

# Probabilistic Algorithm-driven Well Trajectory Optimisation Study for a Green Field Project in the NCS

DEVEX 2022, ABERDEEN

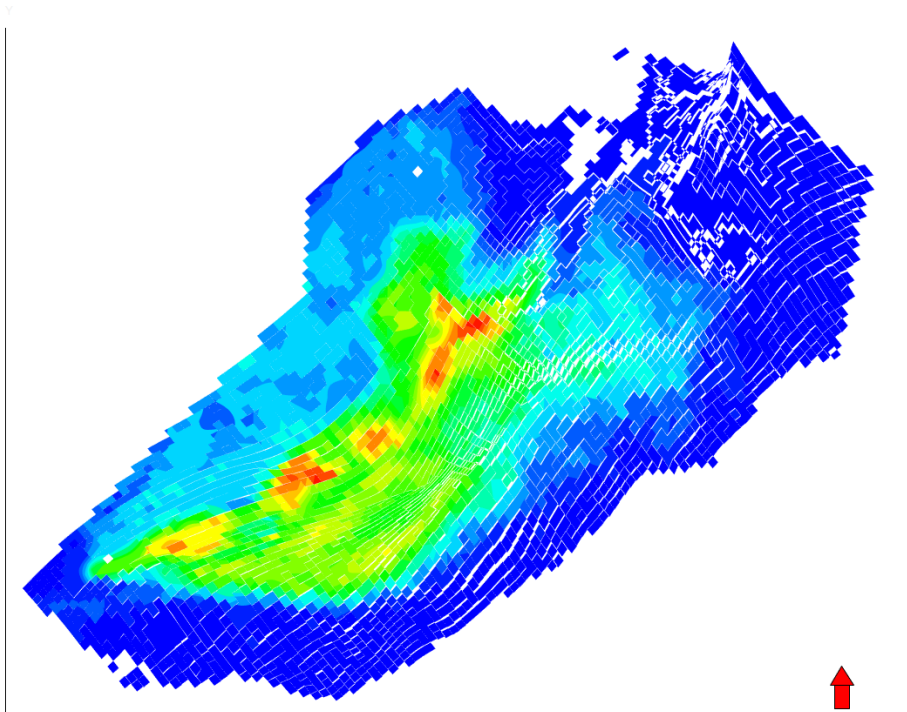
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# WELL TRAJECTORY OPTIMIZATION

## INTRODUCTION AND OBJECTIVES

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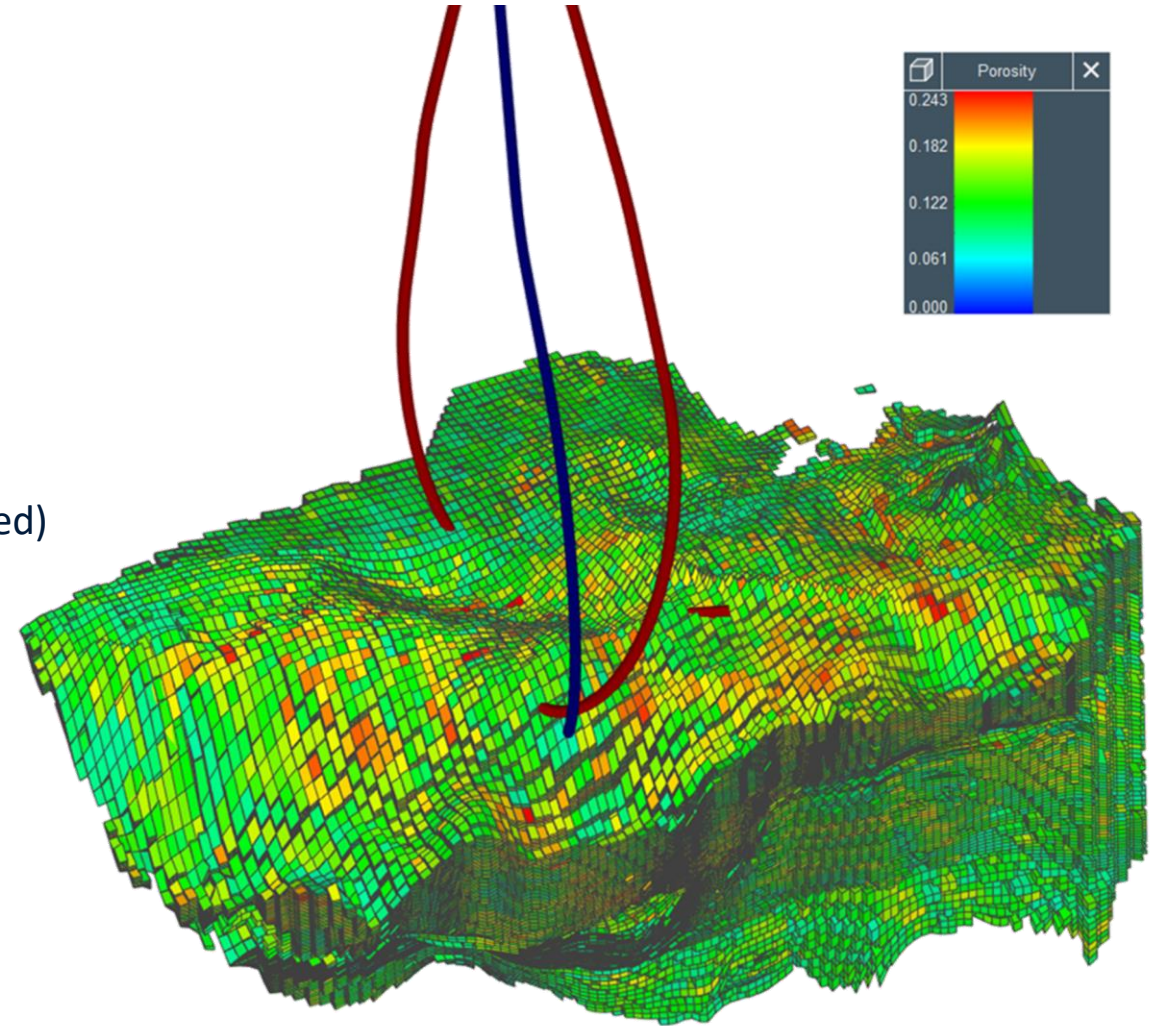


- Optimal well location & trajectory definition for injector-producer is critical
  - Multiple impacting parameters → complex optimisation problem
  - Typical approach: simulation of several deterministic scenarios
  - Objective approach: simultaneous multi-parameter optimisation (standoff, orientation, etc)
  - + eventually add uncertainties (structural models, NTG, permeability, etc)
- What's the optimal location and trajectory for the wells?
- How to make well location optimisation process more efficient?
- **Solution** = Python trajectory discretisation + automated workflow + optimisation algorithm
  - 6.5% increase on field production from optimised well trajectories

# WELL TRAJECTORY OPTIMIZATION

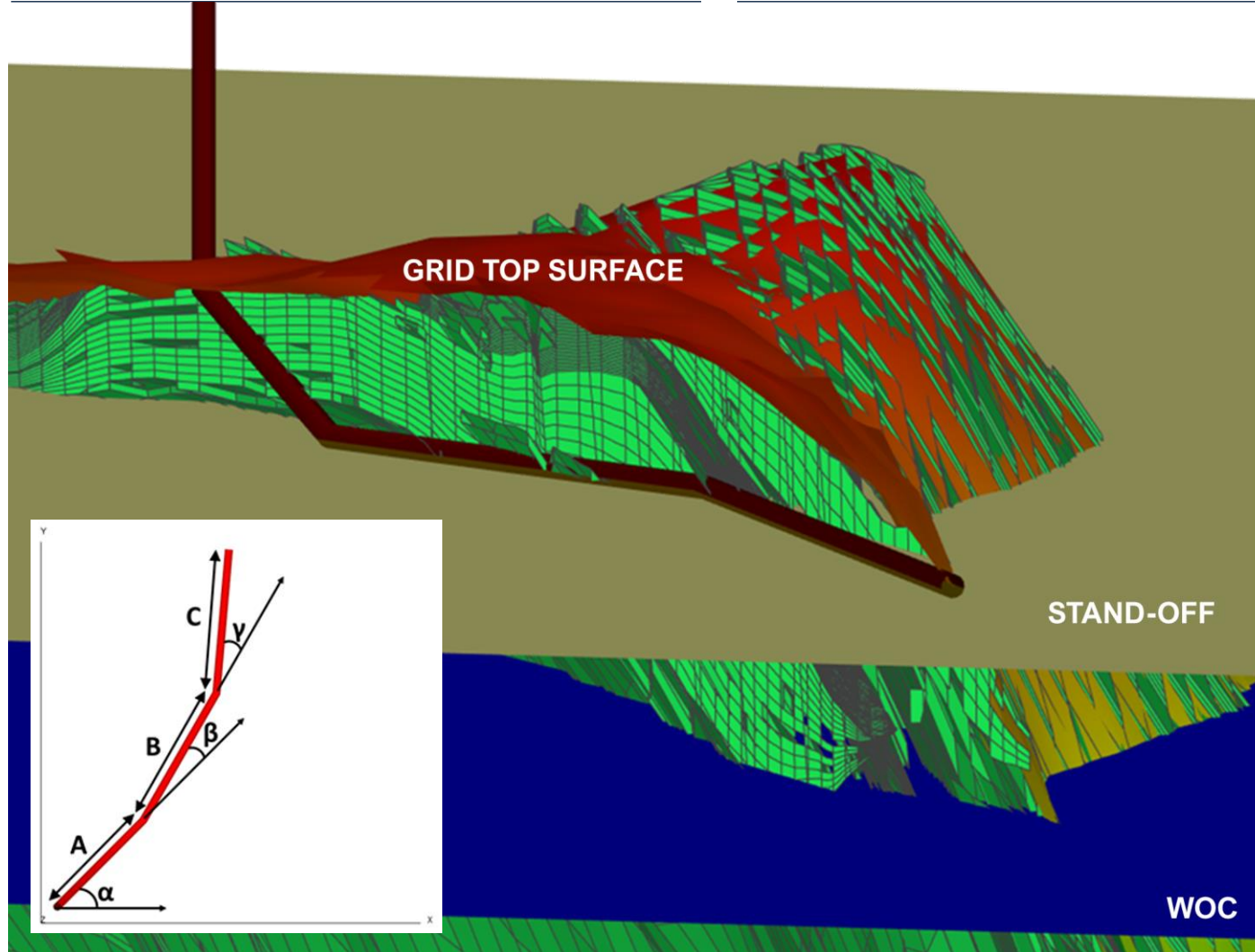
## MODEL DESCRIPTION

- Black oil model
- 2 MM cells → 230K active cells (55mx55mx4m)
- Equilibrium initialisation + endpoint scaling
- Predefined locations for 2 producers (horizontal) + 1 injector (deviated)
- Green field project + 16 years forecast prediction
- Simulation time ≈ 45 min



# WELL TRAJECTORY OPTIMIZATION

## MODELLING THE WELL TRAJECTORIES



- Focus on trajectory *intersecting* the reservoir
- Discretisation of well trajectory into segments (sections) using Python script:
  - 1 segment representing wellhead to entry point
  - 1 segment connects entry point & horizontal section
  - 2 segments representing horizontal section
- Trajectory constrained by grid top/base
- Horizontal section lays on WOC stand-off

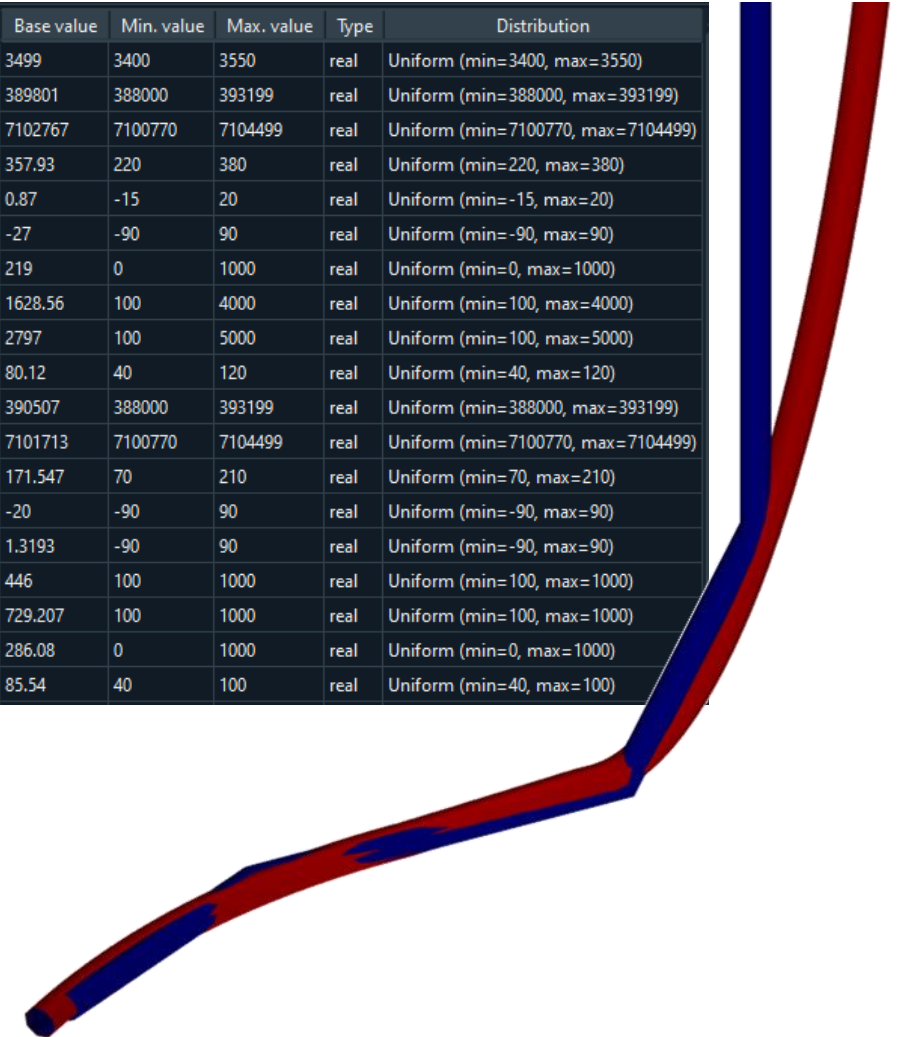
# WELL TRAJECTORY OPTIMIZATION

## MODELLING THE WELL TRAJECTORIES

### Which parameters to optimise for each well?

- Wellhead location (X, Y) – fixed for this model
- Well segments length (A, B, C)
- Well segments azimuth ( $\alpha$ ,  $\beta$ ,  $\gamma$ )
- WOC stand-off
- **Python trajectories** replace **original trajectories** during optimisation
- Input trajectories approximated by trial & error for base model
- Production mismatch with original model/trajectories < 1%

	Base value	Min. value	Max. value	Type	Distribution
WOC	3499	3400	3550	real	Uniform (min=3400, max=3550)
X1	389801	388000	393199	real	Uniform (min=388000, max=393199)
Y1	7102767	7100770	7104499	real	Uniform (min=7100770, max=7104499)
ALPHA1	357.93	220	380	real	Uniform (min=220, max=380)
BETA1	0.87	-15	20	real	Uniform (min=-15, max=20)
GAMMA1	-27	-90	90	real	Uniform (min=-90, max=90)
LENGTHA1	219	0	1000	real	Uniform (min=0, max=1000)
LENGTHB1	1628.56	100	4000	real	Uniform (min=100, max=4000)
LENGTHC1	2797	100	5000	real	Uniform (min=100, max=5000)
STANDOFF_WOC1	80.12	40	120	real	Uniform (min=40, max=120)
X2	390507	388000	393199	real	Uniform (min=388000, max=393199)
Y2	7101713	7100770	7104499	real	Uniform (min=7100770, max=7104499)
ALPHA2	171.547	70	210	real	Uniform (min=70, max=210)
BETA2	-20	-90	90	real	Uniform (min=-90, max=90)
GAMMA2	1.3193	-90	90	real	Uniform (min=-90, max=90)
LENGTHA2	446	100	1000	real	Uniform (min=100, max=1000)
LENGTHB2	729.207	100	1000	real	Uniform (min=100, max=1000)
LENGTHC2	286.08	0	1000	real	Uniform (min=0, max=1000)
STANDOFF_WOC2	85.54	40	100	real	Uniform (min=40, max=100)



# WELL TRAJECTORY OPTIMIZATION

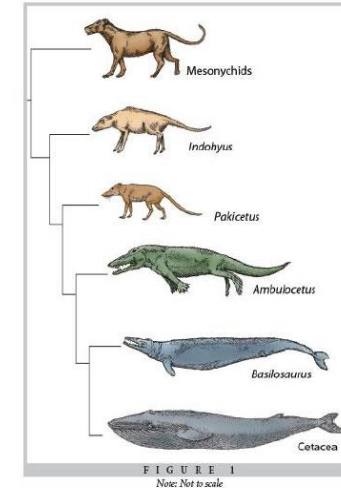
## OPTIMIZATION ALGORITHMS TESTED

### Particle Swarm Optimization (PSO)



- **Based on avian flock behaviour**
- Swarm of particles (*models*) affected by behaviour-like parameters
- Global and Local best positions updated for each iteration
- **Inspired by evolutionary processes**

### Differential Evolution

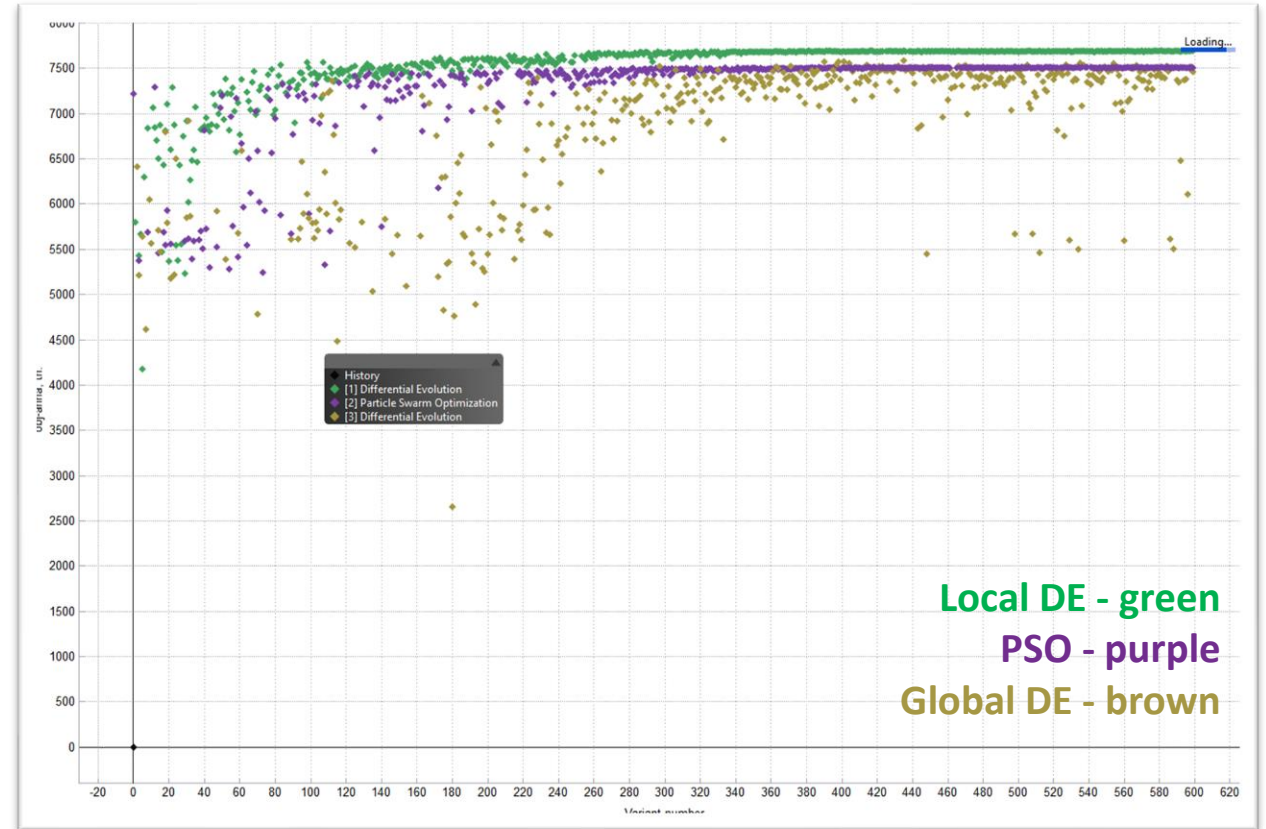


- Best individuals (*models*) selected from each population (iteration) to create the next one
- Local DE option looks for local optimum – fast convergence
- Global DE option looks for global optimum – more iterations needed

# WELL TRAJECTORY OPTIMIZATION

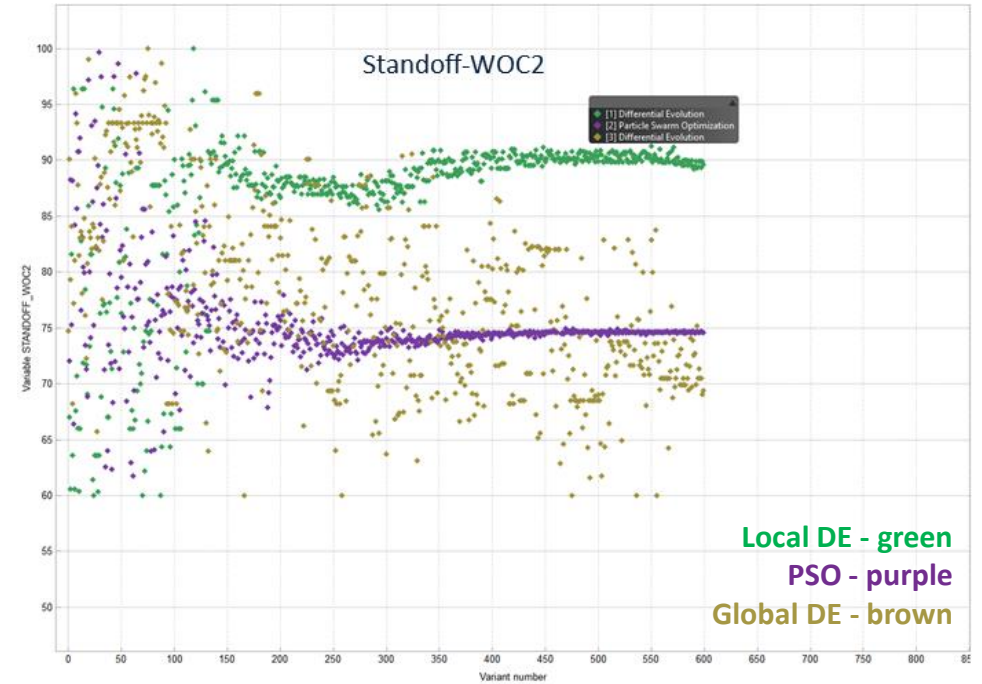
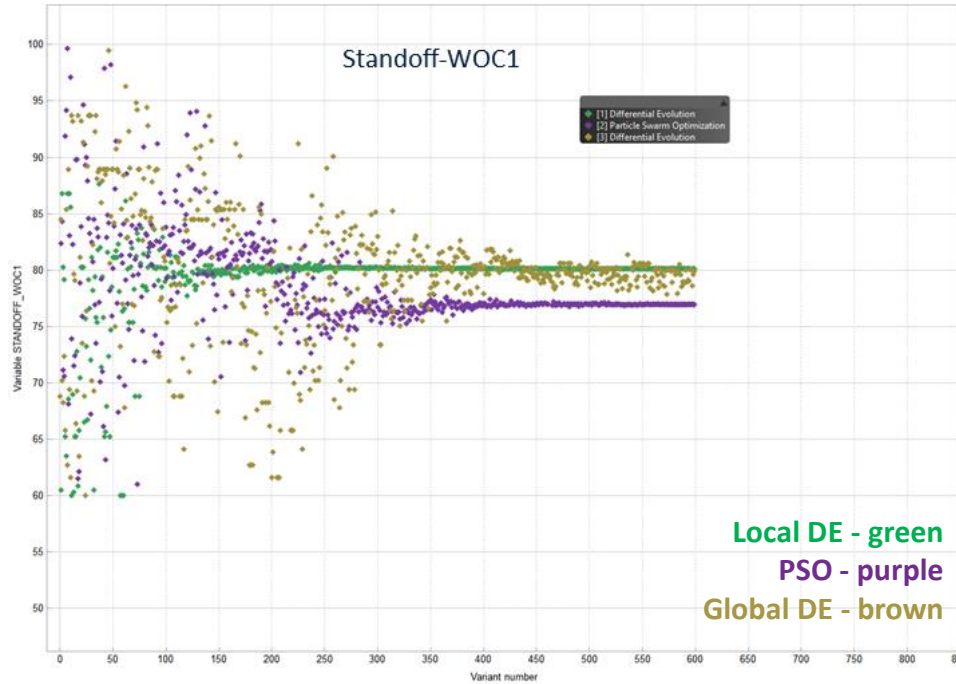
## OPTIMIZATION RESULTS

- 3 experiments x 600 runs each
- Local DE & PSO → convergence at 200 variants
- Global DE → convergence at 400 variants
- ALL three experiments lead to improvement of base case
  - Local DE ~ 3 MMboe (6.5%) increase in oil production
  - PSO ~ 1.8 MMboe (4%) increase in oil production
  - Global DE ~ 1.5 MMboe (3%) increase in oil production



# WELL TRAJECTORY OPTIMIZATION

## VARIABLE OPTIMISATION ANALYSIS: WOC STAND-OFF



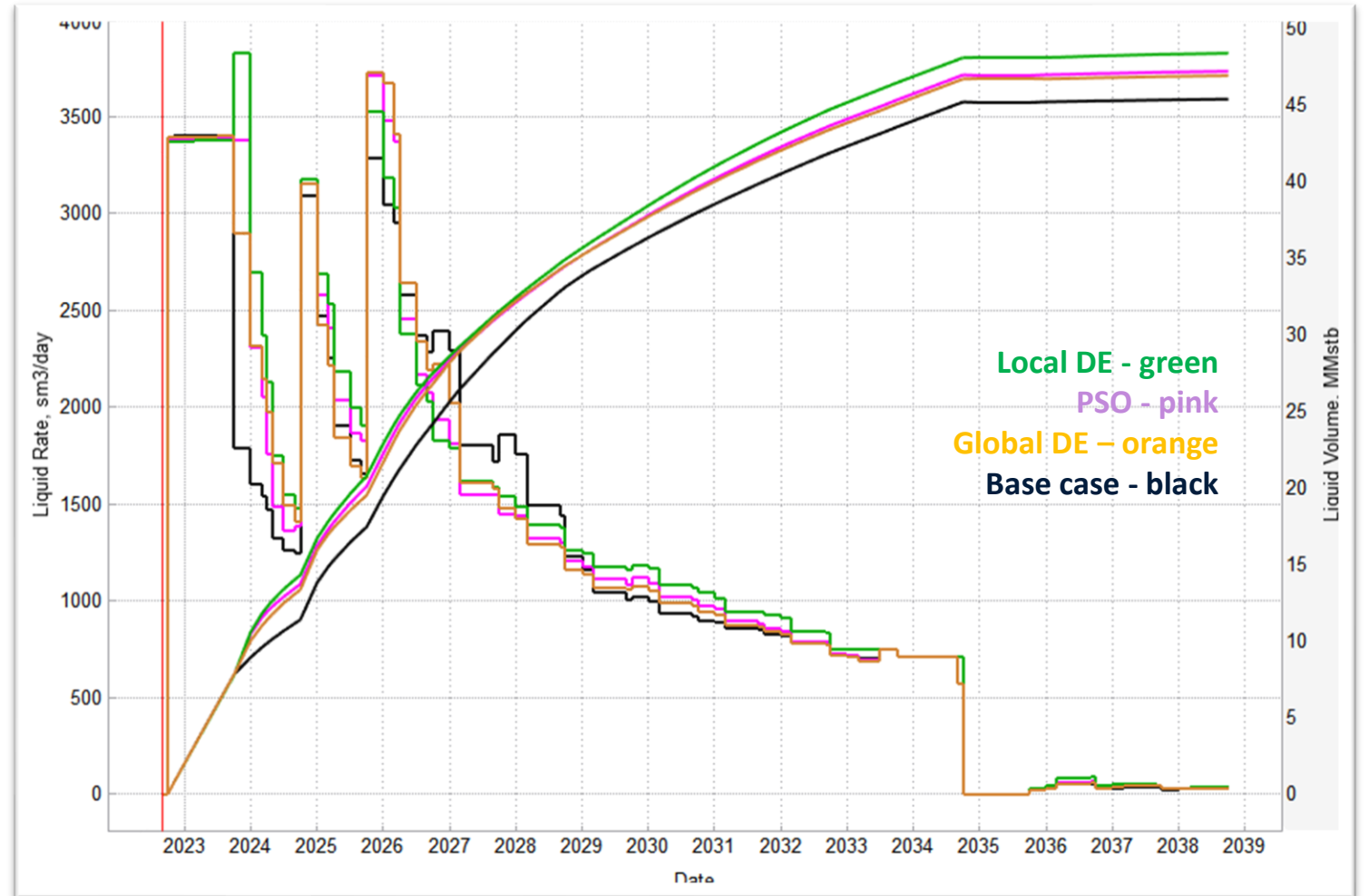
- Parameter search-space fully explored
- PSO converges at different optimum value compared to DE
- Optimisation confirms original stand-off for W1 but 10m reduction suggested for W2



# FIELD PROFILES FROM EXPERIMENT COMPARED WITH BASE CASE

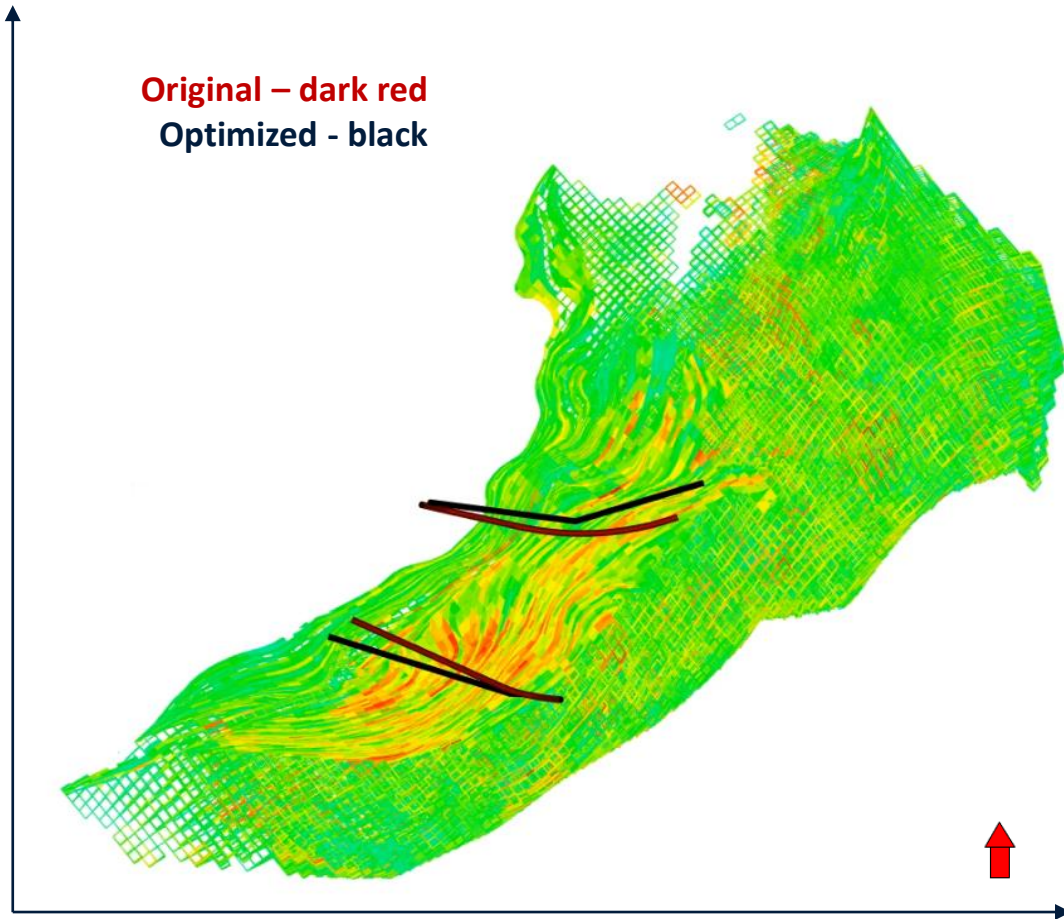
## OPTIMIZATION RESULTS

- Field production acceleration observed for all 3 solutions
- Field production increase observed for all 3 solutions
- Recovery increase for both production wells
- Slight reduction on water injection also



# WELL TRAJECTORY OPTIMIZATION

## OPTIMIZED VS. ORIGINAL WELL TRAJECTORY



- Original trajectories vs optimized for 1 possible solution
- Optimization workflow → several ***different potential solutions*** = trajectories
- QC is recommended to check optimization variables converge to reasonable values
- Several trajectories to be validated with drilling team

# WELL TRAJECTORY OPTIMIZATION

## LESSONS LEARNT AND CONCLUSIONS

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- The routine approach for new well trajectories requires testing alternative trajectories in discrete scenarios → time and money consuming
- The automated approach optimises well trajectories relying on a stochastic process
- 100's of simulations exploring multiple scenarios with minimal user intervention
- Multiple variables can be optimised simultaneously – uncertainties can be added for forecasting stage
- The workflow can be easily transferred to other projects
- Using the optimization process well trajectories were improved and cumulative oil production by approximately 6.5%
- The QC did not find evidence of unrealistic trajectories → a careful selection of the parameters' ranges + flexible trajectory definition workflow can produce consistent results
- Optimization algorithms + automated workflows + parallel calculations is a relevant tool for engineers and geoscientists when looking for more efficient and exhaustive techniques to define well trajectories.
- RE-Geoscience-DR team expertise is always required to select realistic variable ranges and a realistic well trajectory!

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Thank you!

Questions?