OOIP Estimates as a Function of Cumulative Production: A Case Study from the Simulation History Match of the N'Sano Pinda Reservoir, Block 0, Angola*

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Abstract

Estimation of Original Oil-In-Place (OOIP) has traditionally been done using deterministic methods. The estimates improve as dynamic data is gathered through pressure and production and incorporated via material balance or simulation models until field abandonment when little uncertainty remains. Probabilistic methods that use static subsurface uncertainties to provide an OOIP distribution have increased in use in recent years. This paper compares a static OOIP distribution to a set of dynamic OOIP distributions taken from a simulation model history match (HM). The static OOIP distribution is narrowed as a function of percent of hydrocarbon pore volumes (%HCPV) processed. Implications of this work can be used to predict the cumulative volumes (or time, depending on reservoir processing rate) required to significantly reduce a static OOIP distribution.

A technique is shown where reservoir simulation is used to probabilistically analyze HM field data. Static and dynamic uncertainties are used in an experimental design (ED)-assisted HM process. The process uses the folded Plackett-Burman (FPB) ED to generate proxies that represent the quality of the HM. The proxies are used in conjunction with Monte-Carlo (MC) simulation and filters to improve the overall HM and consequently narrow uncertainties. The outcome is a newly defined distribution of static and dynamic subsurface uncertainties. By using these new distributions in a subsequent ED-assisted HM, the process can be conducted in cycles; each successive cycle narrowing or shifting the uncertainty distributions for the next.

OOIP Estimates as a Function of Cumulative Production:

A Case Study from the Simulation History Match of the N'Sano Pinda Reservoir, Block 0, Angola

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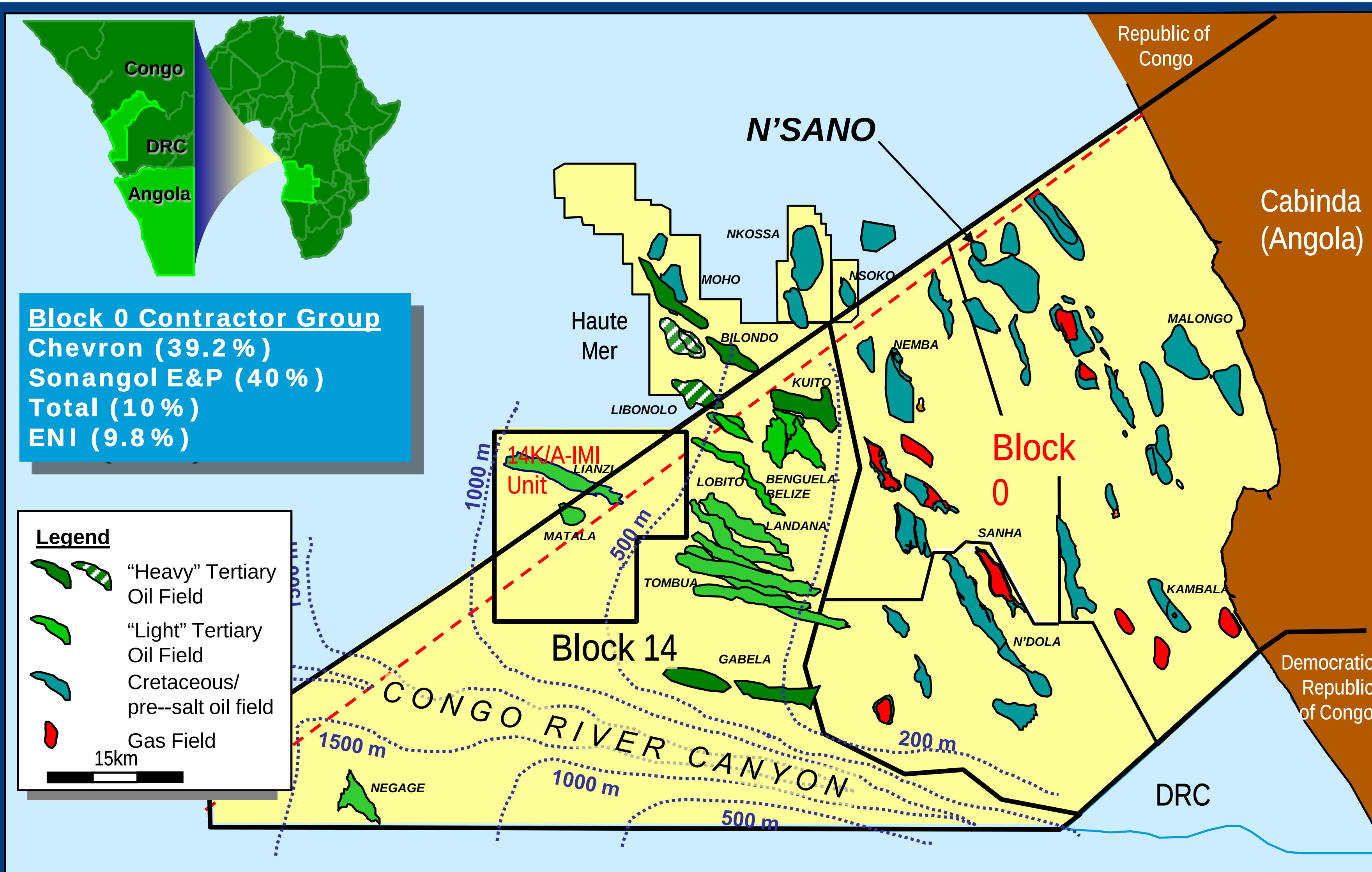
2008 AAPG International Conference & Exhibition – Cape Town, South Africa

Presentation Outline

- Regional Background Information
- Problem Statement
- Conceptual Overview
- ED-Assisted History Matching
- Summary of Results & Implications
- Lessons Learned
- Acknowledgements

Offshore Cabinda Oilfields & Licenses



Block 0 Contractor Group

Chevron (39.2%)

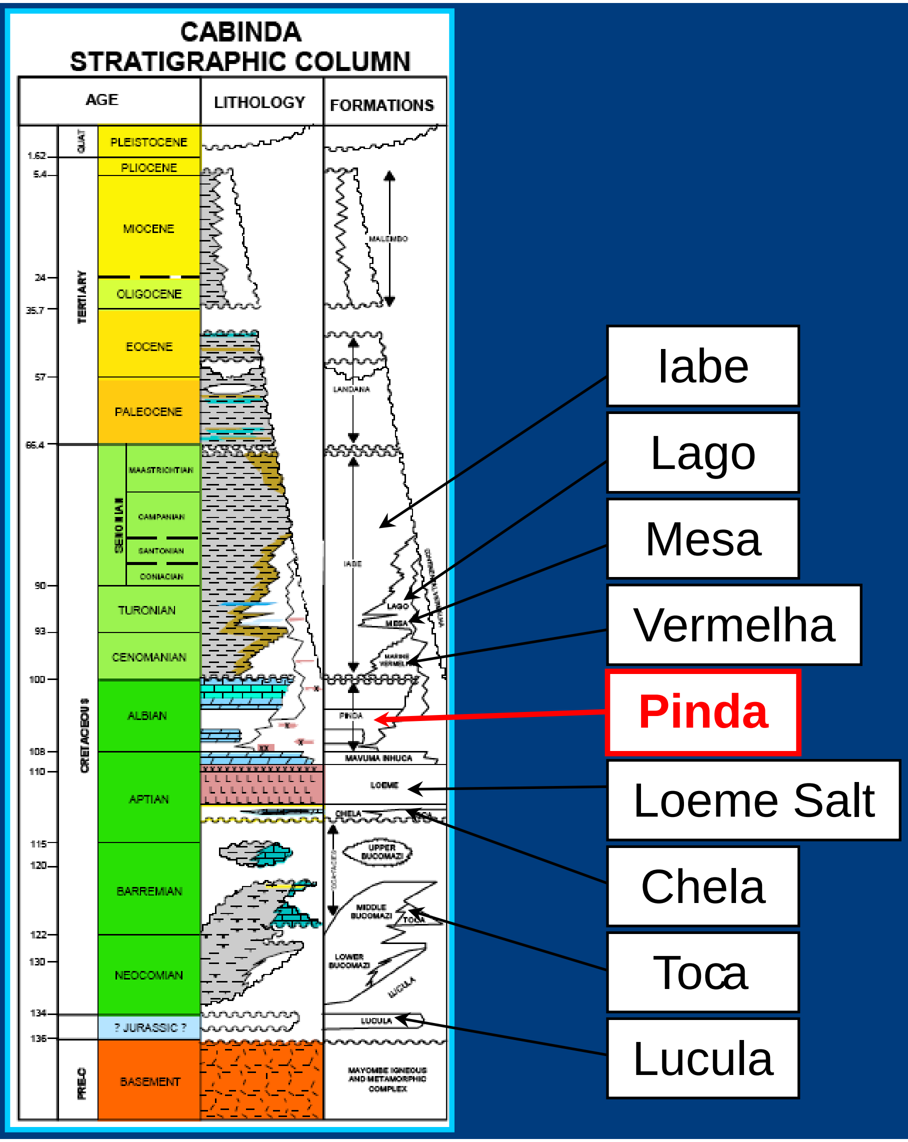
Sonangol E&P (40%)

Total (10%)

ENI (9.8%)

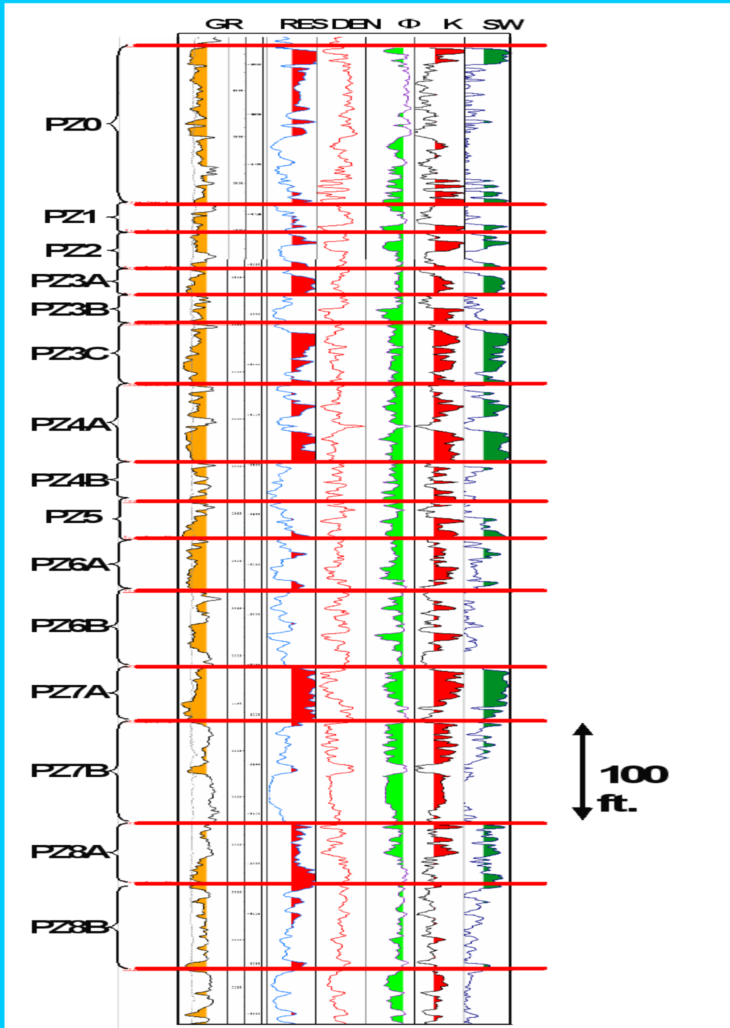
Cabinda Stratigraphic Column

The Albian Age Pinda Formation is a mixed clastic-carbonate system and is the oldest of the post-salt reservoirs. It is also the second most prolific (second to Vermelha) formation in the Cabinda, Block 0 concession.



N’Sano Pinda Reservoir Stratigraphy

N’Sano Pinda Type Log



Mixed clastic-carbonate system

Age: Albian

Lithologies:

- reservoir → thinly interbedded dolomitic limestones/sandstones

  (avg. Φ – 21%; avg. K – 143 mD)

- non-reservoir → massive microcrystalline limestones / siltstones

  (avg. Φ – 16%; avg. K – 36 mD)

Depositional environments: distal shelf muds to proximal tidal environments

Other considerations:

- diagenesis (dolomitization, cementation)
- Pinda facies heterogeneity

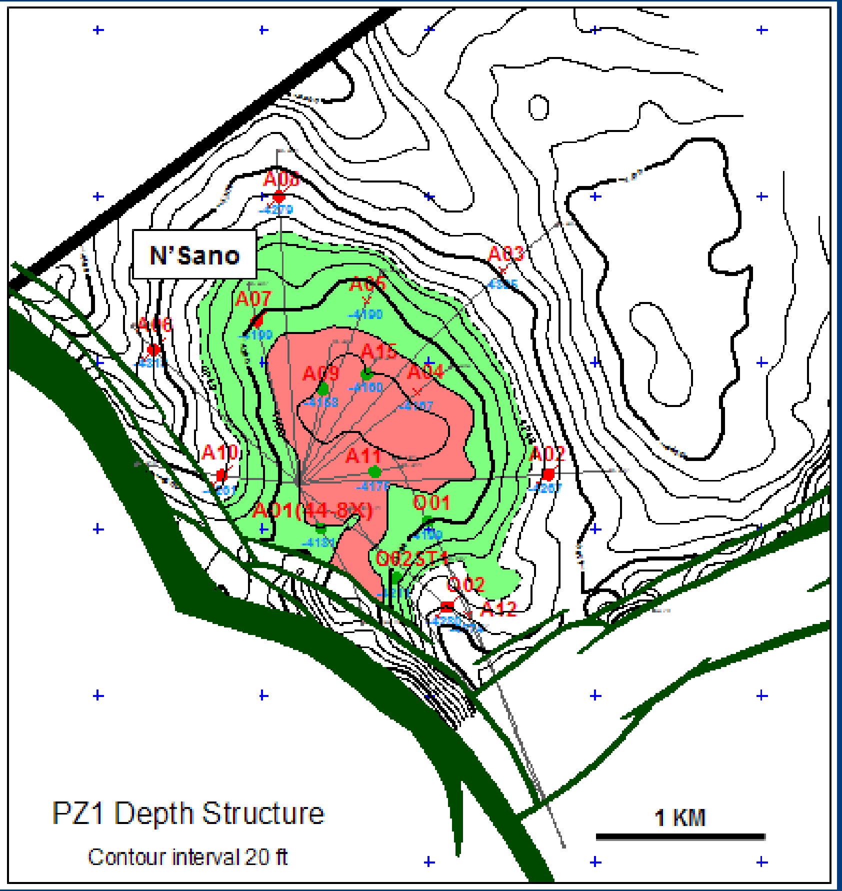
Reservoir thickness: ~700 ft, 7 OWCs

The N’Sano Pinda is comprised of multiple stacked reservoirs defined by multiple oil-water contacts.

OOIP Estimates as a Function of Cumulative Production

PROBLEM STATEMENT: How does one know how much dynamic data (pressure, injection and production) is required to significantly narrow static OOIP estimates?

METHODOLOGY: Match historic data of the mature N'Sano Pinda field using reservoir simulation to understand and narrow key uncertainties. Gain insight regarding time required to 'see' significant uncertainty reduction.



Experimental Design (ED)-Assisted History-Matching Process

ED-Assisted HM Process:

1. Uncertainty Definition

   What parameters? What range?

2. Dynamic Simulation

   Run the ED cases via reservoir simulation.

3. Response Estimation

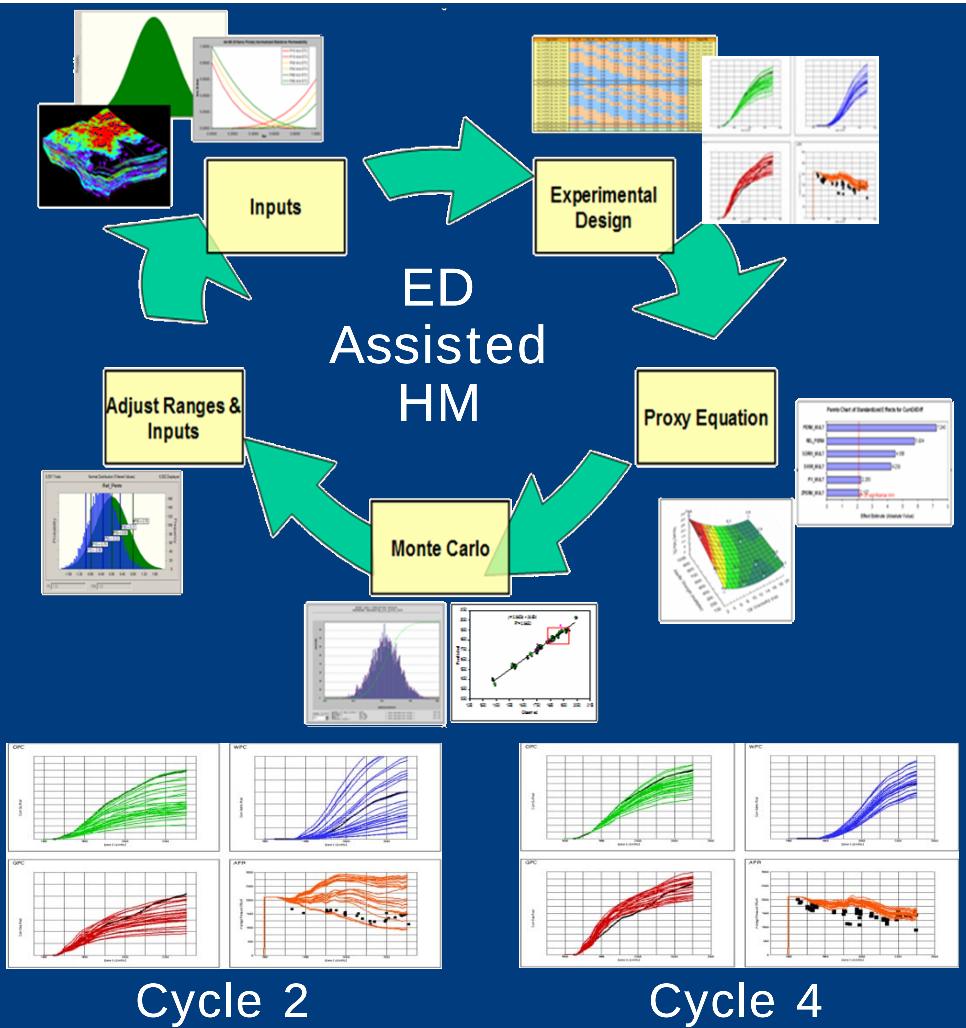
   Generate a response surface for pressure and production to represent the expected results for a given set of inputs.

4. Monte Carlo Simulation

   +100,000 cases to understand ranges, sensitivities and interactions

5. Uncertainty Reduction

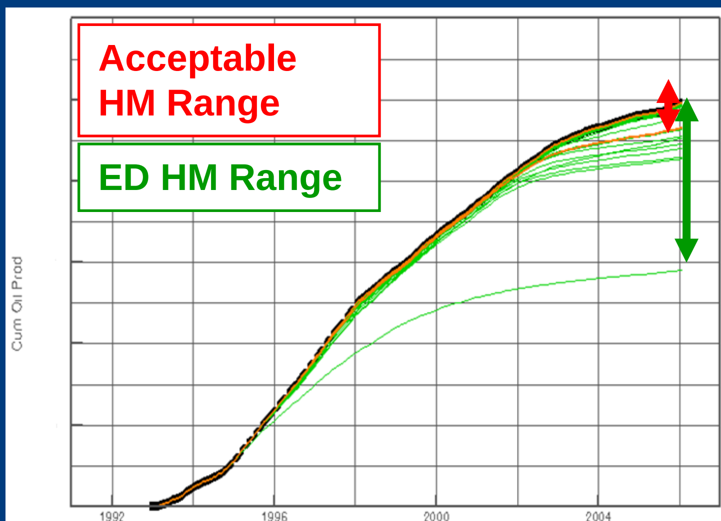
   Keep results that fit the solution (historic data)

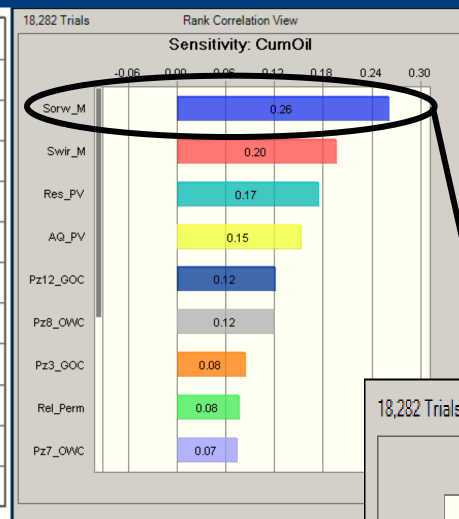


Repeatable, traceable process to narrow uncertainties and gain understanding of both significance and interaction of input parameters.

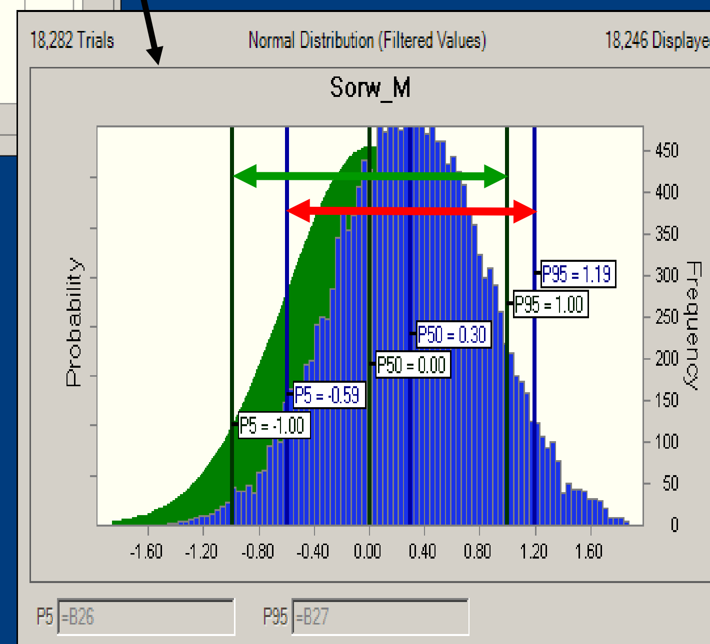
Uncertainty Reduction Example
Cycle 7 – Cumulative Oil

Span of ED cases is too large compared to historic values.





Sorw has the most impact on cumulative oil production for Cycle 7.

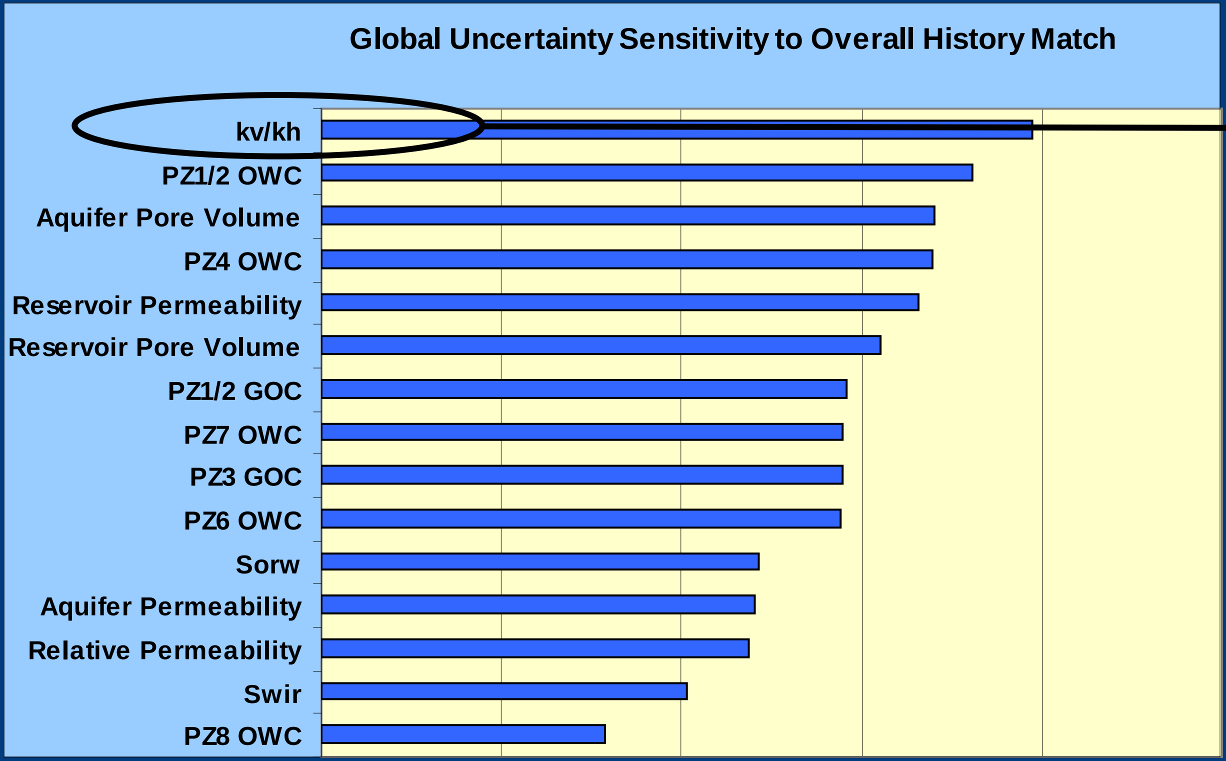


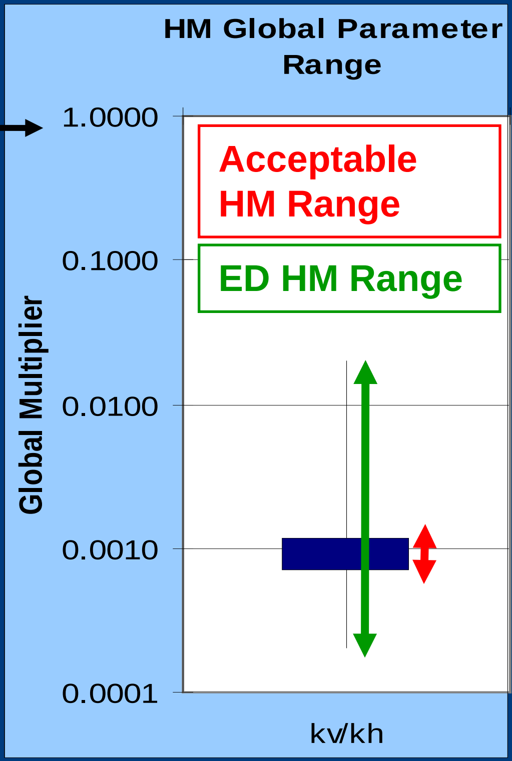
Filtering MC results for acceptable cumulative oil cases shows a shift from the input distribution (green) to an updated more optimistic output distribution (blue).

Multiple pressure and production filters run simultaneously through MC via proxies to filter all input parameters for best ranges.

Uncertainty Reduction
Global HM Sensitivity

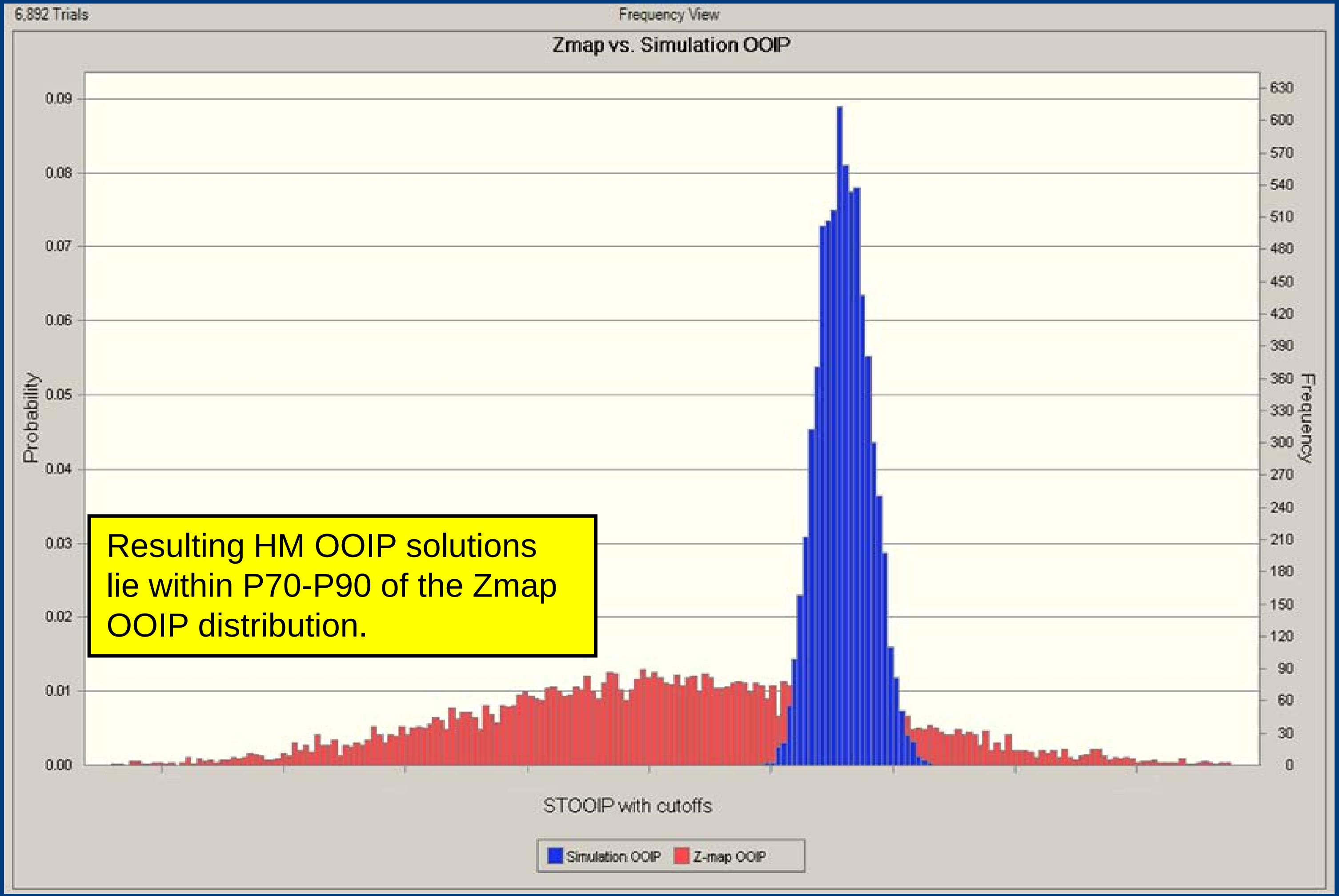
Through the course of ED-assisted HM, uncertainties have been significantly narrowed. Kv/Kh uncertainty range narrowed from an initial 2 log cycles to ~1/4 log cycle.





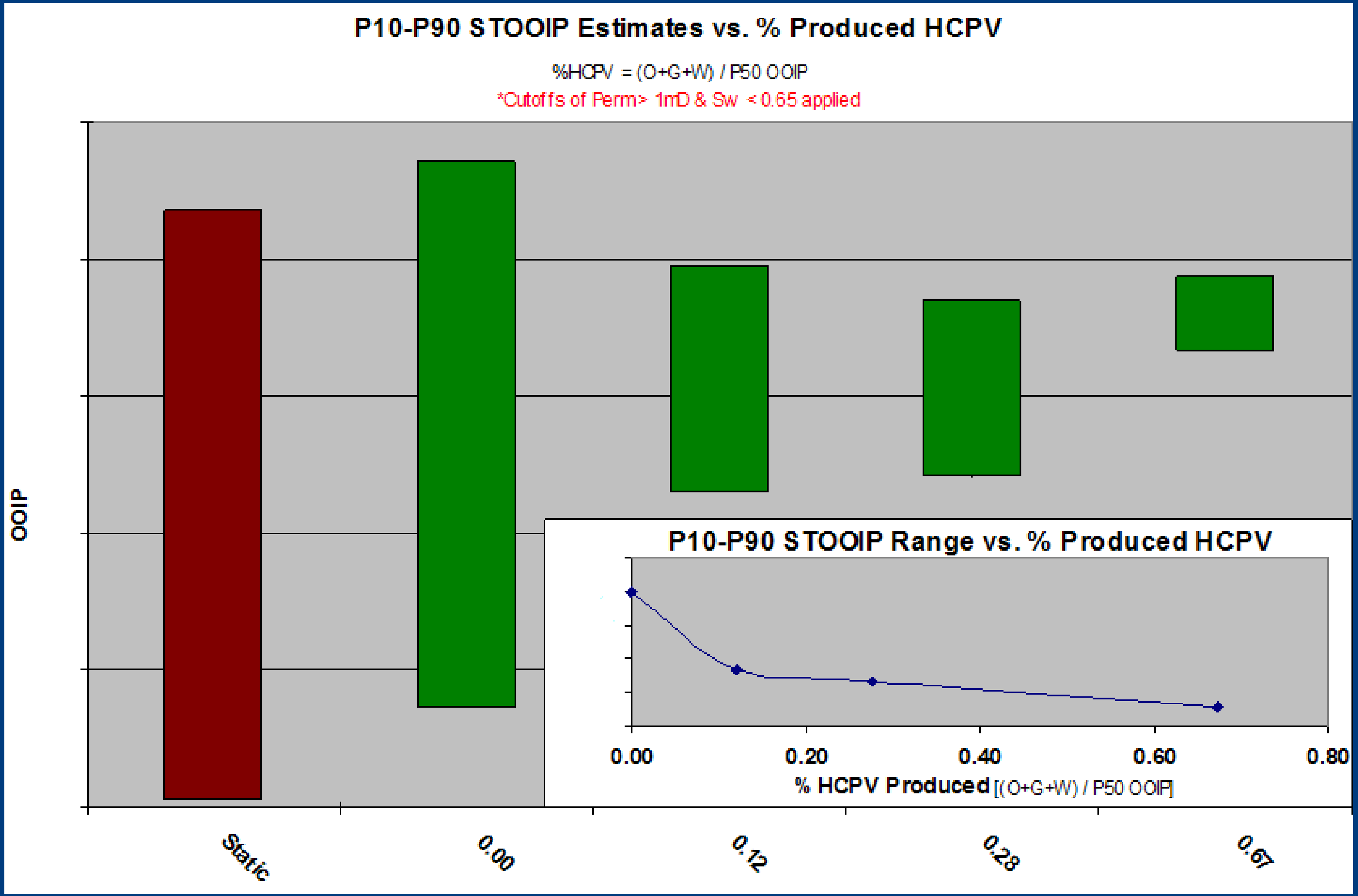
Multiple uncertainties have been significantly narrowed through the use of incorporating dynamic data.

Geologic vs. Simulation OOIP Distribution Comparison



*Static OOIP distribution from Papazis, Ingles, & Glass; "Map-Based Volumetric Calculations of Probabilistic OOIP for Stacked Reservoirs with Multiple Oil Water Contacts", 2007 AAPG Energy Conference & Exhibition – Athens, Greece

STOOIP Estimate as a Function of Hydrocarbon Pore Volumes (HCPV) Produced



Incorporating dynamic data reduced STOOIP range by more than half after only 10% of HCPV were produced.

Summary

PROBLEM STATEMENT: How does one know how much dynamic data (pressure, injection and production) is required to significantly narrow static OOIP estimates?

CONCLUSION: HM solutions from the N'Sano Pinda show the static STOOIP range could be reduced by more than 50% from dynamic data that represents less than 10% of the hydrocarbon pore volume.

- The technique illustrated in this study is a useful and efficient methodology for narrowing uncertainty ranges using dynamic data.
- This study revealed Kv/Kh as the 'biggest' parameter for obtaining a HM. Kv/Kh is the parameter with the least amount of available information.
- The simulation-based P50 OOIP calculated for N'Sano Pinda differs from the map-based P50 OOIP.
  - Permeability and Permeability Cutoff used in the map-based OOIP estimation account for more than 50% of the variation. Values derived during reservoir simulation are on the optimistic end of the map-based study.
  - One would expect much better alignment if static study were repeated with results from simulation study.

Lessons Learned

- Incorporating dynamic-based techniques will narrow static OOIP estimates.
- Forecasting of dynamic information (time) required to 'see' various subsurface realities should be determined and incorporated into development and monitoring plans.
- In order to ensure reasonable results the following guidelines should be taken into account:
  - Have all of the uncertainty parameters defined prior to beginning the study. (Link study to Reservoir Uncertainty Management Plan and Static OOIP estimates)
  - Develop ranges using valid statistical methods or use reasonable assumptions
  - Understand dependencies between reservoir uncertainty parameters. Treat shared uncertainty parameters separate from reservoir specific uncertainty parameters
  - Use Experimental Design as a tool to help test combinations of uncertainty parameters and obtain a proxy equation representative of the entire system. Folded Plackett-Burman proved sufficient
  - Employ Monte Carlo simulation to generate uncertainty parameter distributions and calculate probabilistic OOIP distribution
- Don't always assume that the software is working properly and always check to make sure that your results are reasonable

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Reference

Papazis, Petro, Jerome Glass, and Antonio Ingles, 2007, Map-based volumetric calculations of probabilistic OOIP for stacked reservoirs with multiple oil water contacts: Examples from N'Sano Pinda and Takula Lower Pinda reservoirs, Block 0, Angola (abstract): 2007 AAPG and AAPG European Region Energy Conference and Exhibition; also Search and Discovery Article #90072 (2007).