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Application of machine learning to assess the value of information in polymer flooding

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ABSTRACT

In this work, we provide a more consistent alternative for performing value of information (VOI) analyses to address sequential decision problems in reservoir management and generate insights on the process of reservoir decision-making. These sequential decision problems are often solved and modeled as stochastic dynamic programs, but once the state space becomes large and complex, traditional techniques, such as policy iteration and backward induction, quickly become computationally demanding and intractable. To resolve these issues and utilize fewer computational resources, we instead make use of a viable alternative called approximate dynamic programming (ADP), which is a powerful solution technique that can handle complex, large-scale problems and discover a near-optimal solution for intractable sequential decision making. We compare and test the performance of several machine learning techniques that lie within the domain of ADP to determine the optimal time for beginning a polymer flooding process within a reservoir development plan. The approximate dynamic approach utilized here takes into account both the effect of the information obtained before a decision is made and the effect of the information that might be obtained to support future decisions while significantly improving both the timing and the value of the decision, thereby leading to a significant increase in economic performance.

1. Introduction

Reservoir management is defined as the utilization of available technology, financial assets, and human resources to maximize the economic recovery of a reservoir. This type of management involves a series of operations and decisions, from the initial stage of the discovery of a reservoir to the final stage of field abandonment (Wiggins and Startzman, 1990). A significant number of decision-making problems related to reservoir management are regarded as sequential problems, as most petroleum engineers and geoscientists are used to considering the information gathered, supporting their future decision making, and maximizing the value created by the reservoirs. However, the models for reservoir management decisions may be computationally prohibitive and intractable if several sequential decisions and uncertainties are involved. To solve this issue and successfully execute good reservoir management, decision analysis (DA) is recommended due to its several advantages (Evans, 2000). (Howard, 1988) stated that “DA is a systematic procedure for transforming opaque decision problems into transparent decision problems through a series of transparent procedures.” In the context of reservoir management, DA is used as a consistent means of evaluating different approaches and alternatives to determine the optimal scenario to maximize the net present value (NPV) of any project (Evans, 2000). Enhanced oil recovery (EOR) is an important phase in the field development planning process and is mainly applied whenever the primary and secondary recovery mechanism are not sufficient to displace the hydrocarbon from the remaining reserve. EOR methods include gas-flooding, polymer flooding, surfactant flooding, CO_2 flooding, and thermal flooding. However, EOR may not be applied to the process if it is not cost-effective. Therefore, a key decision in the development the planning process pertaining to the implementation of EOR methods is determining the best time to initiate an EOR process. With this method, oil companies can estimate the period for which the field will be economically profitable. However, since the initiation of EOR demands a high cost, it is important to assess

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its impact on the decision-making process. The value of information is a type of decision analytics that is suited to quantifying the value of prior information (Schlaifer, 1959). was the first to introduce and define the concept of VOI in the context of business decision-making. Since then, the VOI approach has appeared in several textbooks and references, e.g., (Raiffa and Schlaifer, 1961; Howard, 1966; Clement, 1991; Bratvold and Begg, 2010; Howard and Abbas, 2016). The first application of this concept in the oil and gas (O&G) industry was done by (Grayson, 1960). (Bratvold et al., 2009) presented an overview of the use of VOI analysis in the O&G industry. Recently (Eidsvik et al., 2016), and (Dutta et al., 2019) demonstrated a comprehensive application of this method in the domain of earth sciences and subsurface energy. In the O&G industry, two different approaches are used to include the impact of information: closed-loop reservoir management (CLRM) and sequential reservoir decision making (SRDM). These approaches serve as a priori analyses, and each technique is implemented before the collection of additional information. Thus, whenever additional data are gathered, both CLRM and SRDM can be readily applied to make use of those data. However, for a complicated decision-making problem with many uncertain outcomes, alternatives, and decision points, these approaches suffer from the "curse of dimensionality." For a more detailed description of SRDM and CLRM, see (Howard and Abbas, 2016; Bratvold et al., 2009; Barros et al., 2015; Hong et al., 2018).

In previous studies (Hong et al., 2018), illustrated a method for ADP, specifically the Least-Squares Monte Carlo (LSM) algorithm, which was proposed by (Longstaff and Schwartz, 2001). This algorithm can be implemented with a production model based on exponential declines to determine the optimal time to switch from one recovery phase to another. Theoretically, LSM implementation is independent of production models but still suffers from the curse of dimensionality in the action space, where the computational effort of LSM will increase exponentially with the number of both alternatives and decision points, according to (Powell, 2016) and (Hong et al., 2018). Apart from this (Alkhatib and Babaei, 2013), showed that LSM can be used in a homogenous reservoir model in the context of surfactant flooding.

Our approach in the current study is different from that of (Alkhatib and Babaei, 2013) and (Hong et al., 2018). Here, the objective is to do a VOI analysis of in the context initiating polymer flooding in reservoir development plan, where a decision problem is constructed where to determine the optimal time to switch from water flooding to polymer injection based on the information from production profiles and oil prices, and the switch happens only once. The analysis is done on a constructed case study involving both homogenous and heterogeneous reservoir model, Further, we use various machine learning regression approach that lies within the domain of ADP to directly estimate the conditional expected value given the data outcomes without approximating the posterior probabilities of reservoir properties. The ADP approach utilized here accounts for both the effect of the information of both production profiles and oil prices obtained before a decision is made and the effect of the information that might be obtained to support future decisions.

The paper is divided into multiple sections. In the following section, we provide a consistent basic concept and equation for VOI computation. Second, we propose a workflow of assessing VOI using machine learning methods and, following this, we test the proposed methodology by implementing it in an ensemble homogenous and heterogeneous reservoir model, where we perform fast analysis of the optimal EOR switch time using the proposed workflow. Fourth, we include oil price as uncertain economic parameter, and finally, some concluding remarks are added.

2. Value of information and decision making

The VOI in any information gathering activity depends on two fundamental uncertainties; (1) the uncertainties we hope to learn but cannot directly observe; which we call events of interests, and (2) the test results referred as the observable distinctions (Bratvold et al., 2009). In Reservoir management data gathered until time t which a decision will be made is the observable distinction, and future prediction production after time t is the events of interest. We denote the observable distinction as x, since x is very high dimension; it is difficult to represent the distribution of x in analytical form, we usually approximate the distribution of x by Monte Carlo sampling. Assuming a risk neutral decision maker, VOI is defined as:

$$VOI = \begin{bmatrix} \text{Expected value with} \\ \text{additional information} \end{bmatrix} - \begin{bmatrix} \text{Expected value without} \\ \text{additional information} \end{bmatrix}$$

In mathematical form, this is:

$$VOI = \{0, \Delta\} \tag{1}$$

$$\Delta = EVWII - EVWOI \tag{2}$$

The lower limit of VOI is always 0, since if Δ is negative when $EVWOI > EVWII$, the decision-maker can always choose not to gather information.

In a decision-making context, the decision without information (DWOI) is the alternative that optimizes the expected value (EV) over the prior value, and *EVWOI* is the optimal EV over the prior.

$$EVWOI = max_{a\in A}\left[\int v(x,a)p(x)dx\right] \approx max_{a\in A}\left[\frac{1}{b}\sum_{b=1}^{B} v\left(x^b,a\right)\right] \tag{3}$$

where a is the decision alternative from the a set of A, x is the distinctions of interests, $v(x, b)$ is the value function that assigns a value to each alternative outcome pair for a given x and realization b, and $p(x)$ is the prior probability distribution of x.

Similarly, if we have perfect information regarding the value of x that the distinction of interests would take, we would choose the optimal action for that value of x. The decision with imperfect information (DWII) is the alternative that optimizes the expected value over the posterior value:

$$EVWII = \int max_{a\in A}\Bigg[E(v(x,a)|y) \\ \times]p(y)dy \approx \frac{1}{B}\sum_{b=1}^{B} max_{a\in A}E\left[v(x,a)|y^b\right] \tag{4}$$

Where $p(y)$ is the marginal probability distribution over y.

Additionally, the decision with perfect information (DWPI) can also be determined in this decision-making context. For instance, in reservoir engineering, perfect information is the information that reveals the true reservoir properties and the impacts of the recovery mechanism. Taking the EOR initiation problem as an example, the EV With Perfect Information (EVWPI) is the maximum NPV for every path based on prior realizations or distributions. Then, averaging these NPVs over the paths would result in the *EVWPI*. In this way, every path would have an optimal decision with perfect information. The difference between *EVWPI* and *EVWOI* is the value of the perfect information (VOPI).

3. Value computation by ADP

We use an ADP method called the simulation-regression (or least-squares Monte Carlo) method to calculate the expected value with imperfect information. The simulation regression method involves Monte Carlo simulation and regression for (approximately) calculating the conditional expected value given data.

Monte Carlo simulation:

(1) Many possible realizations of state variables (x^b) such as porosity and permeability are generated using Monte Carlo simulation model.
(2) Forward modelling is performed to generate modeled (future) production data (y^b) from t_0 to t_{end}, with the addition of random noises generated from the statistics measurements errors to the modeled production data.
(3) For each decision alternative a, the $NPV(x^b, a)$ is calculated.
(4) The EVWOI is then calculated using the following equation: $EVWOI = \left[\frac{1}{b}\sum_{b=1}^{B} NPV\left(x^b, a^*_{DWOI}\right)\right] \; a^*_{DWOI} = argmax_{a\in A}\left[\frac{1}{b}\sum_{b=1}^{B} NPV\left(x^b, a\right)\right]$

where a^*_{DWOI} is the optimal decision without information and it is identical to each realization.

Backward induction:

(1) Starting recursively from the last decision point in time, in order to estimate the expected NPV (ENPV) with alternative a conditional on the modeled production data, $ENPV(x, a)|y$, we regress $[NPV_{1j}, NPV_{2j}, \ldots, NPV_B(x, a)]$ on the modeled production profiles. This procedure is repeated for each of the alternatives.
(2) The optimal decision is then determined by choosing the alternative that achieves the highest value of conditional ENPV given the known information.
(3) The EVWII is then as follows: $EVWII = \frac{1}{b}\sum_{b=1}^{B} NPV\left(x^b, a^*_{DWII}\left(y^b\right)\right) \; a^*_{DWII}\left(y^b\right) = arg\frac{1}{b}\sum_{b=1}^{B} max_{a\in A} E\left[NPV\left(x^b, a\right)\middle|y^b\right]$, where $a^*_{DWII}\left(y^b\right)$ is the optimal decision with given information y^b
(4) Finally, the VOI is given by $max\{0, EVWII - EVWOI\}$

The process of ADP is further detailed in Hong et al. (2018); Longstaff and Schwartz (2001).

Various methods (linear or non-linear) can be used for regression to calculate the conditional ENPV given data. In the next section, we will review the regression methods used in this study.

Machine learning algorithms (regression methods) are listed:

– **Least Squares Monte Carlo Methods (LSM)**, is a state-of-the-art dynamic programming approach used in financial engineering with real options initially proposed by (Longstaff and Schwartz, 2001). (Jafarizadeh and Bratvold, 2009) recommended the use of the LSM technique as a potential real option valuation technique for the oil industry (Willigers and Bratvold, 2009). explained how LSM simulation can handle more realistic valuation situations with multiple uncertain variables. One of the limitations of the LSM method is its high-dimensional space, through which the computational time can increase exponentially (Hong et al., 2018).

The mathematical depiction of the ordinary least square is the following:

$$y_n = \sum_{i=0}^{k} \beta_i x_{ni} + \epsilon \tag{5}$$

where x_i is the explanatory variable i.e. production profiles, and y is a dependent variable i.e. NPVs. The coefficient β minimizes the error prediction.

– **Partial Least square (PLS)**, is a regression technique that is frequently used for high-dimensional methods (Rosipal and Krämer, 2006 34–51). It takes into account the structures of both the explanatory variable and the dependent variable. This model is linear, as shown in Eq (5). However, β coefficients are found in a different way than with the ordinary least squares method. The principal of PLS regression involves data x and y, which are decomposed into their latent structures in an iterative process such that the covariance of the latent structure is maximized.
– **Principal Component Regression (PCR)**, reduces a large number of explanatory variables x_i in a regression model to a small number of principal components. PCR mainly differs from PLS in that the dependent variables in the former are regressed on the principal components of the data using linear regression Abdi (2010).
– **Neural Network (NN)**, often simply called multilayer perceptron MLP), is a nonlinear method for either classification or regression (Liu et al., 2019). The NN model consists of several layers, each containing a large number of neurons. Each neuron receives an input and provides a corresponding output through functional operations such as weight, bias, and transfer function (see Fig. 1). In mathematical form, the MLP parameters is given as follows:

$$\theta = (W_1, b_1, W_2, b_2, \ldots, W_L, b_L) \tag{6}$$

where W_i is a weight matrix and b_i is the corresponding bias vector of the $L - th$ neural layer. A function can then be given as follows:

$$y(x) = F(x|\theta) \tag{7}$$

For neurons, the standard form is given as:

$$z^l_i = \phi^l\left(\sum_j w^l_{ij} z^{l-1}_j + b^l\right) \tag{8}$$

Where z^l_i denote the value of the $i - th$ neuron in the $l - th$ layer; z^{l-1}_j is the $i - th$ neuron in the $(l - 1)$ layer; and $w^l_{ij} \in w_l, b^l_{ij} \in b_l$. When $l = 0$, $z^o = x$ the input explanatory variables i.e. production profiles, when $l = L, z^L = y$ is the network dependent output variable i.e. NPVs. z^l represents an intermediate variable. The function $\phi(.)$ represents the hidden node output, and is given as an activation function e.g. $Relu, \phi(x) = max(x, 0); Sigmoid, \phi(x) = \frac{1}{1+e^{-x}}$

– **Gaussian process regression (GPR)**, is a non-parametric Bayesian machine learning technique, used to model an unknown value function with the help of a Gaussian process (Rasmussen, 2004). A Gaussian process $V \sim GP(m, k)$, is completely specified by its mean function $m(x) = E[V(x)]$ and covariance function $\sim k(x, \acute{x}) = \frac{1\sqrt{2\pi\sigma^2}}{e}^{\frac{\|x-\acute{x}\|}{2}} 2\sigma^2$. GPR is a kernel-based which does not attempt to identify "best-fit" models of the data. Instead, GPR computes the posterior Gaussian process

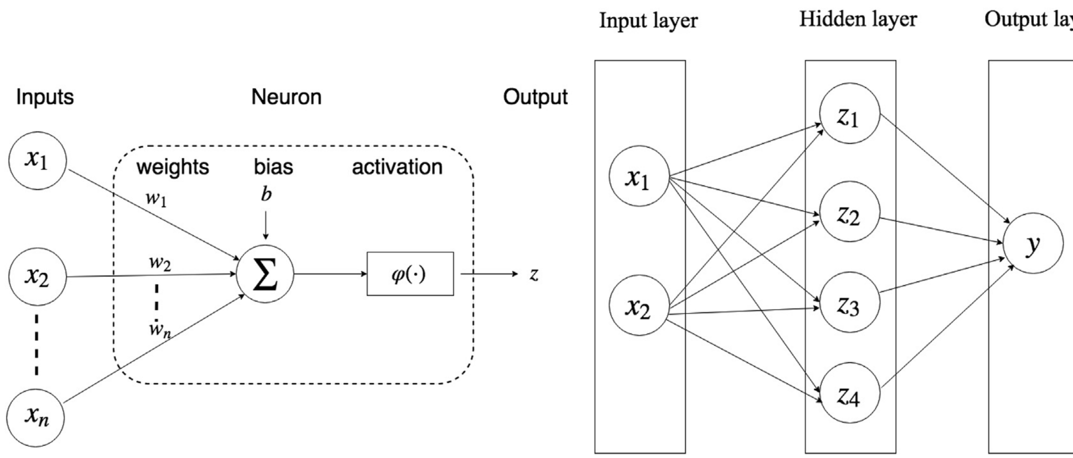

Fig. 1. Illustration of a neuron and multi-layer perceptron configuration (Liu et al., 2019).

by conditioning on the observed the values. In this study, we choose k to be the Gaussian radial basis function, $k(x,\acute{x}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{\|x\|}{22\sigma^2}}$ and assume that we observe $y = V(x) + \varepsilon$, where $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, ε is the gaussian noise …

– **Automated Machine Learning (Auto ML)**, in general, machine learning typically requires substantial human resources to determine a relevant pipeline (including various types of pre-processing and the choice of the regression method and hyperparameters). In response to this, various Auto ML techniques have been developed to build systems that can automate the process of designing and optimizing machine learning pipelines. In our study, we use an Auto ML technique called the Tree-Based Pipeline Optimization Tool (TPOT). TPOT was first proposed by (Olson and Moore, 2019). In short, TPOT optimizes machine learning pipelines using a stochastic search algorithm such as genetic programming.

4. VOI in polymer flooding recovery

In this section, we use two more realistic examples to illustrate how the methodology discussed in sections 2 and 3 can be applied to reservoir simulations and modeled to solve the EOR initiation time problem.

4.1. 2D reservoir model

Consider a simple 2D reservoir model with homogenous permeability and porosity fields. This model simulates the displacement of oil to the producer by two water-well injections. We used an ensemble of N = 500 realizations for the permeability. The top view of this reservoir model and the well position are shown in Fig. 2, and other important reservoir parameters and PVT properties are shown in Table 1.

Problem setting: For the problem setting of this example, a total period of 6 years of production time is supposed. We consider two recovery phases: water flooding and polymer. We will analyze the optimal time to switch from water flooding to polymer injection. This analysis will provide useful insights into the reservoir development plan, and the decision will affect the learning over time. After each year of production, the decision of whether or not to inject a polymer has to be made, but the switch happens only once. This indicates that there will be 5 different switch times and decisions to be made (see Table 2 and Fig. 3).

The oil and water production of 500 ensembles are modeled

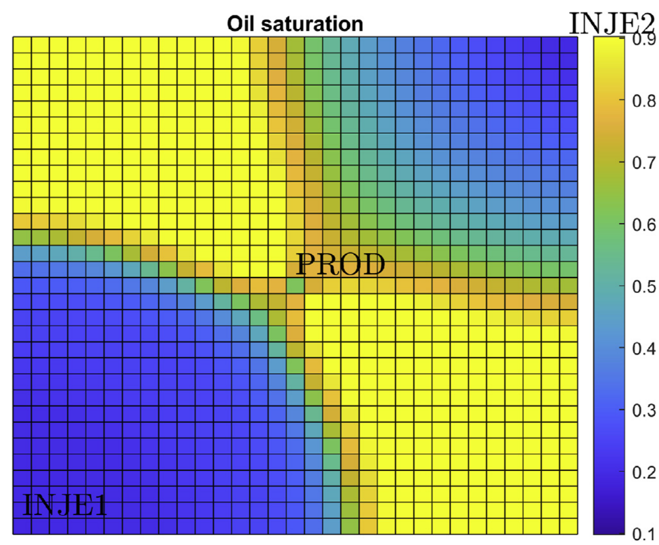

Fig. 2. The front view of the 2D reservoir model.

Table 1
Values of important reservoir parameters and PVT properties – the 2D reservoir model.

Water density, kg/m3	1080
Oil density, kg/m3	962
Water viscosity, pa.s	0.48×10^{-3}
Oil viscosity, pa.s	5×10^{-3}
Water compressibility, 1/bar	4.28×10^{-5}
Oil compressibility, 1/bar	6.65×10^{-5}
Initial reservoir pressure, bar	234
Porosity	0.3
Polymer Concentration INJECT 1, kg	4
Polymer Concentration INJECT 2, kg	1

using the reservoir simulation model and inform the decision-making. Thus, to obtain the measured rates, the measurement errors should be normally distributed with a mean of zero and a standard deviation of 10% of the modeled rates and then added to the modeled rates. Fig. 4 shows the oil and water production for all realization of some decision alternatives.

The value function is defined as the NPV for each decision alternative corresponding to each realization. NPV is a function of revenue from the oil production and costs for water production,

Table 2
Decision problem setting.

Injection period	6 years
Alternative	Continue or switch the injection at times {1, 2,3,4,5}
Uncertainty	permeability and porosity.
Value derived from the decision situation	Net present value
Information data	Oil and water production profiles

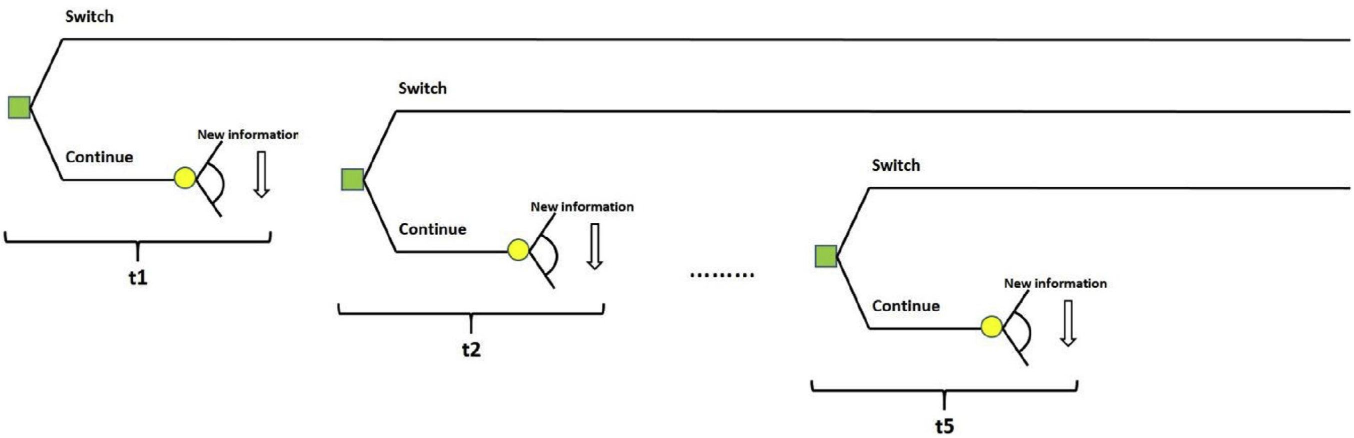

Fig. 3. Decision flow chart for Polymer flooding injection.

water injection, and polymer injection. The NPV is calculated using the following equation:

$$v\left(x^b,a\right)=\sum_{k=1}^{n_T}\frac{\left[q_0^k\left(x^b,a\right)P_0-q_{wp}^k\left(x^b,a\right)P_{wp}-q_{wi}^k\left(x^b,a\right)P_{wi}-q_{ci}^k\left(x^b,a\right)P_{ci}\right]t}{(1+r)^{t_k/\tau}} \quad (9)$$

Where k is the index of time step, n_T is total number of time steps,b realization of reservoir, q_0^k is the field oil production rate at time k, q_{wp}^k is the field water production rate at k, q_{wi}^k is the field water injection at time k, q_{ci}^k is the total polymer injection rate at time t_k; P_0, P_{wp}, P_{wi} and P_{ci}. The values of economic parameters used is also listed in Table 3.

Results: To compute the VOI of the polymer injection, we need to regress the NPVs on the simulated oil and water production profiles for each decision alternative. The various machine learning techniques discussed in section 3 are employed to perform the regression in this case. To prevent and reduce "the overfitting" in the machine learning training process, we use a 10-fold cross-validation (Crowley and Ghojogh, 2019Crowley and Ghojogh, 2019). Fig. 5 shows the box plots of squared logarithmic error regression loss (RMSLE),[1] for each decision alternative under each ML method and LS. GP, LS, PLS, and Auto-ML perform significantly better than PCR and NN. We measured the CPU running time for each ML method. The results show that GP, LR, PLR, and PCR required more-or-less the same time and were notably faster than NN, which required 8 min and approximately 3 h for Auto-ML.

The DWOI is to have the polymer injection finished by the end of first year, and the EVWOI is found to be $ 55.59 million. Moreover, the EVWPI is estimated to be $57.18 million. This makes the VOPI $1.59 million. The highest EVWII corresponding to the machine learning was obtained through the Auto-ML (see Table 4), which is $56.64 million. The respective VOI is $0.842 million. This result indicates that it is not economical to proceed with any information-gathering activity if the cost of the activity is more than $0.842 million. This result also illustrates that including the effect of future information and decisions could improve the EV by 1.73%, which is the percentage of the fraction of VOI to EVWOI.

The cumulative distribution functions (CDFs) of the NPVs associated with DWOI, DWII, and DWPI are plotted in Fig. 6. In this figure, the DWII moves the CDF of the NPV corresponding to the DWOI to the right. In this way, integrating the effects of future information and decisions into the decision-making process would increase the ENPV. Here, some realizations result in a smaller NPV with DWII than the NPV with DWOI since the recovery efficiency increment is very small or ML approach fails to find a near-optimal solution. Furthermore, the DWPI moves the curve of CDF even further to the right, as shown in Fig. 6. This occurs because the NPVs corresponding to the DWPI are always higher, which would lead to a higher ENPV than the values of DWII and DWOI.

The normalized frequency distribution (NFDs) of Waterflooding injection lifetime is illustrated in Fig. 7. Based on these results, it is more worthwhile to switch from water flooding to polymer at the end of year 1 (i.e., there is an 72.8% chance that the polymer recovery mechanism should be used starting at the end of the first

[1] https://www.rdocumentation.org/packages/corer/versions/0.2.0/topics/meansquaredlogerror

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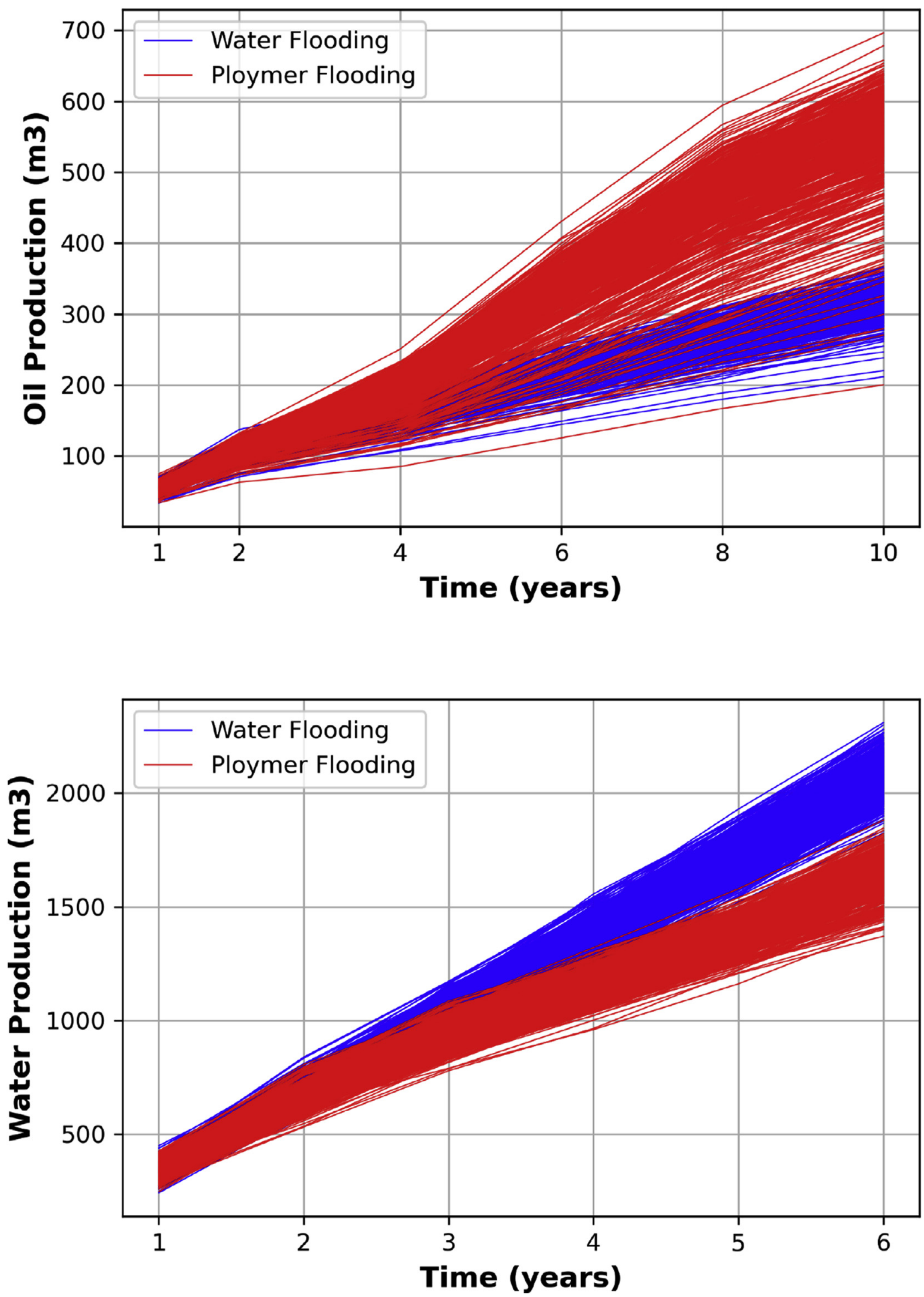

Fig. 4. Ensemble oil production and water production profile for the alternative “inject polymer flooding at the end of the first year” and for the alternative “inject water flooding”.

year). There is only a 23% chance that it is optimal to switch after 5 years and 4.6% after 4 years of water-flooding recovery. The specific switch time depends mainly on the simulated production and the uncertainty geological realization.

4.2. 3D reservoir model

Here, we consider a modified version of the standard Egg reservoir model, which is a 3D channel model (Jansen et al., 2014)

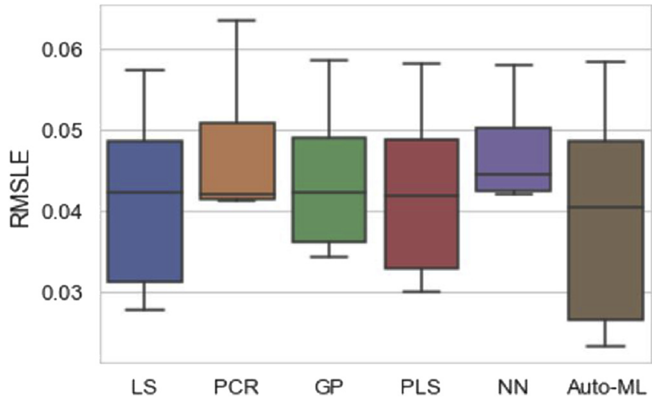

Fig. 5. Boxplot of RMSLE for the entire decision alternative.

Table 3
Values of economic parameters.

Parameter	Value	Unit
P_0	220	$\$/m^3$
P_{wp}	47.5	$\$/m^3$
P_{wi}	12.5	$\$/m^3$
P_{ci}	12	$\$/kg$
r	8%	–
τ	365	*days*
Δt	30	*days*

Table 4
VOI obtained by machine learning algorithms.

	VOI \$ million	**VOI/EVWII**
LR	0.523	0.94%
PLR	0.602	1.08%
Auto-ML	0.842	1.73%
GP	0.536	0.96%
PCR	0.559	1.01%
NN	0.369	0.66%

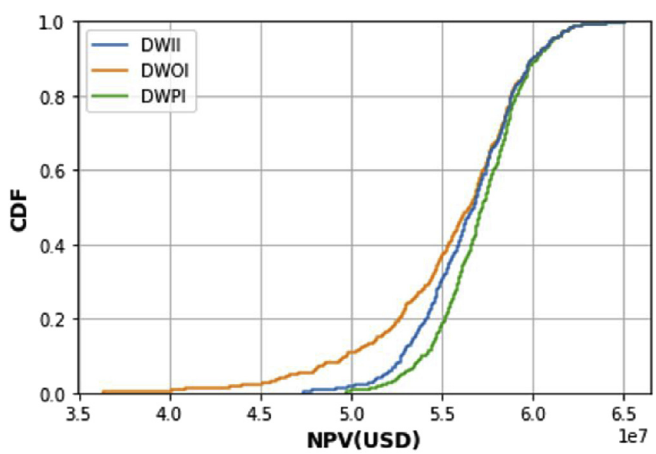

Fig. 6. CDFs of NPVs corresponding to DWOI, DWPI, and DWOII.

that contains 8 injection wells and 4 production wells. The model consists of 100 realizations of channelized reservoirs with 60 × 60 × 7 grid cells of which only 18,553 cells are active, thus producing the shape of an egg, as illustrated in Fig. 8.

The average reservoir pressure is set at 400 bar, and the initial

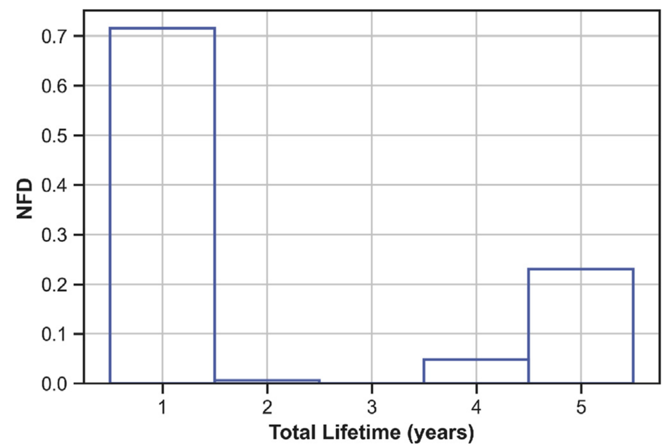

Fig. 7. NFDs of the polymer injection corresponding to decision with ML.

water saturation is considered uniform over the reservoir at a value of 0.1. The remaining geological and fluid properties used in this study are presented in Table 5. We modified the oil viscosity in the standard Egg model to make the reservoir a candidate to undergo polymer flooding.

Problem setting: The problem setting in this example is largely the same as that of the 2D reservoir model. Here, we consider a maximum life cycle of 10 years in total. We will analyze the optimal time to switch from water flooding to polymer injection after each year of production, but the switch happens only once. This indicates that there would be 9 different switch times and decisions to be made.

The oil and water production levels of 100 ensembles are modeled using the reservoir simulation model and inform the decision. Fig. 9 shows the oil and water production for all realizations (i.e., to inject polymer during the ninth year or to maintain the water-flooding recovery process for the whole life of the production cycle).

Results: For the Egg reservoir model, the DWOI involves injecting the polymer by the end of 9 years. The corresponding EVWOI is \$133.91 million, and the EVWPI is estimated to be \$136.7 million. Thus, the VOPI is \$2.79 million. The highest EVWII corresponding to machine learning was obtained by Auto-ML and provides an EVWII of \$135.92 million for information from oil and water production profiles. The related VOI is \$2.01 million. Therefore, the operator should not proceed with any information-gathering activity if the cost of the activity is more than \$2.01 million; further, the effects of future information and decisions would improve the EV by 1.5% (2.01/133.91).

Fig. 10 compares the CDFs corresponding to the different methods. Here, the NPV resulting from the ML approach (DWII) is higher than that of the DWOI, as ML allows learning over time. The DWPI moved the CDF curve further to the right, leading to higher ENPV than that of ML and DWOI.

Fig. 11 shows that for the optimal switch time to inject polymer flooding corresponding to the decision-making with ML, there is a 51% chance of initiating the EOR phase at the end of the year after 9 years, with 33% optimal chances of switching after 8 years, and 16% after 7 years of water-flooding recovery. The mean oil production rate (shown in Fig. 12) decreases significantly with a close similarity measurement, but after 7 years, the rate corresponding to DWII increases slightly, as the decision to switch is applied for some realizations.

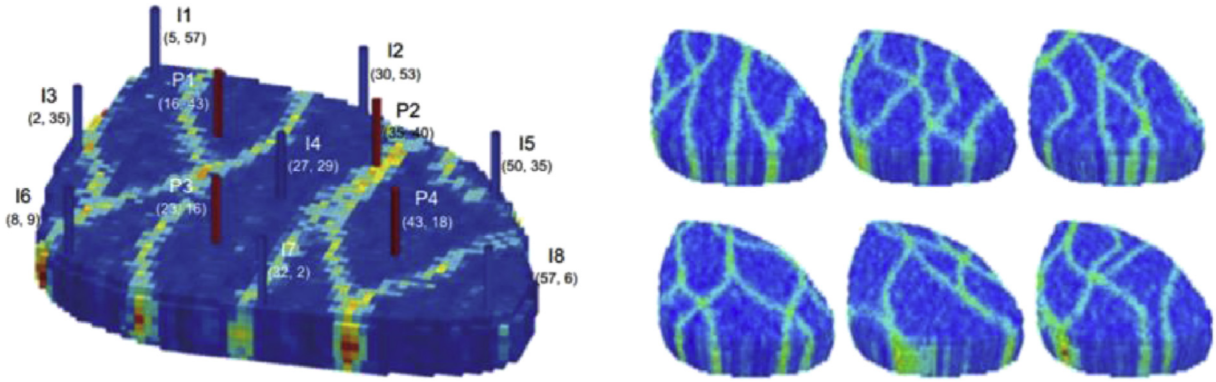

Fig. 8. (Left) Reservoir model displaying the position of the injectors (blue) and producers (red). (Right) Six randomly chosen realizations. (From (Jansen et al., 2014)).

Table 5
Reservoir parameters of Egg model.

Water density, kg/m3	1000
Oil density, kg/m3	900
Water viscosity, pa.s	10−3
Oil viscosity, pa.s	20 × 10-3
Water compressibility, 1/bar	10−5
Oil compressibility, 1/bar	10−5
Initial reservoir pressure, bar	400
Porosity	0.2
Polymer Concentration	2

4.3. Uncertainty in oil price

In both previous studies, we did not include uncertainties into the economic parameters even though they have a significant impact on the decision. Therefore, in this work, oil price is treated as an uncertain parameter and considered in the regression analysis for determining the optimal stopping time given a switch time in the EGG reservoir model. Uncertain economic variables must be modeled as Markovian processes and variants over time. Hence, we follow a stochastic process. There are two commonly used stochastic models for describing uncertainties in economic variables: the Geometric Brownian Motion (GBM; also known as the random-walk model) and the Ornstein–Uhlenbeck (OU) Stochastic Process (also known as the mean-reverting model; refer to Uhlenbeck and Ornstein (1930)for more details).

A process “S” can be stochastically modeled using the Ornstein-Uhlenbeck process as shown below:

$$dSt \ = \theta\ (\mu - S_t)dt + \sigma dW_t \tag{10}$$

where θ is the speed of mean reversion, μ is the long-term mean which the process reverts, σ is the measure of process volatility, and W_t stands for a Brownian motion, where $dW_t \sim N(0, \sqrt{d_t})$. To implement this stochastic equation in a simulation, it must be discretized. (Gillespie, 1996) noted that only when the discretized time, Δ_t, is sufficiently small, the simulation of the process work well. Thus, the discretized equation is shown below:

$$S_t = \left(S_{t-1} \times e^{-\theta\Delta t}\right) + \mu\left(1 - e^{-\theta\Delta t}\right) + \left[\sigma \times \sqrt{\frac{1 - e^{-2\theta\Delta t}}{2\theta}} \times dW_t\right] \tag{11}$$

However, if any commodity price, including oil prices or any other cost, is modeled using the above discrete time expression, negative values might be generated. This is not realistic, as negative commodity prices never exist. To avoid this problem, the lognormal distribution of the commodity price is used. Thus, in this context, the logarithm of the modeled parameter, namely $\pi_t = ln[St]$, is assumed to follow the mean-reverting process. This process can then be mathematically described as follows:

$$d\pi_t = \kappa[\bar{\pi} - \pi_t]d_t + \sigma\pi dz_t \tag{12}$$

where κ is the speed of mean reversion, $\bar{\pi}$ is the long-term mean to which the logarithm of the variable reverts, $\sigma\pi$ stands for the volatility of process, and dz_t describes the increments of standard Brownian motion. Subsequently, to numerically solve for π_t, the stochastic equation is discretized as shown below (by assuming $dz_t \sim (0, \sqrt{d_t})$, where $d_t = 1$ year).

$$\pi_t = \left(\pi_{t-1} \times e^{-\kappa\Delta t}\right) + \bar{\pi}\left(1 - e^{-\kappa\Delta t}\right)\Big] + \left(\sigma_\pi \times \sqrt{\frac{1\ -\ e^{-2\kappa\Delta t}}{2\theta}} \times N(0, 1)\right) \tag{13}$$

After calculating π_t, the value of S_t cannot directly be obtained using the equation of $S_t = e^{\pi t}$. This is because the mean of the lognormal distribution is added with half of the variance, namely $0.5 \times var(\pi_t)$, for the exponential of a normal distribution. Therefore, half of the variance is deducted using the equation below:

$$Var(\pi_t) \ = \left[1 - e^{-\kappa\Delta t}\right] \times \frac{{\sigma_\pi}^2}{2\kappa} \tag{14}$$

To use this model, a decision must be made to determine its parameters. This process is known as calibration, and since the logarithm of the variables is assumed to follow the mean-reverting process, least squares regression, which was suggested by (Smith, 2010), is conducted on the datasets of $\pi_t = ln[S_t]$. To calibrate the OU parameters for modeling the oil price, a set of oil price data is required. For illustration, we used the annual oil price data from the NYMEX future prices of 1985–2020 (considering only historical data) (EIA and U.E.I.A, 2019), as shown in Fig. 13. These data are available on the U.S. Energy Information Administration website.

To begin the procedure of calibration, the following equations are used:

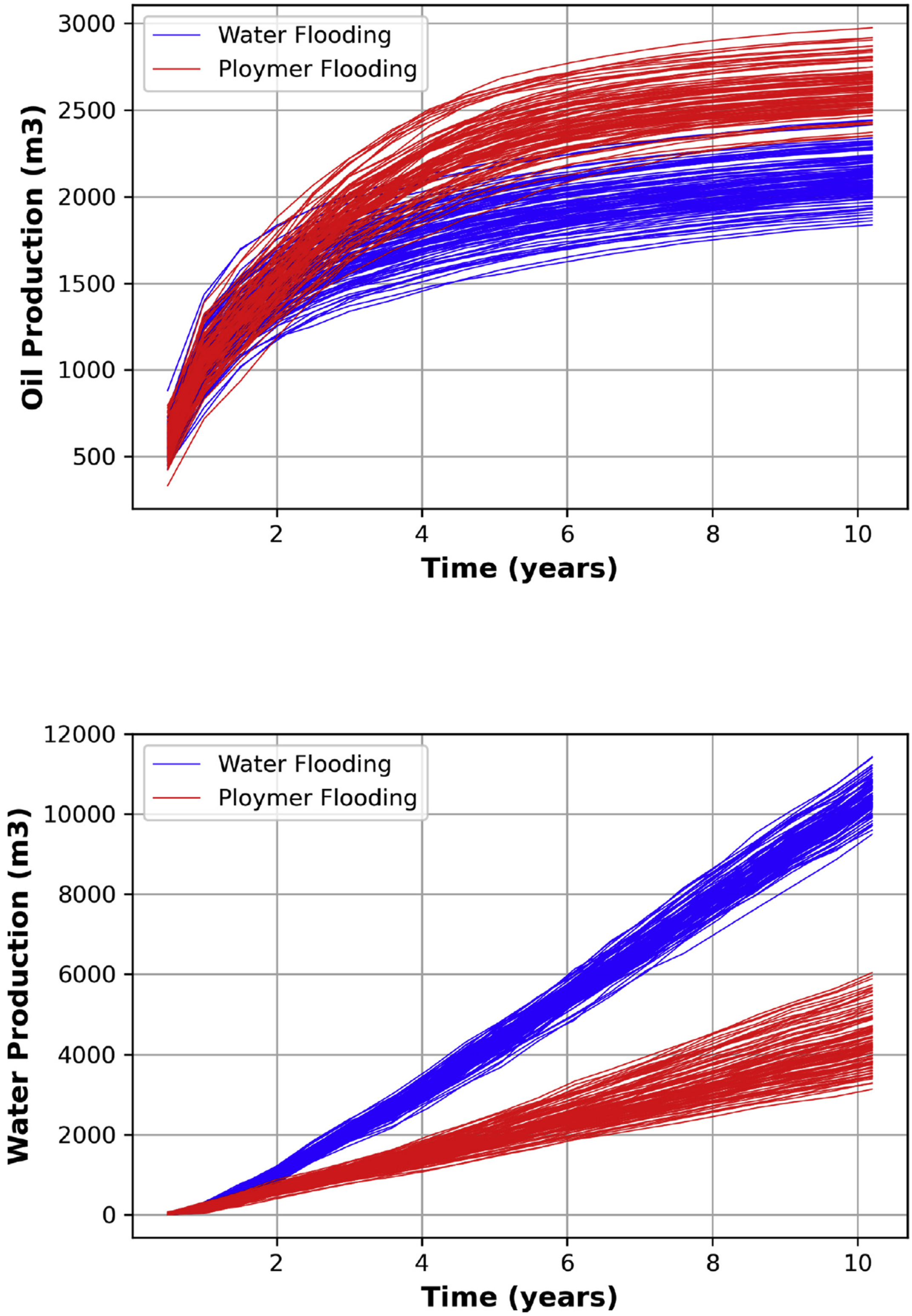

Fig. 9. The oil production and the water production profile for the realization of the alternative “inject polymer flooding at the end of the first year” and for the alternative “inject water flooding”.

$$x_t = \pi_t - \Delta_t = ln[Pt - \Delta_t] \quad (15)$$

$$y_t = \pi_t = ln[Pt] \quad (16)$$

$$y_t = ax_t + b + \delta] \quad (17)$$

The OU parameters are estimated using the values of a and b:

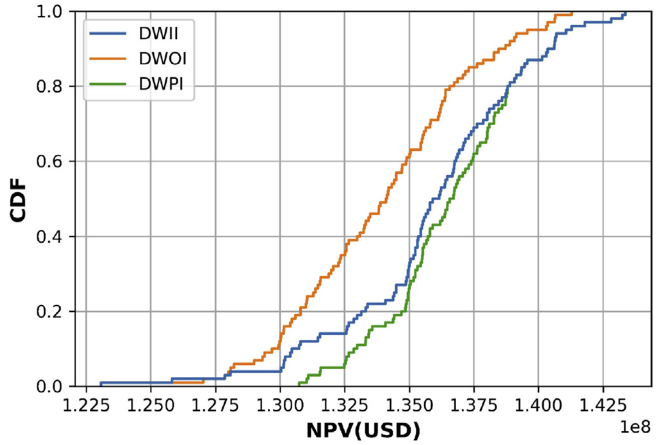

Fig. 10. CDFs of NPVs corresponding to DWOI, DWPI, and DWII.

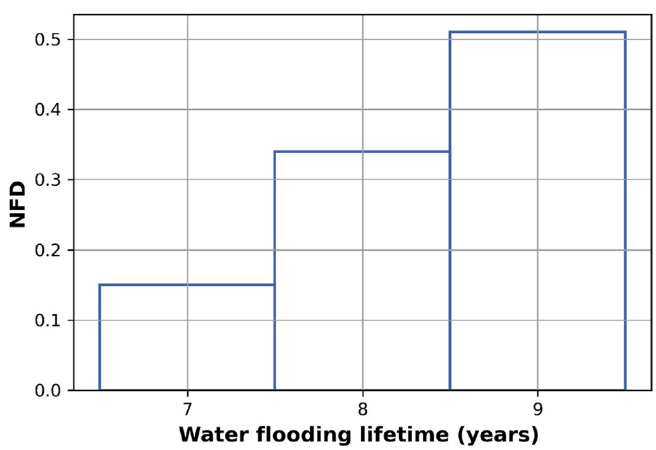

Fig. 11. NFDs of the polymer injection corresponding to the decision-making with ML.

$$\bar{\pi} = \frac{b}{1-a}, \ \kappa = \frac{-\ln a}{\Delta t}, \ \sigma_\pi = \sigma_\delta \sqrt{\frac{-2\ln a}{\Delta t(1-a^2)}} \tag{18}$$

where δ is the approximation error introduced in the least-squares

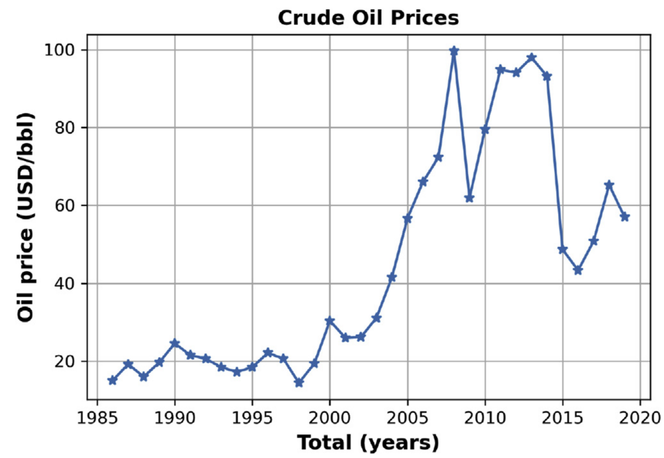

Fig. 13. Historical of annual oil prices from 1985 to 2020.

Table 6
Values of parameters used in the mean-reverting model.

Parameter	Oil price
Initial value	26.25
Equilibrium Value	26.25
Volatility σ_δ	0.2719
Mean reversion speed, κ	0.1165
$\boldsymbol{d_t}$, year	1

regression, σ_δ stands for the standard deviation of the approximation errors, and Δt is the difference in two time-steps. Refer to (Smith, 2010) for more details regarding the derivation of the equations.

Using the parameters in Table 6, the oil price corresponding to the respective costs is modeled forward in time. Fig. 14 presents the probabilistic model of the oil price.

Results: By adding the uncertain oil price to the previous results obtained in the egg reservoir model, the DWOI provides 9 years of water-flooding recovery and then one-year polymer recovery. This results in a total lifetime of 10 years. Thus, the EVWOI is found to be \$134.53 million. Moreover, the EVWPI is estimated to be \$137.98 million, which makes the VOPI \$3.46 million. The EVWII corresponding to the ML approach was obtained with through Auto-ML,

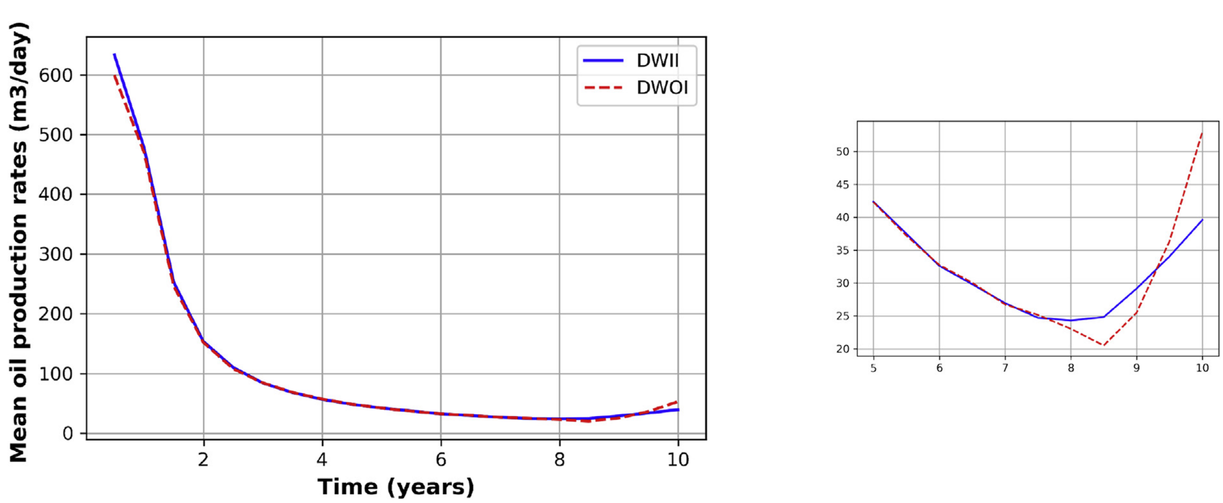

Fig. 12. Mean oil production rate corresponding to the DWOI and DWII. Left: Overview of the rate. Right: zoomed rate (last 5 years).

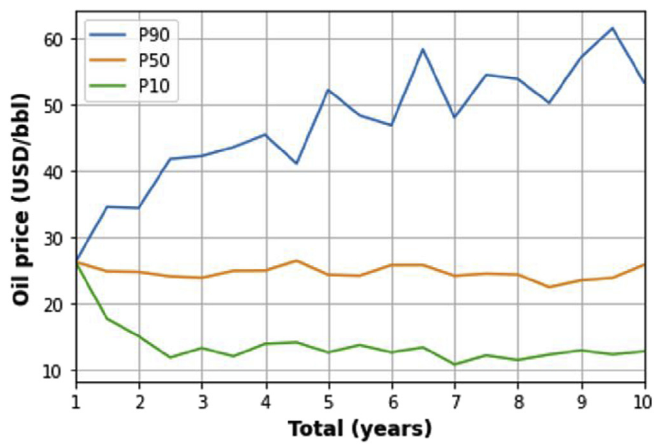

Fig. 14. Oil prices modeled using the mean-reverting process.

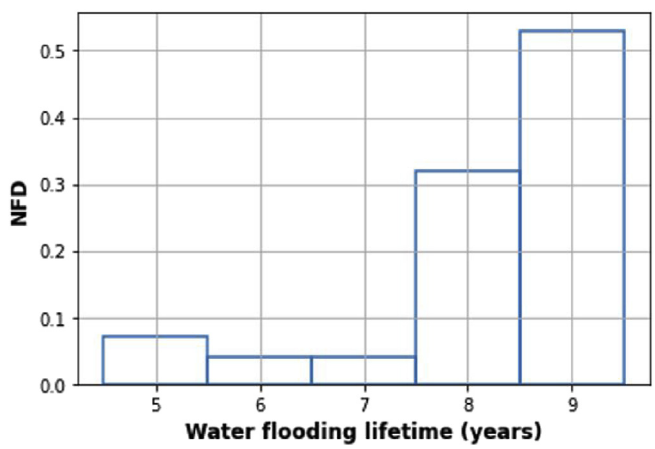

Fig. 15. NFDs of the polymer injection corresponding to the decision with ML.

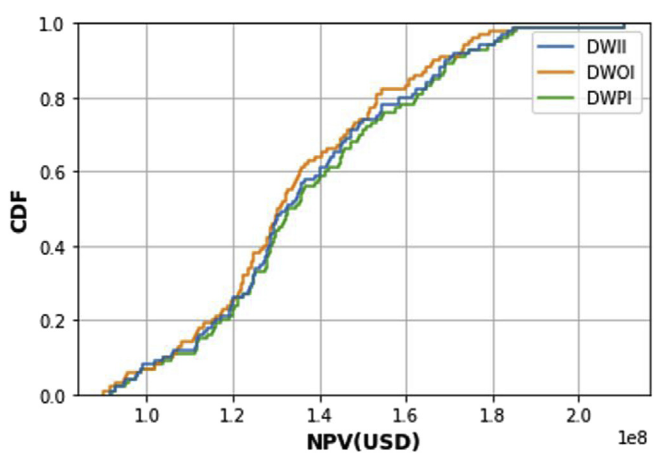

Fig. 16. Graph of CDFs against NPVs with respect to DWOI, DWII, and DWPI.

with an estimate of $136.04 million. This yields a special VOI of $ 1.52 million, which indicates that it is not economical to proceed with any information-gathering activity if the cost of the activity is more than $1.52 million. Moreover, this result also illustrates that including the effect of future information and decisions would improve the EV by 1.13%, which is the percentage of the fraction of VOI to EVWOI.

The NFDs of the total lifetime corresponding to the decisions with machine learning are displayed in Fig. 15. This result recommends switching from water flooding to polymer injection at the end of years 8 and 9 (i.e., there is a 53% chance that the polymer recovery mechanism should be started after year 9). There is only a 32% chance that will be optimal to switch after 8 years and 5% after both 6 and 7 years of water-flooding recovery. The specific switch time depends mainly on the measured production uncertainty of geological realization and oil prices.

Fig. 16 compares the CDFs of the NPVs associated with DWOI, DWII, and DWPI. Here, DWII approaches move the CDFs of the NPVs corresponding to the DWOI to the right (i.e., the ENPV increases), which allows for learning over time. Some realizations ultimately yield a smaller NPV with DWII than the NPV with the DWOI. This is possibly due to a suboptimal decision, as the machine learning algorithm is an approximate method that, for some of the path decisions, makes suboptimal choices. The DWPI further moves the CDF curve to the right, leading to a higher ENPV. This is obvious because when perfect information is available, all realizations will have a higher NPV.

5. Conclusions

In this paper, we demonstrated and described the usefulness of utilizing the concepts of decision analysis and value information to support the recovery phase in the field of oil development with limited computational resources. We applied some linear and nonlinear machine learning regressions to compute the VOI, which yielded comparable results and globally optimal solutions. The methodology could be adapted and applied to other fields such as energy storage and well-placement optimization.

However, the value of machine learning may be small and not very significant, as there is always an approximation error when applying the machine learning regression function. Moreover, how closely a regression function can estimate the actual expected values and the accuracy of this method also largely depend on a prior sample of Monte Carlo simulations, alternatives, and information; furthermore, in some cases, the model choice may not be material.

Therefore, we conclude that for solving the optimal EOR initiation time for both 2D and 3D channel reservoir models, the machine learning regression method can be used to approximate the value functions that appear in dynamic programming and can be considered a robust approach, as it includes and quantifies uncertainties in dynamic and state variables, including uncertainty in economic parameters, which are important to make good and insightful decisions. However, this method's computational effort is still subject to a finite and limited number of alternatives and decision points. Therefore, we believe that a new theory and methodology based on clustering techniques, in combination with proxy models, must be developed to reduce computational costs and reliably solve real-world sequential decision-making problems.

Author contributions

Amine wrote the paper and contributed to tuning the model and analyzing the results. Pr. Bratvold, Dr. Hong and Dr. Hanea supervised the work and providing continuous feedback.

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Nomenclature

2D/3D	Two Dimensional/Three Dimensional
ADP	Approximate Dynamic Programming
AutoML	Automated Machine Learning
CDF	Cumulative Density Function
CLRM	Closed Loop Reservoir Management
DWI	Decision with Additional Information
DWOI	Decision without Additional Information
DWPI	Decision with Perfect Information
ENPV	Expected NPV
EOR	Enhanced Oil Recovery
EV	Expected Value
EVWI	EV with Additional Information
EVWOI	EV without Additional
GPR	Gaussian process regression
LS	Least Squares
LSM	Least-Squares Monte Carlo
MCMC	Markov-Chain Monte Carlo
MCS	Monte Carlo Simulation
NFD	Normalized Frequency Distribution
NN	Neural Network
NPV	Net Present Value
PCR	Principal Component Regression
PLS	Partial Least square
RMSLE	Root Mean Squared Logarithmic Error
VOI	Value-of-Information
VOPI	Value-of-Perfect-Information

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