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Abstract

Portfolio optimization has been in existence for years owing to efforts made to comprehend which aspects of a business drive shareholder value and which may be eroding value. It has been consistently applied in the energy industry to maximize returns and manage risks. Amidst energy transition, changing market trends, value migration, and carbon emission reduction now determine which new assets should be added and which old assets should be shed. A typical energy investment portfolio now includes hydrocarbon assets, renewables, and CCS (Carbon Capture and Storage) assets. The portfolio optimization problem becomes very complex because the oil industry now needs to consider different types of projects and multiple objectives. These objectives may include net profit maximization, net emission reduction and improving green energy technologies. Given these goals and the high uncertainty inherent in the energy industry, a consistent portfolio selection process is needed to achieve these goals.

In this work, we developed, implemented, and demonstrated a decision analysis framework and workflow for optimizing the portfolio of investments in different energy and CCS projects, with the consideration of multiple objectives, based on the multi-attribute utility theory (MAUT). The utility function ranked the decision alternatives according to the decision-maker's preference for achieving each of the multiple objectives. The decision entails possible investment scenarios targeted toward energy transition at different paces.

The main contribution of this work is to apply a decision analysis framework to develop a flexible decision model for handling multiple objectives using multi-attribute utility theory in the decision model. The decision model can be used to generate insights for supporting high-quality decision-making by investigating the effect of changing targets, constraints, and weighting on the portfolio decision. Another key relevance of the optimization model to the energy industry is the ability to demonstrate how different corporate objectives impact a decision in their transition journey. The portfolio model was developed using python programming language because of its computational efficiency and computational complexity of portfolio optimization.

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1 Introduction

In an organization, the projects in view for execution must fulfill the core objectives. In the energy industry today, there are multiple objectives, ranging from increasing net present value (NPV), net-zero emission, and reducing project costs, to enhancing safety practices. Hence a rational decision must be made based on the decision maker's objectives. Today, the energy sector is responsible for one-quarter of carbon emissions (EPA 2022), and the need to mitigate the adverse effect of climate change makes energy transition inevitable. Today, the energy sector is saddled with the responsibility of averting the adverse effect of climate change; perhaps the greatest challenge mankind has faced.

Oil and gas companies are now considering investment diversification to include renewables and cleaner energy sources like wind, solar, blue hydrogen, and water as key to minimizing CO2 emission. They now make efforts to have a positive reputation by taking social responsibility to fund renewable energy and CCUS projects. The recent years have been challenging for the energy industry due to market disruption caused by the COVID-19 pandemic. The need to further strengthen the energy portfolio and develop risk-management capabilities cannot be overemphasized in the years ahead. As oil and gas companies embark on the energy transition journey, they are also concerned with the choice of petroleum assets to invest in, the technologies to adopt, and when to embark on the energy transition journey.

If building a winning portfolio from just two choices (oil and/or gas) was not easy, imagine the complexity when there are n number of resource options. While companies understand the imperative to change, the choice between staying and competing for the remaining value in hydrocarbons (the traditional choices) and embracing energy transition (the new choices) is not an easy one (Deloitte Insights, 2021). Over the years, mathematical frameworks have been developed to evaluate a portfolio of assets such that the expected return is maximized. The simplest method involves allocating resources to projects within capital constraints based on a defined objective. However, it remains the approach most frequently applied across the energy industry, particularly when imposing budget constraints (Wood, 2016). In 1952, Harry Markowitz introduced Modern portfolio theory (MPT), which earned a Noble Prize in Economic Sciences for being a notable discovery in the theory of financial economics. This method quantifies return and investment risk. However, given energy diversification and transition in the oil and gas industry, optimization problems must be approached differently. This thesis seeks to develop a flexible multi-objective optimization model by applying multi-attribute utility theory (Keeney and Raiffa, 1993). It solves portfolio optimization problems in the oil and gas industry that involve multiple objectives and multiple constraints based on hydrocarbon, renewables, and CCS assets.

1.1 Objectives

Most corporate decision-making is based on economic evaluation of projects considering the relevant and material uncertainties involved. The goal is not to reduce the uncertainties but to make good decisions despite the uncertainties. Howard defines a good decision as "an action we take that is logically consistent with our objectives, the alternatives we perceive, the information we have, and the preferences we feel."(Keeney and Raiffa, 1993).

Therefore, the objectives or questions that this research seeks to identify are:

1. Develop a decision analysis framework and implement portfolio optimization methods for optimizing the portfolio of investments in Hydrocarbon, Renewable, and CCS Assets.
2. Develop project models that are applicable to the portfolio evaluation of petroleum, renewables, and CCS assets.
3. Develop a flexible multi-objective optimization model (by applying multi-attribute utility theory) that can represent energy companies' objectives, preferences, and risk behavior as they gravitate toward greener solutions.
4. Demonstrate a robust scenario analysis for specified portfolio scenarios to significantly help energy firms make better decisions with respect to their targets and constraints.

1.2 Diversification

The popular saying "do not put all your eggs in one basket" is attributed to the concept of diversification. Portfolio diversification reduces the chance that all capital investments will encounter the same negative market forces at the same time because returns from different capital investments do not move in the same direction. An essential aspect of risk and risk measurement is portfolio diversification. Diversification is the concept that one can reduce total risk without sacrificing possible returns by investing in more than one asset. This is possible because not all risks affect all assets (Mitra, 2009). For instance, a fall in crude prices would affect returns from oil and gas assets but not necessarily the revenues from energy sales generated from wind farms.

Therefore, one of the key concepts of portfolio management is diversification across sources of returns and risks in a portfolio. A simple way to achieve diversification is to allocate capital equally across multiple investments. Recent studies claim this simple approach can be more effective in achieving an optimal portfolio than a variety of other diversification approaches (Kolm et al., 2014).

Besides its simplicity, an important "advantage" of the equally-weighted strategy is that it does not use return and risk models. Therefore, it is not subject to the estimation errors in such models (Kolm et al., 2014). Another approach to achieving diversification is selecting projects with low or negative correlations.

1.3 Formulation

This section explains the methodology founded on decision theory used to structure the optimization problem, objectives, decision variables, and the decision maker's preference for the objectives. For the scope of this thesis, Figure 1.1 illustrates an influence diagram is used to represent the interconnectivity amongst these decision elements and how they influence one another in making a decision.

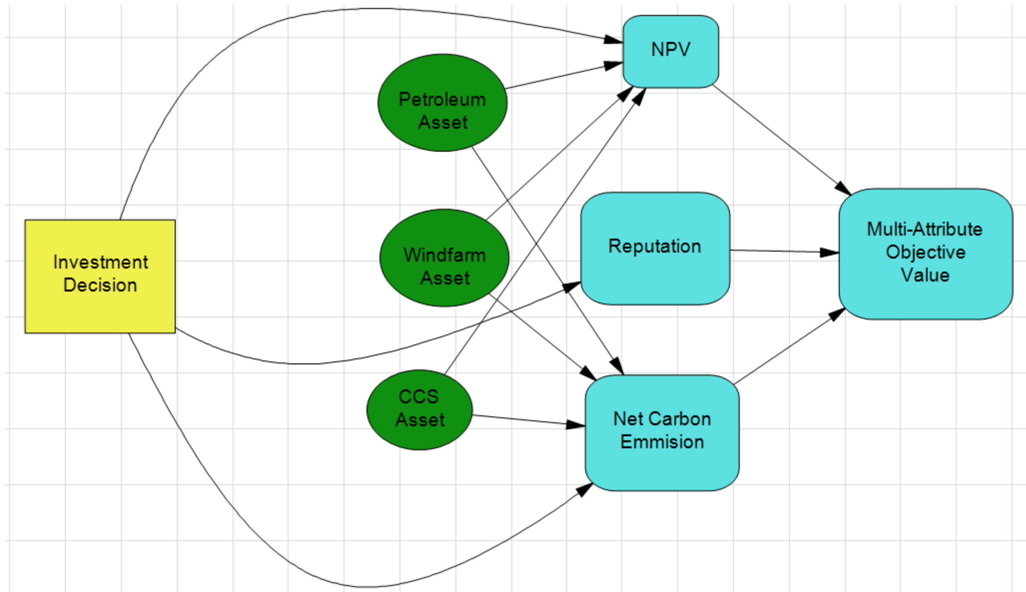


Figure 1.1: Influence Diagram of the Decision Model

Based on diversification of assets amidst energy transition, an energy firm with options to invest in a portfolio consisting of a single hydrocarbon, windfarm, and CCS project is considered. This is the scope of this thesis. The weights of investment for each of these assets in the portfolio are the decision variables. Although the decision variables are unknown information in an optimization problem, they have domains of possible values. For simplicity, these domains are considered as a percentage share of capital investment in the portfolio, and the alternatives are pre-defined based on this consideration.

An absolute prerequisite for rational decision-making is to identify and state clearly a set of objectives by which the worth of each alternative is judged (Bratvold & Begg, 2010). Three key objectives are considered based on the global energy sector's shift from fossil-based systems of energy production and consumption to greener solutions:

1. Maximizing economic worth, measured by the net present value (NPV).
2. Minimizing net carbon emission.
3. Improving the company's reputation by increasing investment share in renewable energy and low emission technologies.

2 Methods

In portfolio optimization of hydrocarbon, renewable energy, and carbon capture and storage assets, three major metrics are essential. They are maximizing NPV, minimizing carbon emission, and improving green reputation. Depending on the assets involved, decision models will be implemented to achieve either single objective optimization or multi-objective optimization in complex scenarios where more than one objective needs to be optimized.

2.1 Rank and Cut Method

The rank and cut method is the simplest optimization method and is extensively applied across the oil & gas industry because of its simplicity in generating good portfolios when faced with budget limitations. It optimizes a single objective using a single portfolio constraint. A common example is optimizing expected NPV given budget limitations. Some organizations have budget limitations and are unable to invest in all viable (positive expected NPV) projects; therefore, a capital allocation method is required to impose budget (i.e. capital investment) constraints while optimizing the objective function. However, this approach can also be applied to other single objectives and constraints depending on the decision maker's choice.

Wood (2016) developed a portfolio optimization algorithm. The algorithm contains four steps:

a) establish the performance metric to be used to rank the asset, typically the objective function that the decision-makers plan to optimize (e.g. maximize NPV, minimize capital expenditure, etc.);

b) rank the assets, and order the assets according to their respective contributions to the selected performance objective;

c) Select the constraint performance metric,

d) Identify and accumulate the assets; begin with the asset ranked #1 and add assets in order (i.e., rank #2, rank #3 etc.) until the constraint limit is reached;

e) As the projects are funded to the constraint limit, only a fraction of one of the lower rank assets can be added without exceeding the performance constraint limit, and all assets ranked below that asset fraction are removed from the portfolio.

This approach is applied to the project pool illustrated in Table 2.1, involving 12 assets available for selection, with the results optimizing the portfolios. The notation 'E' means expected value. For instance, E[NPV] means the expected NPV.

Table 2.1: Project Pool

Project	**E[NPV] US$ (million)**	**E[CapEx] US$ (million)**	**CapEx (R&C) US$ (million)**	**E[CO2)emissions] t CO2(million)**
1	826	540	150	0.40
2	505	842	613	0.27
3	1400	900	268	2.54
4	930	387	12	5.12
5	2314	1760	1507	0.21
6	243	152	56	0.54
7	936	422	217	1.88
8	1730	1555	253	0.92
9	396	214	79	3.57
10	1378	897	780	4.95
11	573	680	401	0.34
12	2470	985	184	1.93

Table 2.2: Ranking based on maximizing expected Profitability Index

Project	E[NPV] US$ (million)	E[CapEx] US$ (million)	CapEx (R&C) US$ (million)	E[CO2 emissions] t CO2(million)	Profitability Index E[NPV]/CapEx	Weight %
12	2470	985	184	4.95	2.51	100.00
4	930	387	12	5.12	2.40	100.00
7	936	422	217	1.88	2.22	100.00
9	396	214	79	3.57	1.85	100.00
6	243	152	56	0.54	1.60	100.00
3	1400	900	268	2.54	1.56	100.00
10	1378	897	780	1.93	1.54	49.05
1	826	540	150	0.40	1.53	0.00
5	2314	1760	1507	0.21	1.31	0.00
8	1730	1555	253	0.92	1.11	0.00
11	573	680	401	0.34	0.84	0.00
2	505	842	613	0.27	0.60	0.00

In Table 2.2, the projects are ranked based on the profitability index (PI). The total Capex constraint (maximum expenditure limits) applied is $3500 million, and the projects are funded to this constraint limit. Accumulated total capex of top ranked six projects is $3060 million. The remaining $440 million is allocated to project #10 while the remaining assets are removed from the portfolio since the ranking of the assets determines in which order the assets are excluded from the selected portfolio.

Table 2.3: Ranking based on minimizing Co2 Emissions

Project	**E[NPV] US$ (million)**	**E[CapEx] US$ (million)**	**CapEx (R&C) US$ (million)**	**E[CO2 emissions] t CO2(million)**	**Weight %**
5	2314	1760	1507	0.21	100.00
2	505	842	613	0.27	100.00
11	573	680	401	0.34	100.00
1	826	540	150	0.40	100.00
6	243	152	56	0.54	100.00
8	1730	1555	253	0.92	26.09
7	936	422	217	1.88	0.00
12	2470	985	184	1.93	0.00
3	1400	900	268	2.54	0.00
9	396	214	79	3.50	0.00
10	1378	897	780	4.90	0.00
4	930	387	12	5.10	0.00

Minimizing Carbon emission is selected as the objective function in Table 2.3, and ranking is done based on the expected emission from the respective projects ranging from the lowest to the highest. In this case, the total emission constraint (maximum emission limit) applied is $2 million, and top-ranked five projects are completely funded, while 26.09% share was allocated to project #8, being the next ranked.

Accumulated total Capex of top-ranked five projects is $3060 million. The remaining $440 million is allocated to project #10 while the remaining assets are removed from the portfolio since the ranking of the assets determines in which order the assets are excluded from the selected portfolio.

Table 2.4: Ranking based on maximizing Green Reputation Index

Project	**E[NPV] US$ (million)**	**E[CapEx] US$ (million)**	**CapEx (R&C) US$ (million)**	**E[CO2 emissions] t CO2(million)**	**Green Reputation Index CapEx (R&C)/E[CapEx]**	**Weight %**
10	1378	897	780	1.54	0.87	100.00
5	2314	1760	1507	1.31	0.86	100.00
2	505	842	613	0.60	0.73	100.00
11	573	680	401	0.84	0.59	0.00
7	936	422	217	2.22	0.51	0.00
9	396	214	79	1.85	0.37	0.00
6	243	152	56	1.60	0.37	0.00
3	1400	900	268	1.56	0.30	0.00
1	826	540	150	1.53	0.28	0.00
12	2470	985	184	2.51	0.19	0.00
8	1730	1555	253	1.11	0.16	0.00
4	930	387	12	2.40	0.03	0.00

Amidst energy transition, one of the key objectives of the E & P industry is to have a good renewable reputation as the industry aims to achieve net-zero emission by 2050. Hence, Green Reputation Index (GRI) is considered the objective function for Table 2.4. Green Reputation Index for a project is the ratio of renewable-allocated Capex to the total Capex of the project. Based on ranking by GRI, three projects with the highest GRI are fully funded using a maximum capex limit of $3500 million, and the remaining $218 million is allocated to project #7.

The project selection varies with respect to the objective function as expected:

PI maximization: Projects #12 ,4, 7, 9, 6, 3

Carbon emission minimization: Projects # 5, 2, 11, 1, 6, 8

Renewable Reputation Index: Projects #10, 5, 2

As the objective function changes from PI maximization to emission minimization, the project selection also changes, with only Project #6 being retained in the portfolio. Project #10 is only selected when ranking is done based on the renewable reputation index. Although the rank and cut optimization method is widely applied in the O & G industry, the inability to optimize a portfolio when multiple objective functions and constraints are considered is a major drawback. It also ignores project uncertainty (Erdogan et al., 2001). Nonetheless, this method serves as a starting point for more robust optimizers.

2.2 Mean-Variance Approach

In 1952, Markowitz (1952) derived a quantitative model called the Mean-Variance Approach which is based on Markowitz's Portfolio Theory or Modern Portfolio Theory (MPT) (Markowitz, 1952). It aims to help investors create optimal portfolios that best meet the investor's goals and risk/return combination. In the model, the expected return is given by the average of the historical data of the stock's return, and the risk is calculated using the variance of these returns. Although MPT was formulated based on stock market investment decisions, the theory can be applied to portfolio optimization of petroleum investments. The main idea of the mean-variance model is to deal with the returns of individual assets as random variables and adopt the expected return and variance value to quantify the return and investment risk (Milhomem and Dantas, 2020). MPT allows for the evaluation of expected return and how much of it can be sacrificed in return for a reduced risk or how much risk can be taken with respect to an increase in expected return. Markowitz divides the portfolio selection process into two stages. The first stage involves the evaluation of available projects, while the second stage pertains to the construction of efficient and optimal portfolios from the selection of these projects (Hightower and David, 1991). The mean-variance method accommodates correlations between assets. As the correlation decreases, risk reduction can be improved by spreading investments around so that exposure to any type of asset is limited. However, Markowitz's model is questioned for its use of variance as a risk measure. Variance calculates both fluctuations above and below the expected value in the same way. However, in reality, only returns below the mean are undesirable and consistent with the notion of risk (Babaei et al., 2015).

Given a set of n assets and a time period J, the mean μ and the variance σ^2 can be calculated from the historical data of the stock price using the following relations:

For each asset

$$\mu_1 = \frac{1}{J}\sum_{j=1}^{j} R_{1j}, \qquad \mu_2 = \frac{1}{J}\sum_{j=1}^{j} R_{2j}, \ldots\ \mu_n = \frac{1}{J}\sum_{j=1}^{j} R_{nj} \tag{2.1}$$

$$\sigma_1^2 = \frac{1}{J}\sum_{j=1}^{j} (R_{1j} - \mu_1)^2, \qquad \sigma_2^2 = \frac{1}{J}\sum_{j=1}^{j} (R_{2j} - \mu_2)^2, \ldots\ \sigma_n^2 = \frac{1}{J}\sum_{j=1}^{j} (R_{nj} - \mu_n)^2 \tag{2.2}$$

where: *j* is the time along the period *J*; *j*=1….., *J*

i is the asset number; *i* = 1………, *n*

R_{ij} is the return value of asset *i* at time *j*

For the portfolio, the expected return $E[P]$, and the variance $Var[P]$, can be expressed as:

$$E[P] = \sum_{i=1}^{n} (y_i . R_i) \tag{2.3}$$

$$Var[P] = \sum_{i=1}^{n} (y_i . \sigma_1^2) + 2 \sum_{i=1,k=1}^{n} (y_i y_k . cov(R_i, R_k)) \tag{2.4}$$

$$cov(R_i, R_k) = E[(R_i - \mu_i)(R_k - \mu_k)] \tag{2.5}$$

Where y_i: corresponding portfolio weight of asset i

$cov(R_i, R_k)$: covariance of returns R_i and R_k

Expressing the expected return μ and portfolio weight y of n assets as vectors, and portfolio variance as matrix Σ:

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \vdots \\ \mu_n \end{pmatrix}, \quad y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} & \cdots & \sigma_{2n} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} & \cdots & \sigma_{3n} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} & \cdots & \sigma_{4n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{3n} & \sigma_{4n} & \cdots & \sigma_{nn} \end{pmatrix} \tag{2.6}$$

Portfolio expected return $E[P]$ can be written as

$$E[P] = y^T \mu \tag{2.7}$$

Portfolio variance $E[P]$can be written as

$$Var[P] = y^T \Sigma y \tag{2.8}$$

However, the portfolio optimization problem can also be reformulated in two ways(Zhou and Palomar, 2021).

1) Maximization of mean return

$$\max_y y^T \mu \tag{2.9}$$

Subject to:

$$y^T \Sigma y \geq \alpha$$
$$1^T w = 1 .$$

2) Minimization of risk

$$\min_y y^T \Sigma y \tag{2.10}$$

Subject to:

$$y^T\mu \geq \beta$$

$$1^T\mathrm{y} = 1.$$

Where α and β are user-chosen positive constants.

Furthermore, as a trade-off between expected return and risk of the portfolio, a risk aversion parameter λ which is a measure of how risk-averse the decision-maker is, is considered:

$$\min_{y} y^T\Sigma\mathrm{y} - \lambda y^T\mu \qquad (2.11)$$

$$for\ \lambda \in [0, \infty]$$

They all require choosing one parameter (α, β, or λ).

Possible portfolios given assets available can be constructed by plotting expected return (y-axis) against variance(y-axis) to identify an efficient frontier that maximizes return while minimizing variance. The efficient frontier concept ensures minimum risk is carried for a given return or maximum return is achieved for a given level of risk. Figure 2.1 shows all possible portfolios, and the curve BC represents the efficient portfolio. All other portfolios below the curve do not maximize return given their risk or minimize risk given their return. In conclusion, the concept of efficient frontier helps a decision maker select a portfolio consistent with his risk tolerance while investing in available assets.

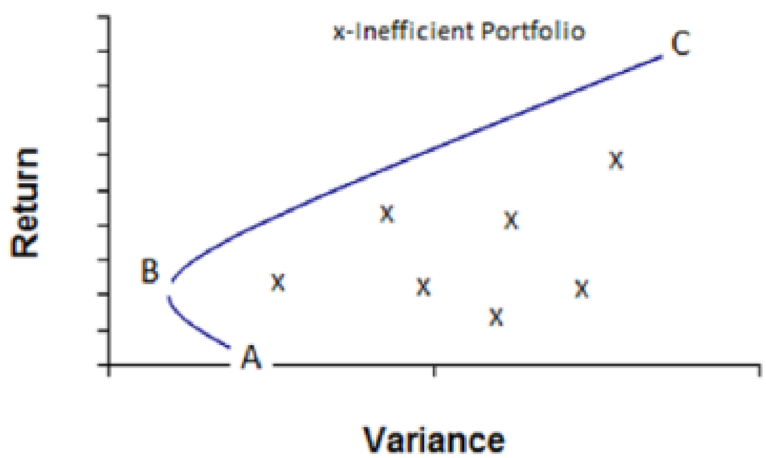


Figure 2.1: Efficient Frontier (adapted from Grasse et al. (2016))

2.3 Multi-Objective Optimization Approach

In the oil & gas industry, most portfolio optimization problems always involve multiple objectives and constraints. However, because the multiple objectives of projects often conflict with one another, single-objective optimizations do not offer practical solutions, as optimizing one objective would often adversely affect other objectives that are not being optimized. Many multi-objective optimization approaches that can help manage projects and achieve the required objectives have been developed, each of which has its own advantages and disadvantages depending on the project structure and the sets of objectives involved.

Golkarnarenji et al. (2019) proposed that two approaches are involved in describing the nature of multi-objective optimization problems. Firstly, all the objectives are aggregated into one function, or all but one objective is moved into the sets of constraints. Methods like the weighted sum technique and multiattribute utility theory are used to deal with the first approach. The problem with this approach is that it is not easy to assign weights and utility functions to multiple objectives. In the second approach, a group of Pareto-optimal solutions (optimal solutions) instead of one best solution is adopted so that the final decision can be made by the decision-maker. Pareto-optimal solution reflects the robustness of the multi-objective method in ensuring multiple objectives are optimized.

2.3.1 Time Series Goal Seeking Approach

Howell and Tyler (2001) proposed the multi-objective portfolio optimization method and used a goal-seeking approach to manage the interactions between projects and business performance goals. The optimization process begins by defining the business performance goals distributed across a future period. The goals may or may not be attainable, but they represent the starting point for the analysis. The second step is to introduce the projects described by the business segments. These projects can be deterministic or probabilistic. For the probabilistic case, a probability density function is used to represent the decision-maker's risk preference, and then the portfolio expected value is calculated using this probability function.

As shown in Figure 2.2 and Figure 2.3, the goals are depicted with purple bars. The blue bars represent the expected portfolio values, and the probabilities of exceeding the goals are depicted with a black line. Decision-makers can use the performance-probability plots to fully assess the issues associated with a given strategy (Howell and Tyler, 2001). Since the goal-seeking approach leverages the interactions between projects and performance goals to generate feasible solutions, various portfolios can be generated from the starting point by evaluating or changing the project selections and performance goals until an optimal portfolio is attained.

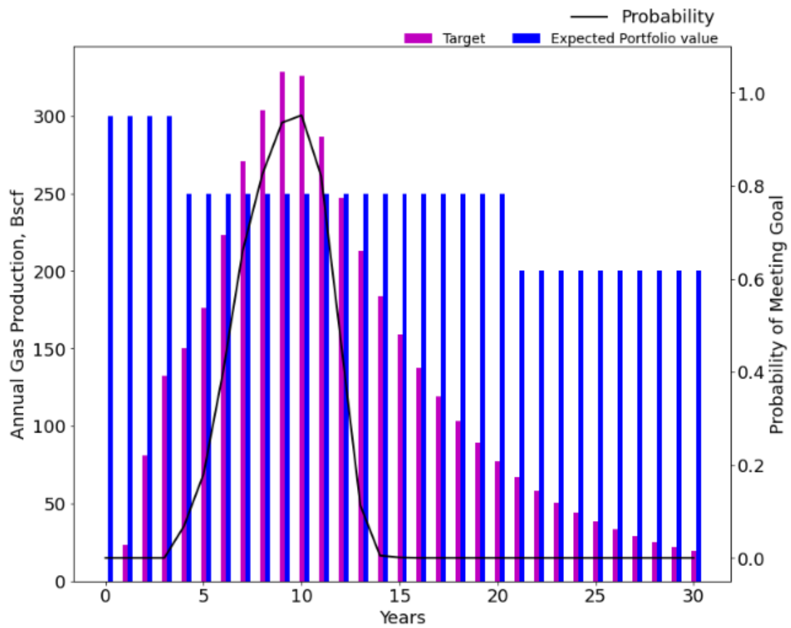


Figure 2.2: Performance Metric Graph for Gas Production

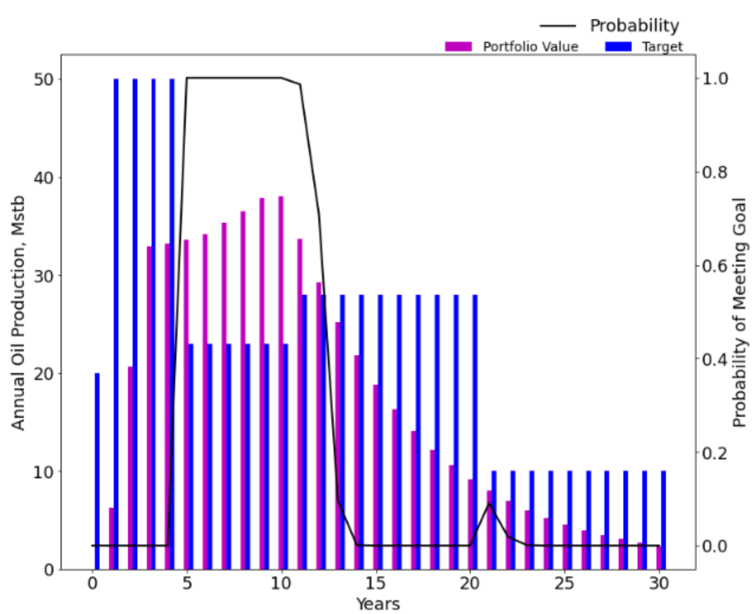


Figure 2.3: Performance Metric Graph for Gas Production

2.3.2 Multi-Attribute Utility Theory

An essential step in decision analysis is the correct representation of the decision maker's preferences. Multi-attribute utility theory is a multi-objective optimization approach that considers the decision-maker's preferences in the form of a utility function defined over a set of attributes. A utility function is a device that quantifies a decision-maker's preferences by assigning a numerical index to varying levels of satisfaction of a particular criterion (Mateo, 2012). In a deterministic decision problem, each alternative results in a single prospect, and a value function defined by the attributes is enough to rank the decision alternatives. However, in a probabilistic case where uncertainty is present, each decision alternative may result in several prospects; therefore, we need to assign utility values to the prospects to maximize the expected utility.

While a value function determines the trade-offs between levels of attributes, the attributes need to be carefully examined to know if there exists additive dependence between them or not. An additive value function implies that the increase in one attribute required to compensate for a decrease in the other is constant across the entire domain of the attributes(Abbas, 2010). In other words, this means the preference for levels of one attribute does not affect the level of other attributes.The advantage of additive independence is that it allows the decision-maker to derive a multi-attribute utility function by finding the simple weighted sum of single-attribute utility functions.

Based on the additive independence assumption, Henrion et al. (2015) developed an approach to constructing a multi-attribute utility function. They can be summarized in the following five steps:

1. Identify the uncertain attributes.
2. Define a precise scale for each attribute, either cardinal, meaning quantified, as in US$ for direct costs, or ordinal, meaning a list of outcomes in order of preference.
3. Define a single-attribute utility function to score the possible levels of each attribute into a utility from 0 (worst outcome) to 100% (best outcome).
4. Select swing weights (or equivalent costs) to model stakeholder preferences about relative value or cost for each attribute
5. Combine the swing weights and attribute scores into an overall multi-attribute utility for each decision option.

Given a multi-objective portfolio problem characterized by n uncertain attributes, $(x_1, x_2, x_3, \ldots\ldots x_n)$ and a scalar utility function, $U(x_1, x_2, x_3, \ldots\ldots x_n)$. The multi-attribute utility function can be expressed as the weighted sum of each attribute utilities.

$$U(x_1, x_2, x_3) = \sum_{i=1}^{n} w_i\, u_i(x_i) \tag{2.12}$$

$$0 \leq U(x_1, x_2, x_3, \ldots\ldots x_n) \leq 1, = \sum_{i=1}^{n} w_i = 1$$

The multi-attribute value function $V(x_1, x_2, x_3, \ldots\ldots x_n)$ can be used to score levels of each attribute into a value from 0 (worst outcome) to 100 (best outcome), and can be expressed as weighted sum of each values:

$$V(x_1, x_2, x_3) = \sum_{i=1}^{n} w_i\, v_i(x_i) \tag{2.13}$$

$$0 \leq V(x_1, x_2, x_3, \ldots\ldots x_n) \leq 100, \qquad \sum_{i=1}^{n} w_i = 1$$

Where x_i is an uncertain attribute for i =1……., n

$v_i(x_i)$ is a single attribute value function for i = 1…………,n

$u_i(x_i)$ is a single attribute utility function for i =1……., n

w_i is the normalized weight for an uncertain attribute for i =1……., n

V = weighted overall value function of portfolio

U= weighted overall utility function of portfolio

Utility functions describe the decision-maker's risk attitude. As shown in Figure 2.4, concave utility functions signify a risk-averse attitude, convex utility functions signify a risk-seeking attitude, and linear utility functions signify a risk-neutral attitude.

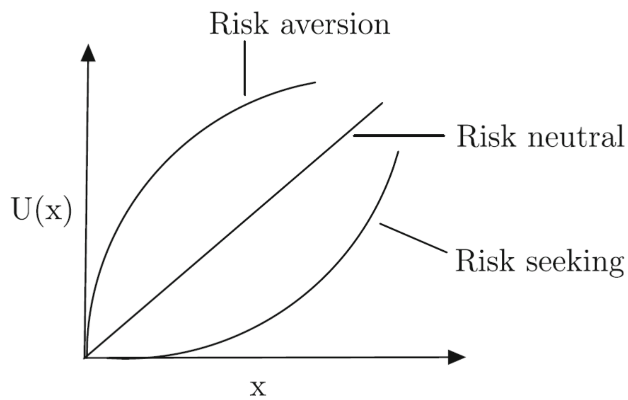


Figure 2.4: Utility Function (adapted from Mateo (2012))

The multi-attribute utility function (MAUT) approach has a wide application in financial, energy policy-making, energy management, portfolio analysis, and other fields when faced with decision problems where the decision-maker needs to select the best alternatives (Wallenius et al., 2008). One limit of this approach is the complicated framework required to solve a typical multi-attribute decision problem. A more comprehensive explanation of the multi-attribute utility theory can be found in the books written by Keeney (1993) and Abbas (2010).

3 Project Model

Three probabilistic asset models were used in the asset evaluation for this work. These models are petroleum, wind farm, and CCS asset models. The three asset models and python codes were developed by Moubarak (2021) and modified to evaluate the project assets used in this thesis work.

3.1 Petroleum Asset Model

The petroleum asset model was developed using a Python class "petroleum asset" and the petroleum project used in the portfolio analysis is represented as an instance of this class. Monte Carlo simulation was adopted to model uncertainties with probabilities and was done with 5,000 iterations over 30 years. This petroleum asset model was modified for this asset evaluation. In evaluating the petroleum asset model, a hydrocarbon reserve model, an oil production model, an economic model, and a carbon emission model were modified and implemented. The input arguments for the class are shown in Table 3.1

Table 3.1: Input Parameter of Petroleum Asset

Input Argument	**Unit/Possible Outcomes**
Current Project Phase [phase]	“exploration”, “development”
Location of the Project[location]	“onshore”, “offshore”
Hydrocarbon Type [hc_type]	“oil”, “gas”
Recoverable Reserves [res_est]	Mstb; Bscf
Unit of Average Maximum Well Rate [well_max_rate]	Kbpd; Mscfpd
Project Start Year [init_year]	years
Time Period [period]	years
Number of Realizations [n]	-

3.1.1 Reserve Model

Volumetric reserve estimation is one method of calculating oil and gas reserves in reservoirs that have been used in the oil industry until now. The required data needed in using this method are obtained from basic data sources such as log data (gamma-ray log data, resistivity log data, density log data, and neutron log data), core rocks or side terraces, area estimates, Rf and fluid properties (Ibrahim et al., 2020). However, a simpler approach was adopted to estimate the reserves due to the uncertainty in reserve estimation during the early development of deep reservoirs solely because of the difficulty in representing these required data with their individual distributions. The reserves Model has eight input uncertainties, as shown in Table 3.2 and Table 3.3, as a function of the project phase(exploration/development) and project location (offshore/onshore). The uncertain reserve estimates are simulated as random variables that follow PERT distribution, and the possible outcomes were estimated using Monte Carlo simulation with 10,000 samples. Figure 3.1 shows the reserve estimation distribution estimated using the reserve model.

Table 3.2: Uncertainty parameters as a function of the project phase

Exploration		Development	
Min	Max	Min	Max
0.20	2.00	0.85	1.50

Table 3.3: Uncertainty parameters as a function of the location phase

Onshore		Offshore	
Min	Max	Min	Max
1.00	1.20	0.7	1.50

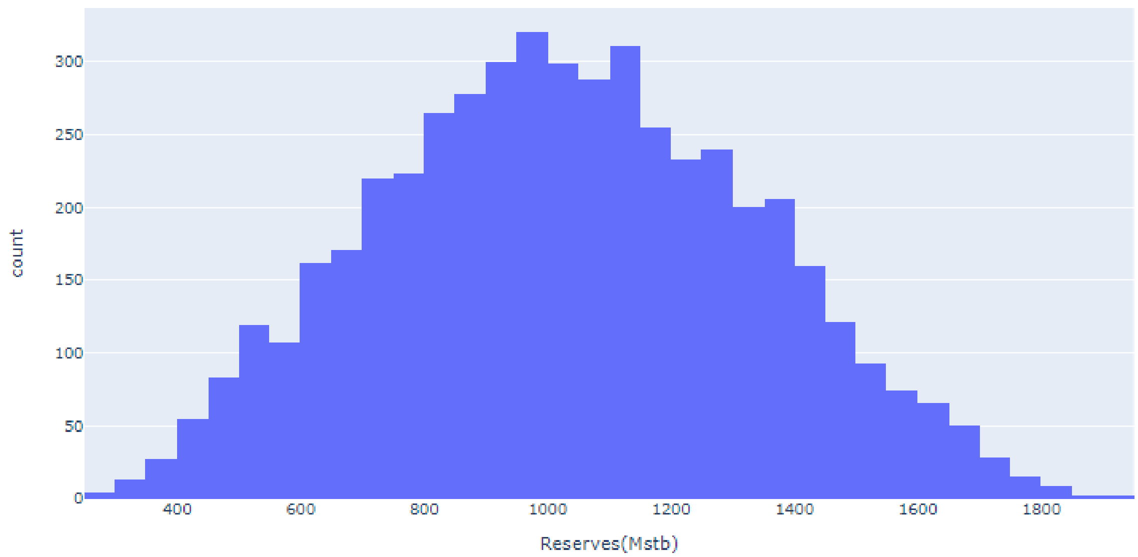


Figure 3.1: Reserves Estimation Distribution

3.1.2 Production Forecast Model

The production model estimates the oil and gas production from the petroleum asset. Some input parameters were also used in developing the model. The function "*year_phase*" calculates the years in which the exploration, development, and production start. The function '*production'* estimates the production from the reserves using the production forecast model.

The oil and gas production forecast was modeled using the exponential decline curve model proposed by Arps (1945). An exponential decline exists when the loss in production rate per unit time is proportional to the production rate(Poston and Poe, 2008). It assumes that oil and gas production drop over a constant interval is a percentage of the initial production rate.

$$q_t(t) = q_i/(1 + bD_i t)^{1/b} \tag{3.1}$$

Where: $q_t(t)$: oil production rate at time t

q_i : initial production rate

D_i : continuous decline rate

b : hyperbolic exponent

Table 3.4: Input Parameters of O&G Production Model (adapted from Moubarak(2021)

Input Parameter	**Possible Outcome**	**Python Argument**	**Distribution**
Length of exploration period	2, 3, 4 or 5	expl_len	multinomial
Length of development period	1, 2 or 3	dev_len	multinomial
Chance of exploration success	0 or 1	expl_succ	bernoulli
Exploration factor	0 or 1	expl_fac	-

Table 3.4 describes the input parameters for the production model. Also, the production profile depends on four time-variables: the development, build-up, plateau, and decline period (Moubarak, 2021). Table 3.5 illustrates the input parameters for the production time variables.

Table 3.5: Input Paramters of Production time-variables Model (adapted from Moubarak(2021)

Parameter	**Unit**	**Python Argument**	**Distribution**
Delay period	years	t_delay	uniform
Ramp-up period	years	t_to_plateau	uniform
Plateau period t_plateau	years	t_plateau	uniform
Decline rate parameter	fraction	a_factor	uniform
Total maximum processing capacity	Mstb; Bscf	[total_max_cap	-
Start of production year	years	start_year	-
Reserves	Mstb; Bscf	reserves	-

A detailed description of the production model used in this work will not be discussed. For a detailed review of the production model, the reader should look into Moubarak (2021), Arps (1945) and Höök et al. (2009).

Using the input parameters in Table 3.4 and Table 3.5, The function '*production'* returns the production forecast and Figure 3.2 illustrates annual production distribution for year 25

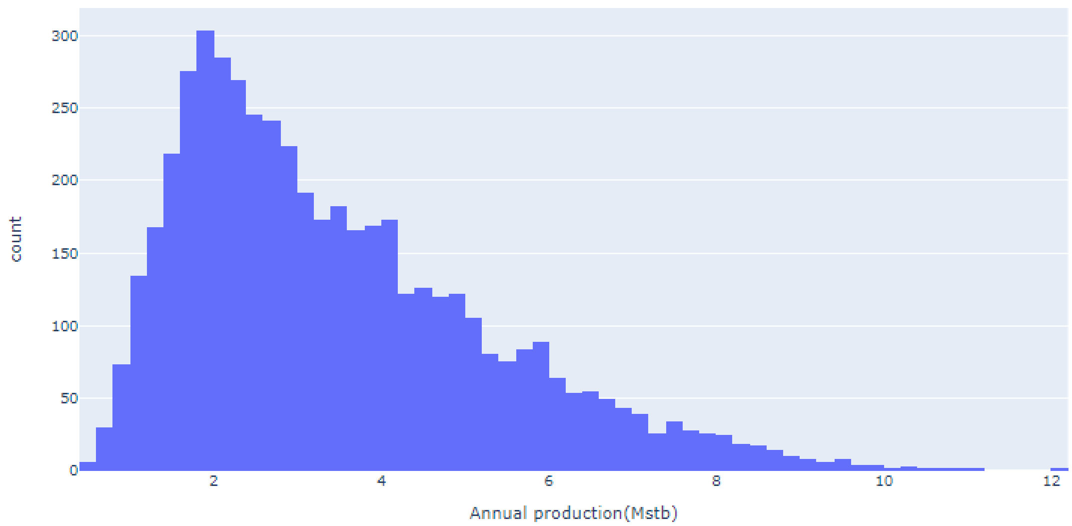


Figure 3.2: Annual Production Distribution for Year 25

3.1.3 Oil and Gas Price Model

Due to the high volatility in oil prices, oil and gas price model must capture the uncertainty in future prices and their impact over time. In this work, oil and gas prices were modeled as mean-reverting process. This approach was used because it addresses the dependencies in price changes and that oil prices tend to be continually pulled towards a long-term mean (Begg and Smit, 2007). Mean reversion is a stochastic process that models such that oil price follows a log-normal diffusion and the logarithmic price variations depend on each other and have a constant long-term equilibrium price and mean aversion rate (Begg and Smit, 2007). The mean-reverting process can be expressed with the following stochastic equation:

$$\frac{dP}{P} = \eta\,(P - P^{*})dt + \sigma\epsilon\sqrt{dt} \tag{3.2}$$

where P: price

P*: long term equilibrium price

t: time period

η : mean reversion rate

σ: price volatility

ϵ: standard normal distribution

dt: increment in time

The parameters used in the price model are illustrated in Table 3.6. The function '*og_price'* estimates the oil and gas price from these parameters using a Monte Carlo simulation of 5,000 realizations over 30 years, and the resulting distribution is illustrated in Figure 3.3.

Table 3.6: Input Parameters for Oil and Gas Price

Input Parameter	**Unit**	**Python Argument**	**Oil**	**Gas**
Time Period	years	period	30	30
Time increment	years	dt	1	1
Price Floor	$/bbl; $/Mscf	oil_floor; g_price_floor	8	0.8
Volatility of Annual Increments	$/bbl; $/Mscf	oil_sd; gas_sd	3	0.7
Half Life	years	oil_half; gas_half	4	8
Initial Price	USD/bbl; USD/Mscf	oil_ini_price; gas_ini_price	40	2.3
Long Term Mean Price	USD/bbl; USD/Mscf	oil_mean_price; gas_mean_price	70	5

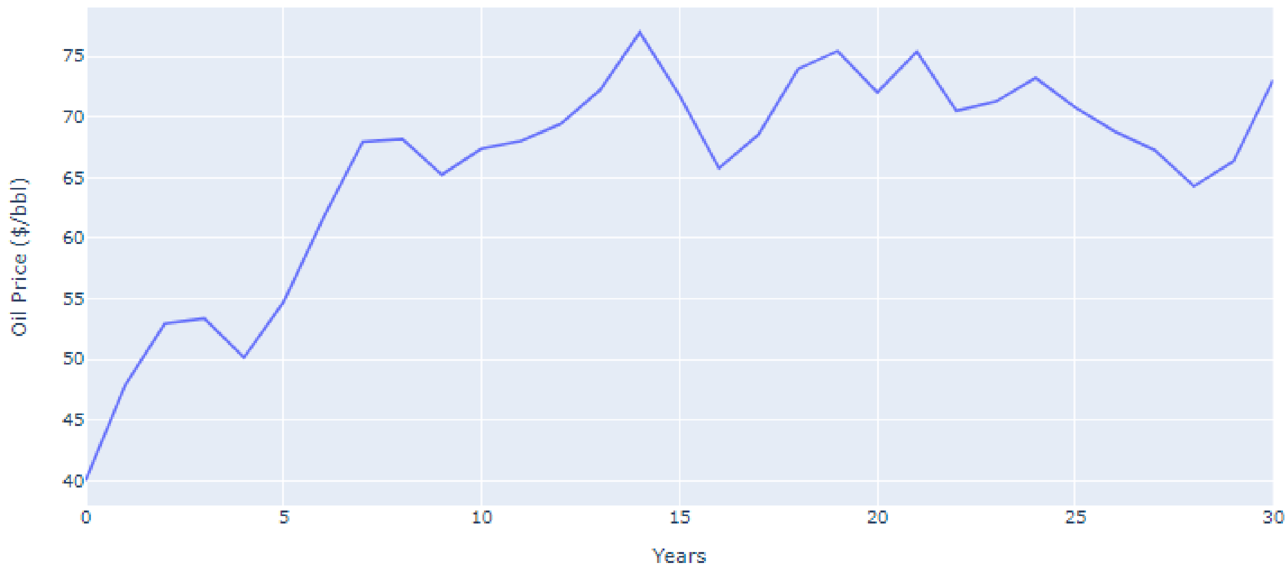


Figure 3.3: One Monte Carlo Realization Showing Oil Price Across 30 Years

3.1.4 Economic Model

Three operation stages were considered in developing the economic model: exploration, development, and production. The cash outflow for the hydrocarbon project includes the annual capital expenditure (Capex) and operating expenditures (Opex), while the cash inflow is the revenue generated from oil sales.

The capital expenditure was modeled as triangular distribution using the input parameters illustrated in Table 3.7. The capex depends on the number of wells required for each operation stage thus, different capex structures were generated for different operation stages, as illustrated in Table 3.5. The offshore capex is calculated using the offshore multiplier.

Table 3.7: Input Parameters of Petroleum Project Capex

Parameters	**Min**	**Mode**	**Max**	**Offshore Multiplier**
Seismic and Data Acquisition Cost ($ million)	8	10	15	2.50
Exploration Well Unit Cost ($ million/well)	90	100	130	5.00
Injection Well Unit Cost ($ million/well)	90	100	130	5.00
Appraisal Well Unit Cost ($million/well)	90	120	140	2.50
Production Well Unit Cost ($million/well)	90	120	140	3.00

The operating expenditure consists of the fixed and the variable operating cost and are modeled as triangular distribution using the input parameters illustrated in Table 3.8.

Table 3.8: Input Parameters of Petroleum Project Opex

		Onshore			**Offshore**		
		min	**mode**	**max**	**min**	**mode**	**max**
Exploration Stage	Fixed Opex ($million/well)	1.30	1.50	1.80	1.50	1.70	2.10
	Variable Opex ($/bbl) – Oil	5.00	10.00	15.00	15.00	20.00	25.00
	Variable Opex ($/bbl) – Gas	8.00	12.00	22.00	21.00	25.00	33.00
Development Stage	Fixed Opex ($million/well)	1.30	1.80	2.40	1.80	2.30	2.70
	Variable Opex ($/bbl)	7.50	10.00	12.50	18.00	20.00	27.00

The annual revenues were estimated as the product of the annual production and the respective annual oil or gas price generated using the oil price model. The net present value was calculated using the annual cash flows, and Figure 3.4 illustrates the resulting NPV distribution for a petroleum asset.

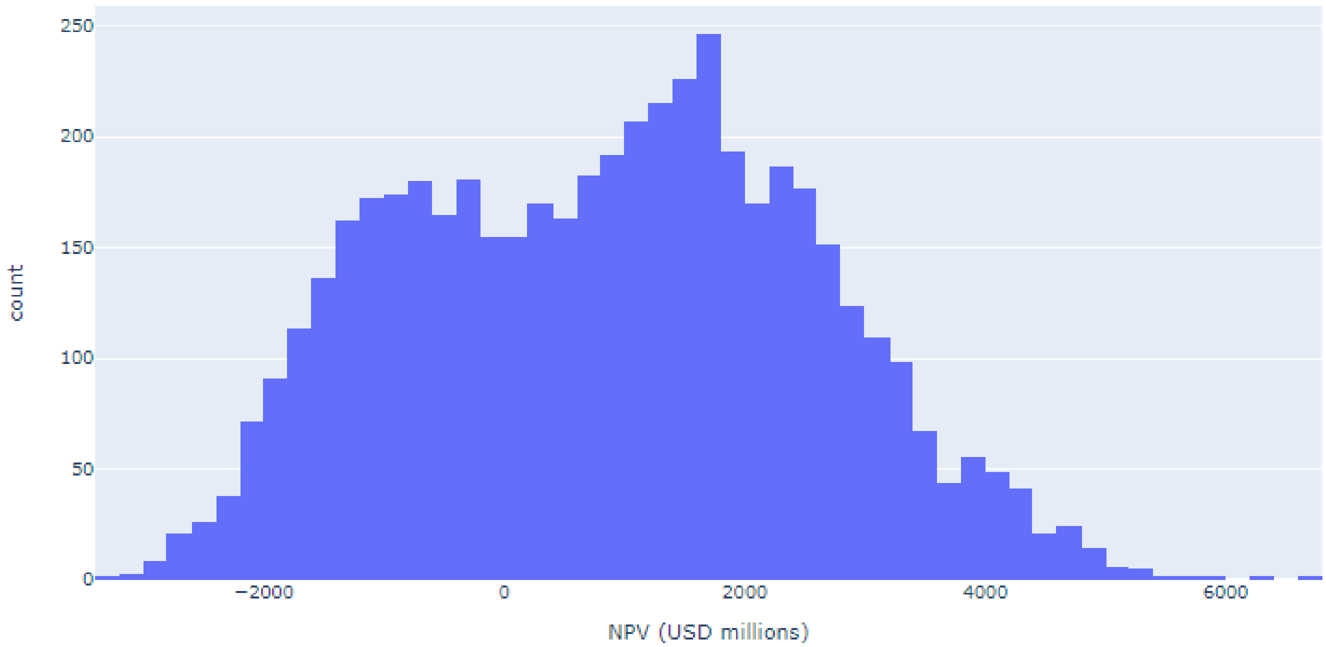


Figure 3.4: NPV distribution of an Oil and Gas Asset

3.1.5 Carbon Emission Model

Greenhouse gas emissions is a global challenge with likely adverse effect on the climate and environment. The global oil and gas industry is saddled with the responsibility of reducing global emissions to ensure that the net-zero emission goal of 2050 is achieved. In order to develop a carbon emission model, the major drivers behind emission intensity need to be considered.

The first driver behind the carbon emission intensity is the oil field production. As the production declines from the peak level, the emission per unit extraction increases enormously. For instance, a field producing 20% of peak level has about three times higher emission intensity than in the peak phase (Gavenas et al., 2015). In an oil field, as the amount of oil production reduces, water production increases, significantly increasing the field's emission intensity.

Secondly, carbon intensity emission also depends on the production infrastructure in place, as opposed to just the production decline from the historical peak level. Once in production, the energy requirement at a production plant is approximately the same, and so are the carbon emissions. The emission projections thus take into account that emissions are a consequence of the time the installation is producing and to a much lesser extent, the production on the installation (Norwegian Ministry of Climate and Environment, 2020). When new gas-fired power plants are added to the pre-existing infrastructure, an increase in the carbon intensity is expected. A reduction in carbon intensity is also expected when the old installation is removed.

Many O&G companies operating on the Norwegian continental shelf are implementing modern technology, and other energy efficiency measures for existing and future development of their fields, resulting in less carbon emission per unit produced compared to global figures. Equinor had some 70 projects offshore in 2020, including operational measures, process improvements, production, drilling and well optimization, and reduced flaring. While eight were modifications, the rest involved operational adjustments identified and implemented during the year. Over the past six years, Equinor has pursued CO_2 reduction programs that have eliminated emissions averaging 200 000 tonnes per annum. That adds up to 1,125,000 tonnes in yearly avoided emissions (Konkraft, 2021). In this same regard, Conoco Phillips implemented low-carbon emission technology measures in the last 20 years, mitigating up to 160 000 tonnes of CO_2 emissions annually.

Thirdly, CO_2 price also affects carbon emission intensity. Emissions can be reduced with a relatively modest carbon price. Figure 3.5 was adapted from Cullen and Mansur (2017) and showed the emission intensity change with respect to the carbon price ($/ton). An increase of $20/ton in carbon price on the vertical axis would reduce emission intensity by 5% baseline emission. For instance, if the baseline emission is 20,000 tons, an increase in carbon price from $0/ton to $20/ton will reduce the baseline emission by 1,000 tons. However, as the carbon price increases significantly from $20/ton, an indistinct decrease in emission intensity is observed. Though high carbon prices result in further reduction in carbon dioxide emissions, it seems that the large impact from a high carbon price is likely to come from retooling the generating infrastructure(Cullen and Mansur, 2017). This implies that the most significant reduction in CO2 emission will come from companies who use technologies to reduce Co2 emissions.

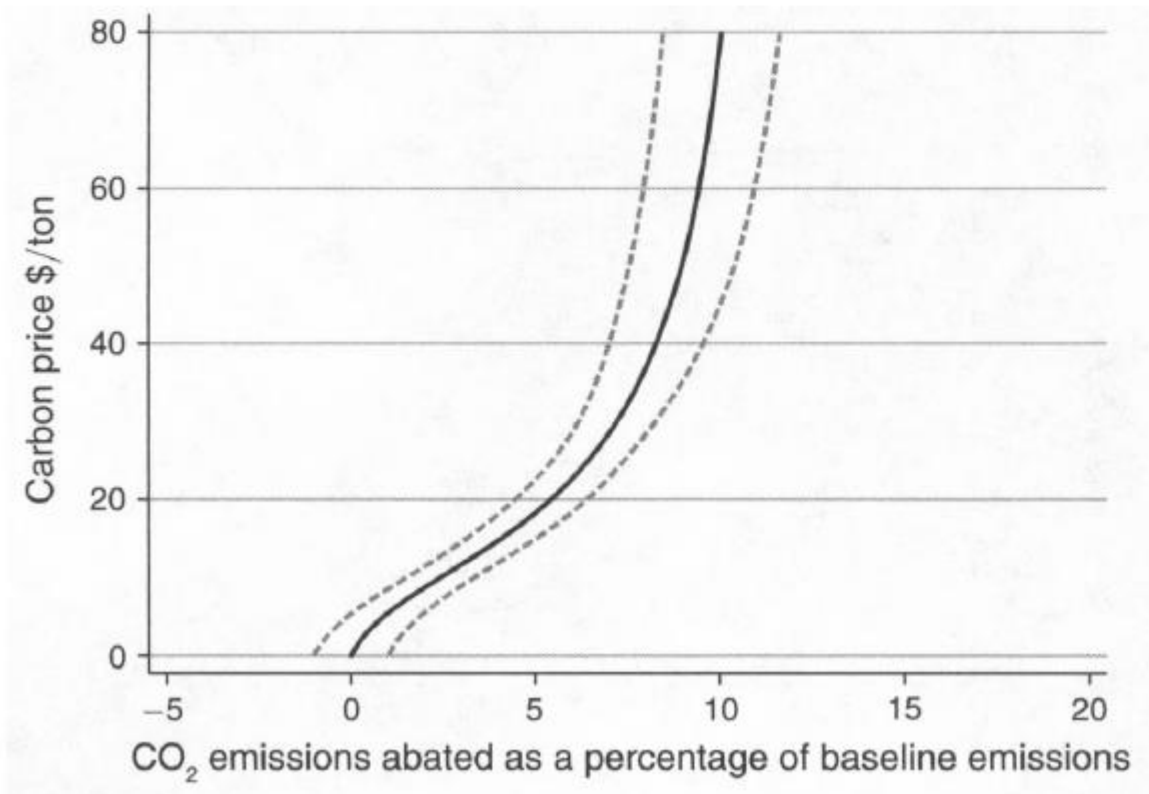


Figure 3.5: Carbon emission intensity change with respect to the Carbon price
(adapted from Cullen and Mansur (2017))

Another reason for variations in carbon emission intensity is the oil share of a field's original hydrocarbon reserves. Oil extraction generates a higher carbon footprint per unit than gas extraction. A likely explanation for this could be that oil generates more revenue than gas. Historically, oil prices are higher than gas prices; therefore, more return is observed on investments in oil production. Since the cost of infrastructure for gas extraction is more capital intensive compared to oil, it seems more likely that a high-cost oil field will be developed than a high-cost gas field, and higher costs are often associated with higher energy use (Gavenas et al., 2015).

The relationship between these emission drivers and carbon emission intensity is incorporated into the carbon emission model used in this thesis. Moubarak (2021) describes a detailed formulation of the carbon emission model used in this work.

3.2 Wind Farm Asset Model

The windfarm asset model was developed by Moubarak (2021) and evaluated using a Python class "wind_farm_asset", and the wind farm project used in the portfolio analysis is represented as an instance of this class. Monte Carlo simulation was adopted to model uncertainties with probabilities and was done with 5,000 iterations over 30 years. The input parameters for the class are shown in Table 3.9. The project is divided into four stages: development, production, repowering, and production. The wind farms in this work are assumed to have three years of development, after which production begins. Repowering commences after a useful life of 15 years before re-production starts and lasts for another 15 years. The capex structure signifies the capex share in percentage made in the first, second, and third year of development. For example, a "30/60/10" capex form signifies that 30%, 60%, and 10% of the total capex were incurred in the first, second, and third year respectively.

In this model, an offshore wind project with a "10/80/10" capex structure, and 200 turbines was considered in the project evaluation. Note that there is a higher estimated capex and opex in an offshore wind project relative to an onshore wind project. Offshore wind farms are larger and require more expensive foundations, difficult installation environment, and higher transport costs, primarily driven by rentals of large vessels. Furthermore, the offshore wind industry is still maturing. This means that technological elements for harsh offshore conditions are still being tested and developed while also the offshore supply chain is developing to match the needs of the industry (Deloitte, 2014). Investment in wind power is quite complex, considering many uncertainties associated with its profitability. Uncertainties in available wind power production, price of electricity, technology, wind speed, and variation in electricity demands are important risk factors for wind investment. We will not discuss the detailed description of these factors as it is beyond the scope of this work.

Table 3.9: Input Parameters for Wind Farm model

Input Parameter	**Python Argument**	**Unit/Possible Outcomes**
Project location	location	"onshore", "offshore"
Number of turbines	n_turbine	100 or 200
Capex structure	const_sc	"10/80/10" or "30/60/10"
Subsidies percentage	perc_subs	%
Time Period	period	years

3.2.1 Wind Energy Production Model

The energy production parameters are selected from a wind power investment case presented by Deloitte Analysis(2014). Theoretical yearly energy production of 8,000MWh and a turbine production capacity of 2.3MW were considered in this section. Both parameters were modeled following a PERT distribution, as illustrated in Table 3.10. A yearly production degradation of 0.5% was also used to account for the wear and tear of wind turbine blades. The energy production is expressed as:

$$Energy\ production = C * P * N * (1 - d)^t \quad (3.3)$$

Where C: turbine production capacity (in %)

N: number of wind turbines

P: theoretical yearly production (in MWh)

t: annual production degradation (in %)

Table 3.10: Input Parameters for Wind Energy Production Model

Input Parameter	Unit	Python Argument	Min	Mode	Max
Annual Theoretical Production	MWh	energy_prod_theo	6500	8000	10000
Energy Production Capacity	%	energy_cap	50	65	85

3.2.2 Economic Evaluation Model

The capex and opex structure varies depending on the nature of the project whether it is offshore or onshore. Opex for an offshore wind farm is somewhat higher than for an onshore farm due to greater costs of accessing and maintaining turbines. Harsh marine environment can also increase the failure frequency of some components (Deloitte, 2014). Input parameters for offshore and onshore projects are illustrated in Table 3.11 and Table 3.12.

Table 3.11: Input Parameters for Offshore Project Costs

Input Parameter	**Unit**	**Python Argument**	**Min**	**Mode**	**Max**
Opex [opex]	$/kWh	opex	0.015	0.03	0.048
Total Capital Variable Cost	million$/MW	capex_var	2.29	3.50	5.42
Total Capital Fixed Cost	million $	capex_fix	43.20	72.12	90.00
Partial Repowering Investment	million$/MW	repower		1.056	

Table 3.12: Input Parameters for Onshore Project Costs

Input Parameter	**Unit**	**Python Argument**	**Min**	**Mode**	**Max**
Opex [opex]	$/kWh	opex	0.01	0.015	0.035
Total Capital Variable Cost	million$/MW	capex_var	1.2	1.8	2.29
Total Capital Fixed Cost	million $	capex_fix	36.03	60.4	75.51
Partial Repowering Investment	million$/MW	repower		0.88	

Note that subsidy is an integral tool used by the government to motivate more investments in wind projects. Nevertheless, the subsidy scheme should be examined to understand the effect on the project. The subsidy size and the conditions for receiving the subsidies are some of the key factors to be considered. Based on the subsidy awarded by Enova to Equinor in the Hywind Tamper project (Enova reports 2020), an 80% subsidy of initial capex is assumed in the wind farm project evaluation. Using the energy production model and the economic model, the cash flow and NPV were estimated and Figure 3.6 shows the NPV distribution of a wind farm project.

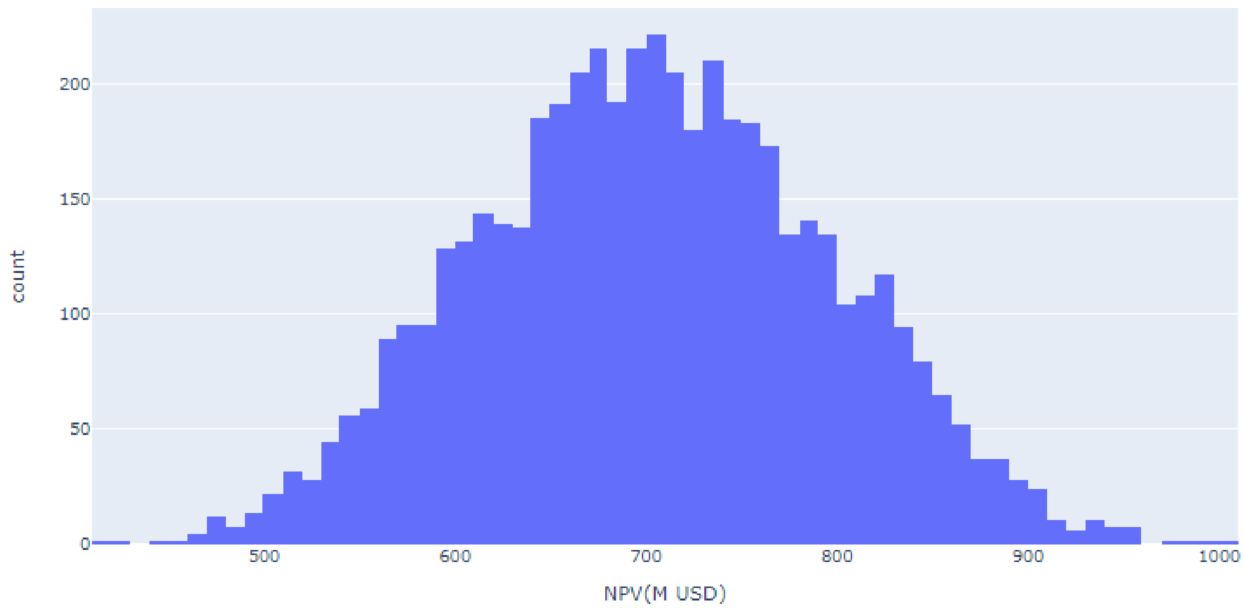


Figure 3.6: Distribution of a wind farm project

3.3 CCS Asset Model

Carbon capture and storage(CCS) is a key tool for abating carbon emissions from anthropogenic sources. This section presents the asset evaluation of CCS projects by examining different stages that constitute the carbon capture and storage process. The CCS asset model was represented as an object of python class "CCS_asset." Table 3.13 shows the input parameter for the class.

The CCS value chain can be divided into three processes: carbon capture, transport, and storage. We considered two stages in developing the CCS asset model: demonstration and commercialization. The demonstration phase is a sub-commercial scale project to validate CCS as an integrated technology at scale, while the commercialization phase is the first full-scale project to ramp up the CO2 abatement potential (Kim and Choi, 2014). Similar to the petroleum and wind farm assets, a project life of 30 years was also considered for the CCS project, with each project phase spanning 15 years. Given these two stages of the project, two different investment costs were developed, and Table 3.14 illustrates the parameters used to model the investment and operating cost. The operating cost is divided into capture, transportation, storage, and leakage costs. All parameters were modeled after PERT distribution by generating 5,000 realizations using Monte Carlo simulation for 30 years.

The CCS utilization is the percentage of the storage capacity in use depending on the project phase. McKinsey & Company (2008) presented the CCS utilization for demonstration and commercial phase as 80% and 86%, respectively, and were used in developing this model. 80% subsidy was considered as the percentage of initial investment provided by the government towards the CCS project. More details about the CCS asset model used in this work are presented in Moubarak (2021).

Table 3.13: Input Parameters for CCS Aset Model

Input Parameter	**Unit**	**Python Argument**
CCS Utilization percentage	%	util
Subsidies percentage	%	perc_subs
Time Period	Years	perc_subs

Table 3.14: Input parameters for CCS Capex and Opex Cost

Input Parameter	**Unit**	**Python Argument**	**Min**	**Mode**	**Max**
Unit Investment of 1st Stage	$ million	capex1	150	178	200
Unit Investment of 2nd Stage	$ million	capex2	100	155	130
Capture Cost	$/t CO_2	capt_cost	30	37	39
Transportation Cost	$/t CO_2	trans_cost	4	4.9	7.3
Storage Cost	$/t CO_2	stor_cost	4.9	12	14.5
Leakage Cost	$/t CO_2	leak_cost	24	31	35

4 Portfolio Case Study

In this chapter, we consider a hypothetical portfolio case study. It is supposed that the management team will choose a combination of energy investments consisting of a petroleum project, a wind farm project, and a CCS project. A multi-objective portfolio optimization will be used to generate optimized portfolios consistent with the management choice and preference. The decision variables for this case study are the shares or amounts of the capital budget invested into petroleum, wind farm, and CCS project.

NPV, carbon emission, and company's green reputation are chosen as the decision criteria and these criteria are evaluated over the complete project lifespan of 30 years.

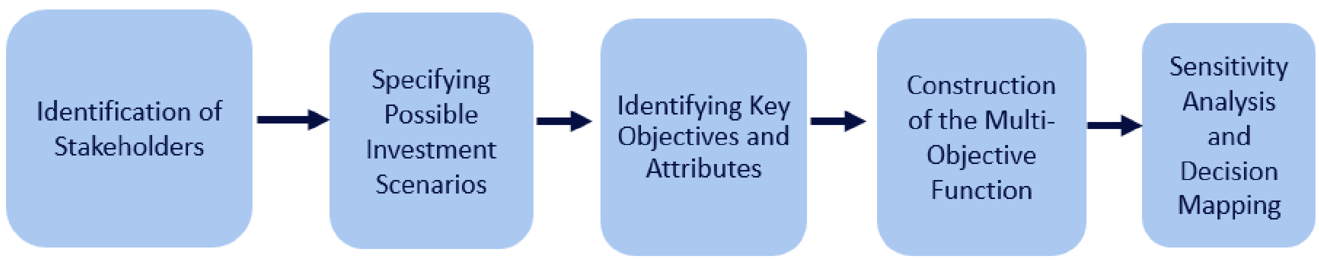


Figure 4.1: Workflow of the Case Study

Fig 4.1 describes the workflow of the case study. The analysis begins with identifying stakeholders, specifying possible investment scenarios, and identifying key objectives and attributes. Based on the decision variables, different investment scenarios centered on achieving energy transition at different pace are generated, and multi-attribute utility theory is applied to attain optimized investment portfolios. Furthermore, a sensitivity analysis and decision mapping will be carried out on the decision model.

4.1 Development of the Portfolio Model

4.1.1 Identification of Stakeholders

The management team are the main stakeholder in a decision context because they outline the corporate objectives and the possible pathways to achieve them. They must carefully examine, evaluate and represent various energy strategies that would fulfill these objectives in a way that allows us to choose the optimal one. The main focus of this work is to select an optimal energy portfolio that attains the energy transition goal; the global energy shift from fossil-based energy production and consumption to renewable energy.

4.1.2 Portfolio Scenario Generation

Energy transition signifies a pathway to achieving gradual transformation from carbon-intensive projects and solutions to greener solutions by integrating renewables and other energy-efficient solutions. Every energy firm will evolve its strategy using various approaches based on its short and long-term goals. This transition can be achieved by increasing the percentage of renewable energy and decreasing the percentage of fossil energy in the project portfolio since the main goal is to reduce emissions and attain net-zero energy in the long run. While the exact speed and path of the transition are unknown, the endpoint of a low-carbon energy system is inevitable. Hence, four energy scenarios were presented by gradually varying the percentage of hydrocarbon and renewables in the portfolio:

Scenario 1 (Conservative):	Hydrocarbon - 70%	Renewables - 15%	CCS - 15%
Scenario 2 (Less Conservative):	Hydrocarbon - 50%	Renewables - 25%	CCS - 25%
Scenario 3 (Less Aggressive):	Hydrocarbon - 33.3%	Renewables - 33.3%	CCS - 33.3%
Scenario 4 (Aggressive):	Hydrocarbon - 20%	Renewables - 40%,	CCS - 40%

Depending on the momentum of transforming the energy portfolio, these scenarios range from the Conservative Scenario being the slowest transition to the Aggressive Scenario being the fastest. Scenario 1(Conservative) has the largest share of O&G assets and the smallest renewable energy share, while Scenario 4 (Aggressive) has the most significant renewable energy share and the smallest fossil fuel assets. Several factors such as technological progress, public and private policies, infrastructure availability, oil prices, and energy production may affect the transition pace at which the company moves. Using these scenarios, we will evaluate the long-term impact of the transition pace on the portfolio value by using the defined value function that represents the decision-maker's preference.

4.1.3 Identification of Key Attributes

The net-zero carbon emission ambition is vital for the industry in limiting global warming increase to 2^0C in 2050. Operators are now developing balanced and integrated energy portfolios. More recently, Equinor has announced the ambition to attain a carbon-emission target of 8 kgCO2e/boe by 2030. O&G companies are now looking beyond the common goal of maximizing their shareholder value to other objectives like building a good energy reputation and reducing carbon intensities of upstream assets based on factors such as technology and infrastructural complexity. Taking this into account, the attributes that quantify the degree of attainment of these objectives are identified and selected. After that, a clear scale for each attribute is defined to show how well a decision alternative meets each objective.

Using the data generated by the project model simulation, the attributes and scales are shown below in Table 4.1:

Table 4.1: Attributes, Scales, and 'Best' and 'Worst' outcomes of any Decision Alternative

Attributes	Scale	Best	Worse
NPV	NPV (million $)	725.68	454.44
Net Carbon Emission	Net C02 emissions(million t CO2)	40770.00	1039978.00
Green Reputation	% of renewable and CCS project	80%	30%

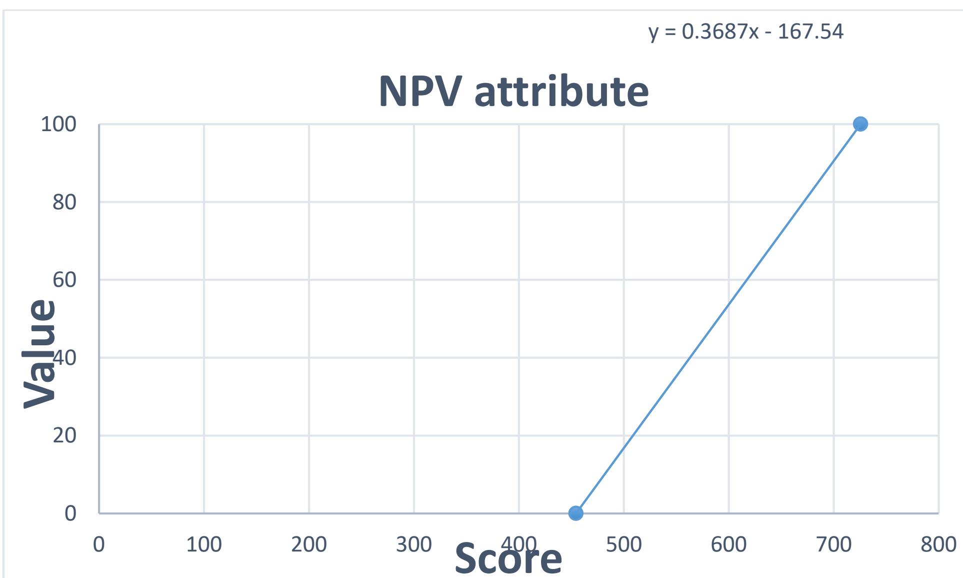
Table 4.1 illustrates the attributes, scales, and their respective 'best' and 'worst' values. These values symbolize the best and worst outcomes for each attribute that any decision alternative could achieve; thus, these values are obtained from the best and worst possible outcomes of various scenarios. For the NPV attribute, the best possible outcome is Scenario 1 with 725.68 million dollars, while the worst possible outcome is Scenario 4 with 454.44 million dollars.

A key assumption in evaluating the net carbon emission of this decision problem is that if the CCS capacity is greater than the CO2 emissions from the oil and wind projects, there is no extra revenue from the CCS project by storing CO_2 from external CO_2 sources. This means that negative net emissions are considered zero emissions.

This methodology used in defining the attributes and scales is vital for developing the value function, as introduced in the next section.

4.1.4 Constructing Multi-attribute Utility Functions Using Value Functions

Having identified the attributes, the next step is constructing the multi-attribute utility function. However, as presented in section 2.3.2, a single-attribute value function to score the possible levels of each attribute into a value form from 0 to 100 is first developed. A linear transformation from attribute scores to attribute values is assumed for all attributes; thus, a linear value function is used to establish a linear relationship between the scores and the scenario performance, as illustrated in Figure 4.2.



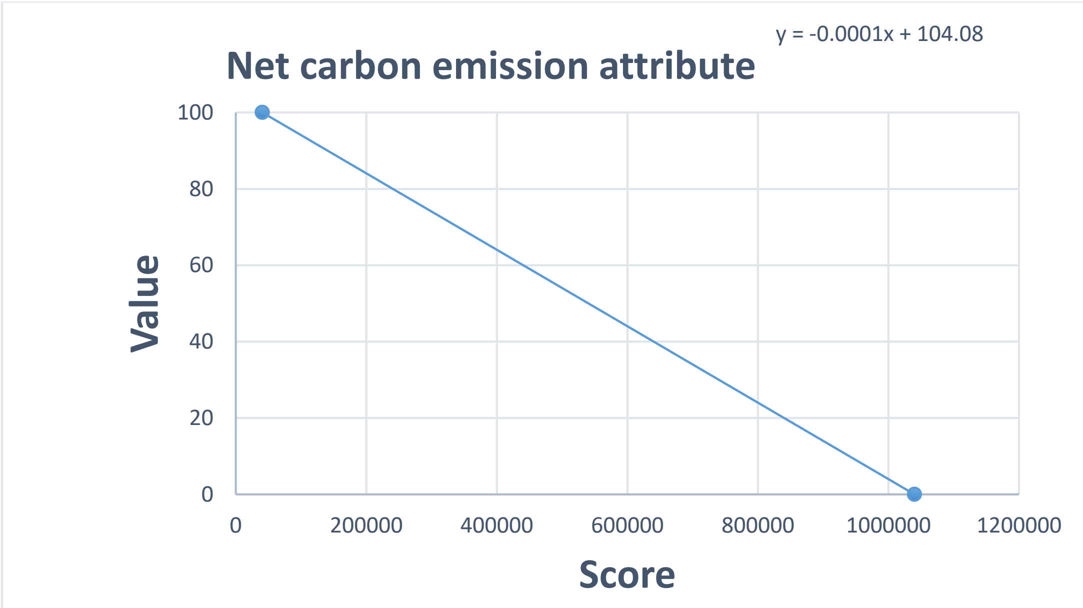


Figure 4.2: Value Function for Key Attributes: NPV, Net Emission, and Green Reputation

The next step is to select swing weights to model stakeholder preferences and combine the swing weights and attribute scores into an overall multi-attribute value function for each decision option. The overall value function for each alternative's pay-off is given as:

$$V = npv\_wt(0.3687 * NPV - 167.54) + emis\_wt(-0.0001 * emis + 104.08) + rep\_wt(200 * rep - 60) \quad (4.1)$$

Where V: Overall multi-attribute value function

npv_wt: NPV preference weight

$emis\_wt$: net emissions preference weight

rep_wt: green reputation preference weight

emis: net carbon emissions

rep: green reputaion

4.2 Applying Portfolio Model To Scenarios

This section defines a base case for the four scenarios by assigning weights to each decision criteria in the multi-objective decision problem. However, the first step of the base case analysis is to assess the strategies against the NPV objective such that any scenario that does not fulfill this single objective is removed. To achieve this, the assigned attribute weights for NPV, carbon emission, and green reputation are 1.0, 0.0, and 0.0, respectively, describing the decision-maker's preference for fulfilling only the NPV objective in this case. These preference weights illustrated in Table 4.2 were implemented in the value function. The expected NPV in the results calculated in Table 4.3 illustrates that the four investment strategies generate a positive NPV.

Table 4.2: Attribute weights describing preference for only the NPV objective

Attributes	NPV	Net C02 emission	Green reputation
Weight	1.0	0.0	0.0

Table 4.3: Scenario results for NPV objective

Scenarios	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected NPV(million $)	719.63	612.76	523.70	452.45
Objective value	98.40	55.18	23.00	0.36

Table 4.3 shows that all four scenarios generated positive NPV. However, Scenario 1 generated the highest objective value. Therefore, Scenario 1 is the optimal portfolio when the portfolio analysis considers only the NPV objective. Scenario 1, being the conservative scenario, retains more investment share of hydrocarbon in its portfolio than the other scenarios, thereby maximizing the NPV objective the most compared to other scenarios.

Moving on to access the investment strategies against multiple objectives, attribute weight is assigned to each objective according to the decision maker's preference. Table 4.4 shows the decision maker's preferred assumptions for the attribute weights.

Table 4.4: Attribute weights describing preference for multiple objectives

Attributes	NPV	Net C02 emission	Green reputation
Weight	0.4	0.3	0.3

The final step is to calculate the portfolio value for each scenario using the multi-objective value function earlier defined in section. From the portfolio results in Table 4.5, Scenario 4 generated the highest objective value.

Table 4.5: Scenario results for multiple objective

Scenarios	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected NPV(million $)	719.63	612.76	523.70	452.45
Objective value	41.58	52.78	58.27	59.40

From Table 4.5, the portfolio result illustrates that Scenario 4 generated the highest objective value and Scenario 1, the lowest objective value, thus making Scenario 4 the optimal portfolio based on the decision-maker's preference. This is expected as Scenario 4 has more green energy solutions than other scenarios, thereby fulfilling the decision maker's goal of reducing carbon intensity in the portfolio selection. However, the optimal scenario for multiple objectives differs from that of a single objective. The optimal scenario for the multiple objectives is the aggressive scenario, while for a single objective (NPV maximization), the optimal scenario is the conservative scenario. This show that when we change the attribute weights, the optimal decision changes. This means the attribute weight is material to our decision.

Using the base case results alone, the optimal portfolio choice from the four scenarios can not be made. The base case only provides an overview for the decision-maker to further evaluate the alternatives by performing a robust sensitivity analysis on the portfolio values while changing the estimated inputs or assumptions, particularly for uncertain quantities and variables over which we have choices. In the section that follows, we will perform a sensitivity analysis on the portfolio model. This will significantly help energy firms make better decisions with respect to their targets and constraints and agree on the optimal choice according to organizational goals and strategy.

4.3 Sensitivity Analysis

To demonstrate the sensitivity of the portfolio decision to the choices made regarding the model parameters, a sensitivity analysis was conducted on the strategies. In the first step, a one-way sensitivity analysis was done on the portfolio value by varying the attribute weights. For simplicity in this analysis, NPV weight is used to represent the decision maker's preference, and the net carbon and green reputation weights are a function of the NPV weight:

$$net\ emission\ weight = \ green\ reputation\ weight\ = \frac{1 - npv\ weight}{2} \tag{4.2}$$

An increase in the NPV weight signifies a decrease in the net carbon and green reputation weights.

The sensitivity analysis was repeated for CCS storage, hydrocarbon emissions, and windfarm emissions. This assessment helps to know to what extent the portfolio decision is sensitive to these input parameters.

4.3.1 NPV weight

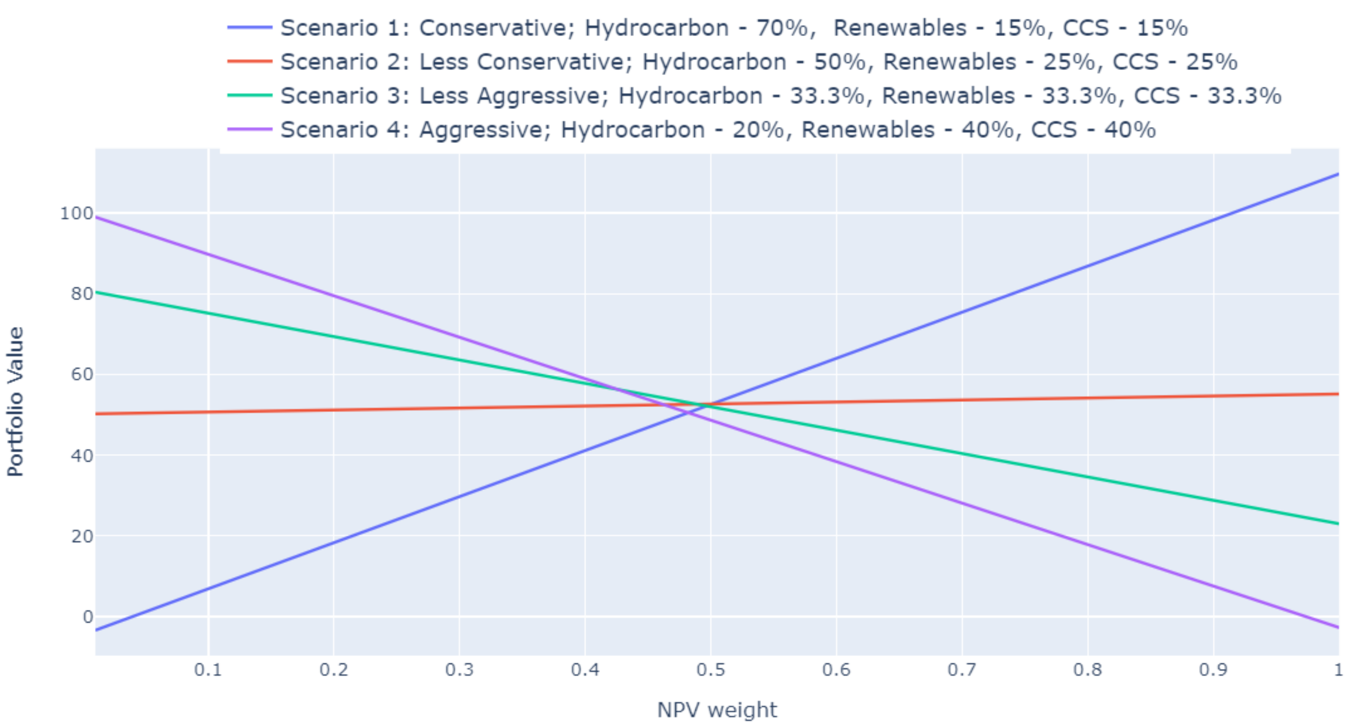


Figure 4.3: Sensitivity Analysis of Portfolio Model to NPV weight

We develop an approach to analyze how the portfolio value changes as a function of the attribute weights and, more importantly, to recognize situations where a slight change in the decision-maker's preference for fulfilling an objective is likely to change the decision.

Figure 4.3 indicates that the portfolio value increases as the NPV weight increases for the conservative and less conservative scenarios. In contrast, the portfolio value decreases as the NPV weight decreases for the aggressive and less aggressive scenarios. This is possible because the hydrocarbon project maximizes net profit the most compared to the renewable and CCS project. In other words, the NPV is the primary driver of the portfolio value. As the NPV weight increases, the NPV objective is prioritized above other objectives across all alternatives considered, and the alternative that best meets this objective generates the highest objective value corresponding to the conservative scenario. However, the optimal decision is most sensitive when the NPV weight is between 0.4 and 0.5, as we see that the portfolio values of the scenarios are the closest to each other and the optimal scenario (alternative) changes across the four scenarios within this range." Another observation from this Figure 4.3 is that Scenario 2 is the optimal only for a narrow range of the NPV weight (around 0.5)

Finally, whether the decision-maker should choose Scenario 4 is insensitive to all NPV weights less than 0.4 since the optimal decision remains Scenario 4. Similarly, this applies to all NPV weights more than 0.5 as the optimal decision remains Scenario 1. Given that the attribute weights are material to the decision, the decision-maker can use this analysis to study the implication of their preferences on portfolio value.

4.3.2 CCS Storage Capacity

Here we study the effect of the CCS storage capacity of the CCS asset on the portfolio value by considering the interaction of other input parameters that influence the portfolio value. Different investment scenarios would generate different carbon footprints depending on the percentage of fossil-fuel projects in the portfolio.

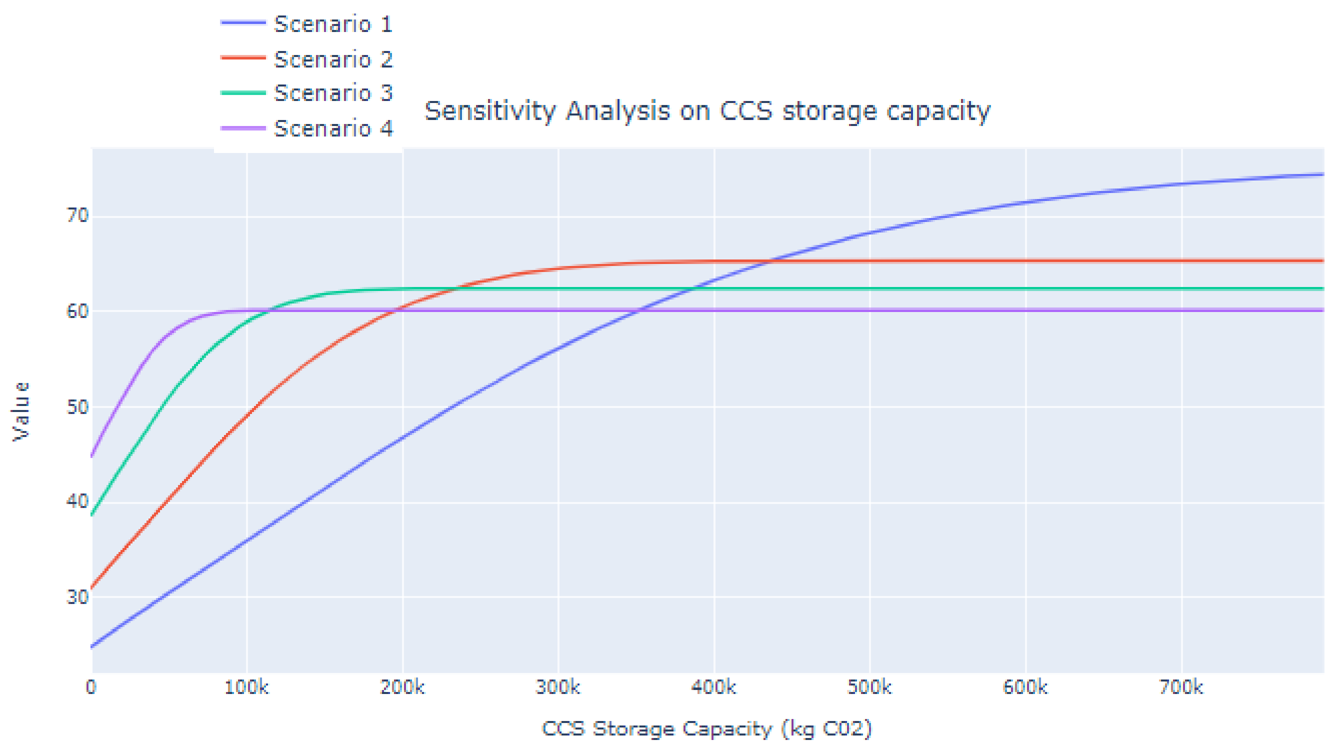


Figure 4.4: Sensitivity Analysis of Portfolio Model to CCS storage Capacity

Fig 4.4 shows that as the CCS storage capacity increases, the portfolio value for all scenarios increases steadily. A possible explanation for this might be that as the carbon storage capacity increases, more carbon emissions can be captured, thereby reducing the net carbon emission and improving the green reputation of the energy company. Also, with a reduction in the carbon footprints, the company can avoid paying excess carbon tax and save more, maximizing the net profit. This observation further explains the significance of the CCS project in an energy portfolio as it maximizes all specified objectives directly or indirectly.

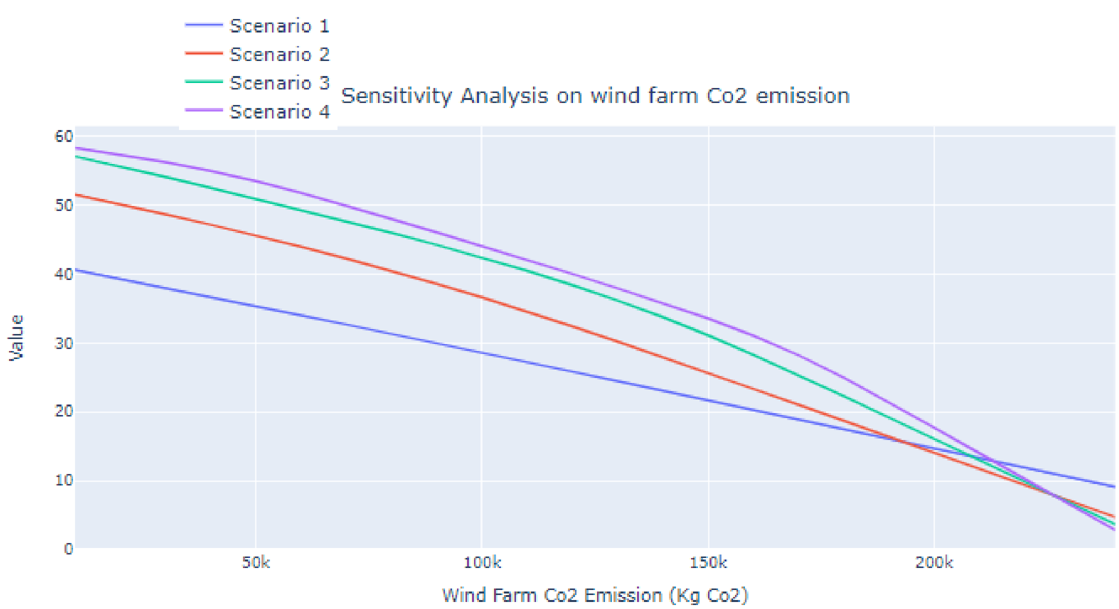
However, the significance of the CCS storage capacity is relative across all scenarios. As the CCS storage increases, we see in Figure 4.4 that the portfolio value increases gradually and remains constant after a certain point, depending on the scenario. There are several possible explanations for this result. As the CCS capacity keeps increasing to the point where all carbon emissions are captured, resulting in a zero net carbon emission, an increase in the storage capacity above this point no longer adds significant value to the portfolio. This is evident in the case of Scenario 4, with a constant portfolio value of 60 for all CCS storage above 100,000 kg CO2.

Since the oil project generates the highest NPV compared to other projects, suppose the CCS storage capacity increases and every other variable of the model remains constant. In that case, we can invest more in the hydrocarbon project because we have more storage capacity to store carbon emissions, thereby making Scenario 1 (Conservative scenario) the optimal scenario at CCS storage capacity above 430,000 kg Co2. Finally, whether the decision-maker should choose Scenario 1 is insensitive to the CCS storage capacity at capacities more than 430,000 kg Co2 since the optimal scenario remains Scenario 1.

4.3.3 Carbon Emission Intensity

The relationship between the carbon emissions and the portfolio value can be inspected in Figure 4.5. As the target windfarm and hydrocarbon emissions become larger, the portfolio value of all the scenarios decreases with a larger variation seen with the hydrocarbon carbon emission. This confirms that the objective value is more sensitive to the hydrocarbon emission than the windfarm emission. If the target windfarm emission is increased, we should invest more in the hydrocarbon project, so the optimal decision changes to Scenario 1, the conservative scenario.

On the other hand, if the target hydrocarbon emission is increased, you should reduce your investment in hydrocarbon and invest more in the wind farm project, changing to the aggressive scenario, Scenario 4.



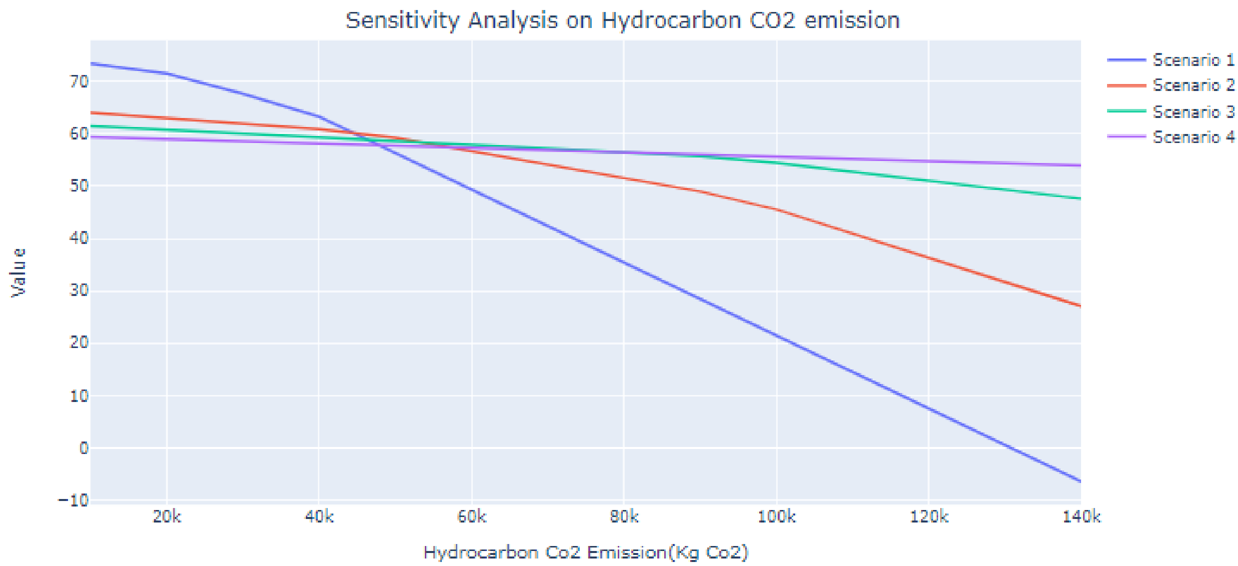


Figure 4.5: Sensitivity Analysis of Portfolio Model to Carbon Emission Intensity

4.4 Decision Map

A decision map approach is adopted to show the optimal portfolio given the underlying uncertain criteria in the quest for more insight and support for quality decision-making. The multi-attribute value model is used to generate a decision map displaying which investment scenario is optimal, that is, the scenario with the largest portfolio value based on bi-criteria slices of portfolio values. The result allows the mannagement board and staff to understand the interaction of the decision criteria with one another in achieving the organizational goals rather than looking at each criterion individually.

4.4.1 CCS storage capacity and NPV weight

First, a decision map was developed with the portfolio value of the scenarios as a function of the CCS storage capacity and the NPV weight criteria. Different values of both model parameters were generated for each as input into the portfolio value model. The maximum and the minimum limits are defined by the management based on their targets and constraints. The vertical axis of the plot corresponds to different

CCS storage capacity levels, and the horizontal axis is graded according to the NPV weights levels. The color map shows the optimal scenarios for a combination of both model variables.

As seen in Figure 4.6, the optimal scenario tends to change according to changing levels in the CCS storage and NPV weights. For instance, for an NPV weight of 0.6, an increasing level of CCS storage from 100,000 kg CO2 to 250,000 kg CO2 causes a change in decision across the four scenarios from Scenario 1 to Scenario 4. Additionally, if the CCS capacity is 200,000kg CO2, a change in the NPV weight from 0.1 to 0.9 causes a change in decision across the four scenarios from Scenario 4 to Scenario 1.

However, for all CCS storage capacity less than 130,000kg CO2, the optimal decision is Scenario 4 – aggressive scenario, regardless of the NPV weight assigned by the decision-maker. Here, the decision-maker would always prefer to invest more in green energy projects at all profit levels, provided the available carbon storage capacity is less than 130,000kg CO2. This observation also applies to all CCS capacity more than 225,000 kg Co2 as the optimal decision is Scenario 1 – conservative scenario, irrespective of the NPV weight. Hence at a storage capacity less than 130,000kg CO2 or more than 225,000 kg, the decision-maker will be indifferent about his preference for NPV maximization as this is inconsequential to the decision. It also showed that the aggressive scenario dominates all scenarios for all CCS storage capacities less than 130,000kg CO2, and the conservative scenario dominates all scenarios for all CCS storage capacities more than 225,000kg CO2.

Finally, the optimal decision is most sensitive to the NPV weight when the carbon storage capacity is between 130,000kg CO2 and 225,000kg CO2, as we see the decision changing across the four portfolio scenarios within this range.

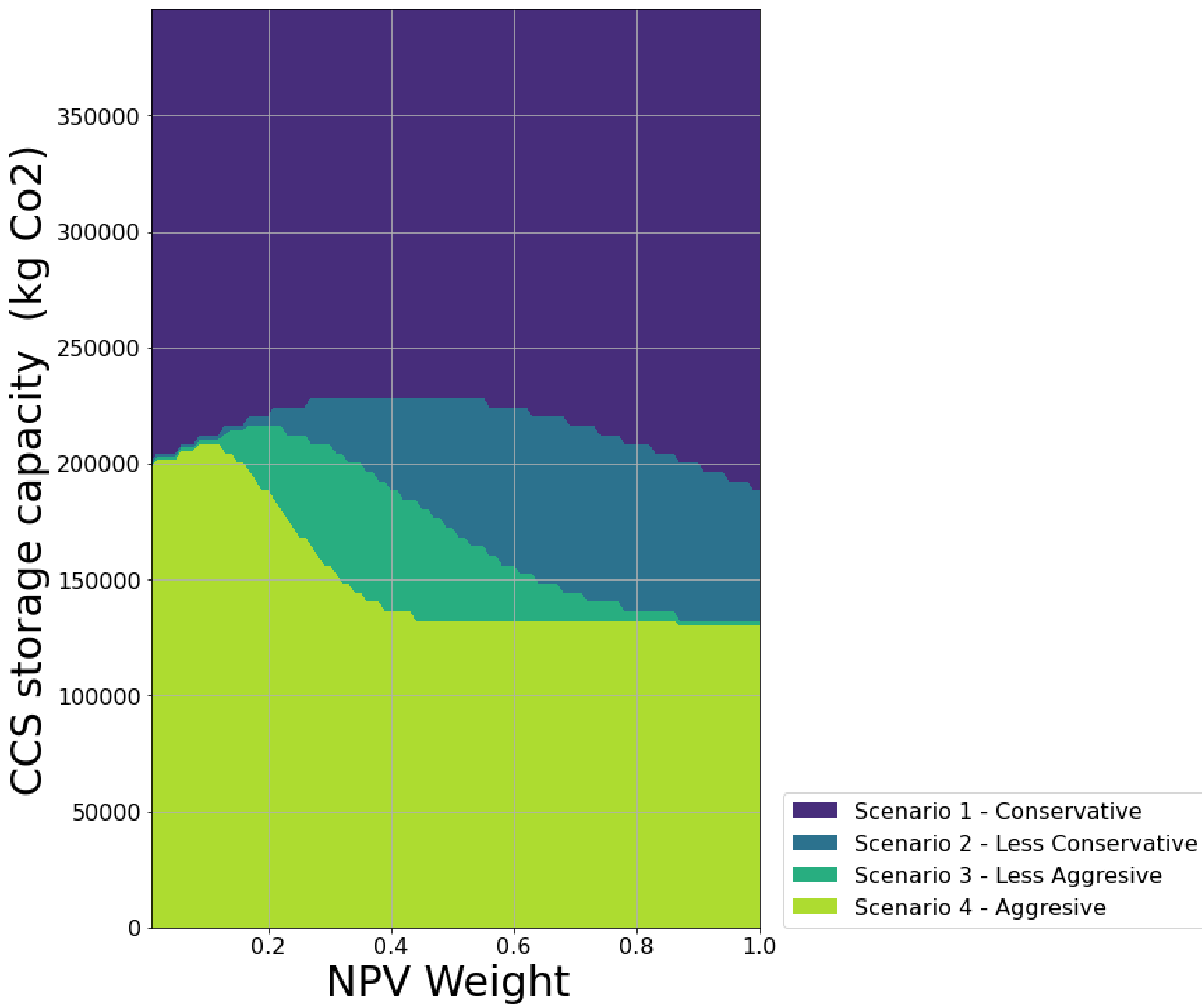


Figure 4.6: CCS storage capacity and NPV weight

4.4.2 Hydrocarbon emissions and CCS storage capacity

Moving on now to consider a decision map that examines the optimal portfolio from combinations of annual hydrocarbon emission and annual CCS storage capacity, provided all model parameters are the same. This analysis helps to understand the relationship between the available CCS storage capacity and the carbon emission from the hydrocarbon project. With this, the decision-maker can determine how a change in the emission target and the CCS storage capacity causes a change in the investment scenario and be able to select the scenario that maximizes value at a given annual hydrocarbon emission target and CCS storage capacity constraint.

The approach used is similar to that of the previous section. 100 different values were generated for each of both annual hydrocarbon emission target and CCS storage capacity as input for the portfolio model. In this analysis, base case weights of 0.4, 0.3, and 0.3 were assigned to profit maximization, carbon reduction, and green reputation attributes to represent the decision maker's preference. We generated a decision map in Figure 4.7 with hydrocarbon emission on the vertical axis and the CCS storage capacity on the horizontal. The optimal portfolio for each slice of both criteria is visualized using a color map.

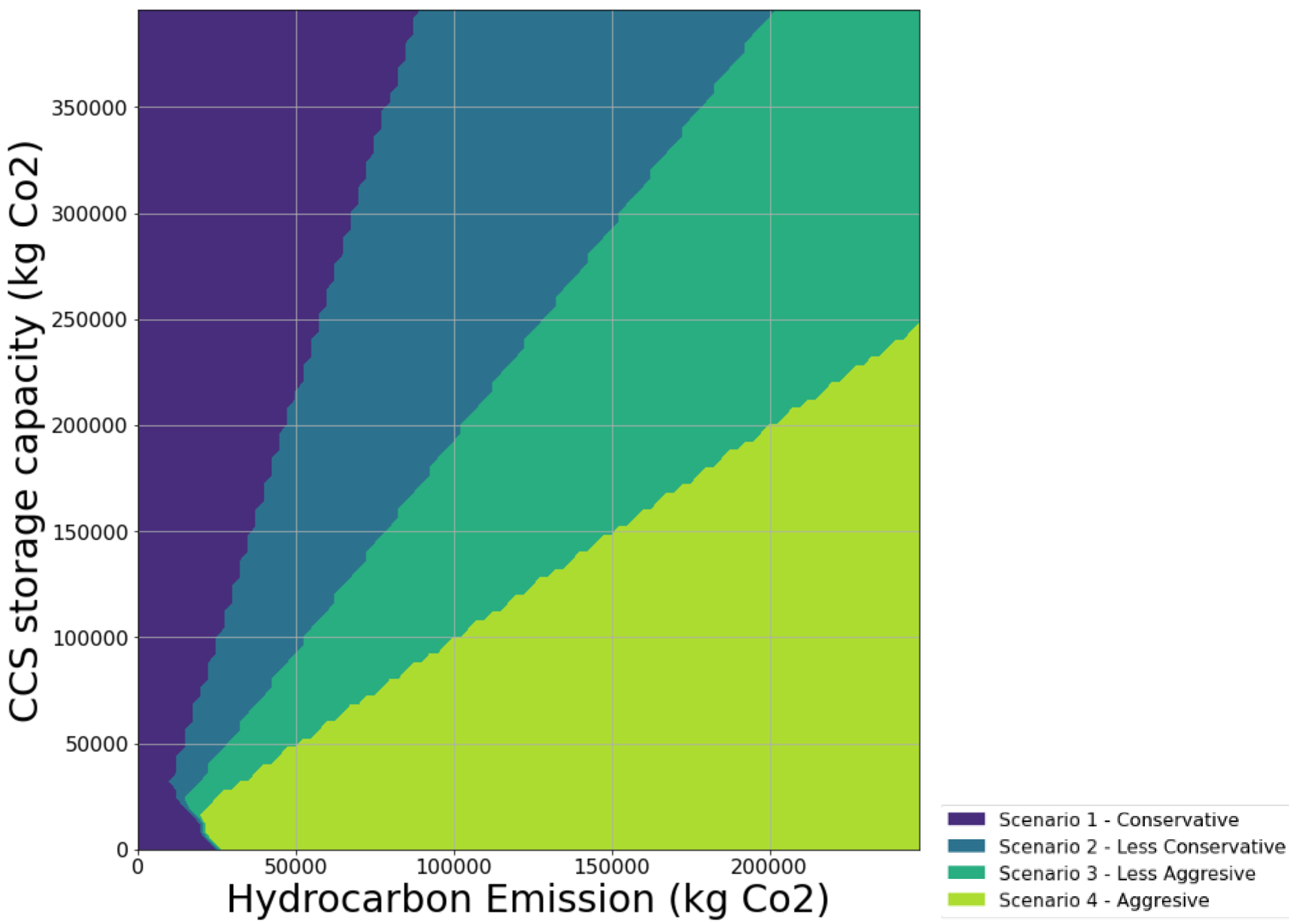


Figure 4.7: Hydrocarbon emissions and CCS storage capacity

As it is easy to see in Figure 4.7, the optimal scenario changes as the hydrocarbon emission and the CCS storage capacity change. Considering a hydrocarbon emission of 100,000 kg Co2, an increasing level of

CCS storage from 50,000 kg CO2 to 150,000 kg Co2 causes a decision change from Scenario 4 to Scenario 3. A further increase from 150,000 kg CO2 to 230,000 kg causes the decision to change from Scenario 3 to Scenario 2. It is observed that for the 100,000kg Co2 emission target, as the CCS storage increases, the optimal scenario tends to shift away from the aggressive scenario. A possible explanation is that at constant emission and increasing CCS storage capacity; the company can invest more in the hydrocarbon project and produce more oil. Increasing CCS storage capacity motivates compannies to increase their oil production since increasing carbon storage can help abate more carbon emissions from oil production. This makes the optimal decision to gravitate towards fossil-dominated energy sources.

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In order to gain more insights to support quality decision making, from the result obtained in Figure 4.6, we will examine four different combinations of HC emissions and CCS storage capacity representing a hypothetical hydrocarbon emission target and CCS storage capacity constraint being considered by the decision-maker. Note that all other model parameters apart from hydrocarbon emission and CCS storage capacity remain constant in this analysis. These four combinations correspond to A, B, C, and D in Table 4.6.

Table 4.6: Combinations of Hydrocarbon Emission and CCS storage

Combinations	CCS Storage Capacity (kg CO2)	Hydrocarbon Emission (kg CO2)	Optimal Scenario
A	300000	50,000	4
B	250000	100000	3
C	200000	120000	2
B	50000	200000	1

Point A constitutes a significant amount of CCS storage capacity and a low hydrocarbon emission in this analysis. The optimal scenario at point A is Scenario 4. However, considering point B with a considerable decrease in CCS storage capacity and increase in hydrocarbon emission compared to point A, we observe a decision change from Scenario 4 to Scenario 3. A further decrease in CCS storage capacity and increase in hydrocarbon emission caused a decision change to Scenario 2, and then to Scenario 1. This analysis is based on the portfolio model and the decision-maker's preference for fulfilling the specified corporate objectives. The optimal scenario may tend to change for points A, B, C, and D if the decision-maker's preference changes.

4.4.3 Three-Way Sensitivity Analysis Using Decision Maps

In the previous section, we adopted a decision map approach to investigate the effect of NPV weight, carbon emissions, and CCS storage capacity on the optimal scenario, using a two-way sensitivity analysis. This section will consider a three-way sensitivity analysis of the portfolio model to changes in the material variables. First, we consider maps that can be used to assess the optimal decision at different hydrocarbon emissions, CCS capacities, and different NPV weights. The concept is to generate decision maps displaying portfolio values as functions of carbon emissions and CCS capacities using different NPV weights.

Figure 4.8 illustrates the decision maps for four different NPV weights. As shown in Figure 4.7, if the NPV is less important and is assigned a weight of 0.3, we will always choose Scenario 4. However, when NPV becomes essential and is assigned preference weights of 0.4, 0.5, and 0.6, we observe visible decision change across the maps that correspond to these preference weights. Therefore, the preference weight is material to our decision.

In order to generate more insight for decision-making, a particular hydrocarbon emission target and CCS storage capacity can be used as a case study. Hence, Point P corresponds to 100,000 kg CCS storage capacity and 60,000 kg hydrocarbon CO2 emission and is identified with a white dot on the four decision maps as shown in Figure 4.8. For an NPV weight of 0.3 which means the decision-maker cares less about maximizing net profit but much about reducing carbon intensity and the company's green reputation, the optimal investment decision for point P is to implement the aggressive scenario. However, as NPV weight increases to 0.4, the less aggressive, Scenario 3 becomes the optimal decision for point P. A further increase in the NPV weight to 0.5 and 0.6 changes the decision at point P to Scenario 2 and Scenario 1.

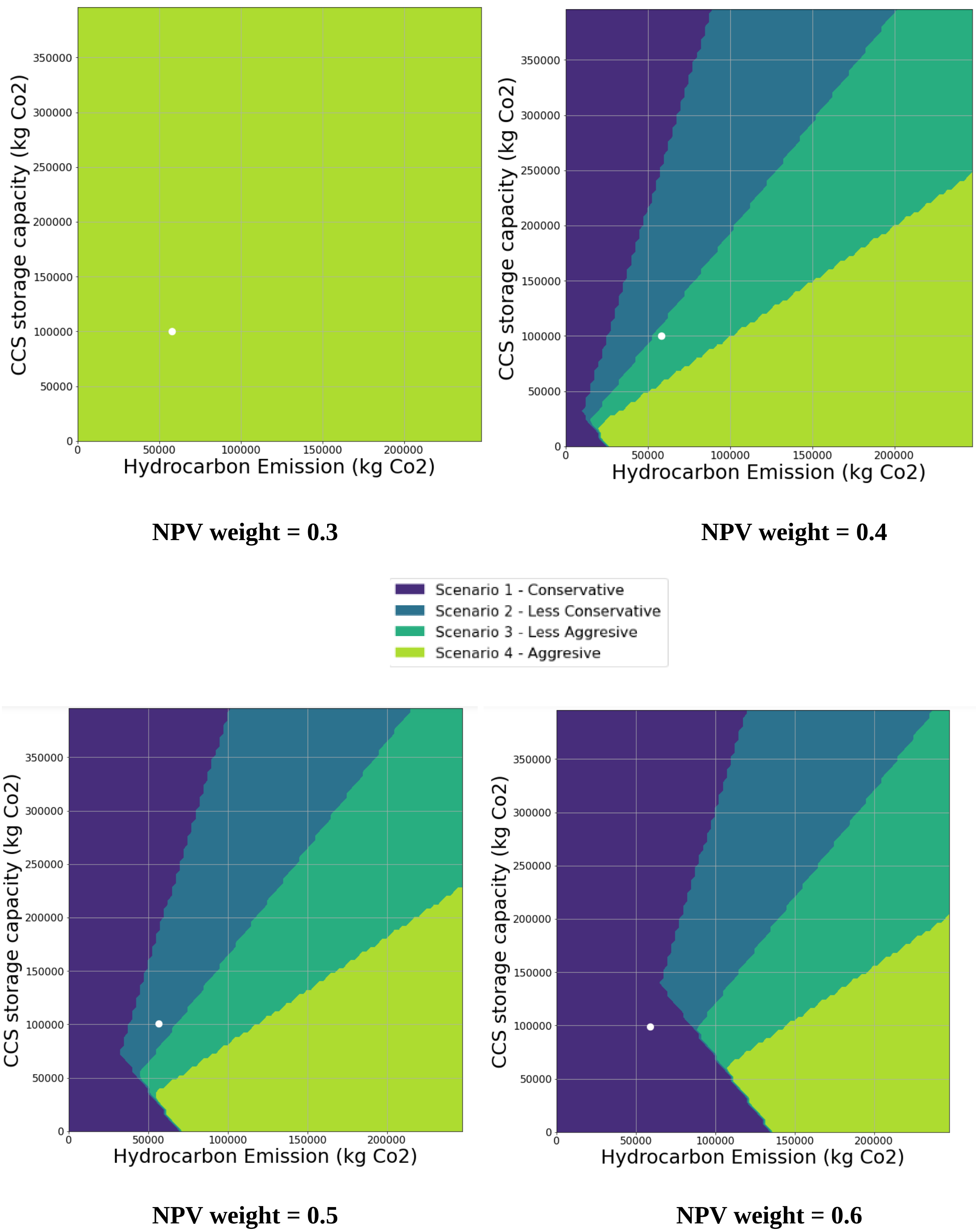


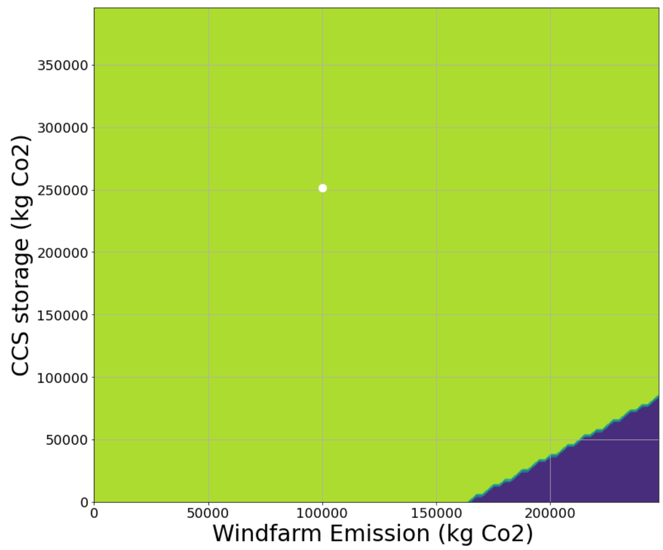
Figure 4.8: NPV weight, CCS storage capacity, and Hydrocarbon emission

In general, what is striking in the decision maps in Figure 4.8 is the continual growth in the area of Scenario 1 with increasing NPV weight. It confirms that the conservative scenario helps to fulfill the net profit maximization objective more than other investment strategies.

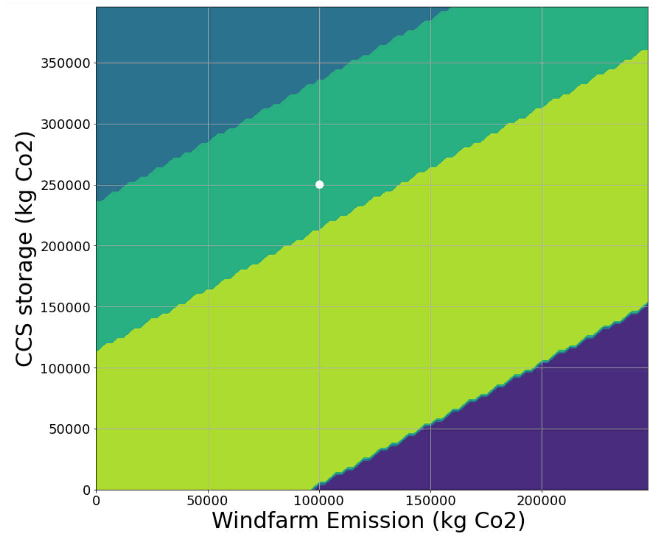
This case study shows the value creation derived from the interaction and flexibility of the uncertain decision model parameters and its significance in making good decisions. The robustness of the decision maps generated in Fig is that they can easily be used to assess the optimal decision for possible values of hydrocarbon emission, storage capacity, and preference weight (NPV, carbon reduction, and green reputation). Hence decision-makers can quantify the expected portfolio values and determine the optimal scenario to implement at any given target or constraint.

Let us consider the effect of the windfarm emission target and CCS capacity on the portfolio decision using similar decision maps in Figure 4.9.

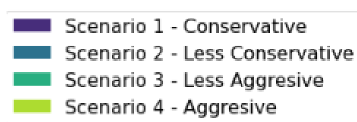
Similar to the approach used in the last section, we conduct a scenario analysis by developing decision maps showing portfolio values as functions of windfarm emissions and CCS capacities using different NPV weights. Fig illustrates that when the NPV preference weight is 0.3, the aggressive scenario dominates other scenarios. Although the conservative scenario is the optimal decision in the slices where the windfarm emission is more than 160,000 kg Co2 with a limited CCS capacity of less than 70,000 kg Co2, we observe that the area of the aggressive scenario is quite larger than the area of the conservative scenario. This explains that when the decision-maker is less concerned about maximizing net profit but more concerned with reducing net carbon emission and improving their green reputation, the aggressive scenario maximizes the portfolio value the most compared to other scenarios. However, as the decision-maker's preference for NPV increases by assigning an NPV weight of 0.4, a comparison of the decision maps generated for both 0.3 and 0.4 weights confirms a decision change across the maps. This is evident from the emergence of the less conservative and less aggressive scenarios as the optimal scenario for some slices in the decision map generated when the NPV weight is 0.4.

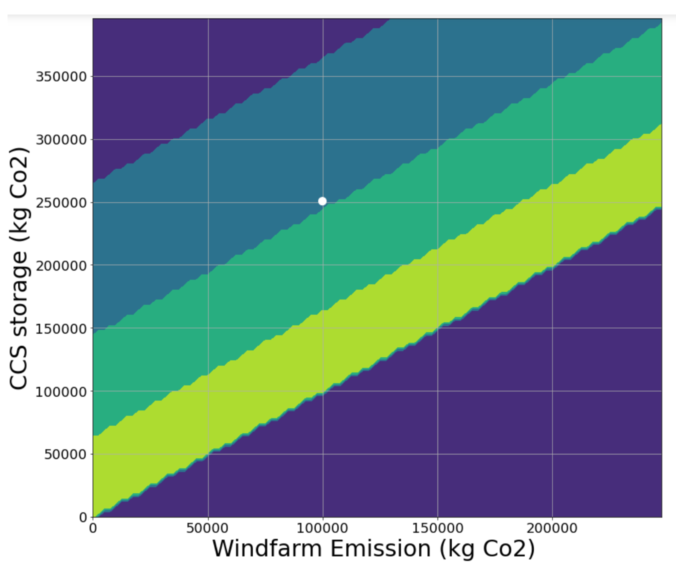


NPV weight = 0.3

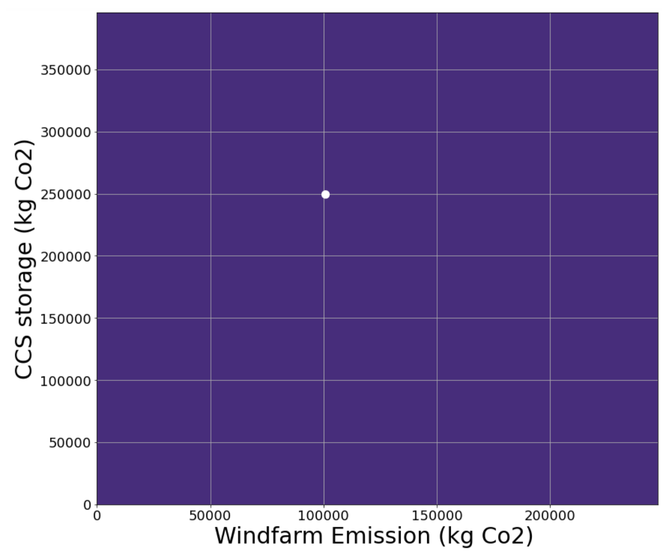


NPV weight = 0.4





NPV weight = 0.5



NPV weight = 0.6

Figure 4.9: NPV weight, CCS storage capacity, and Wind Farm emission

Particular attention should be paid to point Q in Figure 4.9, which corresponds to 100,000 kg Co2 windfarm emission and 250,000kg Co2 storage capacity. As the NPV weight increases across the four decision maps, the optimal portfolio changes from scenario 4 to Scenario 3, to Scenario 2, and to Scenario 1. The three-way sensitivity analysis of these maps shows that the optimal investment scenario can easily be visualized and decided given any combination of NPV weight, CCS storage capacity, and windfarm emission.

In Figure 4.8, as the NPV weight increases to across four decision maps, the area dominated by the conservative scenario grows bigger, while that dominated by the aggressive scenario shrinks. A possible explanation for this result is that the conservative scenario meets the net profit maximization objective more than other scenarios since its area grows as the NPV preference weight increases. On the other hand, the aggressive scenario forfeits the NPV maximization compared to other scenarios since its area reduces when the NPV weight increases.

4.5 Risk-Attitude Analysis

Previously, we conducted the multi-attribute decision analysis without considering risk aversion (i.e., the previous analysis is for a risk-neutral decision maker). In this section, we perform a risk-attitude analysis to model risk aversion in the portfolio model. An exponential utility function is used as a utility function to represent the decision maker's risk attitude and the uncertainty in the portfolio value. The exponential utility form is adopted in MAUT applications, and it models that the decision-maker has a constant risk aversion over the attribute range considered. The exponential utility function has only one parameter - the risk tolerance rho - which is a measure of the level of a decision maker's risk-aversion. The expected utility and certain equivalent were calculated for the possible outcomes of a decision alternative; then the decision alternatives are ranked based on their certainty equivalents (or expected utility).

Table 4.7: Expected Utilities and Certain Equivalents for rho =500

Scenarios	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected utility values	-0.9996	-0.9443	-0.9211	-0.9146
Certain equivalent	0.20	28.67	41.11	44.60

Table 4.7 illustrates the expected utility values, certain equivalent, and the order of preference for the investment scenarios. Note that the expected utilities and certain equivalent for all scenarios show that the decision-maker preferred Scenario 4 the most, followed by Scenario 3, Scenario 2, and Scenario 1 in that same order. This preference is similar to the result obtained in Table 4.5, if the decision-maker is risk-neutral, indicating that the decision-maker's risk tolerance does not impact the decision.

A sensitivity analysis was conducted to study the effect of changes in the company's risk tolerance on the portfolio results. Different values of risk tolerance bounded by a low and high value of 0 and 300, respectively, were generated. A smaller tolerance value signifies the company is more risk-averse, while a larger tolerance value signifies less risk-averse. As shown in Figure 4.10, the certain equivalent for each investment scenario are calculated and plotted against the risk tolerance. When the decision-maker's risk tolerance is in this range the range from 0 to 300, the risk attitude is not material to the decision because it will not change the investment. Therefore, Scenario 4 is the best investment scenario, given the company's risk attitude.

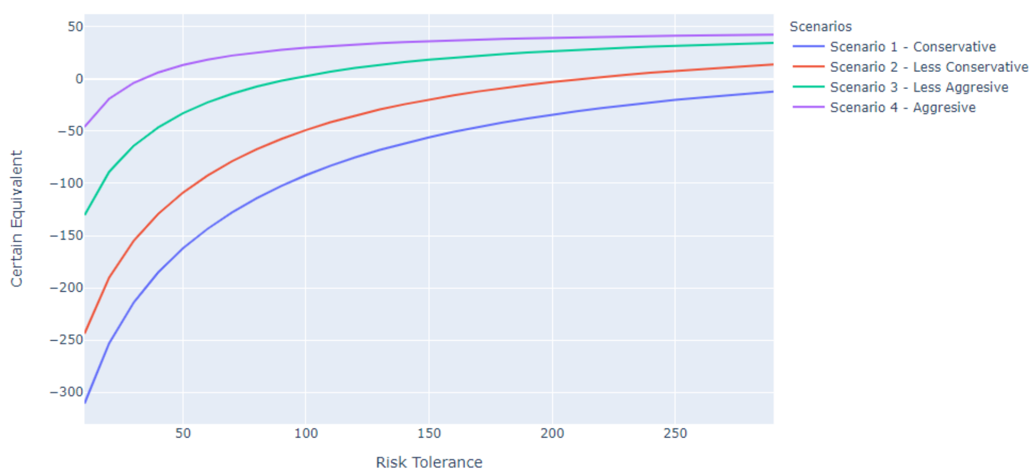


Figure 4.10: Sensitivity Analysis of Portfolio Decision to Risk tolerance

However, suppose the company considers a "no investment" option as a decision alternative; the certain equivalent for this scenario is estimated and plotted together with four other alternatives against the risk tolerance in Figure 4.11.

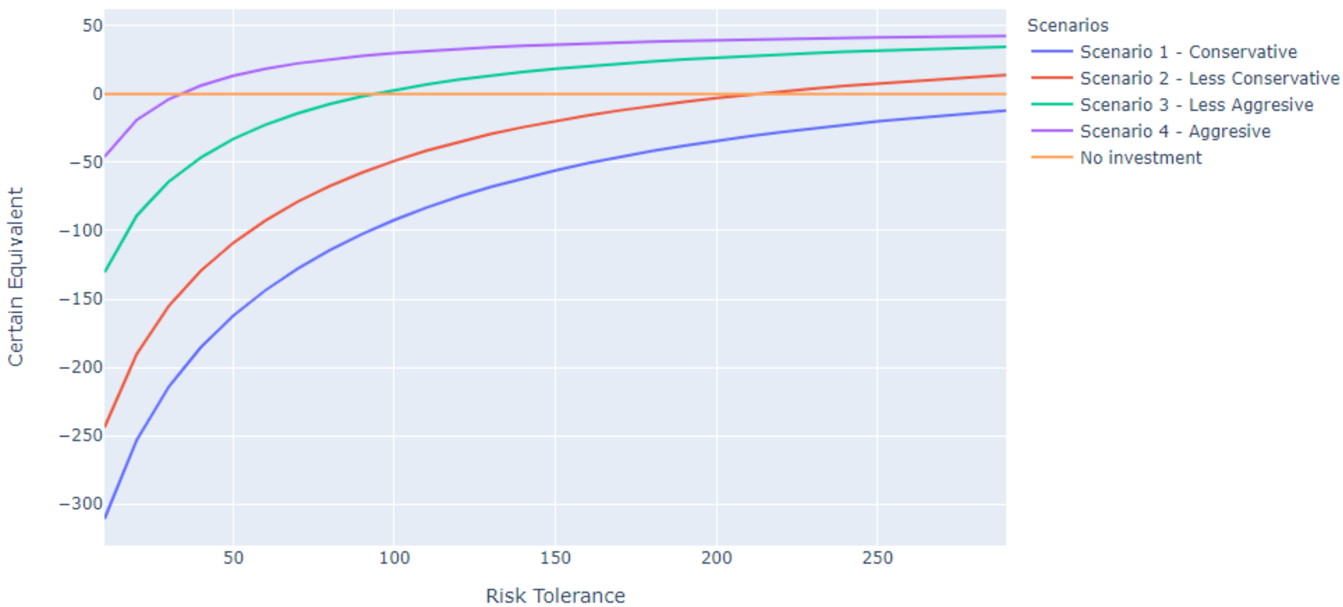


Figure 4.11: Sensitivity Analysis of Portfolio Decision to Risk tolerance with No Investment option

Figure 4.11 illustrates that if the company is very risk-averse, then they would prefer not to invest in any project as the "do not invest" scenario is the optimal decision because its CE is the greatest among the decision alternatives when the risk tolerance is less than 30. In this range, the company is concerned about the risk of losing portfolio value and prefers not to invest at all. However, if the company is less risk-averse (risk tolerance greater than 30), the company will implement Scenario 4, the aggressive scenario.

5 Conclusion

During the energy transition, the portfolio optimization problem becomes more complex because the oil industry now needs to consider more different types of projects and also multiple objectives. The main contributions of this work are:

1) Development of a decision analysis framework and workflow for optimizing the portfolio of investments in different energy and CCS projects.

2) Application and demonstration of the decision analysis framework and workflow with the consideration of a hydrocarbon, windfarm, and CCS project, multiple objectives, and risk attitude.

Oil and gas companies are continually looking for ways to optimize their portfolio and mitigate risks arising from several uncertain decision elements.

In this work, we presented a workflow to make high-quality decisions regarding energy investment strategies. This decision problem focused on multiple objectives; net profit maximization, carbon intensity reduction, and improving the company's green reputation.

The workflow includes the evaluation of the hydrocarbon assets, windfarm, and CCS assets, identification of key objectives and attributes, specifying possible investment scenarios, construction and implementation of the multi-objective function, and sensitivity analysis and decision mapping. Based on the evaluated assets available for selection, four investment scenarios centered on achieving energy transition at different accelerations are specified, and multi-attribute utility theory is applied to optimize investment portfolios. This approach was used to evaluate and compare these different investment scenarios and also to identify the optimal investment decision that is consistent with the decision maker's preference for each corporate objective. Furthermore, in the quest to generate more insight for high-quality decision-making, a sensitivity analysis was conducted that illustrated to what extent individual objectives impact the portfolio decision.

In order to achieve a more robust scenario analysis, decision maps were developed to visualize a bi and tri-parameter analysis of the portfolio values. This analysis can help the management board to understand the interaction of the decision criteria with one another in achieving the organizational goals rather than looking at each criterion individually.

For the decision problem framed in this work, the results of the portfolio analysis can help energy companies understand how their pace towards the transition impacts their organizational objectives and choose the optimal strategy most consistent with their preferences for each performance objective.

Although this decision analysis is based on a small hypothetical energy firm looking to make a good investment decision, the analysis can be extended to actual projects with cash flows, carbon emissions, and CCS storage assets for future studies.

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