# Uncertainty Quantification and Sensitivity Analysis of Reservoir Forecasts with Machine Learning

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## Motivation

- Uncertainty quantification is a key process for informed decision making in the development of oil/gas field.
- Global sensitivity analysis (GSA, Satelli et al., 2008) is based on Monte Carlo sampling and has been widely used in a lot of fields of science and engineering.
- Challenges to use GSA in reservoir forecasting includes multidimensionality of response (spatio-temporal) and large computations.
- In the project the goal is to propose the workflow to quantify uncertainty and sensitivity of reservoir forecasts with high computational efficiency.

## Methodology

- High dimensionality is reduced by functional PCA (FPCA).
- Regressions are performed to obtain a surrogate forward model of a full flow simulator. A boosting with regression trees is utilized.
- The regressors are used to compute sensitivity indices of GSA.

## Global sensitivity analysis

- GSA is based on the decomposition of variance of response $Y$.
- First order sensitivity index $S_i$ quantifies the main effect of each model parameter $X_i$ to $Y$.

$$S_i = V[E(Y|X_i)]/V(Y)$$

- Total effect $S_{Ti}$ quantifies the effects of $X_i$ to $Y$ including all the interactions

$$S_i = 1 - V[E(Y|X_{\sim i})]/V(Y)$$

- For $n$ Monte Carlo samples and $k$ parameters, $n(k+2)$ simulations are required → Computationally expensive to apply to reservoir simulations.
- $Y$ is assumed to be univariate but reservoir responses are multivariate.

## Training data

- **Illustration of case study** – Oil field in central northern Libya (Ahlbrandt, 2001)

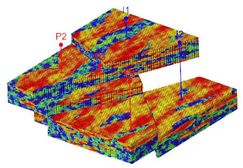


Fig. 1 Reservoir models for the case study

Table 1. Well Plan

| Name | Type | Boundary Condition |
|---|---|---|
| I1<br>I2 | Injector | Constant rate, 10,000 bbl/day |
| P2<br>P3<br>P4 | Producer | Constant bottom hole pressure, 1,000 psi |

- **Distribution of uncertain parameters**

Table 2. List of uncertain model parameters

| Number | Parameters | Abbreviation | Distribution |
|---|---|---|---|
| 1 | Oil-water contact | owc | U[-1076, -1061] |
| 2 | Transmissibility multiplier of fault 1 | mflt1 | U[0, 1] |
| 3 | Transmissibility multiplier of fault 2 | mflt2 | U[0, 1] |
| 4 | Transmissibility multiplier of fault 3 | mflt3 | U[0, 1] |
| 5 | Transmissibility multiplier of fault 4 | mflt4 | U[0, 1] |
| 6 | Residual oil saturation | sor | N[0.2, $0.05^2$] |
| 7 | Connate water saturation | swc | N[0.2, $0.05^2$] |
| 8 | Oil viscosity | oilvis | N[10,$2^2$] |
| 9 | Corey exponent of oil | oilexp | N[3,$0.25^2$] |
| 10 | Corey exponent of water | watexp | N[2,$0.1^2$] |

## Results

- **Dimensionality reduction with FPCA**

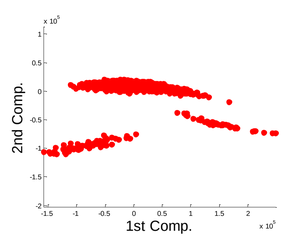


Fig. 2 First two Principle components

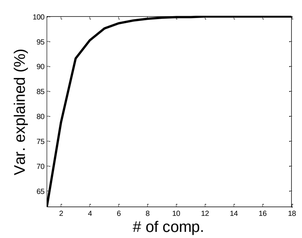


Fig. 3 Cumulative variance explained

- **Regression using boosting with regression trees**
  - The number of trees is determined by cross validation.
  - Predictors are model parameters and responses are principle components.

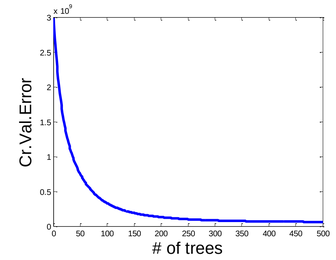


Fig. 4 Cross validation error w.r.t. the number of boosted trees

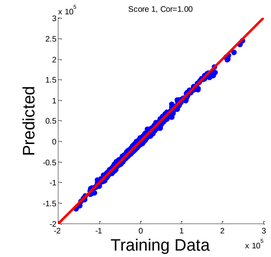


Fig. 5 Training Data vs. Predicted values

- **Uncertainty quantification with regression models**
  - Shows close approximation.

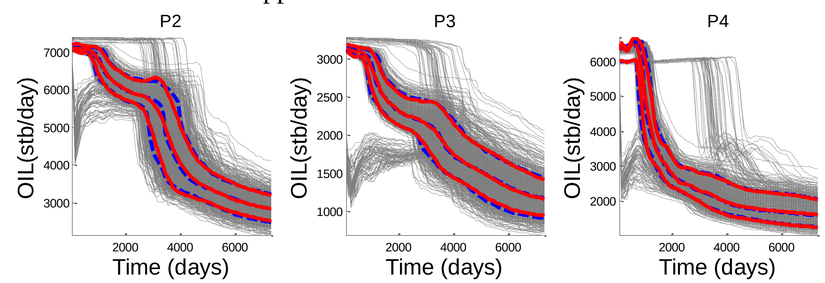


Fig. 5 Forecast of oil rate at each well (gray: every model, blue: observed curves, red: curves from regression models, each three line represents P10,P50, P90)

- **Global sensitivity analysis**
  - 600,000 (n=50,000, k=10) forward runs can be performed rapidly with regression models.

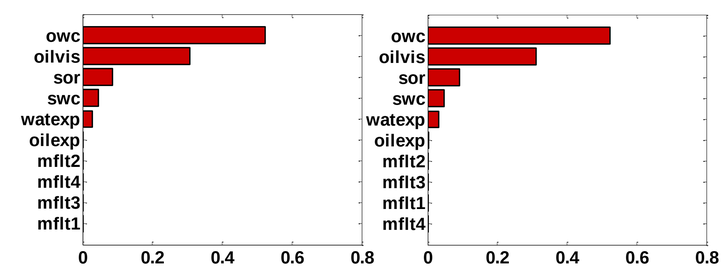


Fig. 6 The first order index (left) and total effect (right)

## References

Ahlbrandt, T. S., 2001. The Sirte Basin Province of Libya: Sirte-Zelten Total Petroleum System
Saltelli et al., 2008, "Global sensitivity analysis: the primer".
Ramsay J.O. and Silverman B.W., 2012, "Functional Data Analysis".