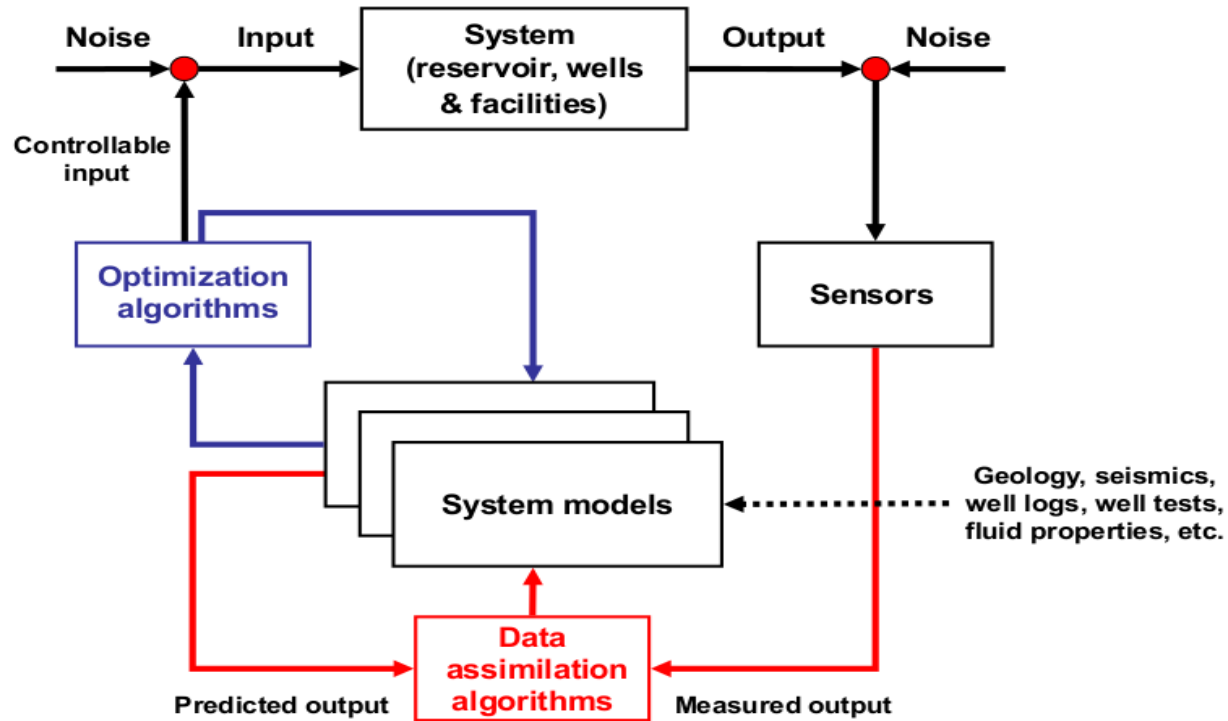


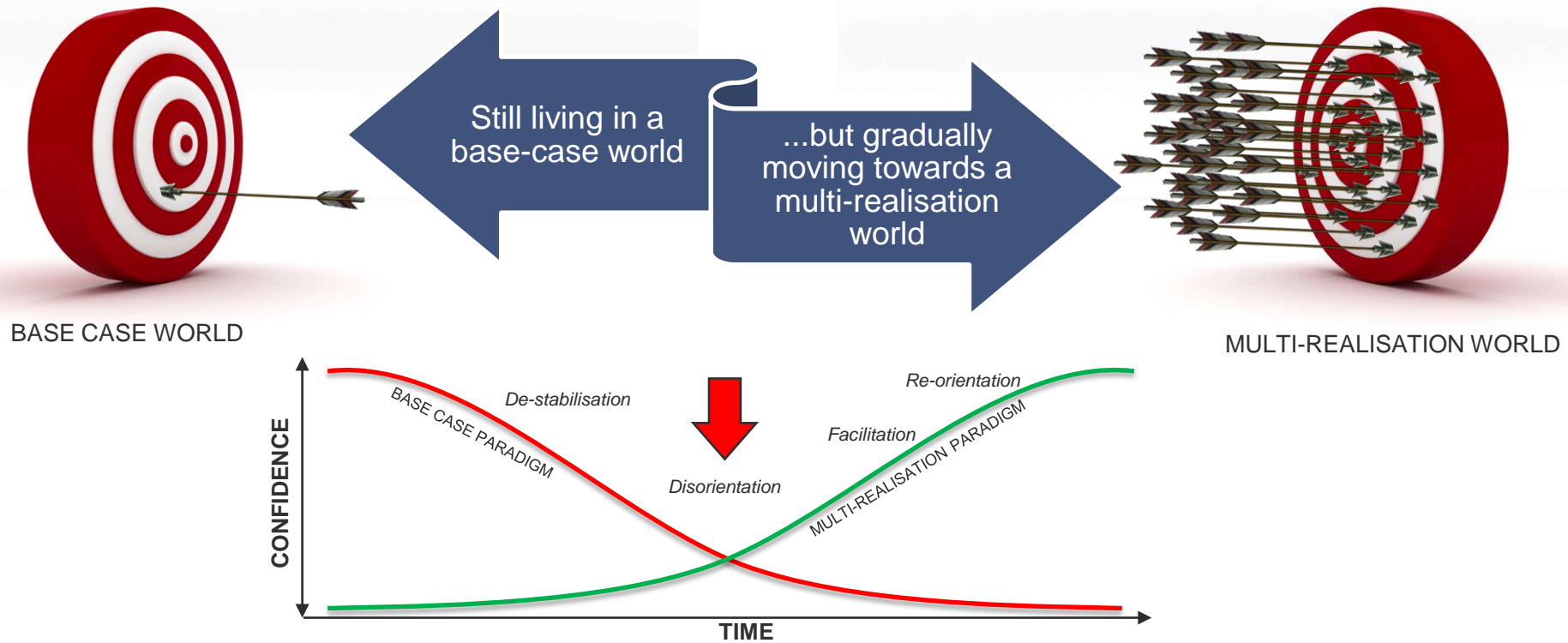
Ensemble-based decision making for reservoir management – present and future outlook

TPD R&T ST MSU DYN and FMU team

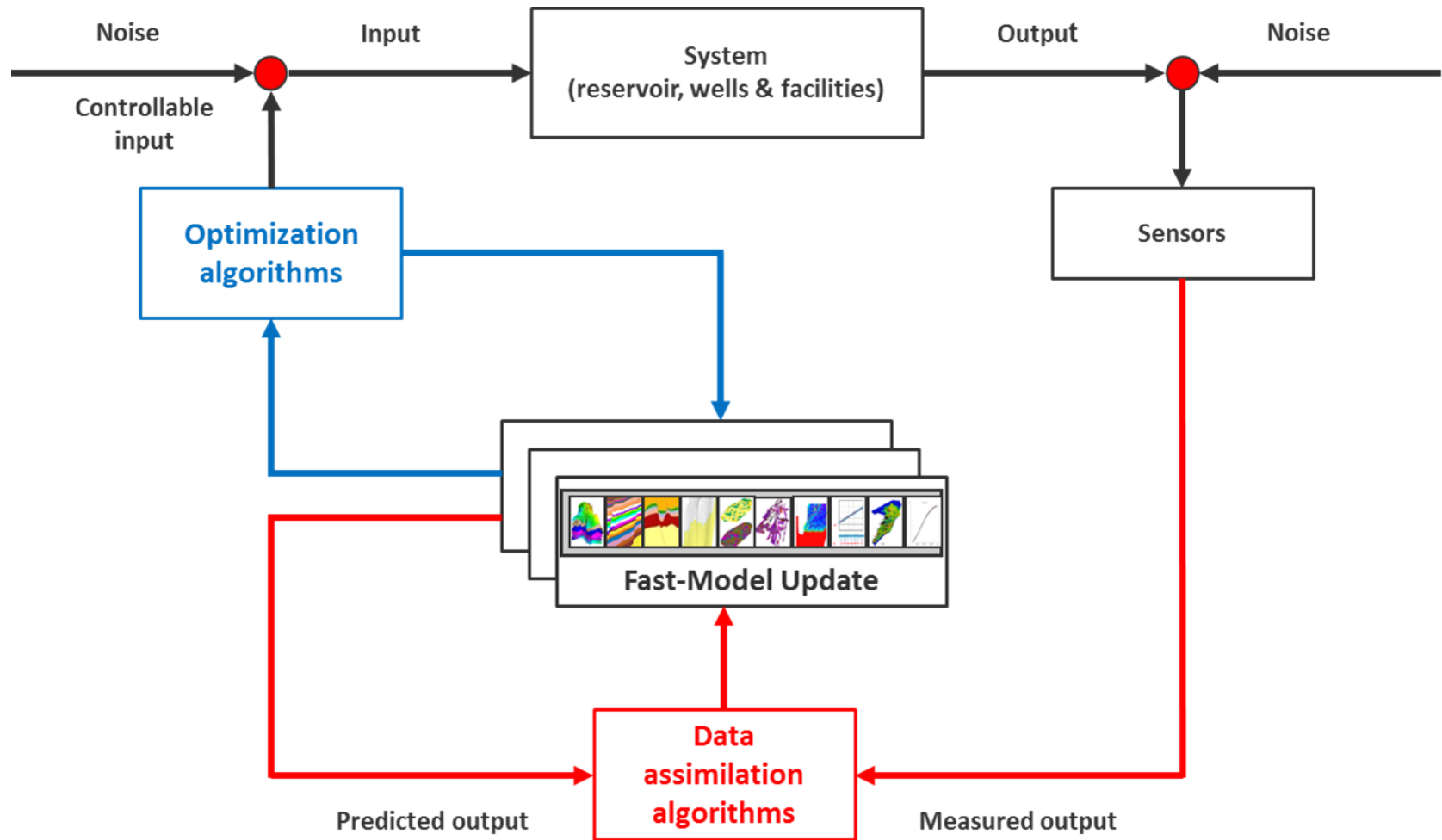
The core – Ensemble based Closed Loop Reservoir Management (CLOREM)



New paradigm shift – multiple realization world



The core – Ensemble based Closed Loop Reservoir Management (CLOREM)



The core – Ensemble based Closed Loop Reservoir Management (CLOREM)

- Assisted History Matching loop
- Optimization loop
- Future outlook

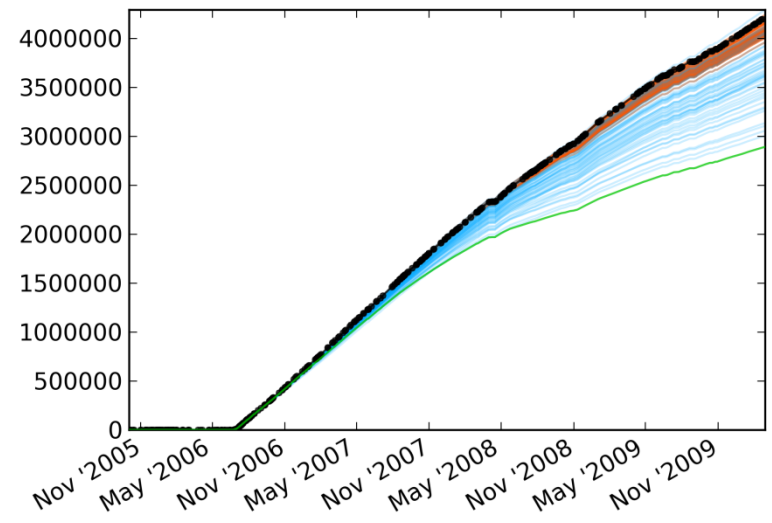
The core – Ensemble based Closed Loop Reservoir Management (CLOREM)

- **Assisted History Matching loop**
- Optimization loop
- Future outlook

Assisted History Matching (AHM)

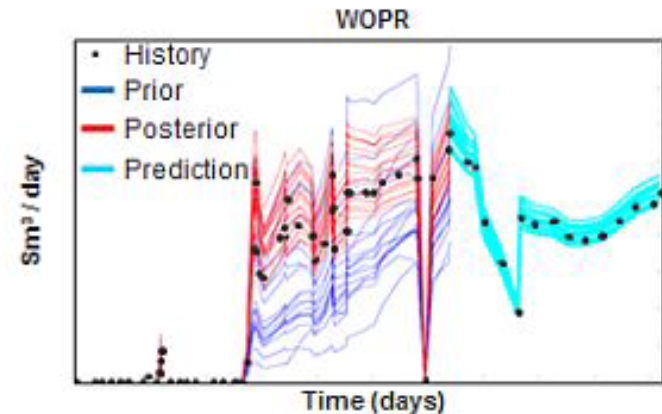
Assisted – not automated!!

History Matching - The act of **adjusting a model** of a reservoir until it closely reproduces the **past behavior** of a reservoir.



Assisted History Matching (AHM)

- Provides multi-model history match for improved uncertainty description
- **Maintains geological realism**
- Incorporates of all quantifiable information (seismic, gravity, tracer etc.)
- **Predicts of the future behavior of the reservoir in existing and new wells with increased confidence – predictive power**



ES vs. EnKF --- fundamentals

Ensemble Kalman filter:

- Recursive updates keep realizations on track and close to observations.
- Linear updates introduces “Gaussianity” into ensemble of realizations.
- Handles well nonlinear and unstable dynamics.

Ensemble Smoother:

- Proposed by *van Leeuwen and Evensen (1996)*.
- Identical to EnKF for linear dynamics (*Evensen, 2009*).
- Very easy to implement.
- Restarts are not required.
- Allows for more flexible parameterization than EnKF - Allows for more flexible parameterization

The core – Closed Loop Reservoir Management (CLOREM)

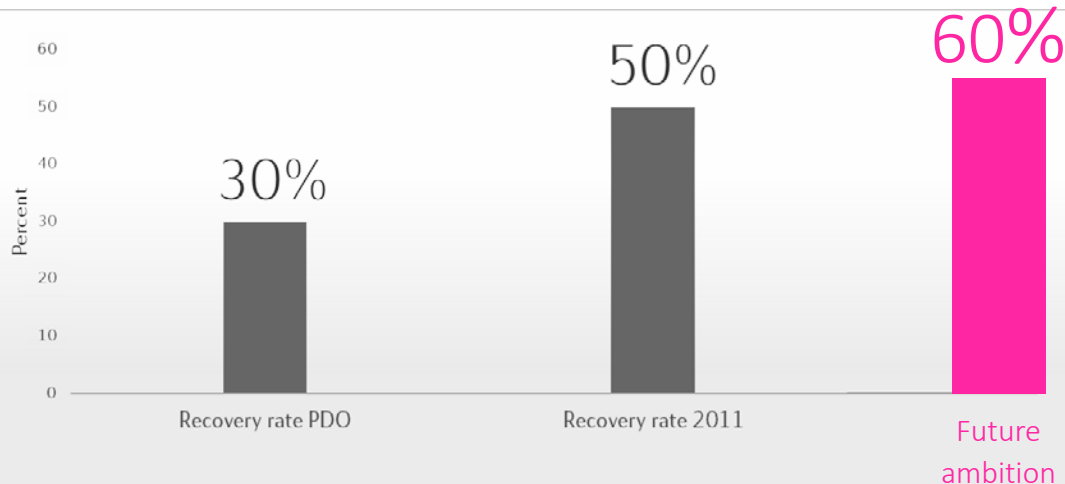
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The core – Closed Loop Reservoir Management (CLOREM)

- Assisted History Matching loop
- **Optimization loop**
- Future outlook

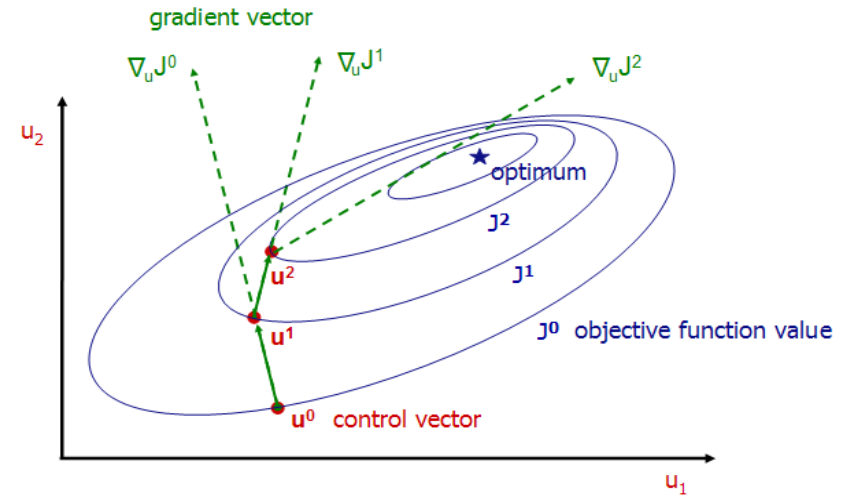
Increase oil recovery philosophy

- Increasing demand \leftrightarrow reducing supply
 - energy demand continues to grow world-wide
 - renewables are developing too slow to keep up with demand
 - 'easy oil' has been already found; few new discoveries; complex fields



**Increased Oil Recovery-
NCS ambition**

Optimization



- General definition:

The process of selecting the “*best*” (with regard to some criteria a.k.a. objective function) element from a set of available alternatives.

- Petroleum industry definition:

Possible objectives: **maximize oil recovery (UR) or cash (NPV)**
minimize risks - economic and/or societal

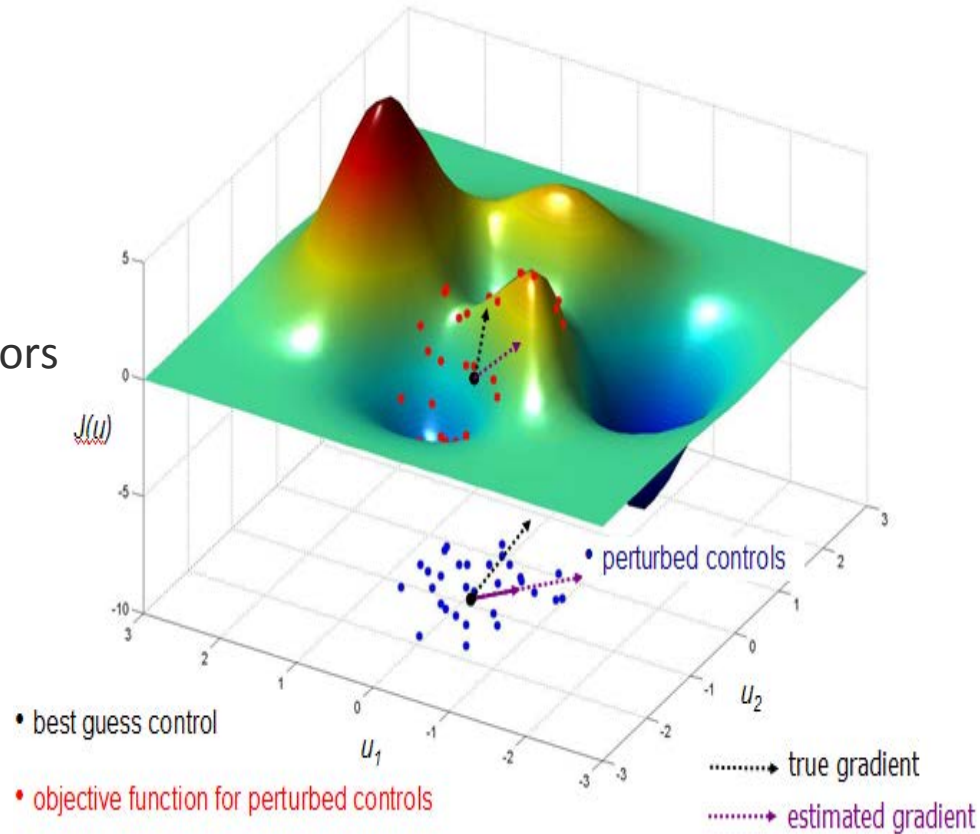
- Iterative methods

Gradient based: Adjoint, **EnOpt**, SPSA etc.

Gradient free: Meta-Heuristic/genetic algorithms

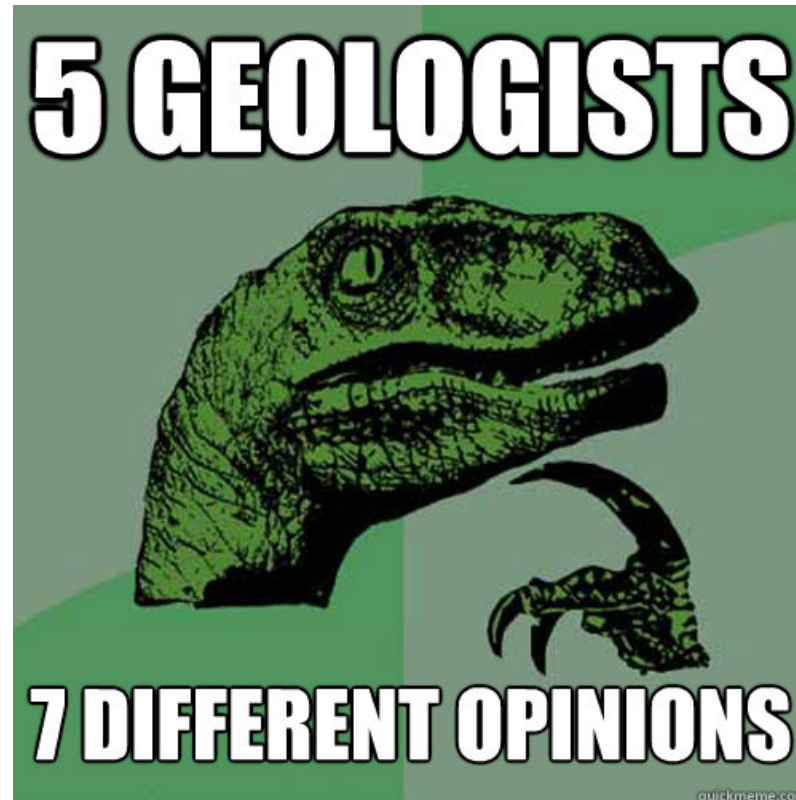
Optimization – Ensemble Optimization (EnOpt)

- Introduced by Lorentzen et al (2006), Chen and Oliver (2008)
- Generate an ensemble of control vectors stochastically (blue dots)
- Evaluate each ensemble member of controls (red dots)
- Estimate a gradient from the ensemble of function evaluations



$$\mathbf{u}_{l+1} = \alpha_l \mathbf{g}_l + \mathbf{u}_l$$

Optimization under geological uncertainty



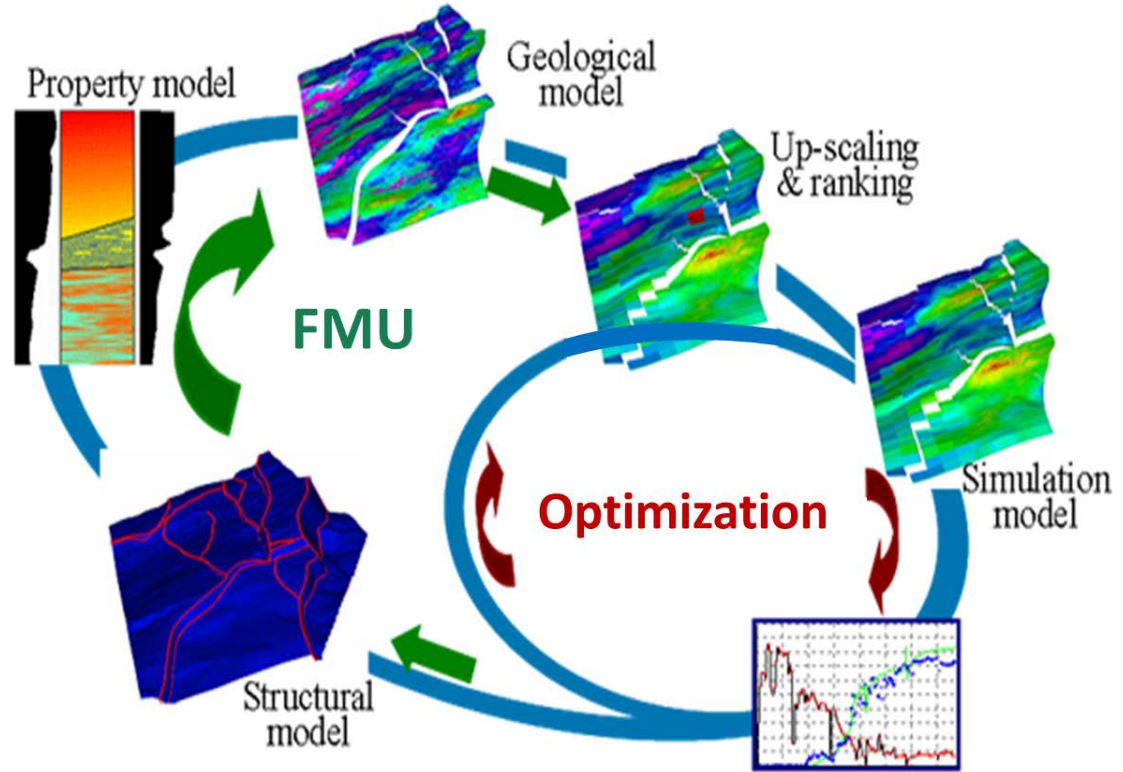
Optimization under geological uncertainty

- Geo-modelling fraught with uncertainties (seismic, logs etc.)
- Optimization over an ensemble of geological realizations, [Van Essen et.al 2009], results of practical value
- Way to account for uncertainty to find a single optimized strategy
- Equal ensemble sizes for controls and realizations for gradient evaluation (Chen 2008)
- EnOpt computationally attractive for robust optimization
- StoSAG formulation by Rahul Fonseca 2014

Ensemble based Closed Loop Reservoir Management

Predicts of the future behavior of the reservoir in existing and new wells with increased confidence – predictive power

- Game changer
- “Culture” changer
- Enhancing FMU
- Boosting IOR and EOR
- Integrated framework



Ultimate goal: Decision Maturation

Well Planning Robust Optimization (WPRO) tool

Optimization

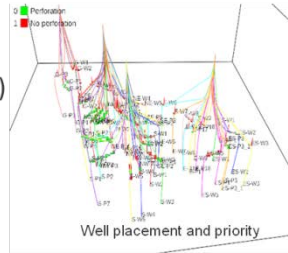
« Is the selection of a **best element** (with regard to **some criteria**) from a set of available alternatives »

- **Best element** (controls):

- Injection and production rates (well controls)
- Well location (targets and the path)
- Drilling priority
- Drilling timing

- **Some criteria**:

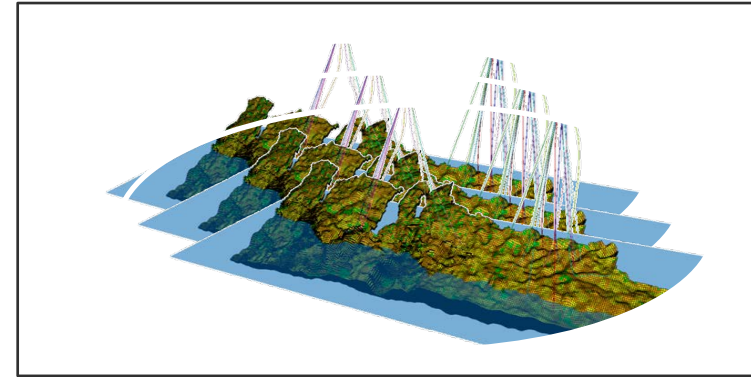
- Higher Net Present Value (NPV)
- Higher recovery factor



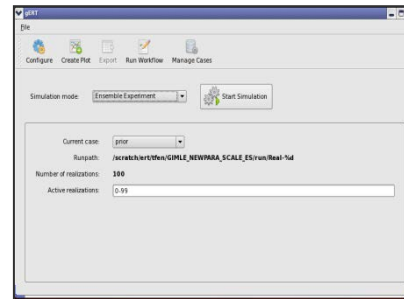
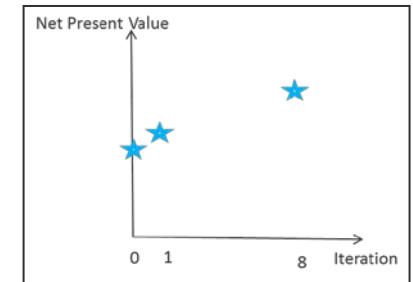
ICD



Reservoir models (uncertainty description)




One final "best element" decision



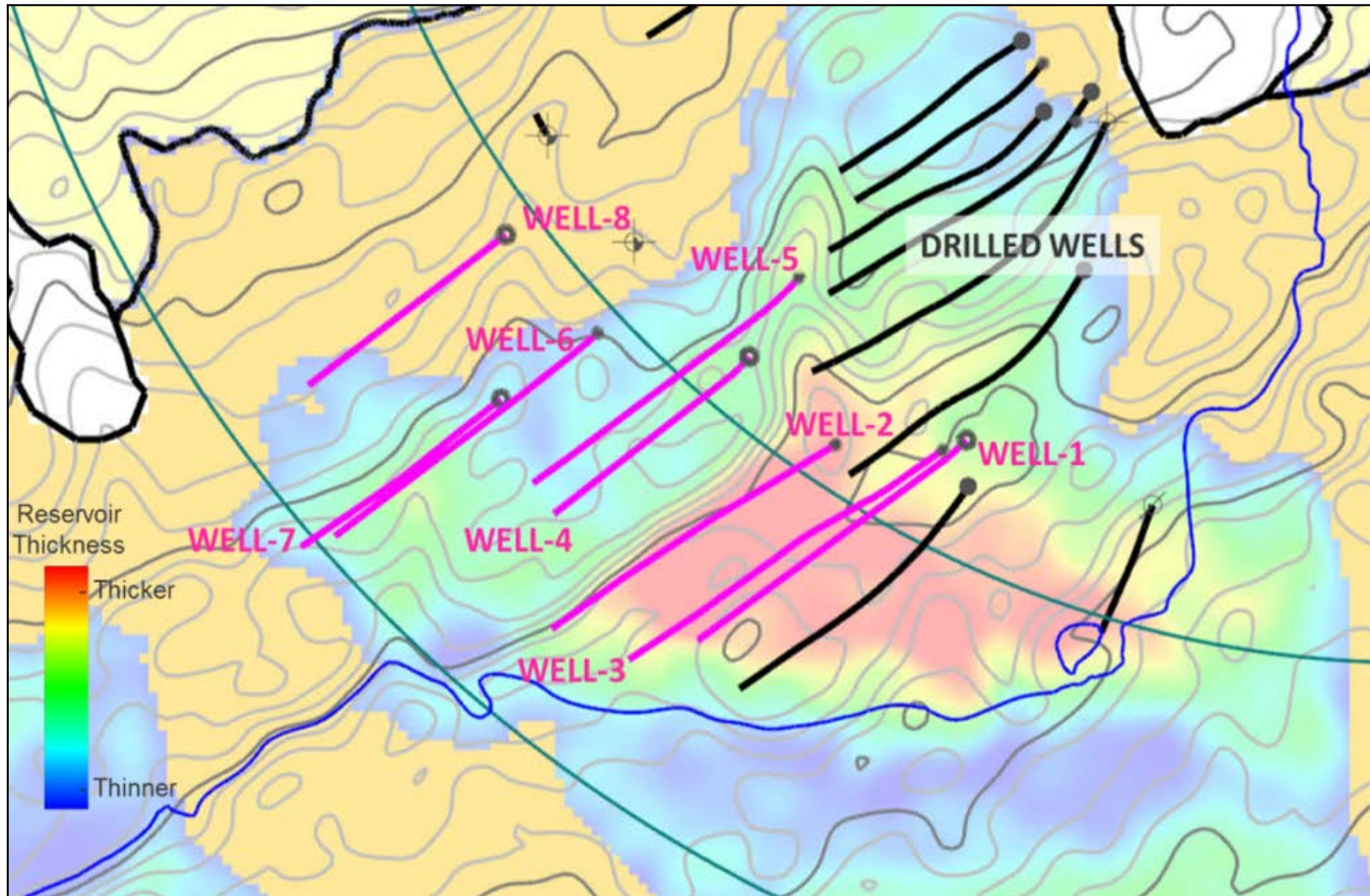
Robust optimization

Intermezzo and some conclusions

- Multiple models setup  FMU setup
- AHM geological realism translated in
 - New facies simulation approach
 - New hybrid engineering localization scheme and faults parameterization
- Optimization translated in
 - Robust ensemble Optimization
- Tool development
 - WPRO tool

Field case – Peregrino

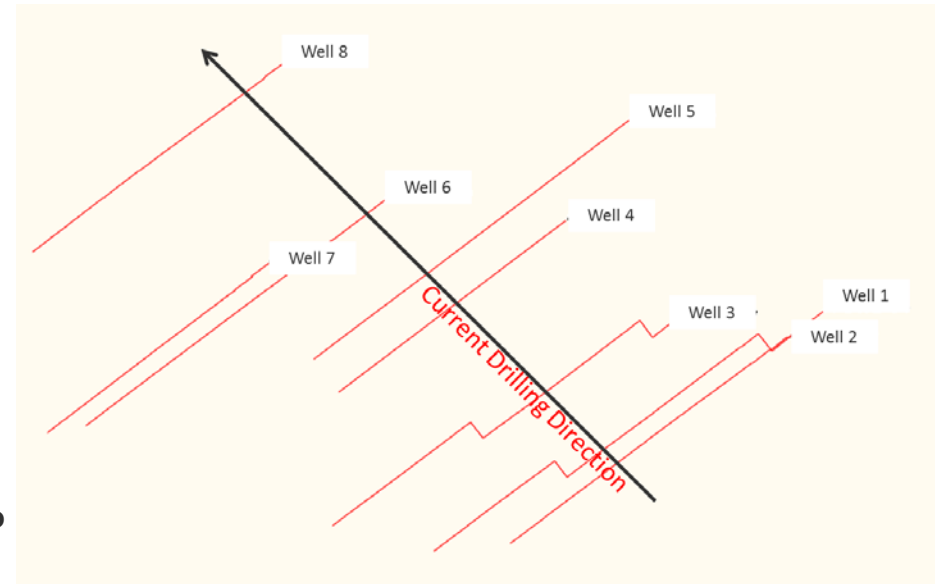
Drilled and planned wells with reservoir thickness maps as background



Blue line is indicative of the aquifer boundary

Peregrino Simulation Model

- 720,000 active grid cells of 100x100x2 m
- No upscaling has been performed.
- Heavy Oil reservoir; 14 °API; Viscosity 360 cP
- Horizontal wells varying from 1000-2000 m drilled as producers
- Reservoir consists of two sections; uncertain connectivity between the sections
- Aquifer support strongest in lower section
- Reservoir pinches out away from the aquifer.



Optimization Experiments

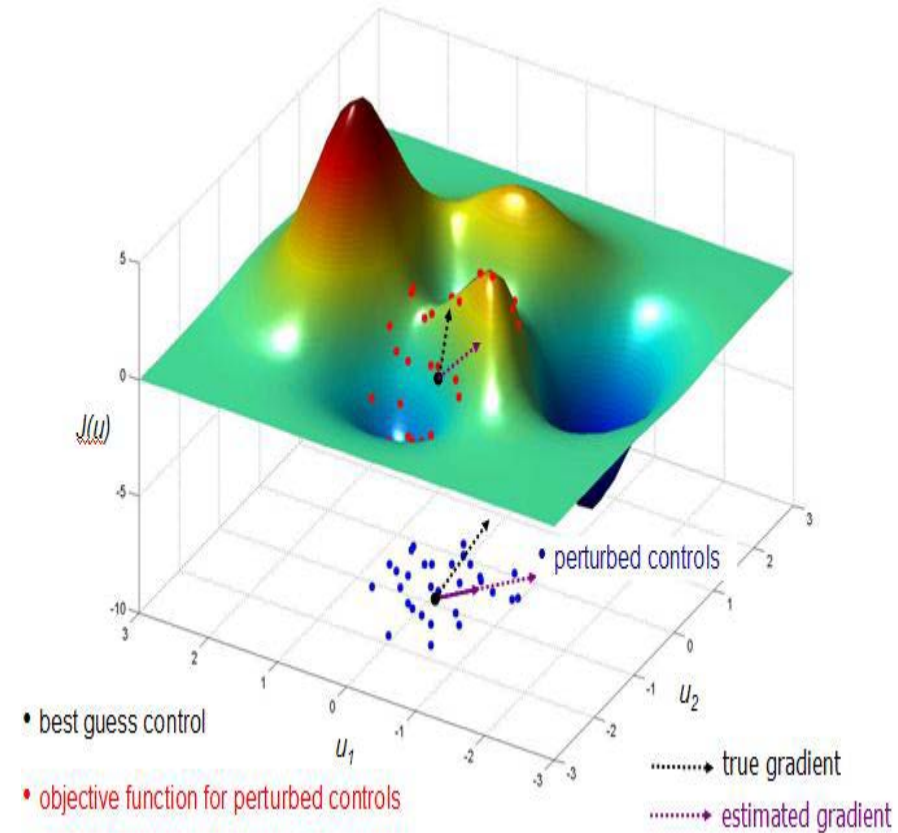
- Drilling Order
 - The order of the 8 producer wells is optimized to achieve an increased economic objective (NPV)
- Drilling Order + Well Type + Rate Capacity
 - In addition to the re-ordering, the 8 producer wells are allowed to either be a producer or an injector at the initial time of well opening
- Drilling Order + Well Time Switch + Rate Capacity
 - In addition to the re-ordering, the 8 producer wells are allowed to switch from a producer to an injector at some later time during life cycle period
- Deterministic & Robust Optimization experiments done.

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Control Parameterization

- Drilling Order for each well is defined as a 'priority' , a continuous variable between 0 and 1
- Each well is given a priority and the drilling order is decided based on the priority values (highest value= well drilled first)
- Well Type Control: Also defined in a range between 0 and 1 and allowed to be continuous.
- Well with a value > 0.5 will be a producer and vice versa for injectors

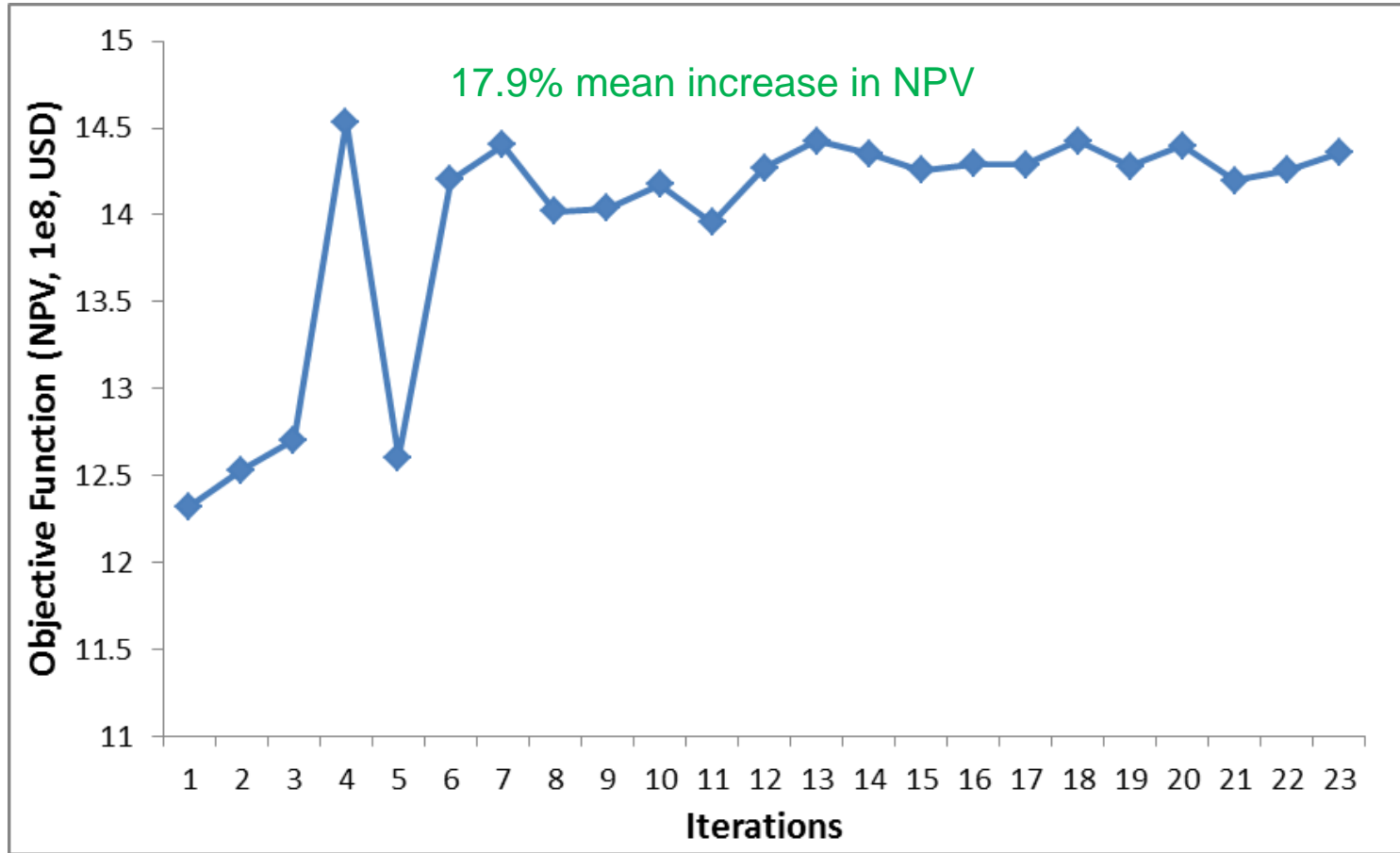


Geological Uncertainty

- Facies Proportions (permeability's X and Z and porosities)
- Oil-water contact
- Fault Properties
- Relative Permeability Curves
- K_v/K_h
- Initial water saturation distribution
- Pore Volume multipliers for different regions

Objective : Find a single optimal strategy applicable to all the realizations with expected value of NPV as the objective function

Optimization Performance



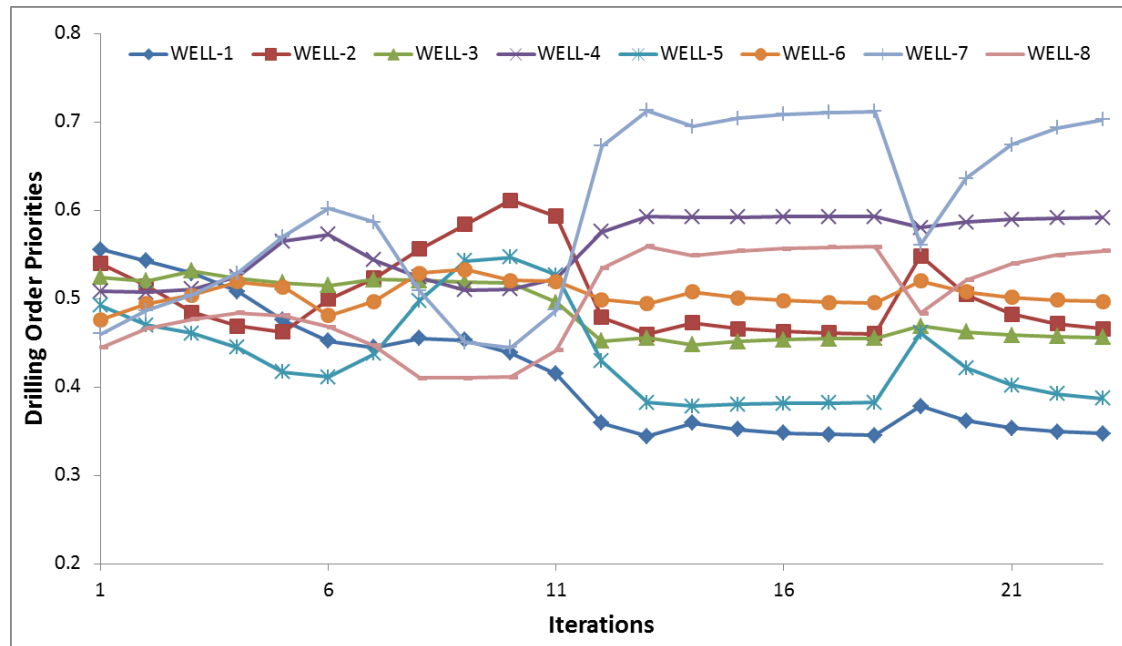
Adding more controls to the optimization helps find better solutions

+0.5% mean cumulative oil production

-1.07% mean cumulative water injection

Results : Optimal Well Order + Well Type

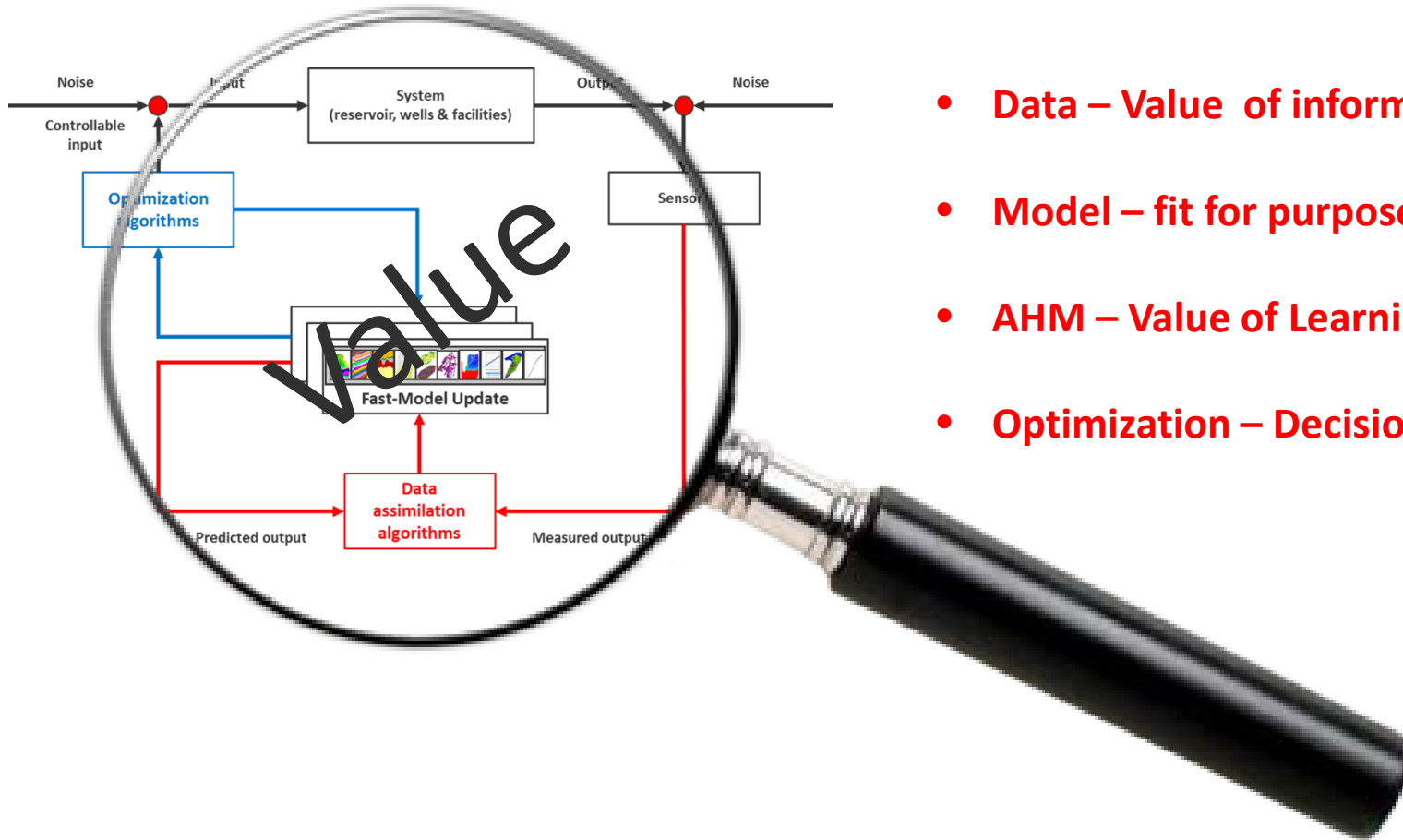
Initial	Optimal
WELL-2	WELL-7
WELL-3	WELL-4
WELL-1	WELL-3
WELL-4	WELL-6
WELL-5	WELL-1
WELL-6	WELL-8
WELL-7	WELL-2
WELL-8	WELL-5



Very different behaviour of drilling priorities compared to optimizing only drilling order. Effect of more degree of freedom in the problem ??

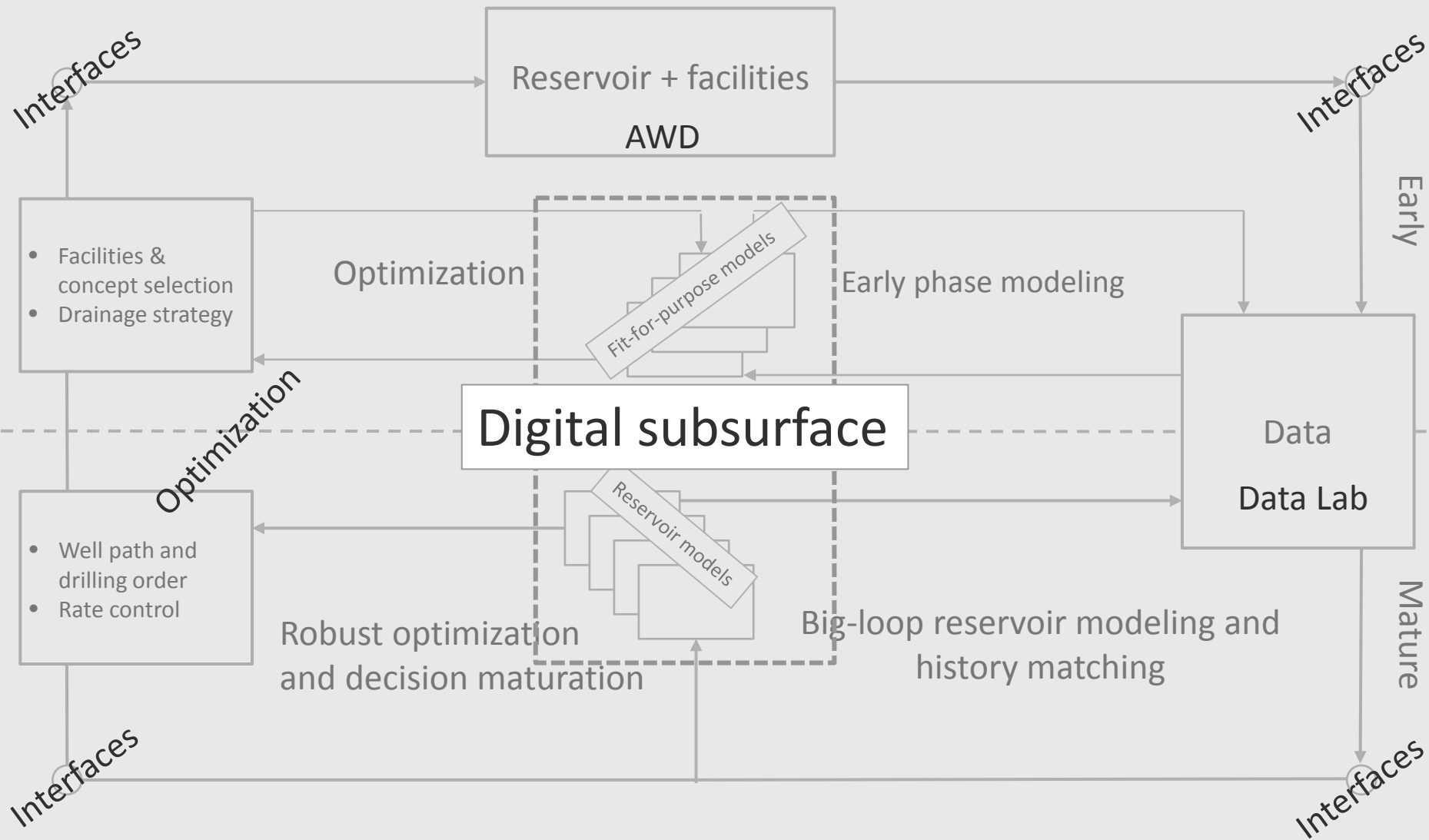
Future outlook

Value = the importance, worth, or usefulness of **something**.

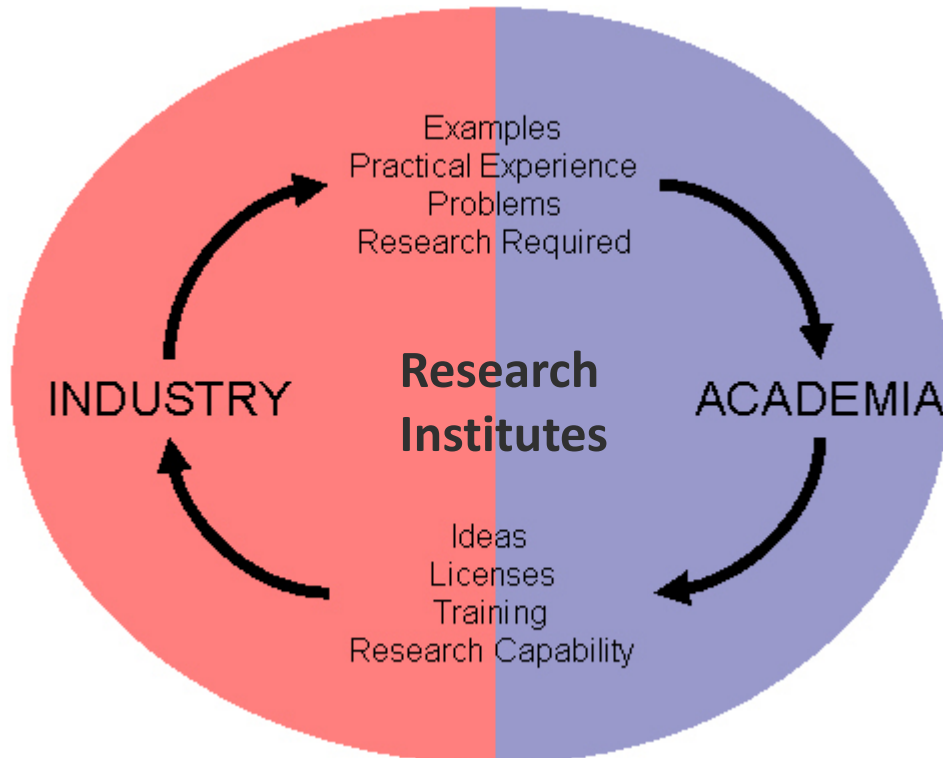


- **Data – Value of information (VoI)**
- **Model – fit for purpose**
- **AHM – Value of Learning (VoL)**
- **Optimization – Decision Maturation**

Decision making for a digital subsurface



Future outlook



Joint Industry Project – Decision making for a digital subsurface

There's never been a better
time for **good ideas**

Ensemble-based decision making for
reservoir management – present and
future outlook

StoSAG Gradient Formulation

Original (Chen, 2008):

$$\mathbf{U} = [\mathbf{u}_1 - \bar{\mathbf{u}} \quad \mathbf{u}_2 - \bar{\mathbf{u}} \quad \cdots \quad \mathbf{u}_M - \bar{\mathbf{u}}]$$
$$\bar{\mathbf{u}} = \frac{1}{M} \sum_{i=1}^M \mathbf{u}_i \quad \bar{J} = \frac{1}{M} \sum_{i=1}^M J_i$$
$$\mathbf{j} = [J_1(\mathbf{u}_1, \boldsymbol{\theta}_1) - \bar{J} \quad J_2(\mathbf{u}_2, \boldsymbol{\theta}_2) - \bar{J} \quad \cdots \quad J_M(\mathbf{u}_M, \boldsymbol{\theta}_M) - \bar{J}]^T$$

StoSAG (Fonseca et al. 2016; IJNME; theoretical proof):

$$\mathbf{U}_{mod} = [\mathbf{u}_1 - \mathbf{u}^\ell \quad \mathbf{u}_2 - \mathbf{u}^\ell \quad \cdots \quad \mathbf{u}_M - \mathbf{u}^\ell]$$
$$\mathbf{j}_{mod} = [J_1(\mathbf{u}_1, \boldsymbol{\theta}_1) - J_1^\ell(\mathbf{u}^\ell, \boldsymbol{\theta}_1) \quad J_2(\mathbf{u}_2, \boldsymbol{\theta}_2) - J_2^\ell(\mathbf{u}^\ell, \boldsymbol{\theta}_2) \\ \cdots \quad J_M(\mathbf{u}_M, \boldsymbol{\theta}_M) - J_M^\ell(\mathbf{u}^\ell, \boldsymbol{\theta}_M)]^T$$