ROBUST TUNING TO IMPROVE SPEED AND MAINTAIN ACCURACY OF FLOW SIMULATION

TNO innovation for life

OPM summit 18-19 October, Bergen | Rohith Nair

OVERVIEW

- Introduction
- Model tuning as an optimization problem
- Methodology
- Experiments and Results
- Conclusions
- Future Work

INTRODUCTION

- Numerical tuning of a reservoir model can considerably affect simulator performance
- Tuning affects both speed and accuracy
- Models are run multiple times for optimization and model updating workflows
- There are multiple tuning parameters which can be changed

Time stepping controls

Convergence controls

Newton and linear iteration controls

```
TUNING
1   365   0.1   1*   3   0.3   2*   0.75 /
4* 10    /
12   1   25   1   3* 1E6       /
```

MOTIVATION

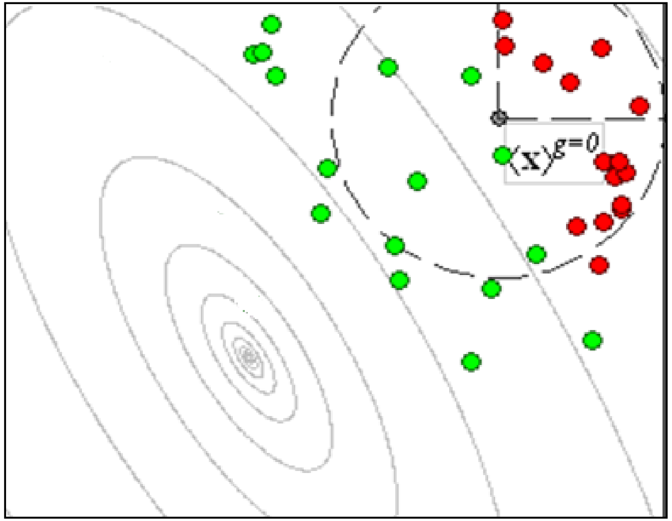
- Limitations
  - Tuning affects both speed and accuracy
  - Is carried out by manual trial and error – no formal way
  - Only a single model can be tuned at a time
- Challenges
  - How to automate model tuning ?
  - How to tune an ensemble of models ?
  - How to improve speed while maintaining accuracy ?

MODEL TUNING AS AN OPTIMIZATION PROBLEM

- Consider the FLOW simulator as a black box
- Carry out robust (ensemble of models) optimization with:
  - Controls = FLOW tuning parameters
  - Objective = Minimize number of linear iterations
- Constraints can be placed on the field production and injection volumes

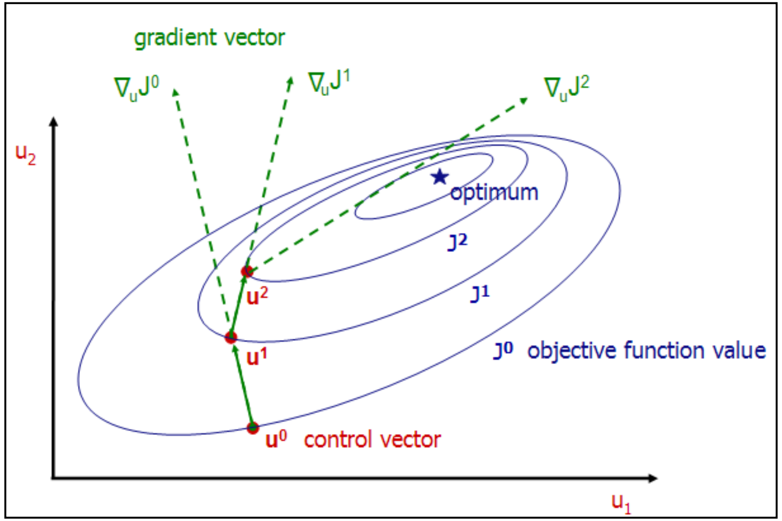
OPTIMIZATION METHODS

Gradient Free Methods



- Move to the point which has the highest objective function value
- Slow convergence rate towards optimum

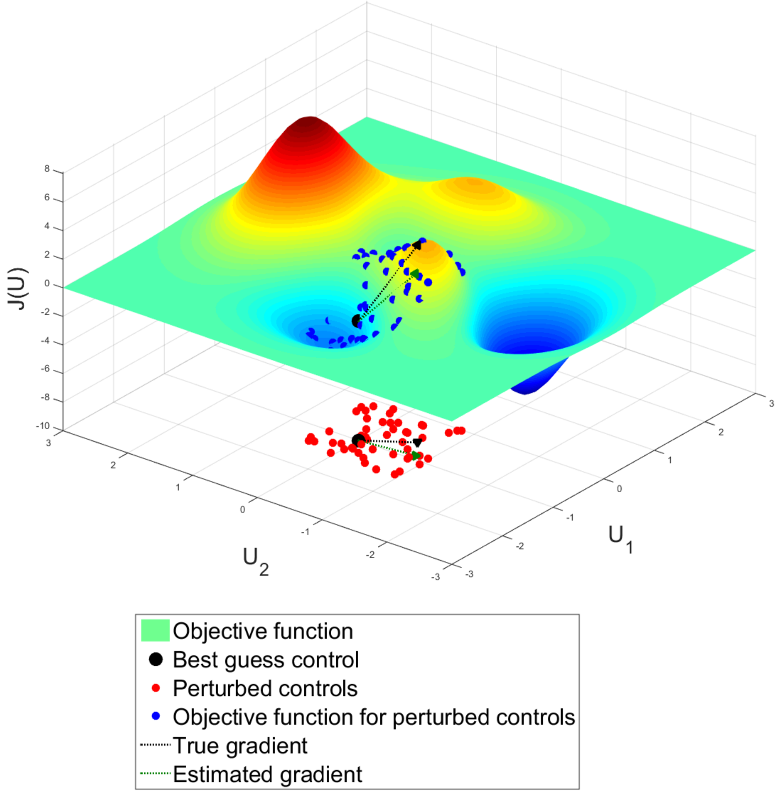
Gradient Based Methods



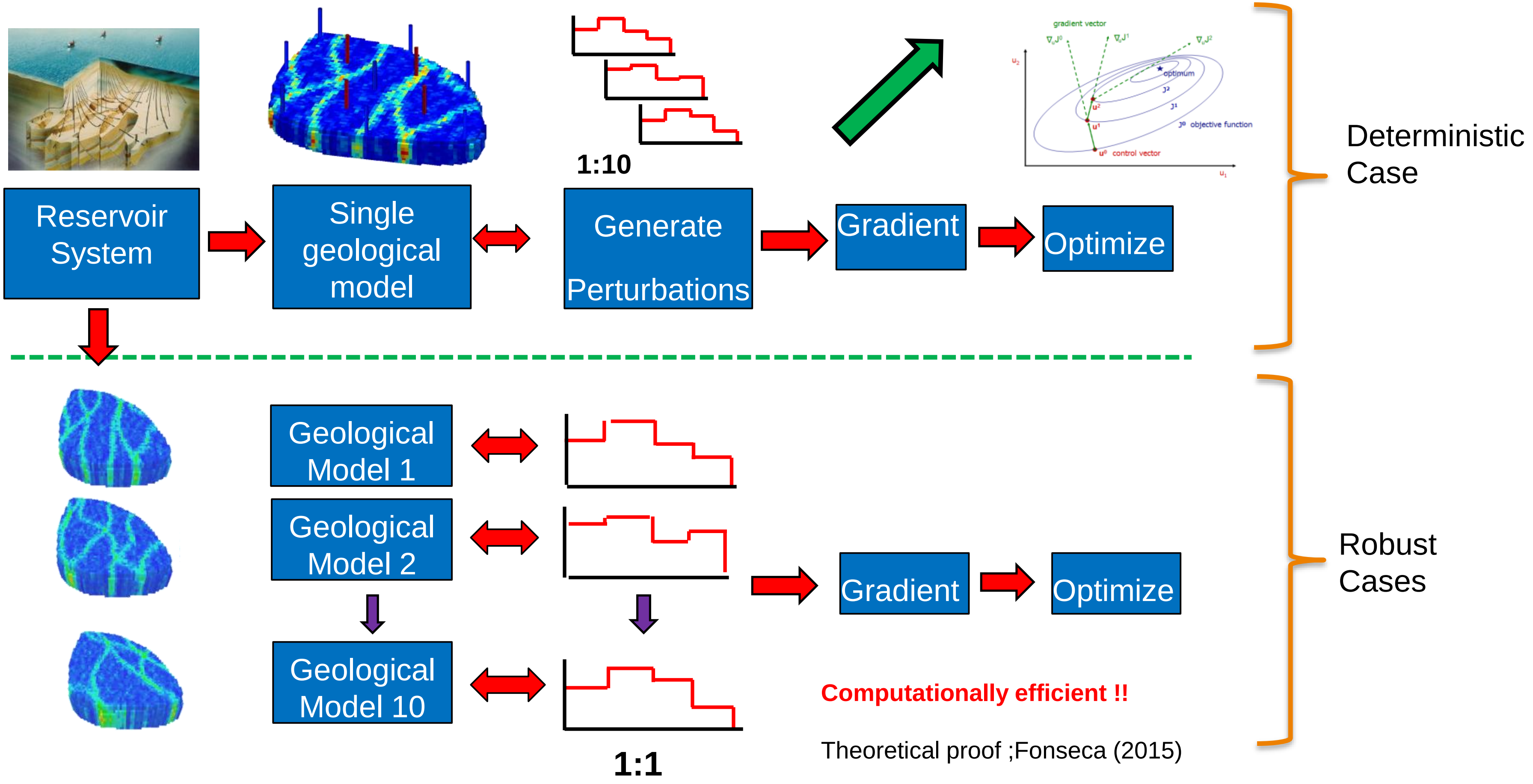
- Calculates a direction in which objective function can be maximized
- Faster convergence rate towards optimum.

STOCHASTIC GRADIENT BASED OPTIMIZATION

1. Choose an initial set of controls
2. Generate an ensemble of control vectors stochastically (red dots)
3. Evaluate each ensemble member of the controls (blue dots)
4. Estimate the gradient from the function evaluations (blue dots)
5. Use an optimization algorithm to find an updated set of controls
6. Repeat from step 2 until convergence is achieved.



STOSAG APPROACH



Computationally efficient !!

Theoretical proof ;Fonseca (2015)

OPTIMIZATION FORMULATION

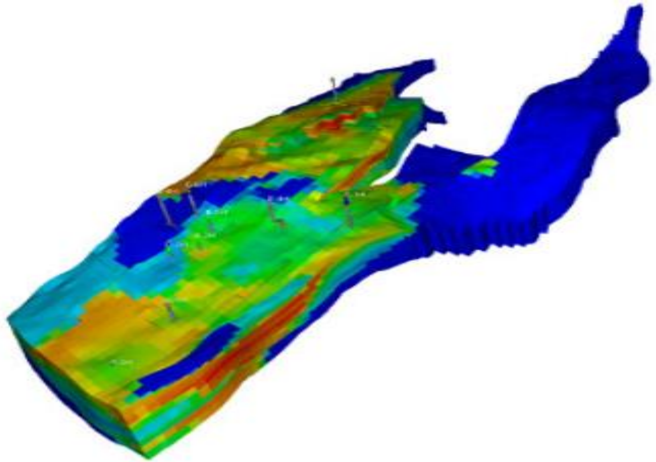
- Objective
  - Minimize Overall linearization's + Overall linear iterations
- Controls
  - Timestepping controls
    - TSINIT, TSMAXZ, TSMINZ, TSMCHP, TSFMAX, TSFMIN, TSFCNV, TFDIFF
  - linear_solver_maxiter (max number of linear iterations)
  - max_strict_iter (max iterations before relaxing max residual condition)
  - max_iter (max number of non-linear iterations)
  - All controls scaled to order 1, Initial guess – defaulted values

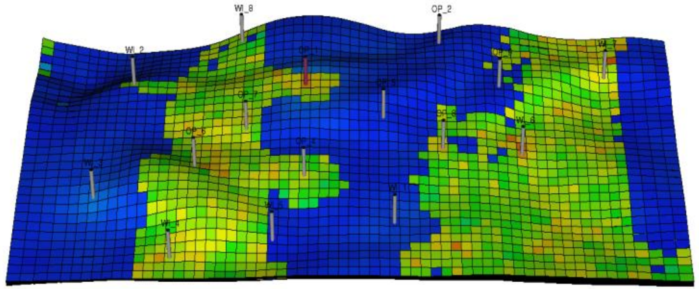
```
================    End of simulation     ===============

Total time (seconds):          1025.75
Solver time (seconds):         998.042
 Assembly time (seconds):      274.027 (Failed: 0; 0%)
 Linear solve time (seconds):  700.196 (Failed: 0; 0%)
 Update time (seconds):        21.4063 (Failed: 0; 0%)
 Output write time (seconds):  19.1645
Overall Well Iterations:       322 (Failed: 0; 0%)
Overall Linearizations:        1021 (Failed: 0; 0%)
Overall Newton Iterations:     832 (Failed: 0; 0%)
Overall Linear Iterations:     14582 (Failed: 0; 0%)
```

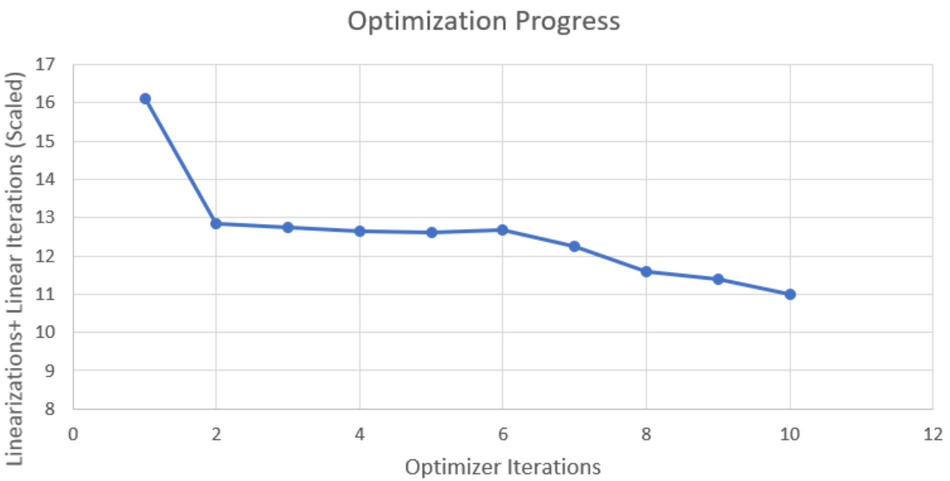
OPTIMIZATION FORMULATION (CONT)

- Constraints
  - max_strict_iter < max_iter – input constraint
  - TSMAXZ < Report step duration - bound constraint
- Reservoir models
  - REEK (20 ensemble members)
  - NORNE (deterministic)
- Gradient definition
  - Deterministic – 10 perturbation
  - Robust – 1 perturbation per realization





RESULTS – NORNE (DETERMINISTIC)



- Objective function = Overall linearizations + Overall linear iterations (Scaled)
- 31 % decrease in objective over 10 optimizer iterations

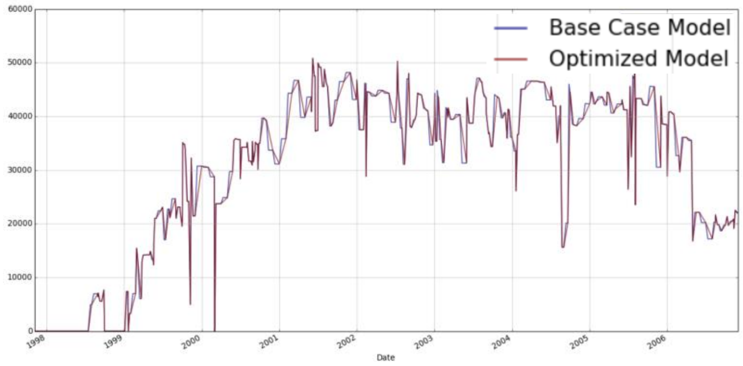
RESULTS – NORNE (DETERMINISTIC)

Simulation Summary	Base case with FLOW default TUNING (Case 1)	Base Case with ECL default TUNING (Case 2)	Optimized Case (Case 3)	Reduction in iterations (Case 1 v/s Case 3)	Reduction in iterations (Case 2 v/s case 3)
Overall Well Iterations	914	1137	817	11%	28%
Oevrall Linearizations	1928	2276	1528	21%	33%
Overall Newton Iteration	1590	1794	1235	22%	31%
Overall Linear Iterations	24275	27999	18865	22%	33%
Overall Convergence Problems	5	1	1		

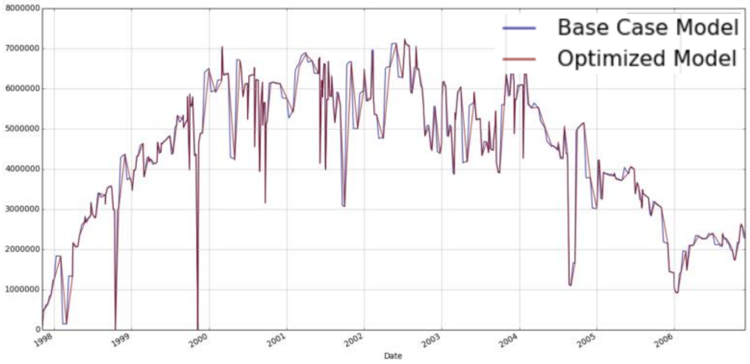
- ~ 22% reduction in overall number of linear iterations (Case 1 v/s Case 3)
- ~ 33% reduction in overall number of linear iterations (Case 2 v/s Case 3)
- Lesser number of convergence problems (Case 1 v/s Case 3)

RESULTS – NORNE (DETERMINISTIC)

FWIR

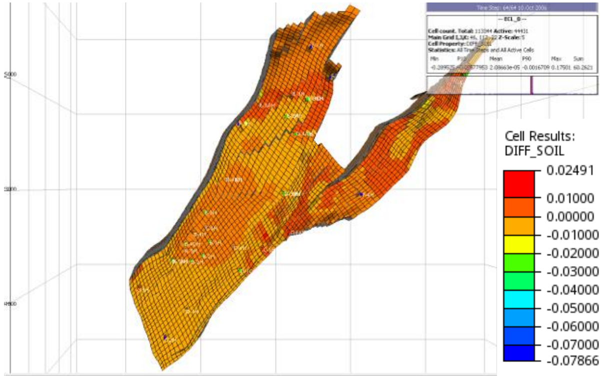


FGPR



Minor differences in field rates and oil saturation between optimized and base case models

DIFF_SOIL



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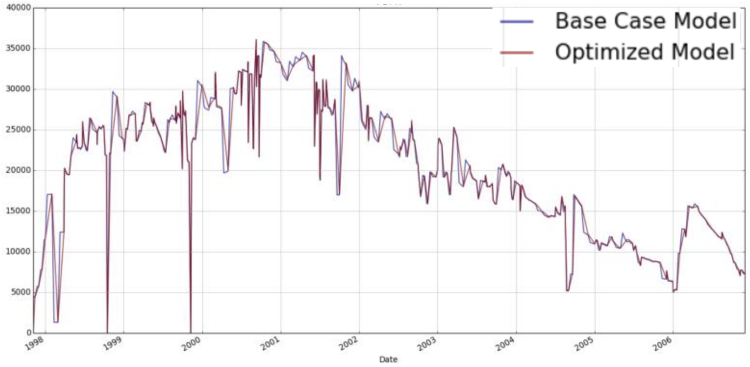
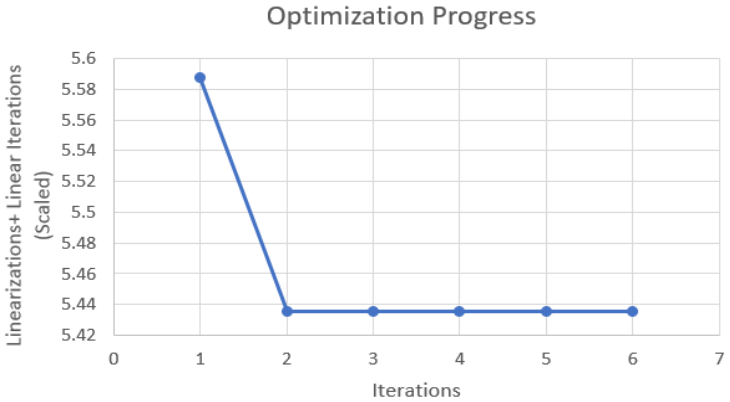
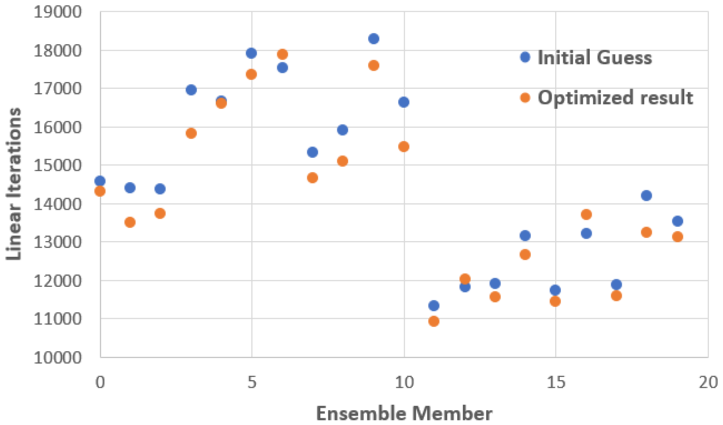


RESULTS – REEK(ROBUST)

- Ensemble Size = 20
- Optimization converges in a single iteration
- REEK model is comparatively simple - need not have lot of scope for optimization
- Majority of realizations have reduced number of linear iterations

- Robust solution - Single set of tuning parameters for all 20 ensemble members which reduces expected overall number of linear iterations
- Robust solution more computationally efficient that having different tuning parameters for each model





RESULTS – REEK(ROBUST)

Simulation Summary	Base Case	Optimized Case	Reduction in iterations
Mean Overall Well Iterations	323.25	324.3	0%
Mean Overall Linearizations	1067.85	1048.45	2%
Mean Overall Newton Iteration	875.15	850.95	3%
Mean Overall Linear Iterations	14564.75	14112.7	3%

- Robust solution - Single set of tuning parameters for all 20 ensemble members which reduces overall number of linear iterations by 3%

APPLICATIONS

- Pre-processing step for model updating and optimization workflows
- Ensemble tuning
- Reduce convergence issues for:
  - Water coning studies
  - Crossflow cases
  - Viscous fingering
  - LGR cases
- Used in conjunction with CO2-EOR optimization, well placement optimization etc.

CONCLUSIONS

- Optimization workflow able to automate model tuning
- Computationally efficient
- Optimization workflow robust solution which reduces overall number of linear iterations for an ensemble of reservoir models
- 33 % reduction in number of linear iterations for the Norne deterministic model
- 3 % reduction in number of linear iterations for the REEK robust case
- Larger and more complex model have a larger scope for optimization

FUTURE WORK

- Constrained optimization with constraints on field production and injection volumes
- Robust Optimization with the Norne field model

THANK YOU FOR YOUR ATTENTION