Fast-Track and Robust Reservoir Modeling Using Probabilistic Neural Network*

Islam A. Mohamed¹ and Basem K. Abd El-Fattah¹

Search and Discovery Article #42205 (2018)**
Posted May 14, 2018

*Adapted from oral presentation given at the GEO 2018 13th Middle East Geosciences Conference and Exhibition, March 5-8, 2018, Manama, Bahrain
**Datapages © 2018. Serial rights given by author. For all other rights contact author directly.

¹Rashpetco, Cairo, Egypt (isoo_27@hotmail.com)

Abstract

In highly heterogeneous basins with complex subsurface geology, as the Nile Delta basin, the accurate prediction of reservoir characteristics is a must. The reservoir characterization is a continuous process that begins with the field discovery and ends with the last phases of production and abandonment. Reservoir static modeling is the final step in the reservoir characterization process and consists of building an upscaled geologic model to be an input to the fluid simulations. The geostatistical reservoir modeling (stochastic modeling) methods are widely used instead of the traditional deterministic modeling methods to consider the spatial statistics and uncertainties. However, the modeling workflows are slow, requiring months from initial model concept to flow simulation or other outputs; Moreover, the early stages errors become cumulative and are difficult to retrospectively change. The neural network inversion gained popularity over the last decades for its ability to establish nonlinear relationships between the petrophysical logs and seismic data. It has been used to predict various reservoir properties with a reasonable amount of accuracy. Its main limitation resides at seismic resolution, and to overcome this problem a resolution-enhancing workflow has been adopted. This case study is from a Pliocene turbidite field in the offshore Nile Delta to illustrate the proposed modeling workflow. As a beginning, the resolution enhancement of seismic data is accomplished using derivative attributes and structural smoothing. Then, after proper well-log data conditioning, the training and cross-validation of Probabilistic Neural Network (PNN) are performed to produce shale volume (Vsh), porosity (φ), and water saturation (Sw) 3D volumes. The permeability (k) is calculated from poro-perm relationship inside the reservoir. The results are then sampled in 3D grids and tested using dynamic simulation method to assimilate production history. After the initial history match process, PNN parameters are adjusted to improve the match. The final model represents the best match to original field measurements and production data, which is then used in drilling decisions and production planning. The proposed neural network workflow reduces the reservoir modeling construction time by 80-90%, mitigates the cumulative error problems, and decreases the statistical uncertainty as it depends purely on seismic data to distribute the reservoir properties.

References Cited

Cross, N.E., A. Cunningham, R.J. Cook, A. Taha, E. Esmaiel, and N. El Swidan, 2009, 3-D Seismic Geomorphology of a Deepwater Slope Channel System: The Sequoia Field, Offshore West Nile Delta, Egypt: Search and Discovery Article 20078, Web Accessed April 29, 2018,


Fast-Track and Robust Reservoir Modeling Using Probabilistic Neural Network

Islam A. Mohamed and Basem K. Abd El-Fattah
Contents

- Introduction
- Methodology
  - Data Conditioning
  - Probabilistic Neural Network
  - Static Modeling
  - Dynamic Testing
- Conclusion
Area of Study

• Location
  – Egypt, Offshore Nile Delta, West Delta Deep Marine (WDDM) concession

• Sequoia field
  – One of the biggest Pliocene gas fields

(modified from Mohamed et al., 2014 and Samuel et al., 2003)
WDDM Major tectonic features

- Rotated Fault Blocks
- Rosetta Fault
- Nile Delta Offshore Anticline (NDOA)/Fault

Cross-section modified after Aal et al., 2006
Pliocene reservoirs draped across tectonic elements
Large-Scale Reservoir Architecture

An arbitrary line through Sequoia channel complex

(modified from Cross et al., 2009)
Sequoia Channel Evolution Summary

*Ibn Sequoia*
Sequoia channel abandonment and minor sheet sands

*Stage III*
Narrower and straighter channels and splays

*Stage II*
High sinuosity channel and associated splays

*Stage I*
Braided, poorly confined channel deposition

(modified from Mohamed et al., 2017)
**Ibn Sequoia**
Sequoia channel abandonment and minor sheet sands

**Stage III**
Narrower and straighter channels and splays

**Stage II**
High sinuosity channel and associated splays

**Stage I**
Braided, poorly confined channel deposition

(modified from Mohamed et al., 2017)
Ibn Sequoia
Sequoia channel abandonment and minor sheet sands

Stage III
Narrower and straighter channels and splays

Stage II
High sinuosity channel and associated splays

Stage I
Braided, poorly confined channel deposition

(modified from Mohamed et al., 2017)
**Ibn Sequoia**
Sequoia channel abandonment and minor sheet sands

**Stage III**
Numerous small channals and splays

**Stage II**
High sinuosity channel and associated splays

**Stage I**
Braided, poorly confined channel deposition

(modified from Mohamed et al., 2017)
Sequoia Field – Reservoir Characteristics

- Multiple stacked channels that are up to 200 m in gross thickness, 77 m of pay
- An average effective porosity of 24%
- An average water saturation of 34%
Contents

• Introduction

• Methodology
  – Data Conditioning
  – Probabilistic Neural Network
  – Static Modeling
  – Dynamic Testing

• Conclusion
Seismic Resolution Enhancement – Band-Pass Filtering

Band-pass filter frequency range (Hz): 0 / 30 / 120 / 130
Well Log Conditioning

Conditioning:
- Resampling @ 4 ms
- Smoothing
Contents

• Introduction

• Methodology
  – Data Conditioning
  – Probabilistic Neural Network
  – Static Modeling
  – Dynamic Testing

• Conclusion
Probabilistic Neural Network

Inversion Volumes ($I_p, I_s, \rho, V_p, V_s, V_p/V_s, \lambda \rho & \mu \rho$)

Full-Stack Seismic Volume

Shale-Volume Logs ($V_{sh}$)

Porosity Logs ($\phi$)

Water Saturation Logs ($S_w$)

Neural Network

Internal & external attributes

Minimize the error

Training & validation

Shale-Volume ($V_{sh}$)

Porosity ($\phi$)

Water Saturation ($S_w$)
PNN Results – Water Saturation

Water Saturation section ($S_w$) through Sequoia D5 well (Blind Test)

Water Saturation section ($S_w$) through Rosetta 10 well
PNN Results – Porosity

Porosity section ($\phi$) through Sequoia D5 well (Blind Test)

Porosity section ($\phi$) through Rosetta 10 well
PNN Results – Shale Volume

Shale volume section ($V_{sh}$) through Sequoia D5 well (Blind Test)

Shale volume section ($V_{sh}$) through Rosetta 10 well

100 m

400 m

1 0

Shale Volume

4 Km

Shale Volume

Variance
Contents

• Introduction
• Methodology
  – Data Conditioning
  – Probabilistic Neural Network
  – Static Modeling
  – Dynamic Testing
• Conclusion
Stochastic Reservoir Modeling Workflow

- Stochastic reservoir modeling
  - Consider the spatial statistics and uncertainties.
  - Require months from initial model concept to flow simulation.
  - Early stages errors become cumulative and are difficult to retrospectively change.
The Proposed Workflow

- Decreases the statistical uncertainty.
- Reduces the reservoir modeling construction time by 80%.
- Mitigates the cumulative error problems.
Static Modeling

- Structure model:
  - Structural framework method
- Cell size:
  - 100m*100m using proportional layering (1.5m Average cell thickness)
Porosity and Water Saturation Resampling

<table>
<thead>
<tr>
<th>Property</th>
<th>resampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity</td>
<td>Arithmetic</td>
</tr>
<tr>
<td>Saturation</td>
<td>Arithmetic</td>
</tr>
</tbody>
</table>
Porosity-Permeability Relationship

Permeability is calculated from the porosity using a polynomial equation.

Permeability is calculated from the porosity using a polynomial equation.
Contents

• Introduction
• Methodology
  – Data Conditioning
  – Probabilistic Neural Network
  – Static Modeling
  – Dynamic Testing
• Conclusion
Dynamic Testing

Dynamic simulation results at the blind well (Sequoia D5)
Dynamic simulation results at the blind well (Sequoia D5), additional multiplier is applied for the pore volume (adding 20%)
Contents

• Introduction

• Methodology
  – Data Conditioning
  – Probabilistic Neural Network
  – Static Modeling
  – Dynamic Testing

• Conclusion
Conclusion

• Probabilistic neural network predicts shale volume, porosity, and water saturation 3-D volumes
  – Fast training process
  – Results show high accuracy
• Integrating the PNN in the static modelling
  – Decreases the statistical uncertainty and mitigates the cumulative error problems
  – Reduces the reservoir modeling time by about 80%
• Some details may be lost during the resampling process
  – Finer grid is required or multi-segment model
  – Apply multipliers
Acknowledgement

Rashid Petroleum Company (RASHPETCO) and Egyptian General Petroleum Corporation (EGPC) are acknowledged for granting permission to publish this work.

THANKS
References


