Abstract

During oil price downturns, many operating companies reduce or eliminate large investments with long time horizons such as exploratory drilling campaigns. This reduction in investments induces rig and drilling services providers to decrease their bids to remain competitive. Consequently, the exploration expense is decreased, lessening the initial expenditure in the project. In this research, a valuation approach is implemented to study the impact of this investment reduction on the decision-making process for executing exploratory drilling campaigns during oil price downturns. It is shown that postponing exploration campaigns during oil downturns does not necessarily maximize value creation.

Value creation from investment in oil price downturns results from the combination of uncertainty and flexibility. Value of flexibility (optionality), also referred to as Real Options value, can be estimated using a variety of methods. In this work, we use the versatile Least-Square Monte Carlo Method (LSM) approach developed by Longstaff and Schwartz (2001) to evaluate the waiting option for exploration drilling. Uncertainties in oil prices and drilling costs are included as they have the largest impact on the alternative chosen and the value achieved. We implement a two-factor stochastic oil price process developed by Schwartz and Smith (2000), as this model provides a good balance between realism and ease of communication. Uncertainty in the drilling costs is modeled as a Geometric Brownian Motion process. We also account for dependencies between oil price and costs by correlating the drilling cost with the previous period’s oil prices.

We show that the real option methodology will identify the optimal time to start exploration drilling. We also demonstrate the effect of correlation between the drilling cost and the oil price on the optimal time to drill; which for this study is the year with lowest expected oil price. Furthermore, we analyze the sensitivity of project value with respect to the correlation factor and the parameters in the stochastic price model. This work demonstrates that including price-cost uncertainties and correlations leads to more realistic value estimates, resulting in investment decisions that maximize value.

This paper contributes to the practice of petroleum project analysis by showing the effect of correlations on the optimal time of drilling and the value of waiting options, demonstrating that it could be optimal to drill exploration wells during oil price downturns. The real option model developed in this paper is applicable to many types of exploration projects in the petroleum industry.
Introduction

The price of crude oil, as other commodities, is governed by the supply–demand relationship in the markets. Low oil prices are signs of higher supply than demand, resulting from increased production levels or weakened demand (Geman, 2005). The term “low oil price” is normally used in the industry to label periods after a significant price drop, as the one observed between the year 2014 and 2015 when it dropped from an annual average of 93.19 to 48.66 USD/BBL. However, calling the price in 2015 “low” would be inconsistent when comparing it with the historical data shown in Figure 1, since the 2015 price was slightly higher than the average price over the past 30 years (43 USD/BBL). Nonetheless, these periods of sudden or extended price drops affect the investment policies of operating companies, inducing them to abandon expensive production and delay investing in new assets. Companies may overreact to short-term prices, ignoring the possibility of increasing prices or reduced costs in the future, and thus, adopting an overly risk-averse attitude in their decision making. The result of this may be that value creating opportunities are ignored which, effectively, leads to value destruction. In this work, we focus on exploration projects, which often are the first investments to be cancelled or delayed. This, in turn, forces rig providers and services companies to substantially decrease their operations, with the consequence that they must reduce their bidding costs to subsist. The result is reduced exploration costs.

![Figure 1](https://www.eia.gov/)

The exploration cost is a major expense for offshore projects. Therefore, a decline in the cost may positively impact the overall value of the project. Although the correlation between oil price and drilling cost is clearly observed in the market, its effect on the project valuation has, to our knowledge, not been explicitly studied. In this work, oil prices and drilling costs are correlated to appraise its impact on the valuation and decision-making process for executing exploratory drilling campaigns during oil price downturns. The objective is to investigate if postponing exploration investments, as most companies do, is a value maximizing decision.

Prospects that involve high uncertainty are classified as “high-risk” in companies’ portfolio. However, uncertainty also implies the possibility of having better than expected outcomes. Rejecting projects that involve significant downside risk could prevent capital lost, but at the same time, by not investing in uncertain projects the company removes the opportunity of investing in a prospect with a positive expected value. Ignoring project uncertainties do not lead to portfolio decisions that maximize the stakeholder value. As discussed in Begg et al. (2002) among others, the traditional deterministic Discounted Cash Flow (DCF) method fails to explicitly quantify and account for uncertainties, and assumes that the investment is a now-or-never decision, which does not reflect the flexibility that managers have in making future decisions based on their future knowledge from revealed uncertainties along the project lifetime.
During oil price downturns it is still possible to generate value from uncertainty by utilizing flexibility. The analysis of the value of flexibility is also referred to as Real Options Valuation (ROV).

ROV has been introduced, illustrated, and discussed in the oil & gas literature (Dias, 1997; Smith and McCardle, 1999; Begg, at al. 2002, 2004; Brandao 2005a, 2005b; Lima, at al. 2005; Smith, 2005; Willigers, 2009; Willigers and Bratvold, 2009; Hem, at al. 2011; Willigers, et al. 2011; Alkhatib and King, 2011; Jafarizadeh and Bratvold 2009, 2012, 2013; Thomas and Bratvold 2015, 2017). Begg at al. (2004) implemented flexibility analysis to assess the abandonment decision when oil prices fall below the break-even value. They demonstrated that the return of investment can increase when the uncertainties are included in the decision-making process. The ROV methodology has also been used for exploration projects (Dias, 2004; Jafarizadeh and Bratvold 2015, 2016). Although those studies included oil price and other type of uncertainties, they have not appraised the correlation between the drilling cost and oil price, and their impact on the optimal time to drill. In this research, we aim to provide valuation and decision support to the case of exploration projects during oil price downturns, by implementing the most flexible and promising ROV method for solving real-world problems: The Least Squares Monte Carlo (LSM) approach developed by Longstaff and Schwartz (2001). This method is versatile and computationally efficient when multiple sources of uncertainty are considered.

The ROV method requires learning models that include the resolution of uncertainty over time in prices and costs and the impact of this on project cash flows. In this work, we used the two-factor stochastic price process developed by Schwartz and Smith (2000) to describe the price dynamics. The two-factor process is sophisticated enough to capture basic characteristics of price behavior and at the same time is simple enough to generate insights and serve as a communication medium. The drilling cost is modeled using a Geometric Brownian Motion (GBM) process which is correlated with the price movements.

The LSM approach evaluates the option to wait and drill by calculating the optimal exercise time. This method has been previously used for evaluating optimal decisions in Oil and Gas (O&G) projects: Thomas and Bratvold (2015) illustrated the implementation of this approach to find the optimal blowdown decision, Alkhatib and King (2011) used it to determine the optimal time to start surfactant flooding in Enhanced Oil Recovery (EOR) projects, whereas Jafarizadeh and Bratvold (2012) implemented it to estimate the optimal time to abandon an oil field case.

This research contributes to the literature of petroleum asset valuation in two aspects. First, based on the results of the ROV model, it demonstrates that it could be optimal to drill exploration wells during oil price downturns. Second, it presents a ROV model for exploration projects that includes correlation between the drilling cost and the oil price.

This paper is organized as follows: the first part illustrates the decision-making process in an exploration license. In the following sections, the stochastic processes used for the oil price and the drilling cost, along with their correlation, are described. Later the example is discussed, and the LSM implementation is introduced. Finally, we present the findings, analysis, and conclusions.

**Offshore Exploration Projects Framework**

Hydrocarbon resources are usually explored through investment vehicles called partnerships. In this arrangement, investors provide capital and a selected member, called the operator, operates and manages the projects. Exploration licenses are usually awarded on a fixed–term basis. The partnership formed by a group of companies has the option to drill the identified prospects at any time until the contract maturity. If commercial hydrocarbons are discovered, the partnership may decide to extend the license. Otherwise, the license is returned to the authorities (Bamford et al.,2004; Jafarizadeh and Bratvold, 2015).

Exploration projects pass through a number of common decision milestones; each with different uncertainties. Perfect information is never available and, hence, there will always be some remaining uncertainties, motivating analysts to employ a range of probabilistic models for more informed decision making. For example, a decision tree model illustrating the main decisions and uncertainties for an exploration project is shown in the Figure 2. Here, the decision to invest in exploration wells depends on
the chance of success and uncertain volume of hydrocarbons. If commercial volumes are discovered, then the development decision will depend on uncertain production rates and future prices.

![Decision Tree](image)

**Figure 2** Decision tree representing the main decisions and uncertainties relevant for an exploration opportunity. Modified from Jafarizadeh and Bratvold (2015)

To assess probabilities used in the decision tree we use geological and market information. For a risk-neutral decision maker, the decision to drill an exploration well should be based on its expected value, calculated using the available information (Jafarizadeh and Bratvold, 2015).

When exploration decisions are considered in the context of licenses, we usually face an option–like structure; we have until the expiry date of the license to drill wells otherwise the license will be returned to the authorities. The decision of when to drill an exploration well depends on geological and petrophysical properties as well as on economic conditions. This option is illustrated in the Figure 3. Every year, the partnership should decide on whether to drill or wait until the next year and observe the price levels. If they decide to wait, they will face the same decision next year. But then new oil prices result in new Net Present Values (NPV) estimates.

![Decision Tree](image)

**Figure 3** Exploration decision tree illustrating the waiting option. Modified from Jafarizadeh and Bratvold (2015)

The NPV for each end–node is assessed by calculating cash flows from future oil price estimates, production forecasts, tax rates, and costs. Figure 4 shows a typical cash flow diagram if exploration ends with a discovery. Drilling cost for exploration wells is the earliest initial investment. Followed by larger investments in facilities, drilling of production wells, and downstream infrastructure. The investments vary depending on the size of the field, production strategy, reservoir characteristics and distance to nearby infrastructure. After a period of construction and development commonly called the lead time, production

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1 After proof of commerciality, the company prepares the plan for development and operations, and delivers it to the government for approval. Regulations may differ across countries. In the Norwegian Continental Shelf (NCS) the government should approve the Plan for Development and Operations (PDO) before execution.
starts and positive cash flow begins to accumulate. Continuous operations incur fixed and variable operational expenditure (OPEX)\(^2\).

![Figure 4 Typical cash flow diagram for an offshore exploration project](image)

**Oil Price Model**

Oil and gas prices are one of the most important drivers of value. Many companies realize this but few are implementing consistent methods of including price uncertainty in their investment decision process. We use the Short-Term/Long Term (STLT) stochastic process developed by Schwartz and Smith (2000) to describe price uncertainties as it provides consistency and relative ease of implementation and communication. It includes a long-term factor that represents the uncertainty in the equilibrium prices (such as technological changes like introduction of improved fracking methods), and a short-term factor that models deviations from the equilibrium price that are expected to fade away in time (such as temporary supply disruptions). The log of spot oil price is the sum of these two elements:

\[
S_t = \exp(\chi_t + \xi_t)
\]

where the short term (\(\chi_t\)) and the long-term factor (\(\xi_t\)) are described in the risk-neutral version as:

\[
d\chi_t = \left(-\kappa\chi_t - \lambda_\chi\right)dt + \sigma_{\chi}d\zeta^*_\chi
\]

\[
d\xi_t = \left(\mu_\xi - \lambda_\xi\right)dt + \sigma_\xi d\zeta^*_\xi
\]

\[
d\zeta^*_\chi d\zeta^*_\xi = \rho_{\zeta\zeta}dt
\]

The model has a total of seven parameters, along with two initial conditions (\(\chi_0, \xi_0\)), to be estimated. Jafarizadeh and Bratvold (2012) presented a calibration method that uses spot and futures prices\(^3\), along with implied volatilities of options\(^4\) on futures. This method was implemented using data reported in the New York Mercantile Exchange on 19th of October 2016\(^5\). Results from the calibration are shown in the Table 1 and illustrated in the Figure 5. A detailed description of the STLT model implementation can be

\(^2\) Variable cost depends on the production rate and includes processing and lifting cost, among others. Fixed OPEX’s are independent of the production rate, and involve expenses such as labor cost

\(^3\) Futures contracts are set for delivering the crude in a specific time in the future, with a pre-determined oil price.

\(^4\) Option is a financial derivative that gives the buyer the right, but not the obligation, to buy or sell a pre-determined asset.

\(^5\) Futures with expiration dates extending 8 years out on 19 of October 2016, plus call options for 1/12, 3/12, and 8 years were used for calibration.

### Table 1 Parameters for the Two-factors price process

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_x$</td>
<td>7%</td>
</tr>
<tr>
<td>$\mu_x^*$</td>
<td>0.96%</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>1.16</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>33.50%</td>
</tr>
<tr>
<td>$\rho_{xx}$</td>
<td>0.34</td>
</tr>
<tr>
<td>$\lambda_x$</td>
<td>0</td>
</tr>
<tr>
<td>$\xi_0$</td>
<td>4.03</td>
</tr>
<tr>
<td>$\chi_0$</td>
<td>-0.11</td>
</tr>
</tbody>
</table>

**Figure 5** Oil price probabilistic model calibrated with data from 19 October 2016

**Drilling Cost**

Exploration cost typically consists of the rig cost, drilling service fees, utilities, and labor. Exploration projects usually have low to medium capital requirements in a company’s portfolio compared with the costs of major field developments (Kassler, at al. 1983). Yet, and perhaps because of their uncertain nature, such projects are often the first to undergo budget cuts during unfavorable economic conditions. During oil price downturns drilling campaigns are suspended, causing a decrease in demand for rigs and drilling services. This, in turn, will exert pressure on the rig and service providers to reduce their rates, and this correlation is clearly observed in the market.

Willigers (2009) studied the relationship between rig rates and oil price from 1995 to 2008. He determined correlation factors analyzing two types of rigs (jack–up and semi–submersible) in the Gulf of Mexico and the North Sea. The highest correlation factor, close to 0.9, was observed between the rig rates and the oil prices of the previous year (one-year time offset), whereas the correlation factor without the time offset was less than 0.8.

In this paper we use a risk–neutral valuation scheme which, put simply, classifies uncertainties into market (those that can be hedged in the market, such as oil price) or private (those that cannot be hedged using market instruments, such as production levels). Market uncertainties are modeled using risk-adjusted probabilities, and private uncertainties using assessed probabilities based on expert’s beliefs or preferences (Smith and Nau, 1995). All relevant and material uncertainties are thus accounted for in the cash flows which are discounted using the risk–free interest rate.

Drilling cost is an uncertainty that falls somewhere between the notion of private and market risks (Brandao, 2005a). In this work, it is modeled by estimating its conditional probabilities on the oil price.
levels (Smith, 2005) or correlating its process with the price process. The total cost of drilling is modeled using a Geometric Brownian Motion (GBM) process, described by the differential equation:

\begin{equation}
    d\theta = \mu_\theta \theta dt + \sigma_\theta \theta dz_\theta
\end{equation}

where \( \theta \) represents the cost of the exploratory drilling campaign, \( \mu_\theta \) is the drift, \( \sigma_\theta \) is the volatility, and \( dz_\theta \) represents the Brownian increment\(^6\). Parameters used for the cost of the exploratory drilling campaign in this work are shown in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_0 )</td>
<td>290 Million</td>
</tr>
<tr>
<td>( \mu_\theta )</td>
<td>3%</td>
</tr>
<tr>
<td>( \sigma_\theta )</td>
<td>20%</td>
</tr>
</tbody>
</table>

The parameters of equation (5) should generally reflect the dynamics of the region. This is to say that in a highly liquid\(^7\) market like the North Sea the costs follow a different pattern than in a less liquid market like the Colombian Caribbean Sea. Generally, the water depth and the geographical location of the prospect influence the rig rate, and hence the drilling cost. These considerations are important when defining the stochastic model for cost (\( \theta \)).

As discussed earlier, the exploration cost uncertainty is correlated with oil prices. In this research, oil prices are modeled by two correlated uncertain variables: the short- and long-term factors. Exploration cost is correlated with the short-term component in the spot price as the exploration costs can only be affected by supply–demand balances in relatively short periods comparable with the license duration. Furthermore, we correlate the process for exploration cost with the short-term factor of prices of the previous year by letting the Brownian increment of the exploration cost (\( dz_\theta \)) be correlated with the Brownian increment of the short-term factor (\( dz_\chi^* \)) (Wiersema, 2008).

**Study Case**

A company holds an offshore exploration license which expires in five years. As the market conditions are characterized by a significant downward trend in oil prices, the company’s immediate reaction is to implement cost-cutting policies and defer major investments. The company must decide whether to start the exploration campaign now, or wait to see if the oil price increases. This was illustrated in Figure 3. The company’s geoscientists identified a prospect in this license and, based on available information, estimated a probability of success of 20% for a wildcat well. The company used available information to estimate reservoir and production values as shown in Table 3. If exploration is successful, it is estimated to take 10 years to develop the field resulting in the cash flows shown in Figure 4 and discussed in the next section. A risk-free rate of 5% was used.

\(^6\) Many books and papers describe the GBM model in detail. Examples include Black and Scholes (1973) and Postali and Picchetti (2006).

\(^7\) A liquid market has many participants and trades on a daily basis.
Table 3 Properties of the study case

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected recoverable Reserves</td>
<td>100 MSTB</td>
</tr>
<tr>
<td>Variable OPEX</td>
<td>15 USD/bbl</td>
</tr>
<tr>
<td>Fixed OPEX</td>
<td>10 MUSD/year</td>
</tr>
<tr>
<td>Production life</td>
<td>30 years</td>
</tr>
<tr>
<td>Development cost</td>
<td>500 MUSD</td>
</tr>
</tbody>
</table>

The company’s managers have noticed that rig providers and drilling services companies are decreasing their day-rates in order to ensure job activities during the current market conditions. Motivated by this reduction in exploration costs, the operating company wants to evaluate the optimal time to drill, considering that if the oil prices increase, the investment would also increase, affecting the value of the project.

It is important to note that in practice, a positive expected value does not necessarily mean the company will commit to investing. The financial position of the company and the size of its project portfolio influence its investment policy. Large investments that involved high uncertainty may not enter the portfolio of small companies, or companies with a limited cash-reserve. Highly uncertain exploration wells may also make large dents in a company’s overall viability and value, leading to a risk-averse attitude toward investing.

In this work, we assume that the operator has a large portfolio of projects, and the cost of exploration is low compared to the rest of its business. This is a company that has the financial strength to create value at low prices by engaging in mergers and acquisitions or pursuing opportunities, that despite unfavorable conditions, might generate value. As the exploration cost is a small portion of their total investments, we assume the company is risk-neutral (Bratvold and Begg, 2010).

**LSM Implementation**

If we assume exploration decisions are made annually, the company can drill the well in the first year, or wait until next years and observe the changing economic conditions. At any date during the license period the decision is made by comparing the immediate value of drilling with the expected value from waiting and perhaps drilling in the future. The value of this option is based on the optimal series of decisions during the license period. We use Monte Carlo simulation and dynamic programming to estimate this value.

Introduced by Longstaff and Schwartz (2001), Least-Squares Monte Carlo (LSM) is a promising method for evaluating real options (Smith, 2005; Willigers and Bratvold, 2009; Hem, et al. 2011; Willigers, et al, 2011; Alkhatib and King, 2011; Jafarizadeh and Bratvold 2012, 2013; Thomas and Bratvold 2015, 2017). The LSM does not suffer from the curse of dimensionality with respect to the number of uncertainties (Willigers and Bratvold, 2009). The approach can be used to generate decision maps that provide additional insights for the decision-makers.

Monte Carlo simulation is used to generate N paths for each uncertainty in the model from time zero until the end of the exploration license (T=5 years). The price and drilling cost uncertainties are described using stochastic processes, generating $N \cdot T$ values for each of the uncertainties. Thereafter, NPV’s are estimated for every single element of the generated paths, thus resulting in a $N \cdot T$ matrix of NPV values. Every element of that matrix is estimated using a single value of the simulated uncertainties (price and drilling cost). The NPV’s themselves are calculated by discounting the cash flows using the risk-free rate\(^8\) and the cash flows at each point in time are functions of production rates, oil prices, and costs:

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\(^8\) In the risk-neutral valuation scheme, instead of risk–adjusting the discount rate, we risk–adjust the probabilities. Then the cash flows are only discounted with a rate that accounts for the time-value of money only, usually referred to as the “risk-free rate”.

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\[ \text{CashFlow}_t = \text{ProductionRate}_t \times (\text{OilPrice}_t - \text{VariabOpex}_t) - \text{FixedOpex}_t - \text{Capex}_t \] \tag{7}

A production profile was estimated considering a peak profile, where the highest value is equivalent to 10% of the total reserves, and it is assumed to occur in the third year of production. A logarithmic function was used for the incremental curve before the peak, whereas the decline curve after the peak was defined with an annual production rate set as the 10% of the remaining reserves. The cost of exploration drilling is deducted in the year 1, whereas the development costs are incurred in the year before production starts (\(t=\)lead time-1)\(^9\). For simplicity, royalties and taxes are neglected in this paper.

In this study, the LSM algorithm presented by Jafarizadeh and Bratvold (2015) for exploration projects is implemented, where the optimal decisions are based on the expected value of drilling, considering the probability of success of the prospect. The expected value of drilling (\(E_d\))\(^10\):

\[ E_d = P_s \times NPV_s + (1 - P_s) \times NPV_f \] \tag{6}

where \(P_s\) denotes the probability of success, \(NPV_s\) is the net present value discovering commercial reserves, and \(NPV_f\) is the net present value for dry hole. Equation (6) calculates value of the branches market as “success” in Figure 3. Therefore, a \(N \times T\) matrix of expected values is created.

The dynamic programming method in LSM uses backward induction on the simulated cash flows to estimate the optimal decision policy at each period. It starts at the lease expiration date (\(t = T = 5\)) when the company must decide whether to drill or let the exploration license expire. This decision is based on the expected value of drilling at that time (\(Ed_{t=5}\)). If the expected value is zero or negative, the company should let the license expire (relinquish), otherwise, the company should drill. The algorithm then moves backward to year 4 (\(t = T - 1\)), when the optimal policy is determined for every simulated path by comparing the expected value of drilling at that year (\(Ed_{t=4}\)), with the expected value of waiting, usually referred as the continuation value. Using least-squares regression of exercise values from next period on the cross-sectional information on time \(t\), the continuation value at time \(t\) is estimated as a function of the oil prices and the exploration cost at time \(t\):

\[ C^i_t = \alpha_1 S^i_t + \alpha_2 D^i_t + \alpha_3 (S^i_t)^2 + \alpha_4 (D^i_t)^2 + \alpha_5 (S^i_t)(D^i_t) \] \tag{8}

where \(C^i_t\) is the continuation value, \(S^i_t\) is the oil price, and \(D^i_t\) represents the exploration cost, for the \(i\)-th path in the year \(t\). \(\alpha_k\) (with \(k=1, \ldots,5\)) are the regression coefficients mentioned above, and are calculated by applying least-squares regression technique on cross-sectional information of the simulated paths (Jafarizadeh and Bratvold, 2015).

The algorithm continues by calculating the optimal decision for every path by comparing the discounted continuation value with the expected value to drill. After the optimal decision is determined for each path, the algorithm moves to the previous period and repeats the same calculations again. At the end, every path will have its optimal time to start to drill and determines the optimal payoff associated with it. For instance, if the optimal decision in one of the paths was to start the exploration campaign in the year three, then the optimal payoff is the expected value of drilling in this year (\(Ed_{t=3}\)). The project value is the average of the discounted optimal payoffs of all the paths.

\section*{Results and Discussion}

To investigate if postponing exploration investments is a value maximizing decision, we implemented the LSM approach using the price-cost uncertainties and their correlation. The results are presented and discussed in four sub-sections; we first show the optimal-time histograms that reflect the change in optimal

\(^9\) The year when the development cost is deducted in the cash-flow structure can be easily changed by the user in the ROV model.
\(^10\) The MATLAB® code used in this work is build on the code presented in Jafarizadeh and Bratvold (2015).
year to drill in response to different cost-price correlation. Then, we discuss how the correlation affects the probability distribution of the expected value of the project by highlighting the sensitivity of the project value with respect to the correlation. Third, we show the sensitivity of the project value to the parameters of the stochastic process for exploration cost. Finally, we present decision maps for exploration drilling.

**Optimal Decision**

Based on historical market observations, drilling cost responds to changing oil prices with a one-year time lag (Willigers, 2009). To account for this, we correlate the short-term price factor in year $t$ and the cost in year $t + 1$.

Figure 6 shows the optimal drilling time for various scenarios: constant cost in panel A, uncertain cost with price-cost independency in panel B, partial price-cost dependency of 0.89 (based on Willigers, 2009) in panel C, and full price-cost dependency in panel D. The expected oil price grows as shown previously in Figure 5. For this reason, year one has the lowest and five has the highest average prices.

The results of the simulations show that, somehow in contrary to industry beliefs, when there is correlation between prices and costs, the majority of paths suggest early exercise, most commonly at year one. For these paths, early exercise means drilling with lowest expected cost. Of course, if exploration

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11 This panel corresponds to the assumptions in Jafarizadeh and Bratvold (2015).
costs are insignificant compared to the expected value of development projects, then the effect discussed above will not be as robust as indicated here.

As shown in Panel A, where exploration cost is constant, the dynamics of prices lead to higher probability of exercise at the end of the license period. The best choice is to wait and observe prices until the later years of the license. This picture will change when the exploration costs are uncertain. Panel B shows that when exploration costs are probabilistic, but in this case, independent of the oil price, the optimal exercise years will change. In other words, the algorithm compares the value of learning from late exercise with the higher cost of late exploration (the exploration costs increase in average). With this comparison, the optimal drilling time is almost equally likely to any year during the license period as shown in Panel B.

Panels C shows the more realistic case where the correlation between costs and prices is 0.89. This additional feature drastically changes the frequency of exercise; it is now more common to drill early rather than later. Panel D shows the case where there is full dependence (correlation = 1) between the costs and prices.

**Expected Project Value**

The correlation between the drilling cost and the oil price affects the expected value of the project. Figure 7 compares the distribution of project values when exploration cost is constant with the case when cost and prices are correlated ($\rho = 0.89$). The expected project values are shown in the Table 4.

<table>
<thead>
<tr>
<th></th>
<th>Mean Expected Project Value (MUSD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Exploration Cost</td>
<td>273</td>
</tr>
<tr>
<td>Uncertain Correlated Exploration Cost ($\rho = 0.89$)</td>
<td>260</td>
</tr>
</tbody>
</table>

Unbiased and consistent estimates of project values are key to sound capital investment decisions. Those that maximize capital efficiency and shareholder value. Here, ignoring the drilling cost uncertainty and the correlations between variables can result in an upward bias of USD13 million. Such an overestimation of project expected value will incorrectly portray an exploration prospect as an attractive investment, or make the difference between relinquishing, selling, or pursuing the exploration license. The cost-price dependency can have a material influence on the project and should be accounted for. As the
The expected project value decreases with cost-price dependency. This is due to the fact that by increasing the correlation, overall uncertainty decreases\textsuperscript{12}, and so does the value of real option. In other words, a change in correlation coefficient impacts project value and may be material for the optimal decision.

**Sensitivity of the Exploration Cost Parameters**

As most valuation parameters are defined by experts based on different interpretations, sensitivity analysis can generate additional valuation and decision support insights. More specifically, the parameters of the stochastic process for exploration cost uncertainty and its correlation should reflect the experts’ knowledge based on the available information (past data, local and global market condition, general knowledge, etc.). When implementing the methodology of this research on other projects, decision supporting teams should observe and estimate relevant parameters individually as they directly affect the value of projects.

We performed sensitivity analyses of the expected project value with respect to the drift and volatility of exploration cost. We investigate three different correlation scenarios ($\rho = 0, 0.5, \text{ and } 1$).

Figure 9.a shows the results from the sensitivity analysis when $\rho = 0$. As mentioned by Brandao et al. (2005a), the aggregate project value volatility is a function of the volatilities of the underlying uncertainties. Therefore, higher cost volatility results in higher project value volatility, and consequently higher option value. The drift has an opposite effect. Increasing the drift means that average exploration cost will be higher over the time, thus decreasing the option value.

Figure 9.b and 9.c show a trend in which higher correlation translates into a reverse relationship between project value and cost volatility. When $\rho = 0.5$ the project no longer increases with higher cost volatility and in the extreme case of $\rho = 1$ the value decreases with volatility.

\textsuperscript{12}The decrease in the uncertainty can be documented using the Standard Deviation. In this case, it decreased from 57 to 45 MUSD, when the correlation factor increased from 0 to 1.
Figure 9 Sensitivity analysis of exploration cost parameters
Decision Maps

Decision maps, sometimes called strategy or policy maps, are very useful for decision support and can be extracted from the data generated by the LSM algorithm. Figure 10 shows a decision map in which two planes, representing the two available alternatives (options) in year one, intersect. The planes are drawn using the regressed project values functions from the LSM results. A correlation coefficient of 0.89 was used.

![Figure 10 3D Decision Map for the year one with \( \rho = 0.89 \).](image)

Figure 10 shows the expected value from the Wait and Drill alternatives with variations in price and exploration cost. We anticipate higher value for both alternatives when prices increase, and lower values when exploration costs increase. These trends are illustrated in the decision map. This figure also shows that when oil prices are low and exploration costs are high, the company should wait.

![Figure 11 Decision maps for the four years](image)
When dealing with time scenarios, decision maps are usually displayed in two dimensions, as shown in Figure 11 for the first four years of the exploration license. The boundary between the areas represents the decision change, which has a positive slope with respect to the exploration cost, indicating that higher costs require higher prices in order to commence drilling. Nevertheless, the boundary slope decreases with the number of license years. This is because when the company decides to postpone the exploration, it also delays the start of production (in case of successful exploration) to a year with higher expected oil price, making these projects attractive for the investors.

Conclusions
Oil price downturns make companies more risk-averse than high-price periods. The operator’s common belief is that postponing the investment during this time will maximize the share-holder value. In this work, a ROV model has been implemented to demonstrate value can be created from investing in offshore exploratory drilling campaigns during low oil prices. Uncertainties in the oil price and the exploration cost were included in the model using stochastic processes. To reflect market reality, these uncertainties were correlated, and the impact of the correlation on the valuation and decision-making was studied. Optimal-time histograms were used to illustrate that, the common market decision of postponing investments during oil price downturns can be a consequence of assuming that the oil price is the only uncertainty in the cash flow model. Including the uncertainty in the exploration cost impacted the optimal time to start the exploration campaign. However, if the correlation observed in the market between the drilling cost and the oil price is ignored, this may lead to suboptimal estimation of the optimal policy. By including the cost-price dependency, the decreasing effect of exploration cost during oil price downturns is accounted. For projects where the exploratory drilling campaign cost constitutes a substantial part of the cash flow, a reduction in this cost clearly impacts the optimal decision policy. However, if the correlation observed in the market between the drilling cost and the oil price is ignored, this may lead to suboptimal estimation of the optimal policy. This is the case of the offshore prospect studied in this research, where the optimal time to start the exploratory drilling campaign is the year with the lowest expected oil price, differing from the common operators’ belief.

From assessing the impact of the cost-price dependency on the expected project value for a specific case, we concluded that the inclusion of the correlation contributes to a more unbiased project value estimation, leading to portfolio decisions that create value.

Although the study case in this work was realistic in terms of its cash flow, valuation, and decision-making components, the conclusions reached in this paper cannot be extended to all investment of this nature without a proper assessment. However, the developed ROV model can be easy modified to be implemented in different type of exploration projects.

References


