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Methods for early-phase planning of offshore fields considering environmental performance

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ABSTRACT

Extraction and processing of oil and gas with current technologies is energy- and carbon-intensive as well as are the manufacture, transport and installation of the facilities needed for oil and gas production. Nowadays, there is a strong emphasis on reducing emissions and energy usage to help mitigate climate change. In this work, we demonstrate a method for decision-support in early-phase field planning based on proxy modeling and optimization. An optimization model is developed to determine drilling and production schedules, as well as the processing capacities of oil and gas that maximize a key performance indicator. The key performance indicator is a linear combination of the normalized net present value and environmental variables, the carbon footprint and carbon dioxide emissions. The weight of each variable in the objective function is adjusted by varying the value of the constants. An offshore field on the Norwegian Continental Shelf is used as a case study.

Results show that there is a clear trade-off between economic and environmental performance. There are cases, however, where a modest improvement in field environmental performance can be achieved without significantly decreasing its economic value or requiring additional technologies. As a result of a 13% and 8% reduction in NPV relative to the maximum achievable reduction, the carbon footprint and CO_2 emissions will be reduced by 30% and 35%, respectively. The paper offers comments and observations about the implementation and inclusion of environmental indicators into early-field development planning. In the near future, this study will be improved to include a more accurate analysis of the impact of environmental indicators and different low-emission technologies on the field development plan.

1. Introduction

Greenhouse gases (GHG) emissions and energy consumption derived from oil and gas usage corresponded to about 20 million tonnes of carbon dioxide (CO_2) equivalent [1] and 93,000 Terawatt hour (TWh) in 2019 [2], which is equivalent to 55 and 53.5% of worldwide emissions, respectively. Emissions from the petroleum upstream sector are significant both globally and in Norway, where they account for about one-quarter of Norway's aggregate GHG emissions [3]. Emissions from Norway's oil and gas industry amounted to 13.7 million tonnes of CO_2 equivalent in 2019 [4].

Most of the Norwegian fields are mature, experiencing production decay and utilize rather old infrastructures with low efficiency. This puts additional public and governmental pressure on companies operating old offshore facilities in the North Sea and the Norwegian Sea [5] to reduce emissions and improve energy efficiency. Norway has set an ambitious target to reduce emissions in offshore fields by 50% of 1990 levels by 2030 and to move towards zero emissions in 2050 [6]. In addition to the initiative from the Norwegian government, there is also increasing pressure from the public and investors for oil and gas companies to set climate targets that are consistent with the goals in the Paris Agreement [7]. To move away from the current path of increasing CO_2 emissions to one that involves keeping emissions flat or reducing them in the future is a huge challenge because most countries are still heavily dependent on fossil fuels [8]. Hence, new and improved technology is usually required to deliver energy with the lowest possible emissions [9]. According to Zhang [10] and Maeder [11], the development of flexibility technologies (in this context, flexibility refers to the ability to adjust the power supply/demand of the system) is expected to mitigate this in the coming decades.

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Nomenclature

α	Weighting factor
η	Efficiency
ρ	Density, $(\frac{Kg}{m^3})$
BONMIN	Basic Open-source Nonlinear Mixed Integer programming
CAPEX	Capital Expenditure, NOK
CCS	Carbon Capture and Storage
CE	CO_2 emissions, tonne
ce	Dimensionless CO_2 emissions
CF	Carbon Footprint, tonne
cf	Dimensionless Carbon Footprint
CF_t	Total Carbon Footprint, tonne
CO_2	Carbon dioxide
DRILLEX	Drilling Expenditure, NOK
EF	Emission Factor, $(\frac{tonneCO_2}{Sm^3})$
FPSO	Floating, Production, Storage and Offloading
GHG	Greenhouse Gases
GOR	Gas Oil Ratio
IOIP	Initial Oil In Place, Sm^3
IP	Integer Programming
LCA	Life-Cycle Assessment
LHV	Lower Heating Value, $(\frac{MJ}{Kg})$
LP	Linear Programming
MINLP	Mixed Integer NonLinear Programming
MW	Molecular Weight, $(\frac{g}{mol})$
NPV	Net Present Value, NOK
npv	Dimensionless Net Present Value
OPEX	Operational Expenditure, NOK
q	Total Production,Sm^3
$q_{\max}$	Max Production, bpd
TWh	Terawatt hour
W	Consumption power, MJ
W_{FPSO}	$Weight_{FPSO}$, tonne
W_{Hull}	$Weight_{Hull}$, tonne
$W_{Topside}$	$Weight_{Topside}$, tonne

However, no single strategy can enable this goal to be reached [12].

Some researchers have worked on different new systems for decreasing energy consumption, such as CO_2 capture and injection, advanced turbine co-generation, and wind farms that are not commonly used in oil and gas fields. For example, Persichilli [13] conducted a trade study to compare CO_2 and steam-based heat recovery systems. Kloster [14] argued that bottom steam cycles are technically feasible and would result in a significant reduction of CO_2 emissions. The concept was theoretically proven in three North Sea case studies [15]. The study of Sanchez [16] also demonstrated that the integration of CO_2-capture is technically feasible but requires a significant amount of energy. Therefore, although it is of advantages for reducing CO_2 emissions, it contradicts the objective of this work, which is to increase energy efficiency. Nguyen [17] also argues that all of these studies focus on a single or a few strategies to reduce CO_2 emissions in oil and gas offshore fields, but none of them evaluate each option from a process, thermodynamic, economic, and environmental perspective. Besides, they are not applicable in all fields while we are looking for a method that can be applied to different types of fields without adding technologies or extra expenditure, although it is possible to consider new technologies as part of this work.

Improved energy efficiency is one of the most effective means of protecting and enhancing the global environment, according to a report from the International Energy Agency called World Energy Outlook [18]. As the overall system efficiency is directly proportional to CO_2 emissions, if the mitigation of CO_2 emissions is studied as one of the primary goals in the field planning, it will bring significant effects on energy consumption reduction as well. A majority of studies have assessed environmental performance after production is complete when accurate data on fuel consumption is known or when there is a more detailed design. But, some studies report methodological and data challenges when attempting to quantify environmental indicators [19]. First, no consistent and widely adopted method exists for measuring and predicting the carbon intensity of oil production. Second, there is a lack of comprehensive and geographically-rich data-sets that allow the evaluation and monitoring of the life-cycle emissions [19]. In fact, the challenge is how to ensure consistent results when neither accurate fuel consumption data nor established emission factors are available for the planned operations [20]. Early phase planning offers many design options that have not been decided yet, and there is a lot of flexibility to make changes that lead to major improvements. Gilbert [20] showed that conducting quantitative forecasts in the planning phase before the field is in operation can have substantial advantages since it helps mitigate emissions at the source and allows engineers to compare different operational strategies. Hence, our objective was to develop a practical and understandable method for estimating environmental indicators using limited data and include them in early development planning which is the best way to provide the most efficient design features.

Field development planning is an essential early phase in the life of an offshore field as many decisions, such as type of platform, production and drilling schedules, and capacity of processing facilities, are made during this stage. In the industry, this is typically done by several discipline teams, that compare and compute economic performance and technical requirements of several field development alternatives and ultimately choose the best. This process is often time-consuming, involves manual work, and does not allow the exploration of all possible designs. In addition, it does not consider uncertainty in a robust manner. To address this challenge, several works have developed automated decision-support methods with the goal of maximising the revenue from oil and gas sales while respecting technical constraints. Some examples are Shirangi [21], Angga [22], Schiozer [23], Gonzalez [24] and Bonti [25] which complement each other's work. The main idea of their work is to make an approximate numerical model of the value chain, often using commercial simulators (or extracting data from them), and apply an optimization algorithm to automatically maximize revenue by changing the design parameters. Stochastic analysis has been performed on the model to evaluate the effect of uncertainty. The production and drilling schedules and the processing capacities of gas, oil, and water directly impact the size and weight of the offshore structure and processing facilities and the number of wells required, which are elements that account for most of the carbon footprint of an oil and gas production system. However, these studies have not considered environmental performance either as a constraint or as part of the objective to minimize environmental effects. Thus, our goal was to improve on the previous models by including environmental indicators in the objective function.

Another important environmental performance parameter is the carbon footprint. According to Wiedmann [26], the carbon footprint is a measure of the total amount of CO_2 emissions that are directly and indirectly caused by an activity or are accumulated over the life stages of a product. In our study, we consider emissions derived only from manufacturing, transport, and installation. We neglect emissions during operations (e.g. maintenance) and after abandonment and decommissioning. There are a number of ways to obtain estimates of the carbon footprint, ranging from simple online calculators to sophisticated Life-Cycle Assessment (LCA). However, there is an apparent lack of an approximate method to estimate the carbon footprint of a floating processing facility for early phase field development. The authors believe this might be because of the relatively small carbon footprint contribution of manufacturing facilities and equipment for oil and gas extraction in comparison to lifetime CO_2 emissions from the operation, which is a highly energy-intensive process. Because of that, few studies include the carbon footprint in their assessment of oil and gas projects. One exception is Kim [27], a study that investigated power generation via combined cycle configurations and post-combustion capture with CO_2 re-injection for carbon-footprint reduction while increasing the gas export and oil production, respectively. However, the procedure was applied on a field with high CO_2 content and an elevated gas-oil ratio (GOR). The carbon footprint from onshore and offshore oil and gas-related infrastructure is material to the cradle-to-gate footprint [28]. As oil and gas companies investigate the cradle-to-gate carbon footprint for ways to reduce their footprint in response to corporate reduction commitments, one potentially interesting area is to study the impact of the large mass of materials (e.g. steel) used to construct equipment and infrastructure for oil and gas operations. Silva [28] reported that the carbon footprint of the infrastructure is considerable, even when spread over the lifetime of a facility because of the substantial infrastructure mass. Studying and quantifying the carbon footprint due to manufacturing can be useful to understand the distribution of energy use and improve infrastructure energy efficiency. Therefore, we attempted to include this indicator in our study.

Having considered all of the above, the novelty of the present research is that it provides an approximate method for estimating both the economic and environmental performance of a project early in its development, while uncertainties are high, by allocating weights to each of them based on the decision makers' viewpoint, and it is applicable to all offshore fields with traditional or advanced technologies. Therefore, we intend to (i) identify a fast, simple, and approximate method of calculating CO_2 emissions with limited data in the field development stage (ii) develop a method to estimate the carbon footprint of Floating, Production, Storage and Offloading (FPSO) systems, and (iii) perform simulation-based multi-objective optimization to identify the potential trade-offs between environmental performance and economics. The study case is taken from the work of Alkindira [29], which considers an offshore oil field with two reservoirs, and subsea wells that produce to an FPSO via risers. We formulate an integer non-linear optimization model instead of using the piece-wise linearization of Alkindira [29].

The rest of the paper is organized as follows. Section 3 presents the study case, and describes the optimization methodology and the optimization model. Following this, several variations of the optimization model are presented. The results are presented in Section 4 and the imitations and drawbacks of the study are stated in Section 5. Section 6 contains the conclusions and plans for the future.

2. Methodology

2.1. Case study

The field considered in this study is an offshore oil field on the Norwegian Continental Shelf in the southern part of the Barents Sea, at the Loppa High area. It consists of two non-communicating reservoirs. The reservoirs are saturated oil reservoirs with the presence of a gas cap. For the purpose of this study, it will be assumed that the production for this field is expected to start in 2025 with horizontal production and injection wells and is scheduled for abandonment in 2045. The first reservoir has higher volumes of oil in place than the second one. Table 1 presents some information for each reservoir.

Table 1
Parameters of the reservoirs.

Reservoirs	First	Second
Initial Oil In Place (IOIP) [MSm3]	56.25	39.25
GOR [Sm^3/Sm^3]	115	150
Productivity index [Sm^3/day/bar]	1500	500
Number of wells	6	3
Pressure Maintenance method	Water injection	Gas injection

2.2. Optimization

In field development, there are usually several development options that could be feasible, and they are ranked according to their economic performance, and technical feasibility, among other factors. Trade-off analysis is usually conducted as part of the decision-making process. In trade-off analysis, we identify the most acceptable production plan among a set of proposed alternatives based on how well the alternative meets the agreed criteria [30]. In this study, the criteria used when making the decision are economic and environmental performance. These criteria define the critical attributes that the ideal option must possess [31]. The overall degree of fulfillment of these criteria is what is considered in the evaluation process. However, there is usually a conflict between economic and environmental performance, i.e. there is a trade-off between the economic performance and the degree of CO_2-abatement of oil and gas platforms. In these cases, a solution is to assign weights to each indicator. The weights determine how heavily a criterion contributes to the overall score. It is assigned based on the level of importance of each criterion for stakeholders and clients. Model-based optimization will allow finding the best among all options, although it does not usually output all other feasible solutions which are sub-optimal. The main idea of this work is to include environmental indicators in the optimization to see if it is possible to find development strategies that have good economic performance (but are sub-optimal in terms of economic performance only). At the same time, these strategies are to be better in terms of environmental performance (optimal in terms of both economic and environmental performance).

The objective function to be maximized is composed of three different parts, as shown in Eq. (1).

$$Obj = \alpha_1 npv - (1-\alpha_1)[\alpha_2 ce + (1-\alpha_2)cf] \tag{1}$$

Where α_1 and α_2 are coefficient weights that range from 0 to 1. We weigh the coefficients based on the relative importance of each objective. To accomplish this, first, we divided the objective into two parts: economic and environmental performance, so that the total weight should equal one. The objective with higher relative importance is given greater weight and vice versa. Therefore, if $\alpha_1 = 1$, the objective does not have an environmental impact, and all importance is placed on net present value (NPV). It should be noted that $\alpha_1 = 0$ was not considered in the model, since there would be no production and all objective parameters would be zero. We also divided the environmental part into two subparts: CO_2 emissions and the carbon footprint. For example, when $\alpha_2 = 0$, we only consider the carbon footprint of construction in the environmental part of the objective.

npv, *ce*, and cf are also defined as follows:

$$npv = \frac{NPV}{NPV_{ref}} \quad (2)$$

$$ce = \frac{CE}{CE_{ref}} \quad (3)$$

$$cf = \frac{CF}{CF_{ref}} \quad (4)$$

Where NPV_{ref}, CE_{ref}, and CF_{ref} are reference amounts for NPV, CO_2 emissions and the carbon footprint while the objective is composed of NPV only. These reference values are used to make the parameters dimensionless and exhibit similar orders of magnitude. Initially, the plan was to determine the reference value of each parameter by finding the maximum in a case where the respective parameter is the sole objective (e.g. maximising NPV to find NPV_{ref}, minimising CO_2 emissions to find CE_{ref}, etc.). However, when the objective is set to minimize CO_2 emissions or the carbon footprint, the hydrocarbon production is set to zero by the optimizer. Therefore, the reference values for all quantities will be extracted from the case of NPV optimization only.

A potential benefit of using a normalized objective function is that the effect of uncertainties is somewhat mitigated as uncertainties will affect both the numerators and denominators in Eqs. (2), (3) and (4).

The rates of oil production in time, the number of producers in time, and the timing of drilling new wells are the main decision variables. The relationship between variables and objectives is captured in the model by mathematical expressions. Variables are computed by the optimizer based on the physical limitations of the system, the equality and inequality constraints, set by the field planner. The solutions are often non-intuitive and difficult to determine using simple logic. One simple example is that a higher oil production rate means higher revenue, but it also means higher expenses due to the required equipment, more CO_2 emissions due to the increased energy consumption, and a larger footprint due to the larger processing facilities required. Full details of the optimization formulation can be found in Appendix A and the work of Guowen [32].

We used integer-nonlinear numerical optimization to solve this problem. The optimization model is created in Excel(r) software and is defined using the interface of the Excel Solver. As the size of the problem exceeds the limits of the Standard Solver (provided by the company Frontline) included by default in Excel, the open-source OpenSolver is used [33], with the Basic Open-source Nonlinear Mixed Integer programming (BONMIN) solver. OpenSolver is an open-source Excel add-in that allows spreadsheet users to solve their Linear Programming (LP) and Integer Programming (IP) models. It does not have any of the size limitations found in the built-in Excel solver, so it can solve larger models as well as provide novel model construction and on-sheet visualization capabilities. BONMIN is an experimental open-source code for solving general Mixed Integer NonLinear Programming (MINLP) problems and is often faster than the built-in Solver. Here, the variable set includes 48 continuous variables and 52 integer variables, and a precision of 10^{-6} is set for the constraints. The tolerance is also set to 1%. The openSolver determines the optimal amount for each of these 100 variables, and calculates dependent variables (e.g., cumulative production rate and total CO_2 tax) to obtain the maximum objective after introducing all inputs (e.g., oil price and tax rate) and constraints. Here, the objective refers to a variable defined in Eq. (1).

A flowchart showing the calculations performed in the Excel sheet is depicted in Fig. 1.

2.2.1. Estimation of CO_2 emissions from operation

In offshore facilities for oil and gas production, approximately 85% of the CO_2 emissions are derived from the gas turbines utilized to generate electricity in the facilities from the combustion of natural gas and diesel. The rest of the emissions to air from petroleum activities originate from natural gas and diesel combustion in engines, boilers, flaring of natural gas for safety reasons, venting and diffuse gas emissions, as well as the storage and loading of crude oil [3]. An example of the contribution of several elements to CO_2 emissions is shown in Fig. 2. Thus, one can conclude that a significant reduction of CO_2 emissions in the oil and gas industry can be achieved if the amount of CO_2 emissions from gas turbines is reduced or eliminated by different methods. Therefore, this study

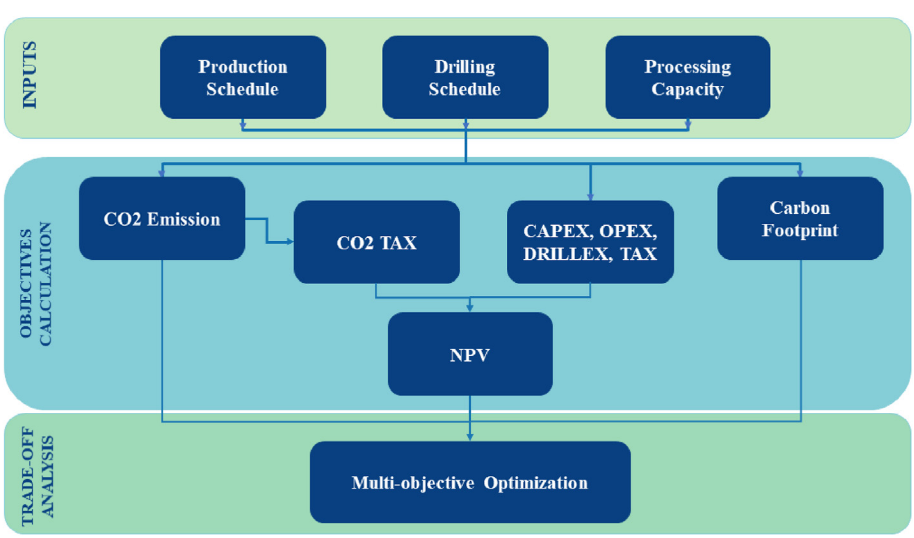

Fig. 1. Visualization of the methodology.

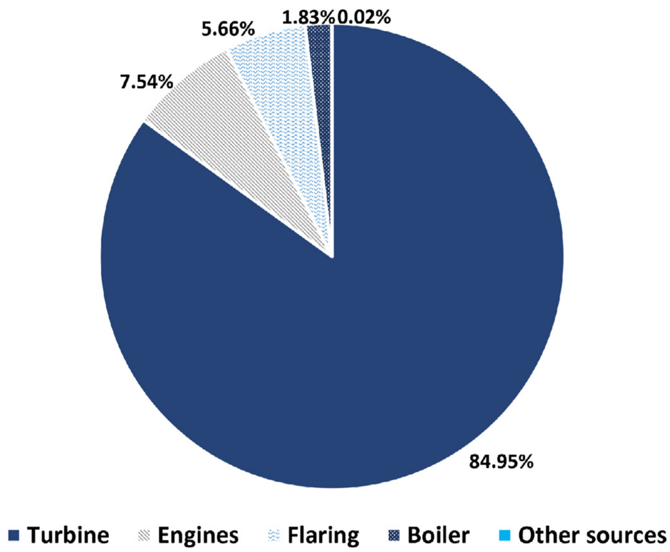

Fig. 2. CO_2 emissions by source.

focuses only on the contribution of CO_2 emissions from gas turbines. Other GHG emitted by the turbine is neglected as we have done the same for the carbon footprint.

The amount of installed power capacity required by the gas turbine, its fuel consumption, and ultimately the CO_2 emissions are proportional to the oil and gas production rates. In this study, CO_2 emissions are calculated assuming a linear relationship with the oil production flow rate. The following equation is proposed using data reported by the Norwegian Petroleum Directorate [3] and the Rystad Energy reports [34]:

$$CE = EF \times q \tag{5}$$

Where the emission factor (EF) is 0.05 $\frac{t_{CO_2}}{Sm^3}$. Another equation to determine CO_2 emissions from oil production was derived using reported values of EROI (energy return on investment) and stoichiometry. The details are described in Appendix B. Both methods yield similar results, therefore Eq. (5) was used in the model.

In Norway, CO_2 emissions are taxed by the government, 543 NOK per tonne of CO_2 [3] and will be increased to 2000 NOK per tonne of CO_2 within 2030. Therefore, in the model, from now to 2030, we increased the CO_2 tax linearly to reach 2000 NOK per tonne of CO_2, and then kept it constant. The amount of total CO_2 tax can be calculated as follows:

$$CO_2TAX_t[NOK] = CE_t[t_{CO_2}] \times CO_2TAX_t\left[\frac{NOK}{t_{CO_2}}\right] \tag{6}$$

2.2.2. Carbon footprint

The production system has an additional environmental impact, not associated with operation and energy consumption, but rather with manufacturing, transport, installation, repairs, and recycling. The term accumulated emissions is often used to describe this part, but in our work, we will refer to this using the term of the carbon footprint. Our study assumes that the construction of the FPSO is the major contributor to the carbon footprint, and we neglect the contribution of other parts of the system, such as the subsea system. Similar to Wiedmann [26], we only considered CO_2 in the carbon footprint analysis, despite the fact that we know that other substances such as methane also contribute to greenhouse warming. Most of those substances are not carbon-based or are more difficult to quantify because of insufficient data and uncertainties, such as maintenance stops and unscheduled events. Because of this, CO_2 was the only GHG included in the carbon footprint analysis here. By this method, this work estimated the carbon footprint using the following assumptions:

1. Most of the carbon footprint comes from steel fabrication. Carbon emissions produced during steel fabrication as assumed to be 1.75 tonnes for each tonne of steel produced [35].
2. Other sources of the carbon footprint, such as yard activities, including electricity, welding, cutting, and plate forming, transport within the yard contribute 11% of the total carbon footprint; the rest (89%) is attributed to steel production. Therefore, one can use a factor of 0.216 (=1.75*11/89)tonnes per tonne of steel processed at the yard to compute the total carbon footprint [35].

Hence, the carbon footprint can be calculated by:

$$CF_t = W_{FPSO} \times (1.75 + 0.216) \tag{7}$$

Therefore, the weight of the FPSO is required. The weight of the vessel and facilities is required to estimate the amount of steel needed for the FPSO. This can be expressed as Eq. (8).

$$W_{FPSO} = W_{Topside} + W_{Hull} \tag{8}$$

A few different estimation methods and equations are available in the literature for calculating the topside weight of FPSO, such as Ha [36], Myung [37], Zou [38], and Zou [39]. The input parameters to these equations vary widely and many do not consider the effect of processing capacities while the weight of the vessel and facilities usually depends on the processing capacities of oil, gas, and water. For the topside weight, we selected the equation proposed by Nunes [40], Eq. (9), because it considers the effect of processing capacity and does not include parameters that are unavailable or irrelevant to our study. Processing facilities, equipment, and so forth are included in this equation as part of topside weight [40].

$$W_{Topside} = 16500 + q_{max}\left[0.01 + \frac{GOR}{10^4} + \left(0.01 + \frac{GOR}{2*10^4}\right)y_{CO_2} + \left(0.01 + \frac{GOR}{4*10^4}\right)\left(y_{CO_2} + y_{H2S}\right)\right] \tag{9}$$

The accuracy and validity of this equation were verified by comparing it against machine learning techniques applied to the Rystad Energy data. The data is made up of 80 data set, including oil production capacity, gas production capacity, total design production, storage capacity, water depth, and the minimum, average, and maximum weight of the topside of the FPSO for 80 projects. In this case, the average topside weight is the target variable expected to be estimated by predicting variables including oil production capacity, gas production capacity, storage capacity, and water depth. To determine the relationships between the target and predictor variables, the Pearson correlation coefficients between them were calculated. In Appendix C, a brief description of the coefficient is provided.

The results revealed that the topside weight is strongly correlated to oil production capacity while the others show a lower correlation but are not small enough to be excluded. Using different modeling techniques, the results found that linear regression is appropriate to capture the relationship between the target and predictor variables provided. Finally, we compared the result of the derived model with Eq. (9). The difference is on average 1.3%, which is acceptable.

Due to the lack of a simple and practical estimation method for the hull weight, we estimated it from the topside weight by assuming a weight coefficient of 2.18 (tonne hull/tonne topside), Eq. (10). This number was estimated from a sensitivity analysis of the data provided by Ha [36], and Jun Zou [38,39]. This approach was preferred instead of using more detailed methods (e.g. Myung [37], and Jun Zou [38]) because it was observed the hull weight is often a function of topside weight. Besides, they often depend on several factors that are irrelevant or unknown in our study.

$$W_{Hull} = 2.18 \times W_{Topside} \tag{10}$$

Therefore:

$$W_{FPSO} = 3.18 \times W_{Topside} \tag{11}$$

2.2.3. NPV

The NPV of the project is defined as the discounted sum of revenue and expenses. Expenses include drilling expenditure (DRILLEX), operational expenditure (OPEX), capital expenditure (CAPEX), tax and CO_2 tax.

$$NPV = \sum_{t \in T}\left(\left(\frac{1}{(1+i)^t}\right)(Sale_t - CAPEX_t - OPEX_t - DRILLEX_t - TAX_t - CO_2TAX_t)\right) \tag{12}$$

where i is the discount rate, t is a given year, and T is the total number of years. Expressions of DRILLEX, OPEX, and CAPEX were taken from the work of Alkindira [29] and Lei [32]. NPV is discounted to its present value using the discount rate *i*, which is a decimal number. The expressions are reproduced in Appendix A for clarity.

3. Results and discussion

Several optimizations were completed with different values of α_1 and α_2 (ranging from 0 to 1), and the resulting values of NPV, CO_2 emissions, and the carbon footprint were recorded. The values of each objective were plotted in a 3D surface plot versus the values of the weighting coefficients. Figs. 3–5, show the resulting plots. Increasing α_1 means the NPV is more prominent in the objective than the environmental part. Therefore, NPV is increased by increasing α_1, and the carbon footprint and CO_2 emissions are also increased since more production results in higher NPV. On the other hand, decreasing α_1 means that reduction of environmental performance indicators is preferred. Due to this, the production decreases to achieve this goal, which results in a reduction of NPV, CO_2 emissions, and the carbon footprint. Moreover, increasing α_2 means CO_2 emissions are more prominent in the objective than the carbon footprint. Therefore, CO_2 emissions are decreased by increasing α_2. However, the carbon footprint is affected by both weights simultaneously. Therefore, we can observe a decrease in some areas and an increase in others. It is worth mentioning that in some cases, the surfaces exhibit some non-smooth variations. This is due to the interpolation used to obtain the surface plot. Additionally, the optimizer could not find a feasible solution for some combinations of α_1 and α_2 because some constraints were not met and the NPV had negative values.

It is possible to see that there is a clear trade-off between the economic goal and environmental performance. By changing the values of α_1 and α_2, several optimal solutions can be found with high economic performance or high environmental performance, or a combination of both. Fig. 6 illustrates the relationship between environmental and economic performance. The color scale represents NPV, and the x and y axes represent environmental indicators, CO_2 emissions, and the carbon footprint, respectively. The region with maximum values of NPV is when CO_2 emissions and carbon footprint are maximum. If one considers a constant value of CO_2 emissions, the NPV value increases as the carbon footprint increases since both correlate with the maximum oil and gas production. Similar behavior is seen when assuming a constant carbon footprint and increasing CO_2 emissions. There are some areas on the plot for which there were no solutions, and some edges are non-smooth because of the magnitude of the step used in the weight coefficients to generate the plot data points (0.1).

Fig. 7 illustrates how CO_2 emissions and NPV relate to each other. Increased production leads to more NPV and more CO_2 emissions. However, there are some values of α_1 and α_2 that give field designs with better environmental performance and still have a good NPV. For instance, if one employs a value of α_1 and α_2 of 0.5 and 0.8, respectively, the resulting solution has 30% less emissions and 13% less NPV relative to the solution using α_1 equal 1 and α_2

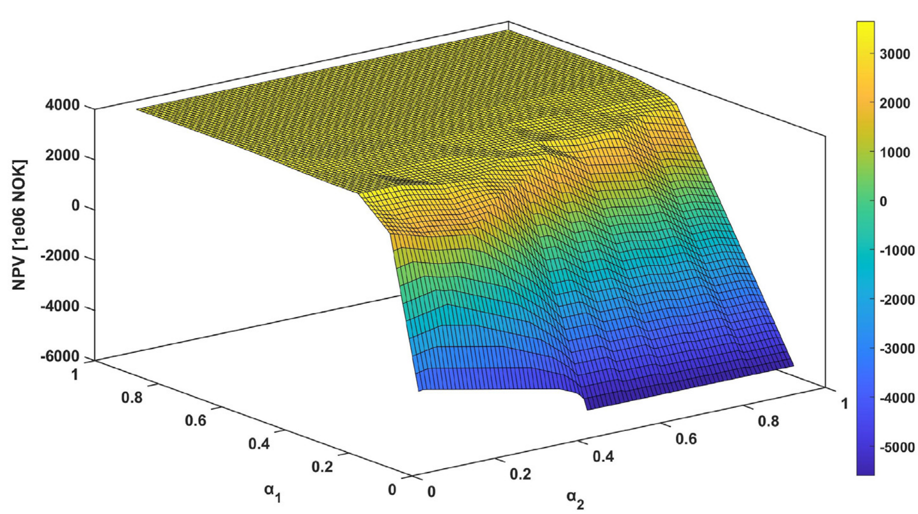

Fig. 3. NPV values for several combinations of weight coefficients.

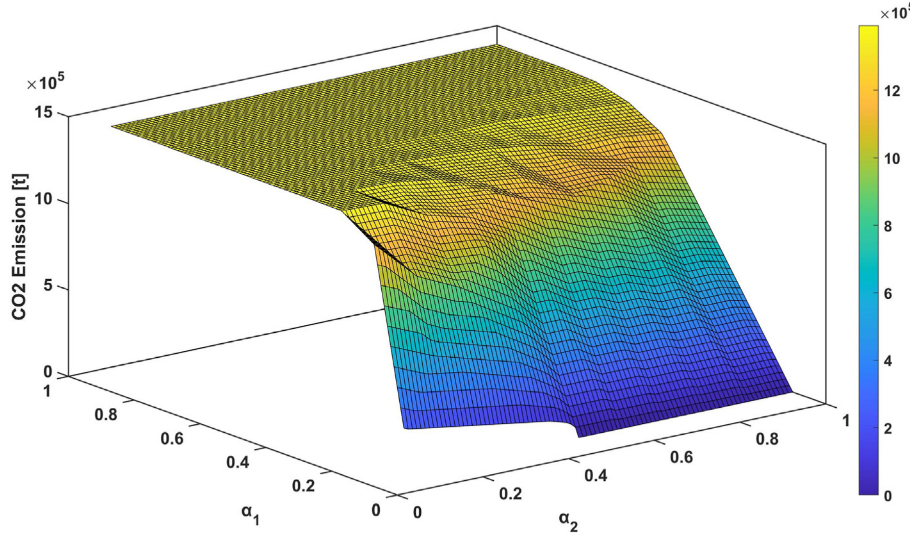

Fig. 4. CO_2 emission values for several combinations of weight coefficients.

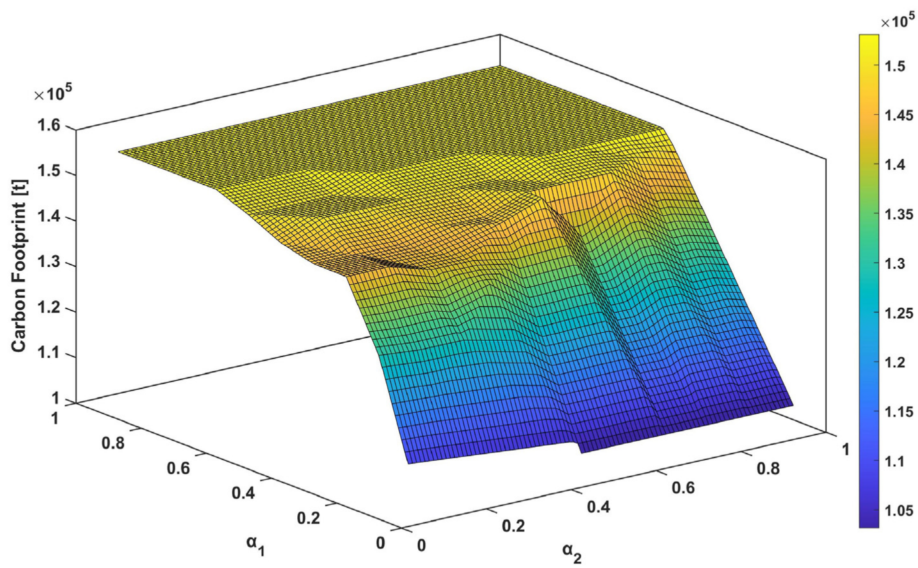

Fig. 5. Carbon footprint values for several combinations of weight coefficients.

equal zero. The oil production rate of both reservoirs is presented in Fig. 8 for these two cases. The difference between the two strategies occurs towards the end of the production horizon. The first and second reservoirs both stop production earlier, and the second reservoir enters earlier in decline. These results are consistent with our expectations. The optimizer prioritizes reservoirs with high productivity and more wells in order to maximize NPV and minimize environmental impact. As a result, the second reservoir enters into decline earlier since its productivity is half that of the first reservoir and fewer wells are allowed to be drilled there. Therefore, the best plan would be firstly to drill wells in the first reservoir and apply the reduction to the second reservoir.

A similar observation can be done about field designs that reduce considerably the carbon footprint but still posses a good NPV. Fig. 9 illustrates how carbon footprint and NPV relate to each other. For example, if one employs a value of α_1 and α_2 of 0.4 and 0.1 respectively, the resulting solution has 35% less carbon footprint and 8% less NPV relative to the obtained window when compared against the solution using α_1 equal 1 and α_2 equal zero. The oil production profile of both reservoirs is presented in Fig. 10 for these two cases. To achieve a reduction in carbon footprint, the second reservoir is produced as it would be when prioritizing NPV only, but the first reservoir is produced with a lower plateau rate but with a slightly longer plateau duration.

Altogether, this means that it is possible to achieve a reduction of approximately 340,000 tonnes of CO_2 (emissions and footprint) over a period of 26 years at the expense of a reduction of 1000 million NOK in NPV. This is equal to a CO_2 cost of approximately 3000 NOK per tonne of CO_2. This value is comparable with published numbers for decarbonization, technologies such as Carbon Capture and Storage (CCS) and hydrogen.

It is worth noting that these reductions and improvements in

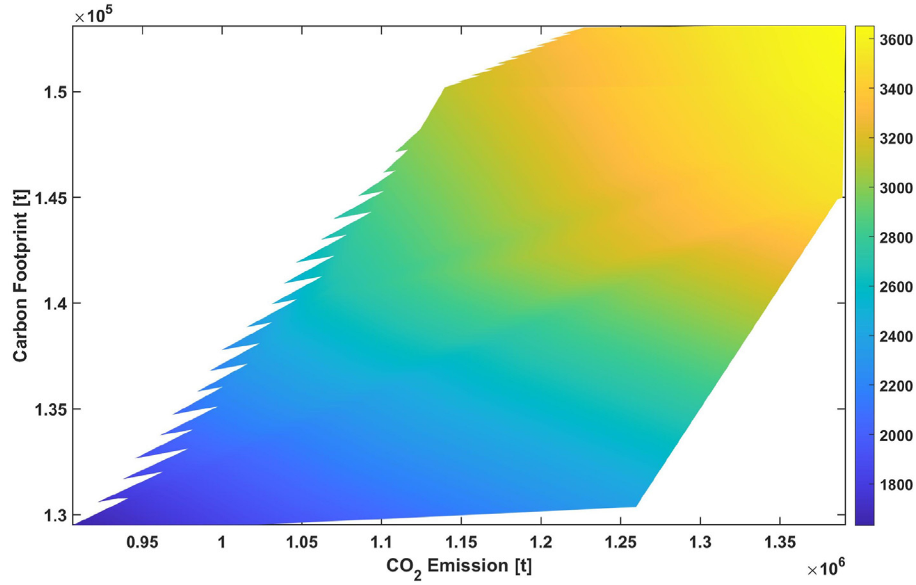

Fig. 6. Optimized NPV spectrum in [million NOK] vs. CO_2 emission and Carbon Footprint.

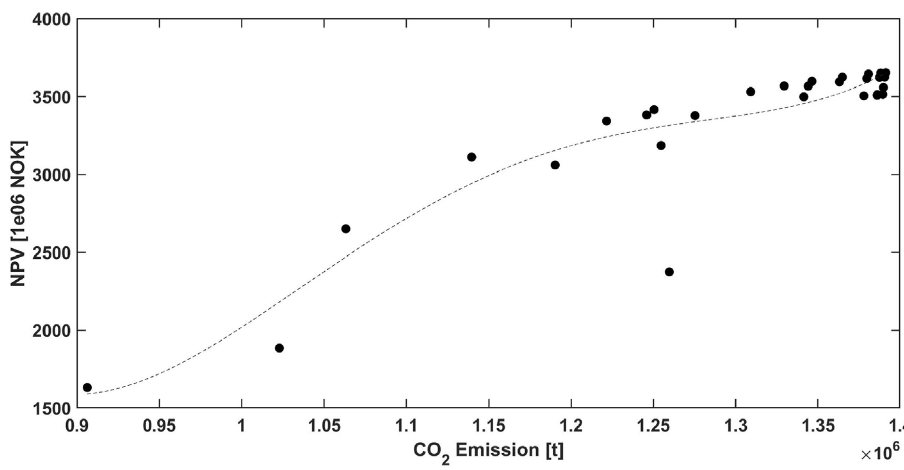

Fig. 7. NPV vs. CO_2 emissions.

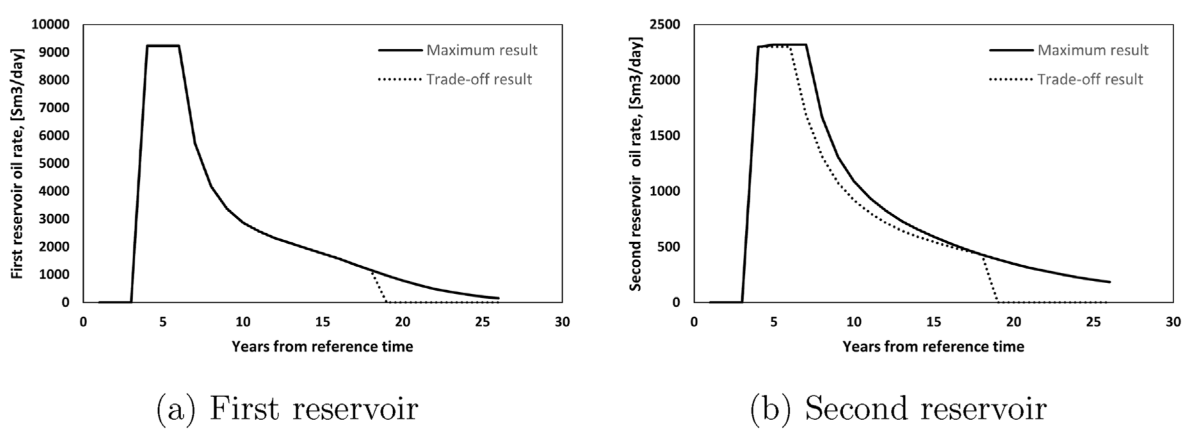

Fig. 8. Production rate vs. years; after changing the weight coefficients from $\alpha_1 = 1$ and $\alpha_2 = 0$ to $\alpha_1 = 0.5$ and $\alpha_2 = 0.8$.

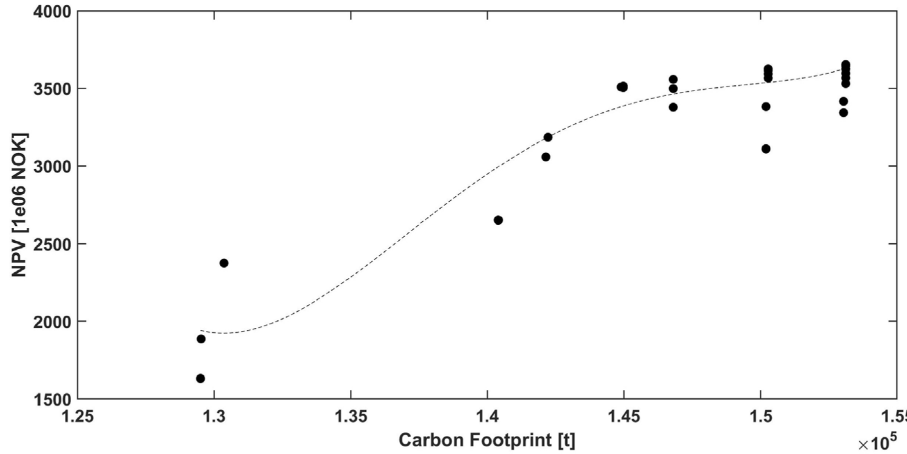

Fig. 9. NPV vs. Carbon footprint.

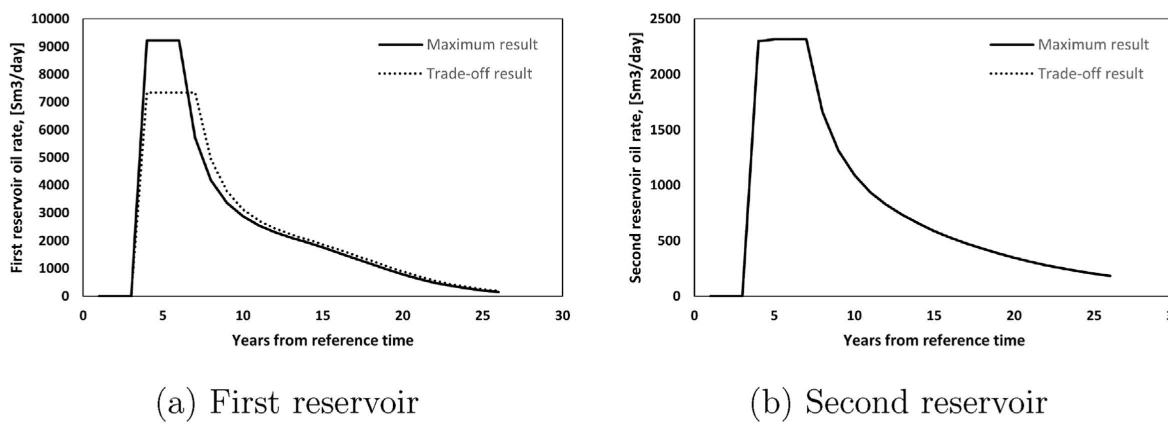

Fig. 10. Production rate vs. years; after changing the weight coefficients from $\alpha_1 = 1$ and $\alpha_2 = 0$ to $\alpha_1 = 0.4$ and $\alpha_2 = 0.1$.

environmental performance require no new technologies. They are achieved by careful design (using optimization) of the production and drilling schedules and capacity of the topside facilities.

Multiplying a CO_2 tax by the emissions is the standard way that CO_2 emissions are taken into account in the valuation of oil and gas projects nowadays in Norway. It is also the way implemented in the current model. However, it could be considered that this coefficient represents also the monetary cost equivalent of the carbon footprint and CO_2 emissions (e.g. to society). Therefore, by changing the value of the CO_2 tax, it could be used to model a variety of hypothetical or real situations, such as: CO_2 tax imposed by the government on emissions, tariffs to dispose safely of the CO_2, economic compensation to society for emitting CO_2, and CO_2 trading schemes. It could be argued that, to find environmentally friendly field designs, instead of using multi-objective optimization with linear scalarization, one could simply increase the value of the CO_2 tax. To study this issue, a sensitivity analysis of the CO_2 tax rate has also been conducted. The optimization process was repeated for three different CO_2 tax rates: the base model in which the CO_2 tax rate was increased from 543 to 2000 NOK per tonne of CO_2 in 2030, and remained constant until the end of the project, a fixed CO_2 tax rate of 543 NOK per tonne of CO_2 (lower tax rate), and a fixed CO_2 tax rate of 2000 NOK per tonne of CO_2 (higher tax rate). Optimizations were performed for several values of α_1 and α_2. Similar to Figs. 7 and 11 illustrates the relationship between CO_2 emissions and NPV for three values of CO_2 tax and for several combinations of α_1 and α_2. It can be observed the lines for base and high CO_2 tax have similar shape, but the curve is slightly different for low CO_2 tax. The right extreme of the chart corresponds to optimization with α_1 equal 1 (considering maximising NPV only). For this value of α_1, all field designs obtained have the same value of CO_2 emissions, the same production and drilling schedule; however, they have a different NPV value. This indicates that increasing the CO_2 tax did not allow to find field designs with less CO_2 emissions, but it rather caused a reduction in the NPV. To study this issue more in detail, we performed several optimizations using several CO_2 tax values between 543 and 4000 NOK per tonne of CO_2, considering NPV only as an objective (α_1 equal 1). Table 2 shows optimized values of NPV and cumulative production of oil for various values of CO_2 tax. The optimal production profile and drilling schedule of all these cases were identical.

Consider that field planners wish to achieve a given target NPV. From Fig. 11, a higher CO_2 tax results in higher emissions, which seems counter-intuitive. However, this could be explained due to the fact that higher tax rates represent more expenses, and therefore, more oil and gas must be produced to generate additional value.

These results indicate that increasing the CO_2 tax rate, does not encourage finding more environmentally friendly field designs, but will simply reduce the economic value of the project, or induce the

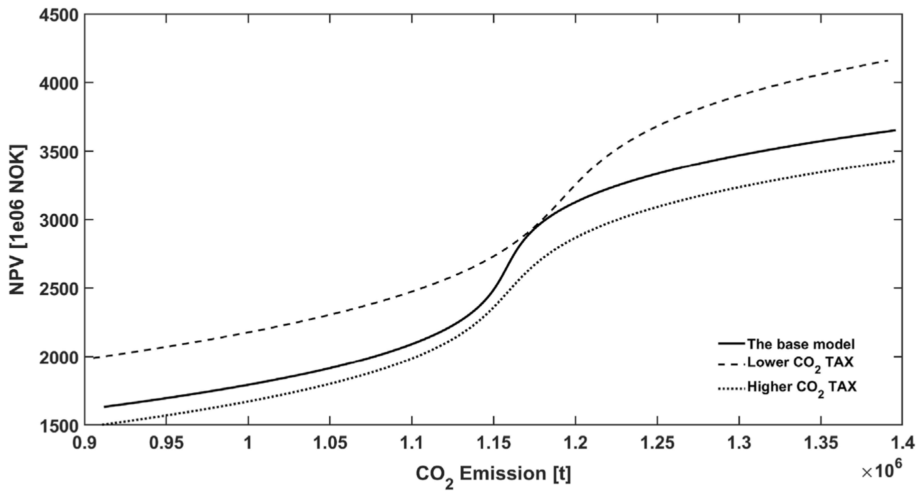

Fig. 11. NPV vs. CO_2 emissions for different CO_2 tax rates.

production of more oil and gas (and more CO_2 emissions) to compensate for CO_2 costs. In Table 2, the field design given in the first row is the decision considering a low cost of CO_2, while the last row is the decision considering a higher cost for CO_2 emissions.

Table 2
NPV and Oil Cumulative Production for different CO_2 tax rates.

CO_2 tax rate $[\frac{NOK}{t_{CO_2}}]$	NPV [$1e06NOK$]	Oil Cumulative Production [Sm^3]
543	4162.91	29,961,564.2
1000	3932.41	29,961,564.2
1500	3680.23	29,961,564.2
2000	3428.05	29,961,564.2
2500	3175.87	29,961,564.2
3000	2923.69	29,961,564.2
3500	2671.51	29,961,564.2
4000	2412.45	29,961,564.2

The Pearson correlation coefficient was calculated with all data points generated in the simulations to determine the relationship between key parameters such as CO_2 emission, carbon footprint, NPV, recovery factors, and cumulative production. The Pearson correlation coefficient measures the strength of the linear relationship between two variables. To make comparison easier, the coefficient values are depicted in a Confusion matrix, Fig. 12. Basically, we only utilized the visual aspect of the confusion matrix in this work. Consequently, the matrix is symmetric, with the number 1 on its main diagonal because each parameter is positively related to itself. All of these calculations have been done in Python. Fig. 12 shows that there is a considerable correlation between most parameters analyzed. Increasing one of them leads to increasing

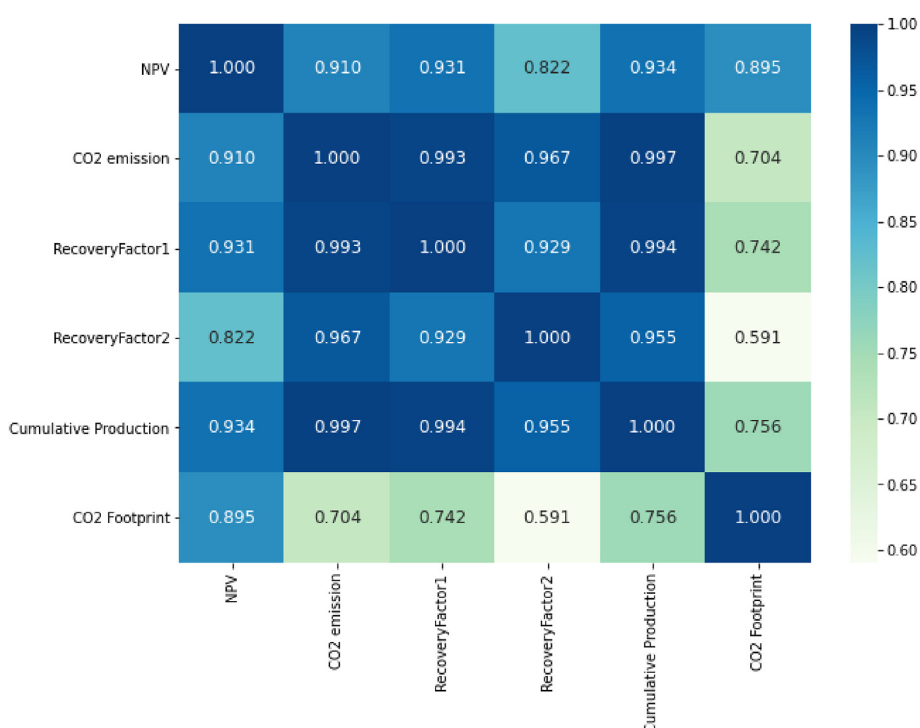

Fig. 12. Confusion matrix.

almost all other parameters. The carbon footprint has a comparatively small relationship with other parameters compared to others. The reason is that it is computed once according to the maximum amount of production and then spread over the lifetime of a facility, while the amount of CO_2 emissions are affected by the production profile. Additionally, the carbon footprint and the recovery factor of the second reservoir show the least relationship. As mentioned, the carbon footprint is tied to maximum production, and the facilities are required to accomplish that. Therefore, the carbon footprint of this development plan is less related to the second reservoir due to its lower productivity than the first reservoir; hence, its Pearson correlation coefficient is smaller in the confusion matrix.

4. Limitations and drawbacks of the study

The presented approach focused on using simplified analytical expressions and correlations that require a limited amount of background information to provide a quick insight into the future plan of the field development. Our model assumed a linear relationship between CO_2 emissions and oil production which has been is used extensively in previous studies and by governmental agencies. However, by assuming a linear relationship in the model, we may underestimate emissions in the later life and overestimate them in the early years of production. This may lead to some uncertainty in the results. In future works, environmental uncertainties should be quantified. A more detailed calculation of CO_2 emissions will also be performed, and this should be just as fast as and more accurate than the current estimate. Additionally, more research on the hull weight of the FPSO is necessary before a definitive answer can be provided on the weight of the FPSO and subsequently the carbon footprint.

An assessment of the environmental impacts of different operation alternatives is also required to help compare quantitatively and decide the best field development plan.

5. Conclusions

In this paper, a multi-objective optimization on numerical models has been used to numerically assess the trade-offs between the gain in reducing CO_2 emissions and the carbon footprint, and increasing NPV. The study case consisted of a multi-reservoir field. The optimization involves determining the drilling and production schedules and processing capacities that maximize a composite key performance indicator that includes a weighted sum of normalized NPV, CO_2 emissions, and carbon footprint. Field planners can benefit from the proposed methodology as it is a valuable decision-support tool in the early stage of development.

The main goal of this study was to explore how the optimal field development solution is affected when environmental parameters are included in the optimization objective. We derived different auxiliary equations for the objectives. Various methods were used to validate CO_2 emissions and the carbon footprint equations. Every objective was designed to be as straightforward as possible to be understandable and practical for the industry.

Several optimizations were performed for different combinations of weights in the objective function. The results obtained are greatly dependent on the weight values. For the specific case studied, there are economically feasible field development solutions with low CO_2 emissions. The results indicate that a decrease of CO_2 emissions by 30% and a decrease in the carbon footprint of 35% will entail a respective decrease of 13% and 8% in NPV.

Lower CO_2 emissions mean lower production and income, which has a negative impact on NPV. However, they also imply a reduction in CO_2 tax, which affects NPV positively. Thus, an optimum can be found, depending on the criteria and constraints. A similar situation occurs for the carbon footprint. Reduction in production gives less revenue but also reduced production capacity, which reduces CAPEX and carbon footprint. The weights could be adjusted by field planners to find development options that have high economic value and better environmental performance. It is also possible to add a constraint such as a specific minimum NPV or maximum CO_2 emissions allowable by the decision-makers. For instance, we can include a minimum NPV that the investors will accept into the constraints, after which the optimization will meet this requirement. A sensitivity analysis of the CO_2 tax rate has also been conducted. According to the results, changing the CO_2 tax rate without providing new solutions or technologies will not result in a decrease in CO_2 emissions.

By considering innovative technologies and methods, the reductions in CO_2 emissions and carbon footprint can be achieved without a reduction in NPV because new technologies or solutions may decrease OPEX and power consumption, such as CO_2 bottoming cycle, CCS, and Cold Flow. This will be studied in future work. Therefore, this research will be extended to show how CO_2 emissions, carbon footprint, and NPV can be reduced by including innovative technologies. Thus, quantitative comparisons could be made between different methods. In addition, an analysis of the environmental performance of different operation alternatives during the planning process would allow better decisions to be taken and ensure that the environmental impact of the field is minimized.

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.

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Appendix A. Optimization formulation

The objective function is to maximize NPV and minimize CO_2 emissions and the carbon footprint formulated in Eq. (1). NPV, CO_2 emissions and the carbon footprint are also formulated in Eqs. (5), (7) and (12) respectively. Other equations are as follow:

$$Sales_t = P_{o,t} \Delta N_{p,f,t} \tag{13}$$

$P_{o,t}$ is oil price in time. The value is input in USD/bbl and then converted to Norwegian kroner using an exchange rate. $\Delta N_{p,f,t}$ is the oil produced by the field in the year t.

$$CAPEX_t = N_{w,f,max} a_{CAPEX} \sum_{r=1}^{N_R} q_{r,max} b(GOR, WC) \tag{14}$$

$N_{w,f,max}$ is the maximum number of wells in the field. a_{CAPEX} is the CAPEX well coefficient. $q_{r,max}$ is the maximum oil rate of each reservoir. b is the coefficient which is a function of GOR and WC.

Besides, OPEX is a function of the field oil rate at the end of the year and the total operative number of wells in the field at the end of the year.

$$DRILLEX_t = \sum_{r=1}^{N_R} \Delta N_{w,p,r,t} \left(1 + N_{\frac{inj}{prod},r}\right) a_{DRILLEX} \quad (15)$$

N_R is the total number of reservoirs in the field. A given reservoir is denoted with the letter r. $N_{\frac{inj}{prod}}$ is the number of injectors per producer in reservoir r. $\Delta N_{w,p,r,t}$ is the number of new producer wells in reservoir r in the year t. $a_{DRILLEX}$ is the DRILLEX well coefficient.

The constraints are:

The oil production at a given end of year t must be less or equal to the production potential $q_{pp,t}$ end of year.

$$q_{o,t} \le q_{pp,t} \quad (16)$$

It is only possible to drill x new producer wells every year in a given reservoir and producer wells cannot be "undrilled":

$$0 \le \Delta N_{w,p,r,t} \le x \quad (17)$$

It is only possible to drill y new producer wells every year in the field:

$$\Delta N_{w,p,f,t} \le y \quad (18)$$

Appendix B. CO_2 emissions calculation via stoichiometry and *EROI* (Energy Return on Investment)

$$CE = MW_{CO_2} n_{CO_2} \quad (19)$$

where:

$$n_{CO_2} = n_C n_{oil} \quad (20)$$

$$n_{oil} = \frac{m_{fuel}}{MW_{fuel}} \quad (21)$$

Additionally, different equipment is supplied with energy from turbines:

$$\eta_{equipment} W_{equipment} = \eta_{equipment} \eta_{turbine} m_{fuel} LHV_{fuel} \quad (22)$$

We also know that the energy consumption is equal to energy released by production:

$$\eta_{equipment} W_{equipment} = \frac{LHV_{oil}}{EROI} \rho_{oil} q \quad (23)$$

where *EROI* is the ratio of energy returned to the energy invested in that energy source, along its entire life cycle.

Combining all these equations gives:

$$CO_2 emissions = \frac{MW_{CO_2}}{MW_{fuel}} \frac{n_c}{\eta_{equipment}\eta_{turbine}} \frac{1}{EROI} \frac{LHV_{oil}}{LHV_{fuel}} \rho_{oil} q \quad (24)$$

Where molecular weight of CO_2 and fuel are 44 and 244 $\frac{g}{mol}$, respectively. Fuel is assumed to be diesel with 12 carbon. $\eta_{equipment}$ and $\eta_{turbine}$ are assumed to be 0.7 and 0.5. EROI is also assumed to be 100. Lower heating value of oil and fuel are 42.7 and 43.4 $\frac{MJ}{Kg}$. Oil density is 850 $\frac{Kg}{m^3}$. Therefore:

$$CE = 0.05 \times q \quad (25)$$

Appendix C. Pearson correlation coefficient

This method is defined as the measurement of the strength of the linear relationship between two variables and their association with each other. In other words, this coefficient calculates the effect of change in one variable when the other variable changes [41]. As a formal definition, the Pearson correlation coefficient of two variables x and y is the covariance of the two variables divided by the product of their standard deviations, and it can be expressed in the following manner [42]:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\left(\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right)\left(\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\right)} \quad (26)$$

Where $\bar{x}$ and $\bar{y}$ denotes the mean of x and y. Coefficient r_{xy} varies from -1 to $+1$ with $r = 1$ indicating a perfect positive correlation and $r = -1$ indicating a perfect negative correlation. If the variables are directly related, the correlation coefficient is positive. If they are inversely related, the correlation coefficient is negative.

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