IJSRM
INTERNATIONAL JOURNAL OF SCIENCE AND RESEARCH METHODOLOGY
An Official Publication of Human Journals

Human Journals
Review Article
October 2020 Vol.:16, Issue:4

Selecting the Optimal Strategy for Oil Well Agent Injection for Enhanced Oil Recovery

IJSRM
INTERNATIONAL JOURNAL OF SCIENCE AND RESEARCH METHODOLOGY
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Submission: 23 September 2020
Accepted: 30 September 2020
Published: 30 October 2020

HUMAN JOURNALS

www.ijsrm.humanjournals.com

Keywords: Enhanced Oil Recovery; Life of a Reservoir; Hierarchy of EOR; Computer Simulations; State of Art

ABSTRACT

The application of enhanced oil recovery methods on oil fields increases recovery efficiency. Technological advances have made possible economical the additional recovery of identified reserves. For this reason, the planning should be considered as early as possible in the life of a reservoir. Since oil prices and demand for oil are growing up rapidly and on the other side declining oilfield productivity is taking place all experts highlight the need for improved and accelerated recovery. The Enhanced Oil Recovery technics are very complex but give best result if only we now from the beginning of the life of reservoirs the hierarchy of selecting the best set of these technics, some of them can be repeated more than one time. Besides the hierarchy, we must know the time period or interval these Enhanced Oil Recovered (EOR) technics must be applied and the duration of each of them. After the problem is conceptualized, we need to do the computer simulations to perform the right hierarchy selection procedure. It can happen that we have not chosen the right selection form the beginning or in some time of production may occur an unexpected problem. In these conditions we must be able to reallocate the problem again, in the actual conditions and run the simulations in computer again and again. There exists no mathematical algorithm to perform all these activities in space and time, so we have to choose the right one for our oil field that must be different for another oil field. So, it is a state of art to choose the proper hierarchy for a certain oil field.

INTRODUCTION

Until now, it is impossible to find a determined strategy or even a stochastic one that can maximize the profit or better to say the Net Present Value (NPV) over a full-time life of a reservoir while taking in consideration the Enhanced Oil Recovered (EOR) techniques. The main reason of this difficult task is the large amount of parameters of reservoir that most of them change continuously just under a single determined EOR, for example when we inject solvent or CO_2. Meanwhile, we don't know the time how long we will inject CO_2 and how the different parameters of reservoirs like permeability, porosity etc. will change with time. From the other side we don't know of which strategy to begin because are some of them to take in consideration; steam injection, CO_2 injection, polymer, surfactant, water injection, bacteria injection, solvents, etc. Another source of uncertainty that make more complicated the problem is the series of wells, the number of them, the positions of them etc. And lastly the NPV is under the terms of a stochastic parameter that is the discount factor. So, it is practically impossible to find a time series for the switching regimes to maximize the expected Net Present Value. There are several articles that address this problem, but to my knowledge, there is not a solution yet. We will try to give aspects, without pretending to find the optimal strategy definitely.

METHODOLOGY

This methodology is taken and reproduced in part from the first and second authors in references. Following **Creemers S [1]** a project can be seen as a graph *G= (V, E)*, where V = {1, …, n}is e set of nodes that represent project activities that in our examples are some of EOR processes, so we have *n* processes to be developed and $E = \{(i, j)|i, j \in V\}$ is a set of arcs that represent precedence relationships that in our case we suppose the process of injecting CO_2 has similarity with that of solvent injection. To start and the competition of a project are represented by dummy activities 1 and n, respectively. Each non-dummy activity $i: i \in V \ \{1, n\}$ has a random duration $\tilde{p}_i$ with expectation μ_i and variance σ_i^2. In addition, $\tilde{p} = \{\tilde{p}_2, \tilde{p}_3, \dots, \tilde{p}_{n-1}\}$ denotes the vector of random variables $\tilde{p}_i$ and $\tilde{p} = \{\tilde{p}_2, \tilde{p}_3, \dots, \tilde{p}_{n-1}\}$ is the vector of random variates (or realizations) of $\tilde{p}$ where p_i is a random variate of $\tilde{p}_i$. Because activities durations are uncertain because they depend of many geological, economical changes**,** activity starting times cannot be determined at the start of the project. Instead, they are determined during project execution using a policy.

Most of the literature on stochastic project scheduling adopts simple list policies that execute activities in the order of a list (see, e.g., Golenko-Ginzburg & Gonik, 1997; Tsai & Gemmill, 1998; Ballestn & Leus, 2009; Ashtiani *et al.*, 2011; Rostami *et al.*, 2017). In this article, on the other hand, we adopt elementary policies; a more general class of policies that allows decisions to be made at the start of the project and at the end of activities. so, we have a beginning time t=0 end an approximately expected end time t = T of the project for exploiting the oil field. A policy can be seen as a set of decision rules that define actions at decision times. Decision times are typically the start of the project and the completion times of activities. An action, on the other hand, corresponds to the abandonment of the project or the start/interruption of a set of activities. In addition, decisions have to respect the non-anticaptivity constraint (i.e., a decision at time t can only use information that has become available before/at time t and this is very important because we consider these like a Markov Chain). In other words, we are not interested how was the permeability or porosity t_{n-2} time ago but their values at time of the step t_{n-1} . When executing a policy, activity starting times become known gradually (i.e., a schedule is constructed as time progresses). As a result, a policy Π may be interpreted as a function that maps realizations of activity durations p to vectors of feasible starting times.

$$S(p,\Pi) = \{S_1(p,\Pi), S_2(p,\Pi), \ldots, S_n(p,\Pi)\}, where\ S_1(P,\Pi) = 0\ and\ S_n(p,\Pi) = \max_{i \epsilon V \setminus \{1,n\}} S_i(p,\Pi) + p_i.$$

Without loss of generality, we assume that a cash flow c_i is incurred at the start of activity i, where $c_1$represents the initial outlay, and c_n represents the project payoff_. We use continuous discounting to determine the eNPV of a cash ow c_i

$$v_i = E\left(c_i e^{-rS_i(p,\Pi)}\right), \qquad (1)$$

Where *r* is the discount rate, and *E (·)*is the expectation operator with respect to p. The eNPV of the project is:

$$v = \sum_{i \in V} v_i. \qquad (2)$$

The optimal policy selects activities such that *v* is maximized. The state of the system is represented by the set of finished activities (F). Upon entry of state (F):F $\neq$V, policy Π determines the set of ongoing activities $O\ (\Pi, F) \subseteq H(F)$.The optimal policy Π^*selects $O(\Pi^*, F)$ from H(F) such that G(Π^*, F) is, maximized, where G$(\Pi, F)$is the value function that returns the eNPV of the project upon entry of state (F) if polisy Π is adopted. Given a set of ongoing activities O, the time until the first completion of activity i: iϵ O is exponentially distributed with expected value $(\sum_{i \epsilon O} \lambda_i)^{-1}$. The probability that activity i: i ϵ O finished first equals $\lambda_i (\sum_{j \epsilon O} \lambda_j)^{-1}$. Therefore, if polisy Π is adopted, the eNPV of the project upon entry of state *(F)* equals:

$$G(II, F) = \frac{\sum_{j \epsilon O(\Pi, F)} \lambda_j}{r + \sum_{j \epsilon O(\Pi, F)} \lambda_j} \sum_{i \epsilon O(\Pi, F)} \frac{\lambda_i}{\sum_{j \epsilon O(\Pi, F)} \lambda_j} \left(G(\Pi, F \Cup \{i\}) + \sum_{j \epsilon O(\Pi, F \Cup \{i\}) \setminus O\{\Pi, F\}} c_j \right), \quad (3)$$

Where$\sum j \epsilon O(\Pi, F \cup \{i\}) \setminus O(\Pi, F)^{c_j}$ is the cash flow that incurred when starting activities for the first time upon entry of state $(F \cup \{i\})$. The optimal subset of ongoing activities is given by:

$$O(\Pi^*, F) = \underset{O \subseteq H(F)}{\arg min} \frac{\sum_{j \epsilon O} \lambda_j}{r + \sum_{j \epsilon O} \lambda_j} \sum_{i \epsilon O} \frac{\lambda_i}{\sum_{j \epsilon O} \lambda_j} \left(G(\Pi^*, F \cup \{i\}) + \sum_{j \epsilon O(\Pi^*, F \cup \{i\}) \setminus O} c_j \right). (4)$$

Finding the optimal set of ongoing activities requires us to enumerate all subsets of H(F). Note, however, that several heuristics may be devised in order to determine a \good" set of ongoing activities. Mathematically speaking, consider a production facility which can run the production in d,d$\geq 2, diffrent\ producion\ modes. Denote$ the set of available modes by $\mathcal{D} = \{1, \ldots, d\}$ and let $\mathcal{D}^{-i} = \{1, \ldots, i-1, i+1, \ldots, d\}$. Let $X = \{X_t\}_{t \geq 0}$ be a vector-valued Markovian stochastic process representing random factors that influence the profitability of the production, e.g., the market price of the underlying commodities, weather, and market demand of the produced goods. The process *X* may be a Brownian motion or some other more general stochastic process, possibly with jumps. Let the running payoff in production mode *i*, at time *t*, be

$f_i(X_t,t)$ and let $c_{i,j}(X_t,t)$ denote the cost of switching from mode I to mode j at time t. A management strategy is a combination of a non-decreasing sequence of stopping times $\{\mathcal{T}_k\}_{k\geq 0,}$ where, at time $\mathcal{T}_k$, the manager decides to switch the production from its current mode to another, and a sequence of indicators $\{\xi_k\}_{k\geq 0}$, taking values in D, indicating the mode to which the production is switched. For a strategy starting in mode *i* at time *t*, we have

$\tau_0 = t$ and $\xi_0 = i$. At τ_k the production is switched from mode ξ_{k-1} to ξ_k. A strategy $(\{\tau_k\}_{k\geq 0}, \{\xi_k\}_{k\geq 0})$ can be represented by the function $\mu\colon [0,T] \rightarrow \mathcal{D}$ defined as

$$\mu_s \equiv \mu(s) \sum_{k\geq 0} \xi_k \Pi_{[\tau_k,\tau_{k+1})}(s) \qquad (5)$$

and which indicates the current mode of the facility. Here, $\mathbb{I}_B(s)$ is the indicator function of the measurable set *B*, i.e., $\mathbb{I}_B(s)$ = 1 if $s \in B$ and 0 otherwise. We will from here on in alternate between the two notations for a strategy (and use them in combination) without further notice. When the production is run using a strategy μ, defined by $(\{\tau_k\}_{k\geq 0}, \{\xi_k\}_{k\geq 0})$, over a finite horizon [0, *T*], the total expected profit is

$$\mathbb{E}\left[\int_0^T f_{\mu s}(X_s,s)\,ds - \sum_{\substack{k\geq 1\\ \tau_k\leq T}} c_{\xi_k-1,\xi_k}\left(X_{\tau_k},\tau_k\right)\right] \qquad (6).$$

Similarly, given that the stochastic process X starts from x at time t, the profit made using strategy, over time horizon (t,T), is

$$J(x,t,\mu) := \mathbb{E}\left[\int_t^T f_{\mu s}(X_s,s)\,ds - \sum_{\substack{k\geq 1\\ \tau_k\leq T}} c_{\xi_{k-1},\xi_k}\left(X_{\tau_k},\tau_k\right) \middle| X_t = x\right]. \qquad (7)$$

The optimal switching problem now consists in finding the *value function*

$$v(x,t) = \sup_{\mu} J(x,t,\mu) \qquad , \qquad (8)$$

And an optimal management strategy μ^*, defined by $(\{\tau_k^*\}_{k\geq 0}, \{\xi_k^*\}_{k\geq 0})$,

such that

$$J(x, t, \mu^*) \geq J(x, t, \mu) \tag{9}$$

for any other strategy μ.

Clearly, the value and optimal strategy of an optimal switching problem depends on the set of available modes D, the (finite) time horizon T, the running payoff functions $\{f_i\}_{i\in\mathcal{D}}$, the switching costs $\{c_{i,j}\}_{i,j\in\mathcal{D}}$, and the dynamics of the underlying process X. We will suppress the dependence on D and T and refer to an optimal switching problem with the above parameters simply as $OSP(f_i, c_{i,j}, X)$.

There are today basically three different approaches available to tackle the optimal switching problem. Two of them are based on stochastic techniques, in particular Snell envelopes and backward stochastic differential equations, and one is of deterministic type, making use of variational inequalities/obstacle problems. In practice, the two approaches are often used in combination. The purpose of this section is to give a brief introduction of these solution techniques and indicate how they are interconnected. For future reference, this section also includes a very brief introduction to stochastic filtering.

Now let take some examples and find the right strategy in the complex EOR processes. In our case we take only 2 agents, polymer and water and see if both **NPV and eNPV** arrive their maximum at the same time for the strategy with polymer and water.

Objective functions: MAXIMIZING NPV AND eNPV

Create objective functions for the different systems. We set up approximate prices in USD for both the oil and the injection cost of the different phases. The polymer injection cost is per kg injected.

```
prices = {'OilPrice',            100 , ...
          'WaterProductionCost',   1  , ...
          'WaterInjectionCost',    0.1, ...
          'DiscountFactor',        0.1 };
```

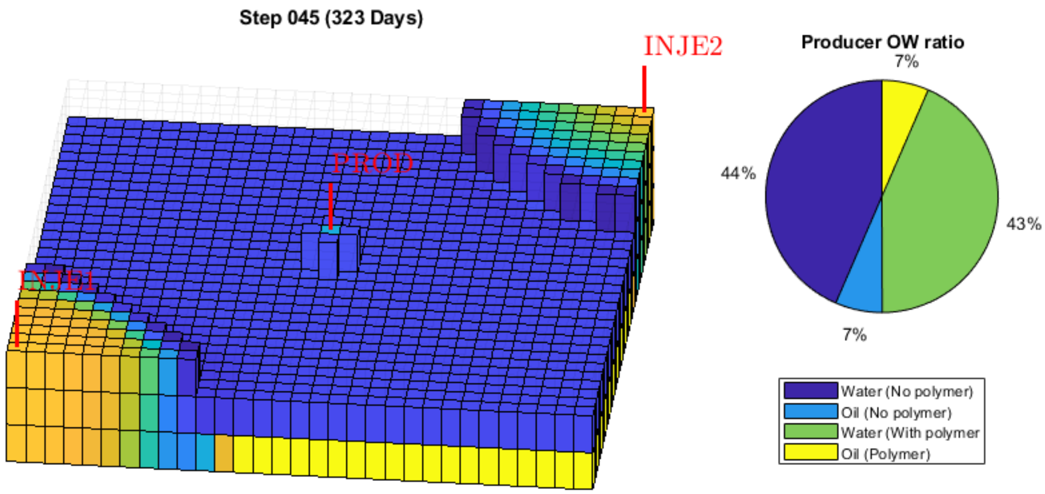

Figure No. 1: Graphical representation of oil with polymer and water of displacement front at time $t=t_1$

From above it is a combined strategy, first water and second polymer. It results to be an optimal strategy because Both NPV and eNPV result at their maximum.

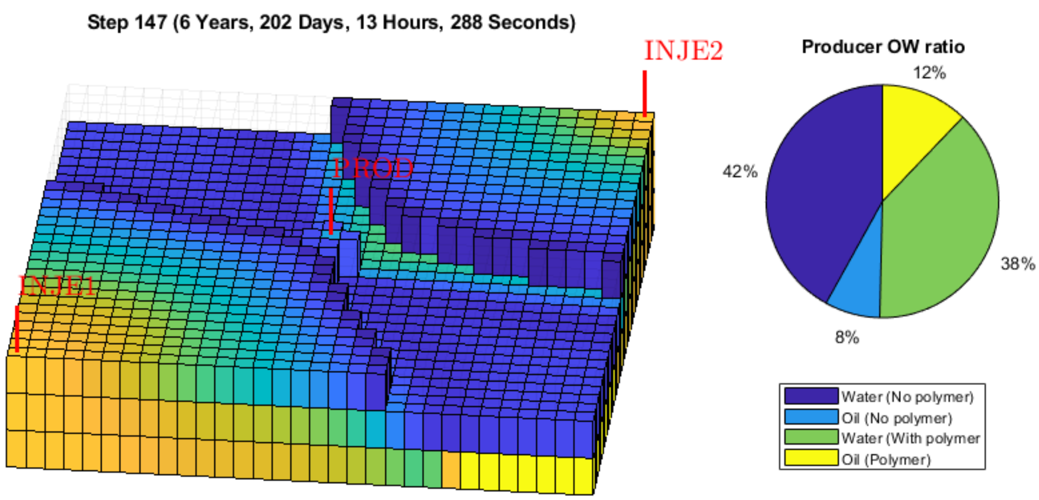

Figure No. 2: Graphical representation of oil with polymer and water of displacement front at time $t=t_2$

From above it is a combined strategy, first water and second polymer. It results to be an optimal strategy because both NPV and eNPV result at their maximum.

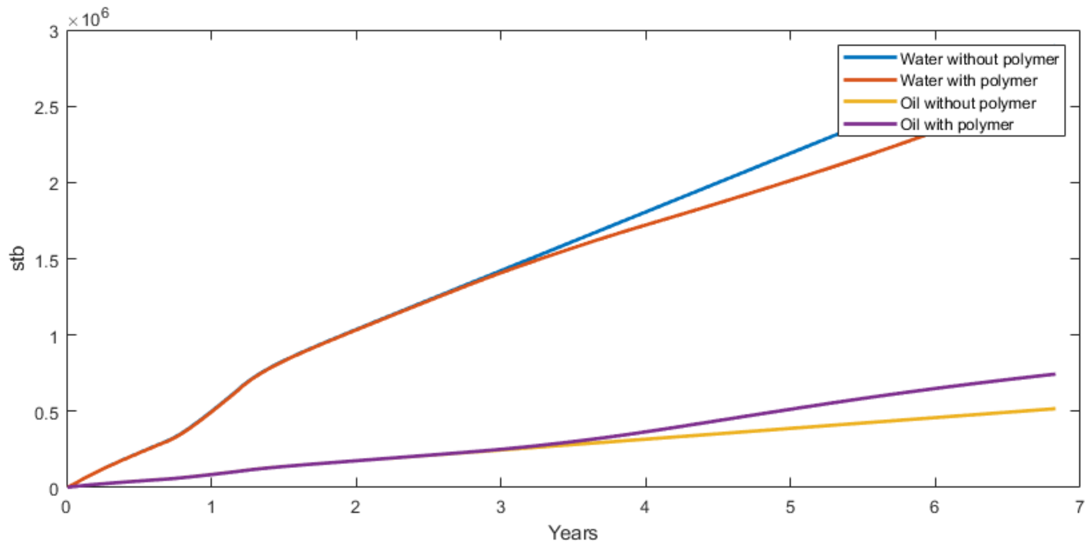

Figure No. 3: Production of oil in standard barrel per day with separated and combined strategy, both with the goal to maximize NPV and eNPV

CONCLUSION

Selecting the optimal strategy for oil well agent injection for enhanced oil recovery is not easy. Several books, articles exist in literature for different scenarios. We have made use of two books, reference 1 and 2 for finding an optimal strategy for both the simple but stochastic NPV (because of price of oil) and the expected eNPV for the hierarchy of injection of 2 agents, water and polymer. In our case, the best strategy is the combined one. Half of time to inject water and half of time to inject polymer. This strategy ensures too (see fig 3) that the production of oil is in time increasing. From the two lines below we see that oil with the polymer gives more satisfactory result. But this conclusion does mean that this is a universal, unified methodology. It is valid for our reservoir conditions. A lot of work has to be done to develop other strategies with more than two component and specially strategies when the processes can be repeatable in time.

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