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A Multi Domain Machine Learning Approach for Reliable Production Forecast

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Summary

Big Loop™ solution meets these evolving needs and provides oil and gas operators with a platform to manage the challenges and complexities of modern reservoirs. The Big Loop workflow results in a calibrated flow model that is consistent with the underlying geology. The workflow is easy to update and allows experts to spend more time analyzing the results and building a common understanding of the reservoir instead of manual adjustments. Big Loop's automated, ensemble based, stochastic workflow tightly integrates the static and dynamic domains, ensuring that all the relevant reservoir uncertainties are captured and used as input parameters integrated to the reservoir simulator. By adjusting uncertainty ranges these input parameters, multiple realizations of the static and dynamic model, constrained by factors such as production history, are created via an iterative loop. (Big Loop - Trade mark of Emerson)

Introduction

Reliable future production forecast is an ultimate goal of oil and gas producers to protect the investments. To achieve this, operators need to obtain a unified representation of the multidomain reservoir observations through a workflow that goes from seismic processing and imaging, through to geomodeling and reservoir engineering, while also balancing availability, and scheduling the technical resources available to asset teams.

Big Loop™ solution meets these evolving needs and provides oil and gas operators with a platform to manage the challenges and complexities of modern reservoirs. The Big Loop workflow results in a calibrated flow model that is consistent with the underlying geology. The workflow is easy to update and allows experts to spend more time analyzing the results and building a common understanding of the reservoir instead of manual adjustments. Big Loop's automated, ensemble based, stochastic workflow tightly integrates the static and dynamic domains, ensuring that all the relevant reservoir uncertainties are captured and used as input parameters integrated to the reservoir simulator. By adjusting uncertainty ranges these input parameters, multiple realizations of the static and dynamic model, constrained by factors such as production history, are created via an iterative loop.
Most of the current workflows are simply ignoring or merging the inherent stochastic uncertainties with other reservoir uncertainties and they aren't providing any qualitative nor quantitative measurements for the impact of these stochastic uncertainties on simulation model performance whereas Big Loop workflow also capture the stochastic uncertainty in a logical manner which causes major variations in simulation model performance (oil production rate, gas-oil ratio, water cut, reservoir pressure etc.).

The result of this calibration is a live earth model that significantly enhances predictive power versus a standard reservoir modeling/simulation workflow. Big Loop workflow, which not only captures reservoir uncertainties across the domain but also uses modern day machine learning technique to speed up the process and provide risk analysis of reservoir uncertainties for reliable production forecast ranges. Compared to traditional production forecast and history matching workflow, Big Loop provides an evergreen workflow which not only provides geological consistent history matched models but also provides an evergreen workflow to update the model with newly drilled well with new reservoir learning with no time. Well placement using multiple HM models helps in optimizing field development plans and reduces the risk in development decisions.

Method

The reservoir in our study is a fluvial depositional environment and structure is faulted in several blocks. The main geological uncertainties lies within structure, fault positions, fluid contacts, channel dimensions and sand volume fraction in each fault blocks. A unified workflow was designed to capture geological uncertainties. Figure – 1 shows an example of structural uncertainties in fault position with multiple horizons realizations. A total of sixty modifiers were identified to start the history matching process using experimental design. The value of each modifier was sampled based on Latin Hyper Cube method to train the proxy using initial uncertainties ranges and their distribution. Figure-2 shows the improvement on quality (a measure of mismatch between simulated and observed data) with the run sets, where each new run set learning from its previous sets and improve history match results. This process also provides posterior modifiers uncertainty ranges and their distribution.

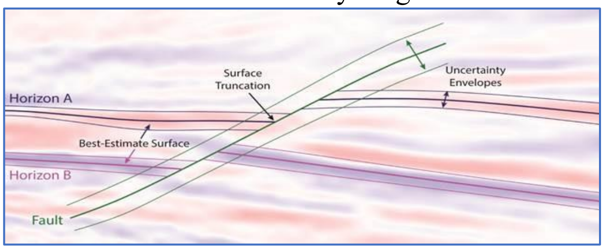

Figure-1: Structural uncertainty in fault position

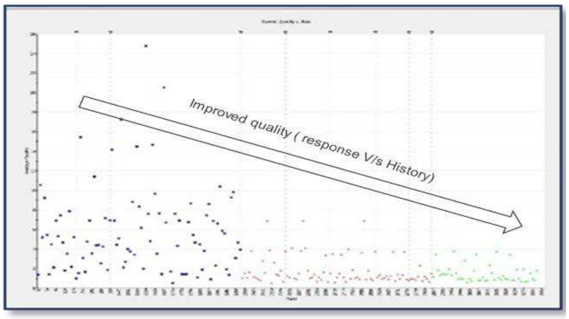

Figure-2: Quality value and its trend

Conclusions

Multiple history matched geological ensemble were produced using Big Loop workflow and the history match quality was analyzed using different tools available in Enable.

1) Tornado plot shown below (Figure-3) was generated to identity sensitive parameters corresponding to total oil production for field at a particular time. It is clear that NTG_POROCUT, OWC, VF_Z1_Ch, KVKH and RES_TOP structure have biggest impact on the total oil production. NTG_POROCUT, KVKH and RES_TOP are negatively correlated with the oil production total and OWC and VF_Z1_Ch are positively correlated. This plot can be helpful in the initial stages of study to identify most influential modifiers and focus more on them, thus improving reservoir engineer's and team's efficiency in identifying parameters which might have relatively less impact on the results.

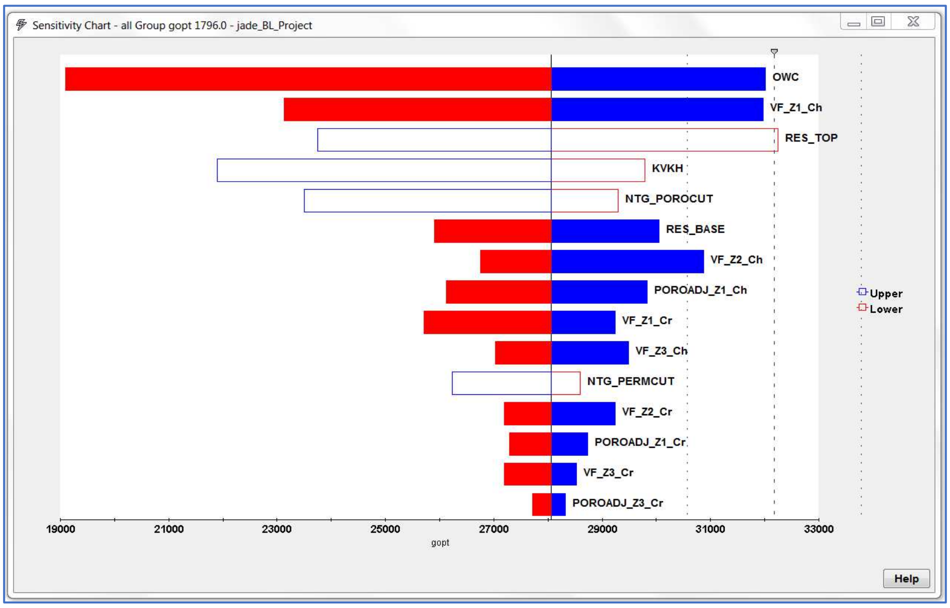

Figure-3: Tornado plot for Modifiers Sensitivity Analysis for Total Oil Production

2) The quality of history match is shown below (Figure-4) with group oil production and water production history data. It is clear that ENABLE is able to match with the history data in refinement runs. This way we obtained multiple history matched model depending on the level of acceptable tolerances of mismatch.

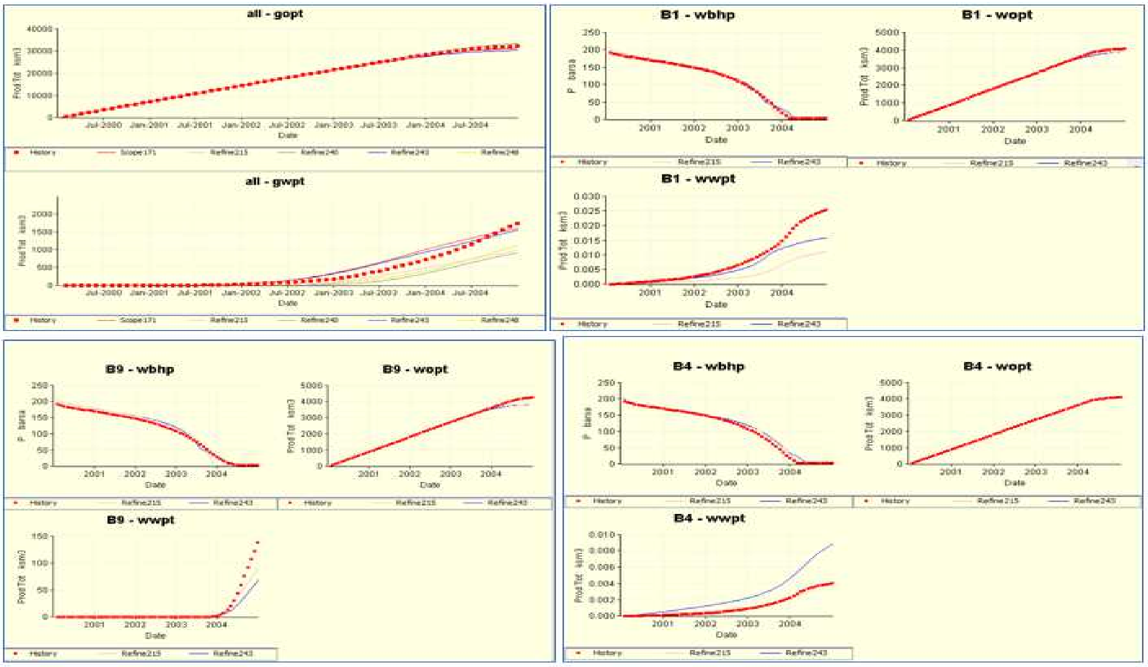

Figure-4: History Match plot for different vectors at field level and wells level

3) The prior and posterior distribution of modifiers are shown below (Figure-5). The prior modifier distribution shows our initial understanding of the distribution of the modifier before commencement of history match exercise and posterior distribution shows the distribution generated from Enable after the history match process was complete. It is clear that the initial understanding of the distribution of modifiers is quite different from history matched results and this information can be quite useful in further analysis and in prediction phase of the study.

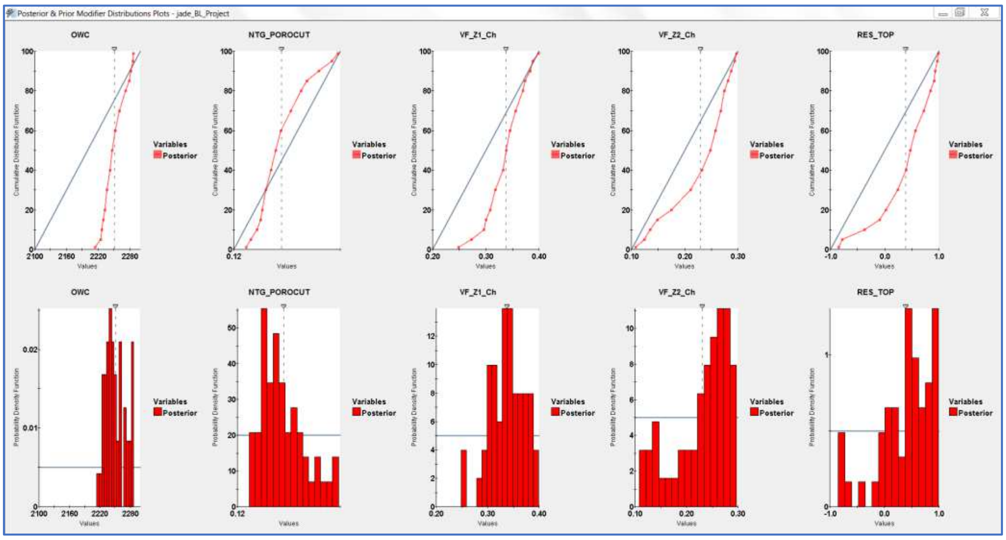

Figure-5: Prior and Posterior Modifiers Distribution

4) The prediction scenario was run extending time period up to 5 years and Ensemble based prediction profiles were obtained. Using the proxy and Markov Chain Monte Carlo sampling technique, Enable will create a set of parameter values taking in to account the posterior knowledge gained during the history match process. Enable calculates prediction statistics at every point in time and is displayed in the below graph at a particular time period (Figure-6)

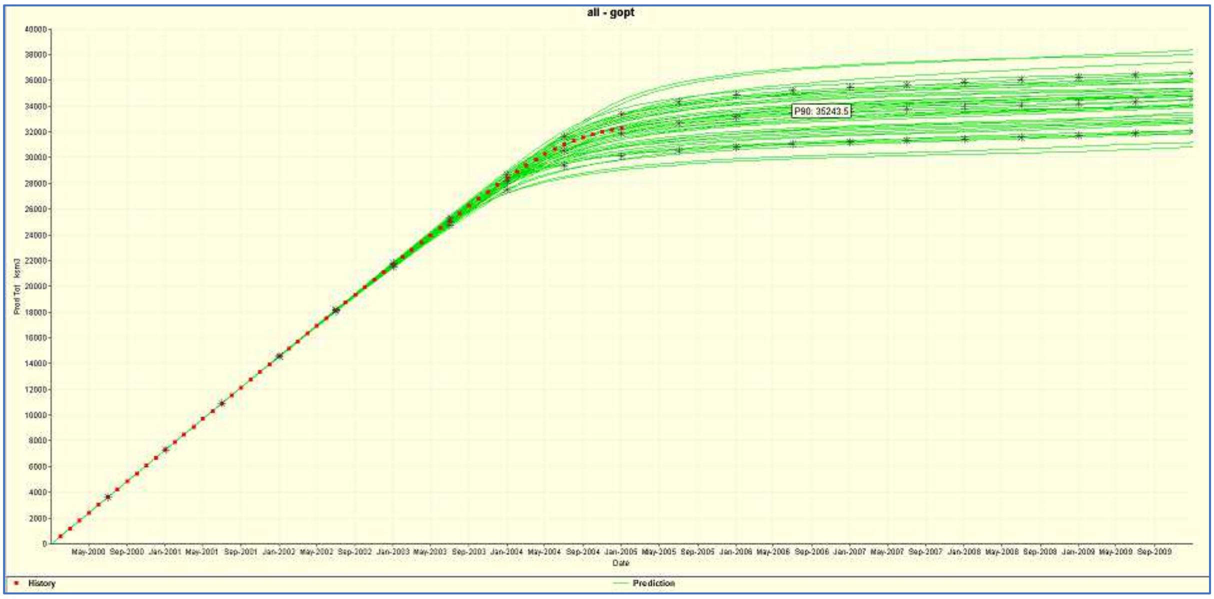

Figure-6: Ensemble runs in Prediction Phase showing yearly statistics for Total Group Oil Production

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