Lifecycle Optimization of Unconventional Reservoirs

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Workflow for producing a subsurface fluid asset

Data Sources
- Drilling data
- Geological data
- Production data

Geocellular Modeling
- Visualize well logs, seismic, core analysis
- Segment to estimate Geo properties
- Geostatistical analysis to interpolate

Uncertainty analysis

Geocellular model

Reservoir History Matching
- Geomodel upscaling
- Sensitivity analysis
- Match HM objectives

History-matched simulation

Operational Strategies
- Resource allocation
- Capital planning
- Equipment management

Macroeconomic drivers
- Heuristic operational knowledge
- Optimization metrics
- Field constraints

Upscaling and Automation

Exploiting production data maximally

Model realism, tracking and matching is time-intensive process

Model run-time complexity

Capturing the geology accurately

Data sparsity, Multi-phase flow

Sustaining the optima

Quantifying uncertainty

Optimizing outcomes

Lifecycle optimization of unconventional reservoirs

Exploiting expert know-how optimally

Capturing well logs, seismic, core analysis
Introduction

Problem Statement
• Optimization methods for drilling, completing, and producing unconventional oil reservoirs are:
  • Expensive
  • Time-consuming
  • Computationally heavy

Objectives
1. Describe two simulation-based optimization methods
  • Design of Experiment
  • Intelligent Sequential Sampling
2. Compare results of methods based on
  • Value of optimized objective function
  • Computation time required
Lifecycle Optimization Methodology

Three-step process

1. Construct reservoir model
2. Validate it
3. Use it to compare the two optimization methods
   - Design of Experiment method
   - Intelligent Sequential Sampling method
Model Description and History Match

- 9000 ft by 10,700 ft by 44 ft
- Depth to top is 10,811 ft
- Two horizontal wells were hydraulically fractured

<table>
<thead>
<tr>
<th>Well</th>
<th>Number of Stages</th>
<th>Fracture Half Length (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16666</td>
<td>27</td>
<td>250</td>
</tr>
<tr>
<td>23699</td>
<td>30</td>
<td>1000</td>
</tr>
</tbody>
</table>

Reasonable HM obtained by tuning connectivity between natural and hydraulic fractures
Optimization Objective Function

Before tax, 5-yr undiscounted net present value ($NPV_0$)

- Assumptions
  - Oil and gas are revenue streams
    - $50/bbl$ oil
    - $2.50/Mscf$ gas
  - Costs include
    - Lease capital costs
    - Drilling costs
    - Completion costs
    - Operating costs
Optimization Parameters

Nine controllable parameters

• Three types
  • Drilling of wells
  • Characterization of hydraulic fracture
  • Way wells are produced
First Optimization Method: Design of Experiment

First, a few definitions

• **Sample**: a single simulation run

• **Experiment**: a predesigned series of samples

• **Transfer function**: an equation relating parameters and parameter interactions to the objective function

\[ Y = f(x_1, x_2, x_3, \ldots x_n) \]

\[ \text{NPV}_0 = f(\text{drilling, completion, production}) \]

\[ \hat{Y} = c_0 + c_1 A + c_2 B + c_3 AB \ldots \]
Design of Experiment (continued)

Transfer Function

\[ NPV_0 = -7783174 + 3380564(A) + 15404(B) + 10080(C) + 84.84(D) - 37.72(E) - 3973(F) + 56259(G) + 1532.2(H) + 13011.8(AB) - 9399.7(AC) - 464.75(AD) - 852.86(AE) + 1505.2(AF) + 157413(AG) - 1342.37(AH) \]

Optimization

- Optimize the parameters using Excel’s solver function

A = well density
B = Frac half length (ft)
C = # of frac stages
D = Well startup delay (D)
E = Initial FBHP (psia)
F = Final FBHP (psia)
G = FBHP step rate (D)
H = FBHP profile
Optimization Method 2: **Intelligent Sequential Sampling**

**Bayesian optimization**
- Next sample based on prior knowledge
- Uncertainty quantified by Gaussian distributions
- Acquisition function (AF) used to define next sample

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After Brochu, Cora, and Freitas (2010)
Intelligent Sequential Sampling Results

• First 10 samples were random
• Second 12 were for optimization of NPV₀
• After 22 total simulation runs, NPV₀ is near a maximum
Comparison of Optimization Methods

**Design of Experiments**
- 62 days of CPU time
- Result is slightly higher, but single value
- Learning takes place at end

**Intelligent Sequential Sampling**
- 6.6 days of CPU time
- Result is slightly lower, but several near-optimal choices
- Learning takes place during
Reservoir simulation is a time-intensive activity

- Hours or days for one simulation run
- Time-consuming to set up the simulation case
- Automation increases productivity by reducing engineer’s time
Automation, Optimization, and Machine Learning

Progress is being made with automatic history matching

- Design of experiments
  - Already implemented
  - Reduces engineer’s time
  - Does not reduce CPU time
  - Dumb automation

- Intelligent sampling
  - Smart automation
  - Reduces engineer’s time
  - Significantly reduces CPU time
Summary

• Demonstrated the intelligent sequential sampling approach for optimization
  • Applied it to lifecycle optimization of an unconventional resource drill spacing unit
• Compared it to optimization by experimental design
  • Shown that order-of-magnitude time savings can be achieved
• Discussed where machine-learning algorithms can be applied
  • History matching and lifecycle optimization

Take-away
• We are at the tip of the iceberg in implementing AI to the oil and gas industry
  • Exciting times!!