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Environmental and economic multi-objective real options analysis: Electrification choices for field development investment planning

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ABSTRACT

Hydrocarbons combustion is one of the primary sources of greenhouse gas emissions, causing climate change. As large volumes of gas are burned to power the energy-consuming oil and gas production on offshore platforms, the Norwegian petroleum industry contributes significantly to the country's emissions, making it a target for environmental regulations. Hence, Norwegian petroleum companies are facing the challenge of finding solutions to comply with increasing environmental requirements while being economically feasible. Offshore platforms electrification helps to reduce carbon emissions, but relevant investment decisions are complicated by uncertainty related to market fluctuations and regulations. In this study, we analyze how considering environmental and economic objectives simultaneously affects optimal investment strategies under uncertainty. We develop a novel methodology for determining the project value and the best investment policy for field development, considering several objectives and uncertain factors. By introducing multi-objective optimization into a real options investment valuation model, economic and environmental objectives are combined using the weighted sum method. The optimization model allows to determine trade-offs between the objectives of the project along with a flexible investment policy. Such optimal solutions result in a significant decrease in carbon emissions at only a marginal reduction in economic value.

1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC) the emission of greenhouse gases is one of the main causes of global climate change (Masson-Delmotte et al. [2]). Combustion of hydrocarbons is one of the primary sources of GHG emissions. In Norway, the oil and gas industry was responsible for 28% of GHG at the national level in 2021 which corresponds to 12.5 mln tonnes of CO_2 emissions (Norwegian Petroleum Directorate Report [3]). To contribute to global climate action, Norway committed to achieving emission reductions of at least 40% compared to the 1990 level by means of strengthening its legislation regulating carbon-intensive industries until 2030.

At the same time, the petroleum industry in Norway is facing the challenge of balancing the increasing demand for Norwegian gas in Europe[1] and decreasing average size of discoveries on the Norwegian continental shelf due to the depletion of the main fields already developed (Norwegian Petroleum Directorate [4]). It drives the operators to explore and invest in new offshore field projects to ensure a consistent gas supply. As environmental regulations continue to reinforce, the Norwegian petroleum industry is under growing pressure to find economically feasible ways to comply with increasing requirements. Oil and gas companies have to identify trade-offs among conflicting objectives when making investment decisions. Meanwhile, the production of CO_2 emissions associated with offshore platform operations is under the focus of the Norwegian authorities that need to ensure compliance with ambitious emission targets. As a result, more and more companies introduce new performance indicators relating to emission reduction goals. For example, Equinor committed to reducing greenhouse gas emissions from its operations by 50% by 2030 relative to the 2015 level due to accelerated deployment of renewables and low carbon solutions (Equinor [5]). Electrification of offshore platforms is the main way to reduce carbon emissions from the Norwegian petroleum industry because power production in Norway is almost entirely based on renewable sources of energy such as wind power or hydropower. The Norwegian government stresses the importance of electrification of platforms on the NCS as a measure contributing to climate targets achievement, technological development of the industries, and a smooth transition of the petroleum industry to other business activities

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[1] The reduction in Russian pipeline flows to Europe is now balanced by increasing gas imports from Norway (European Union Agency for the Cooperation of Energy Regulators [1]).

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Nomenclature

CAPEX	Capital expenses
DCF	Discounted cash flows
DRILLEX	Drilling expenses
EEA	European Economic Area
ETS	Emission trading system
EU	European union
EUA	European Union allowances
GBM	Geometric Brownian Motion
IPCC	Intergovernmental Panel on Climate Change
MOO	Multi-objective optimization
NBP	National Balancing Point
NCS	Norwegian continental shelf
NPV	Net present value
OCGT	Open cycle gas turbine
OPEX	Operational expenses
OWF	Offshore wind farm
PFS	Power from shore
ROA	Real options analysis

(Regjeringen [6]). Nevertheless, when making investment decisions on field development and its electrification, one of the challenges the petroleum companies have to deal with is increasing uncertainty related to market fluctuations, geological unknowns, technological costs, and regulations. All of that makes these decisions and the identification of the optimal investment strategies very challenging.

In this study, we aim to analyze how the consideration of an environmental objective, in addition to the standard economic objective, affects the optimal investment strategies under uncertain conditions. We establish a novel methodology that allows to simultaneously maximize the economic value of the project and minimize its environmental effects by optimizing the investment strategy concerning market conditions or political regulations during the lifetime of a project. The main contributions of our research are: (1) we develop a methodology that allows for determining the project value and the best investment policy for field development considering multiple objectives and several sources of uncertainty, (2) we provide an assessment tool that allows for comparison of economic and environmental potential of different electrification alternatives for greenfields, (3) we provide timely policy insights by analyzing the effectiveness of different regulatory measures in terms of CO_2 emissions reduction.

In this work, we introduce multi-objective optimization into a real options investment valuation model. Specifically, economic and environmental are combined using the weighted sum method. This allows us to provide the decision-maker with the opportunity to perform a robust evaluation of several objectives considering multiple sources of uncertainty. Traditionally only a single monetary objective has been considered in the real options approach in investment valuation of field development. At the same time, traditional multi-objective optimization methods are usually based on deterministic approaches and do not account for uncertain parameters. We show how the extension of multi-objective optimization from deterministic to stochastic allows the company to adjust its decisions over time in accordance with updated information about critical risk factors. The methodology developed can be applied to solve investment decision-making problems with several objectives in application areas beyond field development.

1.1. Literature review

Our research aims to contribute to two strands of literature addressing the decision-making problem. The first includes studies dealing with economic and environmental objectives and focusing on multi-objective optimization methods to determine trade-offs among several objectives. Multi-objective optimization has shown to be a well-suited method to solve decision-making problems that account for environmental and economic objectives. Li et al. [7], Xing et al. [8], for example, apply the MOO approach to address the problem of energy systems optimization considering their facilities' size, equipment capacity, and energy input. The authors identify trade-offs between costs and carbon emissions by incorporating them either as objectives or constraints into the MOO models. Eyni et al. [9], Attia et al. [10] perform multi-objective optimization of hydrocarbon production activities to determine solutions allowing for simultaneous emissions reduction and economic performance improvement. Optimization of offshore installments operation is addressed in several studies using comprehensive MOO methods and covering different objectives related to the reduction of costs, energy consumption, power output, and carbon emissions (Dinga and Wen [11], Wang et al. [12], Cao et al. [13], Mytilinou et al. [14]). De Maigret et al. [15] apply a multi-objective evolutionary algorithm to simultaneously reduce the expenses of an oil refinery plant and improve its environmental performance within a deterministic model setting.

However, the optimization models that account for several objectives are mostly based on a static approach, where variables are represented by deterministic values, and uncertainty is addressed under scenario analysis. There have been several studies extending the MOO models from static to stochastic setting. Among the few examples are Cristóbal et al. [16] and Li et al. [17] that model relevant market uncertainties as stochastic processes and solve the problem of power plant decarbonization under the stochastic multi-optimization models. There are also several attempts to combine the real options approach with multi-objective optimization in the area of water resource planning. Marques et al. [18], for example, develop a multi-objective optimization model that incorporates real options into the decision-making process to improve water distribution systems by determining optimal pipe diameters. Manocha and Babovic [19] formulate a complex multi-objective algorithm based on an adaptation pathways approach and real options analysis to develop adaptive strategies of flood management under several risk factors related to possible climatic and land-use futures. Ahmadi et al. [20] develop a MOO model for improving environmental and techno-economic performance of electric vehicle technologies while addressing uncertainties of technical parameters by using Latin Hypercube sampling. However, there is a gap in terms of applying stochastic MOO to investment problems from a corporate perspective allowing to account for the impact of managerial flexibility. Therefore, our work contributes to this stream of literature by developing a novel model integrating methods of real options valuation and multi-objective optimization while considering investment flexibility and the opportunity to learn from the evolution of uncertain factors.

The second strand of literature represents real options studies addressing field development. Traditionally contributions in the literature strand have focused on economic performance optimization under single-objective stochastic models. Studies considering field projects and addressing optimal decision-making under real options valuation focus mostly on either the economic or the production performance as an optimization objective when evaluating investment decisions (Fedorov et al. [21], Guedes and Santos [22], Fan and Zhu [23], Bakker et al. [24]). To the best of our knowledge, there is one real options study that simultaneously accounts for environmental impact and relevant uncertainties when performing economic analysis and optimization. Liu et al. [25], for example, consider environmental benefit coefficients that are associated with pollutant emissions as uncertain factors (along with market and technological risk factors) to evaluate investment decision-making of field project development. Some other studies account for CO_2 price uncertainty when performing economic evaluation of carbon-intensive projects under ROA (Fan et al. [26,27], Wang and Zhang [28]). The real options analysis of field projects from economic and environmental perspectives has not been extensively applied. Most relevant studies that account for uncertainty and managerial flexibility ignore or present a limited representation of the environmental aspects of the field activities and do not account for environmental performance or relevant risks.

The real options literature is generally limited to account for the single objective of maximizing profit. Literature considering additional perspectives is scarce. Among the few exceptions are Boomsma et al. [29] and Nagy et al. [30], who account for a welfare perspective when studying the impacts of policy measures on the attractiveness of renewable energy investments. In addition, Huisman and Kort [31] present a duopolistic framework that compares a firm's optimal investment decision to the optimal welfare decision. These papers evaluate and compare profit-maximizing and welfare-maximizing decisions. However, in the real world, decision-makers often face complex decision problems where several objectives must be taken into consideration (Bratvold and Begg [32]).

To allow to consider the environmental impact of a project as an objective within a real options framework aspects of multi-objective methodology are used. The resulting methodology contributes to a better-suited evaluation of investment decisions in the face of growing environmental concerns.

The remainder of the paper is structured as follows. In Section 2 we elaborate on the modeling approach and describe the case study. The evaluation results are presented and discussed in Section 3. Section 4 outlines the conclusions drawn from the study.

2. Methodology

In this section, first, the framework of the research is presented (Section 2.1), and the description of the optimized objectives is provided. Next, we represent stochastic processes that we use to model uncertain parameters. In the last part of the section, we describe our solution approach (Section 2.2).

2.1. Model setup

We consider a company that owns the license to invest in a new offshore project to develop a medium-sized oil and gas field on the Norwegian Continental Shelf (NCS) by constructing an offshore platform. The company needs to decide whether it should invest in the project or not and if yes when it should invest. To ensure the power supply of production, the company has to choose among the following mutually exclusive alternatives to power operational processes on the platform:

(1) Power generation by natural gas combustion in open cycle gas turbine (OCGT);

(2) Connection to national power grid located on the shore (PFS);

(3) Connection to an isolated offshore wind farm with partial usage of open cycle gas turbine (OWF).

Each electrification solution accounts for a different volume of carbon emissions produced. Gas turbine is commonly installed on offshore platforms since it is cheap and the most convenient way to generate electricity. However, OCGT combusts natural gas to power the platform's operations and, therefore, leads to large CO_2 emissions. The PFS solution and OWF have no CO_2 emissions. However, in the case of OWF, the power production is subject to wind intermittency. Therefore, it can only partially cover the platform's power demand, meaning that it still needs to use gas turbine along with wind power. The PFS and OWF are not matured technological solutions of platform electrification and require large investments that depend on field location and power demand. Due to high capital expenditures the investment decision is considered irreversible. The company is faced with uncertainty related to the future profitability of the project. Specifically, commodities (oil, gas, electricity) prices and EU carbon allowances are considered to represent the main sources of uncertainty.

Optimal investment timing T_I^* is the main decision variable. The investment in field development and power supply alternative should be made in year T_I^* during the investment decision-making period. It is considered that the firm reevaluates the investment decision at each time period.[2] After the investment is made, the stages of the project are divided into construction (T_c) and production (T_p). Without loss of generality, it is assumed that there is no time lag between the period when the investment decision is made and the commencement of construction. Then the total lifetime of the project is equal to $T = T_c + T_p$. Fig. 1 represents the project's timeline and its key stages.

The company chooses the optimal time that maximizes the objective function that includes economic and environmental objectives and is formulated as follows:

$$obj_t = w_1 \cdot pv_t - w_2 \cdot ce_t, \tag{1}$$

$$w_1 + w_2 = 1 \tag{2}$$

where pv and ce denote the normalized project value (PV) and carbon emissions value (CE), respectively; w_1 and w_2 denote weights of the objectives that can vary in a range [0; 1]. It is worth mentioning that weights determine the impact of each objective on the overall value of the objective function. The weights are allocated to each criterion and indicate its relative importance for the decision-maker. As the original objective values are scaled in different measures, the value of the objectives is normalized as follows:

$$pv_t = \frac{PV_t}{PV_{t_{ref}}} \tag{3}$$

$$ce_t = \frac{CE_t}{CE_{t_{ref}}} \tag{4}$$

where $\mathrm{PV}_{t_{ref}}$ and $\mathrm{CE}_{t_{ref}}$ are reference values that are determined when performing optimization of project value only (PV_t). Originally optimization of carbon emissions was performed only to determine the value of $\mathrm{CE}_{t_{ref}}$. However, such optimization results in zero values of carbon emissions and project values since according to the model, to minimize CO_2 emissions the company should never invest in the project. For that reason, we use reference values from single-objective optimization for economic value only.

The sources of uncertainty are represented by future dynamic of oil, gas, electricity and CO_2 prices. The commodity prices are modeled over the project's lifetime by using a two-factor stochastic process suggested by Schwartz and Smith [33] for spot prices. The choice of the model is motivated by the balance the two-factor model allows to achieve between the representation of commodities price uncertainty and relative simplicity of calibration (Jafarizadeh and Bratvold [34,35], Fedorov et al. [21]).[3] The proposed process accounts for the commodity price dynamic by the use of two stochastic factors: the short-term factor χ_{t+1} that is assumed to follow a mean reverting process developed by Ornstein–Uhlenbeck:

$$\chi_{t+1} = \chi_t - \kappa \chi_t \Delta t + \sigma \sqrt{\Delta t} z_t, \tag{5}$$

where Δt is a time step; κ is the mean-reversion coefficient and σ is the short-term volatility parameter; z_t is an increment of standard Brownian motion process; and the long-term factor (or equilibrium parameter) ξ_{t+1} that is assumed to follow a Brownian motion:

$$\xi_{t+1} = \xi_t + \mu_\xi \Delta t + \sigma_\xi \sqrt{\Delta t} z_\xi, \tag{6}$$

[2] Without loss of generality we consider a time period of one year.

[3] Jafarizadeh and Bratvold [34,35], Fedorov et al. [21] highlight that price models relying on a simple mean-reverting process neglect consideration of the long-term equilibrium price leading to overestimation of uncertainty in options valuation results. Schwartz and Smith [33] stress that the equilibrium, a random walk process, influenced by resource depletion or changes in technology and politics, changes over time, while Short-term deviations, caused by temporary supply disruptions, usually fade away over time and follow a Ornstein–Uhlenbeck process.

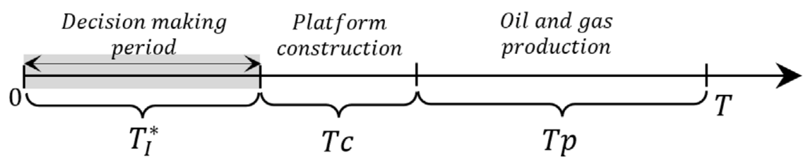

Fig. 1. Key stages of the project.

where μ_ξ is the equilibrium drift rate and σ_ξ is the equilibrium volatility; z_ξ is another increment of standard Brownian motion process.

Thus, the two-factor stochastic process allows to consider both the mean-reverting behavior of commodity prices in short-term and uncertainty in the long-term equilibrium level to which spot prices (P_t) are assumed to converge. The commodity price P_{t+1} is then given by:

$$P_{t+1} = e^{\chi_{t+1}+\xi_{t+1}}, \tag{7}$$

Given that under the considered project, the company expects to receive cash flows only after a certain time lag (T_c) upon investment, the use of estimated future prices of the oil and gas is assumed to better approximate the project's value. Here, the extension of the two-factor model for determining future hydrocarbon price trends based on spot prices was used in accordance with the approach suggested by Jafarizadeh and Bratvold [36].

The commodities price modeling requires a range of parameters to be estimated ($\chi_0, k, \sigma_\chi, \sigma_\xi, \mu_\xi, \xi_0, \rho_{\xi\chi}$) that are unobservable on the market. To obtain the estimations based on available prices a Kalman filter is applied using a maximum likelihood approach based on the procedure described in Schwartz [37] and the computational approach suggested in Goodwin [38] .

As for the CO_2 price uncertainty, some of the previous studies addressing project analysis considering EUA assume deterministic CO_2 price modeling (Ehrhart et al. [39], Cristóbal et al. [40]). In our case, the level of EUA might be crucial for the decision on investing in decarbonizing technologies. Hence, the uncertainty in CO_2 prices is modeled using a dynamic approach to improve the optimal decision-making under the real options valuation. Most of the papers focusing on project optimization model CO_2 prices by a GBM due to their similarities with stock price behavior (Szolgayova et al. [41], Yang et al. [42], Rammerstorfer and Eisl [43], Compernolle and Thijssen [44], Lamberts-Van Assche et al. [45]). Therefore, to generate the future paths of CO_2 allowance prices ($\tau_{ets,t}$) we apply a GBM modeling approach described by the following equation:

$$\tau_{ets,t} = \tau_{ets,t-1} \cdot e^{(\mu-0.5\sigma^2)\Delta t+\sigma(N(0,1))\sqrt{\Delta t}}, \tag{8}$$

where μ is a drift rate; $\triangle\ t$ is an increment of time; σ is volatility. These parameters are estimated based on the calibration of historical CO_2 prices.

Economic objective

The present value of the project invested in year t is formulated as follows

$$PV_t = \mathbb{E}\left[\sum_{t}^{t+Tc+Tp}\left(\frac{1}{(1+r)^t}\right)(R_t - CAPEX_t - DRILLEX_t - OPEX_t - IncomeTax_t - \tau_t)\right] \tag{9}$$

where t is a given year; r is the discount rate; R_t denotes revenue of the project; $DRILLEX_t$ denotes drilling costs; $OPEX_t$ is operational expenditure; $CAPEX_t$ is capital expenditure; τ_t is a sum of CO_2 tax ($\tau_{co_2,t}$) and EUA ($\tau_{ets,t}$) paid per tonne of CO_2 emissions produced by the offshore platform in year t. The future profitability of the offshore project is affected by several uncertain parameters (oil, gas, electricity prices, and EU ETS allowances). Full details of the economic objective function formulation can be found in Appendix.

Environmental objective

The second objective that is considered to be minimized is the total volume of carbon emissions (CE) produced as a result of the platform operation during the whole project lifetime. It is assumed that the only source of emissions on the offshore platform is a gas turbine functioning to power the operation of the platform. The volume of CO_2 emissions is proportional to the volume of natural gas combusted in the gas turbine (Miljodirektoratet [46]). Therefore, the following equations are used to determine the value of CE:

$$CE = \left(\sum_{t=1}^{T} NG_{const,t}\right) \cdot e \tag{10}$$

$$NG_{const,t} = \frac{E_p \cdot 3.6 \cdot 10^9}{\eta_{gt} \cdot HHV_{gas}}\left(1 - f_{OWF} \cdot y_t - x_t\right) \tag{11}$$

where e is the total GHG emissions per unit of natural gas burned; $NG_{const,t}$ denotes the volume of gas used for the electrification in year t, and is given by Eq. (11); E_p is an annual platform energy demand; η_{gt} denotes gas turbine efficiency; HHV_{gas} denotes the higher heating value of the natural gas combusted; f_{OWF} is a share of annual platform energy demand that can be covered by OWF; x_t denotes a binary variable equal to 1 if the company decides to invest in a PFS in year t, and to 0 otherwise; y_t denotes a binary variable equal to 1 if the company decides to invest in an OWF in year t.

Besides its effect on the environmental objective, CO_2 emissions also affect the economic objective due to taxation. In the case of Norway, petroleum companies are in fact facing double taxation, because they should pay both the carbon tax and EU carbon allowances since Norway participates in the EU Emission Trading System. In 2021, the Norwegian government declared a plan to set an upper bound for the combined price of CO_2 allowances and CO_2 tax rate. The new carbon taxation policy aims to ensure that starting from 2030, the maximum carbon tax rate is determined based on total CO_2 pricing including carbon allowance price and the carbon tax, and should not exceed 2000 NOK per tonn of CO_2. To comply with the policy, the Norwegian government will adjust the CO_2 tax to achieve the desired target rate.

2.2. Solution approach

To perform optimization, first, the value of the objective function is estimated considering simulated cash flows resulting from the combination of uncertain variables (EU ETS allowances and commodities prices trajectories). Next, we run optimization based on two evaluation approaches. The first is a *myopic* approach that is based on traditional DCF evaluation that we use as a benchmark. The second is an *options* approach based on real options analysis. Comparing the results of these two approaches allows us to identify the value of flexibility. The framework of the modeling is represented schematically in Fig. 2.

Under the *myopic* approach it is assumed that the company decides whether to invest or not in year $t = 1$. To allow for consistent comparison the objective function value is calculated based on the same simulation paths. This means we determine the trajectories of net present values of the project based on the information about uncertain variables available at the period $t = 1$.

Under the *options* approach it is assumed that the company holds an option to invest in the field based on the information about commodity and CO_2 prices available at the moment of decision-making. This approach allows us to determine the value of waiting during the

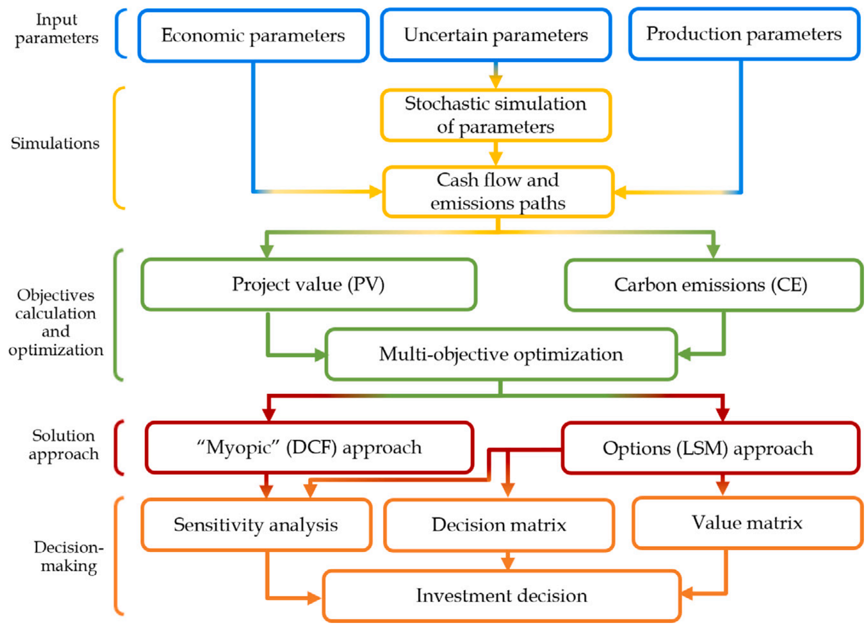

Fig. 2. Optimization model framework.

decision-making period. We identify the optimal time ($t = T_I^*$) to undergo investment in the offshore project assuming that the company makes an investment decision based on the information available.

Following the real options approach, a decision-maker can postpone the investment to get more information about commodities and CO_2 prices. The company optimizes its investment strategy by deciding whether to exercise the option to invest in the project at a given point in time. This problem is solved recursively, meaning that initially the optimal decision strategy is determined for the last point in time of the decision-making period (Cortazar et al. [47]). Next, moving back in time, one can determine the optimal decision strategy by applying a backward algorithm for each of the precedent time points. Here we follow the solution approach proposed by Longstaff and Schwartz [48] that use the least square Monte Carlo (LSM) method to address the similar evaluation problem. The method implies the estimation of values of immediate exercise and continuation (holding option) by performing regression of discounted continuation values on relevant state variables. This approach has been applied to a large number of natural resource-related real options problems and it proved to be well suited to be valid for complex investment decision problems when dealing with several sources of uncertainty and investment decision delay (Jafarizadeh and Bratvold [49]; Cortazar et al. [47]). At the same time, the application of simple least square regression allows for keeping the model transparent and flexible.

Following our modeling approach, in accordance with Eqs. (9) and (10), we, first, determine the objective function values based on calculated volumes of carbon emissions and cash flow paths considering 10,000 trajectories for the commodities and CO_2 prices. We consider that the decision to invest might be made during each year of the decision-making period. Accordingly, several sets of objective function values are generated, where each set represents the simulated values of the objective function corresponding to the time period when the decision to invest is made.

Next, we estimate and compare the expected values to wait (denoted by $\Phi(t,\ P_{o,t};\ P_{g,t};\ P_{el,t};\ \tau_{ets}))$ and immediate project development (expressed as $\Pi(t,\ P_{o,t};\ P_{g,t};\ P_{el,t};\ \tau_{ets}))$ for each time t of the decision-making period. As both parameters Φ and Π are unknown at time t, we set them equal to their expected conditional values $\mathbb{E}_t^*$. The decision on optimal investment timing T_I^* can be made in the period when the expected conditional objective's value reaches the maximum. Within a dynamic programming problem, the Bellman equation is used to obtain the optimal value function F:

$$F = \max \begin{cases} \mathbb{E}_t^* \left[\Pi(t, P_{o,t}; P_{g,t}; P_{el,t}; \tau_{ets})\right] \\ \mathbb{E}_t^* \left[\Phi(t, P_{o,t}; P_{g,t}; P_{el,t}; \tau_{ets})\right] \end{cases} \qquad t_1 \le t \le t_6, \tag{12}$$

where Π is a function of the estimated value of the option to invest; Φ denotes the estimated continuation value (to wait).

Considering the assumptions regarding the commodities and CO_2 price processes, at each period t of the decision-making period the expected values of Φ and Π can be estimated as conditional on the simulated prices. Following the original least-square regression technique suggested by Longstaff and Schwartz [48] previous ROA studies use linear regressions to approximate expected values (Fedorov et al. [21,50], Ahmadi and Bratvold [51], Or et al. [52]).[4]

Accordingly, we apply the 2nd-order polynomial regression to estimate the expected objective function values (determined at the first step) conditional on state variables (simulated commodities and CO_2 prices) as follows:

$$\begin{aligned} &\mathbb{E}_t^* \left[\Pi(t, P_{o,t}; P_{g,t}; P_{el,t}; \tau_{ets,t})\right] = \\ &\alpha_0 + \alpha_1 \cdot P_{o,t} + \alpha_2 \cdot P_{g,t} + \alpha_3 \cdot P_{el,t} + \alpha_4 \cdot \tau_{ets,t} + \\ &\alpha_5 \cdot P_{o,t}^2 + \alpha_6 \cdot P_{g,t}^2 + \alpha_7 \cdot P_{el,t}^2 + \alpha_8 \cdot \tau_{ets,t}^2 + \\ &\alpha_9 \cdot P_{o,t} \cdot P_{g,t} + \alpha_{10} \cdot P_{o,t} \cdot P_{el,t} + \alpha_{11} \cdot P_{o,t} \cdot \tau_{ets,t} + \\ &\alpha_{12} \cdot P_{g,t} \cdot P_{el,t} + \alpha_{13} \cdot P_{g,t} \cdot \tau_{ets,t} + \alpha_{14} \cdot P_{el,t} \cdot \tau_{ets,t}, \end{aligned} \tag{13}$$

where $\alpha_{0\ldots14}$ represent coefficients of regression. The same is performed for Φ, using $P_{g,t-1}$, $P_{o,t-1}$, $P_{el,t-1}$, $\tau_{ets,t-1}$ as input state variables for the regression. Given the amount of simulated price trajectories, the sample size is 10,000.

Following the LSM algorithm, at each decision point t the estimated value of exercising the option to invest is compared to the estimated value of waiting. When the value of the immediate investment is greater than the waiting value, the option is exercised. Otherwise, the investor should wait or exit the project. We consider each path of simulated cash

[4] For such model settings the selection of the regression function is demonstrated to have a minimal impact on the best strategies and the anticipated project value, as long as the options present in the money paths (Ahmadi and Bratvold [51]).

Table 1
Input economic parameters.

Parameter	Variable	Value
Drilling costs (per well)	$DRILLEX_w$	500 mln NOK/well
Capital costs (fixed)	$CAPEX$	1,300 mln NOK
Capital costs (per well)	$CAPEX_w$	50 mln NOK/well
Capital costs for OWF electrification	$CAPEX_{owf}$	3.5 bln NOK
Capital costs for PFS electrification	$CAPEX_{pfs}$	2 bln NOK
Operational costs (fixed)	$OPEX$	723 mln NOK
Operational costs (per well)	$OPEX_w$	55 mln NOK/well
Initial CO_2 tax rate	τ_{co_2}	632 NOK/Tonne CO_2
Discount rate	r	7%
Corporate income tax	$IncomeTax_i$	25%

flows and apply this algorithm for each year to determine the optimal timing for making investments in the project.

The estimation of the regression coefficients α_i in Eq. (13) is performed using Python 3.10 following the LSM procedure suggested by Jafarizadeh and Bratvold [49]. Once the estimated values $\hat{\Pi}$ and $\hat{\Phi}$ are obtained for each point of time t, the optimal investment strategy can be determined. In case the condition $\Pi(t,\ P_{o,t};\ P_{g,t};\ P_{el,t};\ \tau_{ets,t}) > \Phi(t,\ P_{o,t};\ P_{g,t};\ P_{el,t};\ \tau_{ets,t})$ is satisfied, t is the optimal time to exercise the option to invest ($t = T_I^*$). Otherwise, the investor should hold the option.[5]

2.3. Case study

Now the described method is applied to a synthetic but realistic industry case. An offshore oil and gas field on the NCS consisting of one reservoir is considered. To ensure the feasibility of project valuation, a relevant production dataset representing a typical middle-size field with consideration of its main characteristics is used. We aim to develop an evaluation approach facilitating optimal decision-making under given uncertainties and prove its robustness and feasibility on a synthetic case. Therefore, we deliberately disregard specific technical features that are considered to be of minor significance for the research problem and might entail computation complexity and less transparency for the model. The same dataset is applied when performing the valuation of each electrification option separately. The volume of CO_2 emissions produced and the amount of expenses depending on electrification technology are adjusted. Table 1[6] summarizes the main parameters and data describing the economics of the offshore field project.

2.3.1. Production system modeling

It is assumed that a build-up phase takes 4 years before the first oil and gas are produced. The model uses forecasts for the gas, oil, and water production rates until the end of the project's production phase.

In this work, first the production model inputs are determined (Table 2), and cost estimation is performed for the synthetic case. Next, 10,000 simulations[7] of each uncertain parameter: oil, gas, electricity, and EUA prices are generated. Further, project cash flows and carbon emissions are calculated based on input parameters and simulations, so

[5] We recursively move backward in time and determine the maximum value along all simulated paths and for each point of time until the year $t = 1$. By the results of the LSM valuation, we build up a decision matrix [10000 × 6] with objective function values determined for years and simulated paths when the LSM algorithm states the option to invest is optimal.

[6] The average exchange rates in the 4th quarter 2023: 1 NOK = 10.8353 USD and 1 NOK = 11.6525 EUR (Norges Bank [53]).

[7] Running of 10000 simulation cases is proved to be computationally feasible while resulting values are consistent and deviate insignificantly. Each simulation is a particular realization of how price can develop over the 26 time periods.

Table 2
Input parameters for the reservoir.

Parameter	Value
Initial Oil In Place (IOIP) [MSm3]	56
GOR [Sm3/Sm3]	398
Maximum total number of producing wells	20
Production potential per well [Sm3/d]	4,592.47

Table 3
Parameter values for the Schwartz–Smith two-factor price process.

Parameter of the process	Value		
	Oil prices	Gas prices	Electricity prices
ξ_0	4.33	4.8	3.5
σ_ξ	0.18	0.25	0.15
μ_ξ^*	−0.026	−0.05	0.005
κ	0.6	0.91	1.22
χ_0	0	0	0
σ_χ	0.17	0.75	0.47
$\rho_{\xi\chi}$	−0.72	−0.63	0.034
λ_χ	−0.083	−0.07	0.042

the LSM valuation can be performed to determine the optimal decision-making strategy. The decision rule for abandonment of the field based on the project's cash flow is also applied: the field is considered to be abandoned in the year when cash flows become negative. That also affects the total amount of oil and gas produced by the platform and, therefore, the volume of CO_2 emissions.

2.3.2. Commodity and CO2 prices simulations

Following the procedure described in Section 2.1, the Kalman filter is applied to calibrate historical prices of oil, gas, and electricity. The Kalman filter determines the estimations of state variables based on the recursive procedure and information about the data set available at a given time (Hahn et al. [54]). For the calibration, market data set from the Refinitiv database "Eikon" related to the ICE Brent historical spot prices from January 2000 to September 2022, ICE NBP natural gas historical spot prices from August 2010 to September 2022, and Nordpool electricity prices from January 2006 to September 2022 are used. The resulting parameters are provided in Table 3.

Parameters for the GBM process are estimated based on historical CO_2 prices calibration: $\mu = 0.176$, $\sigma = 0.401$. Market data about spot EU ETS allowances retrieved from the Refinitiv database "Eikon" is used to perform calibration of price parameters. When simulating CO_2 prices GBM process results in a strong upward trend and a wider range of prices. Al-Harthy [55], Xu et al. [56], Fedorov et al. [21] provide evidence for a higher price level than realistic when performing simulations under the GBM process. That causes the long-term options to be overvalued. Therefore, an upper limit for CO_2 prices is assumed to amount to 250 EUR/ Tonn CO_2. The upper limit is applied in accordance with the highest carbon price estimations anticipated by analytical agencies and research institutions (Thema [57], BloombergNEF [58], Wangsness and Rosendahl [59]). Fig. 3 illustrates historical NBP natural gas prices and Brent crude oil, as well as electricity and CO_2 prices, confidence bands for simulated price paths, and several examples of the price process.[8]

From 2030 the carbon tax rate in Norway will be adjusted depending on carbon allowance prices. For example, in case the carbon

[8] The historical data on hydrocarbons showed a decreasing trend by the moment when the data was collected which is explained by reduced global demand affected by the concerns about a possible economic recession and COVID-19 containment measures taken by the market actors. At the same time, the Norwegian electricity market is characterized by constant growth of prices following the energy crisis that took place in Europe, low filling levels in the water reservoirs used by hydropower plants, and weak power balance on the market.

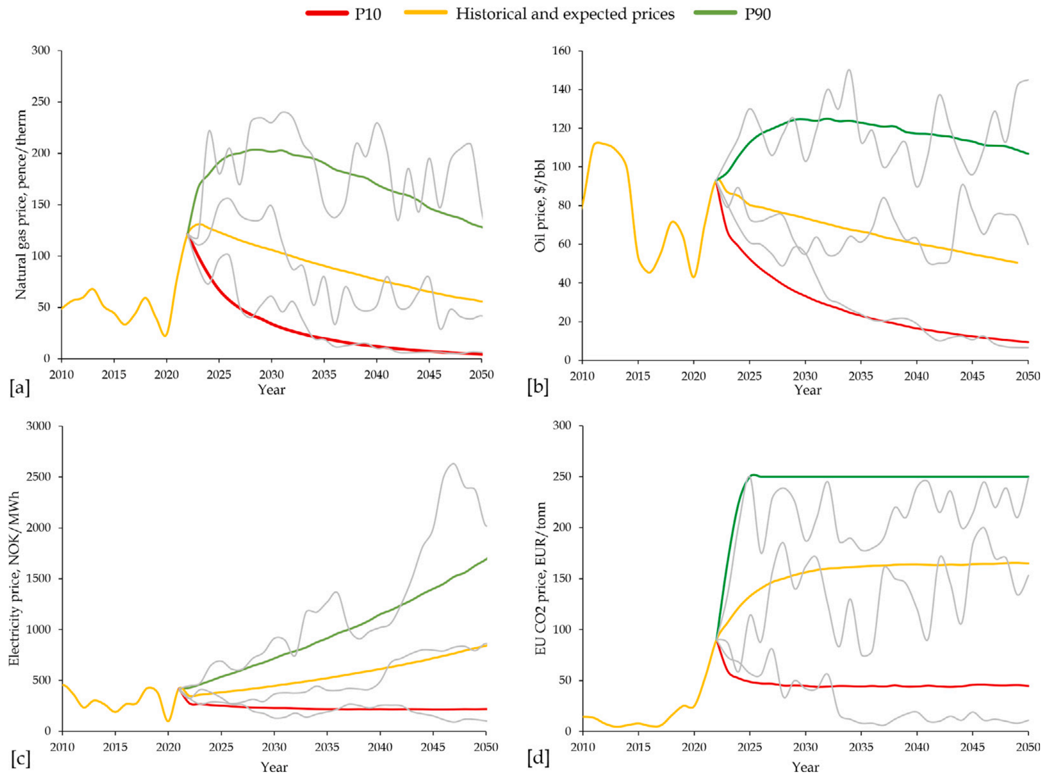

Fig. 3. Historical (a) NBP natural gas, (b) Brent crude oil, (c) electricity, and (d) EU CO_2 prices, confidence bands, and example price paths. P10 is the 10th percentile, indicating the lower boundary below which 10% of simulated prices are expected to fall, P90 is the 90th percentile, indicating the upper boundary below which 90% of simulated gas prices are expected to fall.

allowance price is equal to or exceeds the upper bound in the amount of 2000 NOK, the carbon tax rate would be set to zero. At the same time, during the transition period from 2021 to 2030, the CO_2 tax rate is expected to gradually increase. Therefore, an initial CO_2 tax rate is assumed to be in accordance with the rate set by the Norwegian government in 2022 (see Table 1). The dependency of the carbon tax rate based on the simulated EU CO_2 prices is also formulated. For the total lifetime period of the project, CO_2 tax ($\tau_{co_2,t}$) is calculated as follows:

$$\tau_{co_2,t} = \begin{cases} \tau_{co_2} & \text{for } t = 1, \\ \tau_{co_2,t-1} + \frac{Y_{CO_2} - \tau_{co_2,t-1}}{9-t} & \text{for } t \in [2, 8], \\ max\left[0; Y_{CO_2} - \tau_{ets,t}\right] & \text{for } t \in [9, T], \end{cases} \tag{14}$$

where Y_{CO_2} is an upper limit of CO_2 tax that is equal to 2000 NOK per tonn of CO_2.

3. Results and discussions

Under the considered case the decision-maker has to decide on whether, and if so when to invest in the project to maximize its value and minimize emissions. The decision depends on the objectives weights determined by the decision-maker. The goal of the analysis is to reveal insights regarding potential trade-offs between the environmental and economic objectives and determine an optimal investment strategy that allows for achieving such trade-offs when being exposed to several sources of uncertainty.

The solution approaches are applied to three separate cases: (1) platform powered by a gas turbine, (2) OWF electrification, (3) PFS electrification. When optimizing the third case that allows to reduce emissions to zero we focus on project value maximization only. First, the results for the OWF case in accordance with both approaches are discussed. In the next step, these results are compared to the outcomes received for the gas turbine and PFS cases. In Fig. 4 Pareto fronts resulting from solving the decision problem under both solution approaches are presented for all possible values of w_1 and w_2 (ranging from 1 to 0) referring to the economic and environmental objectives, respectively. The coordinate axis represents the total expected project value and carbon emissions. Solid black and green lines represent Pareto fronts determined based on the *options* approach for the gas turbine and OWF cases, respectively, while dashed lines represent Pareto fronts determined based on the *myopic* approach. For illustrative purposes, the weights for several optimal points on the Pareto fronts for the gas turbine and OWF cases are also displayed. Solid and dashed red stars represent project values for the PFS case optimization under the *options* and *myopic* approaches, respectively. The plot illustrates how the choice of solution approach affects the location of Pareto fronts. Compared to the static approach, incorporating timing flexibility into investment decisions yields better results. The *options* approach allows to observe how commodities and CO_2 prices evolve and adjust the decision-making process based on the observation. For both approaches the outcomes of the optimization are intuitive, high w_1 means that the decision-maker places greater importance on economic performance than environmental. Hence, the optimization algorithm results in a larger share of investment decisions with a higher total production value leading to more emissions. For the extreme case when w_1=1, the optimization model is focused on economic optimization only, so both economic and emission values are the maximum. When w_2= 1, the model solely focuses on minimizing emissions, and as a result, the project is not executed to achieve the minimal (zero) level of emissions. Based on the location of optimal solutions, one can observe that the PFS case yields the best optimization results, followed by the OWF, while the use of gas turbine leads to comparatively inferior results.

For the multi-objective optimization cases, we find that there are combinations of weights that result in a significant reduction of carbon emissions at only a marginal economic value reduction. For example, for the OWF electrification, when w_1 = 0.5 and w_2 = 0.5, the optimal

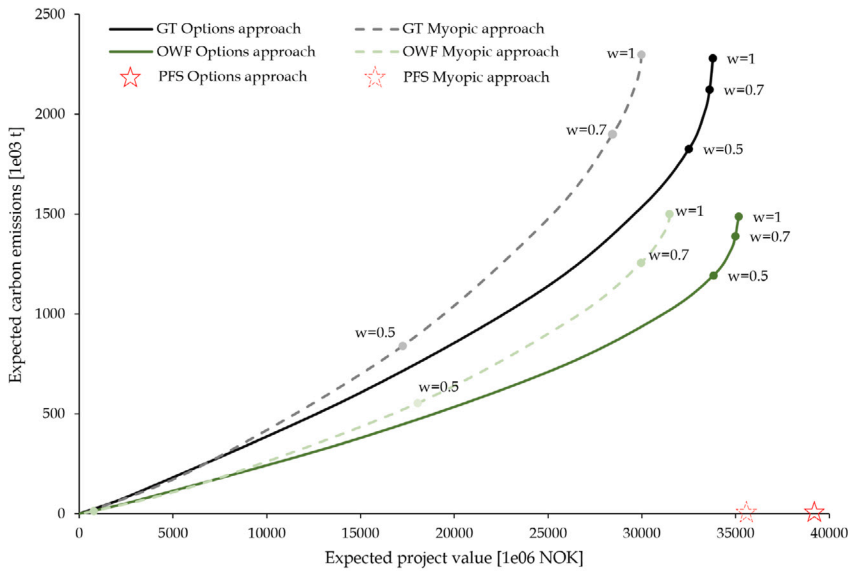

Fig. 4. Pareto fronts illustrating the trade-offs between economic and environmental objectives for the *options* and *myopic* valuation for the gas turbine, OWF, and PFS cases.

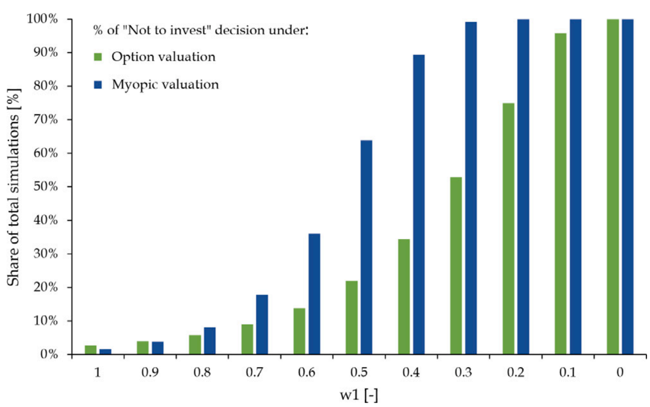

Fig. 5. Share of "Not to invest" decisions determined for the OWF case under multi-objective optimization based on the *options* and *myopic* valuation approaches.

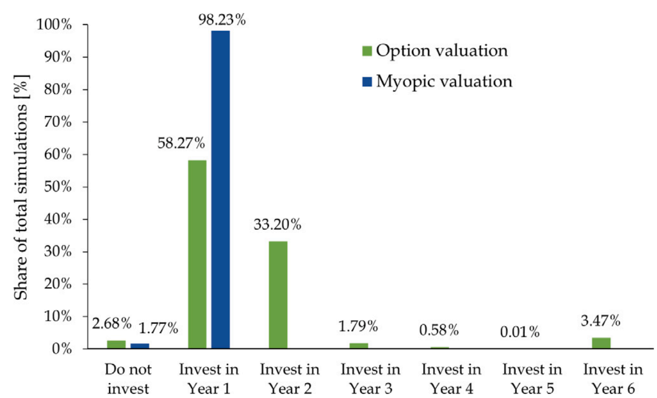

Fig. 6. Optimal investment timing for the OWF case as a percentage of the total number of simulation cases resulting from the *options* and *myopic* valuation.

investment strategy leads to a reduction of emissions by 19% compared to results when $w_1 = 1$ while the project value is only 3% smaller. This outcome is in line with other studies that perform MOO considering economic and environmental objectives for field development (Eyni et al. [9], Svensson and Berntsson [60]).

We now focus on the investment incentive. In Fig. 5, the results in terms of "Not to invest" decisions are illustrated for different combinations of objectives' weights. Under both valuation approaches, a larger value of w_1 leads to a higher share of the decision to invest in the field project. The opposite outcome holds for relatively high values of w_2. The results show that while putting a higher weight on the environmental objective the resulting investment is not economically viable and therefore, the firm will decide not to invest in more cases. For the *myopic* valuation, setting w_1 to a value equal or lower than 0.3 results in almost 100% share of "Not to invest" decisions. Fig. 6 illustrates an example of the optimal investment timing for the OWF case under static and flexible valuation approaches when $w_1 = 1$. The results presented in Fig. 6 show that the firm tends to invest early due to the downward trend in oil and gas prices. The intuition is that the opportunity cost of waiting to invest, meaning the benefits that might be lost if the company delays the investment decision, increases more than the potential benefits from deferring the investment decision.

Fig. 6 illustrates the difference in approaches from an investment timing perspective. As seen in Fig. 6, in contrast to the *myopic* approach, the LSM algorithm accounts for the possibility to delay investment and enables flexible decision-making by identifying different points in time when it is optimal to invest. For the case when $T_I^* = 1$, flexibility in investment timing is accounted for in only 58% of the simulations compared to 98% for *myopic* approach.

When comparing distributions presented in Fig. 7, it is evident that the application of the ROA allows for identifying the positive value of timing flexibility (green area) while the *myopic* approach (blue area) generates negative cash flows in more cases. The fact that timing flexibility allows the decision-maker to mitigate the downside and exploit the potential upside is visualized in the box plots in Fig. 7. Therefore, adherence to the ROA and accounting for price uncertainty allows to improve the project value. The similar results are obtained in terms of optimal values and investment strategies for the cases of gas turbine and PFS.[9] The main difference lies in PV and CE values. Particularly, the optimization results for the gas turbine case lead to overall lower economic value and higher carbon emissions, since the usage of gas turbine only implies large volumes of emissions compared to the OWF case and leads to higher emission-related payments. The PFS case has the highest project value resulting from optimization due

[9] These results are omitted here due to space constraints but can be provided by the authors upon request.

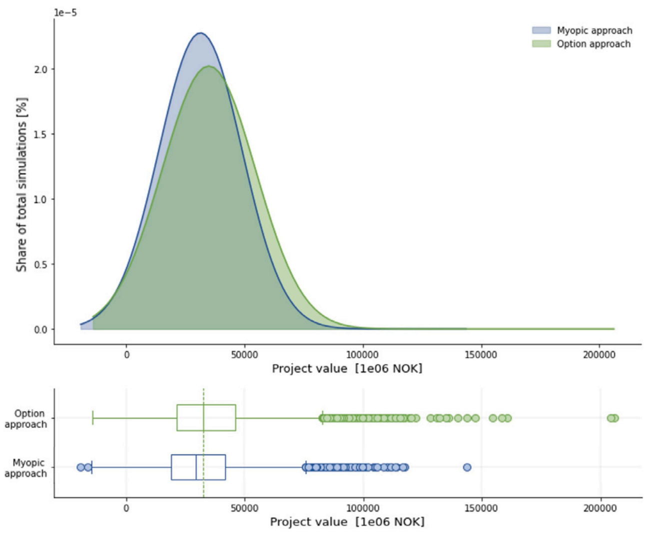

Fig. 7. Project value distribution under the *myopic* and *options* valuation for the OWF case.

to the absence of carbon-related payments and the opportunity to sell extra volumes of gas that are not combusted.

3.1. Sensitivity analysis

The results of our valuation model depend on several uncertain parameters, input data, and initial assumptions. To validate our valuation approach and gain economic insights, a detailed sensitivity analysis of the results (assuming $w_1 = 1$) to the input parameters presented in Section 2.3 is performed.[10] In this section, we describe the sensitivity results for the several factors identified as the most influential.

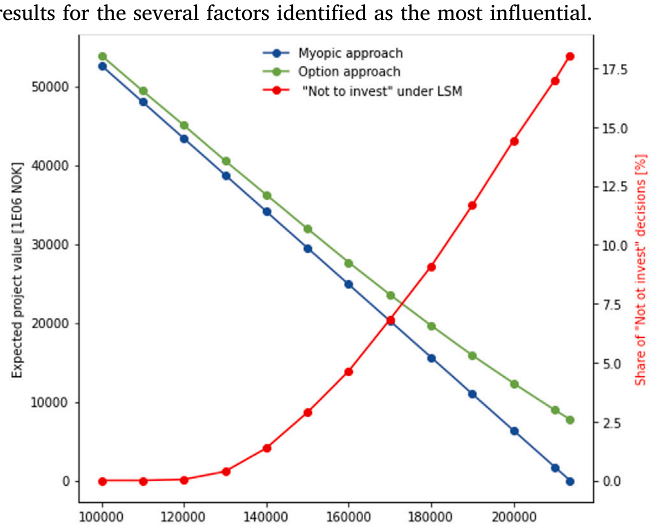

Fig. 8. CAPEX sensitivity analysis for the gas turbine case.

The results of the sensitivity analysis of the input parameters are intuitive showing that CAPEX has the biggest impact.[11] In our case, the major share of investment expenses is assumed to be fixed. However, in practice, the amount of capital expenses required to launch the project may vary significantly and, therefore, influence the cash flows and optimal decision-making strategy. Fig. 8 illustrates the valuation results of two solution approaches for the gas turbine case for different values of CAPEX. The results demonstrate that a CAPEX increase leads to a lower project value and a higher share of paths that result in no investment. This is intuitive because, with a growing share of expenses, the project requires larger revenues to cover them. Furthermore, as seen from the plot, the project value determined under the static DCF procedure is lower compared to payoffs computed using the LSM. The results show that the relative value of timing flexibility increase with CAPEX. Therefore, the ROA becomes more valuable for projects with larger expenses.

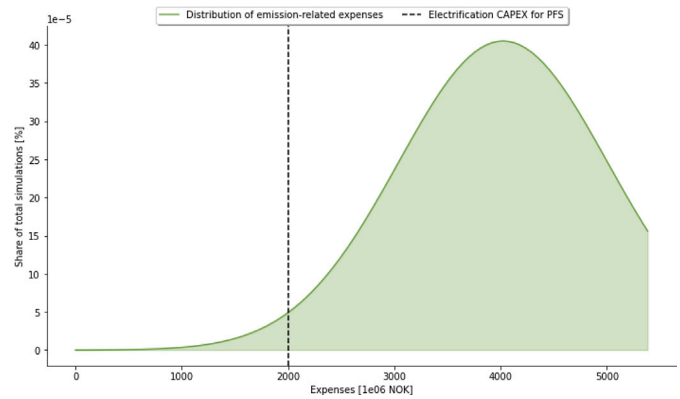

Fig. 9. Electrification CAPEX (for the PFS case) and distribution of emission-related expenses (for the gas turbine case).

Table 4
Project value under different sources of uncertainty (gas turbine case).

Source of uncertainty	Expected value [1e06 NOK]	
	Myopic approach	*Option* approach
No uncertainty	4.6	4.6
Gas prices	16.8	20.7
Gas and oil prices	29.8	32.3
Gas, oil, and CO_2 prices	29.5	31.8

When considering an investment in electrification, comparing the capital expenses associated with electrification against its potential gains can provide valuable insights into its economic viability. For comparative purposes, Fig. 9 illustrates fixed electrification CAPEX paid under the PFS case (denoted as dashed black line) and distribution of emission-related expenses that the investor would pay when using a gas turbine only (denoted as green area[12]). The comparison shows that for our base case, emission-related expenses exceed the capital expenditures on electrification in the majority of the cases. The results from such a comparative analysis give important insights for operators on the choice of electrification alternative that is not always straightforward due to the ranging amount of investment expenses required and fluctuating electricity and CO_2 prices. Therefore, such comparative analysis might be useful for determining the break-even value of electrification CAPEX and likelihood that CO_2 payments will exceed capital expenses on electrification.

In the following, risk factor having the largest impact on the valuation results is identified. Under both valuation approaches for the gas turbine case, the project value is maximized assuming that all or some of the prices are predetermined and equal to the mean (based on Monte Carlo simulation paths). The results are summarized in Table 4.

As can be seen from the results, ignoring price uncertainty lead to a crucial underestimation of the project value. At the same time, the

[10] The remaining results can be provided by the authors upon request.
[11] The sensitivity results for other parameters are available upon request.
[12] The right tail of the distribution is truncated due to the upper limit of simulated paths of CO_2 prices set to 250 euro per tonne of CO_2 (see Section 2.3.2).

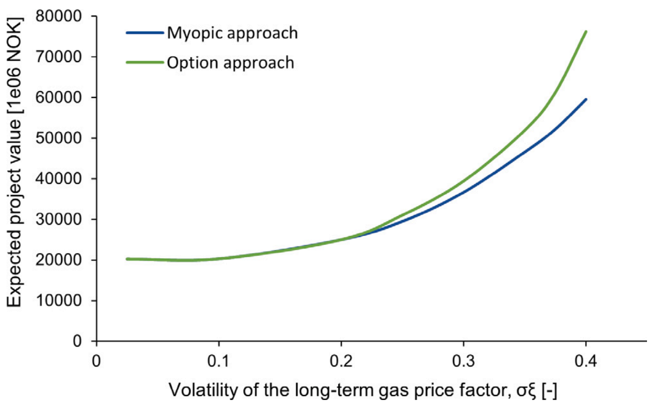

Fig. 10. Project value sensitivity to changes in long-term gas price volatility (for the gas turbine case).

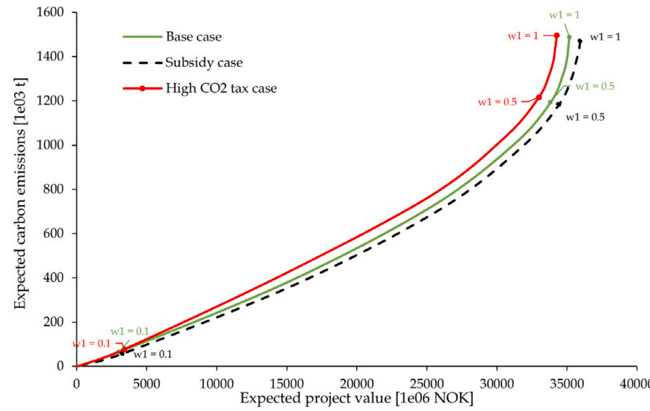

Fig. 11. Pareto fronts illustrating the trade-offs between economic and environmental objectives under *options* valuation for the Base case (green line), High CO_2 tax case (red line), and Subsidy case (dashed black line), respectively.

results of the analysis prove that gas price uncertainty represents the risk factor that has the highest impact on the expected project value. That is intuitive since in accordance with the production model the volumes of gas produced are significantly higher than oil production. On the contrary, the consideration of CO_2 price uncertainty results in marginal changes in project value determined under both valuation approaches. The result is due to the fact that the costs related to CO_2 prices are significantly smaller compared to the revenues earned by selling gas. Even though the contribution of CO_2 price uncertainty to project value is lower compared to oil and gas prices, the ignorance of such factor can lead to unfeasible higher estimates of project value, since carbon price affects the project expenses, and it is expected to increase in the next decade.

We now analyze how changes in the price forecasts affect our results. As illustrated in Fig. 10, our results indicate that as gas price volatility increases, the expected project value also increases. This can be explained due to the fact that a higher volatility factor predetermines an upward trend for future gas prices. Additionally, in the case of growing commodities prices, the opportunity costs of waiting are low. Hence, the delay of investment decision is becoming more attractive for the decision-maker that anticipates a gas price increase.

3.2. Impact of policy measures: taxes and subsidies

To examine the impact of governmental regulations on investment strategies and electrification choices, a sensitivity analysis is conducted considering two measures that are relevant for the Norwegian offshore field projects. We examine the impact of two measures on the investment decisions of a petroleum company and the corresponding economic and emissions values, namely, (1) the strengthening CO_2 tax policy and (2) subsidizing of the platforms' electrification. The first measure, currently applied in Norway, involves a strategy to increase future CO_2 tax rates. The second, also implemented in Norway, involves funding platform electrification through a special state fund. In 2019 the Norwegian state-owned entity Enova made a financing commitment to support the construction of the floating wind farm Hywind Tampen nearby Snorre and Gullfaks oil and gas fields (Anchustegui [61]). Particularly, 2.3 billion NOK (out of 5 billion NOK of total Hywind Tampen investments) are covered by Enova. In general, the fund provides investment support for cost-intensive decarbonizing technological solutions and allocates funds within the agreement with the Ministry of Climate and Environment and the framework of the EEA State aid rules (Enova [62]).

As described in Section 2.1, starting from 2020 the Norwegian government aims to gradually increase the CO_2 tax rate until it reaches 2000 NOK per tonn of CO_2 emissions in 2030. From the perspective of policy-makers, an increase in the environmental tax burden is one of the measures aiming at incentivizing the decarbonization of production. Therefore, we study how a further increase of the upper limit of the CO_2 tax rate from 2000 NOK to 4000 NOK per tonn of CO_2 emissions affects the investment strategy. In accordance with the CO_2 tax rate calculations (see Eq. (14)) the increase of the upper limit also entails the CO_2 tax rate growth during the transition period.

Fig. 11 shows the Pareto fronts for the OWF electrification case determined in accordance with the combined approach. Green and red lines illustrate the set of optimal solutions for the *Base case* and *High* CO_2 *tax case*, respectively, while black dashed line illustrates optimal solutions for the *Subsidy case*. The x-axis refers to the expected project value, the y-axis is the expected volume of carbon emissions.

For the *High* CO_2 *tax case* the main findings are the following: (1) the Pareto front is shifted to the left compared to the *Base case* Pareto line meaning that the higher CO_2 tax rate leads to a lower expected project value. This result is intuitive since the increasing expenses on CO_2 tax payment negatively affect the cash flows from the project development. (2) Following the comparison of the optimal environmental values for the same weights determined under *High* CO_2 *tax case* and *Base case* one can see that under the *High* CO_2 *tax case* the project results in a narrow increase of carbon emissions. This outcome is counter-intuitive at first sight as emissions are expected to decrease due to strengthening environmental tax policy. However, from an economic perspective, the optimal investment policy implies larger hydrocarbon production (in total) to justify increased expenses. Since the volumes of carbon emissions are proportional to the produced volumes of oil and gas (see Eq. (10)) under the *High* CO_2 *tax case* the project ends up with slightly higher emissions. Similar results are also received by Eyni et al. [9] that perform multi-objective optimization of field project development. (3) Along with that, it is intuitive that a higher CO_2 tax affects the investment incentive of the decision-maker. As the expenses related to carbon emissions are expected to increase, the decision-maker is less inclined to invest in the project that contributes to CO_2 emissions production. Specifically, when considering investment flexibility, we find that under the *High* CO_2 *tax case* the optimal investment policy results in a slightly higher share of "Not to invest" decisions. Therefore, from the policy-maker's perspective, the policy measure might miss its intended effect.

Fig. 11 also illustrates the result of the analysis of the subsidy measure impact in the form of reimbursement of CAPEX related to field project electrification when considering investment flexibility. The total amount of capital expenses related to OWF construction and installation ($CAPEX_{owf}$) assumed to be fully covered by the state fund.

For the *Subsidy case* the main results include the following: (1) Full coverage of electrification expenses results in optimal solutions laying slightly to the bottom right compared to *Base case* results. Contrary to the CO_2 tax policy, the CAPEX subsidizing allows for the company's expenses reduction and enhancement of the project's economy. When comparing resulting economic (x-axis) and emission (y-axis) values for the exemplary solutions denoted as green and black dots, one can see that the project with lower expenses (the *Subsidy case*) corresponds to better environmental performance than the *Base case* due to lower total hydrocarbons production required for the decision maker to compensate expenses. This means that a decrease in capital expenditures by the subsidy support allows for a simultaneous improvement in the economic and environmental performance of the project. (2) From an environmental performance perspective, the difference between optimal solutions for the cases under consideration is marginal. (3) Additionally, the elimination of capital expenses leads to an intuitive but slight (less than 2%) increase in the likelihood of decisions to invest compared to the *Base case*. This means that the policy measure might be effective in terms of decreasing emissions and incentivizing investment in platform electrification at a marginal scale.

4. Conclusions

The paper addresses the decision-making problem of offshore field project development with electrification alternatives under uncertainty. We present a multi-objective real options approach addressing several uncertain factors as well as managerial flexibility in terms of investment timing. The resulting optimization model allows to determine and evaluate trade-offs between the economic and environmental objectives of the project along with a flexible investment policy.

Our main findings are as follows:

(1) For the OWF and gas turbine cases, Pareto fronts are obtained representing sets of optimal trade-offs between economic and environmental objectives. That result provides decision-makers with the opportunity to select a solution that satisfies their different attitudes towards the project's environmental implications. When comparing corresponding economic and carbon emissions values of optimal solutions, we identify weights resulting in better environmental impact at only marginal project value reduction. Under the PFS case, the unique optimal solution is determined under single economic objective optimization due to the full decarbonization of operation activities.

(2) We confirm the importance of taking flexibility into account, especially for projects that are exposed to significant uncertainty and that place a higher weight on environmental performance. The comparison of Pareto fronts for different valuation approaches shows higher economic value for flexible projects due to the opportunity to avoid downside risk and capture upside potential. While the comparison of optimal investment strategies for different objective weights and valuation approaches shows that the opportunity to postpone investment decision increases the share of projects undertaken even when environmental performance is prioritized.

(3) We identify important policy insights highlighting the potential contribution of a fiscal and investment support policy in achieving both emissions reduction and providing investment incentives in more environmentally friendly electrification technologies. Our results indicate that governmental subsidies are more efficient in achieving emissions reduction and investment incentives compared to the strengthened fiscal policy. We confirmed that under the subsidy scenario, the operator considering both economic and environmental performance is more motivated to invest in environmentally friendly electrification choices due to the reduced burden of expenses. On the contrary, a reinforcing tax policy may lead to outcomes that contradict its intended purpose. Particularly, when considering an operator accounting for project's economy and emissions, the anticipated increase in taxes might entail more extensive production to compensate for the additional costs at an earlier period of operation leading to higher levels of emissions. At the same time, the impact of a subsidy policy might have marginal results and be contingent on the amount of subsidized expenses.

The approach is based on several assumptions and simplifications regarding some of the model settings. The primary constraint arises from an assumption of a linear relationship between hydrocarbon production rate and the amount of emissions as identified in previous engineering studies. However, such an assumption might lead to an overestimation of emissions during the initial phases of the project and underestimation of CO_2 emissions towards the end life of the project. Reservoir parameters are assumed as deterministic, despite that in real-life conditions the volume of hydrocarbons is characterized as highly uncertain.

Therefore, future research can be extended in several ways: (1) to develop a methodological approach combining more advanced multi-objective optimization techniques and real options analysis. Such a new approach can be used by decision-makers as a more accurate tool facilitating investment decisions under uncertainty, particularly enabling to explicitly specify constraints on certain objectives while optimizing others and determining non-linear trade-offs between objectives; (2) to improve field project modeling, including more accurate estimations of emissions as well as accounting for geological uncertainty as an additional risk factor affecting the identification of optimal solutions and investment policies. Accounting for geological uncertainty allows for modeling the decision problem closer to real conditions and improves the accuracy of the valuations, considering the significant impact of reservoir characteristics on the economic parameters of the field projects; (3) explicitly model the regulator's perspective including public cost of subsidies when assessing the effectiveness of different policy measures.

CRediT authorship contribution statement

Olga Noshchenko: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Verena Hagspiel:** Conceptualization, Methodology, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. Economic objective formulation

The economic objective includes the annual revenue of the project during the production period that stems from the sales of oil and gas produced. In the case of usage of a gas turbine or OWF, part of the total gas produced is consumed to power production operations on the platform and can, therefore, not be sold. Thus, it is deducted from the total volume of gas produced for sale, and the total revenue is then equal to:

$$R_t = P_{o,t} \cdot \Delta N_{P,t} + P_{g,t} \cdot (\Delta G_{P,i} - NG_{cons,t}), \tag{A.1}$$

where $P_{o,t}$ is sales price oil selling price in time t; $P_{g,t}$ denotes price of gas in time t; $\Delta N_{P,t}$ refers to the volume of oil produced by the field in year t; $\Delta G_{P,t}$ is total gas produced by the field in year t; the volume of gas used for the electrification in year t is denoted by $NG_{cons,t}$.

The drilling expenditure ($DRILLEX_t$) represents part of the investment costs and consists of expenses related to the installment of producing wells and water injectors. Drilling costs are considered uncertain, to address the uncertainty of total drilling costs, the parameter is also multiplied by the variable denoting uncertainty ($CostFactor$). $CostFactor$ is determined based on random samples using Latin-Hypercube sampling of probabilistic distribution. Thus the total amount of drilling expenses can be expressed as follows:

$$DRILLEX_t = \Delta N_{w,p,t} \cdot (1 + N_{\frac{inj}{prod}}) \cdot \alpha_{DRILLEX} \cdot CostFactor, \tag{A.2}$$

where $\Delta N_{w,p,t}$ is the number of new producing wells drilled in year t; $N_{\frac{inj}{prod}}$ is the number of water injectors per producing well (fixed in time); $\alpha_{DRILLEX}$ denotes DRILLEX well coefficient.

The capital expenditure ($CAPEX_i$) represents costs related to the construction of the topside of the platform as well as subsea system ($CAPEX_{SUBSEA+TOPSIDE}$). These costs are deducted evenly on an annual basis during the construction period T_c. In case of PFS or OWF electrification, additional capital costs related to connection to an onshore hydropower plant ($CAPEX_{pfs}$) or offshore powering system ($CAPEX_{owf}$) need to be accounted for. In case of PFS, expenses related to turbine purchase and installment ($dCAPEX_i$) need to be deducted. Therefore, the capital expenditures are expressed by the following formula:

$$\begin{aligned} CAPEX_t =& CAPEX_{SUBSEA+TOPSIDE} \cdot F_t + y_t \cdot CAPEX_{owf} \\ &+ x_t \cdot CAPEX_{pfs} - d \cdot CAPEX \cdot x_t, \end{aligned} \tag{A.3}$$

where F_t is a split factor for the year and the total $CAPEX_{SUBSEA+TOPSIDE}$ amount; x_t denotes a binary variable equal to 1 if the company decides to invest in a PFS in year t, and to 0 otherwise; y_t denotes a binary variable equal to 1 if the company decides to invest in an OWF in year t, and to 0 otherwise; d is a share of total $CAPEX$ representing costs related to the gas turbine.

The operating costs $OPEX_t$ constitute an important part of the project's expenditures and are assumed to include a fixed amount of operational costs (α_{OPEX}), expenses related to maintenance of OWF or PfS installments ($OPEX_{owf}$, $OPEX_{pfs}$), and a number of variable parameters that depend on a number of wells drilled in year t ($N_{w,t}$), production rates of oil, gas, and water ($q_{o,t}$, $q_{g,t}$, $q_{w,t}$), and electricity expenses ($ElCosts_t$):

$$\begin{aligned} OPEX_t =& CostFactor \cdot (\alpha_{OPEX} + b_{OPEX} \cdot N_{w,t} + c_{OPEX} \cdot q_{o,t} \\ &+ d_{OPEX} \cdot q_{g,t} + e_{OPEX} \cdot q_{w,t} + OPEX_{owf} \cdot y_i \\ &+ OPEX_{pfs} \cdot x_i) + ElCosts_t, \end{aligned} \tag{A.4}$$

where b_{OPEX}, c_{OPEX}, d_{OPEX}, e_{OPEX} are coefficients denoting the contribution of each variable parameter to the total amount of $OPEX_t$.

The production parameters are formulated based on the equations presented in the studies of Eyni et al. [9] and Sales et al. [63].

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