation**

Onshore substation cost is approximately equal to the 50 percent cost of offshore substation[4,8].

Therefore:

*Cost of onshore substation* = 0.5 \* *Cost of offshore substation*, in EUR

### **5.1.3 Installation and commissioning**

In this section the information on the calculation of the cost of installation of various equipment is provided. The parametric equations are expressed below with reference to [15]:

### **Wind turbine installation cost**

*Wind turbine installation cost* = 1000 \*  $P_{WT}$  \* 1.8 \* 1850, in EUR

### **Foundation installation cost**

*Foundation installation cost* =  $1000 * P_{WT} * 1.8 * 828$ , in EUR

### **Cables installation cost**

*AC installation cost* =  $1000 * (1.25 * n_{WT} + 1.055 * d - 122.64) * AC \text{ unit price inst}$ , in EUR

*SC installation cost* =  $1000 * \text{distance to shore} * SC \text{ unit price inst.}$ , in EUR

*OC installation cost* =  $15000 * OC \text{ unit price inst}$ , in EUR

#### **5.1.4 Decommissioning and disposal**

Based on the results of [1], cost of decommissioning and disposal is assumed to be equal to 40.1 percent of the installation and commissioning cost

#### **5.2 Operational expenditures**

According to the results of [1], the total Operational expenditures and maintenance are considered to be equal to 42.8 percent of total capital expenditures. To include OPEX in the model, it is divided by project lifetime and presented as annual OPEX.

#### **5.3 Net annual power generation**

This section presents net annual power generation. In other words, it is the amount of energy being produced on yearly basis ready to be sold through PPA. Net power generation is calculated as following

*Net annual power generation* =  $n * P_{WT} * CF * 8760$ , in MWh

where n-number of wind turbines, CF – capacity factor, 8760 – number of hours in a year

#### **5.4 Total Revenue**

This section describes the total amount of positive cashflow produced from electrical energy realization. The expression of total revenue is following:

$$\textit{Total Revenue} = \textit{Net annual power generation} * \textit{PPA}, \text{ in EUR}$$

#### **5.5 Cash flow**

Following section is dedicated towards overall cashflows. It is calculated as expressed below:

$$\textit{Cash flow} = \textit{Total revenue} - \textit{CAPEX} - \textit{OPEX}, \text{ in EUR}$$

#### **5.6 NPV**

In order to calculate the NPV of the project, a function in python has been created, which uses previously stated parameters. The output of the function presents the NPV of the project.



## 6. Results and discussion

### 6.1 NPV base case

After running a model in python the value for the NPV of the project is obtained and equals to 191,669,227 EUR.

### 6.2 Sensitivity analysis

The sensitivity analysis of the model has been conducted using wind farm general specifications, namely WACC, capacity, PPA, capacity factor, water depth and distance to shore to estimate the impact of parameters on the NPV value. Specified parameters are not interdependent, thus local sensitivity analysis can be utilized. The variation of parameters is in bounds of 20 percent from the base case values. The results are provided in following sections.

#### 6.2.1 Spyder diagram

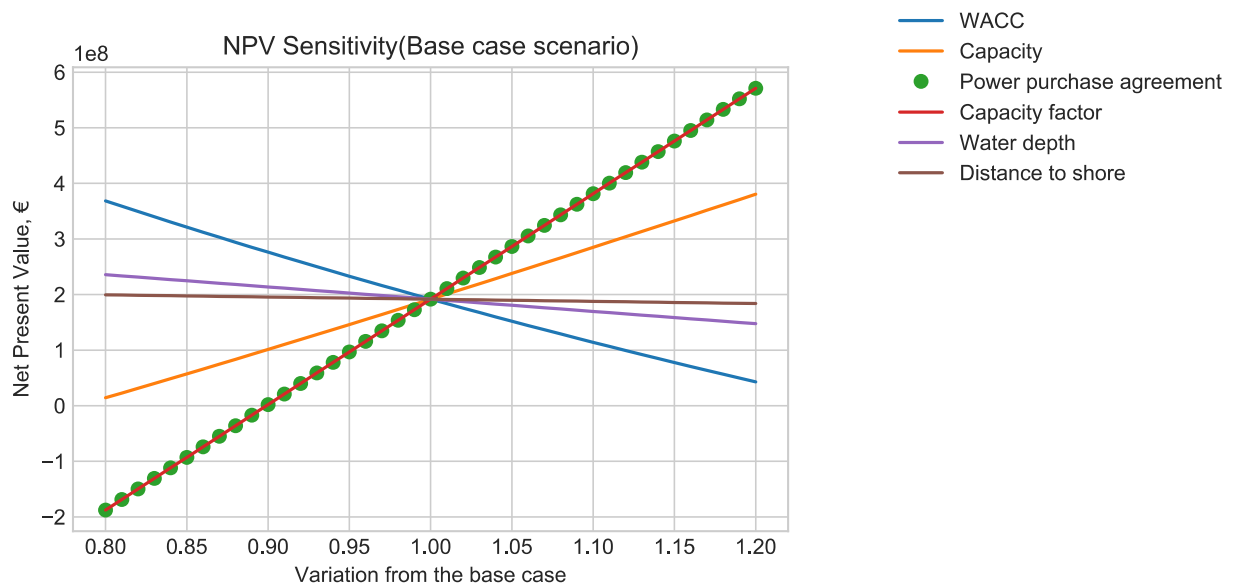
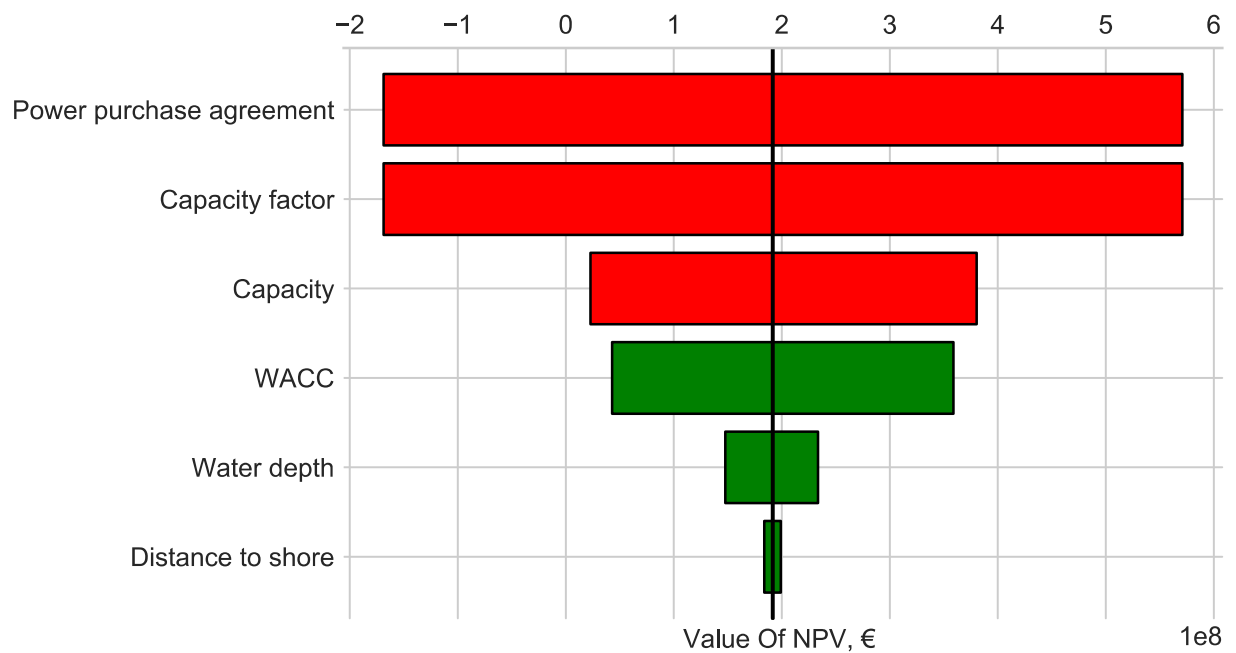


Figure 6.1: Spyder diagram for NPV sensitivity analysis

### 6.2.2 Tornado diagram



**Figure 6.2:** Tornado diagram for NPV sensitivity analysis

The red color bars represent a positive change of the parameters, while green illustrates the negative. Since the objective is to reach a positive NPV, the tornado plot allows concluding that only Power purchase agreement and the Capacity factor are material parameters and, therefore, might change the decision.

### 6.3 Probabilistic analysis for material parameters

As we obtained from a tornado diagram, only PPA and Capacity factor are material parameters. Therefore, the probabilistic analysis will concentrate on only two latter being uncertain.

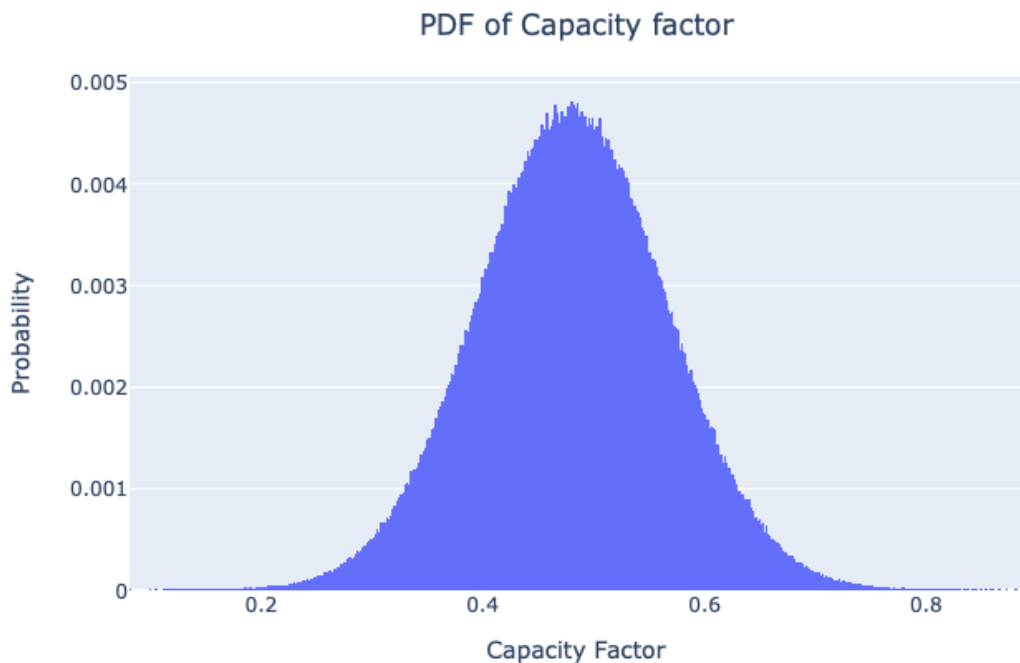
The dataset for Capacity factor is taken from the Renewableninja.com website for specified parameters of the turbine and location. The Gaussian distribution is assigned to Capacity factor with mean and standard deviation equal to 0.48 and 0.085, respectively. However, Capacity factor is restricted within 0 and 1 and Gaussian distribution is normalized from negative to positive infinity.

At this point, we should take into account the 3-sigma rule, which constitutes that the probability of the value being within plus-minus 3 standard deviations from the mean equals to 99.7 percent.

For the Capacity factor, plus minus 3 standard deviations from the mean will not exceed the limits within the restricted boundary. This leaves the remaining 0.3 percent negligible. However, to avoid

calculational mistakes, if a sampled value drops out of the restricted zone, this particular value will be resampled within the Gaussian distribution again.

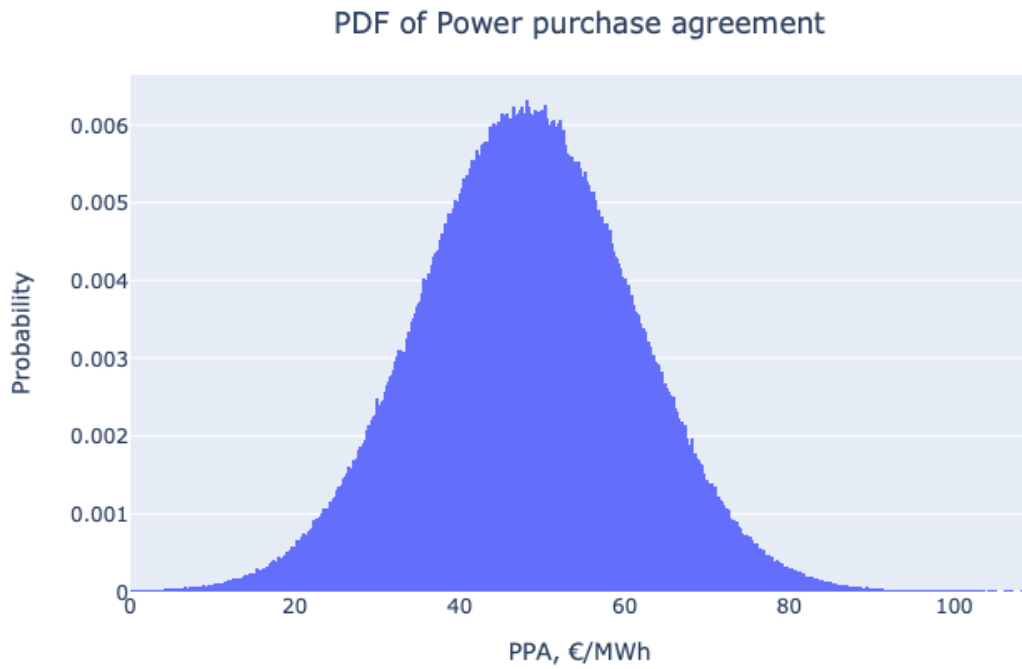
The probability density function of Capacity factor with 1 million sampled values is provided below:



**Figure 6.3:** PDF of Capacity factor

The same procedure applies to the Power Purchase agreement. The dataset is taken from Nord Pool database. The mean value and standard deviation are derived to be 48 and 12.9 respectively. The PPA has limits from 0 to infinity. Therefore 3-sigma rule is applicable. The values out of the restricted boundaries are resampled again within the Gaussian distribution with stated mean and standard deviation.

The probability density function of the Power Purchase Agreement with 1 million sampled values is provided below:

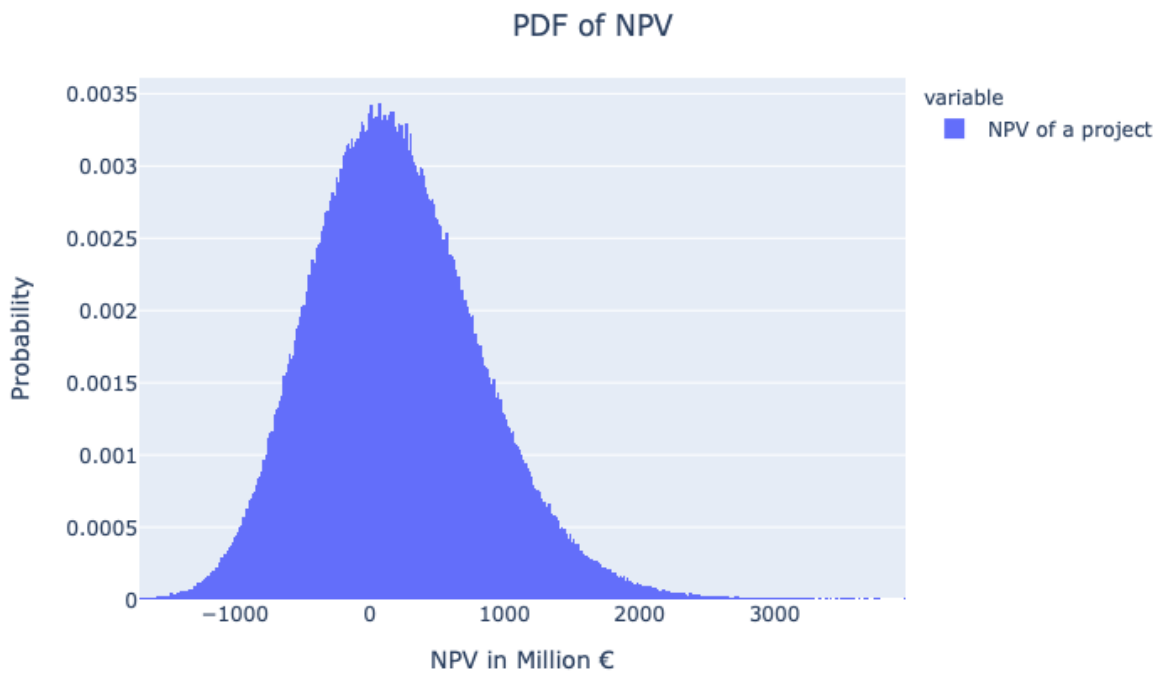


**Figure 6.4:** PDF of Power purchase agreement

The next step is to insert the distributions in the NPV function. The figures with most notable statistical values and the probability density function of NPV with 1 million sampled values are provided below:

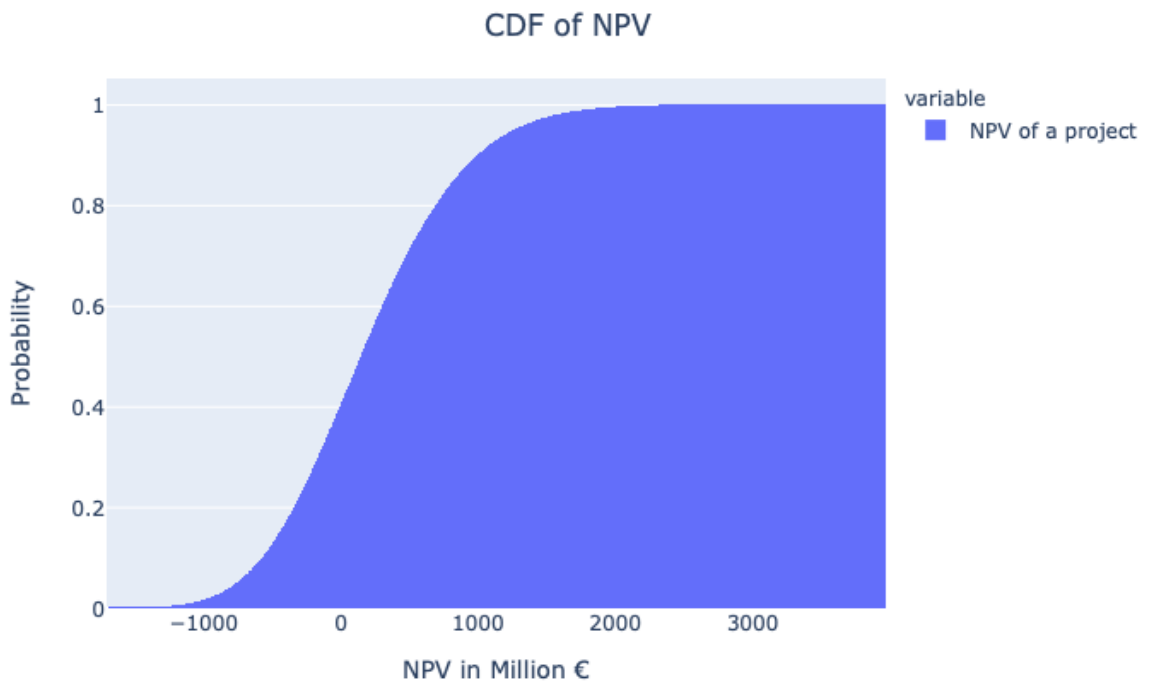
	<b>Statistics</b>	<b>Value of NPV, mil €</b>
<b>0</b>	Mean	192.732401
<b>1</b>	Standard Deviaton	617.305818
<b>2</b>	Minimum	-1704.615886
<b>3</b>	Maximum	3964.995633
<b>4</b>	P10	-565.429761
<b>5</b>	P50	151.813858
<b>6</b>	P90	1004.738076
<b>7</b>	P(NPV<0)	0.400218
<b>8</b>	P(NPV<NPV base)	0.526127

**Figure 6.5:** Notable statistical properties of NPV distribution



**Figure 6.6:** PDF of NPV

The final step of a probabilistic analysis is to construct a Cumulative density function. The CDF of NPV is depicted below:



**Figure 6.7:** CDF of NPV

The CDF allows finding a probability of a value of NPV being less than a chosen value NPV. In case a potential investor has a specific risk profile, he or she might need to take into account different percentiles depending on the risk profile. Considering the potential investor to be risk-neutral, the mean value is assessed in terms of choosing between alternatives. Thereby, choosing the alternative of investing in the project is the best of the given options.

## **7. Conclusion**

Throughout this thesis, the decision-making framework was introduced to help the potential investors assess the investment in the Offshore wind farms on Norwegian Continental Shelf. This framework can be extensively used to ground the idea of investing in such projects and assist the potential investors to pick correct alternatives and, therefore, make the right decisions. Although the main focus of this work is primarily directed towards Norwegian Continental Shelf, the framework can also be applied to any potential location with various parameters since the framework is universal, and the model implemented in python accepts a great variation for parameters selected parameters.

The main observation from the case study constitutes that within the assumptions accepted and parameters determined, the expected NPV of the project was calculated to be positive. This means that for a risk-neutral investor, the correct decision was to pick the alternative of investing in the project. For other than risk-neutral investors, the Cumulative Density Function of the NPV was demonstrated, as well as several important percentiles and corresponding NPV values. That should allow them to make correct decisions based on their risk profile.

As possible future steps to continue research, parameters like operational expenditures and maintenance should be evaluated with higher precision. More datasets and information available in the future will allow us to have a better comprehension of the Power Purchase Agreement in Norwegian reality. Tax conditions and subsidies might also be included in the model as a form of further research.

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## Appendix

Python code utilized in calculations:

line 1: `import matplotlib`

```
import matplotlib.pyplot as plt
import scipy
import seaborn
plt.style.use('seaborn-whitegrid')
from scipy import stats
import math
import numpy as np
##from metalog import metalog # import the metalog package
import pandas as pd
import plotly.graph_objects as go
import plotly.express as px
import numpy_financial as npf
from scipy.stats import truncnorm
```

line 2: `pip install numpy-financial`

line 3: `capacity = 9.5 ## in MW`

```
capacity_factor = 0.48
n = 73 ##number of turbines
```

line 4: `water_depth = 26`

```
distance_to_shore = 20
hub_height = 117
rotor_diameter = 164
project_life = 25
```

line 5: `##cost of cables per unit €/m`

```
cost_array_per_unit = 321
cost_subsea_per_unit = 690
cost_onshore_per_unit = 299.3
##cost of installation per unit €/m
cost_array_per_unit_inst = 135
cost_subsea_per_unit_inst = 639
cost_onshore_per_unit_inst = 687
```

line 6: `## Power purchase agreement in €/MWh`

```
ppa = 48
```

line 7: `## Discount rate`

```
wacc = 0.06
```

line 8: `#Capital expenditures in €`

```
#Development and consenting
cost_of_DC = 202.8*1000000
```

```

#Production and acquisition
##cost of cables per unit €/m
cost_array_per_unit = 321
cost_subsea_per_unit = 690
cost_onshore_per_unit = 299.3
###data analysis devices
cost_of_scada = 75000

```

```

#Installation and commissioning
##cost of installation per unit €/m
cost_array_per_unit_inst = 135
cost_subsea_per_unit_inst = 639
cost_onshore_per_unit_inst = 687

```

line 9: def npv\_base(wacc,capacity,ppa,capacity\_factor,water\_depth,distance\_to\_shore):

```

    # 1.Capital expenditures in €

```

```

    #Production and acquisition

```

```

    ###cost of turbine and foundation

```

```

    cost_of_turbine = 1000*(2.95*1000*np.log(capacity) - 375.2)

```

```

    cost_of_foundation = 1000*320*capacity*(1+0.02*(water_depth-
8))*(1+0.8/1000000*(hub_height*(rotor_diameter/2)**2-100000))

```

```

    ###cost of cables

```

```

    cost_of_array_cables = 1000*(1.125*n + 1.055*rotor_diameter - 122.64)*cost_array_per_unit

```

```

    cost_of_subsea_cables = distance_to_shore*1000*cost_subsea_per_unit

```

```

    cost_of_onshore_cables = 15000*cost_onshore_per_unit

```

```

    cost_of_cables = cost_of_array_cables + cost_of_subsea_cables + cost_of_onshore_cables

```

```

    ###cost of substations

```

```

    cost_of_substation = 539*1000*(n*capacity)**0.678

```

```

    cost_of_substation_onshore = cost_of_substation/2

```

```

    cost_of_substations = cost_of_substation + cost_of_substation_onshore

```

```

    cost_of_PA =

```

```

n*cost_of_turbine+n*cost_of_foundation+cost_of_cables+cost_of_substations+n*cost_of_scada

```

```

    #Installation and commissioning

```

```

    cost_of_turb_inst = capacity*1.8*1850*1000

```

```

    cost_of_found_inst = capacity*1.8*828*1000

```

```

    cost_of_AC_inst = 1000*(1.125*n + 1.055*rotor_diameter - 122.64)*cost_array_per_unit_inst

```

```

    cost_of_SC_inst = distance_to_shore*1000*cost_subsea_per_unit_inst

```

```

    cost_of_OC_inst = 15000*cost_onshore_per_unit_inst

```

```
cost_of_IC = cost_of_turb_inst + cost_of_found_inst + cost_of_AC_inst + cost_of_SC_inst +  
cost_of_OC_inst
```

```
#Decommissioning and disposal
```

```
cost_of_DD = 0.401*cost_of_IC
```

```
cost_of_capex = cost_of_DC + cost_of_PA + cost_of_IC + cost_of_DD
```

```
## 2.O&M in €/annual
```

```
cost_of_opex_annual = 0.428*cost_of_capex/25
```

```
## 3.net power generation in MWh
```

```
annual_net_power_generation = n * capacity * capacity_factor * 8760
```

```
## 4. revenue
```

```
total_revenue = annual_net_power_generation*ppa
```

```
## 5. Total revenue
```

```
#years = np.arange(0,project_life,1)
```

```
cost_of_capex_yr = np.repeat(0,project_life).tolist()
```

```
cost_of_capex_yr[0] = cost_of_capex
```

```
cost_of_opex = np.repeat(cost_of_opex_annual,project_life).tolist()
```

```
total_revenue = np.repeat(total_revenue,project_life).tolist()
```

```
cash_flow = []
```

```
for i in range (len(total_revenue)):
```

```
    cash_flow.append(total_revenue[i]-cost_of_capex_yr[i]-cost_of_opex[i])
```

```
npv = npf.npv(wacc, cash_flow)
```

```
return (npv)
```

```
line 10: npv_base(wacc,capacity,ppa,capacity_factor,water_depth,distance_to_shore)
```

```
line 11: #npv_sen = []
```

```
    wacc_n = []
```

```
    capacity_n = []
```

```
    ppa_n = []
```

```
    capacity_factor_n = []
```

```
    water_depth_n = []
```

```
    distance_to_shore_n = []
```

```

line 12 : change = []
         for i in range (-20,21,1):
             l=1+(i/100) #parameters vary from 0.8 to 1.2
             change.append(l)
             wacc_n.append(wacc*l)
             capacity_n.append(capacity*l)
             ppa_n.append(ppa*l)
             capacity_factor_n.append(capacity_factor*l)
             water_depth_n.append(water_depth*l)
             distance_to_shore_n.append(distance_to_shore*l)

line 13: wacc_s = []
         capacity_s = []
         ppa_s = []
         capacity_factor_s = []
         water_depth_s = []
         distance_to_shore_s = []

line 14: for i in range(len(wacc_n)):
         wacc_s.append(npv_base(wacc_n[i],capacity,ppa,capacity_factor,water_depth,distance_to_shore))

         capacity_s.append(npv_base(wacc,capacity_n[i],ppa,capacity_factor,water_depth,distance_to_shore))

         ppa_s.append(npv_base(wacc,capacity,ppa_n[i],capacity_factor,water_depth,distance_to_shore))

         capacity_factor_s.append(npv_base(wacc,capacity,ppa,capacity_factor_n[i],water_depth,distance_to_shore))

         water_depth_s.append(npv_base(wacc,capacity,ppa,capacity_factor,water_depth_n[i],distance_to_shore))

         distance_to_shore_s.append(npv_base(wacc,capacity,ppa,capacity_factor,water_depth,distance_to_shore_n[i]))

line 15: plt.plot(change,wacc_s,label='WACC')
         plt.plot(change,capacity_s,label='Capacity')
         plt.plot(change,ppa_s,'o',label='Power purchase agreement')
         plt.plot(change,capacity_factor_s,label='Capacity factor')
         plt.plot(change,water_depth_s,label='Water depth')
         plt.plot(change,distance_to_shore_s,label='Distance to shore')
         plt.title('NPV Sensitivity(Base case scenario)')
         plt.xlabel('Variation from the base case')
         plt.ylabel('Net Present Value, €')
         plt.legend()
         plt.legend(bbox_to_anchor=(1, 1),bbox_transform=plt.gcf().transFigure)

```

```
plt.savefig('NPV sensitivity base case.pdf',dpi=1200, bbox_inches='tight')
```

line 16:

```
#####  
# The data (change all of this to your actual data, this is just a mockup)  
variables = [  
    'Power purchase agreement',  
    'Capacity factor',  
    'Capacity',  
    'WACC',  
    'Water depth',  
    'Distance to shore',  
  
]  
  
base = npv_base(wacc,capacity,ppa,capacity_factor,water_depth,distance_to_shore)  
  
lows = np.array([  
    ppa_s[1],  
    capacity_factor_s[1],  
    capacity_s[1],  
    wacc_s[1],  
    water_depth_s[1],  
    distance_to_shore_s[1],  
  
])  
  
values = np.array([  
    ppa_s[40]-ppa_s[1],  
    capacity_factor_s[40]-capacity_factor_s[1],  
    capacity_s[40]-capacity_s[1],  
    wacc_s[40]-wacc_s[1],  
    water_depth_s[40]-water_depth_s[1],  
    distance_to_shore_s[40]-distance_to_shore_s[1],  
  
])  
  
#####  
# The actual drawing part  
  
# The y position for each variable
```

```

ys = range(len(values))[::-1] # top to bottom

# Plot the bars, one by one
for y, low, value in zip(ys, lows, values):
    # The width of the 'low' and 'high' pieces
    low_width = base - low
    high_width = low + value - base

    # Each bar is a "broken" horizontal bar chart
    if value >=0:
        plt.broken_barh(
            [(low, low_width), (base, high_width)],
            (y - 0.4, 0.8),
            facecolors=['red', 'red'], # Try different colors if you like
            edgecolors=['black', 'black'],
            linewidth=1,
        )
    else :
        plt.broken_barh(
            [(low, low_width), (base, high_width)],
            (y - 0.4, 0.8),
            facecolors=['green', 'green'], # Try different colors if you like
            edgecolors=['black', 'black'],
            linewidth=1,
        )

    # Display the value as text. It should be positioned in the center of
    # the 'high' bar, except if there isn't any room there, then it should be
    # next to bar instead.
    #x = base + high_width / 2
    #if x <= base + 50:
    #    x = base + high_width + 50
    #plt.text(x, y, str(value), va='center', ha='center')

# Draw a vertical line down the middle
plt.axvline(base, color='black')

# Position the x-axis on the top, hide all the other spines (=axis lines)
axes = plt.gca() # (gca = get current axes)
axes.spines['left'].set_visible(False)
axes.spines['right'].set_visible(False)
axes.spines['bottom'].set_visible(False)

```

```

axes.xaxis.set_ticks_position('top')

# Make the y-axis display the variables
plt.yticks(ys, variables)

plt.xlabel('Value Of NPV, € ')

# Set the portion of the x- and y-axes to show
#plt.xlim(base - 1000, base + 1000)
#plt.ylim(-1, len(variables))
plt.savefig('Tornado diagram.pdf',dpi=1200, bbox_inches='tight')
line 17: mu_ppa = 48
        sigma_ppa = 12.9

        mu_cf = 0.48
        sigma_cf = 0.085
line 18: ppa_d = np.linspace(-10.,-5.,1000000)#np.random.normal(mu_ppa,sigma_ppa,1000)
cf_d = np.linspace(-10.,-5.,1000000)#np.random.normal(mu_cf,sigma_cf,1000)
for i in range (len(ppa_d)):
    # Checking the value for cf
    while cf_d[i]<0 or cf_d[i]>1:
        cf_d[i] = np.random.normal(mu_cf,sigma_cf,1) # Central Value
        #cf_d[i] = np.random.normal(mu_cf - 0.2*sigma_cf,sigma_cf,1) # -0.2 sigma
        #cf_d[i] = np.random.normal(mu_cf + 0.2*sigma_cf,sigma_cf,1) # +0.2 sigma
    # Checking on the value of PPa
    while ppa_d[i]<0:
        ppa_d[i] = np.random.normal(mu_ppa,sigma_ppa,1) # Central Value
        #ppa_d[i] = np.random.normal(mu_ppa - 0.2*sigma_ppa,sigma_ppa,1) # -0.2 sigma
        #ppa_d[i] = np.random.normal(mu_ppa + 0.2*sigma_ppa,sigma_ppa,1) # +.2 sigma
Line 19: npv_d = []
        for i in range(len(ppa_d)):
            if(i%int(len(ppa_d)/10)==0):
                print('Percentage of completion : ',i*100/int(len(ppa_d)), '%')
                a = npv_base(wacc,capacity,ppa_d[i],cf_d[i],water_depth,distance_to_shore)/10**6
                npv_d.append(a)
line 20: df_trials = pd.DataFrame(data={'NPV of a project':npv_d})
        df_trials
line 21: npv_d_mean = np.mean(npv_d)
        npv_d_sd = np.std(npv_d)
        npv_d_min = np.min(npv_d)
        npv_d_max = np.max(npv_d)
        npv_d_p10 = np.percentile(npv_d, 10)

```



```

npv_d_p50 = np.percentile(npv_d, 50)
npv_d_p90 = np.percentile(npv_d, 90)

npv_d_negative_prct = len([num for num in npv_d if num < 0])/(len(ppa_d))
npv_d_at_least_100m = len([num for num in npv_d if num <=
    191669227.71271017/10**6])/(len(ppa_d))
line 22: stats_name = ['Mean','Standard
    Deviaton','Minimum','Maximum','P10','P50','P90','P(NPV<0)', 'P(NPV<NPV base)']
stats_value =
    np.array([npv_d_mean,npv_d_sd,npv_d_min,npv_d_max,npv_d_p10,npv_d_p50,npv_d_p90,npv_
        d_negative_prct, npv_d_at_least_100m ])
df_stats = pd.DataFrame(data={'Statistics':stats_name, 'Value of NPV, mil €':stats_value})
df_stats
line 23: hist_npv_d_cum = px.histogram(df_trials,histnorm = 'probability', cumulative=True)
hist_npv_d_cum.update_layout(xaxis_title="NPV in Million € ",yaxis_title="Probability ",
    title={'text':"CDF of NPV ",'x':0.5,'y':0.95})
hist_npv_d_cum.show()
hist_npv_d = px.histogram(df_trials, histnorm = 'probability')
hist_npv_d.update_layout(xaxis_title="NPV in Million € ",yaxis_title="Probability ",
    title={'text':"PDF of NPV ",'x':0.5,'y':0.95})
hist_npv_d.show()
hist_npv_d = px.histogram(ppa_d, histnorm = 'probability')
hist_npv_d.update_layout(xaxis_title="PPA, €/MWh ",yaxis_title="Probability ", title={'text':"PDF
    of Power purchase agreement ",'x':0.5,'y':0.95})
hist_npv_d.show()
hist_npv_d = px.histogram(cf_d, histnorm = 'probability')
hist_npv_d.update_layout(xaxis_title="Capacity Factor ",yaxis_title="Probability ",
    title={'text':"PDF of Capacity factor ",'x':0.5,'y':0.95})
hist_npv_d.show()

```