Geological Realism of Deep Water Channel Reservoir Models with Intelligent Priors

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Abstract

The automation of history matching makes very difficult for modellers to preserve the geological realism of reservoir models. Automation incurs a risk of generating reservoir models with unrealistic geometries based on ad-hoc combination of the model parameter (e.g. channels that are 1 m wide and 200 m thick). Moreover, computational effectiveness of history-matching decreases, as the search for optimum extends to a wider domain. Furthermore, the use of geologically unrealistic reservoir models could mislead the development plan for a specific reservoir.

Use of geological prior information in reservoir models provides a way to control relations between geomodel parameters to ensure their realism. Geological prior information is usually obtained from sources like outcrops, seismic data, or modern depositional environments. Geological prior models quantitatively describe the natural relations among the geo-parameters (e.g. channel width, thickness, sinuosity, etc).

Current practice of modelling sand bodies in deepwater channels is based on deterministic or two-dimensional geological priors, which establish relationships between only two parameters at a time.

In this work we propose to tackle the problem of preserving realism in automated history matching by building robust prior models that describe the non-linear multivariate dependencies between geological parameters of the deep water channelized system. We built multi-dimensional realistic priors using intelligent techniques, specifically One-Class Support Vector Machine. OC-SVM allows capturing hidden relations of the deep water channel parameters (Channel Width and Thickness, Meander Amplitude, and
Wavelength). Furthermore, it is possible to predict realistic parameter combinations, not observed in the available data; but still plausible in nature.

In automated history matching we sample from these realistic priors in order to assure geological realism. A Multiple Point Statistics (MPS) algorithm SNESIM is used to model facies in a deep water channelized reservoir. Variability of the channel geometries are produced by SNESIM algorithm using the affinity parameter, which alters the geometry compared to the training image. We developed a technique to link the MPS affinity parameter with the observed geological characteristics described by the intelligent priors used in history matching. History-matched models produced under geological realistic constraints reduce uncertainty of the production prediction.

Selected References


Website

Geological Realism of Deep Water Reservoir Models with Intelligent Priors

T. Rojas, V. Demyanov, M. Christie
and D. Arnold
Heriot-Watt University

AAPG-2012 ACE
Long Beach, April 22-25
Outline

• Introduction
• Geological Prior Information
• One Class-SVM
• Automatic History Matching
• Conclusions
Aims

• Highlight the use of geological prior information to ensure realistic geology.

• Build realistic Geological Prior Models for simulating deep marine channels.

• Include these prior models into the automated history match framework.

• Reduce uncertainty of reservoir models using intelligent prior information.
Automatic History Matching

- Structure
- Facies
- Lithology
- \( \Phi \)
- \( Sw \)
- Temperature
- Pressure
- Viscosity
- \( \rho \)

Multiple Reservoir Models → Flow Simulations

History Match

- NO
- YES

Uncertainty Quantification
Automatic History Matching

- Structure
- Facies
- Lithology
- \(K_v, K_h\)
- \(\Phi\)
- \(S_w\)
- Temperature
- Pressure
- Viscosity

Multiple Reservoir Models

Flow Simulations

History Match

NO

YES

History Matched Model

Uncertainty Quantification
Prior Probabilities

Prior probabilities are based on previous experience, and often used to predict outcomes before they actually happen.

Scheme for the application of the Bayesian framework

Sample from distribution → Generate multiple models → Compare production data & reservoir model → Evaluate misfit → Update probabilities using Bayes rule:

\[ p(m|O) = \frac{p(O|m)p(m)}{p(O)} \]

→ Forecast with uncertainty
Unrealistic Models

Unrealistic Facies Models

History Matched Models
Outline

• Introduction

• Geological Prior Information

• One Class-SVM

• Automatic History Matching

• Conclusions
Geological Parameters

- Amplitude ($A$)
- Wavelength ($L$)
- Thickness ($T$)
- Width ($w$)
Sources of Data for Modeling Priors

Outcrop Description

- Modified from Scholle (1999)

Geophysical Data

- Modified from Posamentier (2003)
Prior Information for Facies Geometry

Uniform Priors

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter a</td>
<td></td>
</tr>
<tr>
<td>Parameter b</td>
<td></td>
</tr>
</tbody>
</table>

Empirical Equations

Modified from Wonham et al., (2000)
Existing Knowledge

- Plausible Region
- Prior Information

657 Data-points

277 Data-points
Building Realistic Priors

- Multidimensional problem
- Avoid uniform ranges and linear regressions
- Predict between data points

Machine Learning Techniques

Capture non-linear multivariate relations

Environment
Medicine
Classification/Regression

Uncertainty Quantification
Outline

• Introduction
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One-Class Support Vector Machine

- Extension of SVM to handle training with only positive examples (“one-class” classification).

(Schölkopf et al., 1999)
OC-SVM Toy example

Parameters

S - SVM type

\( t \) - Kernel type

C - cost (SVR)

\( \eta \) - nu factor

\( g \) - gamma of the kernel function

Using libsvm from:
http://www.csie.ntu.edu.tw/~cjlin/libsvm/
OC-SVM Toy example

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OC-SVM in 4-D

657 Data points

Thickness
Wavelength
Width
Amplitude

Uncertainty Quantification
OC-SVM in 4-D Cloud
OC-SVM in 4-D Cloud
History Match Workflow

1. Static Model
2. Flow Simulation
3. History Match
4. History Matched Reservoir Model

PDF
Outline

• Introduction
• Geological Prior Information
• One Class-SVM
• Automatic History Matching
• Conclusions
Truth Case

Oil Reservoir

Deep Marine

<table>
<thead>
<tr>
<th>Facies</th>
<th>Poro (%)</th>
<th>Perm (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>20</td>
<td>500</td>
</tr>
<tr>
<td>Shale</td>
<td>0.001</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Grid Cells
80140x25
280000

Fluid Properties: Stanford VI
Castro et al., 2005
Facies Simulation

Multiple Point Statistics

Training Image

Conditioning:
Seismic attributes

Hard Data:
15 Wells
6 Producers
4 Injectors
5 Exploration

Width: 500 m
Thickness: 30 m
Amplitude: 1000 m
Wavelength: 2000 m
History Match Parameters

• **Misfit Definition**

\[ M = \sum_{t=1}^{T} \frac{(q_{obs} - q_{sim})^2}{2\sigma^2} \]

- \( \sigma \): 10% of the Truth case data
- 50 time-steps (600 days)
- 6 Producing wells
- WWCT, WOPR, WBHP

• **Sampling Algorithm Definition**

Particle Swarm Optimization

- 15 Particles
- 1116 Iterations
Misfit vs Iteration

Unrealistic Models
Facies Models

Model 132

Misfit: 238171
A: 1635 m
L: 921 m
W: 585
T: 41 m

Channel

Shale

Truth Case

A: 950 m
L: 1550 m
W: 400
T: 40 m

Model 1015

Misfit: 2498
A: 829 m
L: 1453 m
W: 565
T: 35 m
History Match

Total Oil Prod - Well P1

Total Oil Prod - Well P4

Total Oil Prod - Well P5

Oil Prod Rate - Well P1

Oil Prod Rate - Well P4

Oil Prod Rate - Well P5

Uncertainty Quantification
Analysis of the Generated Models

Truth Case
History Match using Uniform Priors

**Truth Case**
- **A**: 950 m
- **L**: 1550 m
- **W**: 400 m
- **T**: 40 m

**Model 918**
- **A**: 444 m
- **L**: 6948 m
- **W**: 1586 m
- **T**: 47 m

UNIFORM PRIORS
History Match using Uniform Priors

INTELLIGENT PRIORS

UNIFORM PRIORS

200000 STB

600000 STB
Conclusions

- Intelligent priors ensure realism of geological models.
- Reduce uncertainty in reservoir prediction.
- Reduce the number of models and computing time.
- Check for realism in geological models is essential, because unrealistic models may produce good history match as well.
Future work

• Generate intelligent prior models for:
  - other depositional environments
  - other geological properties
  - petrophysical properties

• Include improvements on continuity using MPS

• Include multiple training images
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Institute of Petroleum Engineering

The Institute of Petroleum Engineering (IPE) is a specialised centre in teaching, training and research with the largest PE research programme in the UK.

Thank you...
Back up
Probability Estimation

New Grid = OCSVM grid + Unrealistic points

OC-SVM

\[ P(x) = \frac{1}{1 + \exp(A x + B)} \]

\( x \): Decision Values obtained from oc-svm
Probability Estimation

\[ P(x) = \frac{1}{1 + \exp(A x + B)} \]
Facies Modelling

• Increase Geological Realism
• Potentially more complex patterns than those modelled by variogram.
• Incorporate realistic geological prior information.
• Easy incorporation of well and seismic data.

Multiple Point Statistics (MPS)
Channel Geometry in MPS

- Affinity parameters are difficult to interpret

Input DATA
- Well Data
- Seismic Data Trends

Affinity
- x: 2
- y: 1
- z: 1

Realization

Training Image
Channel Geometry in MPS
Geological vs Model Algorithm Parameters

Realistic Geological Parameters
- Width
- Thickness
- Wavelength
- Amplitude

ANN

Affinity Combination

x y z

MPS
SNESIM