Estimation of Prediction Uncertainties in Oil Reservoir Simulation using Bayesian and Proxy Modelling Techniques

Ralf Schulze-Riegert
Schlumberger Information Solutions;
SPT Technology Center, Kjeller, Norway

Abstract

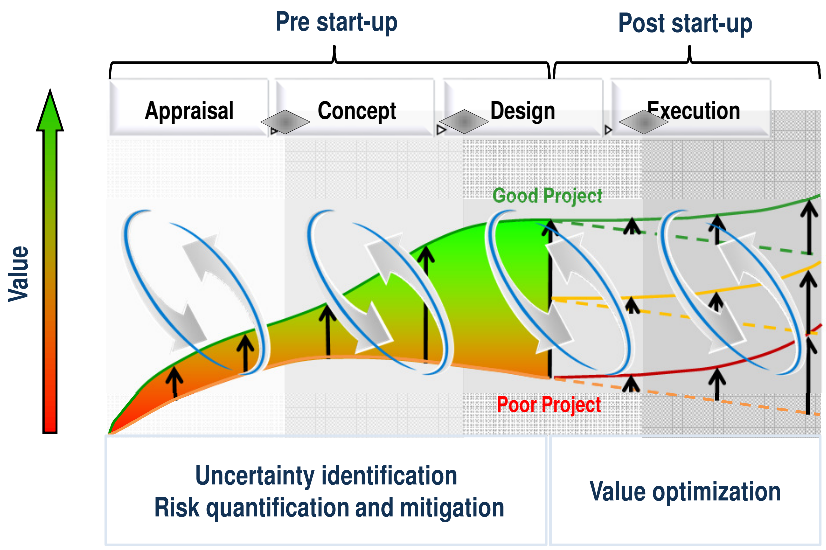
- Subsurface uncertainties have a large impact on oil & gas production forecasts. Underestimation of prediction uncertainties therefore presents a high risk to investment decisions for facility designs and exploration targets. The complexity and computational cost of reservoir simulation models often defines narrow limits for the number of simulation runs used in related uncertainty quantification studies.
- In this session we will look into workflow designs and methods that have proven to deliver results in industrial reservoir simulation workflows. Combinations of automatic proxy modelling, Markov Chain Monte Carlo and Bayesian approaches for estimating prediction uncertainties are presented.

2

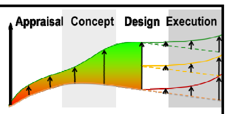
Outline

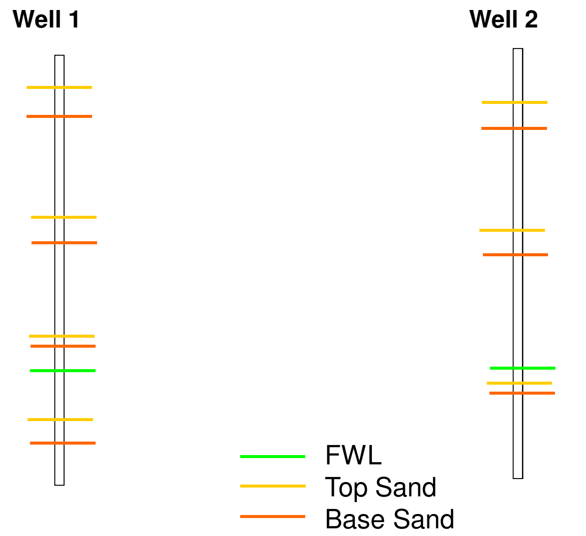
- Introduction – Uncertainty Domains
- Part I: Case Example and Workflow Implementation
  - Problem statement
  - Bayesian approach to „history conditioned forecasting“
  - MCMC & Proxy modeling
  - Method implementation, advantages and limitations
- Part II: Lesson Learned
  - Computation requirements – best practices
  - Outlook

Field Development: Understanding Uncertainty is Key



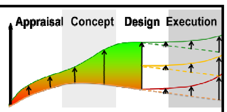
The Geologist's Dilemma

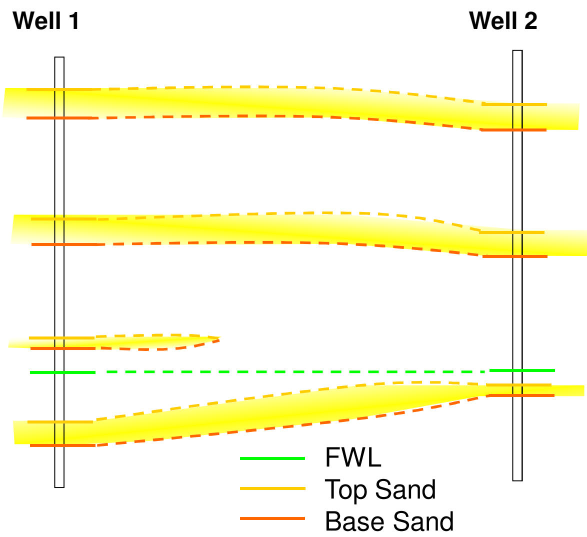




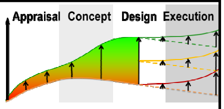
5

An Interpretation

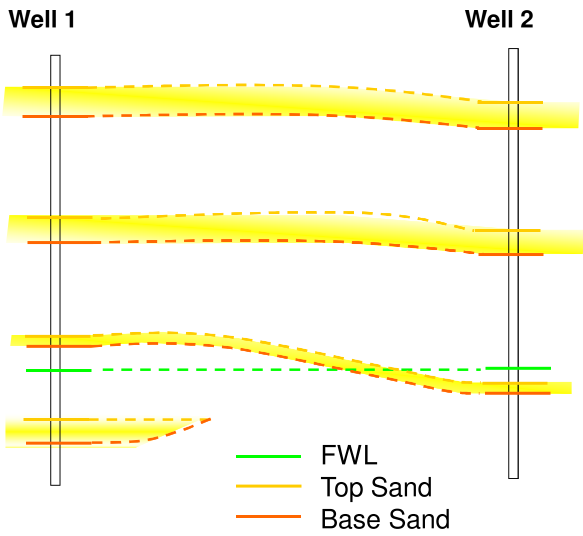


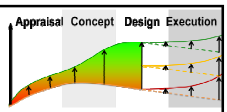


6

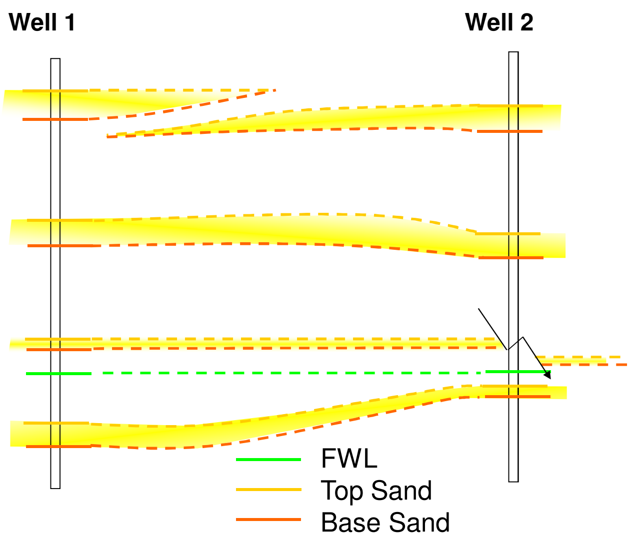


Another Interpretation

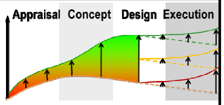


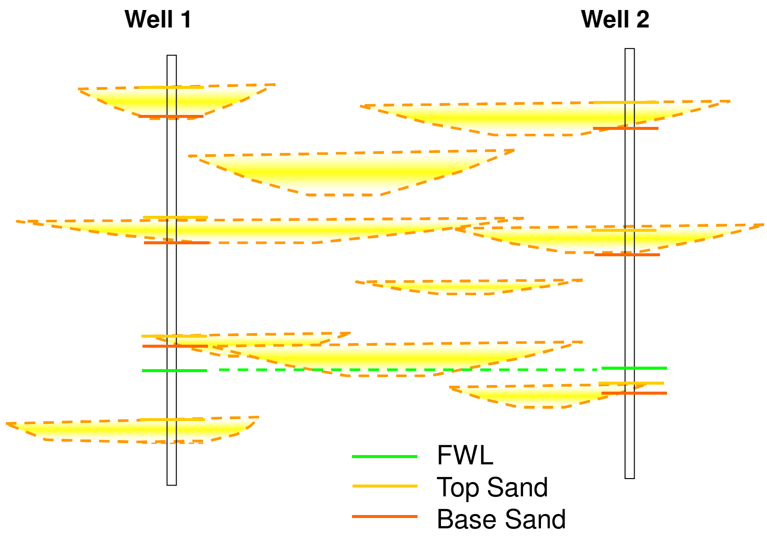


Yet Another Interpretation.....



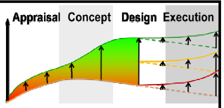
There are lots more interpretations.......

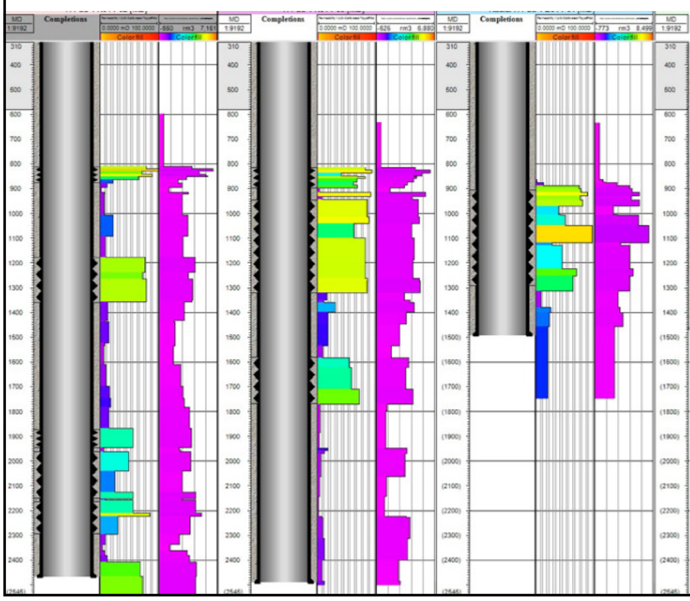




9

Data Collection and Interpretation



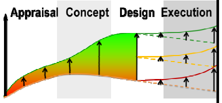


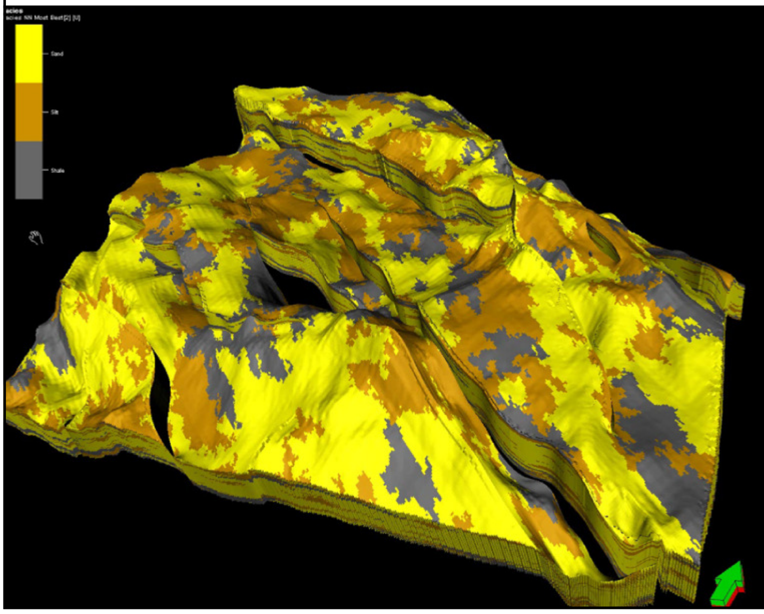
Uncertainty Sources

Grain Size Distribution
Thin Section Analysis
NMR
X-Ray, SEM & Cat Scan
Porosity
Core Data
Well logging data
Well testing data

10

Geological & Reservoir Model





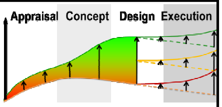
Uncertainty Sources

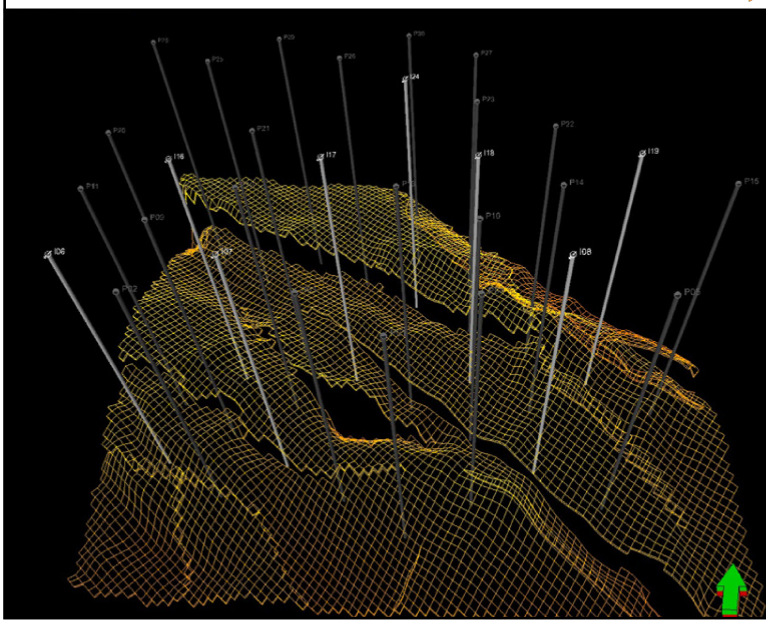
Thickness
Well logging data
3D seismic data
Geology & geostatistics

Reservoir Geometry
3D Seismic data
Facies analysis
Well correlation

11

Geological & Reservoir Model – Grid



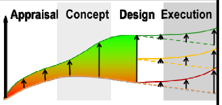


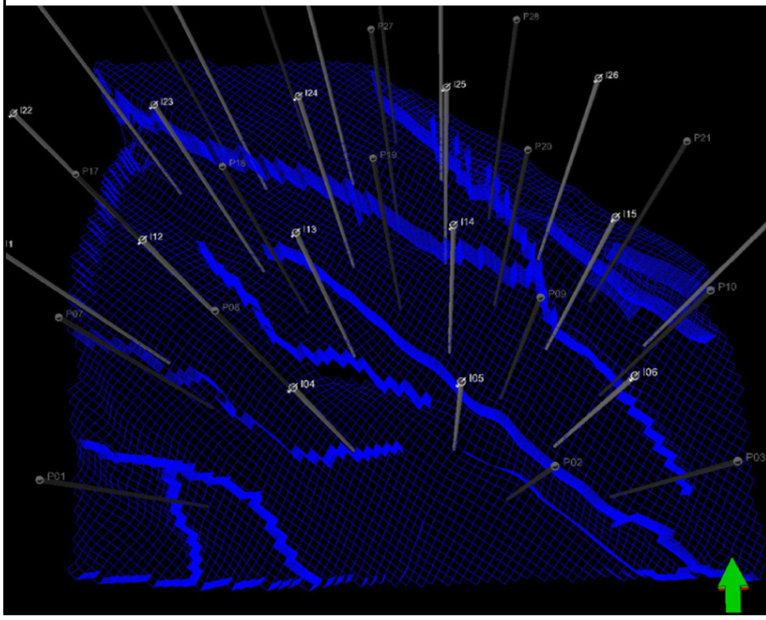
Uncertainty Sources

Structure
Geophysical data
Well tops data
Well logging data

12

Geological & Reservoir Model – Fault Model



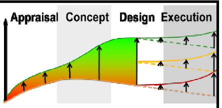


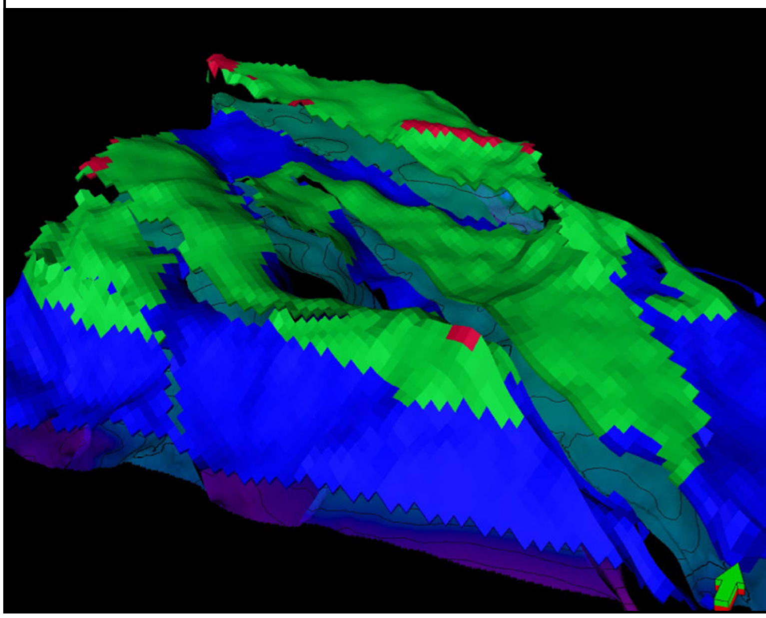
Uncertainty Sources

Structure
Geophysical data
Well tops data
Well logging data

Permeability
Core Data
Well testing data
Log-Derived Permeability

Reservoir Model – Distribution of Hydrocarbons



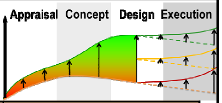


Uncertainty Sources

Fluid PVT Properties
PVT Experiments
Correlations
Equation of State

Fluid Saturation
Core Data
OH and CH logging
Well testing data

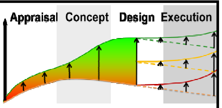
Sources of Static and Dynamic Uncertainties

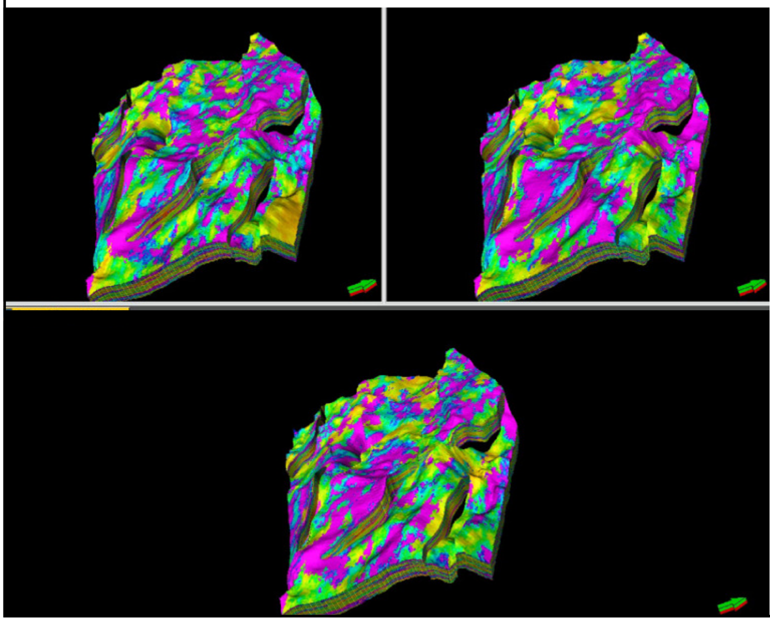


Reservoir	**Structure**	**Thickness**	**Fluid Contacts**	**Reservoir Geometry**
Structural Data	Geophysical data	Well logging data	Well logging data	3D Seismic data
	Well tops data	3D seismic data	well tesing & pres data	Facies analysis
	Well logging data	Geology & geostatistics	seismic data	Well correlation
Reservoir	**Facies**	**Grain Size Distribution**	**PTS Distribution**	**Pore Compressibility**
Geological Data	Geophysical data	Thin Section Analysis	Thin Section Analysis	Special Core Anlysis
	Core data	NMR	Spcial Core Analysis	Correlation
	Well logging data	X-Ray, SEM & Cat Scan	Well log Data??	Field Data
Reservoir	**Rock Texture**	**Porosity**	**Permeability**	**Fractures**
Rock Properties	Core Data	Core Data	Core Data	Core data
		Well logging data	Well testing data	Well logging data
		Well testing data	Log-Derived Permeability	Well testing data
Reservoir	**Fluid Composition**	**Fluid PVT Properties**	**Fluid Viscosity**	**Fliuds IFT Data**
Fluid Properties	PVT Samples	PVT Experiments	Lab Experiments	Lab Experiments
	Production Testing	Correlations	Correlations	Correlation
		Equation of State		
Rock-Fluid	**Fluid Saturation**	**Wettability**	**Capillary Pressure**	**Relative Permeability**
Properties	Core Data	Special Core Analysis	Special Core Analysis	Special Core Analysis
	OH and CH logging		Well logging data	Well testing
	Well testing data			

15

Multiple Realizations



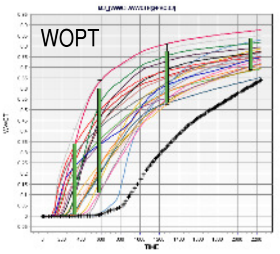


16

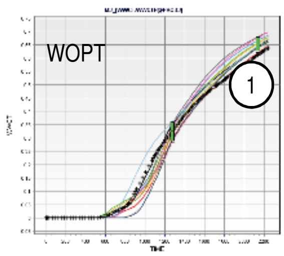
Estimation of prediction uncertainties in oil reservoir simulation using Bayesian and proxy modelling techniques

Part I: Case Example and Workflow Implementation

Estimation of Prediction Uncertainties

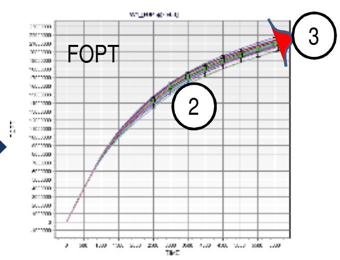


History Matching



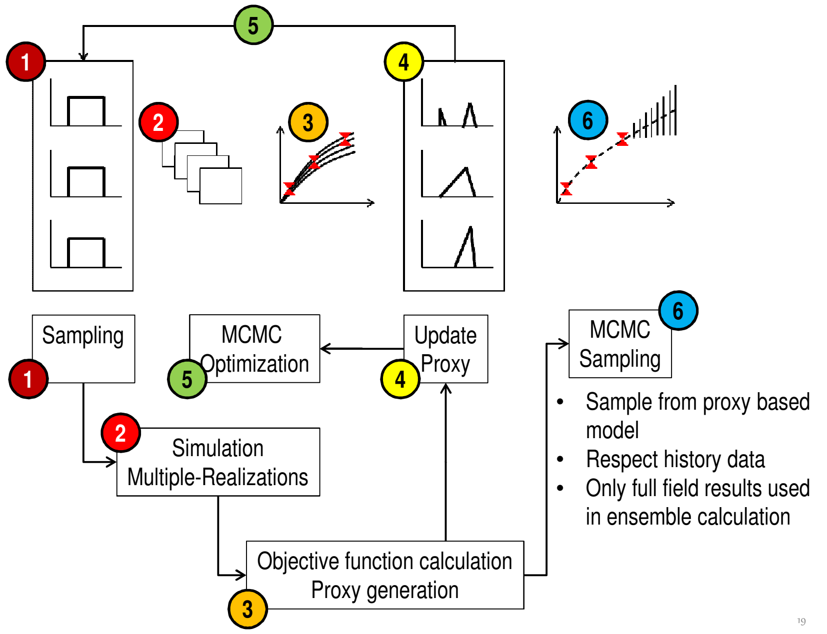
1. Condition simulation model to history data
2. Use history-conditioned simulation models as a basis for forcasting single field development
3. Estimate uncertainty distribution for prediction scenario

History Conditioned Forecast



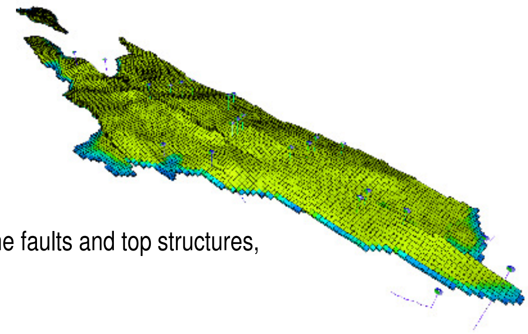
18

Workflow: Bayesian Update using MCMC



19

Case Study: Watt Field



- Semi – synthetic case study
- Based on real field data provided:
  - production data,
  - seismic sections to interpret the faults and top structures,
  - wireline logs to identify
    - facies correlations and
    - saturation profile and
    - porosity and permeability data
- Alternative models are provided based on
  - Grid resolution
  - Top structure
  - Fault models
  - Facies model with different cutoff criteria

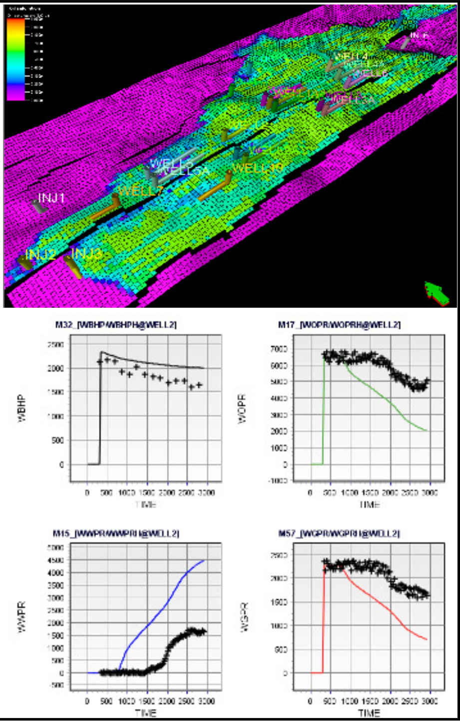
Model property	Description	File name	
Grid	100 m by 100 m by 5 m	G-1	Total of 81 different combinations of these properties
	100 m by 100 m by 10 m	G-2	
	200 m by 200 m by 5 m	G-3	
Top Structure	1	TS-1	
	2	TS-2	
	3	TS-3	
Fault Model	1	FM-1	
	2	FM-2	
	3	FM-3	
Facies Model (Cutoffs)	0.6	CO-1	
	0.7	CO-2	
	0.8	CO-3	

Ref: D.Arnold et.al, 2013

20

Watt Field – Reservoir Model

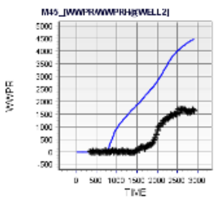
- Under-saturated oil reservoir
- Initial reservoir pressure of 2500 psi
- Reservoir depth around 1555 m below surface.
- 10 faults with East/West direction.
- Porosity varies between 0.05 to 0.3
- Permeability in Z varies between 10 to 1000 mD.
- 16 horizontal production wells and 7 injectors
  - 7 year history data
  - 15% error for all production data
- Peripheral water injection is applied to maintain the reservoir's pressure.



Deterministic Solution Adjoint Approach – For Comparison

- The adjoint system is solved with the sole aim of finding a deterministic solutions to the problem
- The mismatch is quantified by an objective function, Q

$$Q(m) = \sum_i \frac{\left(d_i^{sim}(m) - d_i^{obs}\right)^2}{\sigma_i^2}$$



- Minimize Q; calculate $\frac{\partial Q(m)}{\partial d}$ on a cell-by-cell basis.

- Regression step

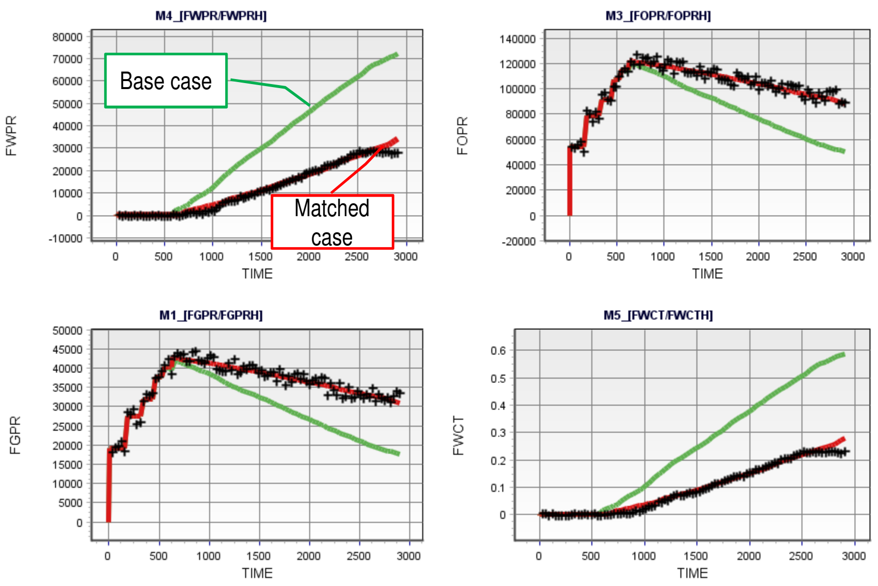
$$m^{l+1} = m^l + \alpha_l \delta m^{l+1}$$

- Optimization, e.g., Levenberg-Marquardt

$$\delta m^{l+1} = \frac{m^l - m_{prior}}{1+\lambda_l} + K\left[\frac{G_l(m^l - m_{prior})}{1+\lambda_l} - \left(g(m^l) - d_{obs}\right)\right]$$

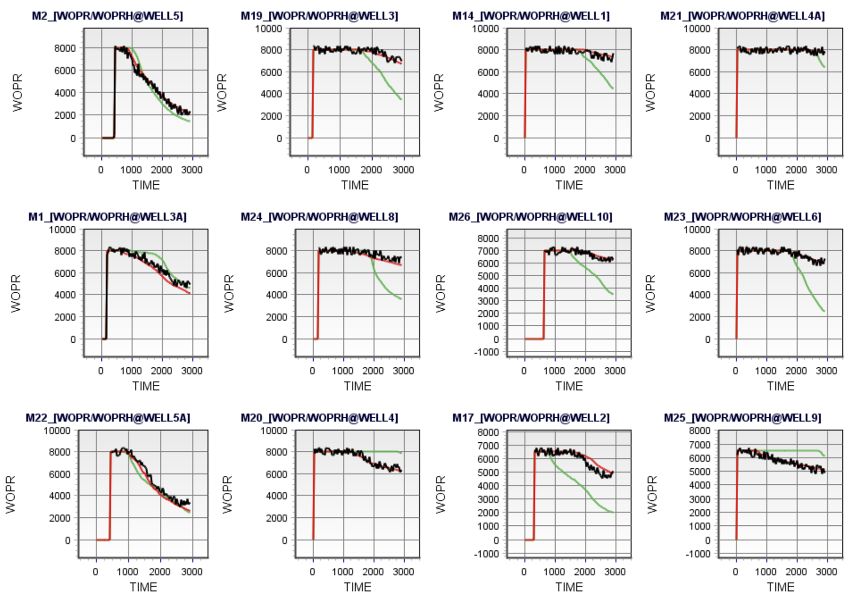
SPE 164337: Schulze-Riegert et al.,2013

Results Field Production Rates



23

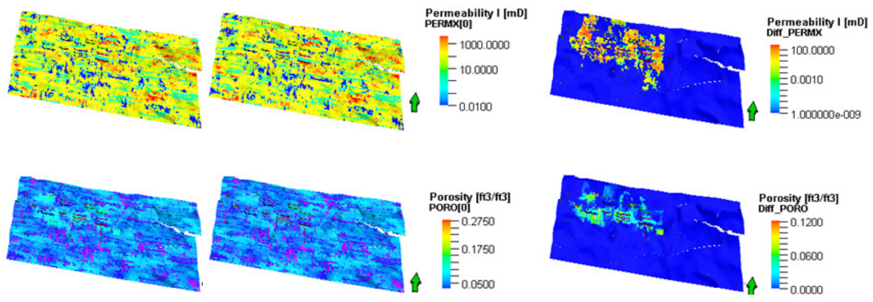
Watt Field – Well-by-Well Match



24

Watt Field – Adjoint: Impact on Rock Property Distribution

Base Case Optimized Case Difference Map



	Base Case	Optimized Case	Relative diff. [%]
PORV	**21.4**60.906.026	**21.5**00.848.891	0.2
OOIP [STB]	**3.84**1.092.109	**3.88**6.724.103	1

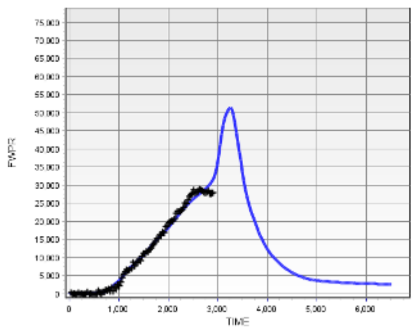
25

Short Coming of the Deterministic Result ?

- Deterministic approach is capable delivering "a" solution to the complex simulation problem
  - Strong dependence on the base case
  - Limited information on uncertainties
  - Prediction may be wrong

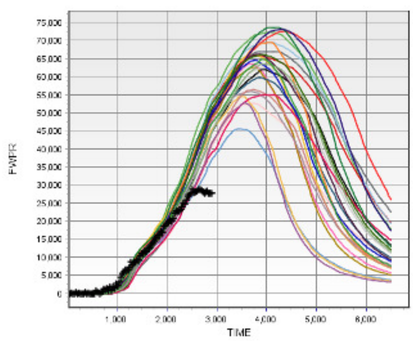
Deterministic prediction

Field Water Production Rate



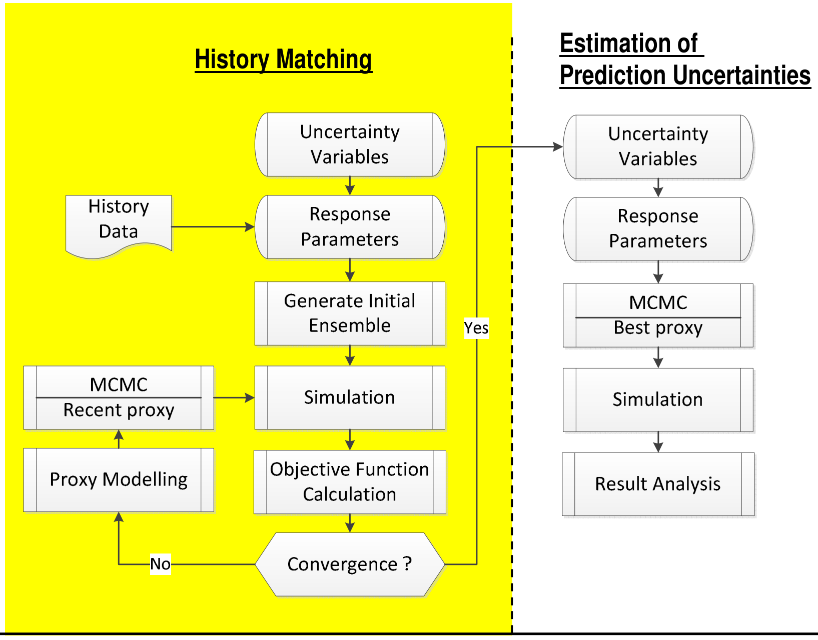
Probabilistic prediction

Field Water Production Rate



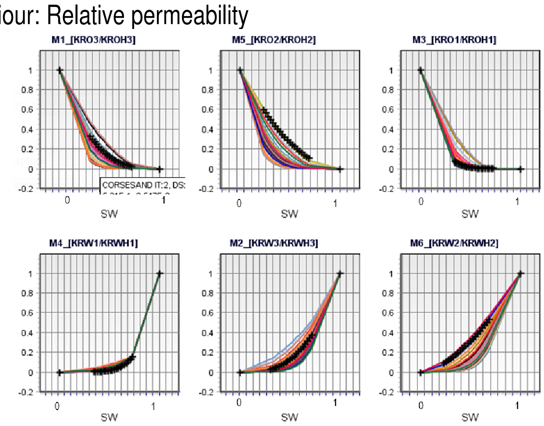
26

Workflow Design



Watt Field – Uncertainty Description

- Selection of **a** representative model out of 81 scenarios
- Uncertainty description according to reference example (Arnold et al.)
  - Volumetric: Porosity modifications
  - Communication: Permeability in vertical direction
  - Relative fluid flow behaviour: Relative permeability
- Example: rel-perm curves:
  - corey description
  - Black crosses show base case data

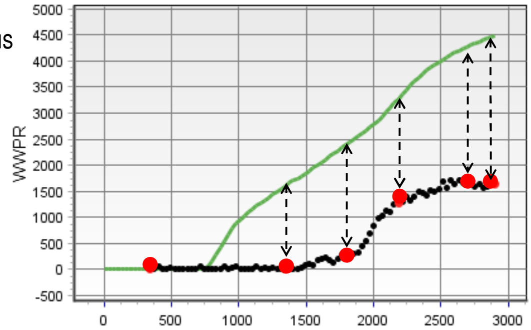


Watt Field – Response Definition

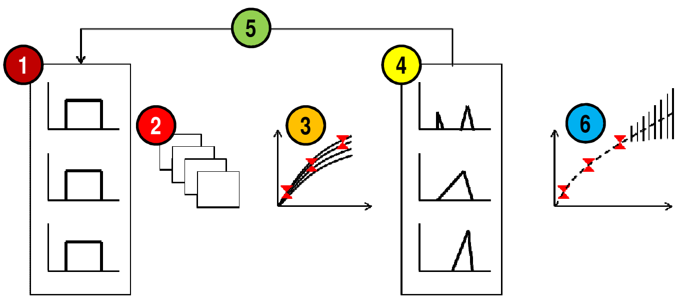
- Objective function definition

$$Q^L(d,m) = \sum_t \left(\frac{d_t^{\mathrm{m}} - d_t^{\mathrm{c}}(m)}{\sigma} \right)^2$$

- Match points are defined to focus on key events / indicators
  - Break through
  - Plateau level
  - ...
- The objective function value is based on mismatches between measured and simulated match points



Workflow: Uncertainty Modelling



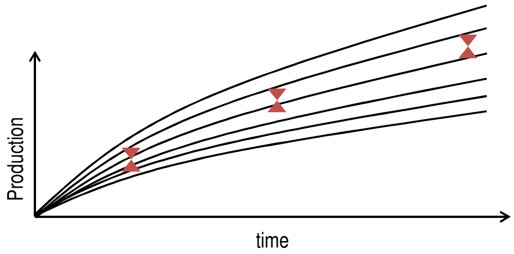
Bayes Formulation:

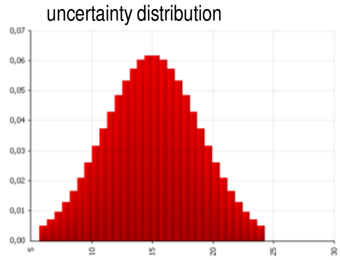
$p(m) = e^{-Q^P(m)}$ — Prior

$p(d \mid m) = e^{-Q^L(d,m)}$ — Likelihood

$p(m \mid d) = \dfrac{p(d \mid m) \cdot p(m)}{p(d)}$ — Posterior

Bayesian Update using MCMC





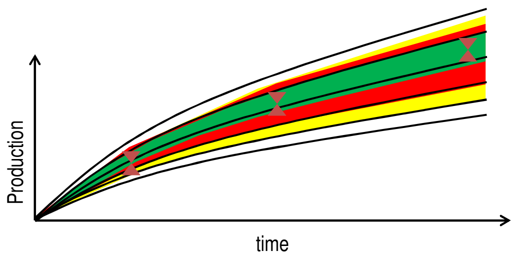
- Mismatch

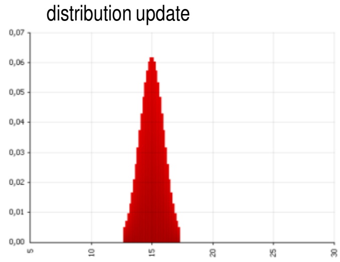
$$Q^L(d,m)=\sum_{t}\left(d_t^{\mathrm{m}}-d_t^{\mathrm{c}}(m)\right)^2$$

- Posterior weight

$$\mathrm{p}(m\,|\,d)\propto \exp\left(-Q^L(d,m)\right)$$

Bayesian Update using MCMC





- Markow Chain, i.e., update depends on previous state only
  $m^{i+1}=m^i+\delta$
- Sampling new candidate

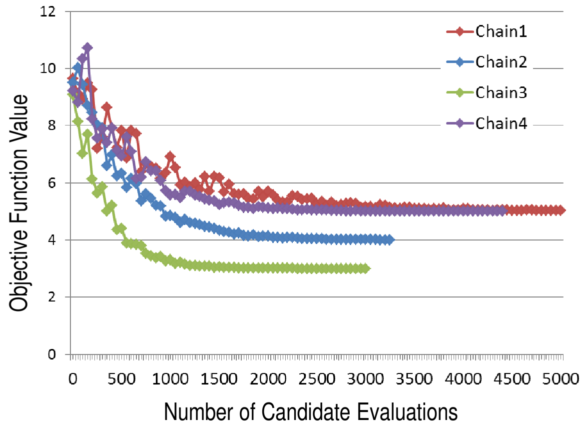
$$\alpha=\frac{\mathrm{p}(m^{i+1}\,|\,d)}{\mathrm{p}(m^{i}\,|\,d)}\quad\begin{cases}\alpha\geq 1 & \text{accept}\\ \alpha<1 & \begin{cases}\text{accept if } \alpha>\mathrm{rnd}(0,1)\\ \text{reject}\end{cases}\end{cases}$$

Chain Evaluation

- Chain evaluations are based on proxy
- A sequence of chain evaluations gradually improves results

$$m^{i+1} = m^i + \delta$$

- In the optimization workflow, each chain delivers one final "best" candidate.



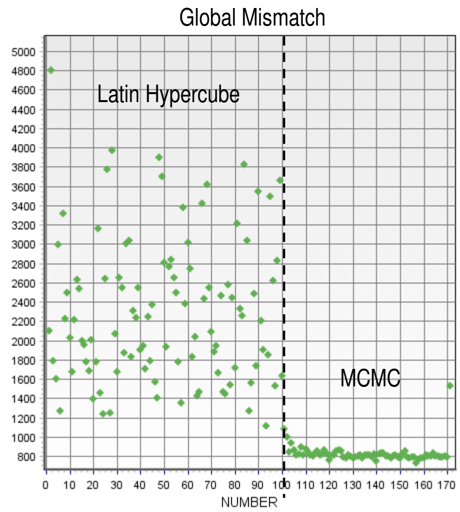
- Best candidates from each chain are added in the experiment list for full field simulation. They also extend the training data set for improving proxies for the next loop of chain evaluations.

33

Results: Watt Field – MCMC

- Screening: Latin Hypercube
  - Screen search space
  - Generate training data set for automatic proxy modeling
- Optimization: MCMC-Optimization
  - Create new set of proxy models before running chains of Monte Carlo runs
  - Select „best" candidate sets based on proxy sampling
  - Verify results
  - Iterative process of selecting and verifying candidate sets until convergence is reached

$$Q^L(d,m) = \sum_t \left(\frac{d_t^{\,m} - d_t^{\,c}(m)}{\sigma} \right)^2$$



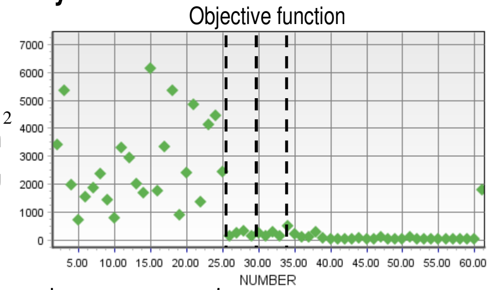
34

MCMC: Sampling from the Proxy

Objective function

$$Q^L(d,m)=\sum_t\left(\frac{d_t^{\,m}-d_t^{\,c}(m)}{\sigma}\right)^2$$

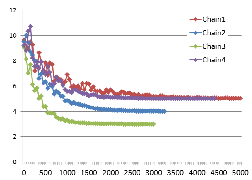
Proxy modeling based on improving training data set



Training data set

$$p(m\,|\,d)\propto\exp\left(-Q^{\text{proxy}}(d,m)\right)$$

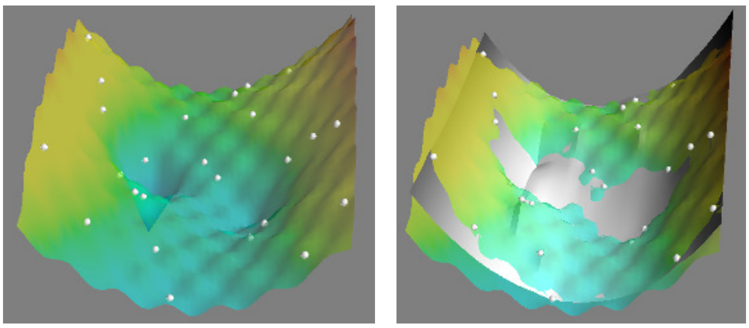
Sampling from proxy



35

Kriging for Proxy Modelling

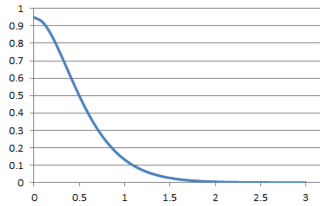
- Kriging is a “data exact” method
- Kriging has the capability to reproduce a training data set exactly
  - Popular universal kriging uses a regression model as a trend model.
  - The error w.r.t. the trend is corrected by interpolation techniques
- The figure below shows a training data set (left) and a quadratic trend model which approximates the training data set. Data points (white spheres) are modelled by the trend model plus kriging terms (right)



36

Kriging definition

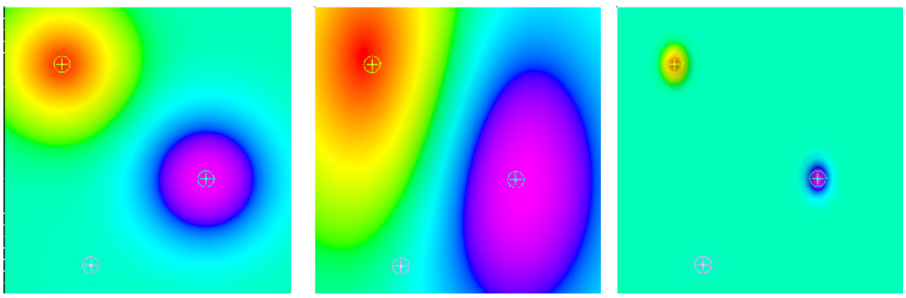
- Kriging is based on a probabilistic modelization of the data
$$y(X) = trend(X) + Z(X)$$
  with $Z(X)$ a random variable
- The $Z(X)$ at each X are not spatially independent, we hypothesize
$$Cov\big(Z(X_1), Z(X_2)\big) = R(X_1 - X_2)$$
  i.e. translation-invariant covariances
- Typically, R is further hypothesized to be of the form $R(U) = \sigma^2 \varphi\left(\frac{|U|}{h}\right)$
  - h is the characteristic length-scale
  - φ is the variogram, and expresses how correlation vanish with distance



37

Kriging as interpolation

- Proxy defined as $f(X) = trend(X) + mean\big(Z(X)\big)$

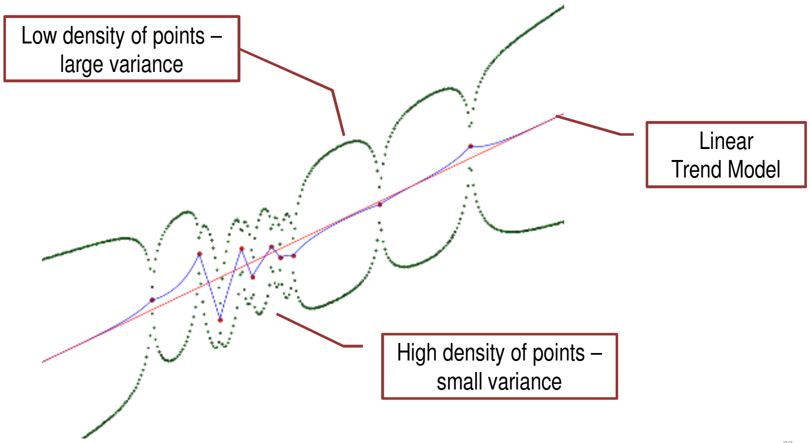


- Properties of the kriging proxy:
  - Interpolates the observed data
  - Trend dominates far from observed points (here the trend is a constant value)

38

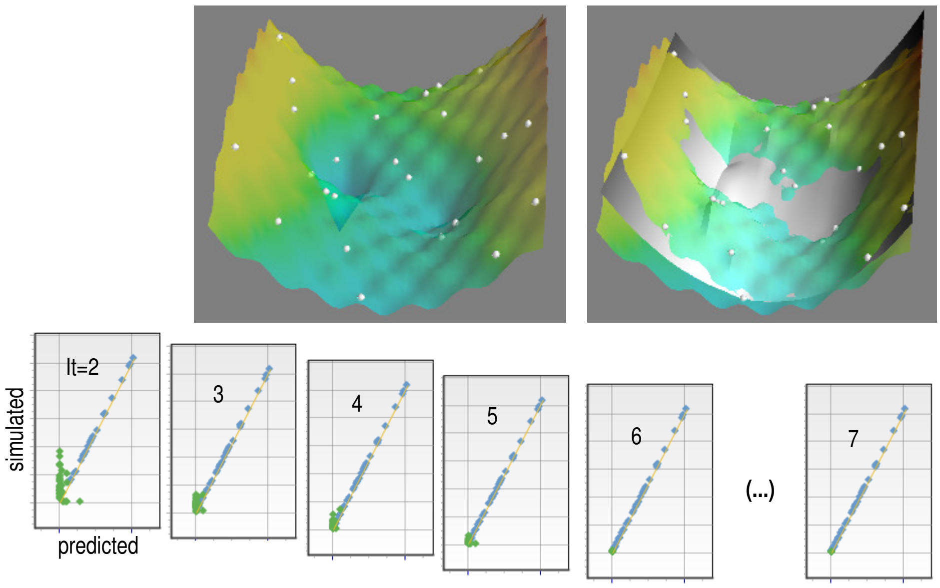
Kriging Variance

- Not only $mean(Z(X))$ but also $\text{variance}(Z(X))$ can be computed
- Variance is 0 at observed points : value is known
- Kriging variances are used in the MCMC sampling to identify unexplored areas



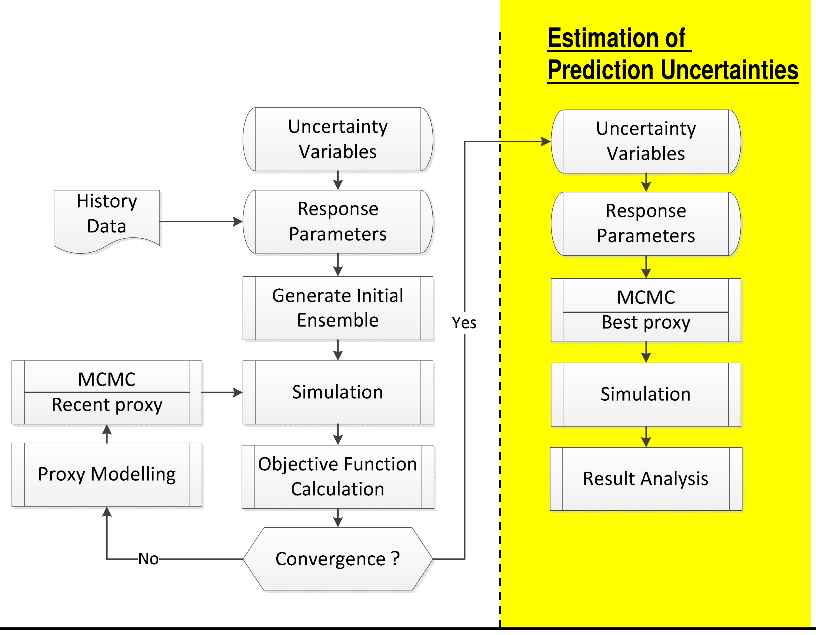
39

Automatic Proxy Modeling – Progression of Proxy Quality



40

Workflow – Estimating Prediction Uncertainties



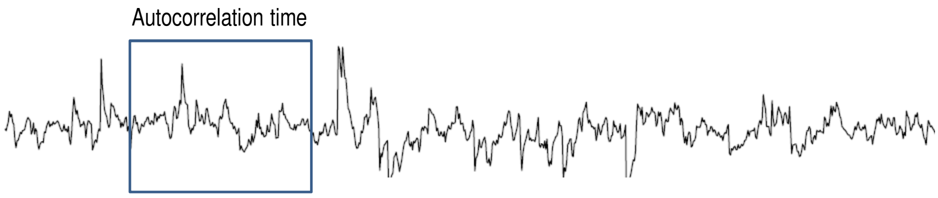
41

MCMC-Sampling: Generation of a Prediction Ensemble

MCMC-Sampling needs to meet two criteria

1. Sampling from the posterior distribution
   - Defining property of the MCMC process

2. Sampled candidates need to be independent
   - An approximate auto-correlation is calculated to measure the independence of consecutive samples



42

Auto-Correlation

- Assume states X of a Markov chain, with

$$\{X_i\}_{i=1}^{n} \qquad EX_i = \mu \quad \text{and } \mathrm{var}(X_i) = \sigma^2$$

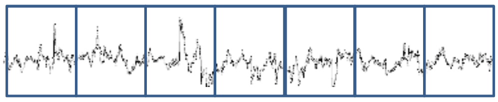
- Autocorrelation time τ :

$$\sqrt{\frac{n}{\tau}} \cdot \frac{\overline{X}_n - \mu}{\sigma} \Rightarrow N(0,1)$$

- Batch means

$$\hat{\tau}_{\mathrm{n,m}} = \mathrm{m}\frac{\mathrm{s}_{\mathrm{m}}^2}{\mathrm{s}^2}$$

  - n: number of samples
  - m: batch size
  - s^2: sample variance
  - s^2_m: batch sample variance



43

Discussion: Chain Evaluations

Selected workflow options:

1. Sampling from the raw distribution
   - Candidates sampled from posterior distribution (MCMC-Workflow)
   - N candidates from one chain
2. Sampling from the minimum distribution
   - Candidates sampled from posterior distribution (MCMC-Workflow)
   - One candidate per chain. N chains
3. Sampling from the raw distribution with a cutoff
   - Candidates sampled from posterior distribution (MCMC-Workflow)
   - N candidates from one chain

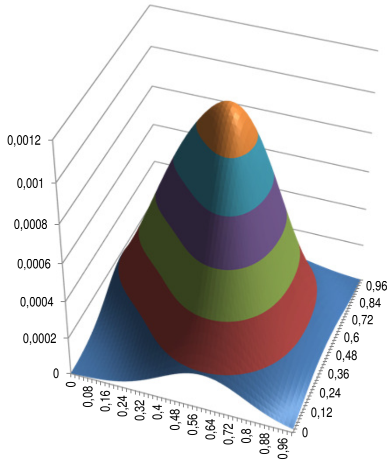
44

1. Sampling from the raw distribution

- The stochastic optimization workflow creates proxies for the GLOBAL objective value
- The likelihood of a given sample is assumed to be

$$\propto \exp\left(-\frac{GLOBAL}{var(GLOBAL)}\right)$$

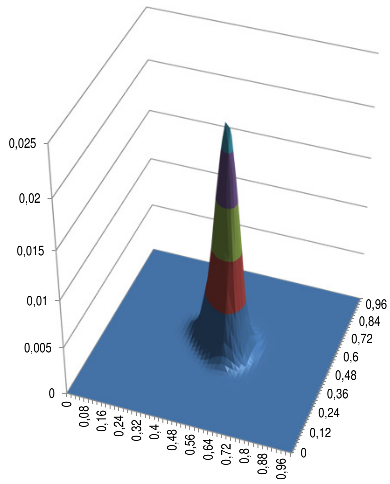
- By definition of the MCMC algorithm, the samples produced this way will be drawn according to their likelihood.



45

2. Sampling from the minimum distribution

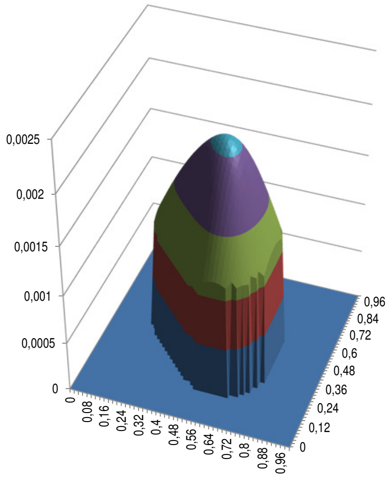
- Focus on samples with the best GLOBAL values is to use a minimum distribution instead of the raw distribution
- This can be achieved with a *MCMC Proxy* method parameterized with as many Markov chains as we need samples, 1 sample per chain.



46

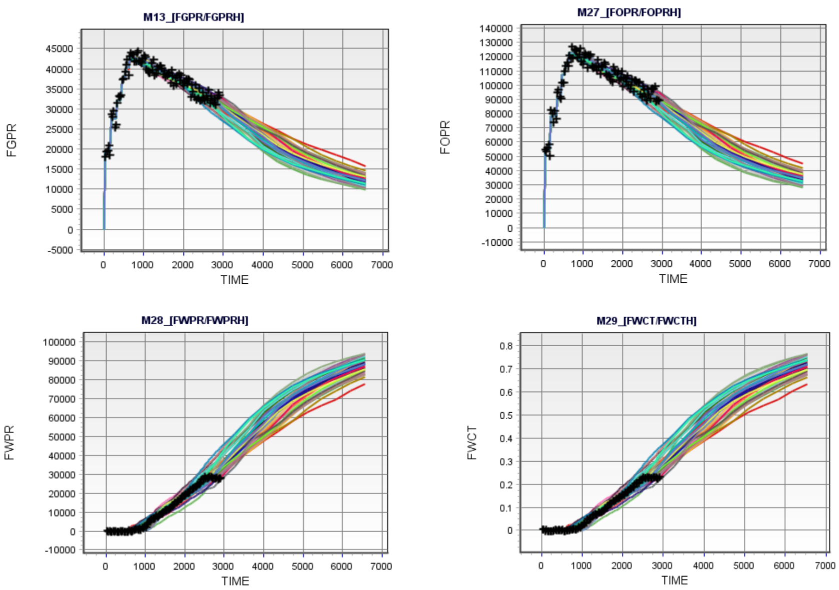
3. Sampling from the raw distribution with a cut-off

- MCMC Proxy method with only one chain but with a cut-off corresponding to the max value of the GLOBAL for the experiment.
- The cut-off value is considered to represent a "good" match
- In this case sampling is done from the raw distribution defined by the proxy GLOBAL, but limited to the regions of the sample space where the predicted GLOBAL is better than the cut-off value



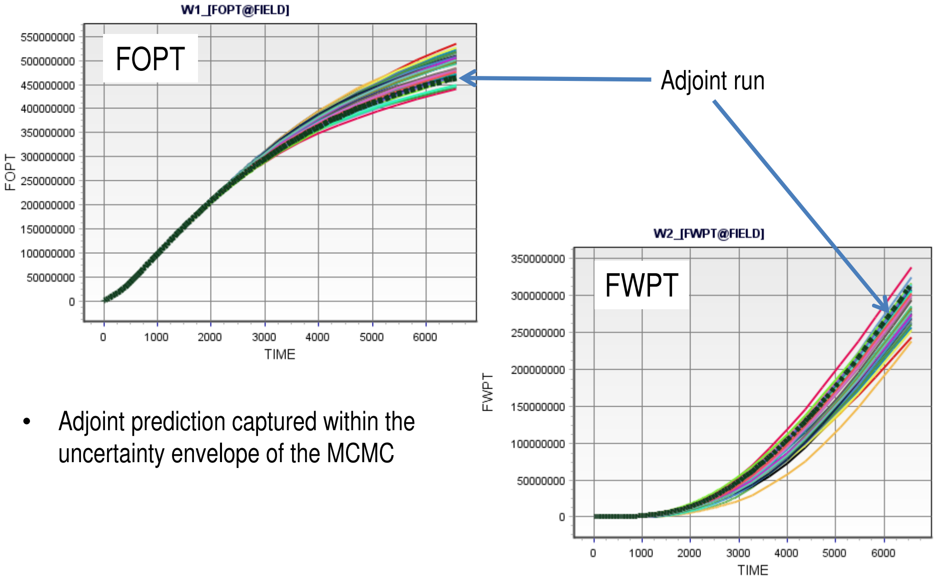
47

Results: Watt Field – MCMC Prediction Ensemble



48

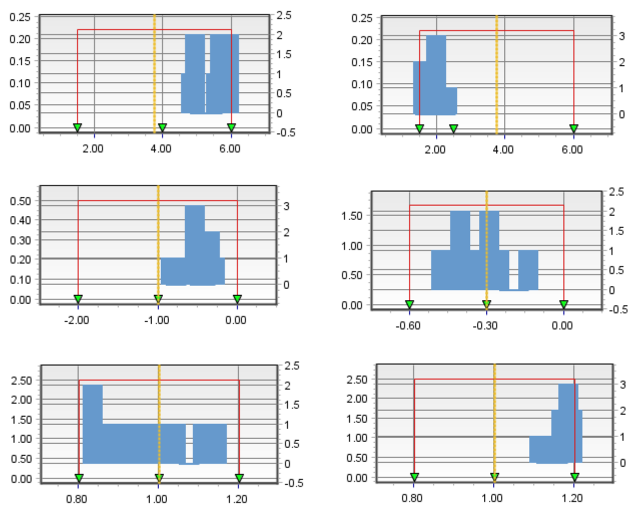
Results: Comparison of Prediction Runs (MCMC vs Adjoint)



- Adjoint prediction captured within the uncertainty envelope of the MCMC

49

Results: Watt Field– HM Result Analysis (posterior)



50

Summary – History Conditioned Forecasting

- Workflow supports estimating prediction uncertainties including history data
- The methodology combines automatic proxy modeling techniques and full field simulation
- Distributions for key parameters of interest are calculated based on full field simulation results
  - Alternatively, distributions can be calculated from proxy modeling results

51

Acknowledgement

Schlumberger Information Solutions:
James Baffoe, Frederic Chataigner,
Niels Kueck, Oliver Pajonk, Akira Shiromizu

Joint Industry Projects:
- History Conditioned Forecasting

- Adjoint techniques

Firmsoft Technologies

References
- ***Uncertainty Quantification Workflow for Mature Oil Fields: Combining Experimental Design Techniques and Different Response Surface Models***, SPE164142, MEOS2013
- ***Strategic Scope of Alternative Optimization Methods in History Matching and Prediction Workflows***, SPE164337, MEOS 2013
- ***Determination of Turnover and Cushion Gas Volume of a Prospected Gas Storage Reservoir under Uncertainty***, DGMK 2013, ISBN 978-3-941721-31-9
- ***Network Optimization Including Gas Lift and Network Parameters under Subsurface Uncertainty***, DGMK2013, ISBN 978-3-941721-31-9

52

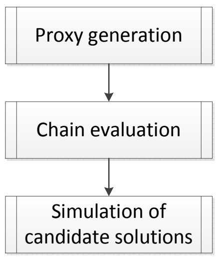
Estimation of prediction uncertainties in oil reservoir simulation using Bayesian and proxy modelling techniques

Part II: Lesson Learned

Challenges

MCMC workflows include three time consuming computation tasks

1. Proxy generation for every response parameter
2. Chain evaluation with thousands of samples
3. Simulation of candidate solutions as an input to the next generation of proxy models



In MCMC workflows all three process can consume significant parts of the overall computing time.

54

1. Proxy Generation

- Two different automatic proxy generation methods are tested and used
  - Regression models
  - Kriging models with a regression trend model

- Proxy models become more complex with the number of input parameters

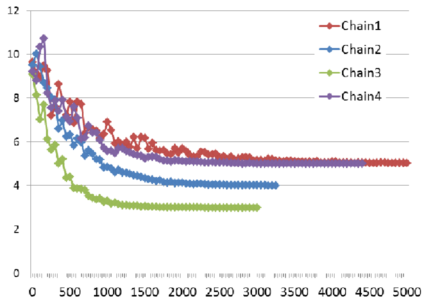
$$y = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon$$

  - Computation time increases significantly with the number of input parameters

- Conclusion
  - Fewer number of input parameters will speed up the proxy generation process
  - Number of response parameters scales linearly with the computation time

2. Chain Evaluation

- The search space scales with the number of input parameters
- The dimensionality has the most important impact on the computing time of the chain evaluation
- A chain evaluation is a sequential process and cannot be split into parallel processes
- Multiple chains are independent



Conclusion

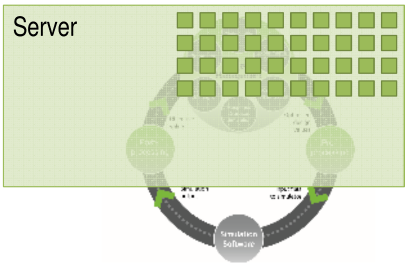
- Reduction of input parameters reduces the computing time of the chain evaluation
- Processing multiple chains in parallel speeds up the elapsed computation time

MCMC Proxy Training and Chain Evaluation

In each iteration, the MCMC optimization method
- creates new Proxies for all objective response parameter
- runs Markov Chains

Both can be time consuming

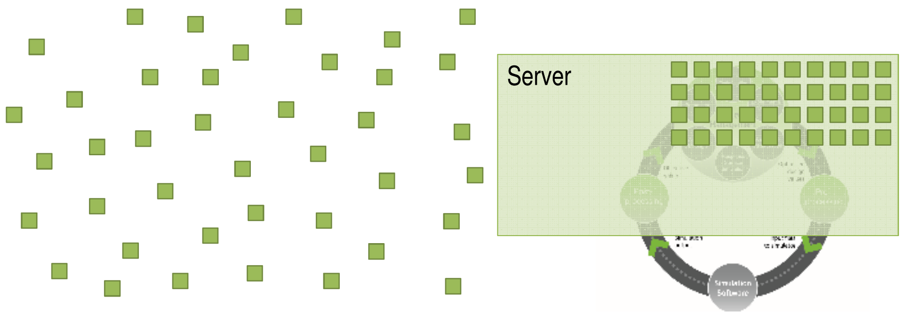
On a laptop or workstation resources are limited, on a cluster hundreds of proxies might be trained at the same time.



57

MCMC Proxy Training and Chain Evaluation

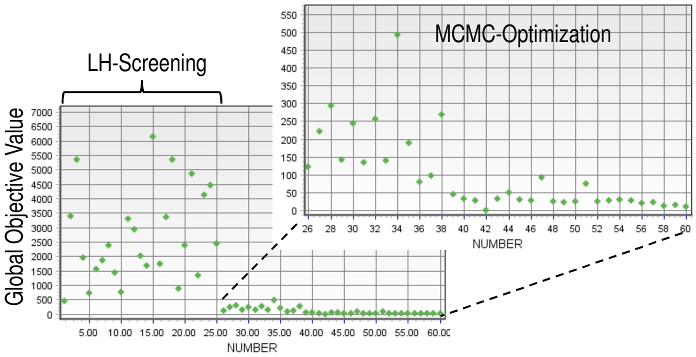
Running proxy training and Markov Chain evaluation externally as own processes in a cluster environment.
Distributing processes, finishing faster simply by concurrent execution.



58

3. Simulation

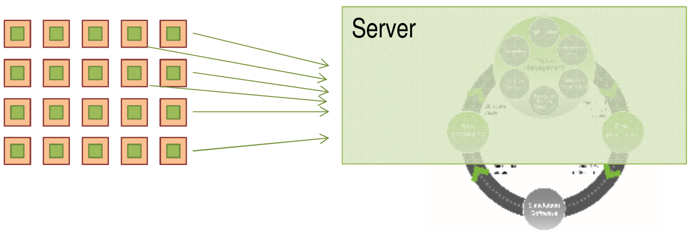
- Simulation runs of candidate solutions are independent from the proxy generation and chain evaluation.
- Results are added to the training data set for the next generation of proxy models
- Convergence criteria for improving performance indicators should be carefully monitored in order to limit the number of simulation runs
- Parallel (concurrent) processing is possible and recommended



59

Best Practices: Project Planning

- MCMC workflows potentially require significant computing resources for
  - Simulation
  - Chain evaluation
- Several processes scale with the number of available computing units/cores
  - Simulation
  - Chain evaluation
  - Proxy modeling
  - Post processing
- Review available resources and design workflow accordingly



60