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Price stress testing in offshore oil field development planning

Guowen Lei [a,*], Verena Hagspiel [b], Milan Stanko [a]

[a] Department of Geoscience and Petroleum, Norwegian University of Science and Technology (NTNU), Norway
[b] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology (NTNU), Norway

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ABSTRACT

Oil & gas field development planning has the objectives of maximizing economic value and also mitigating potential risk. An optimal development concept and strategy depend on the selected oil price trajectory. The conventional scenario-analysis assuming a fixed hydrocarbon price over the lifetime is often inadequate as oil price shocks are likely to occur in the 20-year plus production horizon. In this work, we argue that stress testing, a method widely used in the financial domain, can valuably support field development planning. This work explores the adoption of stress testing to quantify the resilience of field development concepts in the early field development phase. The empirical analysis is presented, a MILP model is formulated, and a new metric is introduced to conduct the price stress testing for field development planning. Additionally, the developed method is applied to a real-world planning case of selecting the development concept and choosing the optimal variables. Results from the case study reveal that the timing and magnitude of oil price shocks can significantly affect the economic value of a project. Consequently, when considering sudden hydrocarbon price drops, it is preferable to chose a resilient field development concept at the early stage of field planning.

1. Introduction

Offshore oil and gas production plays an important role in nowadays' economics and has expanded globally over the last few decades. According to the International Energy Agency (IEA), more than a quarter of today's oil and gas supply is produced offshore [1]. The OECD estimated a value of USD 500 billion in 2010 from the offshore oil and gas sector in value added from the ocean economy [2]. However, oil and gas production is sensitive to the price. For instance, facilities in Norwegian waters or in the Gulf of Mexico previously could only operate profitably when the market price for oil was above a threshold of USD 60 to 80 per barrel [3]. Following the collapse of oil prices in 2014 and after the COVID-19 pandemic, many plans for offshore development were put on temporary hold, and only highly promising drilling projects have been carried out since then. Even though the recent oil price increase is optimistic and world oil markets are rebalancing, the offshore oil and gas industry generally makes efforts to enable more efficient planning.

Offshore field development planning is a complex process that involves input from various subjects and necessitates close cross-domain teamwork. Despite knowledgeable experts and robust project management processes, oil companies are frequently struggling to find optimal solutions in an effective way. One of the main reasons is the high level of uncertainty and the lack of reliable information to support the decision-making. Previous studies show that the two most crucial variables determining the economic performance of a petroleum project are the production rate and product market prices [4,5]. Neither the future production nor the sales price of oil and gas are known when a field development strategy is devised early in the lifetime of a project. As the uncertainties about the production rate and market price can significantly affect the performance of a project, it is meaningful and necessary to study the problem of field development under uncertain conditions.

In this paper, we introduce price stress testing as a tool to assess the flexibility of different field development concepts and investigate its use in choosing among different field development strategies and concepts at the early stage of field development planning. We consider uncertainty stemming from unexpected sizeable changes in oil prices in the commodity market, so-called oil price shocks, which is an extensively discussed topic in economic literature. More specifically, we focus on unexpected sizeable drops in oil prices in the commodity market as these frequently have a severe impact on the economic performance

* Corresponding author.
E-mail addresses: guowen.lei@ntnu.no (G. Lei), verena.hagspiel@ntnu.no (V. Hagspiel), milan.stanko@ntnu.no (M. Stanko).

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Nomenclature

Abbreviations

KPI	Key Performance Indicator
CAPEX	Capital Expenditure
OPEX	Operational Expenditure
aNPV	Average Net Present Value over multiple scenarios
NPV	Net Present Value
NRF	Normalized Resilience Factor
RF	Resilience Factor
LP	Linear Programming
NLP	Nonlinear Programming
MILP	Mixed-integer Linear Programming
MINLP	Mixed-integer Nonlinear Programming
PWL	Piecewise-linear
VOI	Value of Information
OPEC	Organization of the Petroleum Exporting Countries
EIA	Energy Information Administration
WTI	West Texas Intermediate (Crude Oil)
FPSO	Floating Production, Storage and Offloading vessel
HSE	Health, Safety and Environment
CPU	Central Processing Unit

Symbols

D	Annual discount rate
q_i	Production rate, $i \in \{o = oil,\ g = gas,\ w = water\}$
P_i	Price of product, $i \in \{o = oil,\ g = gas\}$
N_w	Total number of wells (producers)
x_w^r	Well status in reservoir r, $\in [0, 1]$
r	Superscripts of reservoir
s	Superscripts of price shock scenario
f	Superscripts of field
$\mathcal{S}$	Set of all price shock scenarios Sc
$\mathcal{T}$	Set of all time steps t
$\mathcal{W}^r$	Set of wells w in reservoir r
$\mathcal{R}$	Set of reservoirs r
N_p	Cumulative produced oil rate
G_p	Cumulative produced gas rate
W_p	Cumulative produced water rate
f_G	PWL approximation function of cumulative gas rate to N_p
f_W	PWL approximation function of cumulative water rate to N_p
f_n	Function of the acting well combination
f_q	Implicit function of the production potential q_p to N_p
f_n^*	Optimal drilling schedule of the acting well combination
N_w^*	Optimal total number of wells (producers)
q_o^*	Optimal production schedule
t_s	Time of price shock
Δt	Duration of price shock
q_i^{max}	Topside processing capacities, $i \in \{o = oil,\ g = gas,\ w = water\}$
q_n	Production potential of oil
$\alpha,\ \beta,\ \gamma,\ \epsilon$	Coefficients of the costs proxy model

of oil & gas projects. In the past, the economic performance of many oil & gas projects has been affected at least once during their lifetime by a negative oil price shock. [1] Stress testing as applied in this work is a form of scenario planning that focuses on extreme risks. Unlike scenario analysis, stress testing focuses on the tails of the distribution.

In order to establish the price stress testing model, we create a mathematical value chain model integrating the full-stream proxy production performance and cost estimation of a field. Then, numerical optimization is formulated to identify the best solution that allows "reactions" to potential future price shocks by adjusting the drilling and production strategy. The price stress test is formulated as an event-driven optimization process with the objective to find the optimal development solutions accounting for potential price shocks. These are defined as a number of extreme price scenarios. We then use the data set of optimal solutions to calculate a new key performance indicator — the resilience factor, which indicates the operational flexibility and scalability of the system under challenging price environments. We propose that this resilience factor is used as an indicator to compare and grade development concepts in addition to the standard KPIs used in practice.

Although most offshore oil & gas projects are likely to experience one or several price shocks during their 20-year plus lifetime, it is difficult to predict exactly when shocks will occur. To mitigate the effect of price shocks, it is possible to carry out counteractive actions, such as selecting a resilient development concept or changing the production strategy or, equivalently, by adding "flexibility" to the system. The importance of including flexibility in oil & gas projects is well known by the industry and has been commented on by several authors [6–10]. Lin et al. (2013) [9] point out that flexibility can be "designed into" the production system during the field planning phase, to provide a way for the designer to reduce downside exposure or capture potential upside. Some others maintain that the project planner has to pay attention to flexibility when selecting the development and depletion strategy as flexibility can create value for the offshore field development [6,8]. Cardin et al. (2014) [11] indicate that enabling flexibility in the design of engineering systems helps generate concepts with improved lifecycle performance under uncertainty.

In this study, we use the term "flexibility" to refer to the ability of the field operator to react to oil price shocks by changing the operation strategy. We evaluate the effect of this flexibility during the early stages of field development planning.

Accounting for potential future oil price shocks in the early planning phase is particularly important when setting a development plan for marginal median or small sized fields as the economic viability of these fields is much more sensitive to the downside risk than large discoveries. Marginal projects often become uneconomic when oil prices drop due to their lower production volumes and high development and production costs per barrel. There are several examples of cases where operators of marginal fields were forced to shut down operations because of negative oil price shocks. For example, in the United States, during the slump in oil price in the mid-1980s, around 200,000 marginal wells (stripper wells) were shut down. In Nigeria, some

[1] In the past 40 years, six sizeable downside oil price shocks occurred: (1) the oil price collapse in 1986, (2) the Asian financial crisis of 1997/1998, (3) the 2001/2002 oil price slump, (4) the financial crisis in 2008, (5) the 2014/2015 oil price decline, and (6) the recent negative oil price in 2020 due to COVID-19, on average every 5.5 years over the period of 1980–2021.

marginal field operators were on the verge of shutting down due to the oil price downturn in 2014/2015, as their revenue was insufficient to cover production costs [12].

We also observe that operators sometimes cut down production output to respond to low oil prices in a passive manner. An example of this was observed during the recent oil price crash at the beginning of 2020 [13]. Due to the impacts of the COVID-19 pandemic, OPEC and its allies reached a deal to cut production, which was distributed among their members [14]. Under such conditions (i.e., when a production quota is imposed on the operator), a production system with built-in operational flexibility can be easier to adjust at lower associated costs than an inflexible one. The potential for cost-saving often depends on the flexibility and robustness of the production system.

The assessment of flexibility of a production system during field development has also been motivated by the fact that it is usually easier to add flexibility to the system during the field design phase than later. This is because during the development planning phase (especially during the early phases of field development), a company decides upon the development concept and the production strategy. At this stage, there are large uncertainties, and as the system is not yet fully defined, it is usually possible to add modifications to later adapt to new information. During operation, the production system is usually fully established, which leaves little room for adjustments unless substantial investments are made. Hence, performing flexibility evaluation analysis for potential oil price shocks during the planning phase will be more effective than conducting this analysis during the operation phase.

There are clear trade-offs between building flexibility into the production system and initial investment costs (typically part of the *CAPEX*). Additional costs are required to add flexibility to a design. These costs are often referred to as *cost of flexibility*. To justify such additional expenses, companies need methods that allow them to quantify the value of flexibility. For this purpose, we propose using price stress testing to account oil price shocks.

The main objective of this study is to propose a method to support decision-making in field development planning considering downward oil price shocks. The proposed method is designed to assist in the selection between various development concepts. To illustrate how the stress testing can support decision-making in field development planning, we demonstrate the proposed method using a real-world case from the Barents Sea.

Compared to other optimization techniques in field development planning that tend to be computationally expensive when dealing with both exogenous (e.g., prices of products) and endogenous parameters (e.g., production rate), our approach that considers market price uncertainty is relatively easy to implement. Another advantage is that scenario optimization is easier to explain than stochastic programming.

There are two main contributions from this work: (1) We present a method based on stress testing for negative oil price shocks that allows companies to assess the potential losses for worst-case scenarios, and identify what actions can be taken to mitigate these potential losses. The results can then be used to assess the value of adding flexibility to the production system in the early field development phase. (2) We introduce a new performance indicator, the resilience factor, which estimates the resilience of a field development concept.

The remainder of this paper is organized as follows. A brief review of field development planning and how the different methods account for uncertainty follow this introduction. The methodology is presented in Section 3. Subsequently, we illustrate a real case using stress testing on the example of development concept selection of an offshore field in Section 4. Section 5 concludes the main observations in this work and presents recommendations for future work.

2. Background and literature review

This section starts with a background introduction to field development and field development optimization. We then review the different approaches to account for uncertainty in optimization. This is followed by a literature review about stress testing and how it is used for risk management in other work. The research gaps from the literature review are summarized at the end of this section.

2.1. Field development

In the early stages of offshore field development, companies usually decide upon two main design features: the development concept and the main field parameters. First, all viable concepts must be analyzed to determine which yields the best trade-off between project value and risk mitigation. The concept is further concreted by choosing development parameters, such as platform size, drilling programs, and production strategy.

Many companies evaluate field development alternatives by using a stage-gate process where several alternatives are evaluated by domain experts. The planner ranks the development concepts using key performance indicators, frequently employing the net present value (NPV). However, selecting development concepts and optimization variables is not always a top-down process, i.e., moving from general to more specific. Any modification to the base parameters may affect other dependent parameters and, ultimately, the priority of the concept selection. Moreover, the modification often occurs when new geological data are available.

Another challenge is that the stage-gate process often involves manual and time-consuming work to explore all alternatives and possible parameters. The transfer and update of information between experts is often cumbersome and inefficient. As an alternative, mathematical programming is advocated as it supports decision-making in field development planning because it allows an optimal set among many alternatives to be identified efficiently.

2.2. Mathematical programming for field development

A growing body of research has been carried out on optimization applied to the field development problem. To the best of our knowledge, Lee and Aronofsky (1958) [15] were the first to employ programming methodology to solve the well drilling scheduling problem. After that, a lot of research has been published on the use of mathematical programming to solve the field development problem. Overall, this problem has been modeled using one of four different programming technologies: (1) linear programming (LP), (2) nonlinear programming (NLP), (3) Mixed-integer linear programming (MILP), and (4) Mixed-integer nonlinear programming (MINLP). A review of this literature can be found in (Durrer and Slater, 1977 [16]; Sullivan, 1988 [17]; Tavallali et al. 2016 [18]; Khor et al. 2017 [19]; Grossmann et al. 2016 [20]). Production allocation and drilling program schedules are listed in the top two variables to optimize due to their significant impact on the economic evaluation of the project. For instance, the main variables considered in the LP model when considering a 15-year development plan by Bohannon et al. (1970) [21] are annual production rate, number of wells, and timing of major capital investments. Iyer et al. (1998) [22] propose a multiperiod MILP model for optimal planning of offshore oilfield infrastructure with considerations of the facility allocation, production planning, and scheduling of the optimization variables. Gupta and Grossmann (2012) [23] propose a multiperiod non-convex MINLP model for a multi-field site that includes decisions related to facility installation and expansion schedule, routing connection, well drilling schedule, and production rates in each period. Isebor et al. (2014) [24] introduce an MINLP approach to generalize field development optimization with variables in the number and type of new wells, the well drilling sequence and locations.

Here, we review applications of optimization techniques in field development planning that consider uncertainty. The uncertainty problem in field development planning can be classified into exogenous uncertainty and endogenous uncertainty [9,25]. Different methodologies, such as real options analysis [26], the value of information (VOI) [27,28], Bayesian analysis [29], and stochastic programming [30], have been developed to manage the uncertainty problem. For instance, Demirmen (2001) [28] evaluate a field development example using VOI methodologies, to assess whether the technology that allows receiving additional information during field appraisal would increase the value of field.

The hydrocarbon price is typically accounted for in two ways: deterministic or stochastic. In most field development planning methods described in the literature and reported by the industry, the long-term future price is typically assumed to be fixed, even though this situation never occurs. More advanced approaches dealing with price uncertainty are employing price trajectories [31], probability models [32], and stochastic modeling [33]. Few oil & gas companies implement probabilistic price models or stochastic models as they easily result in computational complexity and become expensive to solve [33]. A common way to consider price uncertainty is to set the oil price at a long-term constant value and subsequently run a sensitivity analysis. Alternatively, a set of carefully-determined prices, usually guided by a national authority, can be used. For instance, the Norwegian Petroleum Directorate suggests a guiding oil price for use in the revised national budget each year [34]. Some operators use such data to prepare the field development plan. The U.S. EIA is another source of oil price forecasts, but only up to 2-year horizons, which are inadequate for a 20-year plus horizon project. Many companies use long-term deterministic oil price forecasts based on analysis and forecasts of global supply and demand, usually provided by analytic consultancy firms.

A further step to deal with price uncertainties in field planning is combining price scenarios with optimization programming. Specifically, the optimal development plan is the result of from mathematical optimization that considers stochastic parameters through various specified or random scenarios. Several studies formulate an optimization problem using a deterministic oil price method, evaluating field development plans by considering several price scenarios that can be constant in time or exhibit a specific trajectory. Jørnsten (1992) [35] discusses a mathematical programming case for sequencing producing fields in response to uncertain oil and gas prices using a set of 5 different market scenarios. Jonsbråten (1998) [25] presents a mathematical model for optimizing an oil field development using 3 scenarios of future oil price. The intention of the scenario model is to provide an overview of the performance of the project with different price expectations, particularly for obtaining lower bounds to the optimal oil field development.

Another approach is to evaluate the effect of stochastic parameters by performing sampling, creating a set of scenarios given a probability reflecting its relative importance. This approach is popular in the study of subsurface data uncertainty. Nasab et al. (2018) [36] present a reservoir drainage planning study by generating 1000 samples corresponding to uncertain oil price and reservoir production. Maschio and Schiozer (2016) [37] generate 450 models in a production history matching using the Iterative Discrete Latin Hypercube sampling and nonparametric density estimation. The sampling procedure is crucial to have enough scenarios to be representative; otherwise, it may lead to sub-optimal or even unfeasible solutions.

In regards of accounting the uncertain price in field development, the approach of combining price scenarios with optimization programming is appropriate in relatively stable business environments and a few alternative scenarios, such as a long-term contract gas projects. The sampling approach relies on an exhibition of the randomness along with the chosen metric, which might not be appropriate for the market price. One way to overcome the shortcoming of existing approaches is by introducing the price stress testing method.

2.3. Stress testing

Stress testing is a method for risk management. It can be seen as a form of scenario planning that focuses on extreme risks, the tail of the distribution. In the banking sector, "stress testing" presents an important element of risk management and is discussed extensively. It is defined as a computer-simulated technique to analyze how banks and investment portfolios fare in drastic economic scenarios. Two main features of stress testing are its forward-looking character and scenario-based forecast. In the aftermath of the 2008 financial crisis, "stress testing" has become an important tool for supervisory entities to assess risks [38]. Regulators today require banks to conduct and report on comprehensive stress tests.

Stress testing is also frequently conducted in the electricity sector. The event-related stress of grid failure is tested to assess the resilience of an energy system. For instance, Hughes and Ranjan (2013) [39] use newly defined metrics and indicators to describe the energy system and energy security of a jurisdiction. Westgaard et al. (2021) [40] present a case study using scenario analysis and stress testing for producers to manage the risk of low prices in the electricity market. Shandiz et al. (2020) [41] introduce a novel energy resilience framework to allow for structured planning and assessment of energy resilience against extreme events.

Few papers mention stress testing for negative oil price shocks in field development planning. All existing contributions assess the impact of extreme oil price scenarios on static production systems [33,42,43]. To the best of our knowledge, this is the first work to use stress testing to assess the performance of a project by allowing the adjustment of the drilling and production schedule to corresponding price shocks.

We can see from our literature review that there is a lack of optimization methods in early phase field development planning that deal with both exogenous and endogenous uncertainty. Particularly, there are still unresolved questions about how to specify the uncertainties and how to interpret the results for decision support of field development concept selection. Besides, there is a lack of methods that can incorporate stress testing to field development planning, generating fit-for-purpose scenarios tailored to the oil & gas industry.

3. Methodology

In this paper, we formulate an MILP model for decision support in field development. Many case studies in the literature report that the MILP approach generates feasible, good solutions rather fast. The only uncertainty we consider in our model is the future oil price. Stress testing is used when quantifying its repercussions on the model.

We now present the problem statement. Then, we describe the mathematical model, and later introduce the stress testing method and how to calculate a new metric of the resilience factor.

3.1. Problem statement

We study the decision problem of a field operator that has to identify an optimal development plan for an offshore discovery with two reservoirs: a small sized one with 3 candidate producers and a medium sized one with 6 candidate producers. The location and trajectory of the candidate wells are known and considered fixed and result from detailed geology and petroleum engineering studies. The production performance of each well in time is distinct. The production performance of the field at a given time depends on the well combination and the remaining producible oil. The objective is to choose the development concept and select the development strategies that maximize the net present value of the project.

The products of the field are oil, gas, and water. The flow performance of the integrated production system (reservoir, wells, flowlines, and pipelines) is modeled using production potential curves. These curves are analytical functions that express maximum oil, gas, and water production versus cumulative oil production and are dependent on the well combination. The production potential curves are extracted from an integrated coupled model of the production system built in commercial software. Production potential curves enable production profiles to be quickly computed repeatedly without requiring time-consuming runs from commercial simulators [44,45]. Additionally, the use of production potential curves allows efficient white-box numerical optimization to be implemented instead of the black-box implementations which typically used when dealing with commercial software.

All nonlinear functions of the field production in the MILP are approximated and represented by using a piecewise-linear (PWL) model.

We use this mathematical model to answer the following questions:

- Which well(s) should be drilled in each time period?
- How much oil should be produced from each reservoir in a given year?
- What is the NPV of the project for the specific price scenario?

3.2. Mathematical model

In this study, the optimization objective is to maximize the *NPV* of the project. The *NPV* is calculated on a yearly basis, as expressed by Eq. (1):

$$\max NPV = \sum_{t=0}^{T} \frac{Revenue^f(t) - Cost^f(t)}{(1+D)^t}, \ \forall t \in \mathcal{T} = \{0, 1, \dots, T\} \tag{1}$$

where D is the annual discount rate, T is the total number of years to consider in the valuation, t is the integer counter for the number of years, and f is a superscript referring to the field, summarizing all reservoirs.

The revenue is depending on both the field production rate of oil q_o^f and gas q_g^f and the price of the products (P_o, P_g), given by:

$$Revenue^f(t) = q_o^f(t) \cdot P_o(t) + q_g^f(t) \cdot P_g(t), \ \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{2}$$

We split the cost into capital expenditure *CAPEX* and operational costs *OPEX*, defined as:

$$\begin{aligned} Cost^f(t) &= CAPEX^f(t) + OPEX^f(t) \\ &= CAPEX^f_{Drilling}(t) + CAPEX^f_{Subsea}(t) + CAPEX^f_{Topside}(t) \\ &+ OPEX^f_{rate}(t) + OPEX^f_{nonrate}(t), \ \forall t \in \mathcal{T} = \{0, \dots, T\} \end{aligned} \tag{3}$$

Here, the drilling-related expenditure $CAPEX^f_{Drilling}(t)$ is a function of the number of wells drilled at time t. The topside facility cost $CAPEX^f_{Topside}$ is a function of the maximum processing capacity of oil q_o^{max}, gas q_g^{max} and water q_w^{max}. The cost of a subsea system $CAPEX^f_{Subsea}$ is the sum of individual contributions from all subsea components, such as umbilicals, Christmas trees, manifolds, and mooring, among others. Mathematically, it is expressed as a function of well count, manifold number, depth, and length of the flowline. The capital expenditure of $CAPEX^f_{Topside}$ and $CAPEX^f_{Subsea}$ are depreciated over time to spread the cost over several years. We can find a similar set of *CAPEX* functions in papers by Nunes et al. [46,47].

The operational cost *OPEX* includes the cost of maintenance, modifications, services, administration, HSE, logistics, etc. In this study, we divide *OPEX* into rate-dependent costs $OPEX^f_{rate}$ and non-rate-dependent costs $OPEX^f_{nonrate}$. A similar expression of splitting the operational cost into rate-dependent and non-rate-dependent can be found in the paper by Fedorov et al. [48]. The non-rate-dependent costs are typical costs of non-reducible maintenance, inspections, offshore personnel, transport, insurance, etc. In contrast, the rate-depended costs are functions of the production rates of oil, gas, and water. For instance, the more fluids produced, the higher the cost of electricity for processing due to higher energy consumption when using electrical submersible pumps to lift the produced fluids. Depending on the complexity and details of the cost model, the cost proxy model can be expressed as linear or non-linear. In this work the variable operational cost $OPEX^f_{rate}(t)$ is organized as a linear function of the field production rate of oil q_o^f, gas q_g^f and water q_w^f given by:

$$OPEX^f_{rate}(t) = \alpha \cdot q_o^f(t) + \beta \cdot q_g^f(t) + \gamma \cdot q_w^f(t) + \epsilon, \ \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{4}$$

Where α, β, γ and ϵ are the coefficients of the costs proxy model.

The decision variables are:

- N_w, total number of wells (producers) used to develop the field;
- $f_n(t)$, producing well combination (subset) at year t (defined by the drilling schedule);
- $q_o(t)$, $q_g(t)$, $q_w(t)$, production rates at year t.

In the following section, we list all constraints and auxiliary expressions used in the model.

The yearly instantaneous field rates of oil q_o^f, gas q_g^f and water q_w^f must be equal or less than the designed topside processing capacities (q_o^{max}, q_g^{max}, and q_w^{max}), as expressed in Eq. (5).

$$q_i^f(t) \le q_i^{max}(t), \ \forall i \in \{o, g, w\}, \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{5}$$

The field production rate of oil, gas and water equals the sum of the fluid from all reservoirs $r \in \mathcal{R} = \{1, \dots, R\}$ using the following equation in Eq. (6):

$$q_i^f(t) = \sum_{r=1}^{R} q_i^r(t), \ \forall i \in \{o, g, w\}, \forall r \in \mathcal{R} = \{1, \dots, R\}, \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{6}$$

In each reservoir r, the cumulative production of each fluid at time t is computed using Eqs. (7)–(9).

$$N_p^r(t) = N_p^r(t-1) + q_o^r(t-1), \ \forall r \in \mathcal{R} = \{1, \dots, R\}, t \ge 1, \ N_p^r(0) = 0 \tag{7}$$

$$G_p^r(t) = G_p^r(t-1) + q_g^r(t-1), \ \forall r \in \mathcal{R} = \{1, \dots, R\}, t \ge 1, \ G_p^r(0) = 0 \tag{8}$$

$$W_p^r(t) = W_p^r(t-1) + q_w^r(t-1), \ \forall r \in \mathcal{R} = \{1, \dots, R\}, t \ge 1, \ W_p^r(0) = 0 \tag{9}$$

Where N_p^r, G_p^r, and W_p^r are the cumulative produced rates of oil, gas, and water from reservoir r. To simplify the calculations, the time step is assumed to be 1 year, and the unit used for the cumulative production N_p^r, G_p^r and W_p^r is 10^3 Sm^3, whereas the rate unit for the oil q_o^r, water q_w^r and gas q_g^r is 10^3 Sm^3/Year.

The gas rate q_g^r and water rate q_w^r of a reservoir r are back calculated using the cumulative gas G_p^r and water production W_p^r as shown in Eqs. (8) and (9). The cumulative gas and water production are tied to the cumulative oil production N_p^r using Eqs. (10) and (11). The relationship between these variables is expressed using PWL approximations by using the factors f_G^r and f_W^r.

$$G_p^r(t) = f_G^r N_p^r(t), \forall r \in \mathcal{R} = \{1, \dots, R\}, \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{10}$$

$$W_p^r(t) = f_W^r N_p^r(t), \forall r \in \mathcal{R} = \{1, \dots, R\}, \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{11}$$

In each reservoir r, the oil production potential curves are used as the upper bound of the total oil production rate. Eq. (12) ensures that the oil production does not exceed the maximum feasible oil production rate. Eq. (13) calculates the oil production potential of reservoir r at time t, and it is a function of the acting well combination $f_n^r(\sum_{w=1}^{\mathcal{W}^r} x_w^r)$ and the cumulative oil produced N_p^r at time t. The MINLP problems of Eqs. (10), (11), and (13) were transformed into MILP problems by utilizing PWL functions to approximate their nonlinearities. The implementation details are given in Lei et al. [44].

$$q_o^r(t) \le q_p^r(t), \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{12}$$

$$q_p^r(t) = f_n^r(\sum_{w=1}^{\mathcal{W}^r} x_w^r) \cdot f_q^r(N_p^r(t)), \forall r \in \mathcal{R} = \{1, \dots, R\}, \forall t \in \mathcal{T} = \{0, \dots, T\} \tag{13}$$

The total number of production wells in the field N_w^f at time t is the sum of the well status variable (x_w^r equal to 1 if the well is producing and 0 otherwise) of each producer in all reservoirs at time t, as shown in Eq. (14). The total number of producers in reservoir r is $\mathcal{W}^r$, and therefore, the total number of binary variables is $2^{|\mathcal{W}^r|}$. The constraint presented in Eq. (15) accounts for the situation that in most offshore oil and gas projects, there is a limitation on drilling capacity, i.e., how many new wells can be drilled each year N_w^{max}.

$$N_w^f(t) = \sum_{r=1}^{R}\sum_{w=1}^{\mathcal{W}^r} x_w^r(t),\ \forall r \in \mathcal{R} = \{1,\dots,R\}, \forall t \in \mathcal{T} = \{1,\dots,T\} \tag{14}$$

$$N_w^r(t) - N_w^r(t-1) \le N_w^{max},\ \forall t \in \mathcal{T} = \{1,\dots,T\} \tag{15}$$

3.3. Price stress test

We now formulate the price stress test that allows us to assess the economic performance of the project under extreme conditions (worst-case scenarios with low oil price). We first generate a set of oil price scenarios containing oil price shocks. Then, we input the formed price scenario into the mathematical model to run the optimization searching for optimal variables of field design parameters. The resulting NPVs from all scenarios are then used to calculate a resilience factor.

When generating oil price scenarios, we make three assumptions: (1) for each scenario, only one negative price shock can occur during the lifetime of the field; (2) the future oil price is assumed to be constant otherwise; (3) the probability of occurrence of an oil shock is the same for all years in the lifetime of the field.

The assumptions are supported by the fact that most offshore oil & gas projects will likely experience only one price shock during their plateau duration (less than 5–7 years). If another shock occurs, it will affect the economic value of the project to a lesser extent.

In our work, we consider that, besides the price shock, the oil price remains constant in time. This is a simplistic assumption when compared with more complex price forecasting models. However, this is a practical assumption that can be made by field planners in the early stage of field development, and it allows them to get insights into the effect a price shock has on economic value without having to account for additional oil price variability.

Since the response to the oil price shock is always reactive in real life, i.e., action is taken after the price shock occurs, the optimization is formulated as an event-driven optimization framework. In this optimization, the production system is expected to react instantaneously to changes in the event environment, i.e., production and drilling programs are rescheduled to maximize the NPV. This approach is similar to the used to solve the Vehicle Routing Problems, as illustrated in the paper from Pillac et al. [49]. In this paper, real-time information (customer arrival) is fed into the system and decisions (updated vehicle routing) are calculated and executed without delay.

We use a two-step method when formulating the stress testing into the mathematical model:

Step-1: To find the optimal field design at the initial time, an optimization is performed to determine the optimal drilling schedule $f_n^*(t)$, and oil production schedule $q_o^*(t)$. The optimization is performed assuming a constant value for the future oil price. The optimal production allocation of the field is then found and fixed.

Step-2: At the time when the price shock occurs $t = t_s$, a second optimization is triggered optimizing the decision variables for the remaining lifetime of the field from $t = t_s$ to $t = \mathcal{T}$. This is done by implementing the following constraints into the mathematical model:

$$f_n(t) = f_n^*(t),\ \forall t \le t_s - 1 \tag{16}$$

$$N_w(t) = N_w^*(t),\ \forall t \le t_s - 1 \tag{17}$$

$$q_o(t) = q_o^*(t),\ \forall t \le t_s - 1 \tag{18}$$

Eqs. (16)–(18) ensure that the optimization is look "ahead" and performed only on the variables from that point in time until the end of the lifetime of the field.

As an example, let us consider three scenarios (S_c^1, S_c^2, S_c^3) referring to the case of oil price shocks occurring in Year 1, Year 2, and Year 3, respectively. We perform a two-stage optimization for these three cases described above, which results in different optimized drilling schedules. Fig. 1 shows the initial optimized drilling schedule when no shocks are included indicated by "*" and the three optimal drilling schedules (well tags) resulting from the three scenarios. In all cases, the executed drilling program before the oil price shock is equal to the results for the initial scenario. From the time the shock occurs, the drilling program differs. For scenario S_c^1, where the price shock occurs in Year 1, the optimized new drilling well in Year 1 is reduced to $w4$ and the drilling of $w5$ is delayed by one year compared to the initially planned program of drilling both wells in Year 1. The same responses were activated in S_c^2 and S_c^3, delaying the drilling of wells $w6$ and $w7$, respectively, by one year. In this process, the postponed drilling and its associated production reduction are ways to mitigate the price drop in the price shock year and wait for the price to recover. The optimization also prioritizes the drilling sequence. For instance, the optimizer picks $w4$ instead of $w5$ in Year-1 from the initial plan in S_c^1.

Given a field with a T year planned production horizon, we distinguish $S = T$ scenarios ($\mathcal{S} = 1,\dots,S$) with a shock duration of ($\Delta t = 1$) year in Eq. (19).

$$Sc = \{Sc^1, Sc^2, \dots, Sc^S\}, S = T \tag{19}$$

The optimizer will determine the optimized operational parameters of of drilling sequence $f_n^s(t)$, well number $N_w^s(t)$, and production rate $q_o^s(t)$ for each scenario $s \in \{1,\dots,n\}$, where s indicates the year in which the shock occurs. Therefore, for each candidate development concept, there is a subset of optimum of drilling and production strategies corresponding to each scenario, as given in Eqs. (20)–(22).

$$f_n^s(t) = \{f_n^1(t), f_n^2(t), \dots, f_n^S(t)\},\ \forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ S = T \tag{20}$$

$$N_w^s(t) = \{N_w^1(t), N_w^2(t), \dots, N_w^S(t)\},\ \forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ S = T \tag{21}$$

$$q_o^s(t) = \{q_o^1(t), q_o^2(t), \dots, q_o^S(t)\},\ \forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ S = T \tag{22}$$

3.4. Sensitivity analysis

We now discuss the production response in terms of stress test timing and magnitude. The reason for illustrating the response of production but not drilling is that the production profile directly affects the cash-flow calculation in Eq. (1) as opposed to drilling. In this section, schematic drawings are created to illustrate the production response; a change of the production rate is in line with the price change when the shock occurs.

3.4.1. Timing of stress testing

Fig. 2 presents a schematic illustration of a price stress test during the plateau stage and the corresponding reaction in the production profile. The field production rate can be reduced during low oil prices to minimize sale losses and increased later (the dashed line) when the price rebounds (or service costs drop). Fig. 3 shows a schematic illustration of a price stress test during the decline period and the corresponding reaction in the production profile.

In general, when the price drop occurs in the plateau period, the reactive measures have a larger impact than when the price drop occurs in the decline period. This is because of the following reasons:

- During the plateau period the possible production cut is usually much larger than during the decline phase.
- The discounting factor applied to the revenue is much higher during the plateau than during the decline phase.

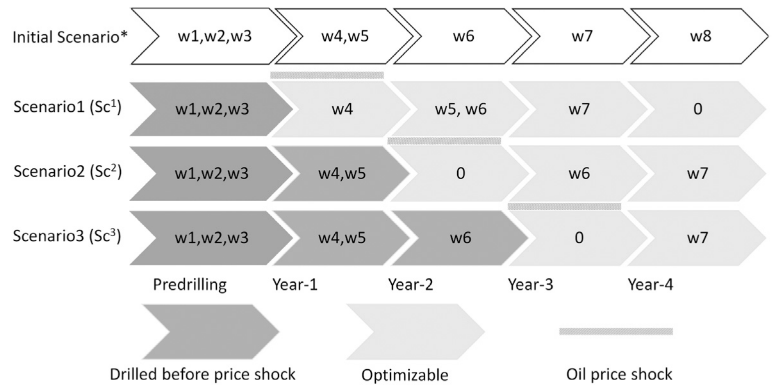

Fig. 1. Examples of the drilling sequence in 3 price shock scenarios. Each drilling scenario contains pre-shock executed drilling wells (indicated by dark gray) and the look-ahead optimized drilling sequence after the oil price shock (indicated by light gray).

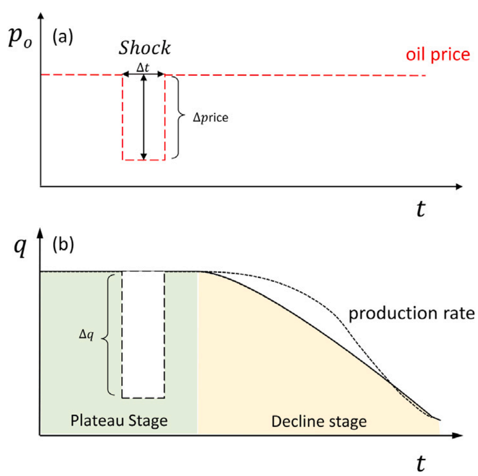

Fig. 2. Stress test schema in plateau stage, large production cutting.

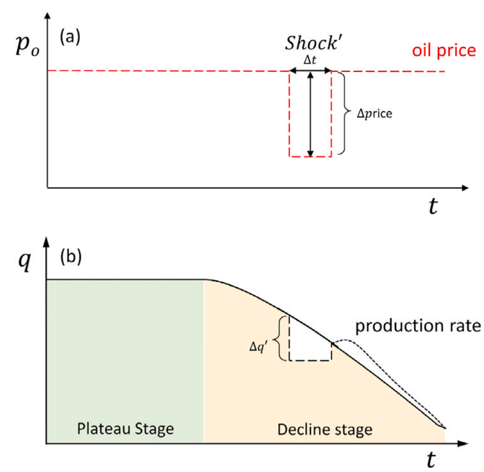

Fig. 3. Stress test schema in decline stage, little production cutting.

- During the plateau period, there is still some drilling that must be conducted to maintain the plateau. If needed, this drilling can be postponed or eliminated, which reduces cost.

In the production decline stage, most of the drilling program is already completed. Reducing production typically entails shutting-in wells. The decision to shut in the production when the oil price is low is likely to depend on how long a field has been in production and how much oil is left. The less the remaining oil, the lower the value to shut-in production and early abandonment is preferred instead. For example, the low oil price in 2014/2015 spurred an offshore decommissioning wave in the North Sea, most notably in the UK part [50].

3.4.2. The magnitude of the price shock

Fig. 4, (a) illustrates these three price shocks of different magnitude occurring in the same year, and (b) illustrates possible rate adjustments to each test. We expect the deeper the drop in price, the larger the drop in produced volumes. The reduced production will be compensated afterward when the oil price returns to a new normal condition, i.e., higher than the break-even price.

The reduction and the subsequent increase in production after a price shock are calculated using optimization.

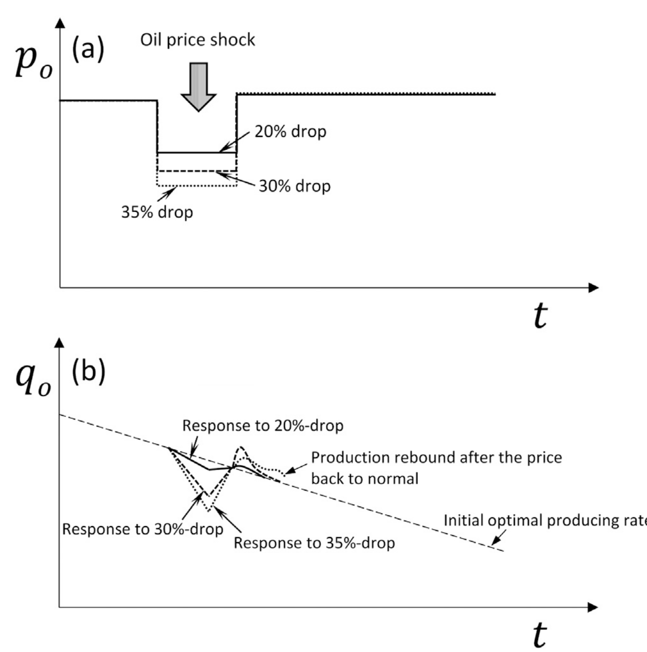

Fig. 4. Examples of the decision process by consensus in different magnitude of price shock.

3.5. Resilience factor

To select the optimal field development concept from the pool of solutions studied under stress testing, we propose using a new metric of a performance indicator — the resilience factor. The resilience factor is based on the expected *NPV* for each solution and given by

$$\text{Resilience factor (RF)} = \frac{aNPV}{NPV} \tag{23}$$

where *aNPV* denotes the average value of the discounted cash flow for the project over S scenarios $s \in \{1, \dots, S\}$ under stress testing. An *NPV* without price shock might be used as the denominator, for instance. Assuming equal probability for each scenario occurring $aNPV$ is given by:

$$aNPV = \frac{1}{S}\sum_{s=1}^{S} NPV_s, \forall s \in \mathcal{S} = \{1, \dots, S\} \tag{24}$$

The *NPV* of each scenario is obtained by performing optimization on the drilling and production schedule.

The resilience factor represents the operational flexibility of the system and scalability counting of the price uncertainty of potential price shocks. The closer the value of the resilience factor to 1, the more resilient the field development concept is. We suggest that the resilience factor can be used to compare and grade development concepts out of several candidates in addition to the standard used KPIs, such as *NPV*, internal rate of return, and recovery factor. For instance, if two development concepts (A and B) have a similar *NPV* value, the operator can use this index to prioritize the concept between A and B. Moreover, the introduced resilience factor could be included in a multi-attribute decision model together with other KPIs and their weights. A more advanced application could be a multi-objective optimization considering several attributes in the objective function, for instance, *NPV* and resilience factor.

4. Case study

We now apply the introduced methodology to the case of the Alta and Gohta reservoirs on the Norwegian Continental Shelf. The Alta and Gohta reservoirs were discovered in 2013 and 2014, respectively. The following three possible development concepts were identified: (1) develop as standalone with a new floating production, storage and offloading vessel (FPSO) (see Fig. 5 for an illustration); (2) subsea tie-back to the nearby processing facilities at Johan Castberg (see Fig. 6 for an illustration); or (3) tie-back to Goliat (see Fig. 7 for an illustration). In previous work, Lei et al. (2021) study these alternatives individually using mathematical programming to determine the optimal drilling and production strategy [51,52]. In both papers, a constant oil price of 60 USD/barrel was used.

In this work, we assess the three concepts using our proposed stress testing method. Specifically, we assume that the price is set to 60 USD/barrel. Once a price shock occurs, the price drops by 20% to 48 USD/barrel. The duration of the oil price shock is set to one year ($\Delta t = 1$). Thereafter, the price returns to 60 USD/barrel. The production horizon is set to 20 years. All assumptions are based on the preference and long-term expectations from the license operator.

The mathematical model and stress testing approach presented in Section 3 were applied to the standalone development concept to determine the optimal drilling program from the 9 pre-specified candidate wells, of which ($w1, w2, w3, w4, w5, w6$) are placed in Alta and ($w7, w8, w9$) placed in Gohta. In total, 20 sets of drilling and production schedules were optimized, corresponding to 20 stress testing price scenarios. The optimization problem is formulated using AMPL [53], solved with Gurobi [54], and computed using ThinkPad of Intel(R) Core(TM) i7-8565U CPU @ 1.80 Hz 1.99 GHz 64 bytes. The CPU times used to run the optimization problem and obtain the optimal solution (with 0% of dual gap) were between 600 and 2000 s.

In this case study, we first study how the price shock will change the drilling schedule and impacts the optimized production allocation. Afterward, a sensitivity analysis of the magnitude of the price shock is conducted to study the impact on the resulting drilling and production schedule. When presenting the results, we use the schedule graph to present the drilling sequence and the number of producer wells; the production allocation is plotted in a time base. The NPV performance and resilience factors are calculated and presented at the end of this section.

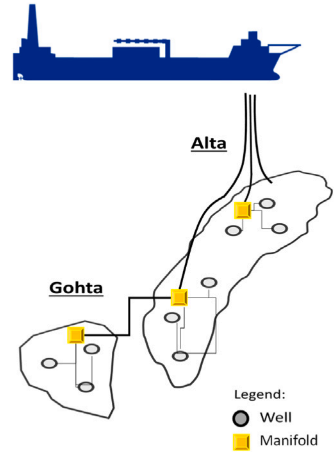

Fig. 5. Concept-1 Alta–Gohta develop as standalone.

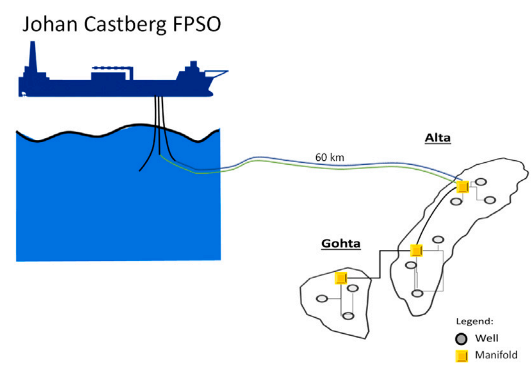

Fig. 6. Concept-2 Tie-back Alta–Gohta production to Johan Castberg FPSO.

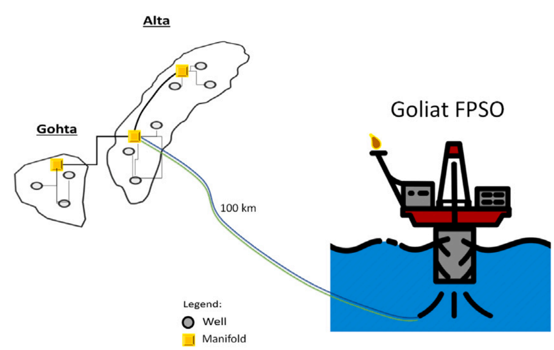

Fig. 7. Concept-3 Tie-back Alta–Gohta production to Goliat FPSO.

The optimized drilling schedules under stress testing for the first 4 years are presented in Fig. 8. The results show that it is always optimal to pre-drill wells $w4$, $w5$, and $w6$ before production starts. Scenarios 1 and 2, i.e., the oil price shock occurs in year 1 ($S_c^{\,1}$) and year 2 ($S_c^{\,2}$) respectively, result in the same drilling schedule, where 7 wells are drilled for production in total. However, if the shock occurs in Years 3 ($S_c^{\,3}$) or 4 ($S_c^{\,4}$), the drilling schedule changes and the optimal number of producers increases to 8 wells. The drilling schedules of $S_c^{\,3}$ and $S_c^{\,4}$ differ from Year 3: in $S_c^{\,3}$, no wells are drilled in Year-3 and the

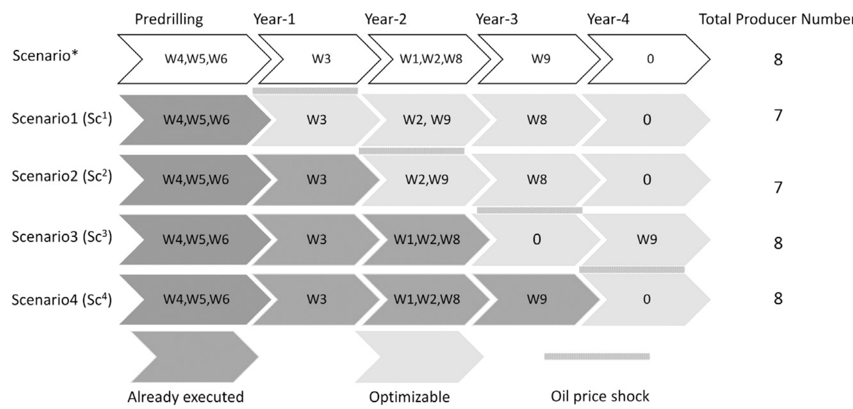

Fig. 8. Drilling schedule under different price shock timing ($S_c{}^1, \ldots, S_c{}^4$).

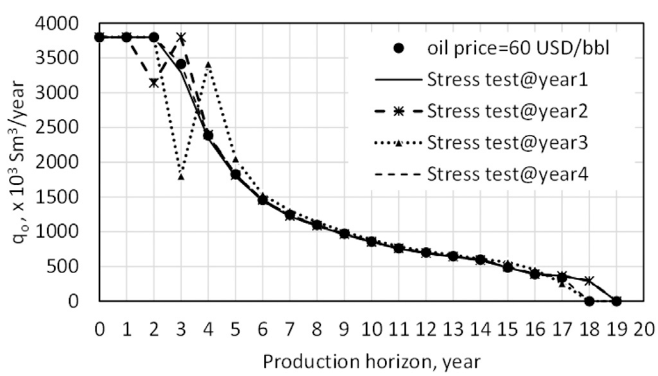

Fig. 9. Production schedule under different price shock timing ($S_c{}^1, \ldots, S_c{}^4$), the dot • denotes the production schedule at a constant price of 60 USD/barrel.

drilling of $w9$ is postponed to Year-4; while in $S_c{}^4$, the drilling of well $w9$ was scheduled earlier in Year-3. The drilling schedule resulting from the scenarios with price shock after Year 4 ($s = \{4, \ldots, 20\}$) are identical and equal to the optimal drilling schedule resulting from Scenario "*" without price shocks. The identical drilling schedule after Year 4 is because the optimizer found that it is optimal to drill all production wells (not all candidate wells) before Year 4, and any price shocks after Year 4 will not influence adjustments in the drilling schedule as Scenario "*".

Fig. 9 illustrates the corresponding optimal production profiles for the standalone development concept resulting from stress test scenarios 1 to 4. Our results show that only price shocks occurring in the first 3 years prompt a change in the production schedule. A price shock occurring in Year 3 results in the largest temporary production cut. Our results also found that it is optimal to increase production immediately after the price shock period to compensate for losses. For instance, the cut-down production of scenario $S_c{}^2$ will be compensated with higher production in Year 3. However, in $S_c{}^3$, the cut-down rate is much more than the reduction in $S_c{}^1$ and $S_c{}^2$ and the cut-down rate must be compensated by production increases in following Years 4, 5 and 6. Price shocks occurring after Year 4 result in a production profile identical to the one without shocks $q_o^*(t)$ (presenting as • in Fig. 9). This indicates that a price shock of 20% occurring after year 4 is not enough to prompt changes in the production strategy.

We then performed a sensitivity analysis with respect to the price shock magnitude for the standalone development concept. The optimal drilling programs and production schedule obtained with different magnitudes (20%, 30%, 35%) of price shocks are shown in Figs. 10 and 11. For all shock magnitudes, the drilling sequence is equal to the reference drilling program $f_n^*(t)$ if the price shock occurs after Year 4. The earlier the shock or stronger the price drop, the greater the change in the number of wells and drilling sequence. For instance, for shocks occurring in Year-2, and a drop of 35%, only 4 wells ($w4$, $w5$, $w6$, $w3$) are used for production, while 5 ($w4$, $w5$, $w6$, $w3$, $w2$) and 6 wells ($w4$, $w5$, $w6$, $w3$, $w2$, $w9$) are used for the 30% and 20% drops, respectively.

From the optimized production schedules in Fig. 11, we conclude that the larger the price drop, the greater the reduction in production compared to the reference case without a price shock. Also, the larger the price drop, the deviation of the production profile from the base case will persist for a longer time after the shock. For an oil price shock of 20%, the optimal production rate overlaps with $q_o^*(t)$ after Year 4 ($S_c{}^4$), while for price shocks of 30% or 35%, the overlap occurs in 5 years ($S_c{}^5$) or 7 years ($S_c{}^7$). The sensitivity analysis also shows that the price shock impacts the lifetime of the field. For instance, with a price shock of 35% in Years 1 or 2, the abandonment timing is postponed to 20 years (Year 19) compared to 19 years (Year 18) in the reference case.

We now repeat the same analysis to calculate the optimum drilling and production schedule for Concept-2 and Concept-3. Fig. 12 presents the normalized value of NPV for the three development concepts for price drops occurring from year 1 to year 20. The values were normalized by the NPV of Concept-1 with no price shocks. This plot was constructed using the data points obtained from the price stress testing studies for all scenarios with a 20% price drop magnitude. The results show that both Concept-2 and Concept-3 have a higher NPV compared to the standalone development concept. The Concept-3, tie-back of Alta–Gohta to Goliat, has the highest NPV except when the price shock occurs in the first two years.

However, we must point out that this result is partly due to the timing and cost assumptions in the tie-back solutions. All concepts use the same timing baseline. In tie-back development, the production rate from Alta–Gohta is dependent on the spare capacity at the host FPSOs, which vary in time. For instance, the plateau observed in Fig. 12 for Concept-3 is because there is no spare capacity at Johan Castberg for its early production period. Therefore there is no production from Alta–Gohta, and any price shock in the first 3 years will not impact the production. Moreover, due to the lack of detailed cost information for the tieback cases, we expressed their cost as a fraction of the standalone cost. The trade-offs of timing and costs between Concept-2 and Concept-3 were further discussed in a previous work by Lei et al. [51].

Lastly, we compute the resulting resilience factor for all 3 development concepts in 3 different price shock magnitudes. The results are presented in Table 1. Concept-2, a tie-back production to Johan Castberg has the highest resilience factor, while Concept-3 scores lowest for a 20% drop in oil price. In other words, Concept-2 is more robust to a 20% oil price drop. What can be clearly seen in this table is the decrease in the resilience factor when a higher magnitude has been assigned. This observation appears to support the expectation that the performance of the project is more stable if the oil price drops less.

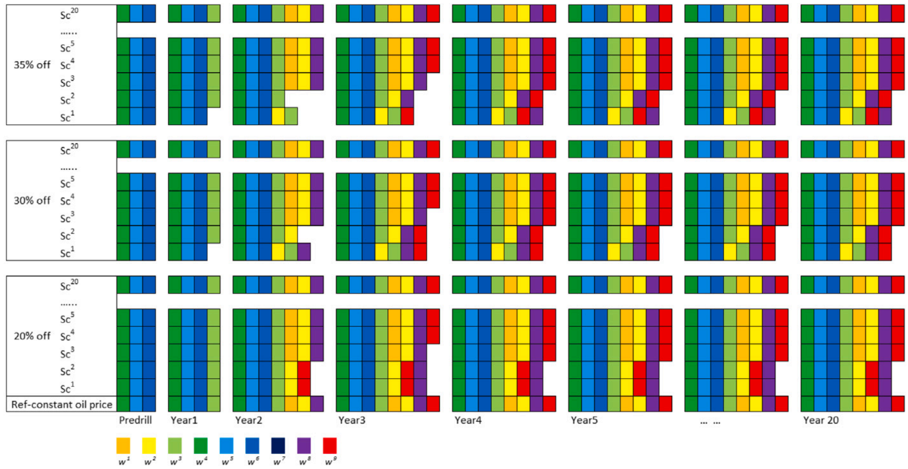

Fig. 10. Drilling sequence under different price shock magnitudes and timing.

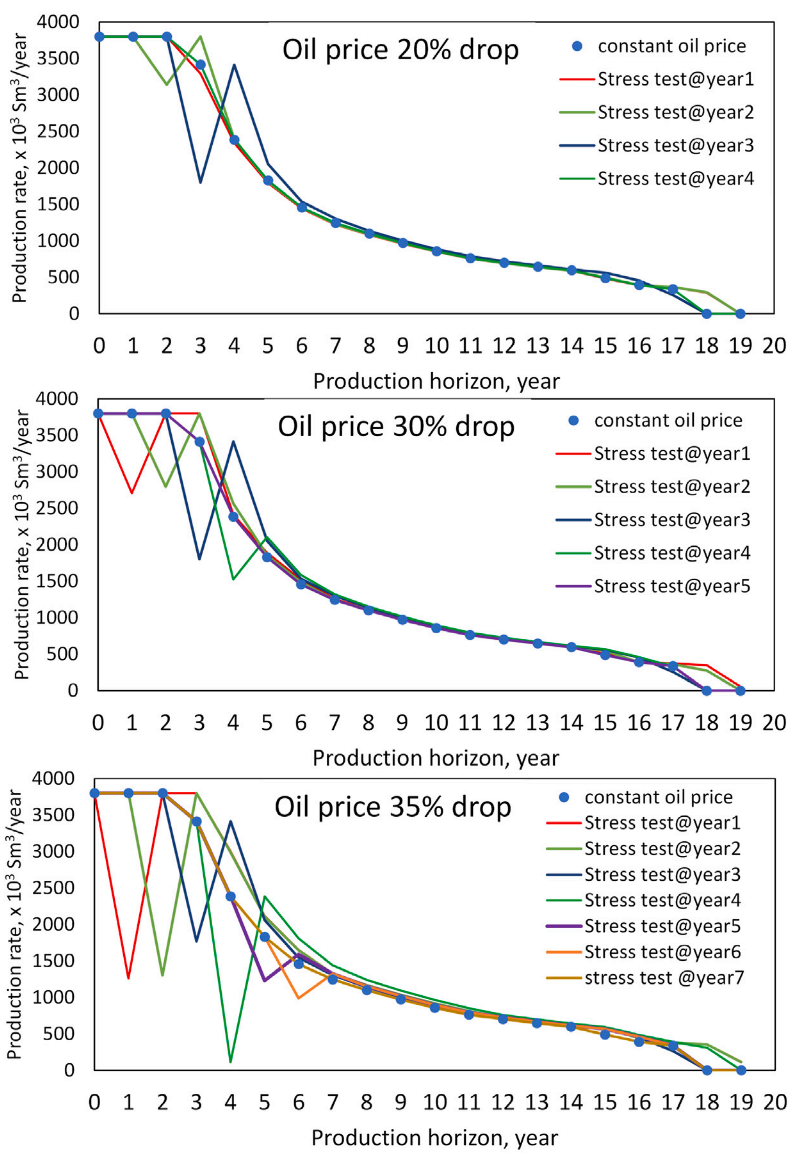

Fig. 11. Production schedule under stress test of different price shock magnitudes.

Table 1
Comparison of the resilience factor of different development concepts for different price shock magnitudes.

Price shock magnitude	Concept-1		Concept-2		Concept-3	
(oil price)	RF	NRF	RF	NRF	RF	NRF
20% (48 USD/bbl)	0.987	0.746	0.990	0.804	0.986	0.714
30% (42 USD/bbl)	0.982	0.644	0.983	0.662	0.984	0.684
35% (39 USD/bbl)	0.980	0.606	0.981	0.618	0.978	0.552

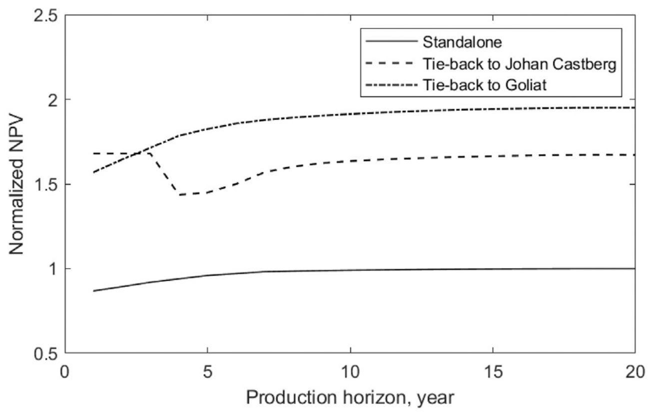

Fig. 12. Normalized NPV value of different stress testing of three development concepts. The NPV value with constant oil price of 60 USD/bbl in Concept-1 is normalized to 1.00, other calculated NPVs refer to it.

However, the difference in the resilience factor between the concepts is modest.

The modest difference observed between the resilience factors of different concepts could be because the stress test used is not severe enough. There is only 1 price shock occurring in the 20-year production horizon, and a constant price is assumed except in the price shock period. The small differences could also be due to some deficiencies in the model; for example, the assumption of a fractional relation between the cost of the standalone concept and a tie-back solution and the use of a linear cost model. It could also be because, in this study case, there are relatively few wells to decide upon and the production horizon is relatively short.

The lower bound of the resilience factor corresponds to the case when the rate is reduced to zero when the price shock occurs and the production is kept equal as initially planned (initial optimum q_o^*) for subsequent years. For this case, the value of the resilience factor would be 0.95 ($= 1 - \frac{\text{frequency of price shock (1)}}{\text{production horizon (20)}}$).

In an effort to obtain more distinct values for resilience factors between concepts, the values presented in Table 1 were normalized as follows:

$$\text{NRF} = \frac{\text{Calculated value of Resilience Factor} - 0.95}{1 - 0.95} \tag{25}$$

The values are provided in Table 1 with the tag NRF. It can be observed that the values are more dissimilar than before.

5. Conclusion and further research

This paper presents a methodology for price stress testing of field development in combination with mathematical programming to: (1) quantitatively evaluate the vulnerability of a field development concept to sudden hydrocarbon price drops; (2) determine optimal drilling programs and production schedules that mitigate the effects of the price drop.

We introduce a new metric, the resilience factor, to estimate the flexibility of a field development concept. This factor can be used to compare field development concepts in addition to the commonly used KPIs, such as NPV. We argue that the new metric indicator could help field planners to compare concepts with similar economic performance in response to a potential hydrocarbon price shock. We also provide a normalized version of the resilience factor which is useful when differences are small.

Using a case study, we demonstrate the application of the price stress testing approach. A standalone development concept and two tie-back concepts are viable solutions for the development of Alta–Gohta discoveries, but with different levels of risk concerning a price drop.

For the cases studied, we find that oil price shocks can significantly affect the economic value of a project depending upon the timing when the shock occurs. The effect of oil price shocks can be mitigated by applying changes to the drilling and production schedule. The scale and level of adjustment or change are dependent on the magnitude and the timing of the price drop. Larger and earlier drops cause greater changes to the original drilling and production schedule. In the study of the standalone development concept of the Alta–Gohta field, any shocks in the first 4 years lead to a change in the number of producer wells and the drilling sequence. A downside price shock of 20% after the fourth year from production start does not cause any changes in the drilling and production strategy.

A possible extension of this work is to check the robustness of the method by changing idealizations or boundary conditions in the model. This could evaluate more magnitudes in the price drop. Another extension is how to define the resilience factor using a more advance metrics (such as the standard deviation or free cash flow to equity (FCFE)) instead of the mean value. A more complicated cost model instead of using linear functions is another interesting topic of study. The assumption of instantaneous reaction to drilling and production may be too optimistic. However, a possible extension is introducing a time lag between the time when the price shock occurs and when the correction in production rates and drilling schedule is made.

CRediT authorship contribution statement

Guowen Lei: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Verena Hagspiel:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Milan Stanko:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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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