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Abstract

Portfolio analysis and optimization has for the past several decades been applied in the oil & gas industry for asset allocation with the goal of maximizing corporate value creation. More recently, the traditional task of deciding between competing petroleum assets has evolved to include CCS (Carbon Capture and Storage) and renewable energy resource assets due to the change in the energy landscape. Although oil & gas companies realize that the energy transition is inevitable, what fossil fuel assets to divest and when to divest them is still open to question as (i) the pace of the energy transition remains undetermined and (ii) even if oil & gas demand and prices were predictable, the asset value consequences could vary as acting too slowly could lead to losses further down the road in addition to reputational problems and acting too quickly could destroy value for shareholders without contributing to emission reductions.

In this work, we have implemented a multi-objective, time-dependent portfolio model to inform and support an oil & gas company's strategic decisions for successfully managing the energy transition. These decisions include several strategies such as reducing the fraction of the overall revenues stemming from fossil fuels and increasing ownership in carbon reduction technologies. The model can easily be extended to include renewable geothermal and solar assets, investments in blue or green hydrogen or negative emission technologies. Given the high uncertainty in future supply and demand for both fossil and renewable energy, the optimal portfolio at any point in time is highly uncertain and must be flexible enough to change over time whilst still meeting the specified objectives.

The main contribution of the work is a decision framework and model to aid oil & gas companies in their energy transition efforts. The portfolio optimization and management model has been developed in Python. It identifies optimal portfolios from a pool of potential petroleum and carbon reduction projects. These projects include traditional oil & gas producing assets, wind farms and CCS (Carbon Capture and Storage) assets. Although upstream oil & gas portfolio optimization methods have been presented in the literature, none of these addresses the carbon reduction objective and the ability to compare petroleum and non-petroleum assets in a portfolio context. Hence, the main advantage of this work is that it provides a unified and comprehensive framework for inclusion of multiple energy related assets in a time-varying and multi-objective portfolio

assessment model, with a focus on energy transition and meeting the net-zero carbon emission ambition of oil & gas companies.

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1. Introduction

The energy transition consists of a global shift in the energy sector from carbon-intensive energy production, such as coal, oil, and natural gas, to renewable and clean energy sources, including wind, solar, and water. The ultimate objective for a company embarking on the energy transition is to minimize greenhouse gas (GHG) effects by reducing carbon emission intensities from fossil-based producing systems.

Supported by a prevalent social and environmental push towards sustainability, the energy transition is primarily driven by electrification and renewables growth (McKinsey, 2021). The fast penetration rate of renewables into the energy mix will result in structural changes in the energy supply and demand, fluctuations in the oil and gas prices, and increased operation and production costs once more sustainable processes have been adopted. Given that the oil and gas (O&G) industry is held responsible for significant carbon emission intensities from both its upstream and downstream operations, bold visions and integrated balanced portfolio adoption have become the center of attention of many O&G companies.

In addition to oil production reduction, minimizing emission from the O&G sector requires the development of green energy alternatives, such as wind power, solar, geothermal, etc., and/or technologies allowing better use of traditional fossil-based energy sources, such as Carbon Capture and Storage (CCS).

As O&G companies face increasing pressure to respond to the energy transition, they must consider various options. Choosing which petroleum assets to invest in, which carbon reduction technologies are the most feasible, and when to embark on the energy transition journey are questions yet to be determined for some companies. Although the direction of change of the energy landscape is given, there are still unsolved challenges ahead, for which price expectations, oil and gas demand predictions, technology innovations and developments, and energy transition pace are key determinants. The implications of this for investment decisions and the company's performance and reputation remain open to question. Moving too slowly or refusing to change could lead to losses in shareholders' trust, as more investors seek confidence and transparency in accounting for climate change exposure in the long term. On the other hand, moving too quickly could result in stranded assets, especially since green technologies' technical and economic feasibilities remain uncertain.

Managing and succeeding in the energy transition requires a relevant and flexible decision framework and model that allows O&G companies to evaluate and compare alternate strategies. As those strategies are based on possible asset combinations that will vary over time, a time-dependent multi-objective portfolio model is proposed in this thesis. Although upstream O&G portfolio optimization methods have been presented in the literature, none of these addresses the carbon reduction objective and the ability to compare petroleum and non-petroleum assets in a portfolio context. Hence, the main goal of this thesis is to provide a unified and comprehensive framework for inclusion of multiple energy-related assets in a time-dependent multi-objective portfolio assessment model, with a focus on energy transition and net-zero carbon emission ambition of O&G companies.

For the realization of this objective, the remaining chapters will cover the following topics:

- In Chapter 2, key aspects of the decision-making problem are covered. The proposed framework includes an overview of the portfolio objectives, decision variables, and performance goals. Moreover, the uncertain nature of the problem and the project's dependencies in the portfolio analysis context are discussed.
- Chapter 3 introduces the traditional "rank and cut" method of asset selection and provides an overview of the Modern Portfolio Theory, also known as Markowitz's Theory, widely used in the financial market. In addition, the multi-objective portfolio analysis problem is formulated, and the concept of Pareto optimality is introduced. Then the chapter gives a brief review of several techniques to solve the multi-objective portfolio problem, such as the weighted-sum method and the multi-attribute utility theory. This thesis's proposed time-dependent goal-seeking approach is also described in detail, emphasizing the critical interactions between business investments and corporation strategies.
- Chapter 4 is divided into three major parts, each covering one type of asset considered in this work. O&G project attributes are calculated in the first part, including annual production, carbon emission intensities, and economic metrics. Then the second part covers wind farm assets evaluation using operational and financial attributes. Finally, an overview

of the CCS technology is introduced, as well as an assessment of its technical and economic potential. All three evaluation models were developed in Python.

- In Chapter 5, the proposed portfolio analysis approach is applied to a set of hypothetical assets, including both petroleum and non-petroleum projects. Different corporate strategies are evaluated and compared to one another. A discussion about the degree of operational and economic trade-offs imposed on O&G companies in the energy transition context is also presented.
- Chapter 6 gives an overview of this thesis and concludes the work presented. Some recommendations and possible research areas are proposed.

2. Overview of the Project Portfolio Optimization Problem

Project portfolio optimization refers to a wide range of optimization tasks since the term "project" is extensive and used in several contexts across different industries. In this study, a project is described as a plan that requires money, time, and other resources, with a primary objective to create value and returns for the shareholders. A portfolio consists of several projects. Portfolio optimization aims to find the optimal combination of projects expected to generate the best outcomes given the decision maker's objectives.

The literature on portfolio optimization is quite rich, which is not surprising given the generality of the concept. While much work has been presented and discussed for portfolios of traded shares and financial markets, the literature discussing portfolio analysis for real projects, including applications in the O&G industry, has grown over the past several decades. Articles related to this topic are reviewed and discussed later in this thesis.

This section will focus on portfolio theory relevant and useful in the O&G sector, reviewing different aspects of the portfolio decision-making problem. First, the objectives of the portfolio are defined, covering both single and multi-objective optimization problems. Then, an overview of the decision variables and performance goals is presented to determine the type of optimization problem needed to assess. The fact that many of the key inputs to the problem are uncertain requires an understanding of uncertainty quantification to evaluate the impact of these uncertainties on future portfolio performance.

2.1. Objectives

In any organization, the executed projects must all together meet the management team's objectives to achieve the organization's goals and targets. This could be increasing net present value (NPV), reducing carbon emission, cutting costs, enhancing safety measures, etc. However, in such contexts, companies face two main challenges. First, the corporation has access to limited capital supply, where budgetary constraints are imposed either on the whole organization or individual units. Luenberger (1998) states that the assumption suggesting unlimited capital supply does not hold in the O&G sector. Unlike what's commonly assumed in financial theory, not every project with a positive NPV can be funded. Second, some of the goals suggested can conflict with each other. For example, the oil production increase objective might be restricted by the company's goal of reducing carbon emission. Bratvold & Begg (2010) addressed this difficulty by first classifying the objectives into two categories, using natural divisions based on the required tradeoffs. Then, a weighted score for each class is calculated. One example could be the use of cost and benefits as division categories. Next, the decision-maker needs to cross-plot the weighted benefit/cost pairs for each alternative. This plot illustrates the dominance of one alternative over the others. It helps the decision-maker assess his willingness to trade off the variation in benefit for the variation in cost. A fuller discussion about dealing with conflicting objectives can be found in Bratvold & Begg (2010).

Therefore, an optimal portfolio should balance particular objectives while maximizing the overall value to prevent the overperformance of one unit of the corporation at the expense of other departments. In addition, even if the optimal portfolio doesn't meet individual objectives at a given time, it should always align with the company's long-term strategic direction (Cooper et al., 1997).

The selection of objectives in terms of their nature and number constitutes the multi-dimensional aspect of the optimization problem. Several attributes are discussed in the literature for O&G portfolios, suggesting the presence of both economic and operational metrics (DuBois, 2001). Financial performance metrics include undiscounted cash flow, earnings before interest tax depreciation and amortization (EBITDA), net present value (NPV), profitability index (PI=NPV/Capex), etc. Some common non-financial metrics used in the literature are annual O&G production and reserves volumes.

Given the current change in the energy landscape, the transition to cleaner energy solutions is now inevitable. Investors are looking for investments that minimize their climate change exposure and reduce the possibility of stranded assets (McKinsey, 2021). This has motivated O&G companies to set net-zero emission targets and diversify their portfolios, focusing on a mix of petroleum and non-petroleum assets. This is illustrated by these facts about a few of the O&G players:

- ExxonMobil (2020) introduced its carbon emission reduction plan, targeting a 15-20% drop in upstream operations emission intensity by 2030 by investing in low emission technologies and supporting local and international policies on carbon pricing.

- Shell (2020) presented a carbon management approach to reach a 20% reduction in carbon intensity by 2030 and 100% by 2050. In addition, the company seeks to deliver this goal by rebalancing its portfolio, where $2-3 billion are expected to be invested annually in Renewables and Energy Solutions.

- Equinor (2020) announced its Climate Roadmap that includes accelerated decarbonization by CCUS (Carbon Capture, Utilization, and Storage), profitable renewables growth, and integrated carbon-efficient O&G production. It aims to reach a 40% emission reduction by 2030 and 100% by 2050.

- Vår Energi (2020) discussed ways of reducing greenhouse gas emissions to reach a 40% emission cut by 2030 and 100% by 2050. The company aims to increase platform electrification, implement low emission technologies, invest in carbon capture and storage, and use renewable energy.

From these examples, we can conclude that the companies consider carbon reduction an essential means of maximizing shareholder value.

Typically, the objective performance is assessed for both individual years and over the whole period of the portfolio planning horizon. Objectives may be set as the "primary objective" or as an "objective function," while other objectives are formulated as constraints. In some cases, authors assign different weights to several objectives and monitor the portfolio's performance on the objective function. In a highly constrained optimization problem, the algorithm might fail to find an optimal solution; therefore, a penalty function must be introduced. The penalty function is added to the objective function and uses a penalty multiplier to measure the violation of each constraint (Anescu, 2017). More details about problem formulation (mathematical program) are presented in section 3.

2.2. Structuring

The purpose of this section is to frame the optimization problem and identify the decision variables. Information going beyond the scope of this thesis will be omitted from the portfolio analysis to avoid problem complexity. Bratvold & Begg (2010) suggest that decisions can be divided into three categories: *policy*, *strategic and operational*.

Policy decisions are assumed to be defined prior to the portfolio analysis; hence, they will not be included in the optimization problem. Such decisions include:

- Geographical diversification: decisions regarding the location (region/country) of the assets. All projects are assumed to be in Norway, covering both onshore and offshore areas.
- Resource diversification: for petroleum assets, only conventional O&G projects are studied. Shale extraction and liquefied natural gas assets are not included in this work.
- Renewable energy and carbon reduction technologies: wind farms (onshore and offshore) and carbon capture and storage (CCS) are the only two non-petroleum projects considered in this thesis.

Strategic decisions are taken in the context of the portfolio analysis are completely in the decision-maker's control. In general, portfolio optimization problems utilize binary strategic decisions for each asset to choose whether the decision-maker should invest or not in a specific project. However, in the O&G context, decision variables go beyond the "invest/don't invest" scheme, allowing the decision-maker to find the optimal working interest needed for each asset. In addition, given that projects, in general, will have different starting periods, the optimal time to invest is added as a decision variable. This approach is expected to be critical when working with the carbon reduction objective, as companies have solid targets for emission intensities in a given period. The following decisions must be considered (Walls, 2004; Wood, 2001):

- Working interest: which assets should the company invest in to maximize value? And what fraction of the overall project should be considered?
- Time to invest: when should the company invest in each of the chosen projects?

Typically, *operational decisions* are addressed after the portfolio selection process and focus on the "how-to-do-it" question rather than the "what-should-we-be-doing" decision (Bratvold & Begg, 2010). Examples of operational decisions include:

- Application of secondary or enhanced oil recovery technologies to boost hydrocarbon production.
- Partnerships possibilities at a portfolio or individual assets level, through joint ventures (JVs), acquisitions, collaboration with niche technology firms or R&D institutions, etc.
- Electrification of operating hydrocarbon assets.

Other elements of the portfolio optimization problem include the company's goals and constraints. Decision-makers set the goals to assess the performance of individual assets, as well as the overall portfolio. As mentioned earlier in the objectives section of this report, the goals can be set on a cumulative basis (over the entire project) or an annual basis. It's important to distinguish between what is considered a goal for the objective function and what constitutes a constraint. Wood (2016) states that goals are aspirations that the portfolio can either achieve or not, while constraints are limits that cannot be ignored. An optimal portfolio should therefore satisfy all the constraints.

Some common constraints found in the literature include capital investment limit, minimum working interest applied to a specific asset, minimum hydrocarbon production, reserves volumes limit, maximum carbon emission, and human and technology constraints associated with the availability of qualified employees or relevant technology.

As the number of constraints applied increases, fewer asset combinations are expected. In some cases, the optimization algorithm might fail to find an optimal solution that satisfies the constraints involved. Therefore, the decision-makers must restate the company's goals and adjust their strategy on an iterative basis to potentially find a feasible solution.

2.3. Uncertainties

In the optimization problem of O&G portfolios, not all information is deterministic. Some information used might be from unknown sources or based on estimations and judgments. Often, the estimation of one parameter might have a significant impact not only on the net present value but on the overall portfolio's performance. Rose (2004) showed that most O&G companies delivered less than half of their reserves estimates during the last few years of the 20^{th} century.

Therefore, understanding and quantifying uncertainties are essential in a portfolio optimization context.

Two types of uncertainties are reported in the O&G industry: underground and aboveground uncertainties (Brashear et al., 1999). Underground uncertainties include reservoir and fluid properties and are dominant in estimating the oil initially in place (OIIP). Aboveground uncertainties represent estimations of cash flow variables, hydrocarbon price forecast, carbon emission intensities, etc. In this work, the OIIP calculation was omitted, where reserve volumes were considered input parameters (modeled later as distributions) for each asset.

Monte Carlo simulation (MCS) was used in this thesis to integrate uncertainty analysis into both asset and portfolio evaluation. MCS is a very popular and robust application in the petroleum field and was initially introduced by Hess & Quigly in 1963 and Hertz in 1964 to generate NPV distributions. It represents the uncertainty propagation from input variables that can be evaluated to variables needed in the decision-making analysis (Bratvold & Begg, 2010). A literature review shows various applications of the MCS in the O&G sector, including exploration and production real options analysis (Willigers & Bratvold, 2008), reservoir simulation modeling (Cremon et al., 2020), and portfolio optimization problems (Bulai & Horobet, 2018; DuBois, 2001; Orman & Duggan, 1999; Wood, 2001; Wood, 2016; Xue et al., 2014).

An MCS requires a choice of a probability distribution for each uncertain parameter and will generate a distribution for individual output variables (such as NPV, carbon emission, etc.). Various studies have been performed on specific variables such as costs, prices, and other well performance attributes, and the corresponding distributions have been established. Examples include triangular distributions for well unit costs estimation and uniform distributions for production time-variables assessment. In this thesis, when no information could be found on the probability density function of the uncertain parameter, a PERT distribution was used. The PERT distribution, a version of the Beta distribution, is a continuous probability distribution that takes as input the mode and the upper and lower bounds of a variable. The advantage of using the PERT distribution, rather than the triangular, is that the former generates a smoother curve by emphasizing values around the mode rather than the bounds (edges). This implies a higher trust in the most likely value while considering the deviations towards the edges (Salling, 2007). Since the

PERT distribution is not part of the statistical functions (scipy.stats) library in Python, it has been derived using a transformed four parameters Beta distribution.

Some studies have been conducted to analyze the impact of uncertainty quantification (for example, using MCS) on the portfolio selection process of an O&G company. Wood (2001) stated that the accuracy of uncertainty measures derived from MCS results depends on the number of iterations used and how representative and comprehensive the model is. Begg & Bratvold (2008) investigated the impact of prediction errors on portfolio selection in the petroleum field. They concluded that even though biases are present in the analysis, they are not considered significant, particularly compared to other prediction errors. In addition, their results showed that a higher number of projects selected in the portfolio would lead to an increase in the expected disappointment. McVay & Dossary (2014) suggested that all biases present in an O&G portfolio analysis model can be divided into two main categories: overconfidence and directional biases. They showed that a moderate degree of overconfidence would result in a 30-35% expected disappointment and 1-5% decision error of estimated NPV. However, at significant overconfidence levels, the disappointment might reach 100% of estimated NPV.

2.4. Correlations

In this work, dependencies have not been discussed so far. The assumption of independent probability distributions of the variables doesn't hold in reality. In an MCS model, dependencies can often be captured by correlations.

Usually, correlations can be classified into two categories: inter-project and intra-project. Inter-project correlations represent dependencies between different projects at a portfolio level. O&G prices are considered the primary source of inter-project correlations as all assets are evaluated using the same hydrocarbon price in portfolio analysis. Since our work includes non-petroleum assets, energy price and carbon pricing policies can also act as sources of inter-project correlations. In addition, geological similarities, shared infrastructures, and similar political and fiscal regimes might increase the degree of correlations between two separate assets, impacting the overall portfolio's volatility.

On the other hand, correlations between input variables to individual projects are classified as intra-project correlations. Examples include the relationship between reserves volumes and capital expenditure (Capex), water saturation and permeability, reservoir thickness and area, etc. When building the projects' production and economic models, the decision-maker tries to include those correlations using functional relationships into the model's equations. For example, in this work, the Capex structure presented was based on reserve volume estimates. However, given the complexity of the petroleum assets structures, it's hard to include all intra-project correlations into the model's equations.

Correlations between input parameters in the petroleum sector have received some attention in the literature. Costa Lima et al. (2012) presented a method for estimating linear correlations between O&G projects. They concluded that fixed and variable costs and oil quality are the most significant determinants of the correlation. They also investigated the impact of correlations between two projects on the efficient frontier and risk reduction[1] by diversification, based on Markowitz's portfolio theory (section 3). The authors suggested that by diversifying (allocating different fractions of the budget to various projects), the portfolio risk is reduced. And as the correlation between the projects decreases, the possibility of risk reduction by diversification is improved. However, it's important to note that only linear correlations were assumed in their study, and only two assets were considered.

Jafarizadeh (2010) introduced a financial factor model to estimate the covariance between variables in a risk-neutral valuation study. He concluded that changes in economic forces (such as O&G prices, steel prices, carbon prices, etc.) would change all micro-variables used in the project simulation. However, the author stated that the final investment decision wouldn't change by including correlations in the analysis in some cases. Xue et al. (2014) suggested that the production profiles of individual projects are independent of each other. Only the following economic parameters dependencies on the yearly bench prices were included in their model: yearly sales prices, yearly Capex, and yearly Opex.

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[1] In financial portfolio optimization, the standard deviation is the most common measure of risk

In reality, dependencies in the petroleum field are very diverse. Hence, it's interesting to assess the added value of integrating all correlations in large-sized portfolios. Further research needs to be done to understand whether the higher degree of complexity in the problem is compensated by improved results quality. However, this analysis is out of the scope of this thesis. Only a limited number of correlations are used in this work, following what's common in the literature.

3. Portfolio Optimization Methods in the O&G Industry

3.1. Rank and Cut Approach

The rank and cut method, also known as the capital rationing approach, is widely used in the O&G industry because of its simplicity in generating "good enough" rankings and portfolios. It's a single-objective optimization method using a single portfolio constraint that allows the decision-maker to evaluate various portfolios while addressing budget limitations. Since companies don't have the required capital to invest in all feasible (positive NPV) projects, a capital allocation method is required to select the portfolio, optimizing the objective function given the capital constraint.

In this approach, the performance metric is first established, which is the objective function that the decision-maker needs to optimize. Examples include maximizing overall NPV, minimizing total Capex, minimizing overall carbon emission, etc. Second, the assets are ranked and ordered according to their respective contributions to the objective function. Then the constraint is selected, and the projects are accumulated to be funded until reaching the constraint limit. Therefore, a 100% working interest is assigned to all selected projects, except the last one, which might receive partial funding (Wood, 2016).

We will now illustrate the rank and cut method through an example using a hypothetical portfolio of 10 projects (Table 3.1 andTable *3.2*).

In Table 3.1, the objective function was to maximize the profitability index (PI), derived from the ratio of E[NPV]/Capex. Assets ranked #1 to #6 were fully funded (100% working interest), and they accumulated for a total Capex of $3672 million. The remaining $328 million were allocated to project #5 (ranked #7), which had a working interest of 21.2%. The remaining assets were thus excluded from the portfolio. As the budget constraint becomes more severe, less projects will be selected.

Table 3.1: Rank and Cut Optimization for NPV Maximization

Objective Function: PI maximization

Asset Ranking Criteria: PI (=NPV/Capex)

Capex Constraint: $4000 million

Project	Ranking	E[NPV] ($ million)	E[emission] (million t CO_2)	Capex ($ million)	Profitability Index (PI)	Portfolio weight (%)
P1	10	420.00	0.68	742.00	0.56	0.00
P2	3	650.00	0.51	324.00	2.00	100.00
P3	2	885.00	0.46	381.00	2.32	100.00
P4	8	1025.00	1.22	862.00	1.19	0.00
P5	7	2312.00	3.19	1547.00	1.49	21.20
P6	4	1784.00	0.98	994.00	1.79	100.00
P7	6	367.00	0.23	225.00	1.63	100.00
P8	1	1546.00	1.05	607.00	2.55	100.00
P9	9	557.00	0.65	696.00	0.80	0.00
P10	5	1896.00	2.48	1141.00	1.66	100.00

In Table 3.2, a different objective function was chosen to illustrate the variation of the portfolio's selection with the optimization parameter. In this case, the objective was to minimize the CO_2 emission, and the ranking criteria chosen was the expected carbon emission (E[emission]) from individual assets. As shown in Table 3.2, only four projects were fully funded, while project #1 was allocated a share of 22.07%. Some of the assets selected for PI maximization were excluded when the objective function changed. This result was expected as different ranking criteria metrics would result in different ranking orders of the projects, reflecting the limitation of the rank and cut method in complex scenarios (Wood, 2016).

In addition to the inability of the rank and cut method to account for multiple objectives and multiple constraints on a portfolio level, this approach ignores correlations between projects and the "time to invest" decision parameter. However, given its simplicity and ease of use and application, this method provides a good starting point for future optimizers.

Table 3.2: Rank and Cut Optimization for Emission Minimization

Objective Function:	Carbon Emission minimization				
Asset Ranking Criteria:	E[emission]				
Emission Constraint:	2 million tons CO_2				
Project	Ranking	E[NPV] ($ million)	E[emission] (million t CO_2)	Capex ($ million)	Portfolio weight (%)
P1	5	420.00	0.68	742.00	22.07
P2	3	650.00	0.51	324.00	100.00
P3	2	885.00	0.46	381.00	100.00
P4	8	1025.00	1.22	862.00	0.00
P5	10	2312.00	3.19	1547.00	0.00
P6	6	1784.00	0.98	994.00	0.00
P7	1	367.00	0.23	225.00	100.00
P8	7	1546.00	1.05	607.00	0.00
P9	4	557.00	0.65	696.00	100.00
P10	9	1896.00	2.48	1141.00	0.00

3.2. Mean-Variance Approach

The mean-variance approach is based on Markowitz's Nobel Prize winning work, also known as Markowitz's Portfolio Theory or Modern Portfolio Theory (MPT), published in 1952 (Markowitz, 1952). MPT is a risk versus return consideration that allows the decision-maker to consider how much expected NPV he/she is willing to give up in return for reduced risk (standard deviation) or how much risk he/she is willing to take on for a given increase in expected NPV.

Markowitz (1952) states that its proposed optimization theory can either minimize the risk of an expected return or maximize the expected return of a given risk by carefully selecting the working interests of several assets.

Markowitz presented the theory in the context of financial markets. Later, the MPT has been applied on real projects that were not traded in the financial market, such as aerospace and electricity generation assets. Literature shows significant applications of the MPT to the petroleum industry, given the high degree of risk associated with investments in this sector (Xue et al., 2014). Several authors illustrated the advantages of adapting the mean-variance approach in assets' selection of an O&G portfolio, given its simplicity and effectiveness (Ball & Savage, 1999; Bratvold et al., 2003; Jafarizadeh, 2010; Zhen & Wang, 2008). However, differences between the stock market and the oil industry raise some concerns related to MV optimization in non-financial assets. Key distinctions between the two application areas can be summarized in the following five categories: risk indicators, periods, type of uncertainties, market characteristics, and impact of budget constraints (Ball & Savage, 1999; Walls, 2004; Xue et al., 2014). In addition to the return target and budget constraint, some petroleum companies consider other goals and objectives, such as reserve volumes and annual production. In such situations, the multi-objective feature of the optimization problem can result in the absence of a feasible solution (Bulai & Horobet, 2018).

MPT defines risk as the standard deviation of the portfolio NPV distribution. It seeks to lower the variance of the portfolio return that is modeled as the weighted combination of individual asset's returns. Markowitz presented the concept of "efficient frontier," illustrated in Figure 3.1. The efficient frontier is a combination of all risky investments that maximize the investor's returns for a given degree of risk or alternatively lower the level of risk for a given value of return. As the standard deviation is increasing, the increase in return diminishes and approaches zero. The feasible portfolios lying below the efficient frontier can have the same risk as those of the efficient frontier; however, their overall returns will be lower. Hence, even though they are feasible, they are no longer considered efficient (Mutavdzic & Maybee, 2015).

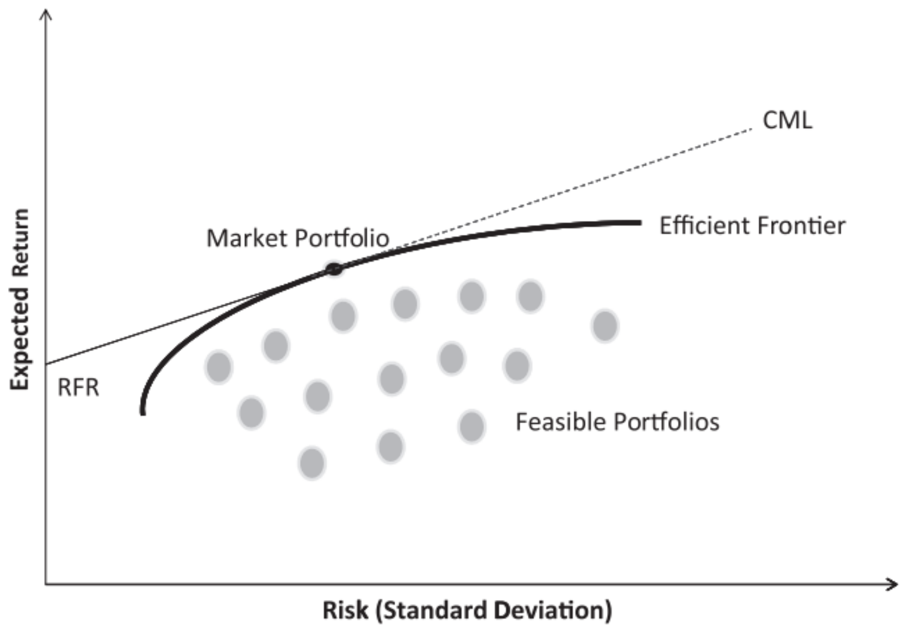

Figure 3.1: Efficient Frontier and CML (adapted from Mutavdzic & Maybee (2015))

Markowitz based his theory on the assumption that investors are risk-averse. If two investments have the same expected value of return, investors will select the investment with the lowest level of risk. However, the degree of risk aversion differs between companies and is often driven by various factors, such as the availability of wealth/risk capital (Mutavdzic & Maybee, 2015). To secure a certain amount of cash in hand, the investor in a risky asset would be ready to divest himself at a price equal to the certain equivalent. Using an exponential utility function to represent the decision maker's risk attitude, the certain equivalent (C_x) of each asset is given by:

$$C_x = -RT\ ln\left\{\sum_{i=0}^{n} p_i e^{-\frac{x_i}{RT}}\right\} \tag{3.1}$$

where:
C_x: certain equivalent
RT: risk tolerance
p_i: probability of outcome i
x_i: value of outcome i
n: total number of possible outcomes

Considering n assets and a period J, the mean and variance of returns of each asset can be calculated using historical data as follows:

$$\mu_1 = \frac{1}{J}\sum_{j=1}^{J} R_{1j}, \quad \mu_2 = \frac{1}{J}\sum_{j=1}^{J} R_{2j}, \quad \dots \quad \mu_n = \frac{1}{J}\sum_{j=1}^{J} R_{nj} \tag{3.2}$$

$$\sigma_1^2 = \frac{1}{J}\sum_{j=1}^{J}\left(R_{1j} - \mu_1\right)^2, \ \sigma_2^2 = \frac{1}{J}\sum_{j=1}^{J}\left(R_{2j} - \mu_2\right)^2, \ \dots \ \sigma_n^2 = \frac{1}{J}\sum_{j=1}^{J}\left(R_{nj} - \mu_n\right)^2 \tag{3.3}$$

where:
i: project number; i = 1,…, n
j: time along the period J (year, month, day, etc.); j = 1,…, J
μ_i: mean of project i
σ_i^2: variance of project i
R_{ij}: return value of project i at time j

The expected value ($E[P]$) and variance ($Var[P]$) of portfolio return are calculated as follows:

$$E[P] = \sum_{i=1}^{n}(x_i R_i) \tag{3.4}$$

$$Var[P] = \sum_{i=1}^{n}(x_i \cdot \sigma_i^2) + 2\sum_{i=1,k=1}^{n}(x_i \cdot x_k \cdot cov(R_i, R_k)) \tag{3.5}$$

where:
x_i is the participation of asset i in the portfolio
$cov(R_i, R_k)$: covariance of R_i and R_k, given by the following formula:

$$cov(R_i, R_k) = E[(R_i - \mu_i)(R_k - \mu_k)] \tag{3.6}$$

Presenting the results in vector form, the participation (x), expected return (μ) and covariance matrix (S) can be written as follows:

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix}, \ X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \ S = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \cdots & \sigma_{2n} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \cdots & \sigma_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{n3} & \cdots & \sigma_{nn} \end{pmatrix} \tag{3.7}$$

Hence the portfolio variance can be written as:

$$Var[P] = X^T S X \tag{3.8}$$

The portfolio optimization problem can have four main classifications:

- Portfolio risk minimization subject to a target expected return:

$$\min_X X^T S X \tag{3.9}$$

subject to:

$$X^T \mu = \mu_{target} \tag{3.10}$$

- Portfolio risk minimization subject to a specific target of various attributes:

$$\min_X X^T S X \tag{3.11}$$

subject to:

$$X^T G = G_{target} \tag{3.12}$$

where: $$G = \begin{pmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \end{pmatrix} = attribute\ vector$$

- Portfolio return maximization subject to a target degree of risk:

$$\max_{X} X^T \mu \tag{3.13}$$

subject to:

$$X^T S X = \sigma^2_{target} \tag{3.14}$$

- Portfolio optimization of the ratio between risk and return, subject to a given risk tolerance factor (λ):

$$\min_{X} X^T S X - \lambda X^T \mu \tag{3.15}$$

where: $\lambda \in [0, \infty)$

MPT promotes asset diversification to protect investors from both market risks and risks associated with the specific company. A more consistent and smoother return on investment is expected by diversification over the medium to long term. Markowitz suggests that understanding the relationship between various stocks can reduce risk exposure. If the assets (or stocks) are positively correlated, less risk reduction by diversification is expected. In contrast, negatively correlated assets increase the risk reduction effect of diversification. Therefore, assets should not be picked individually, but rather it's important to account for an asset's variations with prices relative to changes with prices of all other assets in the investment portfolio (Omisore et al., 2012).

As opposed to the rank and cut method, the mean-variance approach allows for correlations between assets. And as the correlation decreases, the possibility of risk reduction by diversification is improved. However, the MPT does not consider the "when to invest" decision variable and requires quadratic programming algorithms that might increase adaptation complexity. Yu et al. (2009) suggested that to build an optimal portfolio, it's recommended to first select good quality assets using multi-attribute analysis (section 3) and then use the mean-variance model to optimize asset allocations. They based their approach on the fact that Markowitz's theory doesn't account for the assets' characteristics and hence doesn't allow the investor to assess the quality of the pre-determined assets.

Given the limitations of the MPT, extended models have been developed, such as the mean target model (Fishburn, 1977), mean absolute-deviation model (Simaan, 1997), mean semi-variance model (Mao, 1970), mean variance-skewness model (Yu et al., 2008), etc.

3.3. Multi-Objective Optimization

Portfolio optimization problems in the O&G industry often involve multiple objectives and multiple constraints; hence, multi-objective portfolio optimization is needed, going beyond the traditional single-objective or bi-objective approaches.

The multi-objective optimization concept was first introduced by the French-Italian economist Pareto. His theory combines all objectives into one objective function, and a standard solution method of minimizing the total objective is applied:

$$\min F(x) = [f_1(x), f_2(x), \dots, f_m(x)] \tag{3.16}$$

subject to:

$$G(x) = [g_1(x), g_2(x), \dots, g_k(x)] < 0 \tag{3.17}$$

$$H(x) = [h_1(x), h_2(x), \dots, h_l(x)] = 0 \tag{3.18}$$

where:
$F(x)$: vector of m objective functions
$f_i(x)$: objective function i for $i = 1, \dots, m$
$G(x)$: vector of k inequality constraints
$g_i(x)$: inequality constraint i for $i = 1, \dots, k$
$H(x)$: vector of l equality constraints
$h_i(x)$: equality constraint i for $i = 1, \dots, l$
x: vector of decision variables with $x = [x_1, x_2, \dots, x_n] \in X$ (feasible set)

An optimal solution minimizing the objective function is represented by x^*, such as $x^* \in X$ and satisfies inequality and equality constraints. The optimal vector x^* is considered Pareto optimal if all other x vectors, satisfying the problem's constraints, have higher result values for a minimum of one objective function f_i, or have the exact same value for all objective functions. The following two definitions are applied (Deb & Gupta, 2005): (*where* $S = \{x \in X: G(x) \leq 0, H(x) = 0\}$)

- *Weak efficient solution: Point* x^* *is considered weak Pareto optimum for the multi-objective optimization if and only if there isn't any other* $x \in S$ *such that* $f_i(x) < f_i(x^*)$ *for all* $i = 1, \dots, m$.

- *Strict efficient solution: Point* x^* *is considered strict Pareto optimum for the multi-objective optimization if and only if there isn't any other* $x \in S$ *such that* $f_i(x) \leq f_i(x^*)$ *for all* $i = 1, \dots, m$, *with at least one strict inequality.*

Figure 3.2a illustrates an example of a Pareto curve. A Pareto curve or Pareto front is a representation of the efficient set or all efficient solutions. The shape of the Pareto curve (surface) describes the trade-off between the objective functions of the multi-objective problem. The non-dominated (or non-inferior) points are represented by the Pareto front, which is the line between points $(f_2(\hat{x}), f_1(\hat{x}))$ and $(f_2(\tilde{x}), f_1(\tilde{x}))$.

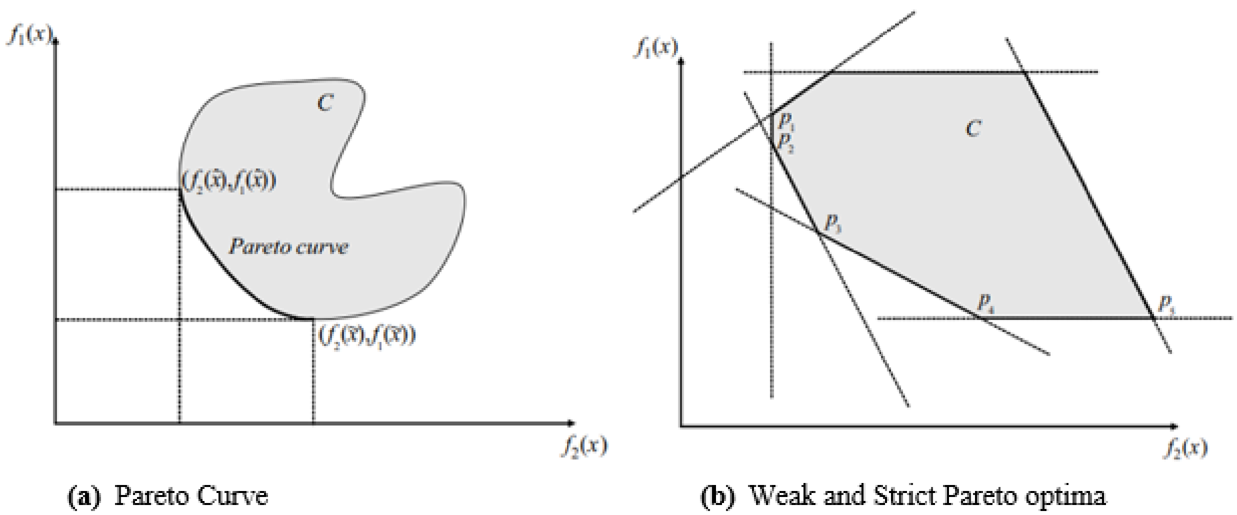

Figure 3.2: Pareto Optimality (adapted from Multi-objective Optimization (2008))

Figure 3.2b gives an example of strict and weak Pareto optima. Points p_1 and p_5 are weak Pareto optima while points p_2, p_3 and p_4 are strict Pareto optima.

Several techniques are presented in the literature for solving multi-objective optimization problems, such as the weighted-sum, ε-constraint, multi-attribute utility theory, goal programming, multi-level programming, etc. As for programming and search techniques, genetic/evolutionary algorithms have been recently widely used, and some other methods such as tabu search, AI techniques using artificial neutral networks, particle swarm optimization, etc.

The main purpose of this section is to introduce some of these methods only briefly. A detailed systematic literature review on portfolio optimization approaches can be found in the paper written by (Milhomem & Dantas, 2020).

3.3.1. Ɛ-Constraint Method

This method was introduced in 1983 by Chankong & Haimes. In this approach, the decision-maker must select only one objective function $f_i(x)$ to optimize, while the remaining are formulated as constraints, bounded by an upper target value ε_i. The optimization problem:

$$\min f_s(x) \tag{3.19}$$

subject to:

$$f_i(x) \le \varepsilon_i\ , \qquad i = 1, \dots, m,\ i \ne s \tag{3.20}$$

$$x \in S$$

An optimal solution x^* is a *weak Pareto optimum* if it satisfies the problem represented by equations (3.19) and (3.20), with $\varepsilon = (\varepsilon_1, \dots, \varepsilon_{s-1}, \varepsilon_{s+1}, \dots, \varepsilon_m) \in R^{m-1}$ (Multi-objectives Optimization, 2008)

x^* is a *strict Pareto optimum* if and only if for each objective s, with $s = 1, \dots, m$, there exists a vector $\varepsilon = (\varepsilon_1, \dots, \varepsilon_{s-1}, \varepsilon_{s+1}, \dots, \varepsilon_m) \in R^{m-1}$ such that one unique objective vector $f(x^*)$ corresponds to the optimal solution of the problem represented by equations (3.19) and (3.20).

The ε-constraint approach has many advantages such as:

- In this method, non-extreme efficient solutions can be produced since the ε-constraint process alters the feasible region suggested at the beginning of the problem. This will create a richer and more diverse representation of the efficient set, given that every run can be exploited to generate a different efficient solution (Mavrotas, 2009).
- Considering the constraints applied in the optimization problem, if the ε-constraint method finds an optimal solution, then it's guaranteed that this solution is Pareto optimal.
- This method is able to produce efficient points on a non-convex Pareto curve (Deb & Gupta, 2005).

Despite its major advantages, the ε-constraint method requires longer solution times when solving problems with several objective functions (more than two). It is often not considered efficient in such scenarios. Another drawback of this method is that the decision-maker should select the appropriate upper bound values, which might become a heavy task when an increased number of objectives is considered. Hence several modifications of the ε-constraint method have been developed in the literature to minimize its computational difficulties.

3.3.2. Weighted Sum Method

The weighted sum approach extends the ε-constraint method by combining several objective functions into one main function to optimize. It assigns an individually weighted coefficient (a_i) for each objective function, and minimizes the positively-weighted convex sum of all the objectives as follows:

$$\min \sum_{i=1}^{m} a_i \cdot f_i(x) \tag{3.21}$$

$$\sum_{i=1}^{m} a_i = 1 \tag{3.22}$$

$$a_i > 0, \qquad i = 1, \ldots, m$$

$$x \in S$$

Deb & Gupta (2005) state that the minimization of the weighted-sum problem described above is an efficient solution of the multi-objective optimization problem, suggesting that its image fits on the Pareto curve. When the weighted coefficients (a_i) are all strictly greater than zero, the solution is a *strict Pareto optimum*. Contrastingly, if at least one of the coefficients is equal to zero, then the solution becomes a *weak Pareto optimum*.

Note that the weighted coefficients don't necessarily reflect the relative importance or impact of the objective functions. The decision-maker must choose the appropriate vector of weights, while there's no inferred theoretical correspondence between the optimization solution and weight vector. Therefore, the decision-maker does not know which weights coefficients are able to produce the optimal solution; hence a long iterative process is expected using the weighted-sum method.

Besides the significant computation time, the weighted-sum method requires scaling the objective functions before the minimization since the solution is highly influenced by the scaling of individual objective functions (Mavrotas, 2009). In addition, the minimization of convex combinations of all the objective functions cannot produce non-convex parts of the Pareto set (Deb & Gupta, 2005).

3.3.3. Multi-Attribute Utility Theory

The investor's attitudes and perceptions towards risk and uncertainty can influence its preferences and investment decisions. When adopting a risk attitude causes nonlinearity of the value function, the value function becomes a utility function (Bratvold & Begg, 2010). Utility theory was introduced by von Neuman and Morgenstern in 1944 and is based on the individual's preferences, accounting for risk attitudes and values simultaneously. In the presence of various attributes, it is known as a multi-attribute utility theory (MAUT).

The application of risk preferences and utility theory in the O&G sector has been studied, mainly for exploration and production projects. While some authors focused on risk analysis quantification, others discussed decision making under uncertainty by incorporating concepts of utility theory and risk attitudes (Bickel & Bratvold, 2008; Bratvold & Begg, 2008; Henrion et al., 2015; Wood & Khosravanian, 2015). One particular application of utility theory for O&G portfolio assets selection is discussed by Xue et al. (2014).

Assuming n uncertainty attributes $(a_1, a_2, \dots, a_n)$ characterizing various alternatives, and a scalar utility function $U(x_1, x_2, \dots, x_n)$, the multi-attribute utility function becomes (Henrion et al., 2015:

$$U(a_1, a_2, \dots, a_n) = \sum_{i=1}^{n} w_i u_i(a_i) \tag{3.23}$$

$$0 \leq U(a_1, a_2, \dots, a_n) \leq 1, \qquad 0 \leq u_i(a_i) \leq 1$$

$$\sum_{i=1}^{n} w_i = 1 \tag{3.24}$$

where:
a_i alternative/uncertainty attribute i for $i = 1, \dots, n$
$u_i(a_i)$: single attribute utility function
w_i: normalized weight corresponding to attribute i

The multi-attribute utility function modeled by equation (3.26) is based on the assumption of additive independence, which means that the level of one attribute does not affect the preferences over the values of any other attribute. Henrion et al. (2015) stated that this assumption is often reasonable when limited uncertainties are present; however, in the O&G context including multiple objectives (NPV, Capex, reserves and production), the NPV objective is a function of the others and hence the additive independence assumption does not hold. The same may be the case for NPV and "risk" as companies are often adding a risk factor to the discount rate. When this is the case, using both NPV and risk as objectives means the company is double dipping in risk.

Using the multi-attribute utility function, the multi-objective optimization problem can be modeled as a single objective problem as follows:

$$\max U(a_1, a_2, \dots, a_n) \tag{3.25}$$

subject to:

$$g_k(a) \leq 0, \quad k = 1, \dots, K, \quad a = (a_1, \dots, a_n) \tag{3.26}$$

Several programming techniques are presented in the literature to solve multi-attribute utility problems, such as dynamic programming and goal programming. Given some of the drawbacks associated with those techniques, Yu et al. (2009) proposed using genetic algorithms to solve two-stage multi-attribute portfolio optimization problems. The authors concluded that genetic algorithms could be effectively used to create optimal portfolios; however, a limit must be set on the total number of assets evaluated to improve the portfolio's performance.

3.3.4. Time-dependent Goal-Seeking Approach

The portfolio analysis presented in this section is based on the work of Howell & Tyler (2001). Their proposed method considers the critical relationship between business investments and corporate strategies in the portfolio analysis context, resulting in higher chances of meeting corporate goals.

Using this approach, the annual performances of individual asset's attributes (such as NPV, carbon emission, etc.) are first compared to the annual corporate goals, then the overall portfolio's performance with respect to the same attributes is evaluated. This method allows the decision-maker to assess the impact of individual investments on the company's ability to reach its strategy.

This portfolio analysis is considered a powerful tool to develop and compare various strategies that the corporation might pursue, given a certain pool of assets. It also evaluates the economic and operational trade-offs following the selection of one strategy over the other. Moreover, questions such as: "what asset combination is needed, when is the best time to invest in individual projects, which constraints are realistic and achievable, and which strategy is the best to pursue?" are addresses in this context Howell & Tyler (2001).

The time-dependent goal-seeking process (Figure 3.3) starts by setting annual corporate goals that might include economic and non-economic performance metrics (blue bars). Then an asset combination (initial portfolio) is selected by the decision-maker as a "starting point", and the expected values of the performance metrics representing this portfolio are calculated following either a probabilistic or a deterministic evaluation of individual assets (red bars). Using the probabilistic case, the probability density function of the parameter must be evaluated first, then its corresponding expected value is calculated. Often, the portfolio selected reflects the company's strategy; for instance, if two oil producing assets are available in the pool, the company might choose a higher working interest associated with the asset resulting in a higher production if its strategy relies on accelerated oil production. Moreover, the portfolio should account for corporate constraints, which as opposed to corporate goals, are metrics that the portfolio should satisfy in all assets' combinations. Finally, the probability of meeting annual corporate goals (black line) is calculated to fully estimate the likelihood of satisfying the targets.

Often, no feasible solution can be found using the initial portfolio, which suggests that either the asset combination is not feasible or the corporate constraints are not achievable given the available asset's pool and constraints. Also, the presence of conflicting performance targets might lead to the portfolio's infeasibility. The decision-maker should then re-evaluate its working interests and corporate targets and redo the same analysis mentioned above until he/she is satisfied with the results. This will eventually give an idea about the possible business implications associated with changing corporate goals.

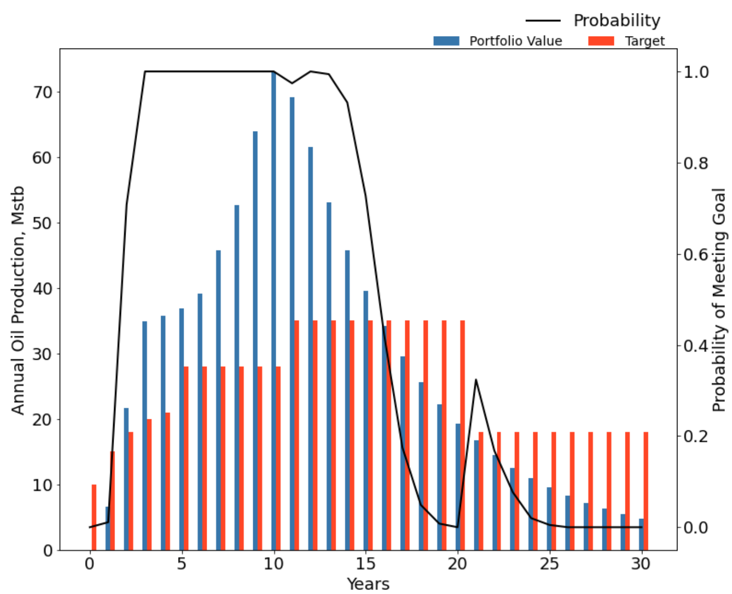

Figure 3.3: Portfolio Annual Oil Production Example

3.3.5. Evolutionary Algorithm Solver

An evolutionary or genetic algorithm is a type of heuristic technique used to solve multi-objective optimization problems. Two main categories of optimization problems generating Pareto-optimal solutions are frequently discussed in the literature: exact and heuristic multi-objective approaches.

Using the "exact" technique, the decision-maker often starts the optimization from either Markowitz's theory (MPT) model or from an extension of the MPT, which includes variations in the mean-variance parameters. Although several new techniques (heuristic/stochastic) have significantly evolved during the past few years, many investors, especially conservative ones, still prefer using exact methods, given they will always provide the optimal solution. Regardless of the required computational spending and expected degree of modeling difficulty, the exact techniques return solutions always belonging to the set of Pareto-optimal.

As for heuristic techniques, they can address single or multi-objective problems with single or multi-period characteristics. They include several methods such as genetic algorithm (GA), fuzzy programming (Fuzzy), or particle swarm optimization (PSO), with variations and extensions of each one of them. The main goal of a heuristic method is to find a solution that is as close as possible to the exact one within a reasonable amount of time. Hence, lower computational expenses are expected using the heuristic technique compared to the exact methods. In addition, solving multi-objective problems with several constraints favors the use of heuristic methods as some of these allow the decision-maker to find several points of the Pareto optimal set during a single run. However, note that a heuristic model might not be able to find the exact Pareto set, but rather it gives an approximation of it that might be considered feasible.

One particular method used in multi-objective optimization is the evolutionary algorithm (EA), based on Darwin's evolution theory. All potential solutions form the *population*, while the decision variables representing these solutions can be perceived as the corresponding genes of each solution. Based on this theory, *parents* are initially selected from the population and used to produce, through a crossover step, a new *generation* of offspring. A random alteration of offspring takes place at the mutation stage. Over several generations, only the fittest generation will survive by genetic operations. A predetermined number of generations is often set as termination criteria (Zitzler et al., 2014).

When modeling a multi-objective EA, two main goals have to be considered. First, in the presence of multiple objectives, the search should be constantly guided towards the Pareto set by assigning appropriate scalar fitness values in the mating selection stage. Second, the algorithm must keep a very diverse set of non-dominated solutions to reduce the possibility of having several populations containing identical solutions (Deb & Gupta, 2005).

4. Individual Asset Model

4.1. O&G Assets Evaluation

For the scope of this thesis, a simplified evaluation model of upstream O&G assets is performed and divided into four steps: reserves estimation, production forecasting, carbon emission estimation, and economic evaluation. An additional section is added to forecast the O&G prices for the given time period.

A list of 15 hypothetical O&G projects was developed and evaluated probabilistically using Monte Carlo simulation with 10,000 iterations over a period of 30 years. The projects are assumed to produce O&G from geologically independent reservoirs.

A Python class "Petroleum_asset" was developed, where each O&G project was represented as an object of this class. Table 4.1 shows the input parameters of each O&G project in the "Petroleum_asset" class.

Table 4.1: Input Parameters of O&G Asset

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

4.1.1. Reserves Module

A detailed calculation of the volume of original oil in place goes far beyond the scope of this thesis. Lund (1997) argues that a detailed description of the asset's reserves and production profiles is unlikely to provide more precise insights about the future performance, compared to a coarser model, in the scope of portfolio optimization. And due to the presence of many uncertainties in the early stages of development, more time and effort is needed to quantify each one of them and assign their individual distributions and parameters. Hence, a less detailed calculation approach was used in this thesis with reasonable simulation time.

The reserves were estimated using an average mode value ("res_est"), as an input to the asset class. Then the function "fac_model" was used to estimate the distribution of the reserves, given the input uncertainties. The function "fac_model" has eight input uncertainties, as shown in Table 4.2. The reserves (Mstb or Bscf) were estimated as random variables, following a PERT distribution.

Table 4.2: Uncertainty Factors of "fac_model" Function

Uncertainty factors as a function of the project phase	Exploration		Development	
	Min	Max	Min	Max
	0.2	2.0	0.85	1.45
Uncertainty factors as a function of project location	Onshore		Offshore	
	Min	Max	Min	Max
	0.8	1.2	0.7	1.5

Monte Carlo simulation with 10,000 (n=10,000) iterations generated the reserves distribution of a given asset shown in Figure 4.1.

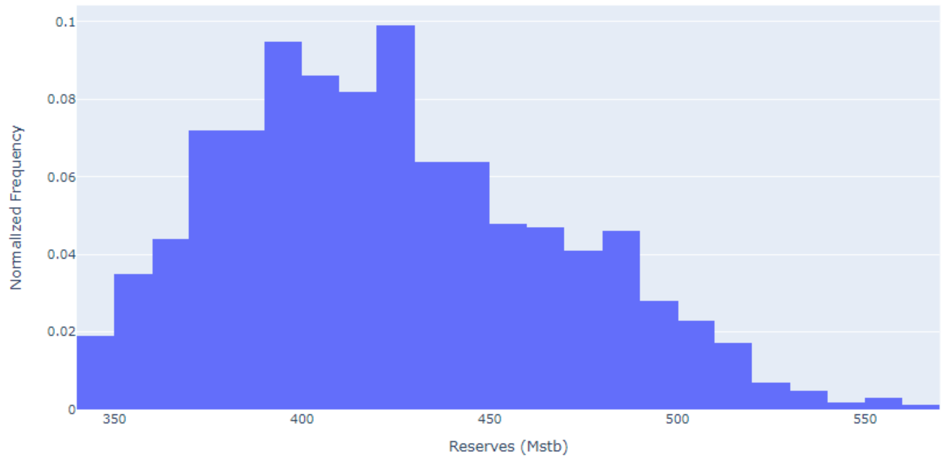

Figure 4.1: Reserves Distribution

Figure 4.1 illustrates a positively skewed distribution of the reserves. This result is expected as the possible oil initially in place (OIIP) values often are log-normally distributed (Kosova et al., 2016). Although the reserves estimates in this thesis were not calculated using the OIIP parameters, it was essential to check that the results we got are reasonable.

4.1.2. Production Module

This module calculates the annual hydrocarbon production from each asset and is divided into two functions: "years_phase" and "production."

The function "years_phase" estimates the length of the exploration and development phases and returns the expected years to start exploration, development, and production. These outputs will be used in the production function and the economic evaluation section. The input parameters of this function are shown in Table 4.3.

Table 4.3: Input Parameters of O&G Production Model

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

The production forecast was performed using the exponential decline curve model, given by the decline curve formula presented by Arps (1944):

$$q_t(t) = \frac{q_i}{(1 + bD_i t)^{1/b}} \tag{4.1}$$

where:
$q_t(t)$: production rate at time t
q_i: initial rate
D_i: decline rate
b: hyperbolic exponent

A strong correlation exists between the reservoir and reservoir fluids' physical properties and the decline rate. This correlation is expressed by the hyperbolic exponent that can have values between 0 and 1, depending on the formation type, fluid type, and drive mechanism. The exponential decline (b=0) is used in this thesis because of its simplicity when dealing with constant bottom hole pressure (Höök et al., 2009). In addition, Arps (1945) noted that most of the reservoirs have values of b less than 0.5.

[2] 2 Exploration factor equals to 1 when exploration takes place, and 0 otherwise

When keeping the production running requires higher energy or more money than it yields, production should be stopped. This cut-off point is expressed by the economic production limit of the facility, used to calculate the decline rate constant (D_i). D_i indicates how steep the production decrease will be and is found by equating reserves volumes to the ultimate production volume of the field (which is a function of the economic limit and the total maximum processing capacity). Table 4.4 provides additional information used in the calculations.

An idealized theoretical production profile is illustrated in Figure 4.2. It depends on four time-variables: the development, build-up, plateau and decline period. The last part of the production profile, the decline phase, is already covered by the decline curve analysis mentioned earlier in this section.

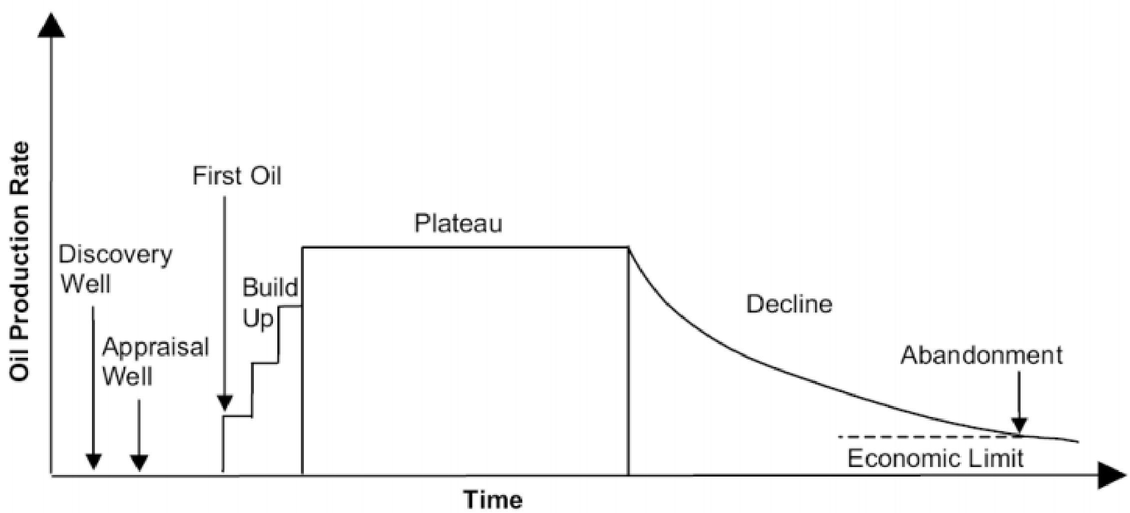

Figure 4.2: Theoretical Production Curve (adapted from Höök et al. (2009))

The delay period indicates the length of the period between the expected start of the production phase (derived from the "years_phase" function) and the actual start of production. This delay can be caused by several factors such as poor site management, shortage of equipment or material, weather effects, etc. The ramp-up period reflects the production increase from 0 to q_i, while the plateau period represents a constant production at a level of q_i.

All three time-variables were estimated by uniform distributions (Table 4.4). The corresponding min and max values were evaluated according to the accelerated production profile type.

The following equation gives the cumulative oil production at time t:

$$Q_t = \sum_{t=0}^{t} q_t \tag{4.2}$$

Table 4.4: Input Paramters of Production time-variables

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

An example of a Monte Carlo simulation with 10 (n=10) iterations produced the following production profiles for a period of 30 years (period=30):

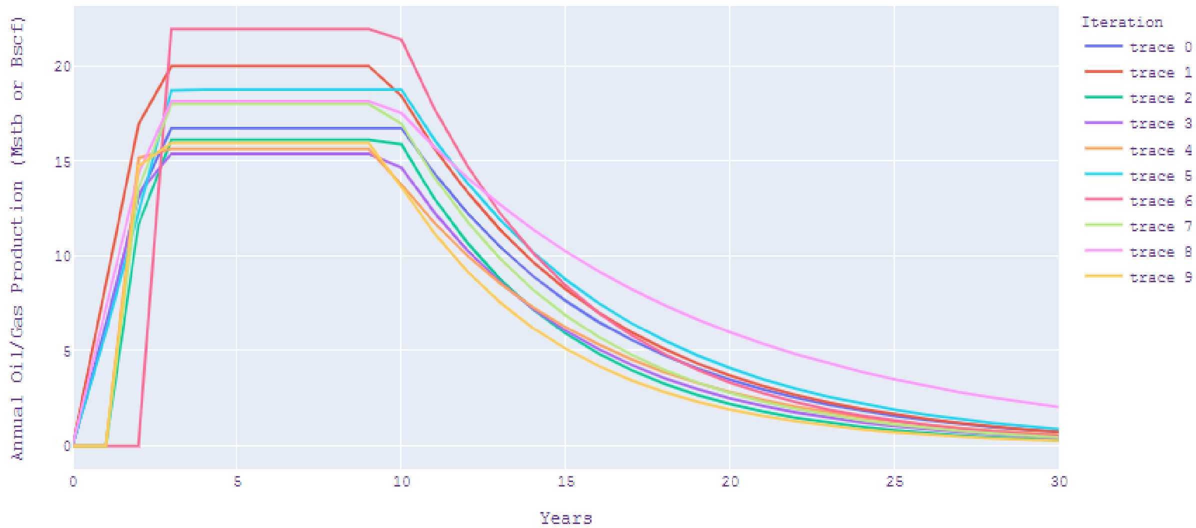

Figure 4.3: Simulated Production Profile

4.1.3. Economic Evaluation Module

In this module, the annual cash flows were calculated for each asset, using both the production and oil price modules. Then the net present value (NPV) was derived. A typical O&G project cash flow is shown below:

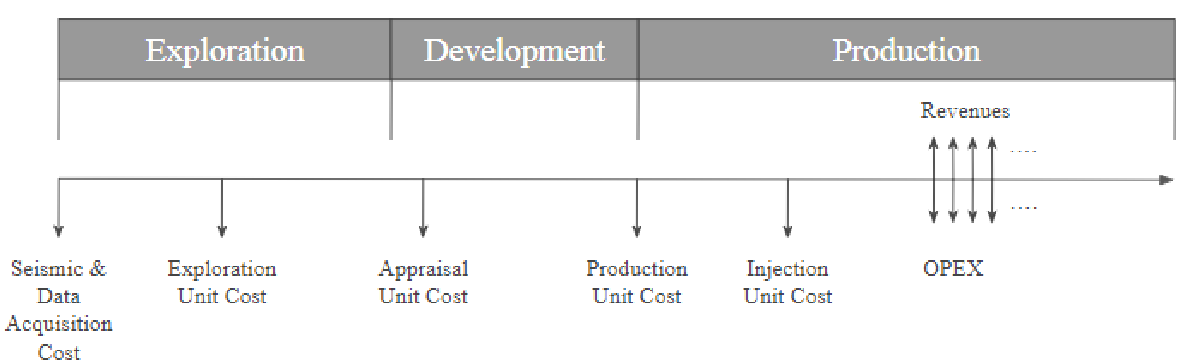

Figure 4.4: O&G Project Phases

The cash flows consist of annual capital expenditures (Capex), operating expenditures (Opex), and sales revenues. Three significant time periods were considered to calculate the cash inflows and outflows: exploration, development, and production. The decommissioning (abandonment) costs were ignored in this thesis since, for most long term projects, decommissioning costs are very far out in time and discounting means they have very little impact on the NPV-based development decision.

First, the capital expenditures were divided into five different parts, invested at different time periods along the project's lifetime. Then a Capex structure was developed based on the number of wells needed for each stage of the project: exploration, appraisal, injection, and production. The number of production and injection wells was defined as a function of initial reserves. One exploration and one appraisal well were considered for all projects. The capital expenditures were then depreciated using the straight-line depreciation method, over 20 years. Table 4.5 and Table *4.6* show the development plan and Capex structure used in this thesis. The offshore multiplier was used to calculate the Capex for offshore platforms.

Table 4.5: Input Paramters of O&G Development Plan

Reserves (million Boe)	**# Prod. Wells per year**	**# Inj. Wells per year**
100	1	1
200	2	2
500	4	3
1000	8	4
2000	14	7
5000	25	15

Table 4.6: Input Parameters of O&G Capex Structure

Triangular Distributions			
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 expenditures were divided into two parts: fixed and variable Opex. The fixed Opex depends on the number of production wells needed, while the variable Opex varies with the production rate. Both Opex structures were modeled as triangular distributions (Table 4.7). As for the annual revenues, they were calculated by simply multiplying the yearly production with the corresponding oil or gas price of that year, derived from the O&G price module.

Table 4.7: Input Parameters of O&G Opex Structure

		Onshore			**Offshore**		
		min	**mode**	**max**	**min**	**mode**	**max**
Exploration:	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 ($/bbl) – Gas	8.00	12.00	22.00	21.00	25.00	33.00
Development:	Fixed Opex ($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

Following the Norwegian Petroleum Taxation Act, the after-tax cash flows were calculated. Figure 4.5 shows the mean values of a cash flow generated from a Monte Carlo simulation of 10000 iterations (n=10000) over 30 years (n=30). The mean, 10th, and 90th percentiles of the cash flow are also illustrated in Figure 4.6.

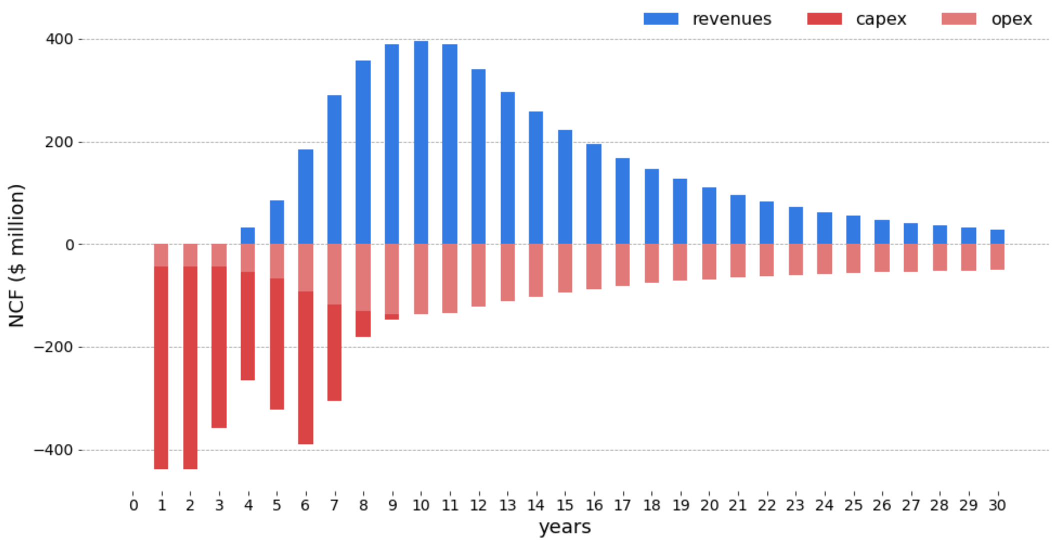

Figure 4.5: NCF Distribution of an O&G asset (Mean)

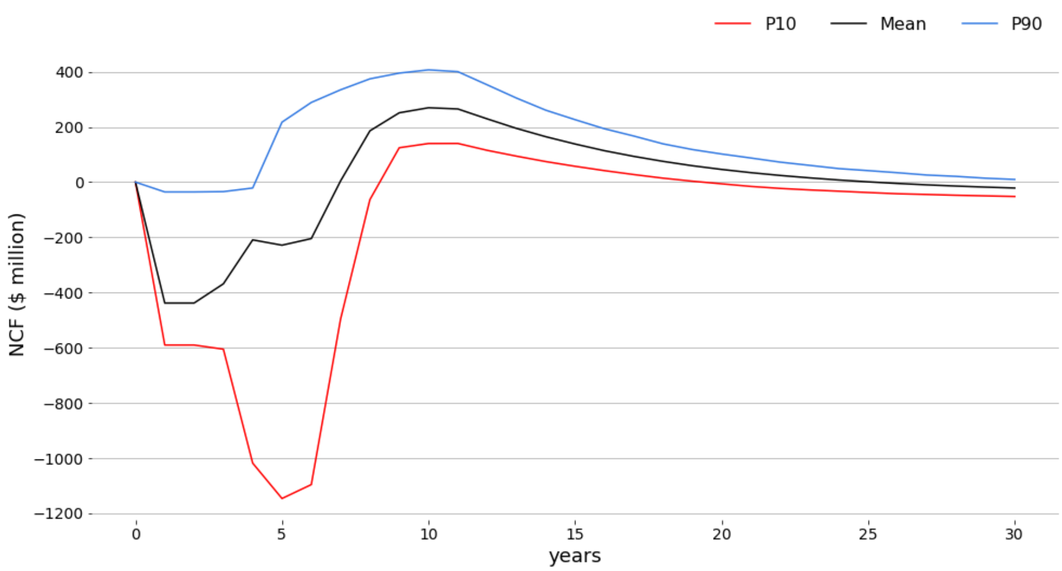

Figure 4.6: NCF Distribution of an O&G asset (P10-Mean-P90)

Since the NPV was chosen to represent the monetary objective of the portfolio, it was calculated for each asset using the following equation:

$$NPV = \sum_{n=1}^{N} \frac{NCF_n}{(1+i)^n} \tag{4.3}$$

where:
NCF_n: net cash flow of year n
i: discount rate
N: project's lifetime

The NPV distribution of the same Monte Carlo simulation is illustrated:

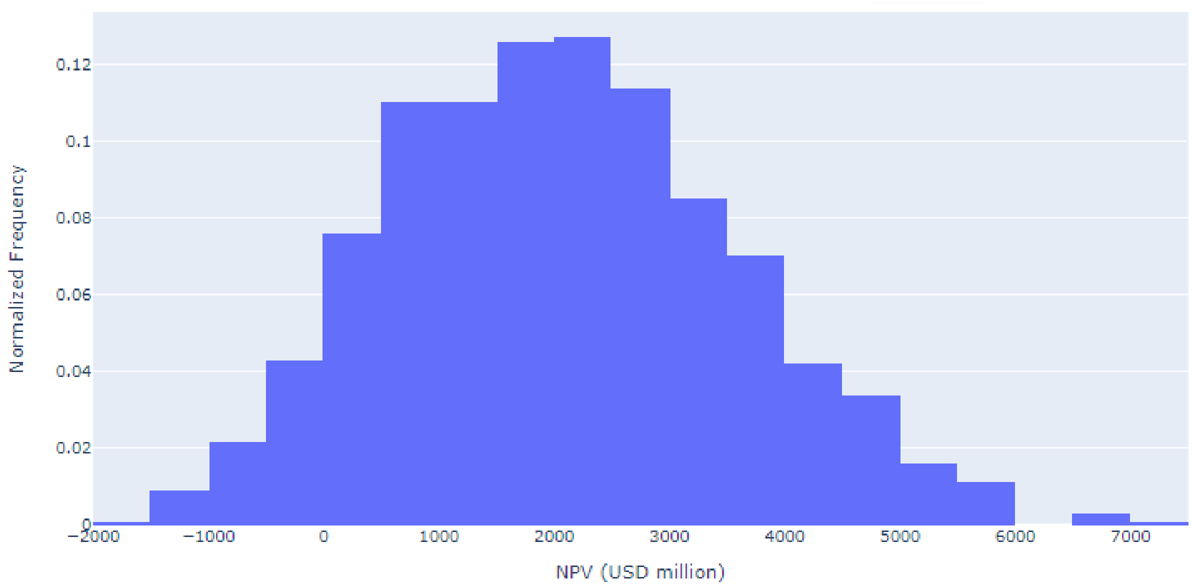

Figure 4.7: NPV Distribution of an O&G asset

4.1.4. Carbon Emission Module

In this section we will first look into the carbon emission levels from O&G extraction of operating fields, and then we'll incorporate this analysis into our model.

The CO_2 emission intensity from O&G extraction varies from one region to the other. One reason for that variation could be the difference in governmental regulations and carbon pricing between several countries. To reduce greenhouse gas (GHG) emission, carbon pricing is applied as a cost the polluter has to pay and can take two different forms: carbon tax and carbon emission trading (also known as "allowances" or "cap and trade" system). The European Union's Emissions Trading System (EU ETS) is considered to be one of the most extensive carbon pricing schemes. All producing facilities participating in this trading system will have a limit (cap) for their total GHG emission. Emission allowances are allocated or auctioned off by the EU ETS and can then be traded between participating companies under the "cap and trade" concept. In Norway, for example, the petroleum industry pays both the EU ETS price and the national CO_2 tax, which might be the reason for the low emission intensity in Norway compared to the rest of the world (Gavenas et al., 2015). For instance, in 2021, the Norwegian Ministry of climate and environment announced a gradual increase of the CO_2 tax rate from NOK 590 to NOK 2000 per ton of CO_2e in 2030 (Norskpetroleum, 2021).

In addition to the carbon pricing policy and the oil price, there are other drivers behind the emission intensity. To better understand the factors affecting the emission levels in upstream activities, it's crucial first to examine the origin of the emission. According to the Norwegian Petroleum Directorate (2020), gas turbines generating electricity account for 85% of total CO_2 emissions from Norwegian petroleum activities. Other sources of emission are boilers, engines, flaring of natural gas, and well testing.

To investigate the effect of several drivers on the carbon emission on the Norwegian continental shelf (NCS), we relied on a similar study done by Gavenas et al. (2015). Annual CO_2-emission data and annual production data from five different fields on the NCS were used. The dataset was taken from the Norwegian Environment Agency (2020) and Norskpetroleum (2021). In addition, data for crude oil Brent Price was extracted from the EIA (2020), while the Norwegian carbon-tax price and the EU-ETS price were accessible from The World Bank (2020).

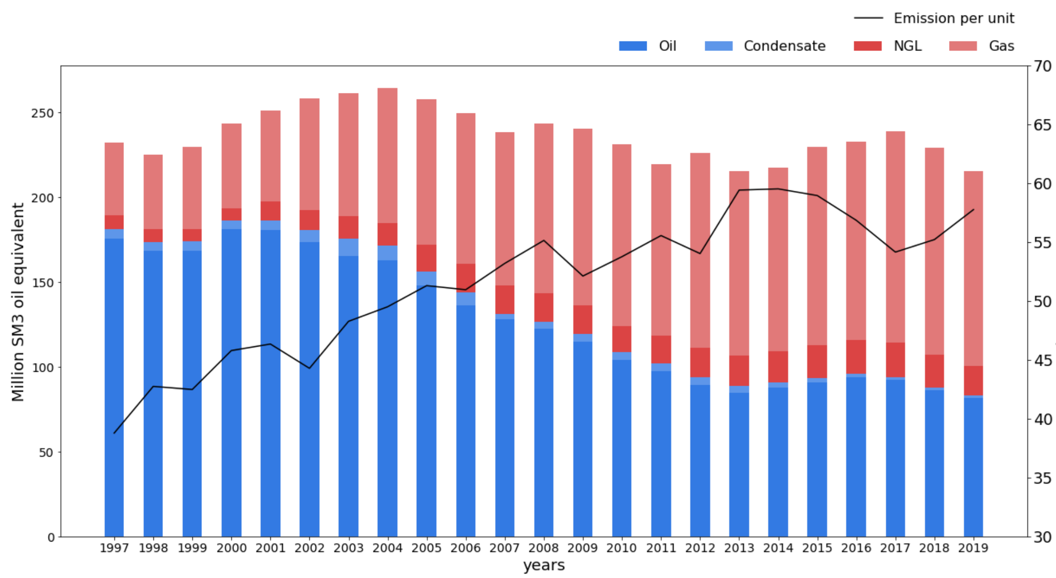

Figure 4.8: Norwegian Total Production and Carbon Emission per unit

Variations of CO_2-emission intensity over the last 20 years on the NCS are shown in Figure 4.8. Despite all the national and international efforts to reduce GHG emission, the Figure shows an increase in the emission intensity by more than 53% during the period from 1997 to 2019. One of the reasons could be that the rise of both the CO_2-tax and the CO_2-price in the EU ETS during that period was relatively low compared to the increase of the region's O&G extraction activities. Figure 4.9 below supports this hypothesis. As seen in the Figure, there seems to be two regions with clear correlations: from 2001 to 2014 and again from 2017 to 2018. However, the correlation is the opposite of what we would expect to see if the taxation mechanism was effective in reducing emissions. A better understanding of the CO_2 price effect could be drawn from comparing a "no carbon price" to a "carbon price" system. Based on a study done by McKinsey (2021), only a quarter of all oil projects are expected to breakeven at a zero-carbon price (with a commodity price of $30 per barrel), while this number decreases to less than 20% at a carbon price of $100/t$CO_2$e, resulting in reduced oil extraction and emission intensity (McKinsey, 2021).

Figure 4.9: Carbon Emission Variation with respect to Regulatory Frameworks

Another reason for the increase in the emission intensity could be related to oil price variations. In the period 1997-2019, the oil price has almost doubled in real-term value, resulting in increasing petroleum activities. Also, the oil price increase motivated O&G companies to extract O&G in more expensive and energy-demanding areas, often delaying the termination of producing fields by implementing enhanced oil recovery projects, which implies higher levels of emissions per unit extracted (Gavenas et al., 2015). However, the sharp drop in oil price in 2014 resulted in only a slight reduction in emission intensities, initiated by a reduction in exploration activities in the area. Since most of the NCS, in general, is in a mature state, implementation of modern technology and EOR remains crucial for future development of the fields, hence resulting in more carbon emission than the one expected by oil price reduction.

Lastly, as O&G production decreases, the emission intensity tends to increase since lower hydrocarbon extraction is linked to more water production. Often, the increased water production leads to an increase in the CO_2/toe ratio, as the energy requirement remains the same and oil production is reduced. Also, with a constant amount of energy used, production will decrease as the natural reservoir pressure gradually drops, resulting in a higher emission per unit extraction

(Gavenas et al., 2015). Examples of this effect are shown in Figure 4.10 andFigure *4.11*, representing the development of Brage and Heidrun fields, respectively.

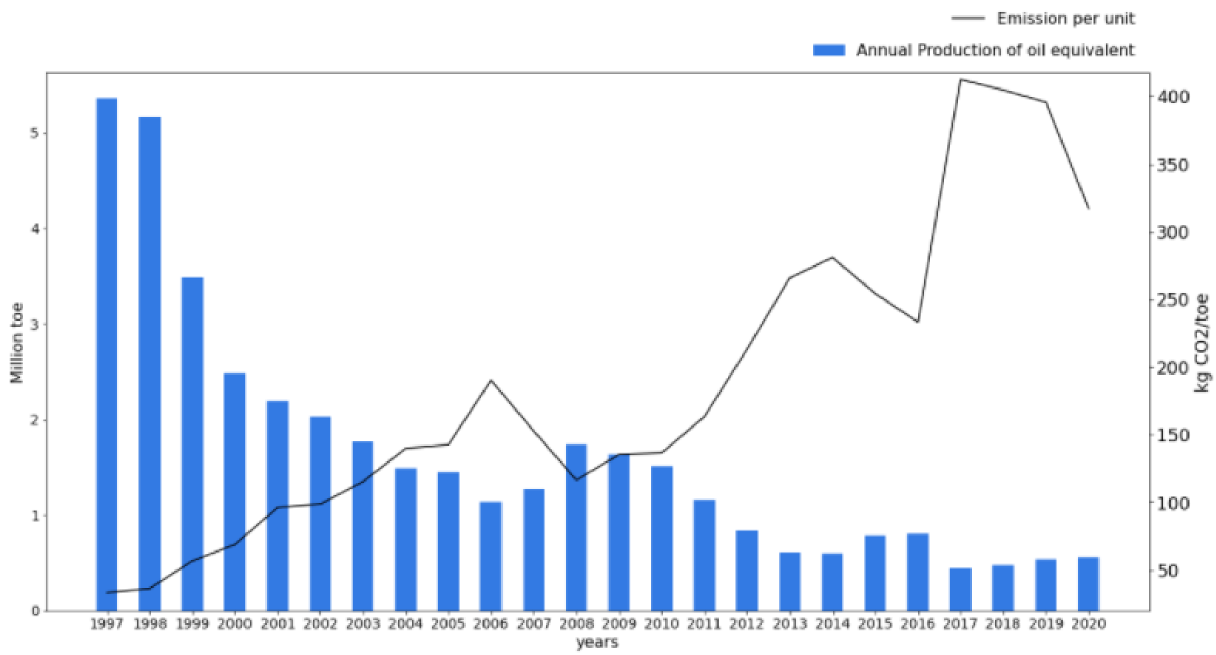

Figure 4.10: Total Production and Emission per unit at Brage Field

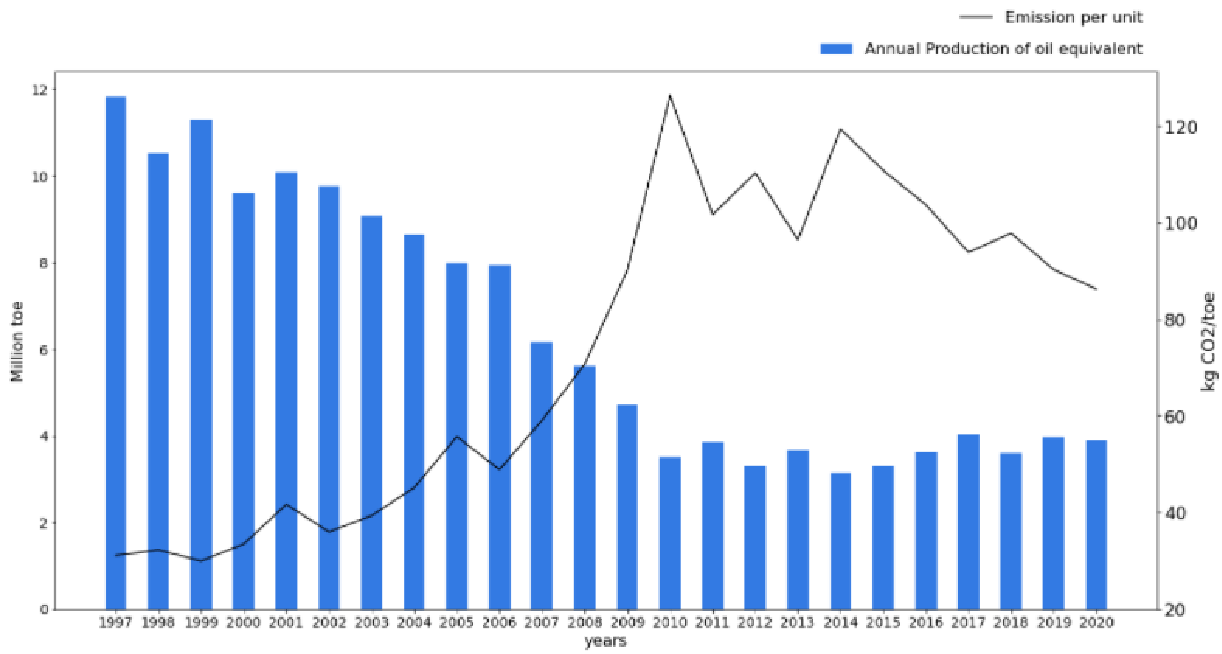

Figure 4.11: Total Production and Emission per unit at Heidrun Field

An illustration (Figure 4.12) of emission intensity change with the production level (as a percentage of peak production) was adapted from Gavenas et al. (2015). On the vertical axis, the point equals to 1 corresponds to the emission intensity factor when the production is at its peak value. For example, if the emission intensity at peak production is equal to 30 kg CO_2/toe, this point corresponds to 1 on the vertical axis. When the share of peak production decreases to 0.4, the emission intensity level becomes two times higher than it was at peak production, hence it becomes equal to 60 kg CO_2/toe.

,

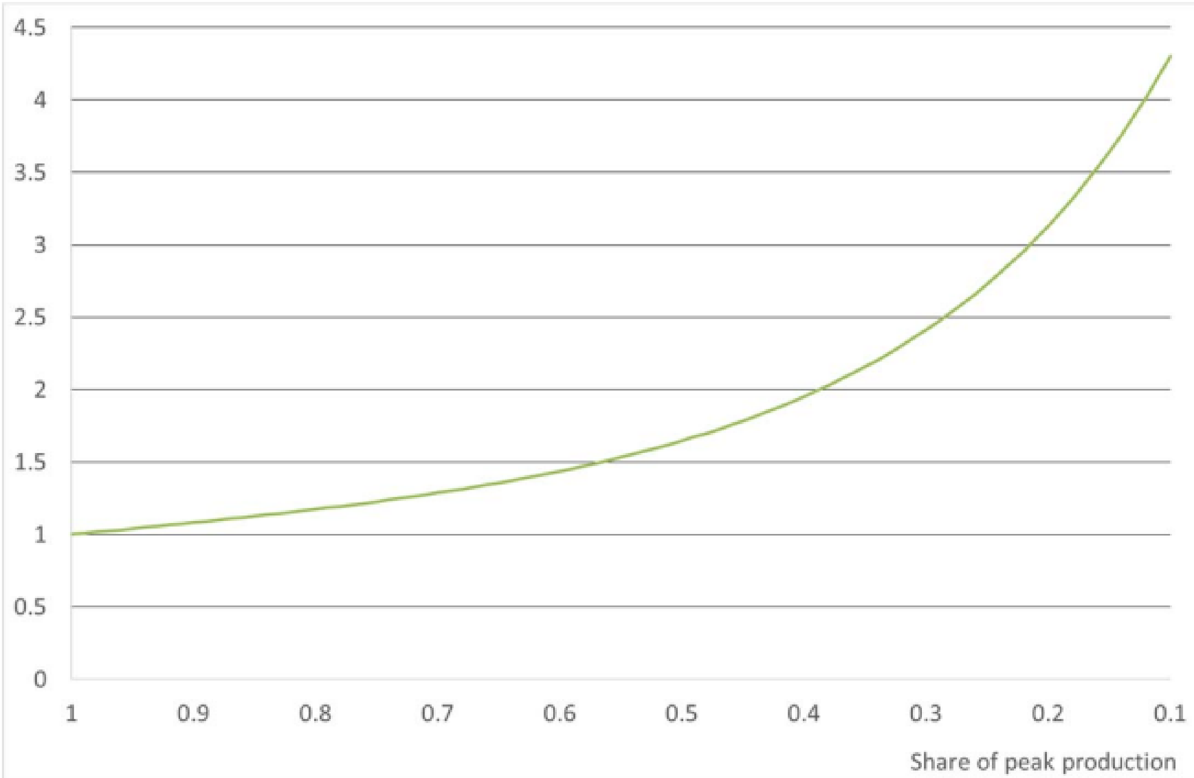

Figure 4.12: Emission Intensity change with the Production Level (share of peak production) (adapted from Gavenas et al. (2015))

As production declines, the emission intensity increases gradually, while a sharper rise of the emission level is observed when production is reduced to more than half of its peak value.

This correlation was used in this thesis to estimate the carbon emission levels from O&G operating assets. Applying it to one hypothetical O&G asset of our portfolio, the following results were obtained:

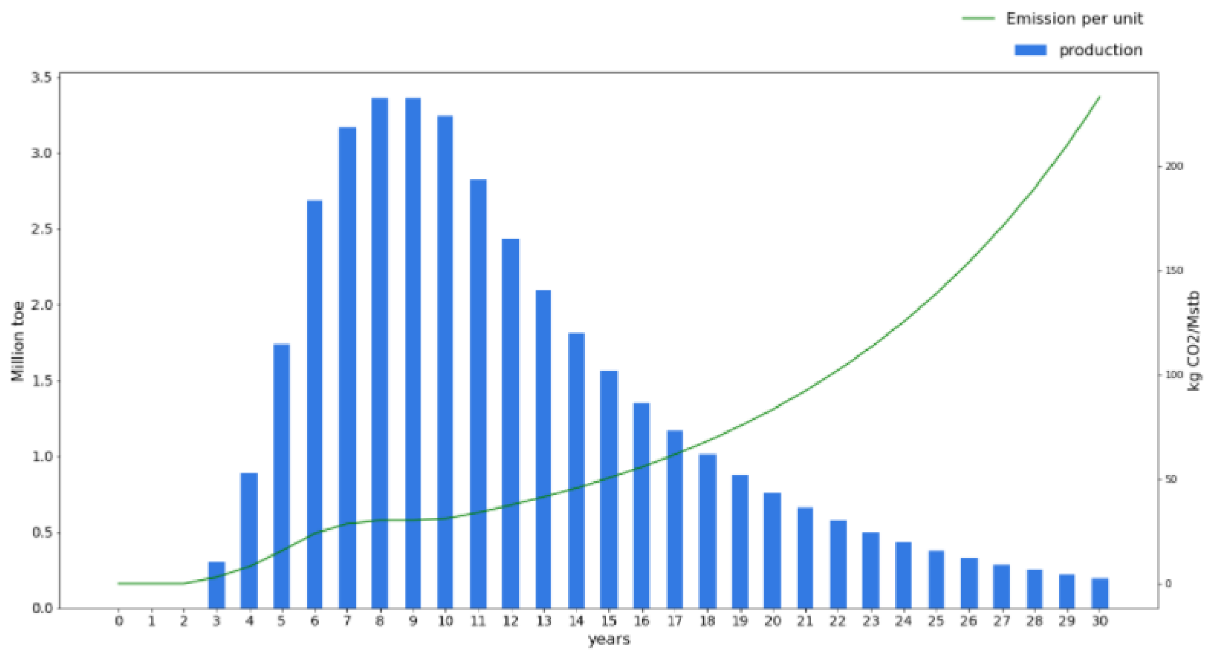

Figure 4.13: Total Production and Emission per unit Results

4.2. O&G Price Module

An economic evaluation of O&G investments requires a detailed description of the oil price variations. Given the uncertainties in the future oil price, it's useful to create a stochastic model that captures the characteristics of oil price fluctuations with time.

The study of oil price modeling is well documented in finance and economic literature. The two most common approaches for continuous time modeling are the geometric Brownian Motion (GBM) and mean-reverting models (Meade, 2010)).

The geometric Brownian motion (GBM) was first introduced by Black and Scholes (1973) and Merton (1973), who modeled the stock prices traded on exchanges. In an attempt to manage a natural resource investment, Brennan and Schwartz (1985) used the geometric Brownian motion to model the oil price as a component of this investment. In their work, the authors described the future prices using a single stochastic factor. The geometric Brownian motion consists of deterministic trend for the mean price, in addition to a probabilistic component modeled around that trend (Begg et al., 2007).

Schwartz (1997) suggested modeling commodity prices behavior using one, two or three stochastic factors, which are spot price, interest rate and convenience yield. The author later concluded that the interest rate, used in a three-factors model, provided only limited additional insights, suggesting that empirical data is better described using a two-variable mean-reverting model (Schwartz, 1997).

Schwartz and Smith (2000) proposed oil price modeling through two combined stochastic processes: short term and long term. The short term process is based on a mean-reversion model, while the long term process follows the geometric Brownian motion.

While there are several opinions regarding the different price models, many studies have shown that the oil price tends to fluctuate on the short term before settling into a long-term equilibrium (Ozorio et al., 2013; Schwartz and Smith, 2000).

In this thesis, the mean reverting process was used to model the O&G prices, to account for the dependencies in the price changes, not covered in the geometric Brownian motion model (Begg et al., 2007). Mean reversion implies that both the periods of high and low oil price volatility will die off with time, and the oil price will gradually return to its long-term equilibrium level (Kuhe et al., 2019). Hence, the changes in the O&G prices follow a mean reversion rate to converge to their equilibrium levels. The motivation behind the mean reversion behavior of the oil price is related the market impact on the price volatility. As the oil price increases above its long-term equilibrium level, the oil supply will decrease, driven by market forces.

The following stochastic equation is used to model the O&G prices for a mean reverting process (Begg et al., 2007):

$$\frac{dP}{P} = \eta(\mathrm{P} - \mathrm{P}^{*})\mathrm{dt} + \sigma\epsilon\sqrt{dt} \qquad (4.4)$$

where:
P: price at time t
P^{*}: long-term equilibrium price
η: mean reversion rate
σ: volatility
ϵ: standard normal random variable
dt: time increment

In order to use the mean reverting price model, the model's parameters had to be determined first, through a process known as calibration. A detailed explanation about the calibration process goes beyond the scope of this thesis. However, a comprehensive review can be found in Thomas & Bratvold (2015) paper. The parameters used in this thesis are found in Table 4.8.

Brown & Yucel (2008) proved that historically, O&G prices have been related. Hence, a correlation between the O&G prices was performed, using the correlation matrix (Table 4.9) presented by Thomas & Bratvold (2015).

The function "og_price" was created on Python for the mean reverting price model. A Monte Carlo simulation of 10000 iterations (n=10000) over a period of 30 years (period=30) was performed.

Table 4.8: Input Parameters for O&G Price

Parameter [Python Argument]	**Unit**	**Value for Oil**	**Value for Gas**
Time increment [dt]	years	1	1
Volatility [oil_sd; gas_sd]	$/bbl; $/Mscf	3	0.7
Price floor [oil_floor; gas_floor]	$/bbl; $/Mscf	8	0.8
Long term mean price [oil_mean_price; gas_mean_price]	$/bbl; $/Mscf	70	5
Initial price at t=0 [oil_ini_price; gas_ini_price]	$/bbl; $/Mscf	40	2.3
Half-life [oil_half; gas_half]	years	4	8

Table 4.9: O&G Prices Correlation

	Oil Price	Gas Price
Oil Price	1	0.63
Gas Price	0.63	1

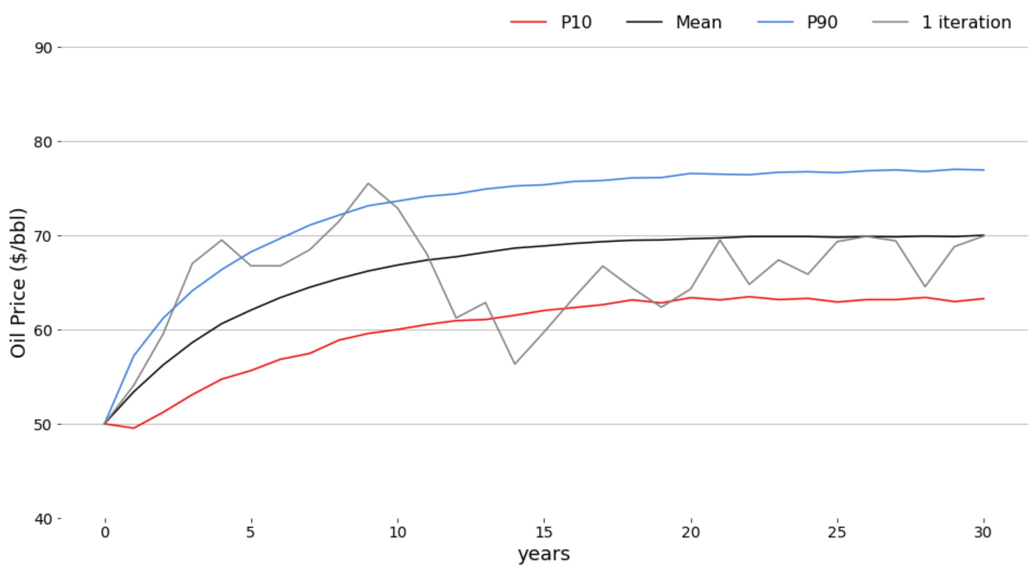

Figure 4.14: Oil Price

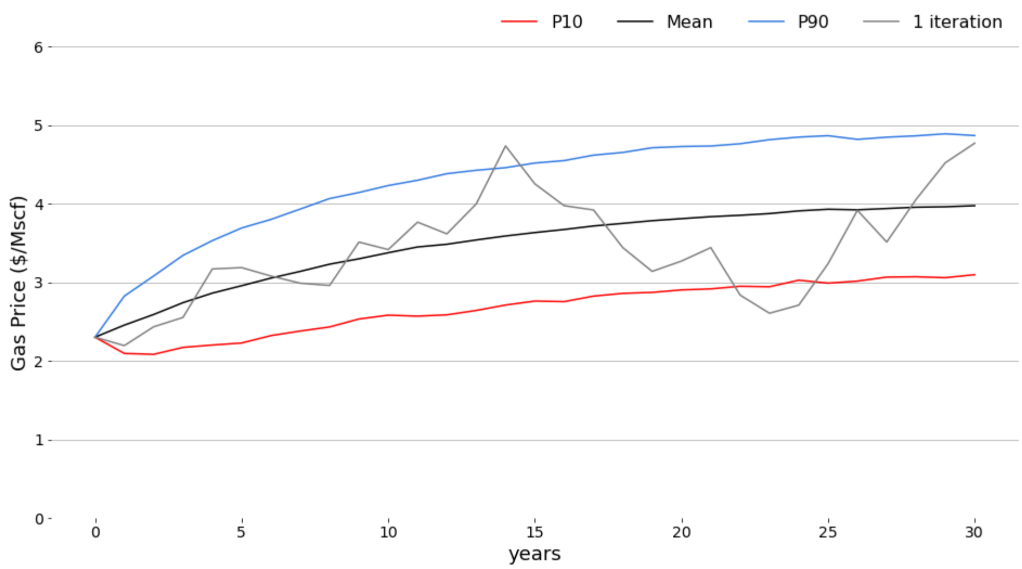

Figure 4.15: Gas Price

4.3. Wind Farms Assets Evaluation

In this section, wind farm projects are evaluated to assess the feasibility of incorporating them in the portfolio of an O&G company. The main outputs of those evaluations are annual energy production and net present value (with annual cash flows). In the scope of this thesis, the wind farm projects are assumed to be independent of the O&G operating assets, as the energy produced from wind farms is not used to power O&G platforms, but rather sold as electricity in the market. The reason behind that approach is related to the fact that the location of the O&G assets is not determined at early stages of the portfolio evaluation, hence the decision maker won't be able to assess how close the wind farms are to the operating hydrocarbon assets, increasing the uncertainties in the development cost of the infrastructure needed to power the platforms from wind farms energy. Also, assessing and comparing the feasibility of various power electrification options such as power from shore, new gas turbines and platform connected wind turbines, goes beyond the scope of this thesis.

Five different hypothetical wind farm assets were developed and their corresponding probabilistic evaluation was performed using a Monte Carlo simulation of 10,000 iterations over a time period of 30 years.

Each of those assets was represented as an object to the Python class "Wind_farm_asset". Table 4.10 shows the input parameters for each project.

Table 4.10: Input Parameters of Wind Farm Asset

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

The Capex structure represents how the Capex is divided during the development period of the project. All wind farm assets have three years of development period before starting production. Hence, the total capital expenditure needed is calculated and the investment is divided into three settlements, one for each development year. For instance, a "10/80/10" Capex structure suggests that 10% of the total Capex is paid during the first year of development, 80% the second year and 10% the last year. More details about the impact of the Capex structure on the cash flow of wind turbines are shown later in this section.

4.3.1. Useful Life Evaluation

A wind farm project's lifetime can be divided in two phases, of 15 years each (Figure 4.16). The first three years of the first phase are used for project development, including feasibility studies, design with environmental impact assessment and final agreements and building application. Operation and production start at the beginning of year four, when the wind farms start producing electricity, hence generating annual cash inflows.

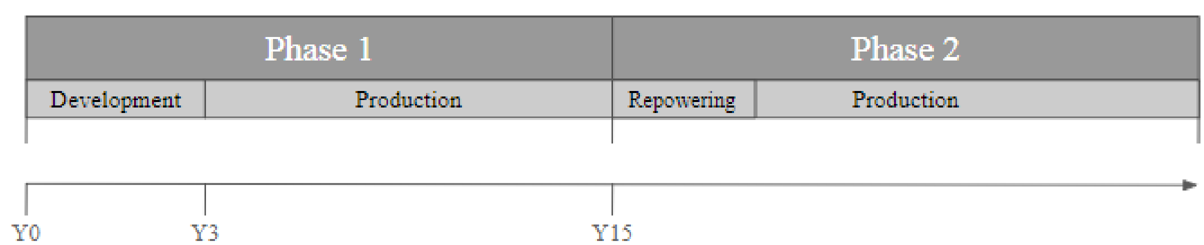

Figure 4.16: Wind Farm Project Phases

One important factor to consider in the evaluation of wind farm projects is the turbine's useful life, which depends on the annual energy production, the level of maintenance during the operational period and the type of wind turbines used. Given that typically wind turbines have a useful life between 15 and 25 years, we assumed in this project that the turbines will last for 15 years with adequate maintenance, keeping the risk of operational failure at its lowest possible level (Deloitte, 2014). At the end of its operational life, a wind farm project have three different exit options:

decommissioning, partial and full repowering (Luengo & Kolios, 2015). In the scope of this thesis, only partial repowering was considered, allowing key components of the turbines to be replaced, such as blades, rotors and drivetrains, while maintaining the existing tower and foundation (Topham & McMillan, 2017). The partial repowering cost is represented by "Repowering" in Figure 4.16, and accounted for as an additional expenditure at year 15 in the cash flow calculation.

4.3.2. Production Module

The expected power production from wind farms depends on various factors, such as wind speed, wind direction, temperature, humidity and air density. In addition, both the turbine model and the rotor blades of a turbine play an important role in the wind energy transformation into power (Deloitte, 2014). In this thesis, 2.3 MW turbines were considered for all the assets.

Based on a study done by Deloitte Analysis (2014) on wind power investments, a theoretical annual energy production of 8,000 MWh is expected. This theoretical production was derived by taking into account the wind speed distribution and 2.3 MW turbines power curves. Due to potential losses in the production, resulting from electric inefficiencies or wake effects, the modified annual production was calculated:

$$modified\ production_t = N * prod * capacity * (1 - x)^{\mathrm{t}} \tag{4.5}$$

where:
$modified\ production_t$: modified energy production at year t (in MWh)
N: number of turbines
$prod$: theoretical annual production (in MWh)
$capacity$: energy production capacity of the turbine (%);
x: yearly production degradation (%).

To account for time-dependent degradation of the turbine efficiency, a yearly degradation factor of 0.5% was used in the equation above. It represents the blades degradation resulting from dust and wind tearing of the blade surface (IRENA, 2012).

Both the theoretical production and energy production capacity were modeled as PERT distributions, to account for uncertainties. More details are shown in Table 4.11.

4.3.3. Electricity Prices

Assessing the power prices is an important part of the economic evaluation of the wind farm projects. Many studies on short term power price forecast are available. However, analyzing long term prices seems more challenging as prices tend to reflect the expectations in the inflation rate, rather than the market price's expected development (Deloitte, 2014). Hence, an analysis on the supply and demand is needed to forecast the power price in the long term. Altman et al. (2018) stated that power prices change significantly across countries, so the analysis used in this report will only reflect the power prices in the EU 28* zone, including Norway and Switzerland. The historical power prices shown in Figure 4.17 were extracted from Nord Pool (2020), while the forecast prices were taken from Energy Brainpool (2019). The red arrows show the deviations from the mean forecast price, based on Energy Brainpool (2019) analysis, and will be modeled as uncertainties in this work.

Figure 4.17: Power Price EU 28* (including Norway and Switzerland)

4.3.4. Subsidies

A significant part of wind farm revenues come from subsidies. Hence, an understanding of the degree of governmental support is essential, at early stages of the project development. The main challenges here lay in the assessment of the size of the subsidy, the terms needed to receive it in the first place and the period over which the project is eligible to subsidies. Those factors vary significantly from one country to the other, given that each country follows its own incentive scheme structure. Hence, in our analysis, we'll be focusing on the Norwegian subsidy scheme, administrated by Enova, a state-owned company, responsible of the reduction of greenhouse gas emissions and the development of climate and alternative energy technologies (NordVind, 2011).

In 2019, a total support of NOK 2.9 billion was awarded by Enova for projects contributing to the development of the energy system only (Enova, 2019). While the factors identifying the decision support by Enova in a certain project are not published, Enova (2019) states that once the decision is taken to award financial support for projects, the money is earmarked as commitments in the Climate and Energy Fund. Then, based on the project costs, the relevant amount is distributed in arrears. The project will have to pass several decision points before disbursement starts from Enova. At the moment, these decision points are still unclear, and the total amount granted varies from one project to the other, meaning that the subsidy percentage granted doesn't depend on the project's cost only, but also on other factors that are still to be determined.

Given the high ambiguity level in the subsidy granted for each project, we decided to base our analysis on Equinor's Hywind Tamper offshore wind project. This project consists of 11 wind turbines of 8 MW each, used to supply power to Gullfaks A and Snorre A oil platforms in the North Sea. Equinor (2018) estimated the total capital expenditure in this project to NOK 5 billion, and secured a NOK 2.3 billion subsidy from Enova in 2019. Hence, a 46% subsidy of initial Capex will be assumed based on this example.

However, note that the 46% subsidy is still highly uncertain for the following reasons. First, the underlying conditions behind Enova's significant support in the Hywind Tamper project are unclear, as the NOK 2.3 billion reflects around 80% of the total support awarded by Enova that year for all projects in the development of the energy system. Second, Equinor was granted an additional NOK 566 million in support from the Norwegian Nox-fund for the same project

(Equinor, 2018). Lastly, the initial Capex estimated by Equinor (NOK 57 million per MW) ranges above most wind farm commercial Capex estimations published in the industry.

4.3.5. Cost Evaluation Module

First, the Capex was estimated for both onshore and offshore wind farms. It consists of the cost of turbines, grid connections, construction, installation and other platform costs. It can be divided into two main categories. The first category covers the cost of turbines, cables, towers and foundations and accounts for 73% of the total Capex. While the second category consists of infrastructure, licenses and station transformer costs and accounts for 27% of the total Capex (Morthorst and Kitzing, 2016).

Many studies have been conducted on the cost estimation of wind farms, such as The European Wind Energy Association (2012), DNV (2011) and Deloitte (2014). Those estimates depend on various factors such as the stage of development of the project, which can be classified as prototype, commercial or pre-commercial project. Only commercial projects are considered in this thesis. Other factors affecting the capital cost include the technology used, the availability of infrastructure in the area of development and the bargaining power of the turbine suppliers based on the project's profitability (Deloitte, 2014). Note that offshore projects have greater initial capital cost, as the cost of foundation, construction and grid connections tend to be higher offshore compared to onshore wind farms. Deloitte (2014) shows a positive correlation between the site water depth and Capex for offshore turbines. More details about the Capex structure used in this thesis are available in Table 4.11.

Second, the operating expenses (Opex) were estimated. They consist typically of insurance, maintenance and management costs and vary with annual production levels. As has been shown in the Capex estimation, the literature has used different Opex estimates. Different consultancy institution reports were analyzed in our work such as Roland Berger (2013), Douglas-Westwood (2010) and Deloitte (2014) and the resulting Opex structure implemented in this thesis is described in Table 4.11.

Krohn et al. (2009) claimed that the operating expenses of wind farm projects increases over the project's lifetime due to the worn out effect and damage of the components. This factor was taken into account in our analysis, with a 1.5% yearly cost increase of the Opex.

Bolinger et al. (2019) suggested that the increase in global wind capacity will result in an Opex reduction over time. Their conclusion was based on a detailed study of historical Opex variations. Also, we believe that rapid technology evolutions in the field consolidates this hypothesis. Hence, a 9% Opex decrease is considered in the second phase of the project (after partial repowering of the plant).

Finally, capital expenditures were depreciated over 15 years, using the straight line depreciation method. The after tax cash flow and net present value were calculated following the same method used for the O&G assets.

Table 4.11: Input Parameters of Wind Farm Cost and Production Structures

Parameter [Python Argument]	Unit	Min	Mode	Max
Offshore Project				
Opex [opex]	$/kWh	0.015	0.03	0.048
Total Capital Variable Cost [capex_var]	million$/MW	2.29	3.5	5.42
Total Capital Fixed Cost [capex_fix]	million $	43.2	72.12	90
Partial Repowering Investment [repower]	million$/MW	-	1.056	-
Onshore Project				
Opex [opex]	$/kWh	0.01	0.015	0.035
Total Capital Variable Cost [capex_var]	million$/MW	1.2	1.8	2.29
Total Capital Fixed Cost [capex_fix]	million $	36.03	60.4	75.51
Partial Repowering Investment [repower]	million$/MW	-	0.88	-
Common Parameters for all Projects				
Annual Theoretical Production [energy_prod_theo]	MWh	6500	8000	10000
Energy Production Capacity [energy_cap]	%	50	65	85

Note: All parameters in Table 4.11 follow a PERT distribution.

Figure 4.18 shows the NPV distribution of two different wind farm projects, illustrating the difference between onshore and offshore operations.

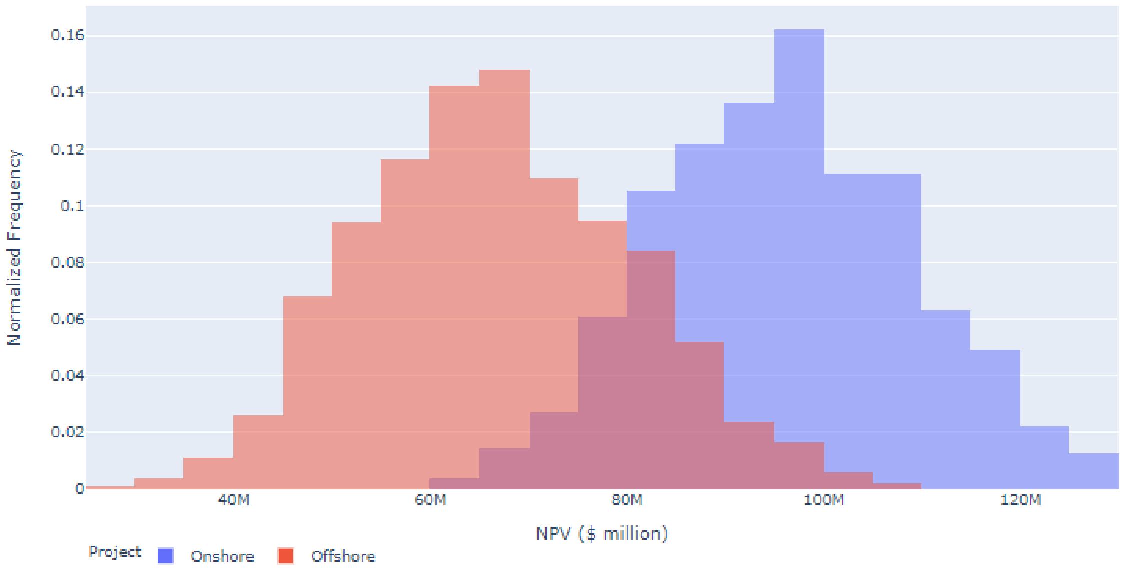

Figure 4.18: NPV Distribution of a Wind Farm asset (overlapped) (onshore vs offshore)

Also, the difference between using a "10/80/10" and "30/60/10" Capex structures was assessed (Figure 4.19). The highest NPV obtained with a "10/80/10" structure is due to the fact that 10% of the initial capex was invested at the end of year 0, compared to a 30% in the other structure, while one third of the total subsidy was received the same year in both cases. Taking into account the time value of money, a higher NPV is thus expected using the first Capex structure. However, the main drawback of using this approach is that it requires the availability of the adequate Capex budget at the end of year 1 to cover not only the cost of wind farm development, but also other operating assets within the portfolio. This budgetary constraint is analyzed more in details later in this report.

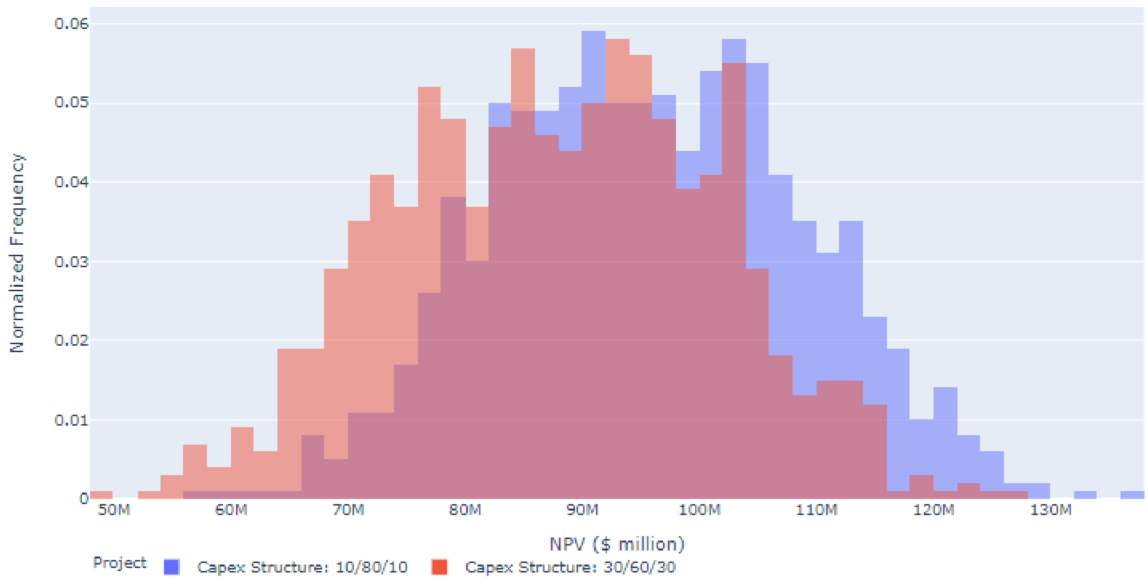

Figure 4.19: NPV Distribution of a Wind Farm asset (overlapped) (different Capex Structures)

4.4. Carbon Capture and Storage (CCS) Evaluation

4.4.1. Background Overview

The development of low-carbon and non-carbon energy solutions (such as solar, wind, nuclear, natural gas, etc.) and the implementation of high efficiency energy systems will decrease the CO_2 emission and accumulation in the atmosphere. To remain below the 1.5 °C temperature increase target, IEA suggested that no new exploration for fossil fuels should be done after 2021 (IEA, 2021). However, the use of green technologies alone won't be sufficient to reach the GHG emission targets by 2030, in line with the Paris Agreement (McKinsey, 2008). Moreover, high carbon fuels (such as gas, oil and coal) are forecasted to remain the dominant source of energy needed to meet the global demand in the near future. The reason behind this assumption is based on the fact that high carbon fuels present various advantages over alternative low-carbon energy sources including the ease of storage and transportation, competitive cost and availability (Aydin et al., 2010). Hence, it's required to sustain the utilization of fossil fuels, while implementing new technologies to reduce CO_2 emissions.

One of the solutions presented and discussed is Carbon Capture and Storage (CCS). The Intergovernmental Panel on Climate Change (IPCC), the International Energy Agency (IEA, 2012) and the World Energy Council (WEC, 2007) all identified CCS as a key tool for GHG emission reduction. A CCS plant includes the capture and extraction of the CO_2 emitted from industrial sites and power plants, followed by CO_2 compression, transport and storage in a suitable geological sink (Feron & Hendriks, 2005).

For the past few years, a considerable amount of research have been conducted on the CCS technology, addressing its economical, technical and environmental aspects. Feron & Hendriks (2005) analyzed the cost and emission reduction potentials of CCS, using an integrated eight steps system-chain approach. Their paper evaluated and compared various electricity production technologies in two scenarios: with and without CCS integration. They concluded that the electricity production cost is expected to increase by 0.015-0.03 euro/kWh when CO_2 capture and storage is applied, while the carbon avoidance cost is expected to increase substantially, especially for coal-based systems. Adu et al. (2018) examined some current CCS projects performances and suggested various ways to improve their economic value, including the use of the hub and cluster approach and/or CO_2-EOR (enhanced oil recovery) for O&G reservoirs. They stated that injecting the captured CO_2 to improve the well's oil recovery can achieve up to 60% carbon sequestration (capture). Consoli et al. (2017) analyzed the importance of CCS in the O&G industry and concluded that this sector have a solid technological advantage for expansion and upscaling of CCS. In addition to the opportunity of reducing its own carbon emission, an O&G company can build a separate global business out of the CCS plant, allowing other companies to use it, and hence creating additional revenue streams (tax credits scheme). However, to meet international emission targets, CCS must be backed and supported by strong emission reduction policies, legal frameworks and sustainable governmental incentives (Adu et al., 2018; Consoli et al., 2017; Feron & Hendriks, 2005; Singh, 2013; Yan & Zhang, 2019).

4.4.2. Overview of Process Model

Often, the general CCS process involves three major steps, as seen in Figure 4.20 (Equinor, 2021):

- CO_2 Capture: CO_2 is emitted from industrial plants or alternative combustion sources as a flue gas, containing both nitrogen and CO_2. In order to simplify transport and storage activities, an additional compression step is required, to ensure an adequate CO_2 pressure of 100 bars. Three principle CO_2 capture processes are available: post-combustion, pre-combustion and oxy-fuel combustion method (Feron & Hendriks, 2005). Additional details about advantages and drawbacks of each capture method can be found in Leung et al. (2014) paper.

- CO_2 Transport: since different locations are often used for CO_2 capture and storage, a transport system is needed to link the emission sources to the adequate storage sinks. Often, CO_2 is transported in a gas, liquid or solid state, using pipelines, tanks or ships, depending on the component physical state (Aydin et al., 2010).

- CO_2 Storage: CO_2 should be stored in areas where it can stay isolated from the atmosphere for a long period of time. Such areas include depleted O&G fields, deep saline aquifers and coal beds. In addition to safety and low migration risk within the formation, several criteria must be considered when choosing the geological storage such as capacity, cost, applicability and carbon release to the surface (Aydin et al., 2010).

In the scope of this thesis, little details about the technical aspects of the CCS asset used are discussed. The focus will be mainly on the economic performance and carbon capture potential of the CCS plant, in line with the portfolio's objectives and thesis topic.

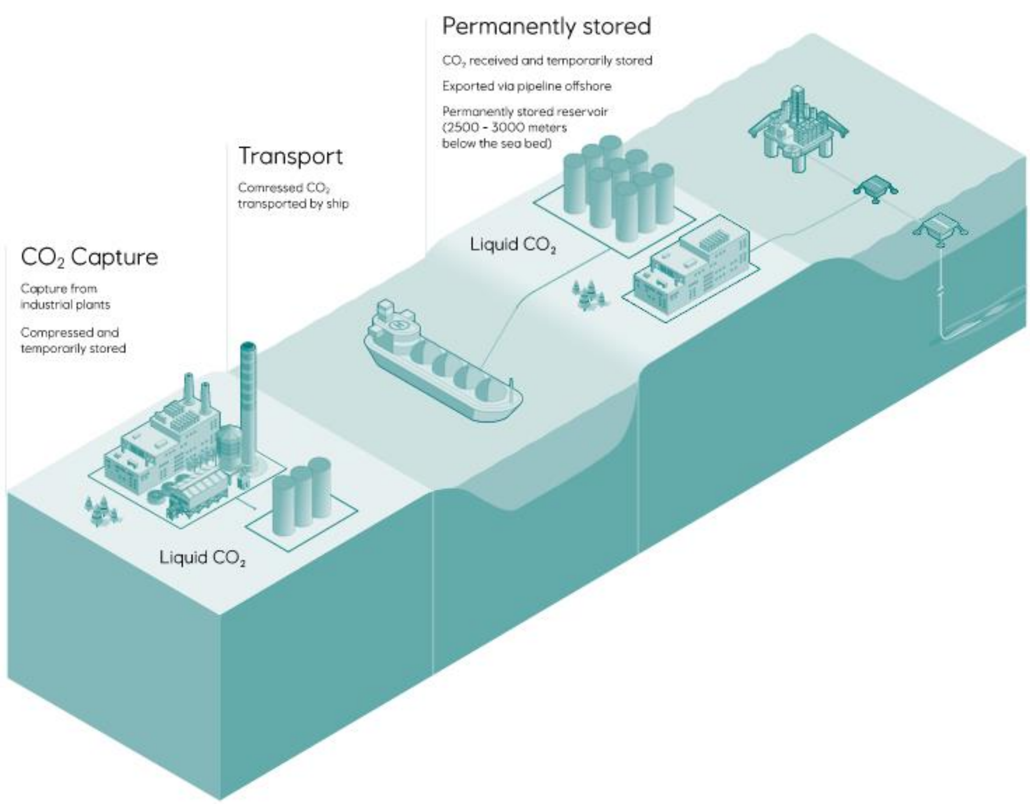

Figure 4.20: CCS Operating Steps (adapted from Equinor (2021))

4.4.3. Innovations & Applications

In this section, some examples of major O&G companies' investments in CCS are presented:

- The **Northern Lights** project is part of the full-scale CCS initiative "Langskip", supported by the Norwegian government. The full-scale project initially captures CO_2 from industrial capture sources. Then the Northern Lights project aims to transport liquefied CO_2 via ships for permanent storage in an offshore subsea location in the North Sea. The first phase of the project included a total transport, injection and storage capacity of 1.5 million tons of CO_2 annually, accounting for around 11% of the total emission on the NCS. Operations are scheduled to start in 2024. The Northern Lights project is governed by a collaboration agreement between three O&G companies: **Equinor, Shell and Total** (Equinor, 2021).

- The **Quest** project, one of the largest CCS projects in the world, is a fully-integrated carbon capture and storage plant, compromising of CO_2 capture, transport and storage of more than one million tons of CO_2 per year. The project captures around one third of the total emissions from Shell's Scotford oil sands Upgrader and stored the captured CO_2 in the impermeable rock formation of the Cambrian Basal Sand. Quest is supported by the Canadian and Alberta governments and is a partnership between **Shell, Canada Energy and Chevron** (Shell, 2021).

- The **HyNet North West** project includes hydrogen production from natural gas and a fully-integrated CCS infrastructure model. The project, supported by the UK government, is being led by a group of regional industrial companies in the UK, in addition to **ENI**, who will play a major role in the CO_2 transportation and storage. One of ENI's depleted O&G reservoirs will be used to store the CO_2 captured. The project is expected to reduce CO_2 emission in the UK by up to 10 million tons annually by 2030, significantly contributing to government's the net-zero emission target at 2050 (ENI, 2021).

- The **Gorgon** project injects and stores CO_2 into deep sandstone formation next to the Gorgon gas fields (Western Australia). The CO_2 is separated at the liquefied natural gas (LNG) plant and transported using pipelines to nine different directional injection wells, used to store the CO_2 in trapped formations. A 40% GHG emission reduction over the project's lifetime is expected. Shell and ExxonMobil are partners in this project, led by **Chevron** (Chevron, 2021).

4.4.4. Economic & Capture Potential Evaluation Module

In this section, the cost of a CCS project is estimated and used in the economic evaluation of the asset for portfolio analysis. As for wind farms and hydrocarbon assets, a hypothetical CCS project is modeled in Python using the class "CCS_asset", and a probabilistic evaluation was performed using Monte Carlo simulation of 10000 iterations for a period of 30 years.

The input parameters for the CCS project are listed in Table 4.12.

Table 4.12: Input Parameters of CCS Asset

Parameter [Python Argument]	Unit/Possible Outcomes
CCS Utilization percentage [util]	%
Subsidies percentage [perc_subs]	%
Time Period [period]	Years
Number of Iterations [n]	-

The subsidies percentage represents the amount of governmental support the company is expected to receive for this investment, as a fraction of the total Capex required. The CCS utilization percentage illustrates the percentage of the total CCS capacity that is being used for carbon capture and storage. This parameter varies depending on the project's phase. A project in the demonstration (sub-commercial) phase is assumed to have a utilization percentage of not more than 80%. For early commercial and mature commercial phases, this percentage is expected to increase to up to 86% (McKinsey, 2008).

In this thesis, the CCS project is divided into two stages (Figure 4.21). First, in the demonstration phase, the CCS technology is still not very mature; however, a fair amount of carbon emission is expected to be captured. At this stage, governmental policies and carbon trading market potential are still unclear. A 15-year economic life is considered for this phase. Once the CCS project has been evaluated and developed, a commercial operation phase begins, where significant CO_2 capture is expected. In addition, a CCS project in a mature commercial phase can generate additional commercial utility income by tax credits trading and/or carbon utilization (such as EOR). Typically, a commercial scale CCS asset have a lifetime of 40 years (McKinsey, 2008); however, in this thesis, since all hydrocarbon and wind farms assets are evaluated for a total period of 30 years, the CCS project's evaluation stops at 30 years for consistency in the analysis.

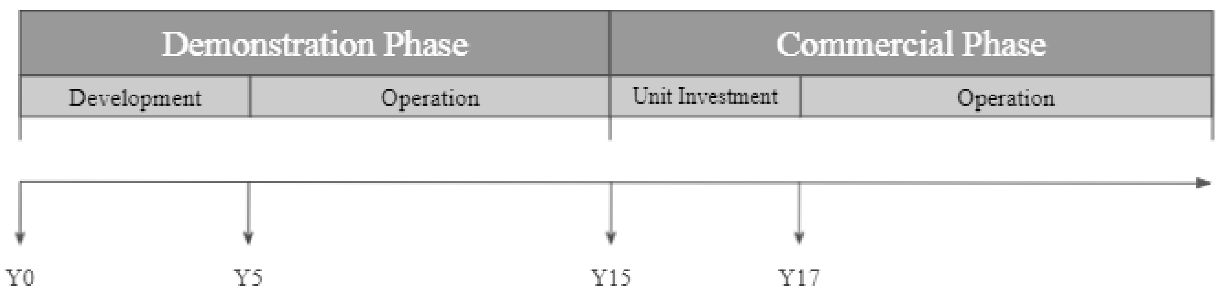

Figure 4.21: CCS Project Phases

The cost evaluation of a CCS project depends on various parameters such as the type of CO_2 capture technology, the facility's capacity, the distance from emission sources to the storage location and the geological CO_2 storage area (Adu et al., 2018). Publicly available data shows significant cost differences between various CCS operating projects. For example, the Quest project has an estimated investment cost of around \$40 per tons of CO_2 captured over the project's lifetime, while for the Gorgon project it's around \$20 per tons (Consoli et al., 2017). In addition to the uncertainties associated with actual cost estimations, there is also significant uncertainties in the prediction of cost development over time (McKinsey, 2008).

In this thesis, the cost structure of a CCS project was divided in three parts: initial unit investment cost (Capex), operation and maintenance running cost (O&M) and cost per tons of CO_2 abated. The initial unit investment cost represents only the total capital cost required to design, buy and install the equipment. Since the CCS project is divided in two phases, two separate capital costs are considered, reflecting the investments at each stage of the project. Installations are depreciated using the straight-line depreciation method over the project's lifetime (Feron & Hendriks, 2005). As for the cost per tons of CO_2 abated, it consists of the sum of the costs of CO_2 capture, transportation and storage. Often, the capture cost represents around two-third of the total abated cost (Adu et al., 2018). Another component of the cost structure is the operation and maintenance (O&M) running cost which compromises the cost of planned and unplanned maintenance, assurance, spare parts, labor, etc. (Franki et al., 2019). O&M costs are considered equal to 5% of the total initial investment. Another key factor affecting the overall cost structure is the project's location, where offshore projects have higher estimated costs compared to the onshore costs (Aydin et al., 2010).

Given the variations in cost estimations with several parameters, the following assumptions were considered with regards to the CCS unit's characteristics:

- Capture using post-combustion capture absorption technology.
- Compression at the capture site and injection using directional wells
- Transportation through a pipeline network of 200-300 km, keeping the component in supercritical state.
- Storage in a depleted hydrocarbon field at a depth of 1000-3000m.

The applicability of these assumptions depends on the project's location, company's level of expertise and availability of storage capacity and adequate geographic formation, among many other factors.

The CCS unit presented in this work have capture and storage efficiencies of around 90% (Adu et al., 2018; McKinsey, 2008), and a total unit capacity of 1.5 and 5 million tons of CO_2 per year, for the first and second project phases respectively.

Information on costs presented in this section (Table 4.13) is obtained from Adu et al. (2018), Aydin et al. (2010), Consoli et al. (2017), Feron & Hendriks (2005) and Franki et al. (2019).

Table 4.13: Input Parameters of CCS Cost Structure

Parameter [Python Argument]	Unit	Min	Mode	Max
Unit Investment of 1st Stage [capex1]	$ million	300	332	350
Unit Investment of 2nd Stage [capex2]	$ million	120	150	170
Capture Cost [capt_cost]	$/t CO_2	30	37	39
Transportation Cost [trans_cost]	$/t CO_2	4	4.9	7.3
Storage Cost [stor_cost]	$/t CO_2	4.9	12	14.5

Note: All parameters in Table 4.13 follow a PERT distribution.

4.4.5. Drivers for CCS development

Even though individual parts of the CCS unit can be considered mature, this technology still faces various development challenges, due to its high cost of operation and uncertainties about its profitability and technical feasibility in the future (Consoli et al., 2017). However, technological uncertainties and capital requirements are expected to be reduced by implementing additional demonstration projects and improving and/or making current CCS methods more cost effective (Franki et al., 2019).

In order to offset the high perceived cost of CCS, strong and stable regulatory frameworks must exist. McKinsey (2020) states that from an economical point of view, a CCS cannot create value of itself unless particular economic conditions are present. These include governmental support through incentives, subsidies and carbon tax schemes, in addition to a strict cap and trade system. For example, in Norway, both Snøhvit and Sleipner projects (operating carbon storage projects) were feasible because of governmental support and CO_2 tax. Another example is the Quest CCS project in Canada that received significant financial support from the government and benefited from the emission reduction incentives (Consoli et al., 2017). As mentioned earlier, under the European Emission Trading Scheme, CO_2 emitting companies are freely-assigned emission allowances every year. In case those companies exceed their GHG emission limits, they are required to purchase additional emission allowances on the open markets, under the "cap and trade" scheme. Therefore, a CCS project can benefit from this trading system to first reduce its spending on open market allowances due to carbon emission reduction from its operating assets.

Second, a CCS asset can generate additional revenues by selling emission allowances to other companies. Even though O&G companies' spending on emission allowances are often not publicly shared and change significantly over time, a good estimation is based on ENI's example. In 2019, ENI purchased allowances on the open market corresponding to 11.6 million tons of CO_2 emission, estimated for a cash cost of €290 million (ENI, 2020). Stricter regulations on the free-assignment of allowances are expected in the foreseen future.

In addition to regulatory frameworks, CO_2 utilization can significantly affect the overall project's economics. Industrial captured CO_2 can be used across various industries such as plastics, chemicals, biological conversion, food, etc. One area of current interest is CO_2-EOR with CCS, where the captured CO_2 is injected in a depleted O&G reservoir to increase downhole pressure and enhance the oil recovery from the well. Then the injected CO_2 is stored there permanently. Adu et al. (2018) suggest that the goal of CO_2-EOR application with CCS is not only to maximize oil recovery but also increase the amount of CO_2 stored during operation. Therefore, one limitation of this process that must be taken into consideration is the high mobility of CO_2 during injection, resulting in higher CO_2 fingering and channeling and lower storage efficiency. Foam flooding and water alternating gas (WAG) flooding are two common techniques used in the industry to mitigate the CO_2 mobility limitation, but as expected, they come with additional operating costs. Other limitations include the risk associated with CO_2 leakage in geological storage after EOR. CO_2-EOR sale prices are estimated around $20 per tons, based on the Boundary Dam public report (Consoli et al., 2017); however, this price significantly depends on O&G prices, resulting in higher uncertainties in the forecast of the CO_2-EOR CCS economics potential. In addition, the applicability of EOR depends on the reservoir's characteristics, and most experts agree that EOR have very limited economics potential in Europe (McKinsey, 2008). Some examples of successful CO_2-EOR with CCS projects include Weyburn Project in Canada, Abu Dhabi CCS Project in UAE, Sinopec CCS Projects in China, among many others (Adu et al., 2018).

In this thesis, CO_2-EOR is not considered in the asset evaluation analysis; hence, the hypothetical company evaluated should carefully target governmental support and penalties associated with CO_2 emissions, as it was the case for both Norwegian Sleipner and Snøhvit projects (where no EOR revenues were generated).

5. Portfolio Case Study

In this section, the executive management team must select the optimal asset combination from a pool of petroleum and non-petroleum projects. The decision criteria include expected NPV, carbon emission and O&G production, while the primary constraint is the annual expected Capex. The decision-maker's objectives are evaluated annually, and the probabilities of meeting the annual targets are calculated. Various corporate strategies with a focus on energy transition and net-zero carbon emission ambition are evaluated, then time-dependent portfolios in line with those strategies are identified.

We considered a hypothetical portfolio of 16 assets. Stochastic aggregation including time-dependent goals and constraints is used for multi-objective portfolio optimization.

The portfolio includes the following asset types: ten hydrocarbon, five wind farms and one carbon capture and storage (CCS). Individual project characteristics are presented in Table 5.1. The choice of the year to start the project depends on the decision-maker's preference, in addition to the project's technical feasibility in the chosen year. It's assumed that only non-petroleum assets are expected to receive support from the government or other organizations in the form of subsidies.

Project evaluations described in Section 4 were conducted using a Monte Carlo simulation of 10,000 iterations and a period of 30 years. Simulation results are summarized in Table 5.2 below.

Table 5.1: Portfolio Pool

Project	**Asset Type**	**Location**	**Phase**	**Govt. Subsidy %**	**Mode of Reserves Mstb/Bscf**	**Start-up Year**
P1	Petroleum - Gas	Onshore	Exp.	-	800.00	0
P2	Petroleum - Oil	Onshore	Dev.	-	300.00	0
P3	Petroleum - Oil	Onshore	Dev.	-	520.00	0
P4	Petroleum - Gas	Onshore	Dev.	-	1060.00	0
P5	Petroleum - Oil	Onshore	Exp.	-	250.00	1
P6	Petroleum - Oil	Offshore	Exp.	-	680.00	4
P7	Petroleum - Oil	Offshore	Dev.	45	140.00	0
P8	Petroleum - Gas	Offshore	Dev.	45	1520.00	0
P9	Petroleum - Gas	Offshore	Exp.	45	970.00	3
P10	Petroleum - Gas	Offshore	Exp.	45	2040.00	1
P11	Wind Farm	Onshore	-	45	0.00	0
P12	Wind Farm	Onshore	-	45	0.00	0
P13	Wind Farm	Onshore	-	45	0.00	0
P14	Wind Farm	Offshore	-	45	0.00	0
P15	Wind Farm	Offshore	-	45	0.00	0
P16	CCS	Offshore	-	45	0.00	0

Year 0 indicates that the project is expected to start right way (the same year that the portfolio analysis is performed).

Table 5.2: Portfolio Simulation Results

Project	Start-up Year	E[Oil Res]	E[Gas Res]	E[NPV]	Sum over the project's lifetime: E[Oil Prod]	E[Gas Prod]	E[CO_2 Emission]	E[Capex]
	year	Mstb	Bscf	$ million	Mstb	Bscf	million t CO_2	$ million
P1	0	-	823.19	-690.51	-	286.03	1.77	2122.92
P2	0	316.11	-	714.74	139.42	-	0.81	745.42
P3	0	549.64	-	1231.43	342.20	-	1.41	1308.73
P4	0	-	1120.08	-416.23	-	893.58	2.87	1981.75
P5	1	260.21	-	21.93	81.73	-	0.52	1218.46
P6	4	1388.52	-	278.98	917.20	-	2.26	4568.44
P7	0	294.58	-	512.14	130.16	-	0.76	1033.74
P8	0	-	3213.29	1001.11	-	1402.73	8.18	4902.64
P9	3	-	2015.89	-1550.68	-	1502.60	3.48	5795.19
P10	1	-	4195.16	572.95	-	3327.81	0.52	6632.24
P11	0	-	-	179.42	-	-	-	301.29
P12	0	-	-	90.37	-	-	-	150.94
P13	0	-	-	82.28	-	-	-	150.54
P14	0	-	-	90.19	-	-	-	486.77
P15	0	-	-	61.50	-	-	-	243.35
P16	0	-	-	-574.65	-	-	-56.10 [3]	678.18

5.1. Time-dependent Portfolio Analysis

Many O&G companies increasingly focus on the energy transition from fossils to renewables and portfolio management and optimization can be an important contributing factor to plan, decide and implement this transition which includes actions to reduce their carbon emissions and targeting a net-zero emission by 2050. Their approaches are often two-folded as several factors such as the

[3] The negative CO_2 emission amount reflects the amount of CO_2 captured by the CCS asset

company’s regional presence and size, infrastructure availability, social acceptance and degree of public sector intervention, are key determinants of the company’s action plans.

First, companies must reduce their emission by increasing the percentage of renewables in their portfolios. Due to budgetary constraints and investors’ pressure towards a less risky and low-emission future, a gradual phasing out of O&G production in favor of renewables assets is necessary. However, process optimization, cheaper reserves and infrastructure availability might become key motivations for further hydrocarbon production in the future. Moreover, the ability of renewable energy to satisfy the world’s growing energy needs in a timely manner is still open to question. Hence, high carbon fuels are forecasted to remain the dominant source of energy in the near future.

Second, companies need to offset their carbon emissions from operating hydrocarbon assets by investing in net-negative emission technologies, such as CCS. Even though this technology has significant potential in emission reduction and is highly compatible with the current hydrocarbon infrastructure, its economic feasibility requires the presence of a clear, predictable and sustainable regulatory framework that actively help and support companies seeking to achieve net-negative emission. In addition, CCS is a means to continue producing fossil fuels and, hence, hinders, or at least slows down, the energy transition to renewables.

Therefore, the energy transition’s plan of an O&G company is often a double-edged sword. Moving too quickly into renewable and CCS implementation might result in stranded assets, while refusing to change by increasing or maintaining oil production at its current level might cause losses in shareholders’ trust and investors’ willingness to make “more risky” investments.

In this section, two separate case studies are presented. In the first scenario, O&G production targets are kept the same over the portfolio’s lifetime, while CCS and wind farms assets are incorporated into the portfolio. Given more production will result in higher emission intensities, a working interest of 100% in the CCS asset is considered to reach the emission target set by the corporate team. The second scenario includes a major shift from oil to wind energy production, where the company will have partial ownership of the CCS asset, as less emission is expected in this case.

Both scenarios are evaluated using time-dependent stochastic aggregations of cash flows and carbon emissions, where the probabilities of delivering on the annual portfolio targets, determined by the executive management team, are calculated. The analysis also includes changes in the assets' working interests or annual targets in each scenario in order to create an optimal portfolio.

5.1.1. Scenario 1

Initially, a portfolio including 100% of all assets is considered. This analysis helps to understand whether the annual goals are realistic and achievable. The decision-maker might decide to lower the targets or change the working interests of the assets after this analysis, depending on how flexible the targets are. However, with fixed budgetary constraints, and limited access to capital, the Capex target is unchangeable. Table 5.3 shows the initial corporate performance goals set by the executive management team.

Again, O&G productions are assumed to be kept at their current levels, i.e. no reduction in hydrocarbon production over the portfolio's lifetime. Corporate targets on electricity production were not considered in this analysis. The feasibility of a wind farm project is hence assessed only based on its emission reduction potential, compared to hydrocarbon assets, and on its economic contribution to the overall portfolio.

The projects were all evaluated over 30 years. Usually, executive management teams don't make plans that far into the future. However, a shorter time horizon, of 10 years for example, is too short for the energy transition portfolio. Many O&G companies have set net-zero carbon emission targets for 2050; hence, we believe that a long horizon is needed to show that even if the company reaches 30% or 50% of its objectives during the first 10 years, it is still on its way to become net-zero (or negative) by 2050.

Table 5.3: Corporate Targets (Scenario 1)

Year	Time-Dependent Corporate Targets				
	Capex	**NCF**	**CO_2 Emission**	**Oil Prod**	**Gas Prod**
	$ million	$ million	million t CO_2	Mstb	Bscf
0	-1000	100	1	10	400
1	-4000	100	1	15	400
2	-3500	100	0.95	18	400
3	-3000	100	0.95	20	400
4	-3000	100	0.7	21	400
5…10	-2000	100	0.6	28	400
11…20	-2000	100	0.3	35	400
21…30	-2000	100	0.05	18	200

After defining the annual corporate targets and constraints, a probabilistic aggregation of the various objectives (NPV, carbon emission and O&G production) is performed. Then the expected values of the portfolio's objectives are calculated based on the weights attributed to each asset. An example is illustrated in Figure 5.1. The corporation can choose any working interest in assets 1 through N. The mean, P10 and P90 of the assets' cash flows are shown on the left. The annual NPV expected values of the portfolio resulting from the combination of those assets is represented by red bars and the annual NPV corporate targets by blue bars. The black line, which requires the run of the Monte Carlo simulation sampling from the assets (using the chosen working interest), shows the probability of delivering on the portfolio target for each year.

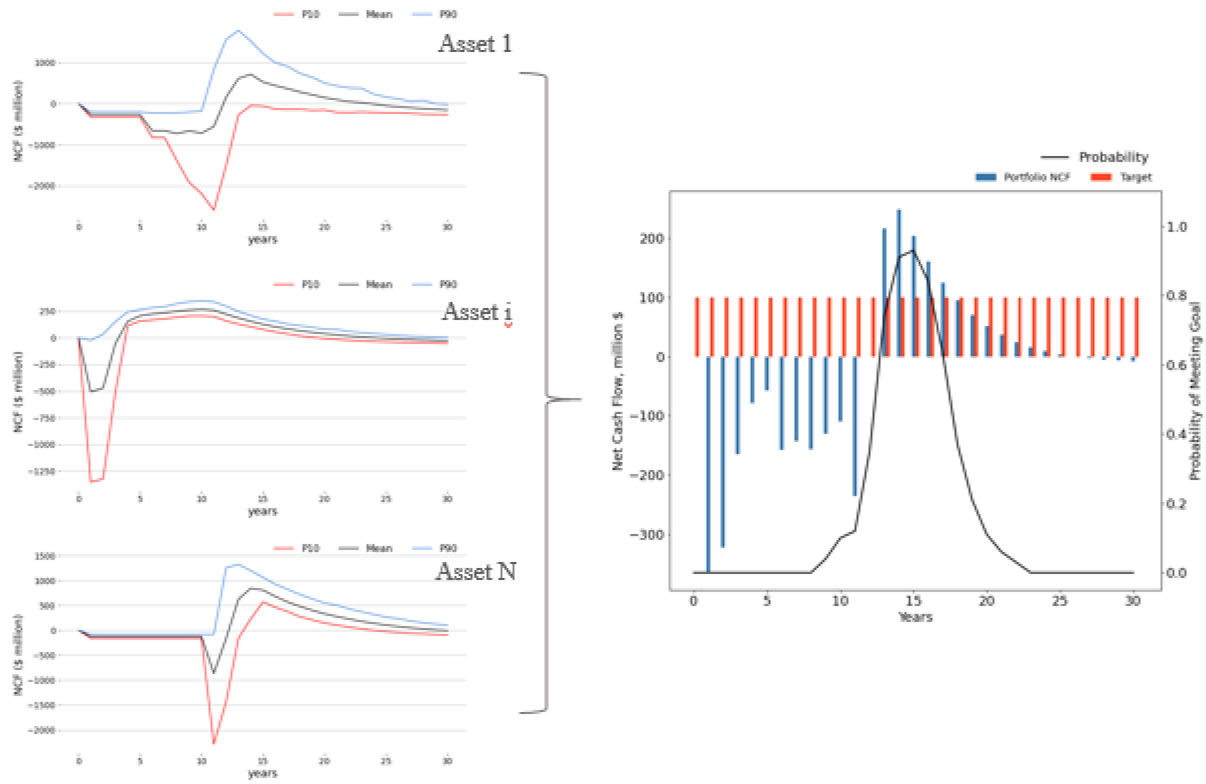

Figure 5.1: Time-dependent Probabilistic Aggregation of Cash Flows Example

The probabilities of meeting corporate goals using a full portfolio are shown in Figure 5.2 (*portfolio value represents the expected values of the portfolio*).

Clearly, the probability of meeting the majority of corporate goals over the entire time horizon is quite low. Beyond year 20, when hydrocarbon production decreases, the probability of meeting annual NCF targets decreases significantly, as CCS operating expenses exceed annual revenues from wind farms and petroleum assets. However, the carbon emission target is fully met from year 15 onwards suggesting that the CCS unit have additional capacity to capture more emission. This might introduce some opportunities for the company to balance its cash flow by either selling emission allowances or utilizing its additional CCS capacity to capture CO_2 emitted from nearby operating assets. However, assessing the annual probabilities of meeting the emission goals, it can be seen that a full portfolio will produce more emission than the target, even in the presence of a full CCS project operating. Hence, some petroleum assets must be reconsidered.

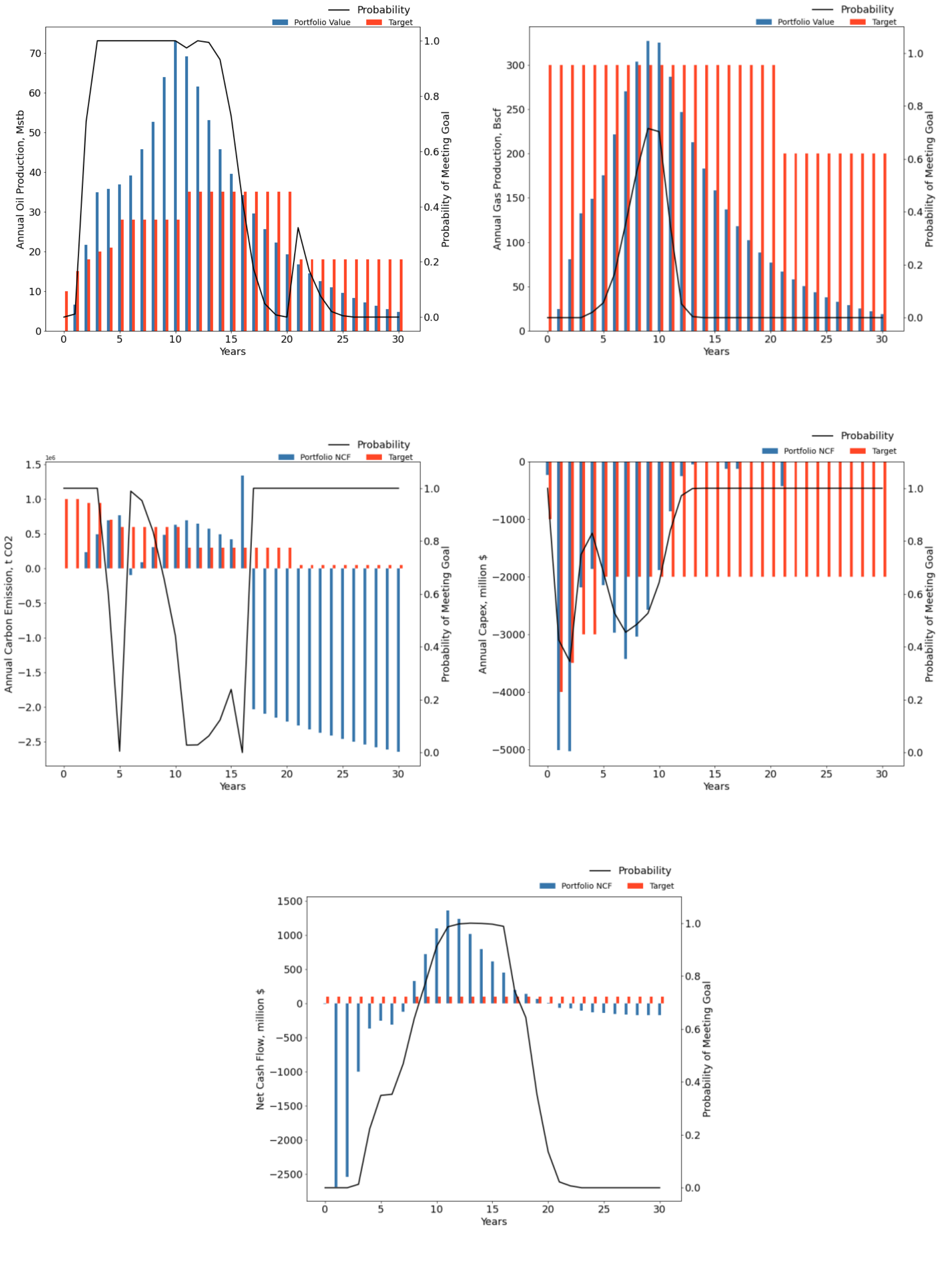

Figure 5.2: Time-dependent Portfolio Analysis Results (100% WI Portfolio)

In addition, the company will fail to meet its production goals when all O&G projects are expected to start early in the portfolio's lifetime. This notion is also seen in the Capex targets, where between years 0 and 10, the annual Capex goals are met between 35% and 60% of the time only. With the target budgetary limits, the full portfolio cannot be implemented.

Three alternative portfolios are proposed and their individual overall performances are summarized in Table 5.4. Portfolio A is the full portfolio analyzed earlier, consisting of 100% of all assets. It's included in the table as a reference case. Portfolio B includes petroleum assets only, whilst portfolios C and D focus on O&G reserves maximization, respectively. In this part of the analysis, NPV is considered the main objective, since carbon emission targets are met through the full ownership of the CCS operation. The shaded values represent the performance metrics that breach the corporate targets.

Note that in the portfolio analysis and optimization proposed in this thesis, no computerized portfolio optimization algorithms (such as quadratic or evolutionary algorithms) were used. Working with multiple time series, each with its own objectives, there will be hundreds of weighting factors to determine, and even if the decision-maker is willing, and able, to do this, the resulting optimization problem cannot be solved by a computerized algorithm in a reasonable time (if at all). Therefore, the analysis proposed is "manual", where the assets' working interests are manually adjusted to meet corporate goals. Hence, there might exist a "more optimal" asset combination maximizing the objectives given the corporate constraints. However, the goal here is to assess the impact of implementing the CCS technology and wind farms on the portfolio's performance, rather than finding the optimal asset combination. Moreover, a second, but perhaps just as important, objective is to facilitate good conversations in the executive management team leading to a thorough understanding of decision alternatives and their uncertain consequences.

Table 5.4: Portfolios Performance Metrics (Scenario 1)

Project	Asset Type	Portfolio:	A	B	C	D
P1	Gas	Asset	1.00	0.00	0.00	0.00
P2	Oil	Combination	1.00	0.80	1.00	1.00
P3	Oil		1.00	1.00	1.00	1.00
P4	Gas		1.00	0.00	0.00	0.60
P5	Oil		1.00	0.30	1.00	0.00
P6	Oil		1.00	0.60	1.00	0.10
P7	Oil		1.00	0.70	1.00	0.70
P8	Gas		1.00	1.00	1.00	1.00
P9	Gas		1.00	0.00	0.00	0.00
P10	Gas		1.00	1.00	0.33	1.00
P11	Wind		1.00	0.00	1.00	1.00
P12	Wind		1.00	0.00	1.00	1.00
P13	Wind		1.00	0.00	1.00	1.00
P14	Wind		1.00	0.00	1.00	1.00
P15	Wind		1.00	0.00	1.00	1.00
P16	CCS		1.00	1.00	1.00	1.00
Performance Metrics	**Total Targets**[4]					
Capex (million $)	≤18000		32320.31	17948.35	17977.15	17969.62
NPV (million $)	≥ 3500		1604.98	3335.11	3878.53	3586.01
Carbon Emission (million t CO_2)	≤ 1		-25.52	-35.29	-39.34	-34.69
Oil Reserves (Mstb)	≥ 2000		6768.21	1919.90	2809.05	1882.85
Gas Reserves (Bscf)	≥ 8000		11367.60	7408.44	4597.69	8080.49

[4] Total targets, over the entire time period

The results in Table 5.4 show significant improvements in the portfolio performance in terms of NPV and Capex, compared to those obtained in Portfolio A. The highest NPV value is met using Portfolio C, focusing on maximizing oil production and reserves (probabilities of meeting annual targets using this portfolio are shown in Figure 5.3). While this portfolio doesn't breach the majority of the performance metrics targets, it results in very low gas reserves and also a decrease in annual gas production as well. Since three of the gas producing assets have the lowest NPVs among all other projects, excluding them from the portfolio resulted in a noticeable increase in the expected portfolio's NPV. However, this had a negative impact on the probability of meeting the annual gas production constraints (Figure 5.3). Thus, the company should reconsider its performance targets, and overall strategy with respect to its natural gas business.

Even tough Portfolio D meets as many corporate targets as Portfolio C, it has a higher overall emission intensity. In the presence of a full CCS project, this doesn't create any limitation on the portfolio's performance in terms of emission. However, the extraction of more emission intensive assets by CCS exploitation is subject to social and economic issues related to technical uncertainties and degree of social and environmental acceptance.

In Portfolio B, only the Capex constraint (that was manually monitored) and the carbon emission target were met. While some optimization can be done on petroleum assets combinations to increase the performance metrics of this portfolio, excluding wind farm projects seems to decrease the portfolio's value. This is because wind farm assets have the lowest Capex and emission intensities among all other projects, with positive expected NPV values. However, based on the projects evaluated in this thesis, it's highly unlikely for companies to meet their NPV targets relying on wind farm projects only.

Another possible challenge for wind farm energy is to be trapped in a bubble of extreme optimism. A technical failure of this technology and/or a saturation of the electricity market could result in stranded assets. While Norway has a large potential of offshore wind power expansion due to its windy coastline, the Norwegian Ministry of Petroleum and Energy (2021) states that, in 2020, Norway produced more electricity than its consumption. However, since only 6.4% of the total electricity production came from wind power, an expansion of this sector is expected, driven by the public electricity certificate scheme, increasing electrification of the offshore O&G fields and the possibility of reducing the domestic production of hydropower (which is dispatchable and hence can be traded in the international market) in favor of wind power.

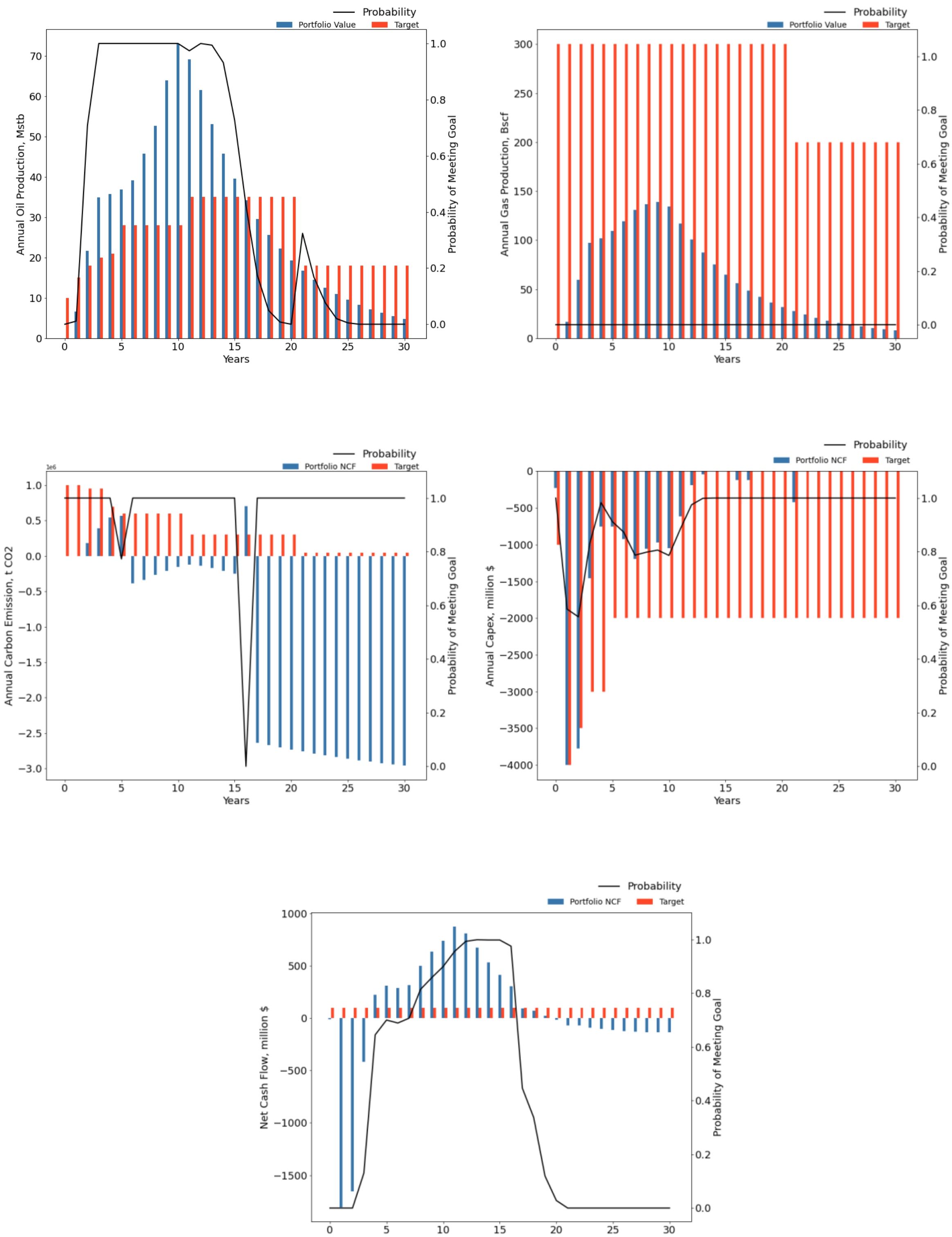

Figure 5.3: Time-dependent Portfolio Analysis Results (Portfolio C)

5.1.2. Scenario 2

In this section, a different corporate strategy is adapted, where O&G production levels decrease significantly over the portfolio's lifetime. A lower working interest in the CCS asset is also considered, given that less emission is wanted. In addition, more severe constraints are applied on the Capex goal. This is because the company wants a lower fractional ownership in the CCS whilst still being able to deal with all its CO_2 needs.

The asset combinations given by Table 5.5 were evaluated with various Capex constraints. Since projects P1, P4 and P9 have negative NPVs, they were excluded from the portfolio. The working interest of the CCS project was gradually decreased from Portfolio E to G to assess the impact of this technology on the performance metrics. As for wind farm assets, a 100% participation was assumed throughout all cases, since the company's strategy here involves a reduction in the hydrocarbon production in favor of renewables.

In the first two portfolios (E and F), the results performed well against the majority of the performance metrics, especially the NPV targets. This is because although the Capex constraint was decreased (became more severe) compared to scenario 1, the lower participation in the CCS asset increased the overall NPV of the portfolio. However, a tradeoff between NPV maximization and carbon emission minimization must be considered. Table 5.5 shows that a 10% working interest in CCS fails to meet the emission performance target, even for a low Capex constraint. Increasing the Capex constraint from $10,000 to $15,000 million would give the company the opportunity to add more petroleum assets to its portfolio, hence increasing its carbon emission even more. Since Portfolio E has the highest NPV and met the majority of the performance metrics, it was considered for further detailed analysis (Figure 5.4).

Table 5.5: Portfolios Performance Metrics (Scenario 2)

Project	**Asset Type**	**Portfolio:**	**E**	**F**	**G**
P1	Gas	Asset Combination	0.00	0.00	0.00
P2	Oil		1.00	1.00	1.00
P3	Oil		1.00	1.00	1.00
P4	Gas		0.00	0.00	0.00
P5	Oil		0.30	0.20	0.00
P6	Oil		0.12	0.12	0.30
P7	Oil		0.78	1.00	1.00
P8	Gas		1.00	0.50	0.16
P9	Gas		0.00	0.00	0.00
P10	Gas		0.70	0.61	0.50
P11	Wind		1.00	1.00	1.00
P12	Wind		1.00	1.00	1.00
P13	Wind		1.00	1.00	1.00
P14	Wind		1.00	1.00	1.00
P15	Wind		1.00	1.00	1.00
P16	CCS		0.50	0.35	0.10
Capex Constraint:			15000	12000	10000
Performance Metrics	**Total Targets**				
Capex (million $)	≤15000		14991.41	11947.04	9959.68
NPV (million $)	≥ 3500		4004.32	3648.87	3434.96
Carbon Emission (million t CO_2)	≤ 1		-10.66	-6.99	3.62
Oil Reserves (Mstb)	≥ 1500		1340.20	1379.99	1576.88
Gas Reserves (Bscf)	≥ 5000		6149.90	4165.69	2611.70

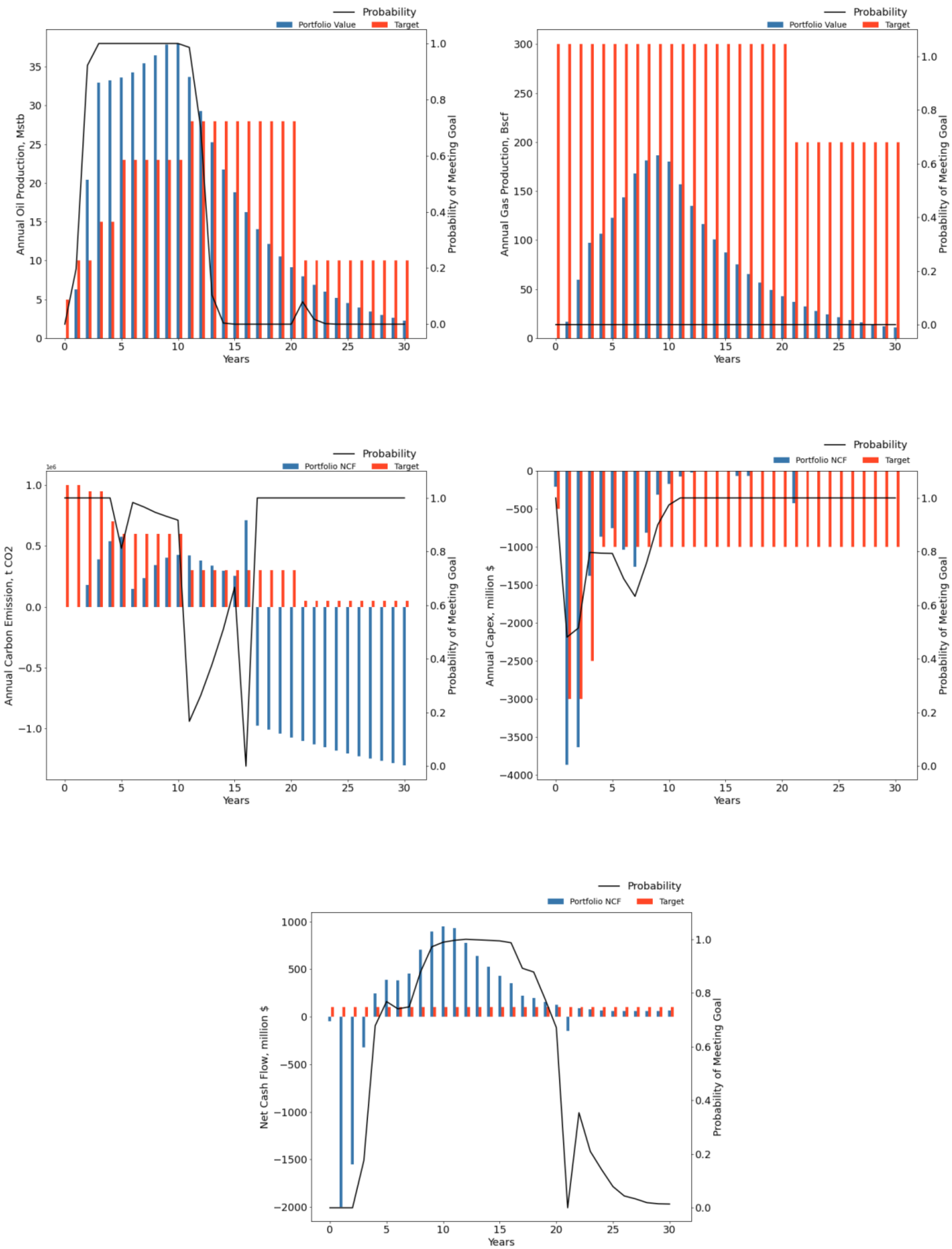

Figure 5.4: Time-dependent Portfolio Analysis Results (Portfolio E)

Comparing portfolios C and E, with 100% and 50% ownership of the CCS asset respectively, it can be seen that higher probabilities of meeting the NCF targets are met using Portfolio E. This result was expected since this portfolio have a higher NPV and lower working interest in the CCS asset. However, the increase in the expected NPV came at the expense of the emission targets that were breached regularly during the first 15 years of the portfolio's lifetime. The reason why the overall emission target of 1 million t of CO_2 is met (Table 5.5), is because the CCS unit's capacity increases after year 15, in the second phase of development. By that time, petroleum production from all hydrocarbon projects would be significantly lower, since all those projects started early in the portfolio's lifetime.

It's apparent that if the company has full ownership of the CCS asset, it will meet the majority of its annual corporate targets in terms of emission reduction and annual oil production. However, the NPV is expected to be lower in that case. On the other hand, a 50% working interest in the CCS project combined with a lower hydrocarbon production strategy and a lower required Capex are expected to generate higher NPV values. However, the company may want to reconsider this strategy given that the emission constraints are not fully met in the time period considered.

Even though there might be a percentage between 50% and 100% CCS ownership resulting in NPV maximization and emission reduction, the choice of the company's degree of ownership in the CCS technology goes beyond the NPV and emission parameters.

At this point, the CCS solution seems unprofitable. If it fails to gain governmental support and additional revenue streams in the near future, it could become a stranded asset. Given that a technical failure of this technology might lead to significant losses, the executive management team might find it "safer" to limit ownership in the CCS asset so that it only captures its own carbon emissions.

5.2. Overall Portfolio Performance Evaluation

In section 5.1, we showed that portfolios C, D and E meet the highest number of corporate goals. We also illustrated and compared the probabilities of meeting annual targets for the three portfolios.

To support portfolio decision and address the multi-objective nature of the problem, the portfolio alternatives (portfolios C, D and E), the objectives sets and the decision-maker's preferences are modeled and evaluated in this phase. The goal of this section is to reach a final decision on the optimal portfolio by accounting for the relative importance of individual objectives for the decision-maker. This approach is based on the work presented by Bratvold & Begg (2010).

The first step includes assessing the portfolios against the objectives. The expected values of the performance metrics (objectives) calculated in section 5.1 are used in this part. Table 5.6 illustrates the expected payoffs of the three portfolios for each objective metric. Payoffs represent the extent to which the objective is met once the decision has been taken. To combine the performance of one portfolio on multiple objectives, a transformation, using a value unction, from *attribute scores* to *attribute values* on a common scale is needed. For example, a carbon emission score of -20 million t CO_2 transforms to a value of 50, while an NPV score of $3,700 million transforms to a value of 30. In this work, all the transformation value functions were assumed linear and defined using the minimum and maximum score of various portfolios. Some examples are shown in Figure 5.5.

Table 5.6: Expected Payoffs Scores

Objectives	**Portfolio Payoffs (v_{ij})**		
	C	**D**	**E**
NPV (million $)	3878.53	3586.01	4004.32
Carbon Emission (million t CO_2)	-39.34	-34.69	-10.66
Oil Reserves (Mstb)	2809.05	1882.85	1340.20
Gas Reserves (Bscf)	4597.69	8080.49	6149.90

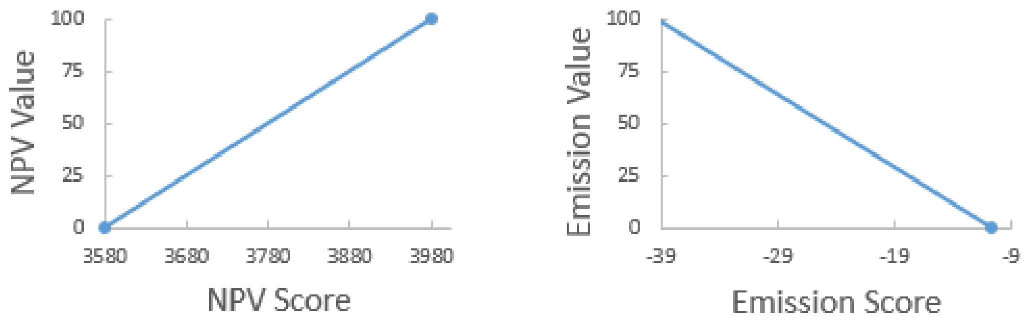

Figure 5.5: Value Functions

The next step is applying weights to the objectives. The weights represent the decision-maker's preference for fulfilling one objective over another. The *direct-weighting* method is illustrated:

Table 5.7: Direct Weight Approach

Objectives	**Rank**	**Weight**	**Normalized Weight**
NPV (million $)	1	100	0.4
Carbon Emission (million t CO_2)	2	90	0.36
Oil Reserves (Mstb)	3	30	0.12
Gas Reserves (Bscf)	3	30	0.12

In the last step, a weighted overall value is calculated for each portfolio:

$$V_j = \sum_{i=1}^{N_i} w_i v_{ij} \tag{5.1}$$

where:
V_j: normalized weighted overall value of jth portfolio
w_i: normalized weight of the ith objective
v_{ij}: payoff of the jth portfolio for the ith objetive

Table 5.8 illustrates the application of this approach to portfolios C, D and E.

Table 5.8: Portfolio Evaluation using the decision-maker's preferences

Objective	Norm. Weight (w_i)	Portfolio Value (v_{ij})		
		C	D	E
NPV (million $)	0.4	70.10	0.00	100.00
Carbon Emission (million t CO_2)	0.36	100.00	83.79	0.00
Oil Reserves (Mstb)	0.12	100.00	36.98	0.00
Gas Reserves (Bscf)	0.12	0.00	100.00	44.49
Portfolio Weighted Value (V_j)		76.04	46.60	45.34

As mentioned earlier, Portfolio C's strategy includes oil production maximization with 100% working interest in the CCS asset. The results of Table 5.8 shows that this portfolio results in the highest weighted value. The main drivers of the overall value of this portfolio are the carbon emission and NPV metrics, both of which are weighted highly given the decision-maker's preference.

The sensitivity analysis (Figure 5.6) on the normalized weights of the carbon emission and oil reserves objectives shows the dominance of Portfolio C in most cases. The normalized weights of the NPV objective shows a dominance of Portfolio E only when the weight is above 0.8. Note that the strategy implemented in Portfolio E includes a 50% ownership of the CCS asset and, as discussed earlier, this leads to a decrease in the portfolio's ability to meet the carbon reduction objective. However, violating the emission target is compensated by an increase in expected NPV.

The change in the gas production objective's normalized weight has the largest influence on the optimal portfolio. For weights less than 0.3, Portfolio C is the dominant option as it results in the lowest expected gas production. As the weight increases, the decision-maker is more likely to select Portfolio D, as his preference for gas production increases. However, a normalized weight larger than 0.3 for the gas production objective is highly inconceivable, because it will impose less normalized weights on the carbon emission and NPV objectives. In an energy transition environment, most O&G companies focus on meeting their net-zero emission targets whilst maximizing their NPV. The oil and gas production objectives become less dominant.

We concluded the following insights: Portfolio C dominates irrespective of the emission and oil production weights. Portfolio D becomes dominant as the gas weight increases and Portfolio E dominates when the NPV weight is high enough. Therefore, all of the portfolios are optimal depending on the decision-maker's preferences.

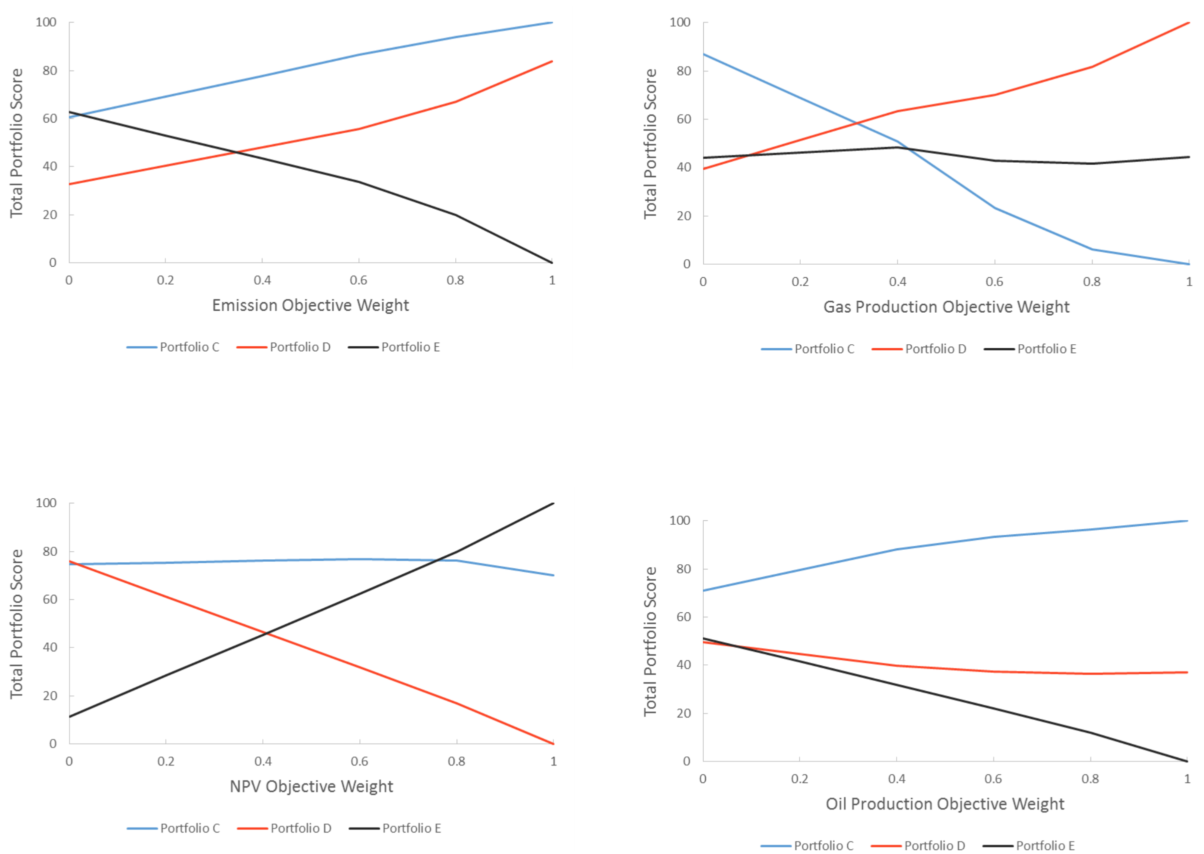

Figure 5.6: Sensitivity Analysis on the decision-maker objectives' weights

6. Conclusion

For successfully managing the energy transition, O&G companies must consider various strategies to meet their net-zero carbon emission targets, whilst improving their long-term profitability. In this work, we have developed, illustrated and discussed a time-dependent multi-objective portfolio optimization methodology and model to support and inform energy transition decisions in an O&G company. This methodology is a powerful tool to develop and compare various strategies that the corporation might pursue, given a certain pool of assets. It also evaluates the economic and operational trade-offs following the selection of one strategy over the other, and allows the decision maker to select the optimal portfolio based on its preference for each performance objective.

The following strategies were presented and discussed: reducing the fraction of the overall revenues stemming from fossil fuels, increasing ownership in carbon reduction technologies and switching from a gas production to an oil production dominated portfolio.

The portfolio optimization and management model was developed in Python. It identified optimal portfolios from a pool of potential petroleum and carbon reduction projects. These projects include traditional oil & gas producing assets, wind farms and CCS (Carbon Capture and Storage) assets. Before being included in the portfolio analysis, each asset type was evaluated individually. Financial and operational objectives contributing to shareholder value maximization, such as NPV, oil and gas production volumes, and carbon emission intensities, were included. Due to limited annual capital supply and imposed annual performance targets, the portfolio selection problem considered multiple goals, distributed across the same future energy transition timeline. Given the high uncertainty in future supply and demand for both fossil and renewable energy, the optimal portfolio at any point in time is highly uncertain and must be flexible enough to change over time whilst still meeting the specified objectives.

We have argued that despite their significant long-term abatement potential, low carbon technologies such as CCS must be backed and supported by strong emission reduction policies and sustainable governmental incentives to offset their high operating costs. Moreover, we demonstrated that integrating wind farm assets into the company's portfolio offers a good combination of low carbon emission intensity and high NPV. The diversification offered by wind energy can reduce the company's exposure to O&G related products and retain shareholder's trust. However, it's highly unlikely for companies to meet their NPV targets relying on wind power only. Finally, we concluded that reducing the fraction of the overall revenues stemming from fossil fuels will require using an optimal working interest in the CCS unit for a successful energy transition.

Some areas that would benefit from further research include understanding whether CO_2-EOR can offset the CCS cost while meeting emission reduction and NPV targets. Moreover, we believe the reduction in oil and gas companies' spending on emission allowances through CCS projects is an area where further research could be conducted. Another recommendation is testing the portfolio optimization approach used in this thesis using a corporate dataset with real-world assets.

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