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A Decision Analysis Framework for Optimizing Electrification of Offshore Hydrocarbon Production Facilities for CO2 Emission Reduction

IAMMAS-1 20H Individual Project in Industrial Asset Management

By

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This work is dedicated to my late Abuelita. May her soul rest easy now.

Abstract

The oil and gas industry has been increasingly focusing on sustainability and emissions in their offshore production facilities, where 80% of emissions come from the generation of electricity for powering their platforms (Aker BP 2020*a*). Electricity is commonly generated through the use of inefficient gas turbines equipped on the offshore facilities. In this thesis, a Multi Attribute Decision Analysis (MADA) framework is developed to support the decision on which electricity generation technology should be used to reduce CO2 emission in an economically viable manner.

The MADA framework consists of three phases, namely: structuring, modeling and finally assessing and deciding. Within the structuring phase we defined the decision context and its core objectives, namely: maximizing net present value (NPV) and minimizing lifecycle CO2 emissions of new offshore electricity generation technology (Bratvold & Begg 2010).

A small field with a reserve of 50.7 MMbbl in the Norwegian Continental Shelf is used as a case study. Within the modeling phase, a Monte Carlo simulation is performed to assess the uncertainties in the Net Present Value (NPV) and lifecycle CO2 emissions of each alternative - no change (i.e., the base case), offshore wind turbine integration, new (more energy-efficient) gas turbine integration, and power from shore (onshore electricity supply).

The Monte Carlo analysis yielded an average NPV of $134.7 million for the wind turbine integration alternative, $101.4 million for the new gas turbines alternative, $89.9 million for the base case analysis and $-1.8 million for the power from shore alternative. The lifecycle CO2 emissions for the alternatives are 0.06 million tonnes (power from shore), 0.15 million tonnes (wind turbine integration), 0.2 million tonnes (new gas turbines), and 0.3 million tonnes (the base case). We conclude from our multi attribute decision analysis that, in general, the best alternative is the offshore wind turbine integration, given a higher weight is set on maximizing NPV. The sensitivity analysis on reserves indicates that the new gas turbine integration alternative is the best for a field with a reserve of greater than 253.5 MMbbl. The sensitivity analysis on the weighting of objective attributes shows that the power from shore alternative is the best when the objective of CO2 reduction has a higher priority (i.e. a greater normalized weight at 0.82) than the NPV maximization. The results from the multi attribute decision analysis generate useful insight on the economic and environmental effects that an oil and gas operator should consider with changing priorities (NPV vs. CO2 emissions) to conform with shareholder opinion and governmental policy when looking for sustainable development and production on new and existing hydrocarbon fields.

This thesis also highlights the importance for considering a wide range of creative alternatives before field development that can be extended in future works. In retrospect, future works can also explore a broader variety in analysis techniques, models, alternatives and scopes, to increase insight on field-specific infrastructure decisions, and understanding their economical and environmental impact.

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1 Introduction

1.1 Background

The current oil and gas industry in Norway is undergoing a centennial change. The advent of substantially lower oil prices starting in 2020 due to overproduction by OPEC member Saudi Arabia pressured oil and gas corporations worldwide to find new measures to stay resilient (Brower et al. 2020). Additionally, European operators face immense pressure to meet their promises to investors of decreasing debt, paying larger margins, and increasing shareholder payouts while investing in carbon-reducing measures adhering to increasing climate concerns (Brower et al. 2020).

With the focus of becoming more sustainable and environmentally friendly, Oil and Gas companies operating in Norway are undergoing a unique and conflicting challenge to satisfy varying external stakeholders' concerns, including but not limited to governmental, non-profit, and environmental organizations and the general public; while simultaneously maximizing Net Present Value (NPV), and operating capacity.

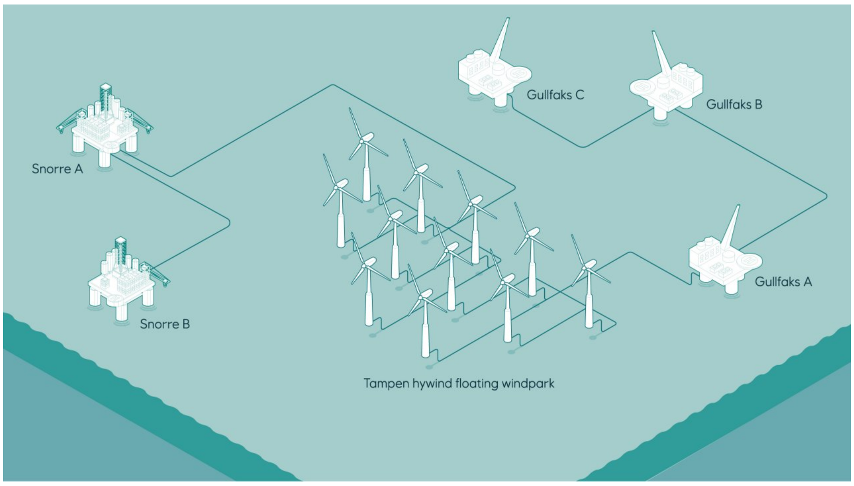


Figure 1: Proposed Wind Farm - Oil Production Integration, (World Oil 2020)

The Norwegian oil and gas industry specifically is defined by a paradox where environmentally viable choices are made and encouraged onshore while still relying on the production of non-renewable resources offshore that get exported. While the exportation and use of oil and gas in Norway does not adhere to a positive climate change solution, the production process of extraction and processing is very energy-intensive and sometimes conducted with outdated electricity generation technologies. As mentioned by DNV GL CEO Liv A. Hovem (2021), the worldwide industry is currently too slow in recognizing and placing emission-reducing technologies into their operations to reach the International Paris Agreement's requirements. Despite 75% of industry emissions coming from Scope 3 emissions, meaning the combustion of Oil and Gas product, 4% is accounted for the production stage. This margin, although small, has not been critically examined to be tackled as quickly by individual operators. However, some do recognise that the 4% of Scope 1 and 2 emissions during production have an impact on their longevity in future production (Brower et al. 2020).

A special case is Norwegian Continental Shelf O & G operator Åker BP. Åker BP recognizes that power generation alone in their offshore production accounts for roughly 80% of emission intensity within the corporation, as mentioned in their 2019 sustainability report (Aker BP 2020*b*). As a result, they promised to reduce their CO2 equivalent (CO2e) emissions from an average of 7 kg CO2e per barrel to 5 kg CO2e per barrel in 2020 while simultaneously promising to return significant value to its stakeholders.

1.2 Problem Presentation

Currently, the shift towards greener and more sustainable production methods in the Norwegian O & G Sector is being held in high esteem by the total electrification of the Johan Sverdrup Oil field. Additionally, O & G operators' profit margins now heavily depend on long term effective cost-cutting as suggested Hovem (2021) due to the high supply generated in other parts of the world, which is decreasing the oil price.

Berge (2007) highlights a need for further investment for CO2 reduction through Power From Shore (electrification) as Norway's offshore power plants account for 25% of the countries emissions, yet points out that it is not always economically viable neither uncomplicated. Hence, assessing the offshore electricity production methods is necessary to maintain an operator's economic viability yet reduce CO2 emissions.

1.3 Research question

After giving the general background and context, we can frame the relevant research question as:

How can a Norwegian continental shelf O & G operator maximize their shareholder value while reducing their CO2 emissions through implementing different electricity generation alternatives?

1.4 Research objectives and relevance

The research objectives within this paper are listed below:

1. To investigate the current production powering means within the Norwegian O & G sector of offshore facilities

2. To collect and process open-source data of O & G operators for use within a decision analysis

3. To introduce and build an effective multi attribute Decision Analysis framework

4. To gain a better understanding of the economic and carbon emission effect of carbon-reducing measures employed in an O & G company's production facilities
5. To identify the sensitivity of decision metrics with regards to estimating changes of core inputs and/or assumptions
6. To identify the best alternative available to a Norwegian O & G operator to reduce their production emissions significantly.

1.5 Methodology

The core of this paper will consist of a multi attribute Decision Analysis model closely following guidelines provided in the book "Making Good Decisions" Bratvold & Begg (2010) as reference material. The methodology will consist of structuring and framing the model, which includes defining the decision context, setting objectives and defining the alternatives. Subsequently, the modelling and evaluation will be an economic Monte-Carlo analysis also obtaining lifecycle emissions. Finally, a sensitivity analysis and tradeoff assessment is conducted. The software used for the Monte-Carlo Analysis in Excel, with the free SIPMath Probability Management modeller tools extension Probability Management (2021).

1.6 Scope of the Thesis

The scope of this paper will focus on the electricity production methods of Hydrocarbon production operations in the Norwegian Continental Shelf (NCS). This geographical scope is within the background context previously described. The time horizon of this analysis will consist of a 30-year outlook to satisfy a complete picture for implementation of new operative strategy and technology over a field's lifetime. Similarly, a collection of data from Norwegian operators and previous papers will be used for processing and building the various models. This will be limited to a single field, namely the Fenja field that consists of 50.7 MMbbl (Norwegian Petroleum Directorate 2014), and is located approximately 100 km northwest of Kristiansund mainland. The field's general location is shown in Figure2.

The primary values and objectives will align with that of a publicly traded hydrocarbon production company, namely maximizing shareholder value with measurable objectives being NPV and lifecycle CO2 emissions as objectives.

1.7 The structure of the thesis

The structure of this paper consists of various sections. The upcoming section will be a presentation of theoretical background, including a literature review and theory on

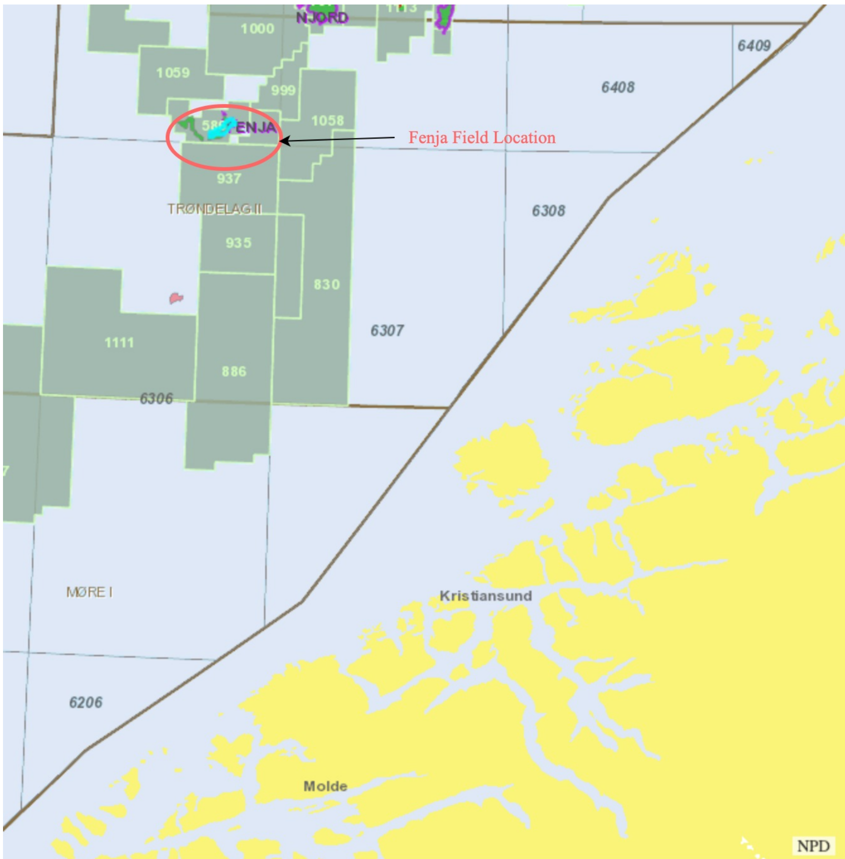


Figure 2: Fenja Field Location, consisting of 50.7 MMbbl of recoverable reserves, Norwegian Petroleum Directorate (2014)

decision analysis, theory of selected alternatives to be decided on, revealing previous works that analysed their performance. The theoretical background will also highlight the gaps in analysis and models of previous works conducted to determine this paper's academic contribution. Hence, the research methodology section presents the framing of the decision procedure and the analysis process. The research methodology is followed by the data collection, where the individual data inputs are laid out for the Monte Carlo analysis. Subsequently, the analysis will take place, which will present the results of the decision analysis' objectives and are followed by a sensitivity analysis. The discussion will highlight some key points in the results and define the quality of the analysis. Finally, this paper will be finalized with concluding remarks and suggestions for improvement.

2 Theoretical Background

2.1 Literature Review

Multi-criteria decision making (MCDM) methods have seen prevalent use within various industries, such as economics, engineering, natural sciences, and multiple other fields. Zavadskas et al. (2016) states that MCDM models are a key component within today's operational research and help decision-makers, no matter the context, choose the best course of action to reach the desired outcome (Bratvold & Begg 2010). MCDM combines the computational and mathematical tools to give a subjective evaluation of performance criteria to those decision-makers (Zavadskas et al. 2016). Zavadskas et al. (2016) also explores the large amount of different MCDM models and come under review for their application with respect to sustainability. Here the author mentions the natural fit of MCDM in sustainability as it takes into account criteria subsets such as: economics, environmental, and social aspects, while a fourth subset regarding engineering and technological dimensions can be included. Within the renewable resources and energy efficient applications, Zavadskas et al. (2016) points out the works of Mardani et al. (2015), where the MCDM techniques for sustainability are often split between conventional MCDM methodology and fuzzy multi-criteria decision making (FMCDM) methods. Likewise, Abdel-Basset et al. (2021) compares different FMCDM approaches to gain more nuanced results to reach a final decision when it comes to offshore wind-farm location. While FMCDM does provide advantage of including a large amount of criteria satisfactions using various mathematical methods and boolean operators within its analysis, its high complexity is beyond this paper's scope. Bratvold & Begg (2010) clarifies that assessing tradeoffs for conflicting objectives can be done by setting the alternatives on a plot with weighted benefit values against weighted cost values which allows finding an *efficient frontier*. To use stochastic modelling for the objectives, trade-offs between alternatives can be assessed by *first-order stochastic dominance* and *second-order stochastic dominance* depending on the decision maker's (DM) risk aversion. While not the most complex, core elements within this methodology still account for a MCDM method and taking into account uncertainty. The stochastic dominance method implies the need to first obtain probability density functions for the various performance values of interest within the multi-attribute decision method for a given decision.

The stochastic uncertainty modelling technique of interest is the Monte-Carlo Simulation (MCS), which considers randomly generated uncertain input parameters and a high number of iterations to quantify distribution of possible outcomes. This is a highly versatile tool, like MCDM, which finds many applications to quantify and assess uncertainty or risk of the desired parameter (Bratvold & Begg 2010). Fermi Dwi Wicaksono (2019) mentions the techno-economic application of MCS to obtain Net Present Value (NPV) in an oil and gas production sharing contract and highlights the uncertainty of NPV to acquire economic viability. While Fermi Dwi Wicaksono (2019) takes into account a projection of gas prices, the researchers states to do so without the consideration of price volatility and a limited prior calibration period for the linear regression forecasting. Alternatively, Nam et al. (2013) uses a monte-carlo simulation for oilfield asset evaluation and highlights the oil price volatility through the use of Geometric Brownian Motion (GBM), Mean Reversion (MR), and Mean Reversion with Jumps (MRJ). Nam et al. (2013) also evaluates the technical uncertainty for the production rate of an existing developed field to attain various NPV for different production scenarios and oil price forecasting methods. Similarly Fonseca et al. (2017) also uses the GBM method with a Monte-Carlo simulation to assess NPV of an oil field investment. The major implications oil price volatility and uncertainty has on NPV as mentioned by (Fonseca et al. 2017, Nam et al. 2013) warrants the inclusion of an appropriate oil price forecasting method (either GBM or MR) in techno-economic MCS for determining uncertain parameters in the MADM process. The use of MCS to model and forecast CO2 emissions were also reviewed to be a viable possibility by Tsai (2019).

Alternatives in power production for offshore oil and gas options, Korpås et al. (2012), He et al. (2010) explore the possibility of an offshore wind farm inclusion for an offshore oil and gas platform. The analysis cites KORPAS201218 confirms, is a significant saving in fuel and greenhouse gas reduction, given 2006 to 2009 natural gas prices were set to 0.11 $/SCM and operational costs of 64 €/MWh for wind generation with an initial 20 to 35 MW power consumption per year and start/stop gas turbine usage. Riboldi et al. (2019) Presents nuanced economic and environmental results for power from shore (PFS) or onshore electrification by considering the geographical location of PFS sourcing and method of onshore power generation (e.g. wind, nuclear, gas, hydro). The reduction of CO2 is presented as plausible for power generated in Norway and its neighbours with a CAPEX investment lower than 1052 M€ (Riboldi et al. 2019).Marvik et al. (2013) takes into account a combined approach of electrification and wind farm electrification for offshore oil and gas assets. The literature states the advantage of providing reactive power from the wind turbines to recover the platform to regular operation in case of emergency Marvik et al. (2013). Over-compensating the need for power production on an individual platform with doubled the wind farm capacity however, does not prove as effective due to technical difficulties associated with an excess of power available and a broken PFS connection. Mæland & Chokhawala (2010) confirms the positive implications of integrating PFS with reduced operational expenditures and lower greenhouse gas (GHG) emissions, yet do not include uncertainty as part of the analysis and comparison between land cables and conventional gas turbines. Santibanez-Borda et al. (2021) used a multi-objective optimisation model and concluded a 25% reduction of GHG emissions with an average cost of 370.9 $/tonne of CO2e over a ten-year time frame by integrating offshore wind farms for offshore production platform networks while considering the energy balance and demands of the network and the platforms own gas turbine loads.

It is important to note that a robust decision analysis framework needs to be created for this paper, with a valid uncertainty inclusion and relatively proven alternatives. While many MADM methodologies exist, as described by (Zavadskas et al. 2016) and Mardani et al. (2015) for sustainability-centred decisions, it is important to note that thorough framing and modelling is of priority. Hence, techniques and tools given by Bratvold & Begg (2010) are taken for coherence in decision analysis infrastructure. To account for uncertainty within the desired attributes that will define the alternative's performance, Monte-Carlo Simulation will be the primary driver in model generation to obtain NPV and CO2 emissions as well as reserves (Fonseca et al. 2017, Nam et al. 2013, Fermi Dwi Wicaksono 2019, Tsai 2019, Bratvold & Begg 2010). Major importance is to be put on the inclusion of stochastically forecasted oil and gas price values using one of the common forecasting methods, either MR or GBM Nam et al. (2013). Various alternatives to reduce CO2 emissions are present in the literature and have concluded potential CO2 reduction through PFS systems (Riboldi et al. 2019, Mæland & Chokhawala 2010, Santibanez-Borda et al. 2021), and wind farm integration (Marvik et al. 2013, Korpås et al. 2012, He et al. 2010). The literature also provide sufficient data availability to analyse standalone gas turbine usage, where Mæland & Chokhawala (2010) provide optimized gas turbine performance data by including waste heat recovery units and steam turbine. All the alternatives will hence be considered as a supplementary investment on a base case analysis which considers an already present, inefficient gas turbine.

2.2 Multi-Attribute Decision Analysis (MADA)

A high-level decision analysis framework ultimately focuses on obtaining a good outc. Whenime the decision is made, only the quality of the decision is within the decision maker's control (Bratvold & Begg 2010). The may outcome vary with the success of implementation and favourable factors of chance. The high-quality decision methodology aims to assess and maximize the chance of a good outcome and has a specific process with various elements.

Within MADA, the decision elements are: alternatives, or the set of choices to be chosen from, objectives which are criteria the alternatives are set against with allocated preferences; information, that includes data and uncertainties; payoffs which are outcomes and consequences of each alternative concerning each objective; and finally the decision which is the final choice identified between the alternatives (Hahn et al. 2012, Bratvold & Begg 2010). With these four elements, a certain process can be established to consistently arrive at highly valuable decisions.

2.2.1 Decision Analysis Elements

Decisions: Decisions are clarified as a "conscious, irrevocable allocation of resources to achieve desired objectives" Bratvold & Begg (2010). This element is often separated between tactical or operational, strategic, and policy. While not fully defined within time frames, the strategic decision is to be decided now, while the policy is a given. Operational or tactical decisions are to be decided later.

Alternatives: Within the decision analysis, a range of alternatives or choices is the primary action and component. Without alternatives, there is no decision to be made. Hence, the correct identification of alternatives is crucial. Alternatives can range in context, from choices in location as demonstrated by Zavadskas et al. (2016), or analysis of uncertainty and a wider strategic decision of reservoir assessment by (Bratvold & Begg 2010).

Objectives, Goals and Preferences: It is important to clarify core values, objectives and preferences before setting each alternative against these parameters. The values or goals are identified to give the decision-maker a clear core measure that often reflects and aligns with a broad organizational policy or mission statement (Bratvold & Begg 2010, Keeney 1996). Objectives are subset values or criteria that are drivers of the primary goal or value. Objectives are often identified as maximizing or minimizing statements that the alternatives should satisfy. Additionally, attributes and scales are given for every objective that allows thedecision-makerr to measure each alternative's performance, like for example, monetary value, physical dimensions or qualitative measures (Bratvold & Begg 2010, Hahn et al. 2012). Common values and objectives in a decision analysis may include, maximizing company corporate social responsibility, or maximizing shareholder value, maximize NPV, or minimize bad publicity. The ranking of objectives are up to the decision maker and the decision context, usually defined as a preference. To visualize, determine and prioritize values and objectives, a common method is the creation of a value tree, or value/goal hierarchy as seen in Figure 3 (Hahn et al. 2012, Bratvold & Begg 2010, Keeney 1996). This tool and visualization helps increasing transparency and communicating the intent, attribute scaling and preferences of the decision maker clearly.

In Figure 3 the weights and preference rating are useful for allocating more desirability or higher performance of a specific objective concerning another (e.g. maximizing visibility over minimizing CO2). Here, the weights should follow a common scale, such as 0 to 1 or 0 to 100, to clarify the respective preference of each objective.

Information and Uncertainty: Information about various parameters helps influence a decision situation. This often comes in the form of quantitative data or qualitative and descriptive information. Uncertainty is a necessary inclusion within the decision analysis.

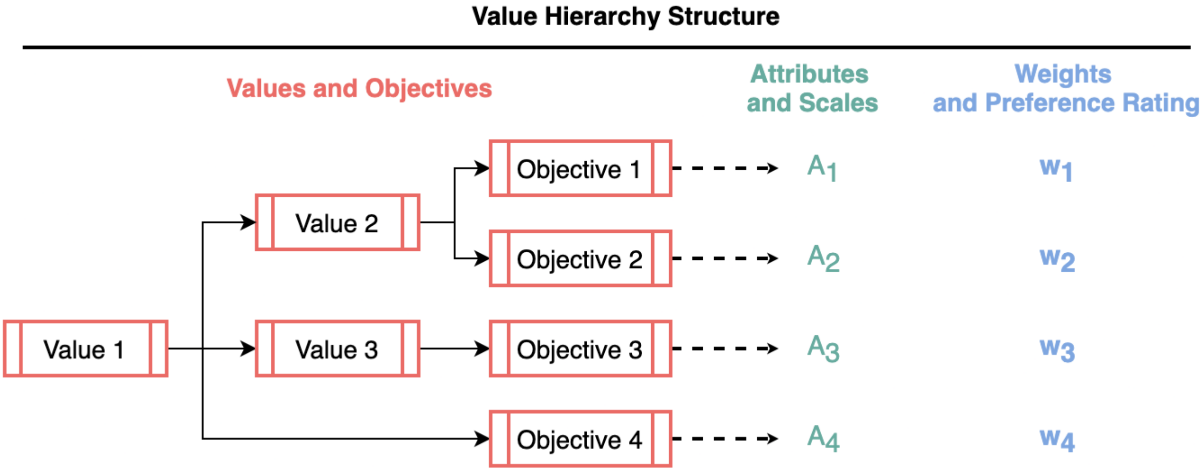


Figure 3: General Structure and Concept of a Value/Objective Hierarchy tree (Bratvold & Begg 2010)

When a decision is made, it is the unknown outcomes of a specific event that is defined as uncertainty (Bratvold & Begg 2010). Uncertainties warrant probabilistic analysis that enhances decision making later on.

Payoffs: Payoffs are described as events once all outcomes of uncertain events are resolved concerning all objectives, defined by their attribute scales for each alternative. These may be the CO2 emissions or the choice of a new enterprise-wide operating system. Here, some payoffs may be known through their deterministic nature, while forecasted values warrant the need for modelling to gather a more accurate payoff value to assess, often through the use of MCS (Bratvold & Begg 2010).

2.2.2 MADA Methodology

Stage 1: Framing

The figure 4displays the multi-attribute decision-making structure, with its core elements discussed in the previous sections. The procedure commences with the framing or structure phase, highlighted in Figure 4 in red boxes. It is important that the correct decision context is to be defined, considering the setting, whether it is a physical, financial, hierarchical position or based on the sentiment of a population. These contexts then define the appropriate objectives to be achieved, and consequently, a collection of alternatives can be identified (Bratvold & Begg 2010). As discussed in the previous section, the objectives can be identified through the use of a Value Hierarchy, with its given attributes, scale, and weights. Once the value hierarchy is clearly defined, a review of the decision framing can question its robustness.

The value hierarchy context has to satisfy five criteria questions, namely (Bratvold & Begg 2010):

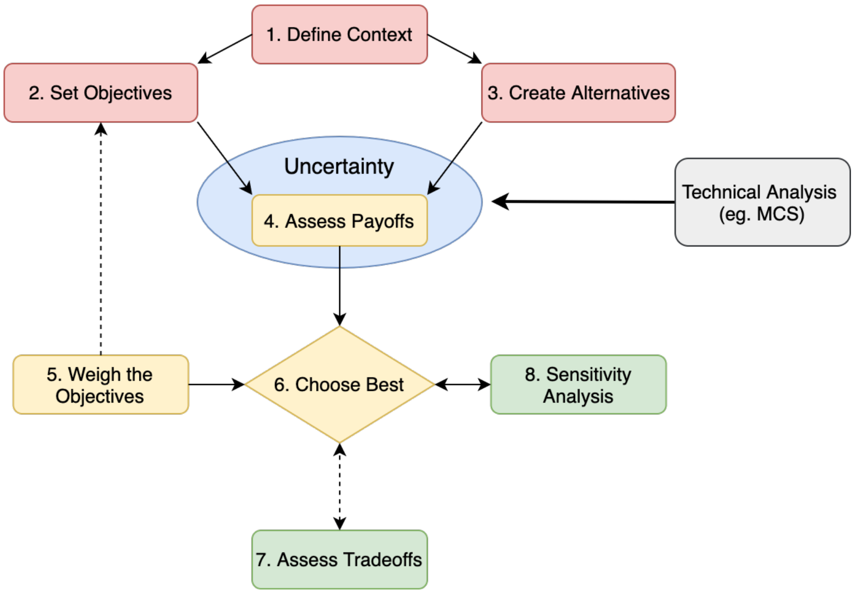


Figure 4: Multi Attribute Decision Analysis Methodology (Bratvold & Begg 2010)

1. Is the decision context complete in its form?
2. Are the objectives clearly defined to set them against the alternatives?
3. Are the objectives as independent from another as possible?
4. Do the objectives not overlap, contradict or repeat themselves?
5. Are the objectives set as compact as possible, i.e. are they reduced to the most common denominator that assess the decision?

Hence, the alternatives can be selected, generally following the notion that the best decision can only be as good as the chosen alternative.

Stage 2: Modeling and Evaluation

The yellow boxes define this stage in Figure 4, namely "Assessing Payoffs", "Weighing the Objectives", and "Choosing the Best" alternative. Often in decisions with a high number of alternatives, the payoffs may be assessed to determine any outperforming alternatives or under-performing alternatives with respect to its other options that do not resonate with clear competitiveness. This can be done through a payoff matrix such as Table1. Notice in Table 1that alternative B, C and D outperform alternative A on almost every objective except cost, validating alternative A's removal. Subsequently, as alternative C and B demonstrate higher desirability with reputation and safety, D is removed, leaving a choice between alternatives B and C.

Here arise two conflicts that hinder the determination of a final choice. First, the valuation of importance of each objective and a common comparative value as alternative

Table 1: Example Payoff Matrix for a Contractor choice

	Alternatives			
Objectives and Attributes	**A**	**B**	**C**	**D**
Average Cost, USD	95	100	120	90
Reputation, 0-5 scale	0	2	4	1
Safety, lost hr/person/year	0.02	0.01	0.01	0.05

B sustains a lower cost and a lower reputation, whereas alternative C retains a higher cost yet compensates with a better reputation. The issue of missing comparative scales can solve the case of comparative scales by creating attribute scales, which converts the scores to values. Constructed either naturally, as the objectives may be determined through calculation or a constructed scale, the values are usually set between 0 to 1 or 0 to 100. Such can be seen in Figure 5.

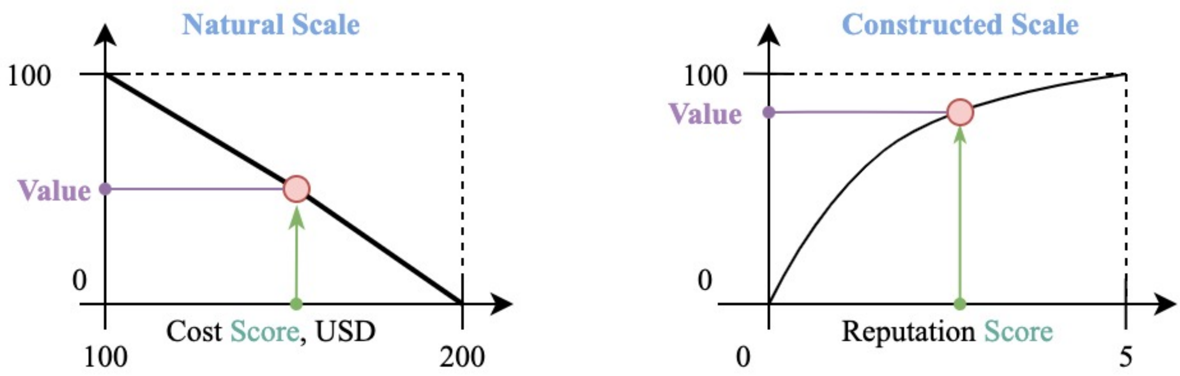


Figure 5: Attribute scales that determine a common Value, set between 0-100 (Bratvold & Begg 2010, Hahn et al. 2012)

Solving the second issue of determining which objective holds more importance is done by assigning a subjective weight for each objective from a common scale, either 0 to 100. The weights are then summed and then normalized, yielding a sum of 1 as demonstrated by the ranking and weight application in the Table 2 below.

Table 2: Ranking of Objectives with subjective weighting and normalization (Bratvold & Begg 2010)

Objectives and Attributes	Rank	Weight	Normalized Weights
Safety, lost hr/person/year	1	100	0.42
Reputation, 0-5 scale	2	80	0.33
Average Cost, USD	3	60	0.25
		240	1

The final decision can be determined by converting each objective scores to values and multiply them by the normalized weight. The summation of each alternative's attributed and weight normalized values, hence allowing for individual comparison as represented in the finalized evaluation spreadsheet in Table 3and calculation characterised in Equation1.

$$V_j = \sum_{i=1}^{N_j} w_i v_{i_j} \tag{1}$$

The final weighted value V_j is obtained for each alternative N_j, over the present objectives N_i. It is a summation of the products of ith objective weight (w_i) and the jth alternative for each ith objective (v_{i_j}). Through the application of Equation 1on Table,3 the highest-ranked alternative is C.

Table 3: Sample evaluation spreadsheet (Bratvold & Begg 2010)

				Alternatives			
Objectives and Attributes	**Rank**	**Weight**	**Normalized Weights**	**A**	**B**	**C**	**D**
Safety, 0-10 scale	3	30	0.15	40	10	0	100
NPV, USD million	1	100	0.50	70	0	100	30
IRR, %	2	70	0.35	100	40	90	0
		200	1	76	15.5	81.5	30

Stage 3: Assessing and Deciding

In this final stage, the decision analyst prepares to make trade-offs between competing objectives and conducts a sensitivity analysis of various inputs to see how it changes the final results. The tradeoffs between alternatives are whether we are willing to accept a change in costs over some benefits. However, through a stochastic analysis such as the Monte Carlo Simulation, we may use stochastic dominance, which Bratvold & Begg (2010) goes into detail in Section 5.5.1. Subsequently, a sensitivity analysis of the objectives' weights can be conducted, where one of the normalized weights is put under analysis and changed in gradual steps from 0 to 1, while the other objectives not in question automatically change to be a sum of 1. This allows us to observe the change in the final score for the best alternative with respect to a changing allocation of preference (i.e. weights). An example of such is displayed in the Figure 6 below.

Finally, the sensitivity analysis can also undergo through the changing of core input variables and plot the results of an objective as this input variable increases or decreases (Bratvold & Begg 2010). Although the final decision may not change, a consideration for the changes in its input variables can determine its effect on the final decision.

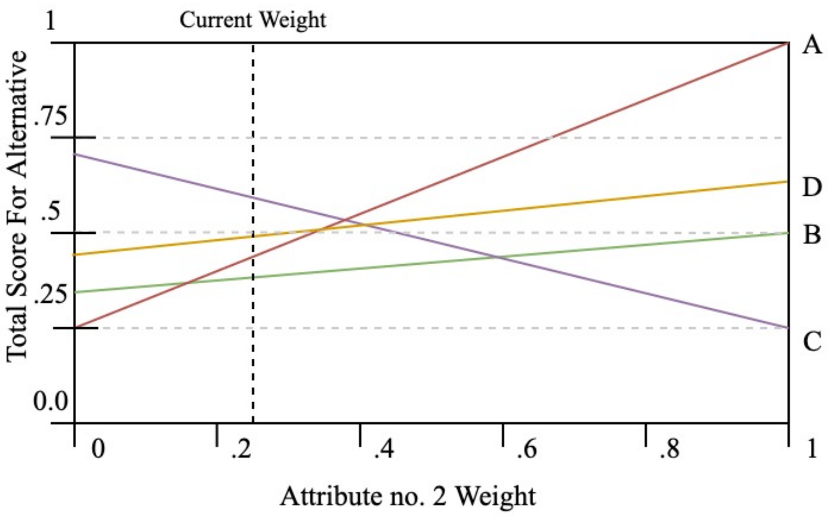


Figure 6: Sensitivity Analysis of a change of an Objetive's Normalized weight (Bratvold & Begg 2010)

2.3 Monte Carlo Analysis

The Monte Carlo simulation is described in Bratvold & Begg (2010) and used by Fermi Dwi Wicaksono (2019). The input variables receive a certain input probability density function. Then, a random input value is chosen according to the input distribution set and inserted into a defined function (i.e. the mod), as seen in step 2 in Figure 7. This is repeated for a number of iterations in order to build a plethora of results that can then be used to generate a histogram and cumulative density function. The results can then be assessed, while taking into account uncertainty.

2.4 Oil & Gas Price Forecasting

In order to forecast the revenue streams from liquids and gas for NPV calculations, the Oil and Gas prices will have to be forecasted with a dynamic pricing model in order to take into account uncertainty. Begg & Smit (2007) states that "at a minimum, the dynamic pricing model is required to predict future cash flows, and assess risks and opportunities." The common oil price characteristics have been listed as:

- High Volatility
- Near to uniform Gaussian or Normal Distribution of price fluctuations
- Exceptional price fluctuations characterized by price surges
- A history and tendency to revert to a long-term mean price

Hence, to continue with a cash flow projection to assess the alternatives, a solid dynamic oil pricing model must be chosen. A common model that represents three of these

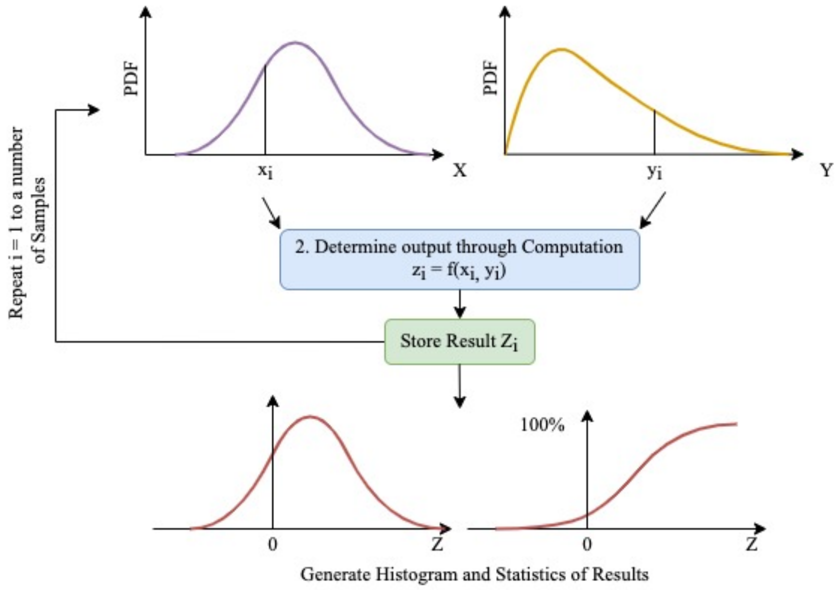


Figure 7: Monte Carlo Simulation Process (Bratvold & Begg 2010)

characteristics is the Mean Reversion (MR) model, where the volatility effect (σ), normal distribution of fluctuations ($\varepsilon\sqrt{dt}$) and reversion to a long term average price (P^*) are included in Equation 2.

$$\frac{dP}{P} = \eta(P - P^*)dt + \sigma\varepsilon\sqrt{dt} \tag{2}$$

Where:

t : time period (years)

ε : the normal distribution or N(0,1)

η : the mean reversion rate or speed at which price reverts to

σ : price volatility

P^* : long term average/equilibrium price

P : price

2.5 Cash Flow Modelling and Net Present Value

Within decision making of investments of assets, a set of economic indicators are used to compare different alternatives against each other (Wheaton 2016). The Net Present Value (NPV), seen in equati,on 3 is described as the summation of the total present value of a series of Discounted Cash Flows (DCF) (equation 4) ,taking into account the time value of money as a specific discounting rate (r) also known as the cost of capital for a defined time period (Wheaton 2016).

$$NPV(\%r) = \sum_{i}^{n} DCF \tag{3}$$

$$DCF_i = NCF_i/(1 + r_D)^n \tag{4}$$

Where:
NCF: Net Undiscounted Cash Flow at Period i (currency)
r_D: specified discount rate (fraction)
n: Number of time intervals most commonly in years or months.

Likewise, the NCF for a period (i) is a summation of that period's capital expenditures (CAPEX), operating expenditures, and Sales seen in the equation5.

$$NCF(i) = Capex(i) + Opex(i) + Sales(i) \tag{5}$$

The calculation of NPV is often used as a total valuation of assets within an organization and is seen as a primary indicator for defining shareholder value (Bratvold & Begg 2010). However, Woods & Randall (1989) argues that there are general discrepancies between NPV and Shareholder value due to market inefficiencies and are biased towards long term future investment opportunities, applicable to Oil and Gas projects that have a lifetime of 20 or more years. Nonetheless, for the scope of this paper, NPV will be analysed in combination with lifecycle emissions as primary indicators for maximizing shareholder value.

3 Research methodology and design

The methodology within this paper bases on the multi-attribute decision analysis tools (Bratvold & Begg 2010) to arrive at a viable power production alternative to implement on offshore hydrocarbon facilities. This section will highlight the use of the multi-attribute decision analysis structure and the Monte-Carlo simulation methods to acquire the final result of data for later sensitivity analysis and discussion. We begin by framing the decision analysis, reiterating its context and boundaries, setting its objectives to measure performance, and the alternative's boundaries. The correct framing and structuring is arguably the most important step to bring forward a structurally viable and balanced decision towards the end of this paper.

3.1 Phase 1: Structuring & Framing

3.1.1 Decision Context

The decision context relies on the best decision of maximizing the shareholder value with the implementation of CO2 emission reduction strategies and technologies. Here, the decision-makers are board executives responsible for applying strategies and solution to best facilitate long term business viability and meeting relevant corporate social responsibility milestones to maximize shareholder value. The context extends with a consideration of operational expenditure reduction due to oil and gas price volatility and increasing shareholder's environmental awareness. Hence, the value hierarchy set is based on the factor of maximizing Net Present Value (NPV) and minimization in lifecycle CO2 emissions as seen in Figure 8.

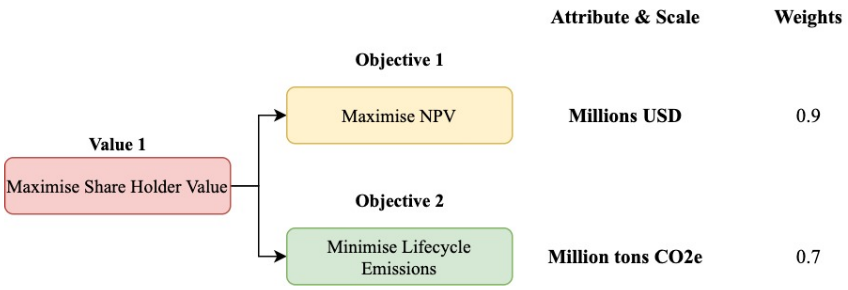
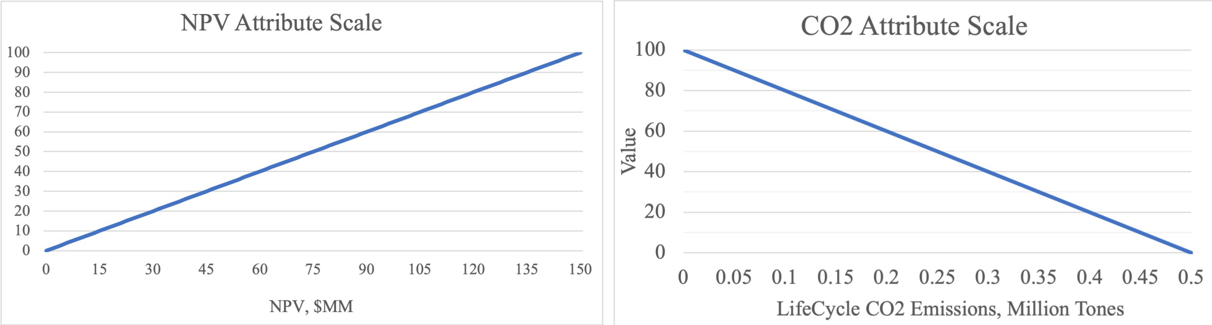


Figure 8: Value Hierarchy

As discussed in Section 2, the implementation of new power production assets into oil production platforms allow for the mitigation of CO2 emissions and therefore we can attribute the best alternative to a specific field. The feasibility of this analysis bases on the instance where a new field is to start production, in order to analyse the extent of this mitigation of each alternative across the start and end of a field's production phase. The value hierarchy in Figure 8 requires the generation of attribute scales for each objective which are displayed in Figure 9.



(a) Objective 1 Attribute scale

(b) Objective 2 Attribute scale

Figure 9: Natural attribute scale for Multi Attribute Decision Analysis

The weights applied to the objectives were decided on the level of preference and are subject to sensitivity analysis later on. The decision analysis example spreadsheet for this paper will be expected to take the form as seen below in Table 4.

Table 4: Decision Analysis Spreadsheet

Objectives			**Alternatives**			
Name	Rank	Weights	Reduced Production	Wind Turbines	Efficient Gas Turbines	Power From Shore (Land Cable)
Net Present Value (NPV) (M $)		0.9				
Lifecycle CO2e Emissions (tons CO2e)		0.7				
Total Score						

To attain the required values for each alternative the Monte Carlo modelling method will be applied. Table 5 breaks down the individual process to attain the NPV and lifecycle CO2 emissions for every alternative. Each alternative's analysis will receive its unique capital expenditure (CAPEX) and operational expenditure (OPEX) components displayed in Section 4. The revenue will be calculated through the Oil production and the oil price model using mean reversion and is applicable to all models. For a higher degree of confidence the Monte-Carlo simulation will have 10,000 realizations applied through the SIPMath Excel extension. For consistency, the oil production, power capacity, oil price, gas price and any base capital expenditures, and operational expenditures will be kept the same across all alternatives, except expenditure related to electricity production. The different individual CAPEX and OPEX for each alternative will then determine its new NPV and lifecycle CO2 emissions.

Table 5: Analysis and Modeling breakdown

	Analysis Section		Method	Unit
1	Oil Production Curve		Ramp up - Plateau - Decline	MMbbl
2	Power Capacity Curve		Multiplication Factor	MW and MWh
3	Oil Price		Mean Reversion	$/bbl
4	Gas Price		Mean Reversion	$/SCM
5	CO2e Tax Price		Linear extrapolation	$/ton
6	Electricity Price		Uniform Distribution	$/MWh
7	Base Case Analysis			
7.1		NPV	Discounted Cash Flow Process	$MM
7.2		Lifecycle Emissions	Emissions from Electricity	Tons of CO2 emitted
8	Wind Turbine Integration			
8.1		NPV	Discounted Cash Flow Process	$MM
8.2		Lifecycle Emissions	Emissions from Electricity	Tons of CO2 emitted
9	Gas Turbine Integration			
9.1		NPV	Discounted Cash Flow Process	$MM
9.2		Lifecycle Emissions	Emissions from Electricity	Tons of CO2 emitted
10	Power From Shore			
10.1		NPV	Discounted Cash Flow Process	$MM
10.2		Lifecycle Emissions	Emissions from Electricity	Tons of CO2 emitted
11	Tradeoffs	NPV	Stochastic Dominance	
12	Sensitivity Analysis			
		Reserves on NPV	linear change in Reserves	$MM
		Normalized Wegiths		

4 Data Collection

For the Net Present Value and lifecycle CO2 emission Monte Carlo Simulation to commence, the data to be employed in the model needs to be displayed. Since this paper does not gain its data from a single enterprise, the data inputs are gathered from state authorities, Oil and Gas company reports, consulting company research papers, and personal communications. The data collection entails numerical inputs required for the oil production curve, the electricity capacity curve, price models for hydrocarbons (oil and gas), and the CO2 emission penalization tax. Additionally, the data points used for each alternative model will also be displayed. The basis of data inputs relies on a series of input distributions of randomly generated values through the SIPMath excel add-in. The number of realizations in this analysis consists of 10,000.

4.1 Production Model Inputs

The data collection for the production model requires the input of initial field reserves to be produced from. The field reserves parameters are allocated from the National Petroleum Directorate of Norway. The field of choice is the Fenja Field which has a recoverable oil in place of 8.07 million sm^3 which is equivalent to 50.7 $MMbbl$ of recoverable oil as seen in Table 6. This value is set to be independent and true to set a precedent to achieve a realistic analysis (Norwegian Petroleum Directorate 2014).

Table 6: Field reserves data parameters

Field	Block No.	License No.	Recoverable Oil in Place [million sm3]	MMbbl/scm^3	Reserves (MMbbl)
Fenja	6406/12	586	8.07	6.29	50.7

Hence, for the production model Monte Carlo analysis, the inputs for the production model and its parameters were decided by approximation and supervisory suggestion to primarily to account for, and solidify the notion of uncertainty within this analysis. However, as a rule of thumb, the yearly plateau rate is between 7% and 9% of the total reserves given. Hence, these inputs simulate a possible range of scenarios as the distributions for each model input. The realisation values seen in Table 7, is the visualization of a random generated value between the given parameters of P5, P50 and P95. For a triangular distribution these percentiles are taken as equivalent to 'minimum', 'most likely', and 'maximum' values. The randomly generated values are stored separately and then called upon, by Excel, to execute the Monte Carlo simulation. The triangular inputs were chosen to provide specified boundaries, unlike log-normal or Myerson distributions that have asymptotic properties.

Table 7: Production model input parameters

		Real.	P5	P50	P95	Rand	Input PDF type
Np	Reserves, MMbbl	50.70				Indep.	
yR	Length of Ramp Up (to plateau), yrs	2.51	1	2	4	0.63	Triangular
qP	Yearly Plateau Rate, MMbbl/yr	3.88	3.6	4.1	4.6	0.21	Triangular
P	Fraction reserves produced at end plateau	0.54	0.35	0.40	0.70	0.76	Triangular
qL	Field Economic Rate Limit, bbls/yr	0.26	0.20	0.25	0.30	0.55	Triangular

For the electricity production a special ratio was used to identify the electrical capacity required per million barrel per year (Sagstad 2014). With reference to Figure 10, the peak production was said to be 100,000 SCM/day which corresponds to 229.6 MMbbl per year. Since a base capacity of 150 MW is needed, the ratio between power capacity and million barrels produced per year is 0.67 MW/MMbbl/year. To take into account any operational risks where a higher electrical capacity is required a 20% buffer was added which makes the official electricity capacity to production ratio be 0.80 MW/MMbbl/year (Sagstad 2014). In our analysis we wish to extend the likelihood of a higher power requirement and set the power requirement between 0.8 and 1 MW/MMbbl/year on a triangular distribution. We can then determine a unique power requirement profile that follows the oil production curve, as well as calculate the power usage (MWh) for each alternative.

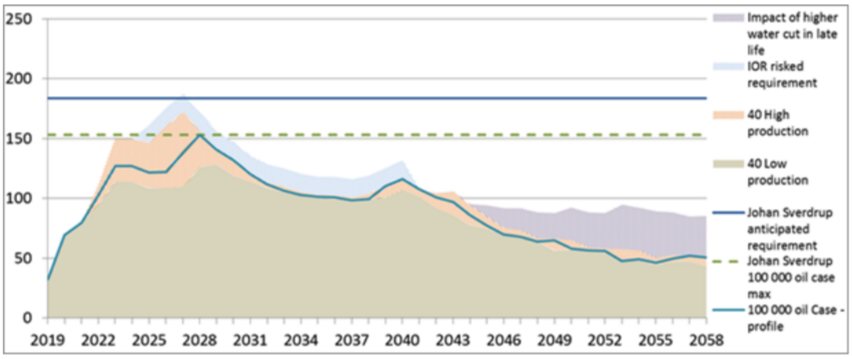


Figure 10: Johan Sverdrup's expected power profile

Table 8: Power capacity to oil production ratio

Current Model	Power Production Requirement	Real.	Min	Most Likely	Max	Rand	Input PDF Type
Power per Barrel Ratios	MW/MMbbl	0.87371	0.80	0.80	1.00	0.49	triangular

4.2 Price Model Data Inputs

Price forecasting models bear a prime uncertainty component for analysing financial options. Hence, price modelling with a forecasting method and inclusion of Monte Carlo simulation warrants different inputs. As outlined in section 2, and 3, the forecasting method suitable for hydrocarbon prices is the Mean Reversion method. Hence, it requires an initial oil price (IOP), a long term mean (LTP), a reversion speed (HF for half-life), volatility in prices are defined by sigma (σ) and mean growth in price which defines the growth rate of the price and are listed in Table 9. These inputs do not adhere to an input probabilistic distribution. The only probability distribution input is a standard normal distribution defined as ϵ, in Formula 2 and defines the randomization within the mean-reversion process.

Table 9: Oil and Gas mean reversion input parameters

		Oil	Gas
Type		Mean Reversion	Mean Reversion
IOP	Initial Price	65 $/bbl	0.18 $/SCM
LTP	Long Term Mean ($/bbl)	45	0.22
HF	Reversion Speed	2	8
ln(LTP)	ln(P(mean))	3.81	-1.51
η	Eta	0.35	0.09
σ	Volatility	0.15	0.01
α	Mean Growth	0.001	0.001
ϵ	Normal Distribution Factor	0.790	-0.382

Data allocation for this mean reversion process in oil and gas was taken as the current approximate spot prices from Aker BP's sale prices in 2019 (Aker BP 2020*a*). The LTP was determined through a general approximation of historical prices. Furthermore, the reversion speed, volatility and mean growth are taken by a prior analysis and personal communication

4.2.1 CO2e Tax price data inputs

The second price modelling input includes the CO2 prices and their predicted increase as proposed by the Norwegian Petroleum Directorate. Currently, the price stands at 42.25 Euros per ton of CO2e (CO2 Equivalent) emitted (Mæland & Chokhawala 2010). However, a gradual increase until the year of 2030 is expected where the CO2e price will stand at 240 Euros per ton of CO2e. This increase in price provided it is linear, has a rate of 18.9 euros per year until 2030. After 2030 it is important to note that no set price increase is predicted for the next 20 years. Hence, a triangular distribution between 10% and 20% is applied to each year's prior price to account for an uncertain price increase rate.

4.2.2 Electricity price data inputs

For the scenario given the power from shore integration to the platform, the O & G company needs to buy electricity. Since the scope limits electric power only being bought from the Norwegian sector, an array of 15 years worth of electricity prices from 6 regions were taken to determine the standard deviation and average price to apply a normal distribution on yearly electricity prices (Nord Pool AS 2021). The electricity prices stated in Table 10 are the core input data values for the electricity price predictions.

Table 10: Electricity Prices in Norway

El price (EUR/MWh)	Oslo	Kr.sand	Bergen	Molde	Tr.heim	Tromsø	Average	Variance
2020	9.29	9.29	9.17	9.46	9.46	8.88	9.26	0.05
2019	39.29	39.27	39.27	38.96	38.54	38.31	38.94	0.18
2015	19.85	19.82	19.75	21.28	21.28	20.43	20.40	0.52
2014	27.33	27.23	27.14	31.54	31.54	31.44	29.37	5.48
2013	37.56	37.33	37.60	38.96	38.96	38.60	38.17	0.57
2012	29.56	29.16	28.95	31.48	31.48	31.17	30.30	1.44
2011	46.41	46.09	45.85	47.49	47.49	47.48	46.80	0.59
2010	54.25	50.82	51.79	58.04	58.04	57.33	55.05	10.45
2009	33.74	33.74	33.74	35.55	35.55	35.53	36.64	0.98
2008	39.15	39.15	39.15	51.17	51.17	49.81	44.93	40.38
2007	25.74	25.74	25.74	29.59	29.59	29.43	27.64	4.33
2006	49.23	49.23	49.23	48.97	48.97	48.98	41.10	0.02
2005	29.13	29.13	29.13	29.39	29.39	29.39	29.26	0.02

4.3 Individual scenario model inputs

The allocation of data inputs used for each analysis scenario consists of various CAPEX and OPEX parameters unique to the various alternatives. The allocation of inputs requires the base case data inputs for creating the general scenario on which the subsequent alternatives are built. Hence, the wind turbine integration, power from shore connection, and new gas turbine alternatives have unique measures used for their CAPEX and OPEX parameters, including efficiency ratios, CO2e emission rates, and power loss compensation.

4.3.1 Base Case data input allocation

The base case scenario represents the standardized development and operations cash flows, with general rules of thumb. This includes a CAPEX generally given by the CCCOP as a measure between 3 to 5 dollars per barrel in the reservoir (Kjemperud n.d.). This rule of thumb determines and represents the entire structures, including platform, risers, turbines, pumps, etc... The fixed OPEX, including wages, maintenance procedures, and fuel costs is defined between 8 to $22 million per year upon personal communications. Likewise, the variable OPEX, depending on the number of barrels produced is initially defined between 10 to 15 $ per barrel and increases between 0% and 6% per year. All these inputs are defined by a triangular distribution. The variable OPEX change is first allocated through a prior triangular distribution and then multiplied by a normal distribution set to gain a more fluid and randomized OPEX change.

Table 11: Base Case - CAPEX and OPEX inputs

CAPEX and Fixed Opex	Real.	min	most likely	max	average	Rand	Input PDF type
Capex ($MM/bbl)	3.308	3	4	5	4	0.047	Triangular
Fixed Opex ($MM/year)	15.475	8	14	22	14.7	0.620	Triangular
Variable OPEX	Real.	min	most likely	max		Rand	Input PDF type
Initial ($/bbl)	11.149	10	15	20		0.026	Triangular
Opex Change Prior Triangular	0.0281895	0	0.01	0.06		0.6626966	triangular

To determine the CO2 Emissions in the base case scenario Table 12 describes the various initial inputs. The first being the turbine efficiency, which is lower by standard means in the oil and gas industry, set to be in the range of 25% to 35%. Here the Power requirement is calculated from 59 MW into MWh per year. The CO2 rate released at 100% efficiency is a set value to be 0.21 tons per MWh Mæland & Chokhawala (2010).

Table 12: Base case turbine inputs

CO2 Emissions	Real.	Min	Most Likely	Max	Rand	Input PDF type
Turbine Efficiency	0.321024531	0.25	0.3	0.35	0.8320844	triangular
CO2 Released at 100% efficiency (ton/MWh)			0.21			

4.3.2 Wind Turbine Integration Inputs

Wind turbine data inputs focus on adding the CAPEX, and OPEX parameters to the base inputs. First, the number of turbines has to be determined. In Table 13 the calculation is based on maximum wind turbine capacity.

Table 13: Wind Turbine allocation

WT Parameters	Value
Platform Production Capacity (MW)	3.00
Turbine Rating (MW)	5
No. of Turbines	1

Additionally, the data inputs for wind turbine CAPEX and OPEX are defined below in Table 14. The CAPEX and OPEX for offshore wind turbine installations were taken from considerations of a Deloitte paper that assessed 40 offshore wind turbine projects (Deloitte 2014). The capacity factor is determined as the maximum amount of power production the turbines cover effectively throughout the year and is set between 35% and 50% (Norwegian water resources and energy directorate (NVE) 2013). The remaining power required is upheld by the turbine figures described in the base case (Table 12) that are expected to produce CO2e.

Table 14: Wind Turbine CAPEX and OPEX data allocation

WT Production CAPEX and OPEX Parameters							
	Real.	min	most likely	max	average	Rand	Input PDF type
Capex ($MM/MW)	3.83	1.90	3.20	4.50	3.20	0.94	Triangular
Fixed OPEX	Real.	min	most likely	max	average		Input PDF type
OPEX ($/MWh)	35.39	17.00	29.10	41.20	29.10	0.84	Triangular
OPEX Change (%)	-0.01						
Capacity Factor	Real.	min	most likely	max	average		Input PDF type
Factor Offshore North Sea	0.44	0.36	0.43	0.50	0.43	0.28	Triangular

4.3.3 New Gas Turbine Inputs

The inputs for the final alternative consists of installing new more efficient gas turbines and waste heat recovery units (WHRU) are seen in Table 15. The CAPEX for a LM6000PF turbine and WHRU are taken from the paper by Riboldi et al. (2019). The OPEX data was taken from the ABB paper where much of the power from shore data is included Mæland & Chokhawala (2010). The primary difference is the inclusion of a higher range of efficiency which the newer turbines should perform at. As the maximum electricity capacity is set to be 3 MW and with each turbine satisfying 50 MW, only one gas turbine and WHRU are required.

Table 15: New Gas Turbine Inputs

GT Production CAPEX and OPEX Parameters							
	Real.	min	most likely	max	average	Rand	Input PDF type
Capex GT ($MM/unit)	28.072		28.072		28.072		
Capex WHRU ($MM/unit)	2.42		2.42		2.42		
Total Capex	30.492						
	Real.	min	most likely	max	average		Input PDF type
Fixed OPEX Rate ($MM/25MW installed)	4.623	4.084	4.538	4.991	4.538	0.67032493	Triangular
Power Output (MWh/year)	Real.	min	most likely	max	average		Input PDF type
Fuel To electricity conversion @ 100% efficiency (MWh/SM3)	0.0108						
Turbine Efficiency	0.4168	0.35	0.4	0.5		0.53844641	Triangular
Fuel to Electricity Conversion @ Real Efficiency (MWh/SCM)	0.0045						
CO2 Rate released at 100% efficiency (ton/MWh)	0.21						

4.3.4 Power From Shore Inputs

The Power From Shore integration data inputs are taken from CAPEX and OPEX studies published by ABB and Equinor for applying a land cable electrification solution to a platform (Mæland & Chokhawala 2010, *Dagny, Draupne and Luno Power from Shore Cooperation Report* 2011). These values taken from the papers reflect the core expenses in this analysis.

Table 16: Power From Shore data source

PFS Parameters			Value
Platform Production Capacity (MW)			59
Distance from Shore (km)			100
Maximum Power Requirement (MWh)			518256
ABB CAPEX Study			(million NOK)
Feeder to Onshore HVDC Converter			26
HVDC Converter Stations onshore/offshore Equipment			502
Subsea Cable 220 km incl. installation			1094
HUB Topside			494
ABB Project Cost			13
ABB OPEX Study	low	Base	High
Maint. OPEX (MNOK/year)	0	25	50
Electricity Transmission Loss	0.03	0.06	0.1

The values given in Table 16, are transferred and given appropriate distributions. The cable length is given an input PDF type distribution as the variation in cable price is dependent on the exact distance between the onshore and offshore connection. The cable price per kilometre was obtained by dividing the existing approximated price for the proposed connection in the Equinor project by the distance (220 km), hence arriving at the given "most likely" price in Table 17 (*Dagny, Draupne and Luno Power from Shore*

Cooperation Report 2011). The cable length price was then given a 10% price buffer above and below the 'most likely' price to account for a variation. Additionally, the Equinor report gives price ranges for the Maintenance OPEX and is directly applied to the model input. Since NPD considers the oil and gas operator to only purchase the electricity and not produce it, the CO2e taxes while using PFS measures are considered by the National Petroleum Directorate to be nil.

Table 17: Adjusted and arranged input Data Values for Power From Shore Analysis

PFS CAPEX and OPEX Parameters	Real.	min	most likely	max	average	Rand	Input PDF type	
Cable Capex ($MM/km)	0.600	0.54	0.60	0.66		0.54690647	Triangular	
HUB Topside ($MM)	59.28		59.28					
Feeder to Onshore HVDC Converter ($MM)	3.12		3.12					
HVDC Converter Stations ($MM)	60.24		60.24					
Total Capex ($MM)	182.60							
	Real.	min	most likely	max	average	Rand	Input PDF type	
Maintenance OPEX ($MM/yr)	1.558	0	3	6	3	0.13492823	Triangular	
Variable OPEX	Real.	min	most likely	max	average	SD	Input PDF type	Random Variable
Electricity Cost ($/MWh)	17.56	10.74	41.91	70.23	42.24	14.86	Triangular	0.894611951
Transmission Loss Compensation	0.06	0.03	0.06	0.1	0.063	0.04	Triangular	0.4957113

5 Analysis and Results

The analysis and results of the Monte Carlo simulation for assessing the NPV, CO2 emissions and reserve maximization for 4 different alternatives are broken down into their subsequent components, highlighting the uncertain nature of their distributions. Subsequently, the resulting total scores will be shown to come to a decision. Finally, the robustness of the analysis and values warrants the need for a sensitivity analysis.

5.1 Oil and electricity production profiles

The production curve bases on a generalized production model called the "tank model" that employs Arp's exponential decline curve. Given the input of recoverable reserves from the discovered Fenja Field of 8.07 $MMscm^3$ (Norwegian Petroleum Directorate 2014) as given in table 7. The generation of inputs was decided in Section 4.2. Figure 11 represents the production profiles at different percentiles, visibly with different plateau periods, and production cut-off periods generated from the Input variables given by Table 7. The production plateaus for 6 years after which Arp's decline curve comes into effect with changing rate of production until year 30. Coherent with the proposed table inputs, the production has a peak of 3.77 MMbbl for the P90, and has a maximum lifetime of 31 years where the full exhaustion of reserves is completed. On the other hand, the P10 shows the lowest possible plateau height and the shortest production period, ending at 25 years.

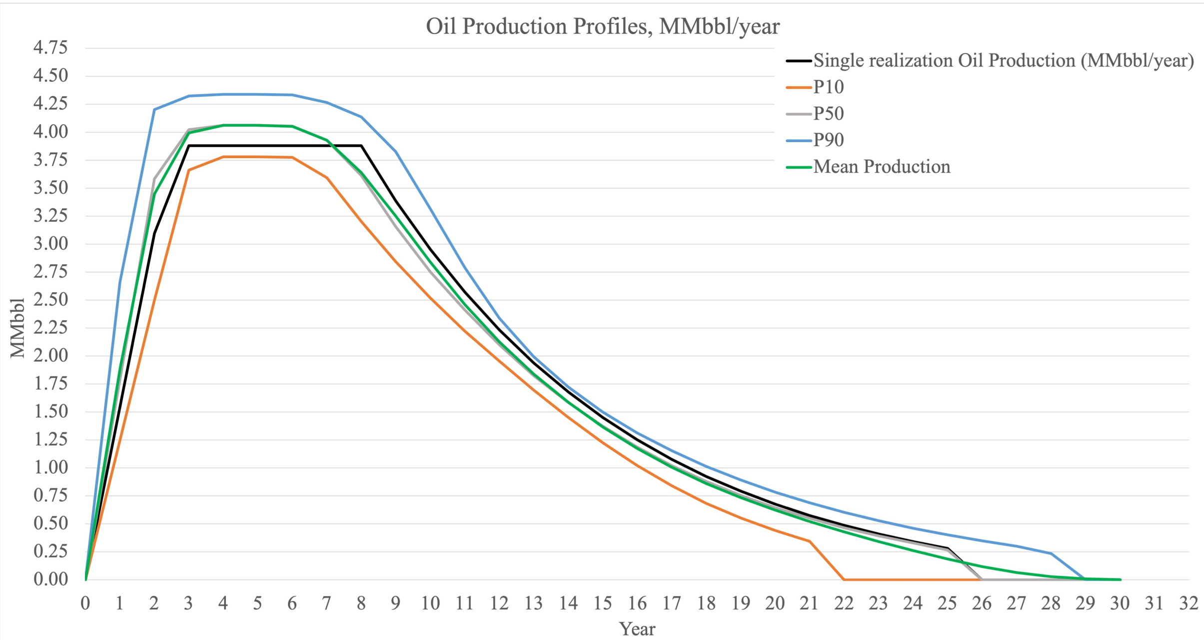


Figure 11: Production Profiles with percentiles, $MMbbl/year$

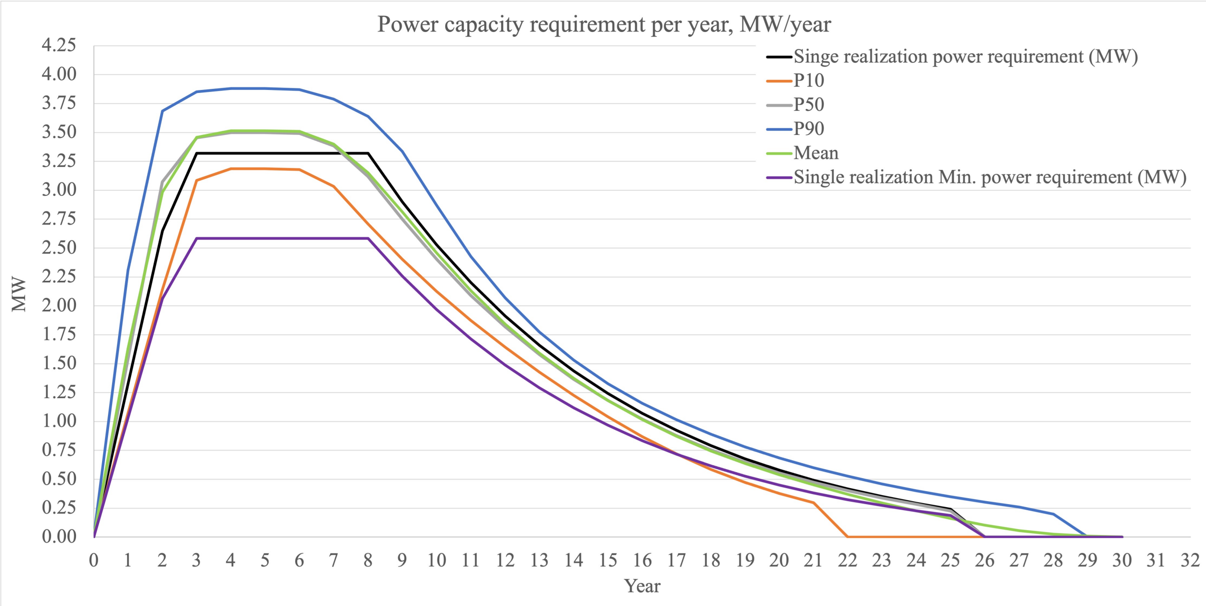


Figure 12: Power Production profile with percentiles, MWh

5.2 Price model profiles and results

In this Section the price models are presented to build on the final NPV and CO2 values for each alternative. All instances of price modelling, except the oil price model which is a revenue driver, represent a cost factor that will affect the NPV negatively and increase the CO2 emissions.

5.2.1 Hydrocarbon Price Model

The oil price projection seen in Figure 13, shows the general trend of decreasing. The projected blue line represents the live price used in the upcoming analysis. However, each year and each oil price point has its own distribution. Here the P10, P50 and P90 are the percentiles for the oil price. This indicates that while the oil price has an initial price of \$65 per barrel, it reverts back to its long term mean of \$55 per barrel, with fluctuations in and around the mean. Noticeable is that the P90 is skewed to \$100 per barrel as time progresses and the P10 floor being at \$25 per barrel, which is much closer to the mean and P50.

Unlike the oil price model in Figure 13, the gas price projection has an increase in its mean to revert back to \$0.22 per SCM. As seen in Figure 14, the P90 extends drastically to \$0.285, while the P10 has barely dropped below \$0.180. Here the difference in reversion speed becomes evident as for the oil pice model it is 2 years, while for the gas price it is taken as 8 years. Hence the slower rise towards its long term mean. We may also note that the volatility in price increases as time progresses. The single projection line in both, the oil price model and the gas price model have approximately an equal number of spot prices that fall above and below their respective mean curve. This indicates that

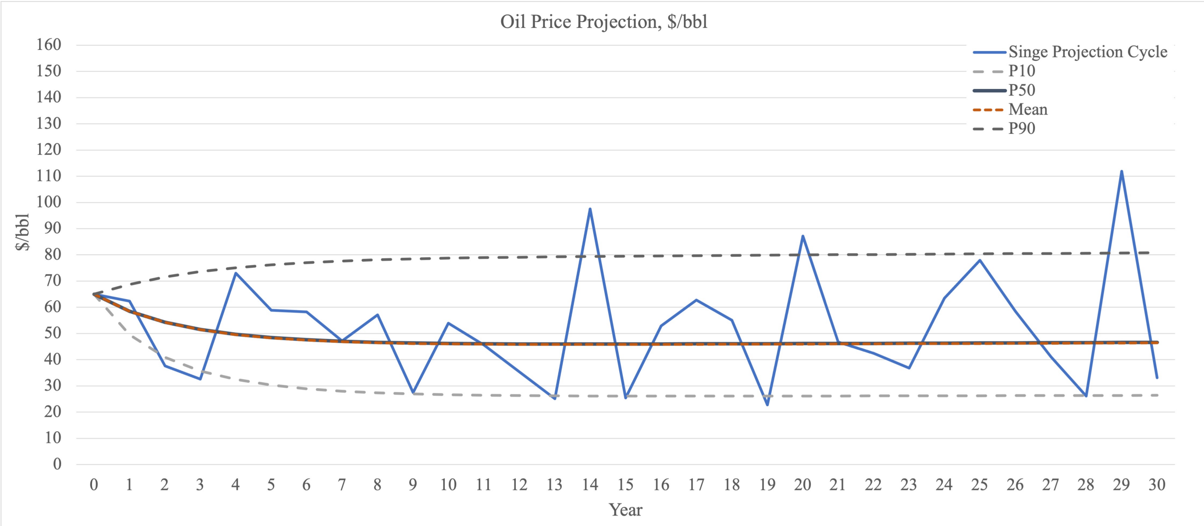


Figure 13: Mean Reversion of Oil Price, with percentiles

the mean reversion formula applied follows its predetermined characteristics and is fit for use in the model for gas fuel expenses.

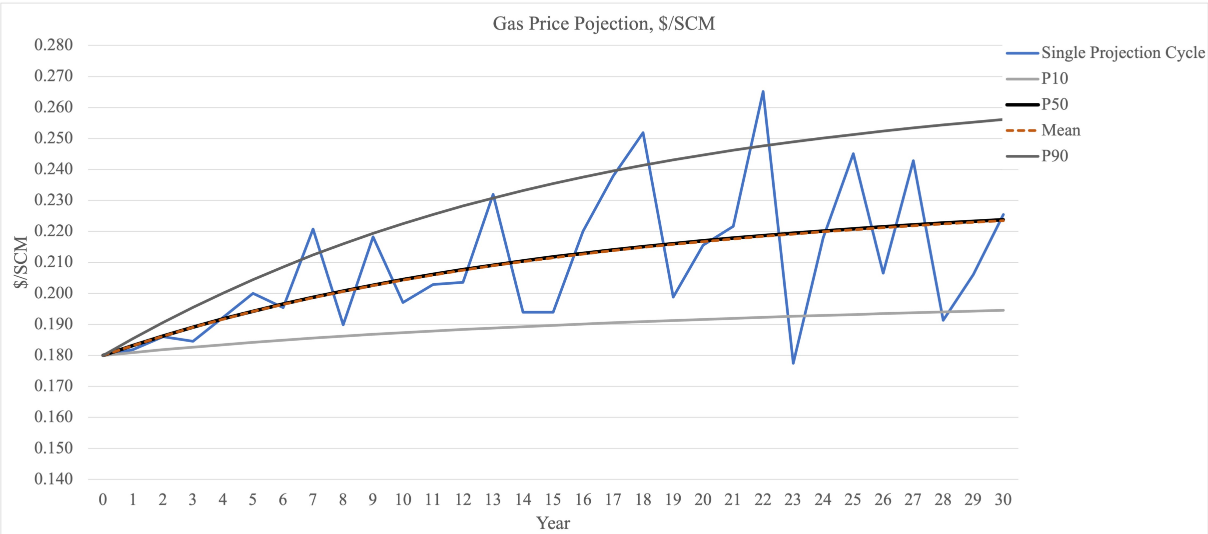


Figure 14: Mean Reversion of Gas Price, with percentiles

5.2.2 Electricity Price

The electricity price model generated bases on a collection of prices gathered from the different regions of Norway. Here the entire data set was taken as a sample and therefore are receiving a normal distribution as fluctuations along the years may be possible between the previous year sample values. As the analysis is contained within the Norwegian Continental Shelf and electricity generated limited to Norway these prices are given to act independently of the wider European electricity market. Figure reffig:ElectricityPDF represents the PDF and Figure 16 the CDF. The average is expected to be 42 $/MWh with a standard deviation of 14.86 $/MWh giving the PDF and CDF a very widespread.

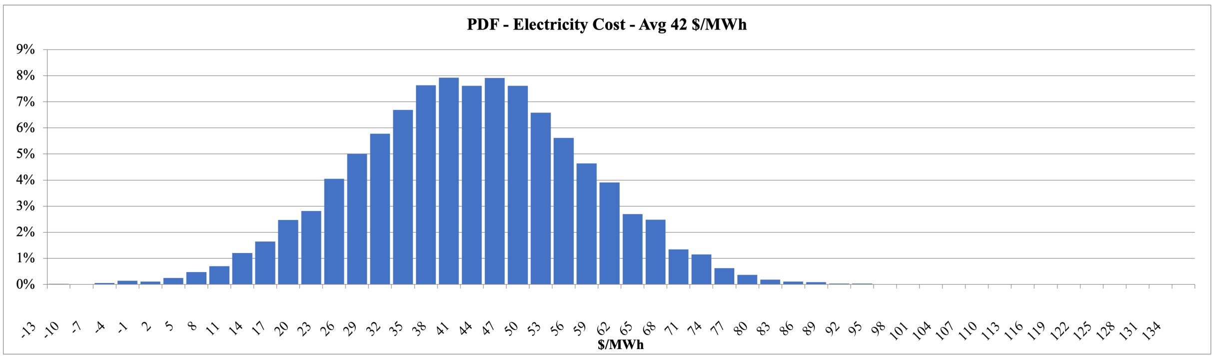


Figure 15: Electricity price random generation - PDF, $/MWh

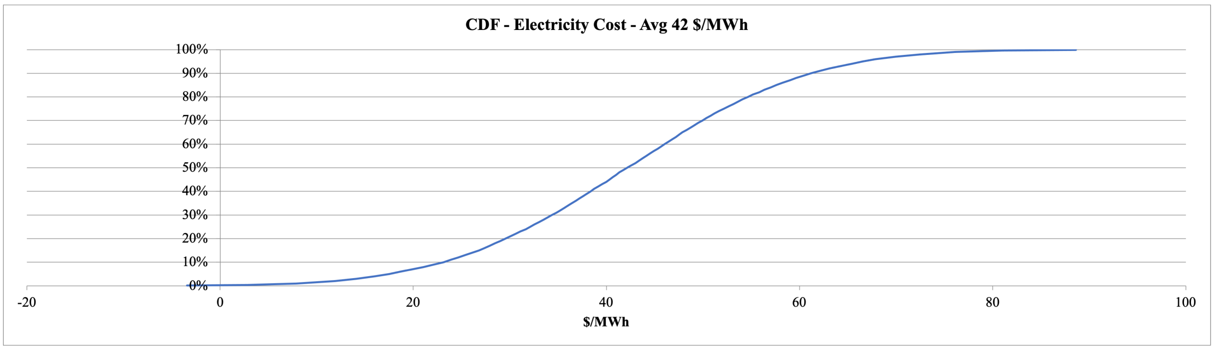


Figure 16: Electricity price random generation - CDF, $/MWh

5.2.3 CO2 Price Model

As seen in Figure 17 the rise in CO2 tax prices in the next ten years follows a steep linear pattern. Following year 10, the price's slope is determined via triangular distribution and then added to the previous years' price. It is important to note that the projected increase is not certain, yet is expected to increase as pressure for de-carbonization takes precedence. The first ten years are projected to make the sharpest impact on any future development project an Oil and Gas Company is planning for, from years 11-30, as seen in Figure 17 have different possible trajectories as seen between the P10 and P90 boundaries. The P50 and Mean trajectories indicate a lower price increase for the foreseeable future, compared to the initial 10 years.

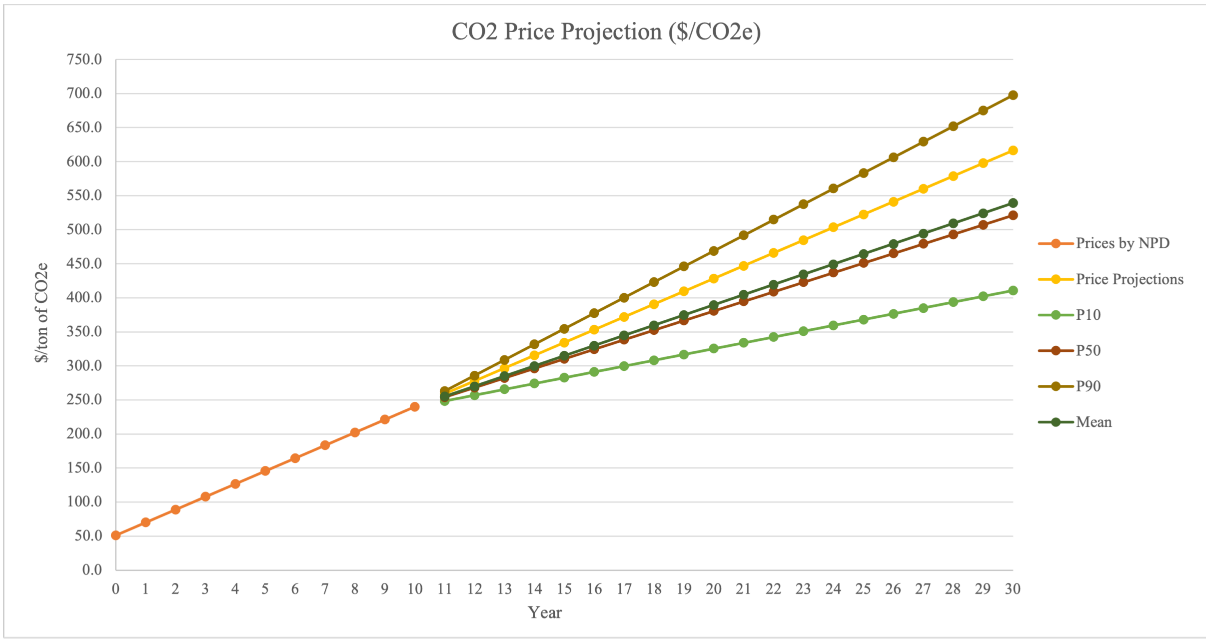


Figure 17: CO2 prices, NPD prices from years 0-10 by NPD, linear projection from years 11-30 with percentiles

5.3 Alternatives' Model NPV and Lifetime CO2e emissions results

After presenting the analysis for the pricing models, the individual NPV can be further assessed and reasoned with given the Data Selection inputs shown in Section 4. The primary objective is to observe the individual alternatives' Probability and Cumulative distributions NPV measures of analysis and expand on the findings. We determined the viability of each alternative considering the different CAPEX and OPEX burdens that have unique effects on the development and may influence the final decision. We commence with the base case model NPV, followed by the Wind Turbine integration analysis, new gas turbine integration, and finally, the power from shore analysis.

Base Model analysis

The base case analysis builds on the implication that the production follows the same Arp's decline curve and a set of rule of thumb determining OPEX and CAPEX values. As seen in Figure 18, the distribution takes a common bell curve, or normal distribution with an average NPV of 89.91 $MM. Visible in Figure 18and Table 18, the Base Case analysis indicates a large spread, with its 10th percentile being 30.44 $MM and the 90th percentile being 144.7 $MM. The lifecycle CO2 emissions from this analysis have an average of 0.296 million tonnes of CO2, the 10th percentile of 0.272 million tonnes, and the 90th percentile of 0.325 million tonnes. These values are visualized in the PDF in Figure 20 and CDF in Figure 21.

Table 18: Monte Carlo simulation results for Base Case Analysis

	P10	P50	P90	Mean
NPV, $MM	30.14	75.40	144.98	89.91
Lifecycle CO2 , million tonnes	0.272	0.295	0.325	0.297

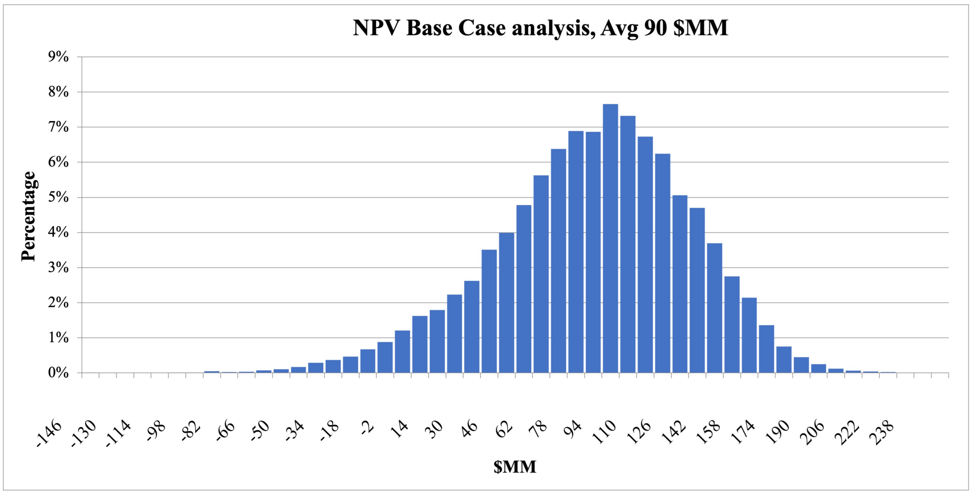


Figure 18: Base Case Analysis - PDF, $MM

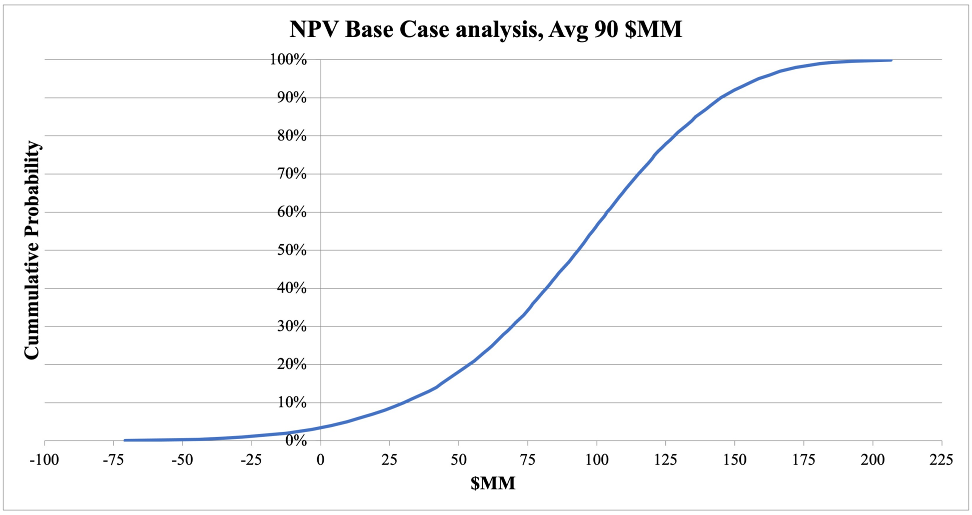


Figure 19: Base Case Analysis - CDF, $MM

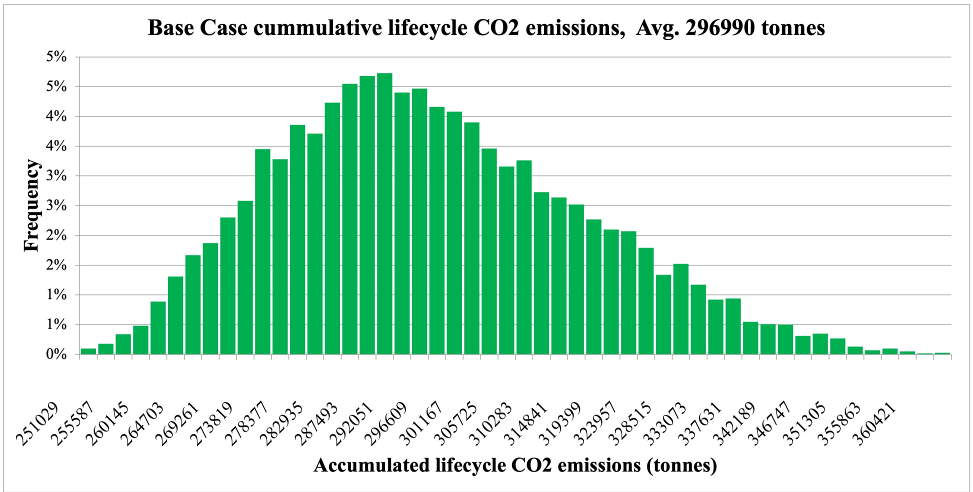


Figure 20: Cumulative lifecycle CO2 emissions of base case - PDF, tonnes

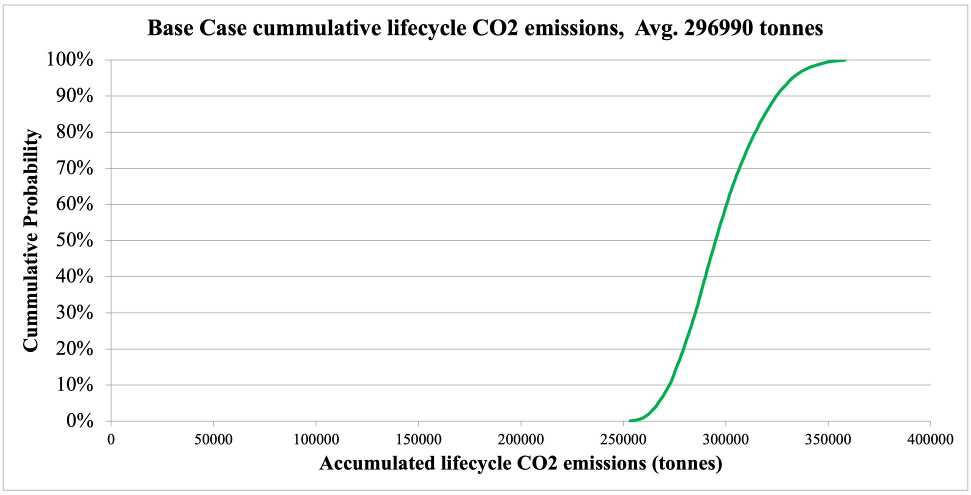


Figure 21: Cumulative lifecycle CO2 emissions of base case - CDF, tonnes

Wind turbine integration analysis

For the wind turbine integration analysis, the maximal coverage of the power capacity was covered accordingly with a single wind turbine, as the turbine is rated at 5 MW. However, due to the unpredictability of the weather conditions, a power input from the wind turbines was limited between 36% and 50% on a triangular distribution. Hence, the remaining power demand, which at a maximum consists of approximately 33901 MWh per year had to be covered by the conventional turbines applied through the base case analysis. What we therefore receive are PDFs and CDFs seen in Figures 22 and 23 with an observable normal distribution and a mean NPV of 139.52 $MM. The spread between the 10th and 90th percentile NPV, in this case, is smaller than that of the base case analysis. Likewise, a considerable reduction in CO2 emissions is visible in the PDF in Figure 24 and CDF in 25 where the percentiles are almost halved from the base case emissions.

Table 19: Monte Carlo analysis results for Wind Turbine Integration

	P10	P50	P90	Mean
NPV, $MM	96.85	139.66	179.35	138.52
Lifecycle CO2 , million tonnes	0.130	0.154	0.181	0.155

New Gas Turbine analysis

The inclusion of new efficient gas turbines also warrants a positive NPV seen by the PDF and CDF (Figures 26 and 27). The gas turbines are considered as an extra asset to the base case analysis, replacing the current turbines in the production platform. The analysis has various extra CAPEX and OPEX measures influencing the base case analysis. The CAPEX includes 1 turbine and 1 WHRU to cover the power capacity requirement and have higher efficiency. Here, the Average NPV resulted to be 101.39 $MM as presented

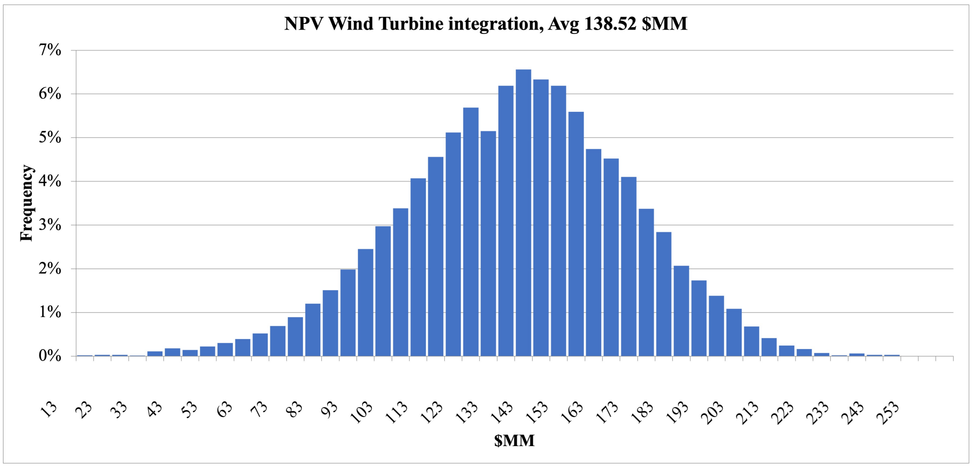


Figure 22: Wind Turbine Integration - PDF, $MM

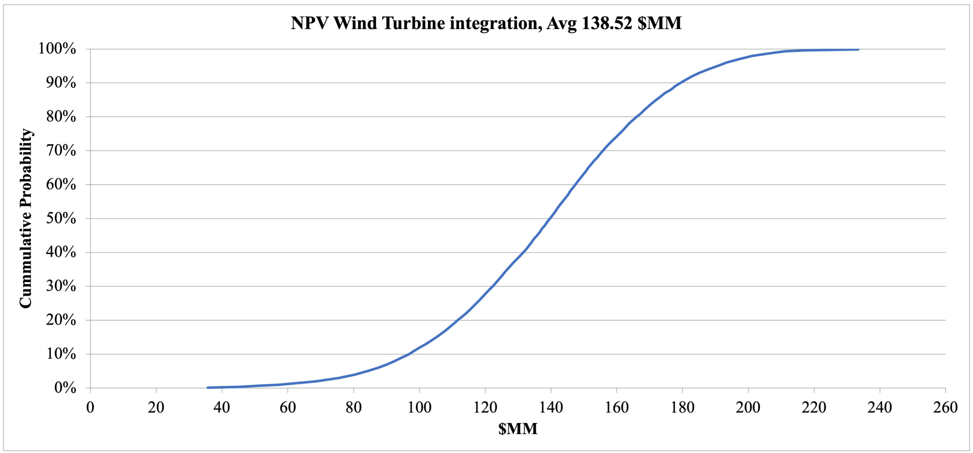


Figure 23: Wind Turbine Integration - CDF, $MM

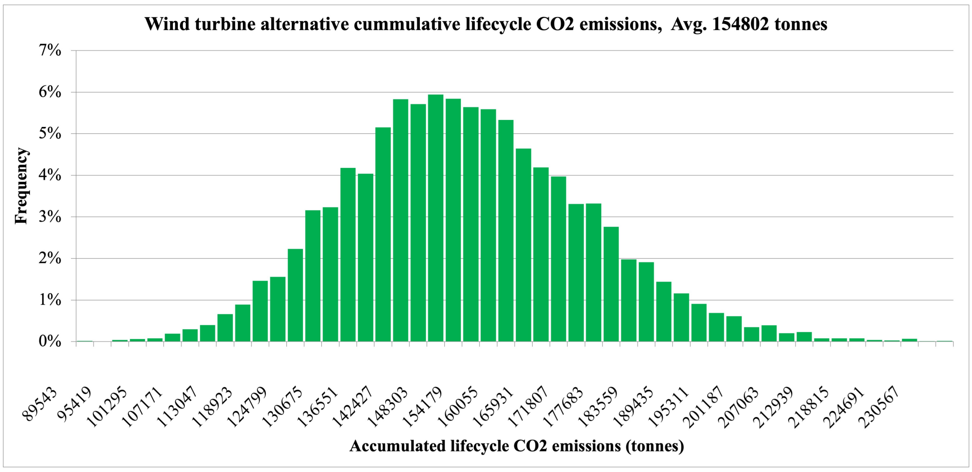


Figure 24: Cumulative lifecycle CO2 emissions of wind turbine inclusion - PDF, tonnes

in Table 20. The lower NPV may be due to the high CAPEX of gas turbine purchase as well as the maintenance expenditures. However, it fares better than the base case analysis due to its higher efficiency.

This higher efficiency is also reflected by the lifecycle emissions in Table 15, the PDF

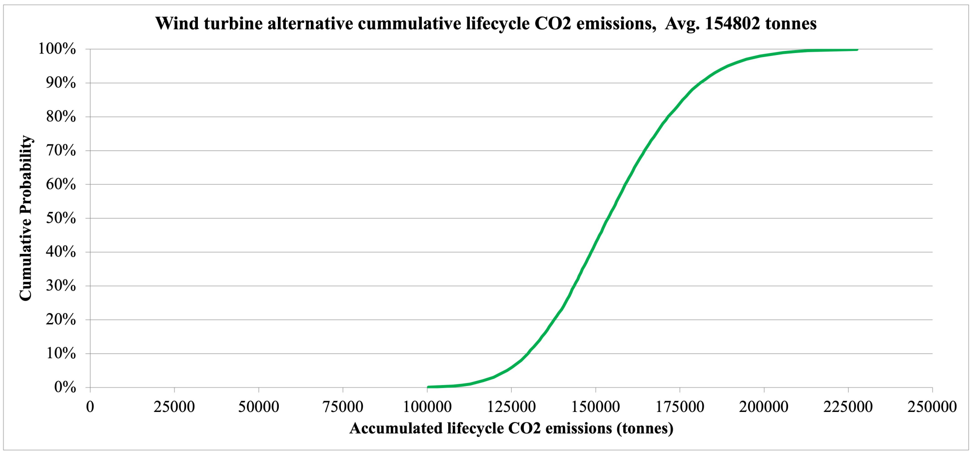


Figure 25: Cumulative lifecycle CO2 emissions of wind turbine inclusion - CDF, tonnes

Table 20: Monte Carlo Model results for New Gas Turbine Integration

	P10	P50	P90	Mean
NPV, $MM	55.88	103.26	144.74	101.39
Lifecycle CO2 , million tonnes	0.173	0.195	0.220	0.196

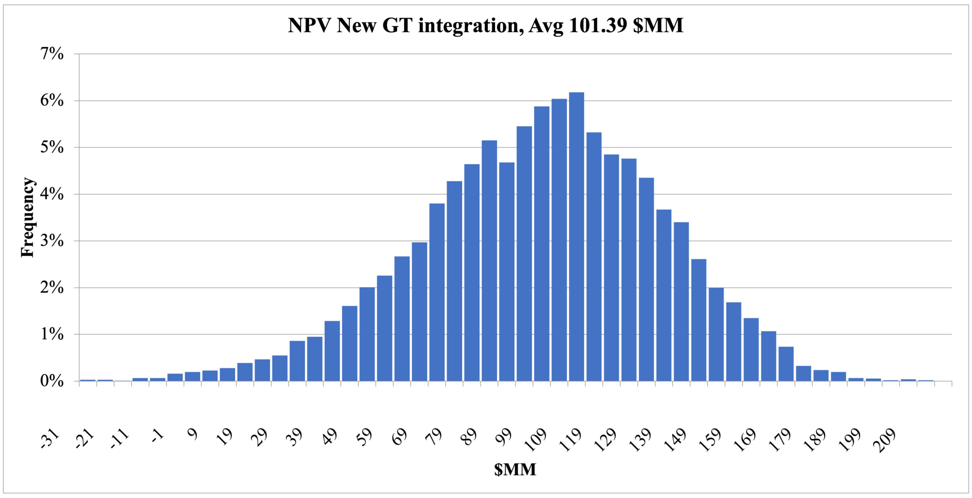


Figure 26: New Gas Turbines - PDF, $MM

in Figure 28 and CDF in Figure 29, with smaller average lifecycle emissions than that of the base case. The difference between the 10th and 90th percentile in lifecycle emissions is also less than that of the wind turbine alternative and the base case. Likewise, there is an overlap between the wind turbine alternative's 90th percentile emissions with the 10th percentile lifecycle emissions of new gas turbines.

Power from shore analysis

The power from shore analysis provides insight of a large spread and skew to the negative region. Visible in Figure 30, Figure 31 and Table 21, show an almost equal likelihood of

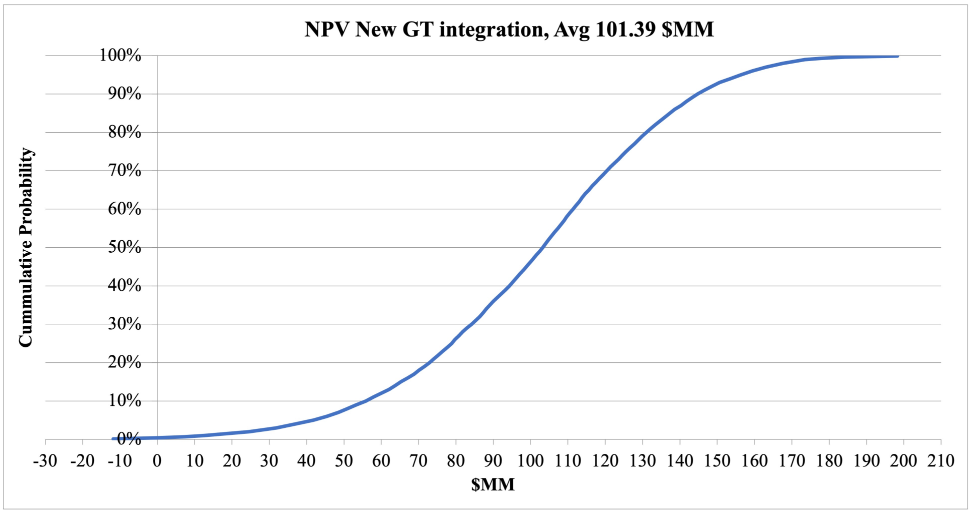


Figure 27: New Gas Turbines - CDF, $MM

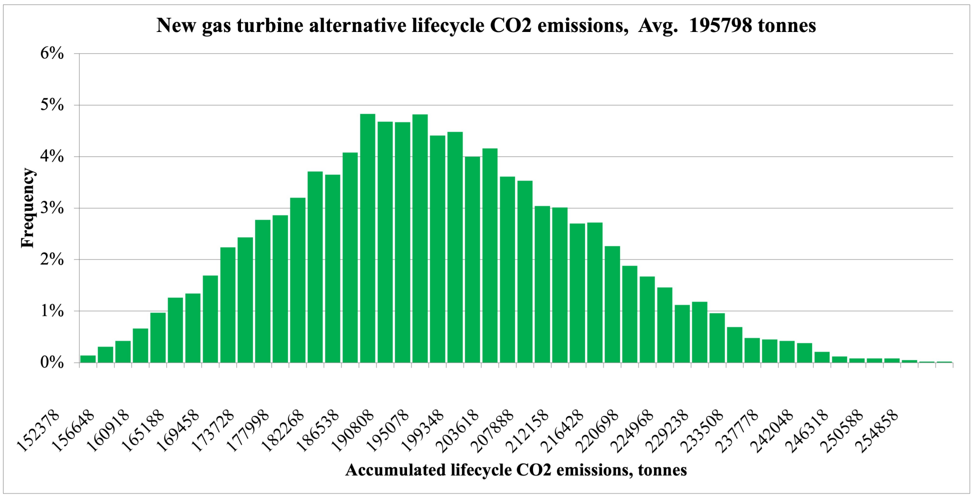


Figure 28: Cumulative lifecycle CO2 emissions of new gas turbines - PDF, tonnes

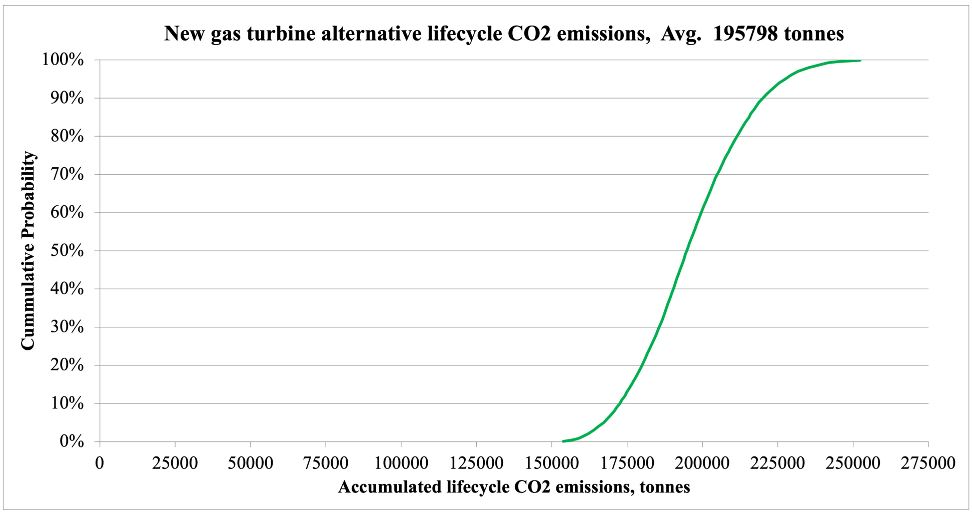


Figure 29: Cumulative lifecycle CO2 emissions of new gas turbines - CDF, tonnes

a negative and a positive NPV should this alternative be chosen. Given the nature of the power from shore system, primary HUB units and onshore connection facilities are a predetermined infrastructure CAPEX irrelevant of capacity requirement, while a primary dynamic adding to the negative spread is the distance from shore that requires a cable whose cost is determined through a probabilistic distribution. The average NPV is $-1.8 million, with P10s at $ 60.85 million, P50 at $0.15 million, and a P90 $55.41 million, which coincides with the spread of the PDF and CDF in Figures 30 and 31. It is important to note that the Norwegian Petroleum Directorate considers emissions to be nil, should an operator use a Power From Shore cable. However, to consider the electricity generation by the electricity provider from onshore gas turbines, their much higher efficiency results in minuscule lifecycle emissions compared to the other alternatives.

Table 21: Monte Carlo Analysis results for Power From Shore (electrification)

	P10	**P50**	**P90**	**Mean**
NPV, $MM	-60.88	0.12	55.39	-1.84
Lifecycle CO2 , million tonnes	0.010	0.057	0.131	0.065

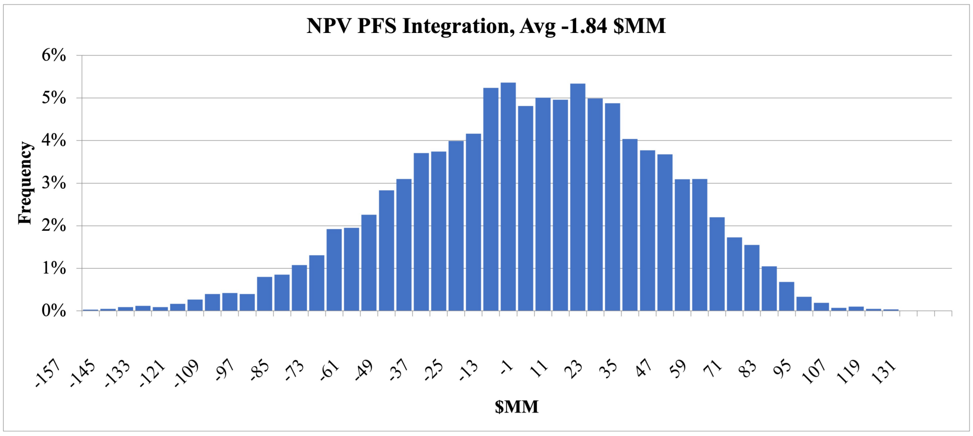


Figure 30: Power From Shore NPV - PDF, $MM

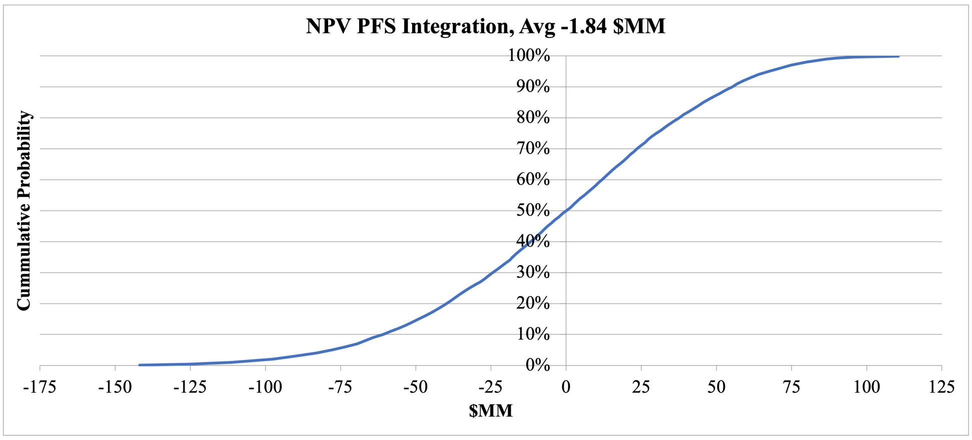


Figure 31: Power From Shore NPV - CDF, $MM

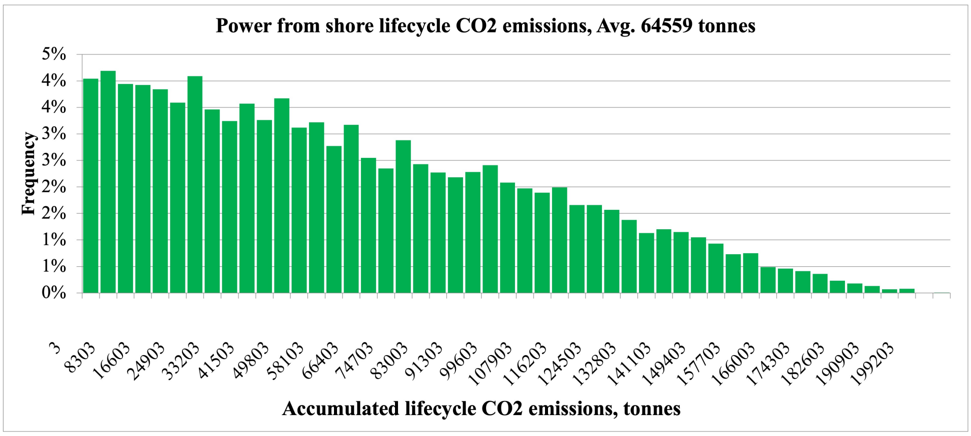


Figure 32: Cumulative lifecycle CO2 emissions of power from shore - PDF, tonnes

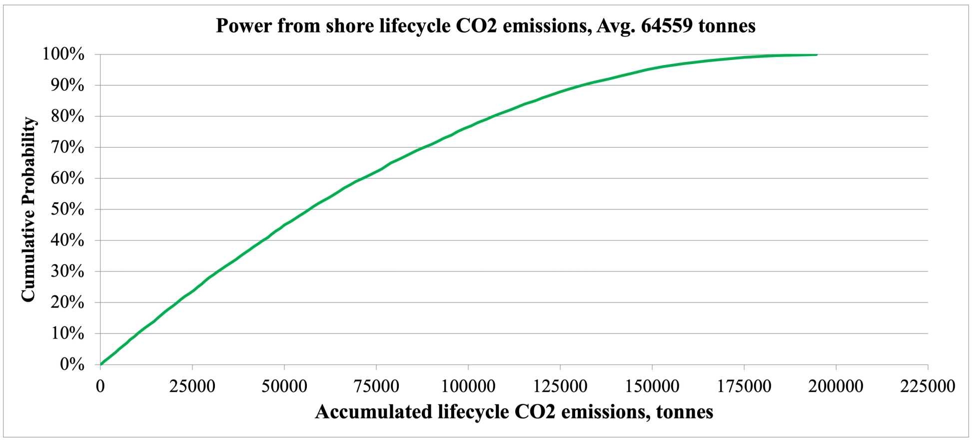


Figure 33: Cumulative lifecycle CO2 emissions of power from shore - CDF, tonnes

5.4 Decision evaluation, Trade-offs & Sensitivity Analysis

Once the NPV analysis and CO2 emissions have been assessed for each alternative, the final decision and model evaluation can be done, as visualized in Table 22, followed by a sensitivity analysis of primary factor changes as seen in Figures 37 and 38 below. The values used for this decision evaluation are the average NPVs and lifecycle CO2e emissions gained from the Monte Carlo Simulation's 10,000 trials. Additionally, the use of the common attribute scales defined in Figures 9 help set a common score to value conversion process, with a linearly increasing NPV attribute scale, and a linearly decreasing CO2e emissions attribute scale. The weights applied are defined by personal preference and reflect those set in the value hierarchy (Figure 8) in the Research Methodology chapter, with high importance of 90 for the NPV objective and 70 for the lifecycle CO2e emissions. The normalization of weights and use of attribute scales then allowed us to calculate a total score for each alternative between 0 to 100. The final scores are 80.71 for the wind turbine integration alternative, followed by the new efficient gas turbine alternative with a score of 64.64, coming in third is the base case analysis with a total score of 51.48 and finally the power from shore alternative with a total score of 38.10.

Table 22: Decision spreadsheet with final scores

Objectives	**Attribute Scale**	**Weight**	**Normalized Weight**	**Base Case Analysis**	**Wind Turbine Integration**	**New Gas Turbines**	**Power From Shore**
Maximize NPV, USD million				89.9	134.7	101.4	-1.8
Score (0-100)	0.6667	0.9		59.94	89.78	67.59	0.00
Normalized Weighted Score			0.5625	33.72	50.50	38.02	0.00
Minimize CO2e Emissions, Mtons				0.30	0.15	0.20	0.06
Score (0-100)	=-200*X+100'	0.7		40.60	69.04	60.84	87.09
Normalized Weighted Score			0.4375	17.76	30.20	26.62	38.10
Total		**1.6**	**1**	**51.48**	**80.71**	**64.64**	**38.10**

Noticeable in table 22, due to the negative average NPV of the Power from shore alternative, the attribute scale and normalized weighted value received a score of 0 as the attribute scales set in Figure 9 dictate. However, due to the extremely low CO2e life-cycle emissions of this alternative, with an average of 0.06 Mtons over the course of 30 years, it received the highest value in the emissions attribute scale and normalized total score of 87.06 and 38.10 respectively. The Base Case alternative coming second to last due to high CO2e life-cycle emissions and third-largest NPV. Alternatively, the normalized weight score for Wind Turbine Integration emissions has a great effect on the final score with the second-highest CO2e normalized weight score after the Power From Shore alternative. Within Figure 34 the cumulative emissions of single generated CO2e emissions is shown and give insight to the general relationship to the results in table 22 and Figure 35.

Figure 34 expresses the consistent linear rise during plateau region and a slowing of the slope of the emissions as the power usage drops with the base case analysis with the most inefficient turbine input, while it is evident that the bottom fixed turbines cover enough electricity for a halving of the CO2e emissions until it peaks in year 24. In this generation, the New Gas Turbine integration case has an efficiency of 0.461, which generates a total life-cycle emission of 0.174 million tons, which is lower than the average of 0.20 million tons, as seen in Table 22, and just higher than the 10th percentile.

In this case, the New Gas Turbine Case life-cycle emissions should be higher. Likewise, the power from shore generation is above the 90th percentile with a total of 0.185 million

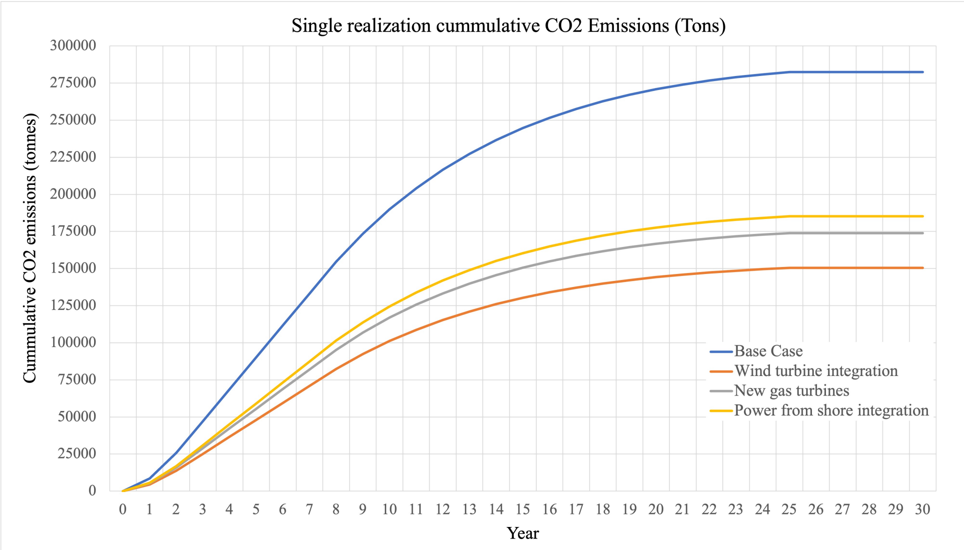


Figure 34: Single Generation Analysis of CO2 emissions over time, Million Tons

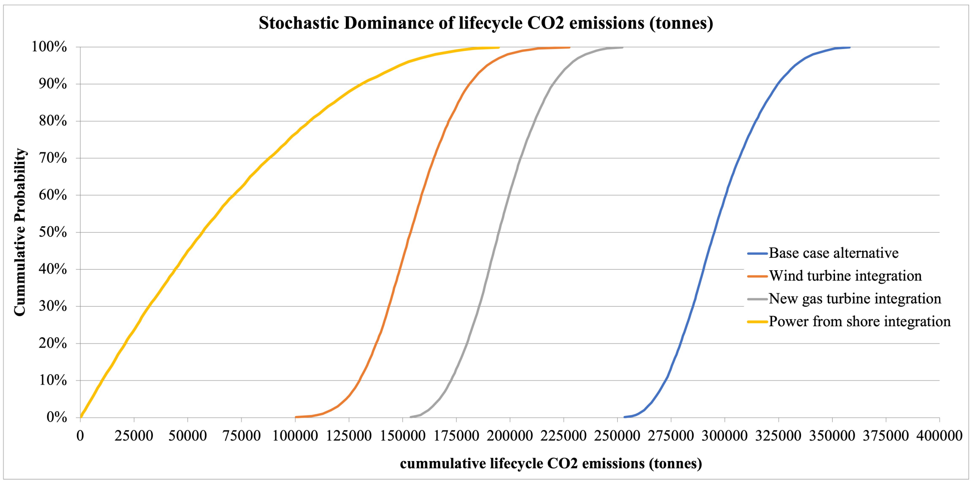


Figure 35: Cumulative Density Functions of Lifecycle CO2 emissions, Million Tons

tons. In Figure 35 clearly indicates a difference in the distribution of CO2 emission in Power From Shore with a large spread from 0 million tons to a P90 to 130821 Million tons and overlaps from the 70th percentile on-wards with the Wind Turbine integration. The wind turbine, gas turbine, and power from shore integration CDFs have a smaller spread than the power from shore CO2e emissions, wherein the 55th percentile wind turbine integration overlaps with the start of the gas turbine integration CDF. The base case analysis has a similar CDF spread as the New Gas Turbine alternative yet the 10th percentile is 272407 Million tons and a 90th percentile at 324594 Million tons.

5.4.1 Tradeoffs

When considering the tradeoffs of the different alternatives using the stochastic dominance technique may add some more insight about the different alternatives' NPV probabilities density functions. Within figure 36 the Power From Shore is dominated in comparison to

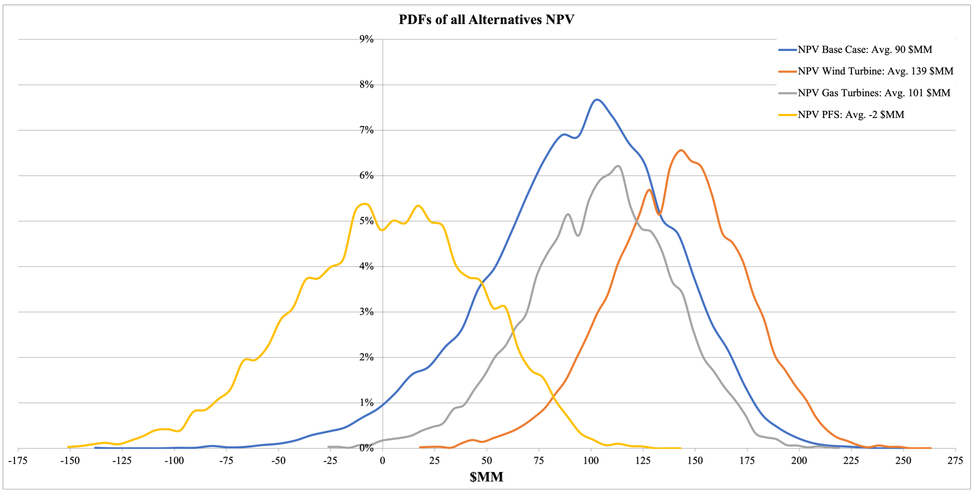


Figure 36: Stochastic Dominance of the Alternative's NPVs

all other alternatives. Furthermore, the Gas Turbine alternative displays more favourable results due to its lower likelihood of negative NPVs in comparison to the Base Case scenario. Likewise, the Wind Turbine PDF is an exemplary display of first-order stochastic dominance over the Gas Turbine PDF, with a better outlook on Average NPV and a higher likelihood of a positive NPV.

5.4.2 Sensitivity Analysis

The sensitivity analysis has two primary components, primarily the sensitivity analysis of the NPV with respect to changes in the initial reserves and the consecutive sensitivity analysis is with respect to the objective's normalized weights applied to each alternative. In Figure 37 the sensitivity analysis on reserves and its effect in the NPV has presented with a reserves change up to 500% which corresponds to 304.6 MMbbl and a 50% reserves reduction corresponding to 25.4 MMbbl. Visible in 37 at the 200% reserve increase, consisting of 153.3 MMbbl shows the instance where the NPV of Power From Shore integration at $432 million, surpasses the NPV at the Base Case Analysis of $409 million. Likewise, at a 400% reserves increase the Gas Turbine integration NPV consists of $916 million and the Wind Turbine NPV of $914 million with intersecting but extremely parallel trajectories.

It is evident that the Power From Shore has the highest increase in the NPV sensitivity Analysis. This garners the question at what Reserve level the NPV for the Power From Shore Alternative outperforms the other alternatives. Upon further extrapolation of the graph in Figure 37 it occurs at a 1200% reserves increase, corresponding to 659.9 MMbbl, with a NPV of $2497 million. However, the difference between the Power From Shore alternative and its runner-up, the New Gas Turbine integration, is $1 million. After having analysed the alternatives' NPV sensitivity to a change of the Reserves, another primary sensitivity analysis worth noting is with respect to the normalized weights applied

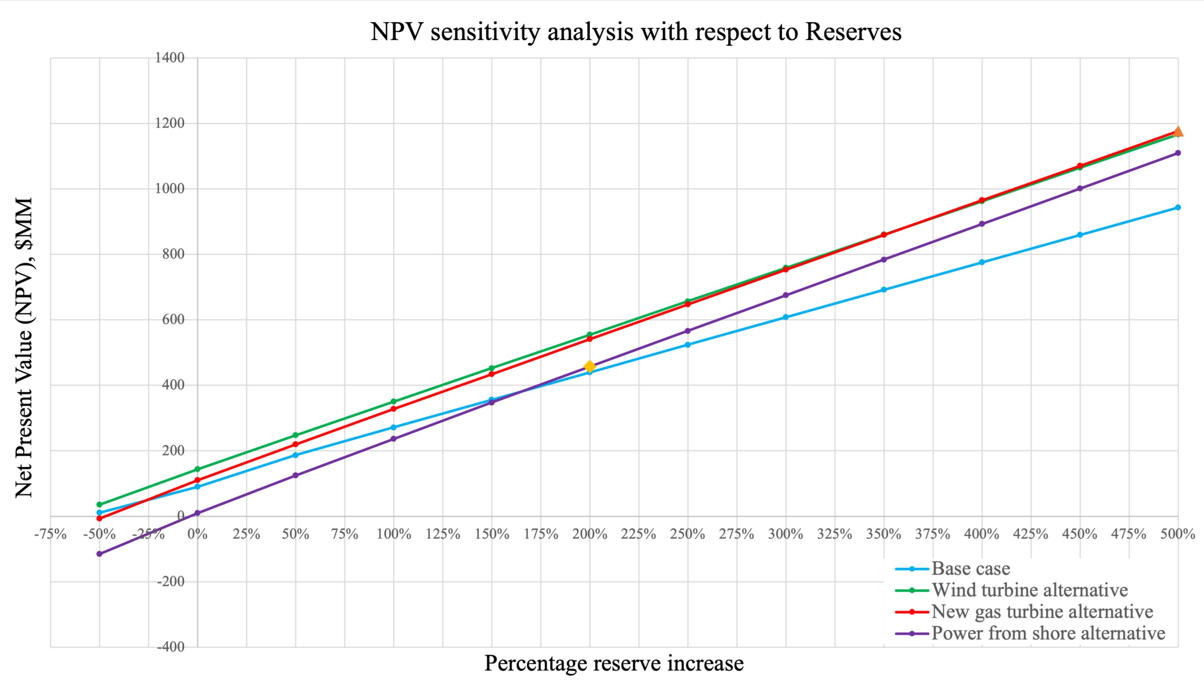


Figure 37: Sensitivity of NPV with respect to Reserves

within the analysis. Since the sum of the normalized weights are equal to one, and with two objectives present, the changing normalized weight on the x-axis in Figure 38 coincide with the Lifecycle CO2e emissions' normalized weight by taking the difference between the total and the implied NPV normalized weight.

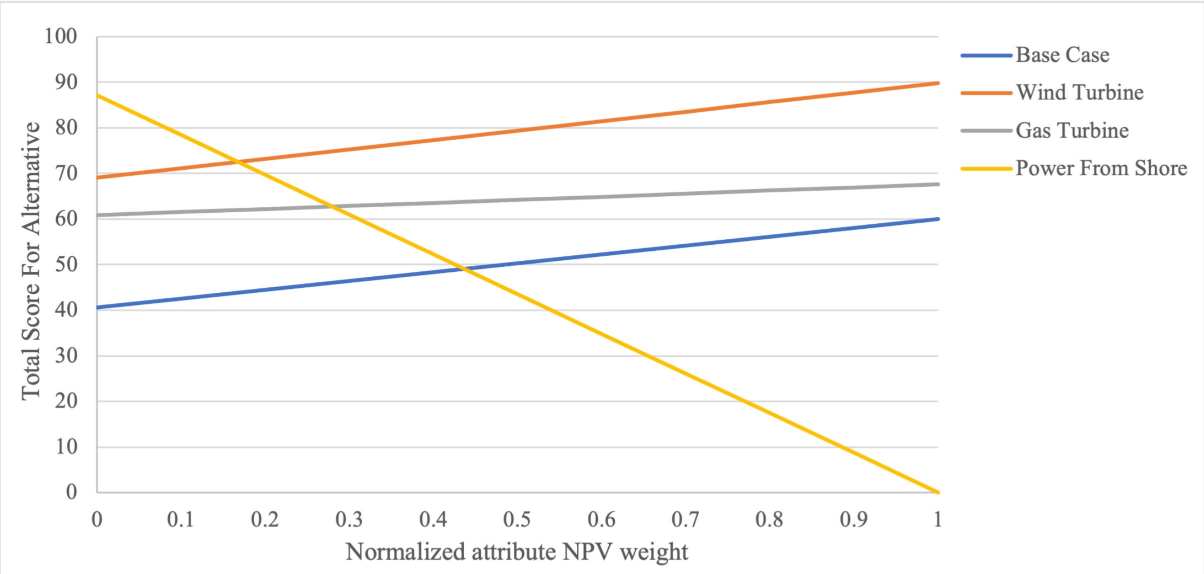


Figure 38: Normalized weight sensitivity analysis

With the presented results given in Table 22, the change in the NPV's normalized weight shows that as the normalized weight approaches 0, the Power From Shore total score intersects with the Base Case Analysis at approximately 0.44 (0.56 Lifecycle CO2e normalized weight). The second intersect occurs at 0.275 NPV normalized weight (0.725 Lifecycle CO2e weight), where the total score of the Gas Turbine Alternative is surpassed by the PFS alternative, given the CO2e emissions have a normalized weight that affects the total score, despite the PFS alternative having an Average negative NPV of -$1.8 million. Finally, the power from shore alternative is the best choice once the normalized NPV weight is set to 0.18, which corresponds to a normalized weight of 0.82 for the lifecycle CO2 emissions. It is important to note the little change the normalized weighting has on the Gas Turbine NPV, while the Wind Turbine objective does not favour a higher normalized weight for the lifecycle CO2e emissions, and gains 20 units across the unitary spectrum, moving in parallel with the Base Case analysis.

6 Discussion

After having conducted the analysis and decision evaluation, the results can be discussed to further deepen the understanding of these results. Taking the average values presented in Table 22, the clear indication for replacing offshore powering methods is the integration of offshore wind turbines given the very low power capacity required, at a mean of 3.5 MW and mean oil production plateau of 3.88 MMbbl from year 3 to year 8. This alternative presents an average NPV of $134.7 million and average lifecycle CO2e emissions of 0.15 million tonnes. If regulations are put in place that restricts the use of less efficient gas turbines such as in the base case analysis, lifecycle emissions will play a much larger role. Here, the decision maker's best choice would be the power from shore alternative, given that higher proven reserves are available that increases the confidence interval. As the Norwegian Petroleum Directorate considers the emissions from power from shore as 0, from the operator's perspective (Sagstad 2014), the platform operator may see this alternative as the safest choice. The emissions that are included in the power from shore alternative are allocated if the onshore power production is to commence from a fossil fuel power plant by the electricity supplier. Given Norway's high hydro power coverage of 90%, it carries a limited likelihood that emissions from power production will arrive from fossil fuels for this alternative (Energi Fakta Norge 2021).

The power requirement in this analysis derived from the Johan Sverdrup field's own power requirement per MMbbl. From this analysis it is important to point out the presence of complexities and nuances of financial Monte-Carlo assessments for offshore oil and gas operations with respect to the power/electricity requirement for production. The power capacity profile in Figure 12 succeeded to reflect the maximum power requirement from Statoil's Johan Sverdrup's electrification paper by Sagstad (2014), through its peak production while maintaining a 20% buffer. However, in comparison to the power profile of Johan Sverdrup seen in Figure 10, the decline phase in this analysis' power profile follows that of the oil production profile in Figure 11 and does not carry over the same pattern of a sustained higher power capacity of 100 MW to 50 MW as in Johan Sverdrups expected decline and maturity phases from 2034 to 2058. Nonetheless, due to different contexts and expected field conditions (primarily reserves) we have already tried to counteract this by increasing the 20% buffer to a maximum of 50%. However, the impact of a higher water cut in later life was not implemented, which by the Johan Sverdrup power solution paper is expected to be nearly double (95 MW) than its anticipated requirement of 50 MW (Sagstad 2014).

Both hydrocarbon price forecasts were conducted by mean reversion. With the price per barrel starting at 65 $/bbl, the mean reversion process took the price down to an average of 49 $/bbl. While the inputs were taken as approximations, the initial inputs gave such extreme fluctuations up to 185$/bbl that it did not reflect the underlying current price volatility, whereas the analysis seen in Figure 13 displays boundaries of 10th and 90th percentile of possible price movement between 28 \$/bbl and 80 \$/bbl, respectively. While predicting financial trends is impossible, these lower margins allowed for a more conservative analysis due to a cap on revenues per year. The gas price projection in Figure 14 also uses mean reversion, yet takes more time with a gradual increase to reach the long term mean to 0.22 \$/SCM. Unlike in Figure 13 the gas price model the 90th and 10th percentile increases gradually from 0.18 \$SCM to 0.257 \$/SCM and 0.18 \$/SCM to 0.185 \$/SCM, respectively. Similarly, the future of natural gas prices are unknown, yet as a conservative measure, a steady increase, to a sale price from Aker BP, proliferates a more viable option (Aker BP 2020*a*). The prices for electricity, unlike the oil and gas prices, are limited to the Norwegian market and the analysis input is determined through a normal distribution from a collection of electricity prices. A certain price model for electricity prices with a price increase would affect the analysis of the power from shore alternative positively. However, the context of these electricity prices bases on the independent nature of the Norwegian electrical grid unlike continental Europe and fluctuating historic prices between very similar prices, which warrants the use of a distribution price range with an average and standard deviation. The variance between the regional yearly prices shown in Table 10 ranges from 40.38 \$/MWh (2008) to 0.05 \$/MWh (2020), and 0.02 \$/MWh (2005), yet a coherent price movement pattern is not present. A +50% increase of the input variables of the electricity prices changes the power from shore alternative's mean NPV to -5.16 \$MM, whereas a 50% price decrease gives an NPV of 1.53 \$MM. The difference between price increase and decrease and the core analysis consists of -3.33 \$MM and +3.33 \$MM, respectively. Despite the mean NPV being affected by the electricity prices, the spread in NPV of percentiles visible in Figure 31, lie between -60.88 \$MM and 55.39 \$MM for the 10th and 90th percentile, respectively. The NPV percentile for the power from shore alternative that viably competes with the base case analysis is the NPVs 80th percentile with a of 37.7 \$MM and a final score of 52.23.

The CO2e emissions of each alternative carry a different value with the same means mainly due to power production not including flaring and tertiary emissions through a subsidiary. Important to note is that the base case analysis' CO2 emissions come from an inefficient gas turbine, with a combination of input values such as the Gas to CO2e emissions ratio coming from Mæland & Chokhawala (2010) and the initial CAPEX rule of thumb from Kjemperud (n.d.), on the predicament that the base case CAPEX includes the entire platform infrastructure. While the base case analysis carries the highest CO2e, the lifecycle emissions are halved on average by the Wind Turbine integration which is the viable option. However, the viability of this alternative carries conditional limits such as water depth, operational lifetime and weather conditions which influence NPV and lifecycle CO2e emissions when considering CAPEX and OPEX parameters in further detail. The sensitivity analysis on weights (Figure 38) that no matter the change in normalized weights, the newer gas turbine and base case scenario alternatives never become the best choice, hence eliminating them from contention.

7 Conclusion

After having reviewed many previous works that discuss different decision analysis techniques and varying implementations for CO2 emission-reducing technologies on offshore hydrocarbon production platforms, the objective of this thesis is to develop a decision analysis framework to allocate a financially viable and emission-reducing electricity production technology on offshore oil production assets.

To achieve an informative and high-quality decision analysis, previous works of relevance referring to sustainability, offshore production and decision analysis were discussed in the literature review. Hence, we concluded that the decision making process, that is consistent to a decision maker's preference, should include a multi-attribute decision analysis model, with its primary objectives of maximizing the NPV and minimizing life-cycle CO2 emissions of an offshore hydrocarbon production platform in the Norwegian continental shelf. The decision alternatives that have been evaluated are, the base case, the integration of wind turbines, integration of new gas turbines and the power supply from shore (electrification) connection.

The values/distributions of input variables of the models for assessing the uncertainties in NPVs and CO2 emissions of all these alternatives, including a probabilistic production profile, and electricity demand profile, are based on previous studies, reports and personal communications.

The uncertainties in NPVs and CO2 emissions have been assessed using Monte Carlo simulation. For the case with a reserve of 50.7 MMbbl (corresponding to the Fenja field), the best alternative is the offshore wind turbine integration, significantly reducing the burden of the already installed inefficient gas turbines with half the emissions of the base case. The wind turbine integration alternative leads to an average NPV of $134.7 million and an average life-cycle CO2 emissions of 0.15 million tonnes. Given the weights applied for NPV and life-cycle CO2 emissions are 0.9 and 0.7, respectively, its final score through the decision table is 80.71. In second place is the new gas turbine integration (with higher efficiency), yet it fails to outperform the wind turbine integration option, as its average NPV is $101.4 million and average life-cycle CO2 emissions are 0.20 million tonnes, giving it a final score of 64.64.

The sensitivity analysis in reserves (Figure 37) shows that at a 400% increase in reserves, the new gas turbine alternative's average NPV surpasses that of the wind turbine integration's average NPV. Likewise, the sensitivity analysis on the normalized weights applied on NPV and CO2 has shown that the power from shore alternative will become the best if the normalized weight for NPV is smaller than 0.18, confirming the significance of new electricity supplying technologies on offshore hydrocarbon production facilities. The sensitivity analysis with respect to reserves shows that, while the case study's reserves are rather small, the NPV is highly dependent on the type of electricity production method that is chosen. As the Norwegian government and O&G industry is putting more and more weight on environmental issues, an O&G company should optimize the means of offshore electricity supply based on the size of a field in order to mitigate its shareholders' concerns of environmental impacts and retain its reputation because a majority of CO2 emissions are released through the electricity production from offshore gas turbines.

In retrospect, future analysis of this topic may extend on details within the analysis parameters such as: a wider variety of quantitative and qualitative objectives, like safety and reliability parameters, to highlight out the ergonomic and operational effects of new technologies on current oil and gas production assets in the Norwegian Continental Shelf. While this thesis has addressed a broad set of solutions of economically viable and emission-reducing offshore electricity supplying alternatives, with the backing of internal company data, this type of research can contribute to an extension of knowledge and awareness of sustainability in the Oil and Gas Industry.

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