Bridging The Gap Between Material Balance And Reservoir Simulation For History Matching And Probabilistic Forecasting Using Machine Learning

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essence Managing uncertainty

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Acknowledgements

- Colleagues at Energy Scitech during 2000's
- Hundreds of worldwide users of EnABLE during 2000's
  - Statoil, Hess, Shell, Saudi Aramco Event team, etc.
- Users of EssRisk since 2013
- Statisticians from biomedical, molecular modelling, physics, hydrology, etc
- Academic institutes
  - Columbia, Durham, Warwick, Bristol, UK MRC, NASA, Edinburgh, Toronto, Ottawa, UT, Helsinki, UCL, Leicester, MIT, Oxford, Cambridge, Harvard, etc. etc.

Agenda

- Introduction
- Field example of history matching
- Proxy models
- Work flows
- Markov Chain Monte Carlo
- Proxy model details
- Data driven and physics hybrids
- Field example of data driven modelling
- Conclusions

What do I expect to learn?

- Modern techniques for probabilistic forecasting
- Limitations of commonly used forecasting techniques
- How we can assist history matching for complex fields
- How we can leverage data driven methods
- Why purely data driven methods fail and we need to include physics
- Some deep dive into the maths for awareness

Overview

- Introduction to methods based on reservoir simulation
  - Proxy models
  - Uncertainty quantification
- Extension to data driven approaches
- Field examples

Why simulation?

- Why do we do reservoir simulation and HM?
  - Make probabilistic uncertainty forecasts of our assets
  - Make optimal operational decisions on our assets
  - Improve our understanding of the statics and dynamics of the reservoir
- The purpose of history matching is not to get a history match
- Historically production forecasts have been biased and optimistic, and under estimate uncertainty

History of history matching tools

- 1980's first generation (Scientific Software Intercomp)
  - Early experimental design
- 1990's second generation
  - Early assisted history matching tools
  - Evolving genetic algorithms
  - Some adjoint local optimisation approaches
- 2000’s third generation (Energy Scitech, MEPO)
  - Commercial and internal tools
  - Hundreds of history match studies
  - Typically 50+ modifiers
- 2010’s fourth generation (Essence Analytics)
  - Valid fully probabilistic uncertainty quantification
  - Ensembles of equiprobable models
- 2020’s fifth generation
  - Include data driven/physics based capabilities

What is the problem with current approaches?

- Good at history matching but poor at probabilistic forecasting
- Similar stage to reservoir simulation in the 1970's
  - Little validation of prediction uncertainty results
- Uncertainty methods have significant limitations
  - Over optimism on convergence behaviour
  - Under estimation of uncertainty
- Too much 'trust me' – is the ensemble of simulation runs valid?
- Shift in focus from regarding history matching as an optimisation problem to regarding it as an uncertainty quantification problem.

Statistician quotes

- All models are wrong – some are useful (Box)
- The Quiet Scandal of Statistics is the use of a single model for prediction (modified - Breiman)
- Exactly wrong or roughly correct?
- How much wrongness is acceptable?

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Probabilistic forecasting

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- An encapsulation of the team's beliefs about models, parameters and their ranges, quality of measurement data, and quality of simulation model, within a probabilistic/Bayesian framework which can generate accurate and validated probabilistic cumulative distribution curves (S curves) for quantities of interest at times of interest, which can then be represented by a suitable set of simulation runs.

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Slide 11

BP1 Brilliant slide!
Bob Parish, 3/8/2006

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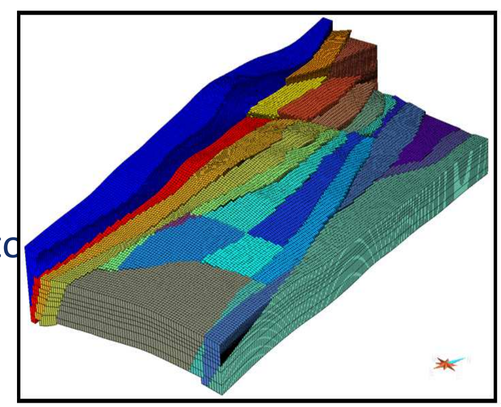
Simulation Model

- 787 thousand active cells
- 308 possible compartments
  - 28 fault block multiplied by 11 zones
- 13 PVT regions
- 140 wells with over 30 years of histo
- Averages 27% porosity
- Average 420 mD permeability



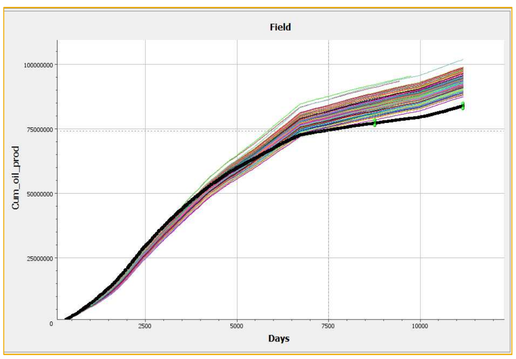
Major Fault Blocks

Uncertainty parameters

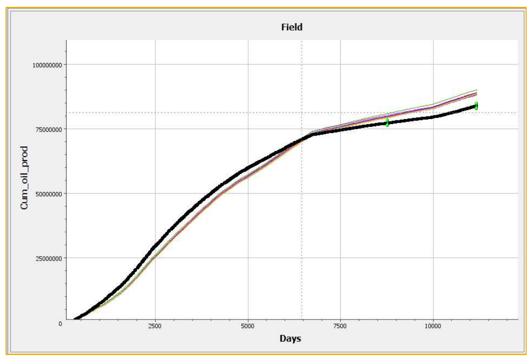
For this study, we focused on 145 modifiers

- 22 fault transmissibilities multipliers
  - ranged from 0.0 to 1.0
- 75 inter-regional transmissibilities multipliers
  - ranged from 0.0 to 1.0
- 48 regional horizontal and vertical permeability multipliers
  - range 0.2 to 5.0
- Full probabilistic uncertainty after 225 simulation runs
- Total assisted history match can be done in order of hours vs days

Field results

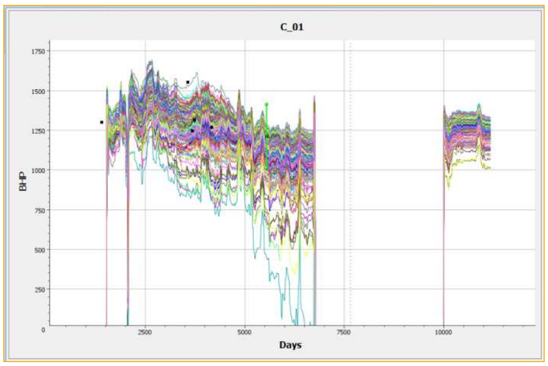


All simulation runs

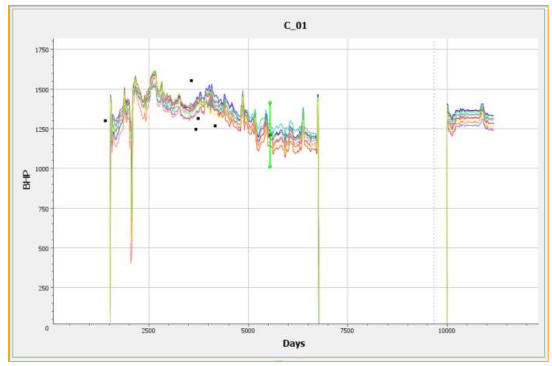


10 best simulation runs

Individual well results

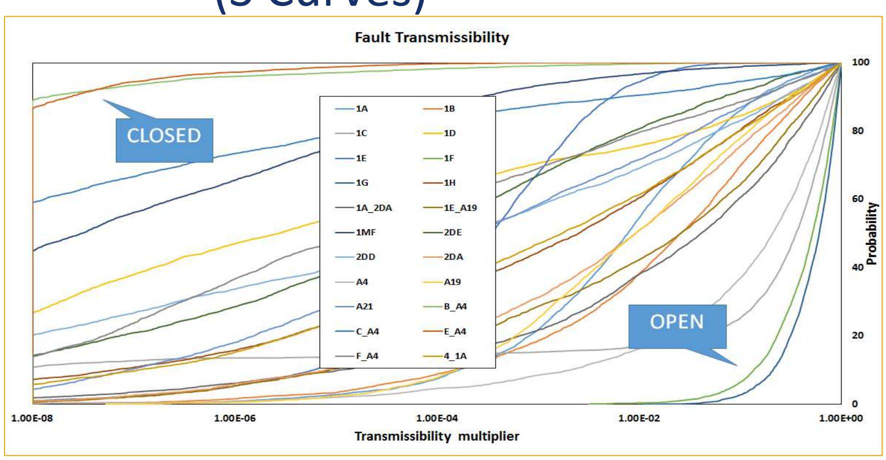


All simulation runs



10 best simulation runs

Uncertainty in fault transmissibility modifier (S Curves)



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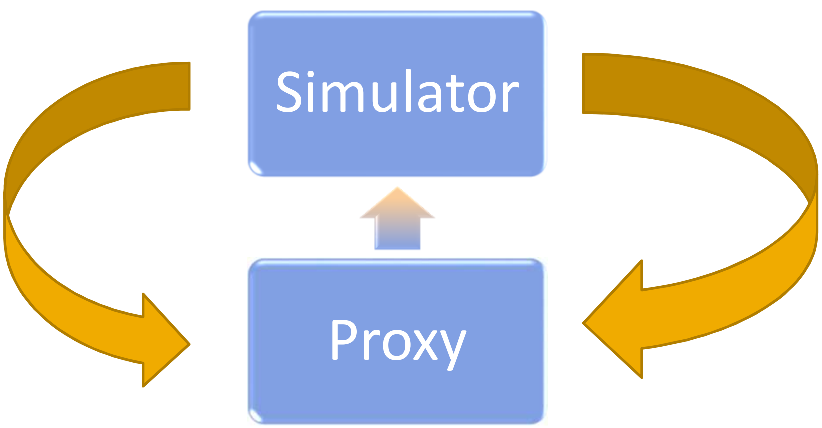
Simulator and proxy models



How can proxy models help us?

- We can sample tens of millions of times in Monte Carlo Markov Chain process to calculate valid probabilistic uncertainty
  - Completely impossible to perform MCMC directly with simulations
- An aid, not a replacement, for reservoir simulations

Proxy models

- EssRisk proxy models
  - Represent input v. output
  - May be hundreds of proxy models
  - Are fully interpolating – fit data exactly
  - Optimise the correlation lengths and directions
  - Details are published (see references below)
  - Are very fast
    - 2 - 10 secs to build each one
    - 0.024 millisecs per calculation

S curves for prediction uncertainty

- An S curve is a cumulative probability curve
  – Calculated using numerical integration
  – Use some form of Monte Carlo method
- We may calculate S curves for different results and times (e.g. field cum at 2020, field cum at 2030, field water at 2025, water breakthrough time for well A)
- S curve calculations are prone to very significant error and involve a very large number of calculations

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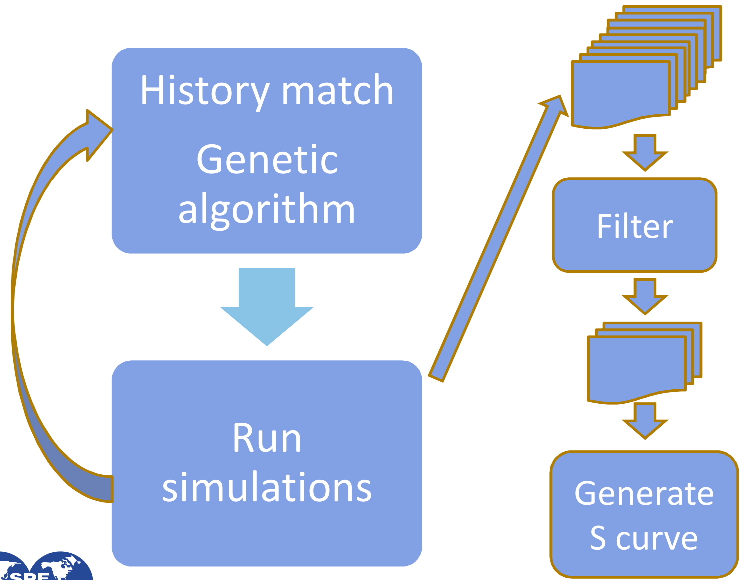
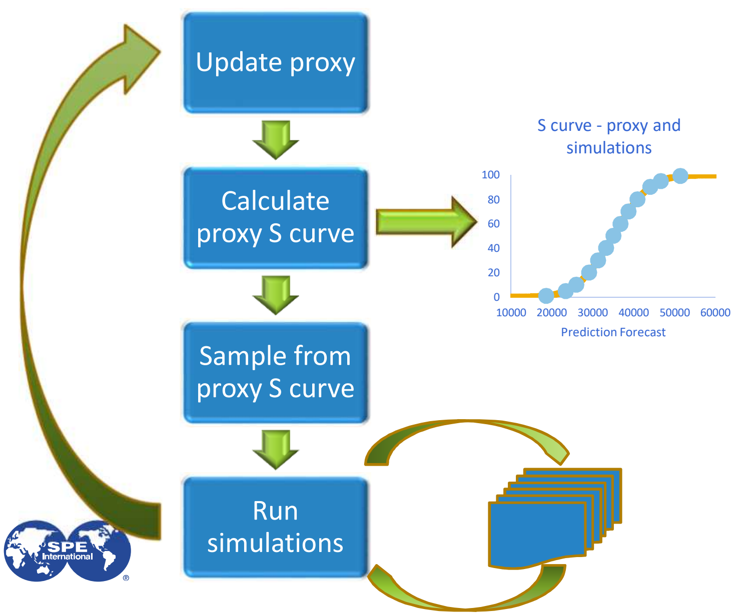
Possibilistic Workflow



- S curve is created from runs
- No likelihood/probability function
- Ranking by sum of squares
- S curve and Runs are statistically invalid
- Genetic algorithm is not designed for statistics

Probabilistic Workflow



- S curve is created from proxy
- S curve from simulations is synergised
- Prediction is fully integrated with HM, no special workflow
- Easy to find P10, P50, P90 runs by inspection

Update proxy

Select polynomial models

GA + MCMC

↓

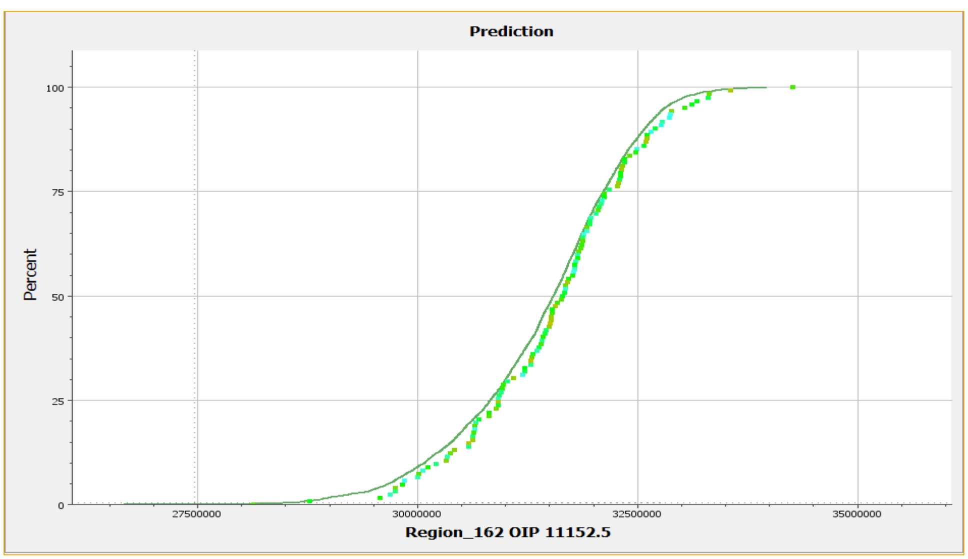
Create Gaussian Process proxy with averaged polynomial model

↓

Optimise restricted likelihood

GA followed by BOBYQA

- Which variables to include in polynomial?
- Bayesian weighted polynomial average
- Gaussian Process to interpolate data points
- Optimise correlation lengths and directions



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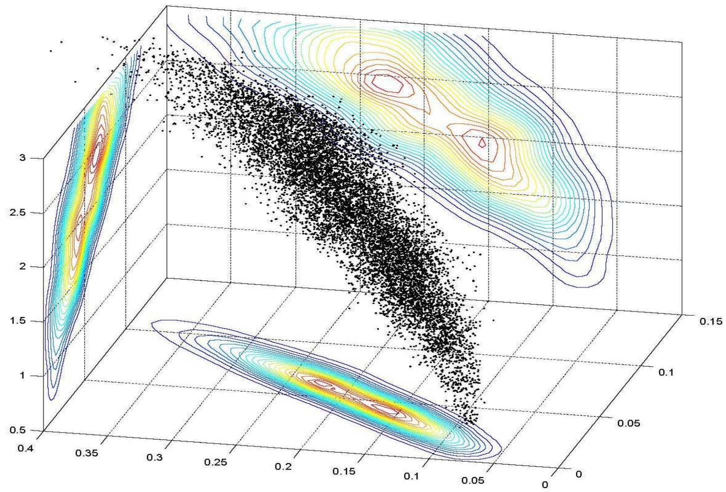
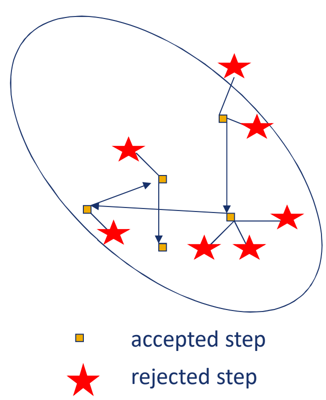
Intro to Markov Chain Monte Carlo

- A way to integrate and generate S curves
- Commonly used but needs care
  - high dimensions, complex functions, multiple modes
- Various tuning parameters to self adjust
- Burn-in to reject initial samples
- Lots of theory
  - Reversibility, ergodicity, volume preserving
  - Easy to devise Markov Chains which disobey rules
  - Convergence proven with infinite samples
  - Practical convergence tests difficult
- All samples are equi-probable
  - Frequency is higher in more likely areas

Monte Carlo example





MCMC approaches

- Markov Chain Monte Carlo – the gold standard for uncertainty quantification for complex functions
  - Converges if you wait long enough
- Random Walk (RWM)
  - Fairly widely used in probabilistic forecasting
  - Can be grossly misleading for high dimensions
- Hamiltonian (NUTS) (2012)
  - Recent new method for high dimensions/complex problems
  - Requires derivatives

Hamiltonian MCMC

- Requires derivatives

$$H(\boldsymbol{x}, \boldsymbol{p}) = -L(\boldsymbol{x}) + \frac{1}{2}\boldsymbol{p}^T \boldsymbol{M}^{-1}\boldsymbol{p}$$

$$\frac{\partial \boldsymbol{x}}{\partial t} = \boldsymbol{M}^{-1}\boldsymbol{p}$$

$$\frac{\partial \boldsymbol{p}}{\partial t} = -\boldsymbol{\nabla}_x L(\boldsymbol{x})$$

$$\boldsymbol{p}\left(\tau + \frac{\epsilon}{2}\right) = \boldsymbol{p}(\tau) - \frac{\epsilon}{2}\boldsymbol{\nabla}_x L(\boldsymbol{x}(\tau))$$

$$\boldsymbol{x}(\tau + \epsilon) = \boldsymbol{x}(\tau) + \epsilon \boldsymbol{M}^{-1}\boldsymbol{p}\left(\tau + \frac{\epsilon}{2}\right)$$

$$\boldsymbol{p}(\tau + \epsilon) = \boldsymbol{p}\left(\tau + \frac{\epsilon}{2}\right) - \frac{\epsilon}{2}\boldsymbol{\nabla}_x L(\boldsymbol{x}(\tau + \epsilon))$$

100 dimensional Gaussian

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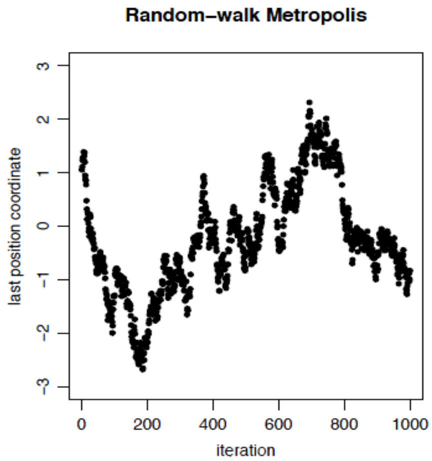

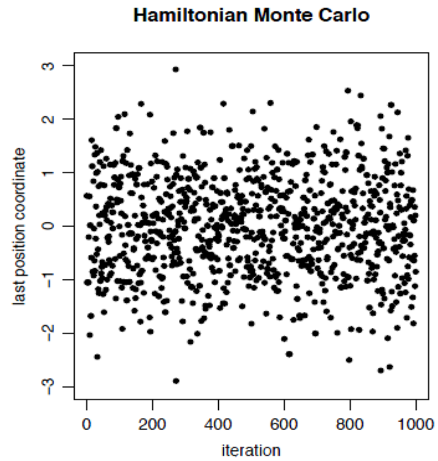

Validity of statistical methods

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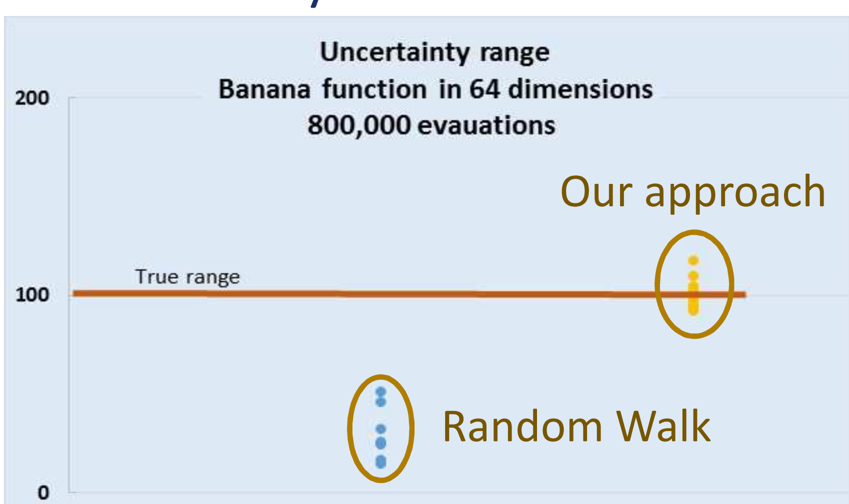
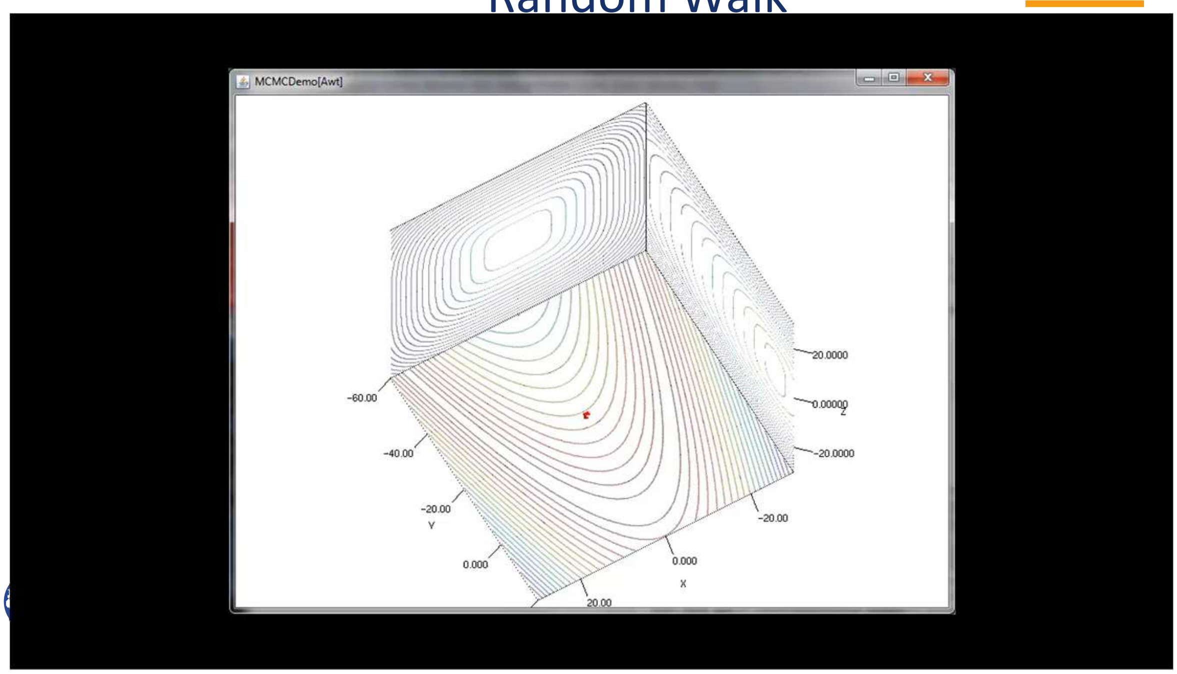


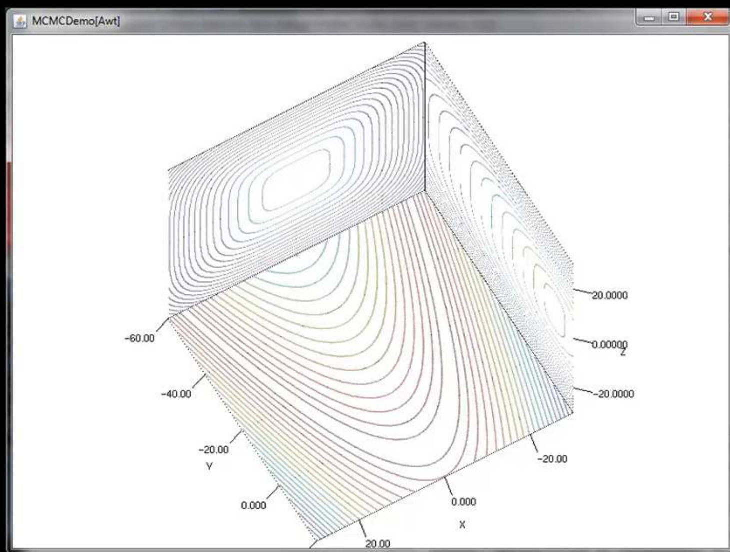
Validity of statistical methods

- Videos
  - Random Walk method for 64 dimensional banana function
  - Hamiltonian method for 64 dimensional banana function
- We show 3 dimensions

Random Walk



EssRisk



Validity of statistical methods

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- Commonly used random walk methods are only reliable for small number of dimensions
- Statistics on convergence (e.g. Gelman-Rubin) are very rarely reported
- Hamiltonian with automatic tuning is vastly superior
- Hamiltonian with proxy models is necessary
  - Large number of function evaluations
  - Derivatives necessary
  - Fast performance necessary

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Simulator and proxy

$$\mathrm{E}(\mathrm{y}(\mathbf{x})) = \overbrace{\underbrace{\mathbf{f}(\mathbf{x})^{\mathrm{T}}\boldsymbol{\beta}}_{\text{Ensemble of linear regression models}} + \left(\mathbf{f}(\mathbf{x})^{\mathbf{T}}\mathbf{Var}(\boldsymbol{\beta})\mathbf{X}^{\mathbf{T}} + \sigma^2 \emptyset(\mathbf{x})^{\mathbf{T}}\right)\phi^{-1}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})}^{\text{Gaussian Process model}}$$

- Constructing the proxy model takes around a second
- Evaluating the proxy model takes around 0.025 milliseconds

101 statistics in 2 slides

Linear regression

$$Y = X\beta + \varepsilon$$

$$y(x) = f(x)^T\beta \qquad \hat{\sigma}^2 = \frac{rss}{n-p-1}$$

$$\hat{\beta} = (X^TX)^{-1}X^TY$$

$$var(\hat{\beta}) = var\left((X^TX)^{-1}X^TY\right) = (X^TX)^{-1}X^Tvar(Y)X(X^TX)^{-1} = \hat{\sigma}^2(X^TX)^{-1}$$

$$LL = -\frac{(n-p-1)}{2}ln(2\pi\sigma^2) - \frac{(Y-X\beta)^T(Y-X\beta)}{2\sigma^2}$$

$$AIC_c = 2LL - 2(p+2)\frac{n}{n-p-3}$$

Proxy model

$$E(y(x)) = f(x)^T\beta + \varphi(x)\Phi^{-1}(Y - X\beta)$$

$$Var(y(x)) = f(x)^TVar(\beta)f(x) + \sigma^2 - \left(f(x)^TVar(\beta)X^T + \sigma^2\emptyset(x)^T\right)\phi^{-1}\left(f(x)^TVar(\beta)X^T + \sigma^2\emptyset(x)^T\right)^T$$

101 statistics in 2 slides

Optimise correlation function hyper parameters

$$REMLL = -\frac{(n-p-1)}{2}ln(2\pi\sigma^2) - \frac{1}{2}ln|\phi| - \frac{1}{2}ln\left|X^T\phi^{-1}X\right| + \frac{1}{2}ln\left|X^TX\right| - \frac{(Y-X\beta)^T\phi^{-1}(Y-X\beta)}{2\sigma^2}$$

Bayesian averaging

$$Y = X_M\beta_M + \varepsilon_M$$

$$\hat{y}(x) = \tilde{f}(x)^T\tilde{\beta}$$

$$var(y(x)) = \tilde{f}(x)^T\sum_M w_M\left[var(\beta)_M + (\hat{\beta}_M - \tilde{\beta})(\hat{\beta}_M - \tilde{\beta})^T\right]\tilde{f}(x)$$

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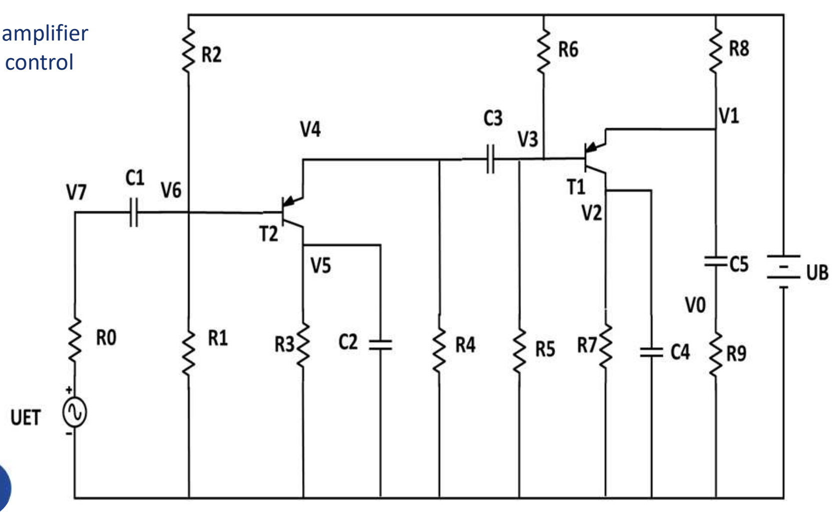
Reverse engineering

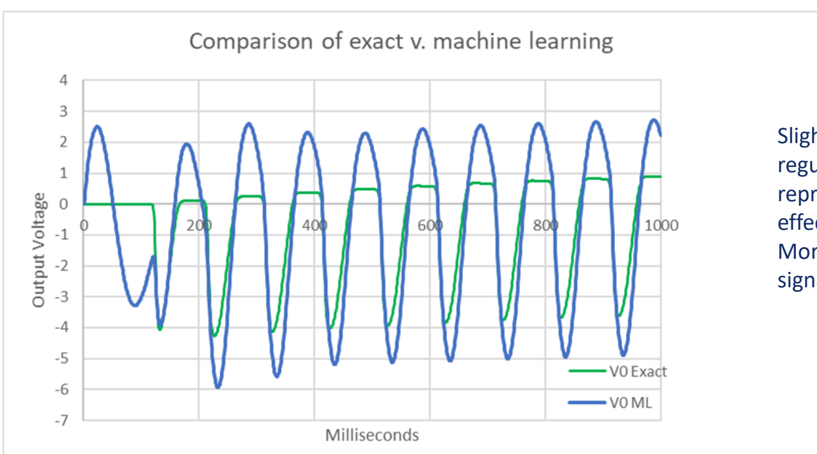
Two stage amplifier with input control voltages



Reverse engineering

- We can construct ordinary differential equations from the circuit and generate voltages over time.
- Can we take these voltages over time and reconstruct the circuit and parameters and solve new ODE's and regenerate voltages?
  - Data driven reverse engineering
  - Non-linear transistors
  - How much physics? Not obvious as we don't know layout.
  - Causality? We don't know.
  - Stability? Very easy to reverse engineer unstable solutions.

Reverse engineering



Slight cheat used to regularise. Circuit not reproduced. Non-linear effects not reproduced. More complex input signal would help

Benefits of data driven forecasting

- Full simulation is always technically best
  - never say always
- But can we do better than material balance for a quick look?
- How do we use fully probabilistic approaches for forecasting?
- Can we leverage machine learning advances?

New approach

- Based on fully probabilistic approach to reservoir simulation, history matching and forecasting
- Proxy models and Hamiltonian Monte Carlo Markov Chain
- Replaces reservoir simulator PDE’s with approximate DAE’s
- Vertical (proxy model) and horizontal (DAE) approximations

Machine learning and reservoir simulation

Statistical time series modelling – many flavours

$$A_0 Y_t = \beta_0 + A Y_{t-1} + \varepsilon_t$$

Y is a vector of measurements at time t. A is a matrix. ε_t is an error at each time step. We calculate values of A_0, A, β_0 to minimise error, using regression.

DAE/ODE modelling

$$M(t)\frac{dY(t)}{dt} = F(Y(t)) \qquad A_0(t)\frac{dY(t)}{dt} = \beta_0 + A(t)Y(t)$$

A set of differential algebraic equations (DAE). ODE's with algebraic constraints. Reservoir simulators use PDE's. Needs an integrator.

DAE v. machine learning

- Statistical Time Series is curve fitting
  - Error at each value so very good fit to history
  - Poor forecasting – increasing funnel
  - No control values
  - No physical constraints
- DAE is integration of equations over time
  - Overall model error
  - No error in ODE/DAE solver
  - Includes control values
  - Include known physics
  - Controlled by mass/momentum/energy balance
  - Requires ODE/DAE solver with constraint handling

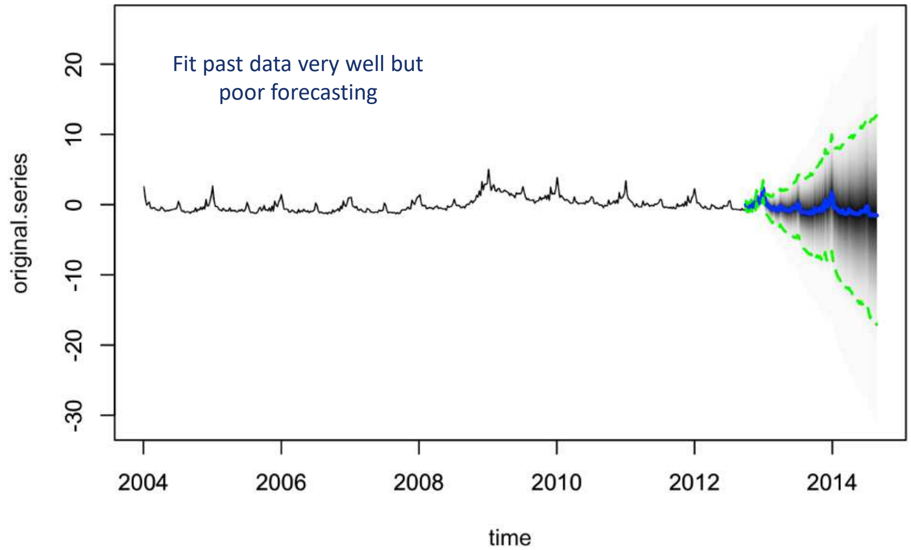
Statistical time series modelling

$$A_0 Y_t = \beta_0 + A Y_{t-1} + \varepsilon_t$$

DAE/ODE modelling

$$M(t)\frac{dY(t)}{dt} = F(Y(t))$$

Machine learning structural time series



Where does machine learning come in?

- Use of automatic feature selection to choose sparse structures in DAE equations
- What is the most likely value of these parameters, and their range?
- Quadratic and interaction terms
- We have for each producer BHP, water rate, gas rate, oil rate
- How do these relate for the well, and for neighbouring wells?
- E.g. what is affecting a well BHP and by how much?
  - Which neighbouring wells?
  - Liquid rates
  - Neighbouring injection rates?
  - Simple time series/decline rates
- What is affecting well gas rate?
  - Well pressures and liquid rates?
  - Neighbouring wells?

$$\mathbf{A}_0(\boldsymbol{t})\frac{dY(t)}{dt} = \boldsymbol{\beta}_0 + \mathbf{A}(\boldsymbol{t})\boldsymbol{Y}(t)$$

Material balance

- Include full material balance equations in the DAE
- Model BHP as a deviation from field pressure
- Include uncertainty in initial field pressure, initial water saturation, pore volume compressibility and water compressibility
- Use PVT and Z factor tables

HM workflow

- The fully probabilistic history matching and forecasting workflow described above
- Now extended to use generalised DAE equations as well as reservoir simulators
- Vertical and horizontal proxies

Probabilistic Workflow

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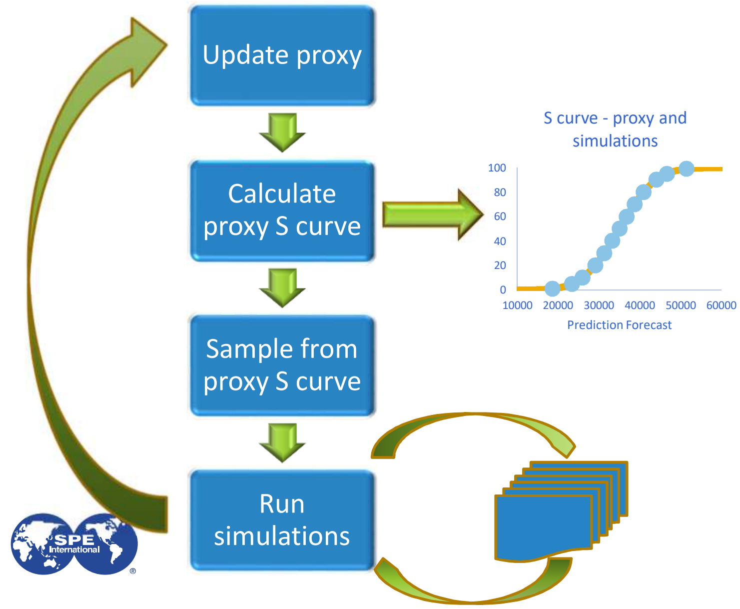

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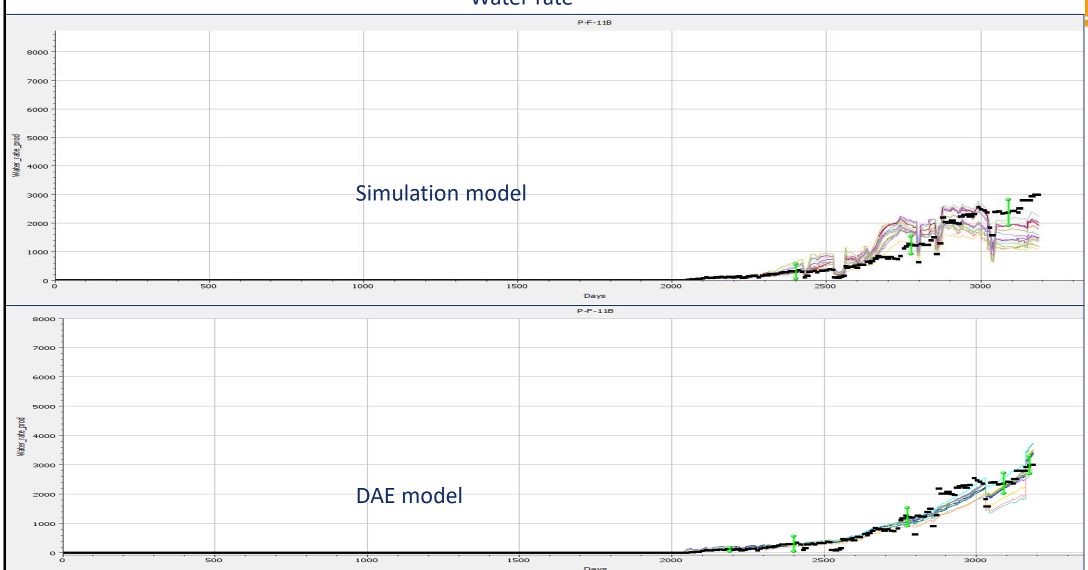
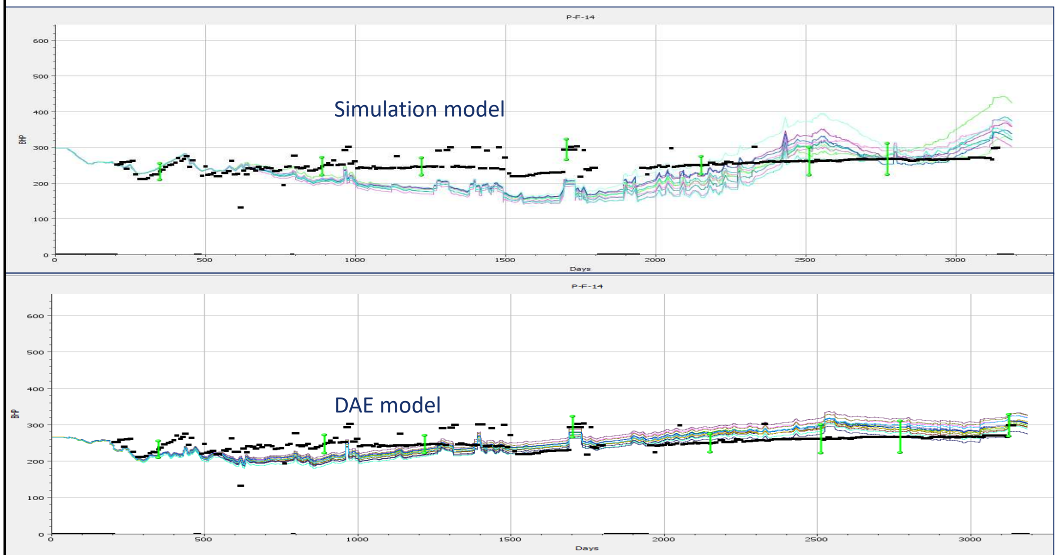
Example case – Volve (Equinor)

- 7 producers, 4 injectors
  - Oil, gas, water rates
  - BHP
  - 36 variables
- Reservoir simulation model: 37 unknown parameters
  - Fault transmissibilities, porosities, permeabilities
- DAE model: 374 unknown parameters
  - Initial conditions
  - Matrix values in the DAE equations
  - Sparsity structure from machine learning feature selection
  - Values and uncertainty ranges from regression
  - Quadratic and interaction terms included
  - Material balance equation uncertainties

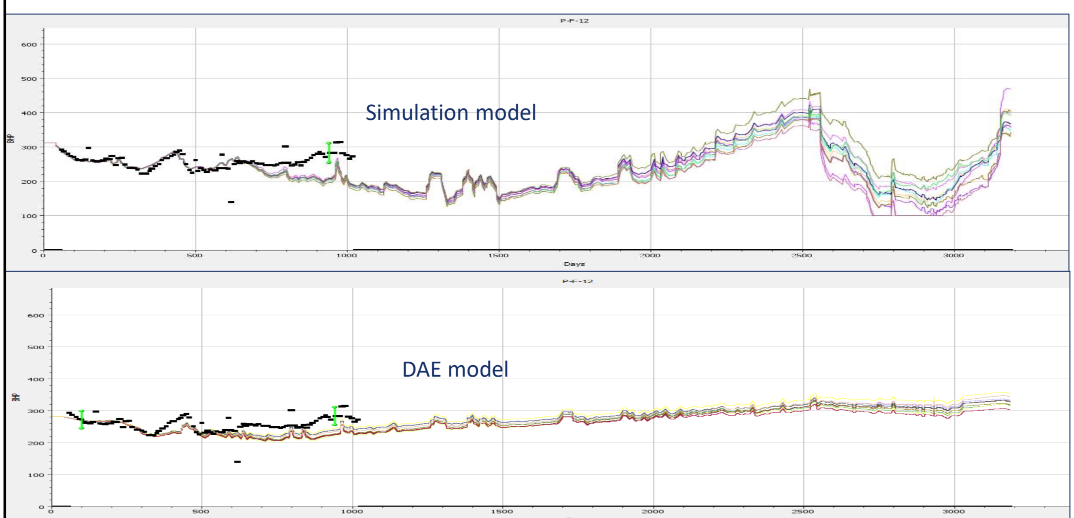
Water rate



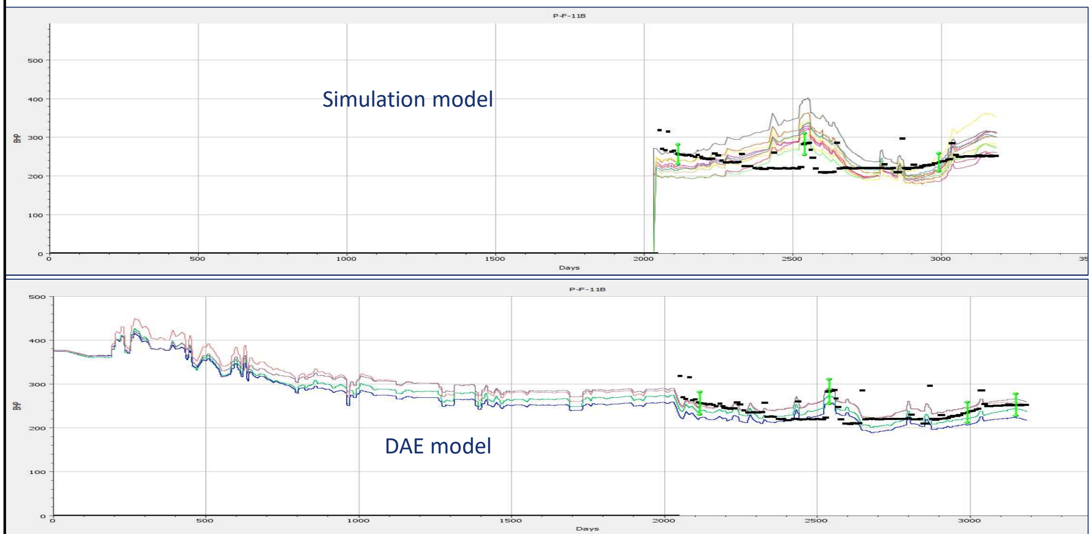
BHP


P-F-14
Simulation model
BHP
Days
P-F-14
DAE model
BHP
Days

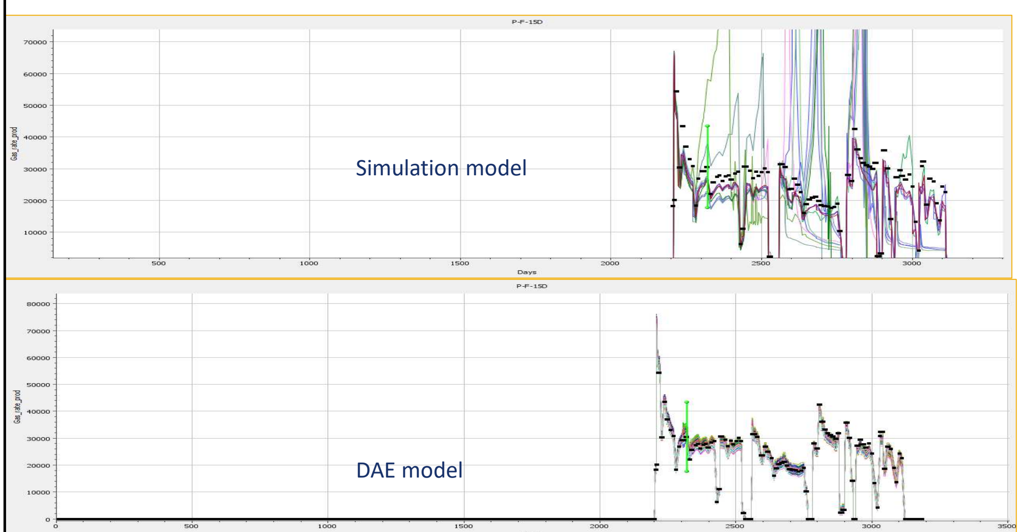
BHP


P-F-12
Simulation model
BHP
Days
P-F-12
DAE model
BHP
Days

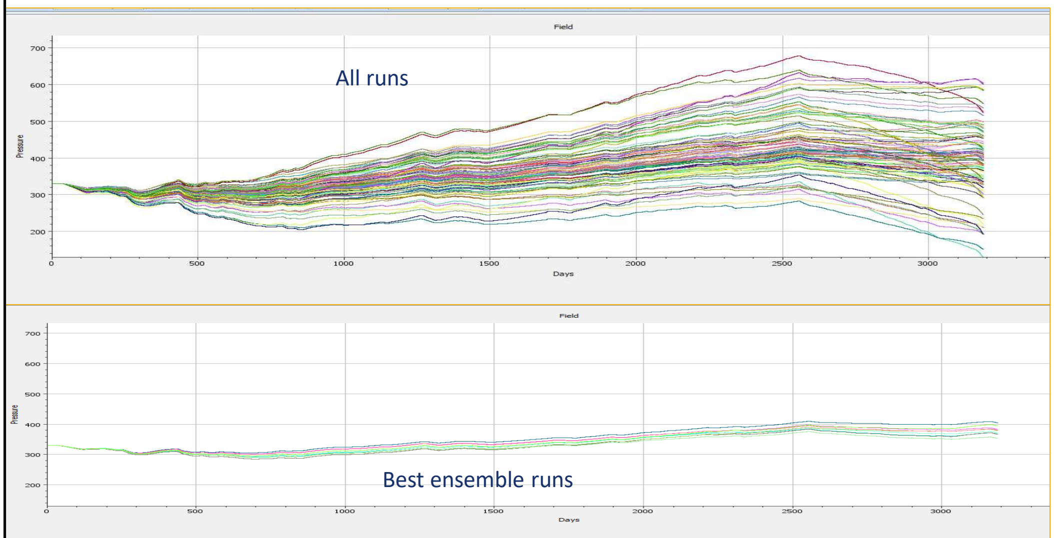
BHP


P-F-11B
Simulation model
Days
P-F-11B
DAE model
Days

Gas rate


P-F-15D
Simulation model
Days
P-F-15D
DAE model
Days

Field pressure DAE model



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Conclusions

- Horses for courses
- Embrace uncertainty and error
- Demand validation of probabilistic forecasts
- Be sceptical of commonly used techniques

Technical references

SPE-182637 Probabilistic Uncertainty Quantification of a Complex Field Using Advanced Proxy Based Methods and GPU-based Reservoir Simulation
N. Goodwin, SPE, Essence Products and Services Ltd,; K. Esler, M. Ghasemi, K. Mukundakrishnan, Stone Ridge Technology; H. Wang, J.R. Gilman, iReservoir.com, Inc.; B. Lee, Memorial Resource Development Corp.

SPE 173301 Bridging the Gap Between Deterministic and Probabilistic Uncertainty Quantification Using Advanced Proxy Based Methods
N. Goodwin, SPE, Essence Products and Services Ltd

SPE-203941 Bridging The Gap Between Material Balance And Reservoir Simulation For History Matching And Probabilistic Forecasting Using Machine Learning
Nigel Goodwin, Essence Analytics;

SPE-177427 Novel Workflow for the Development of a Flow Control Strategy with Consideration of Reservoir Uncertainties
Kousha Gohari, Heikki Jutila, Carlos Mascagnini and Andrey Gryaznov, Baker Hughes RDS; Nigel Goodwin, Essence Products and Services; Murray Howell and Peter J. Kidd, Baker Hughes; and Behrooz Bijani, Quadrant Energy Limited

Thank you