Reservoir Simulation Symposium

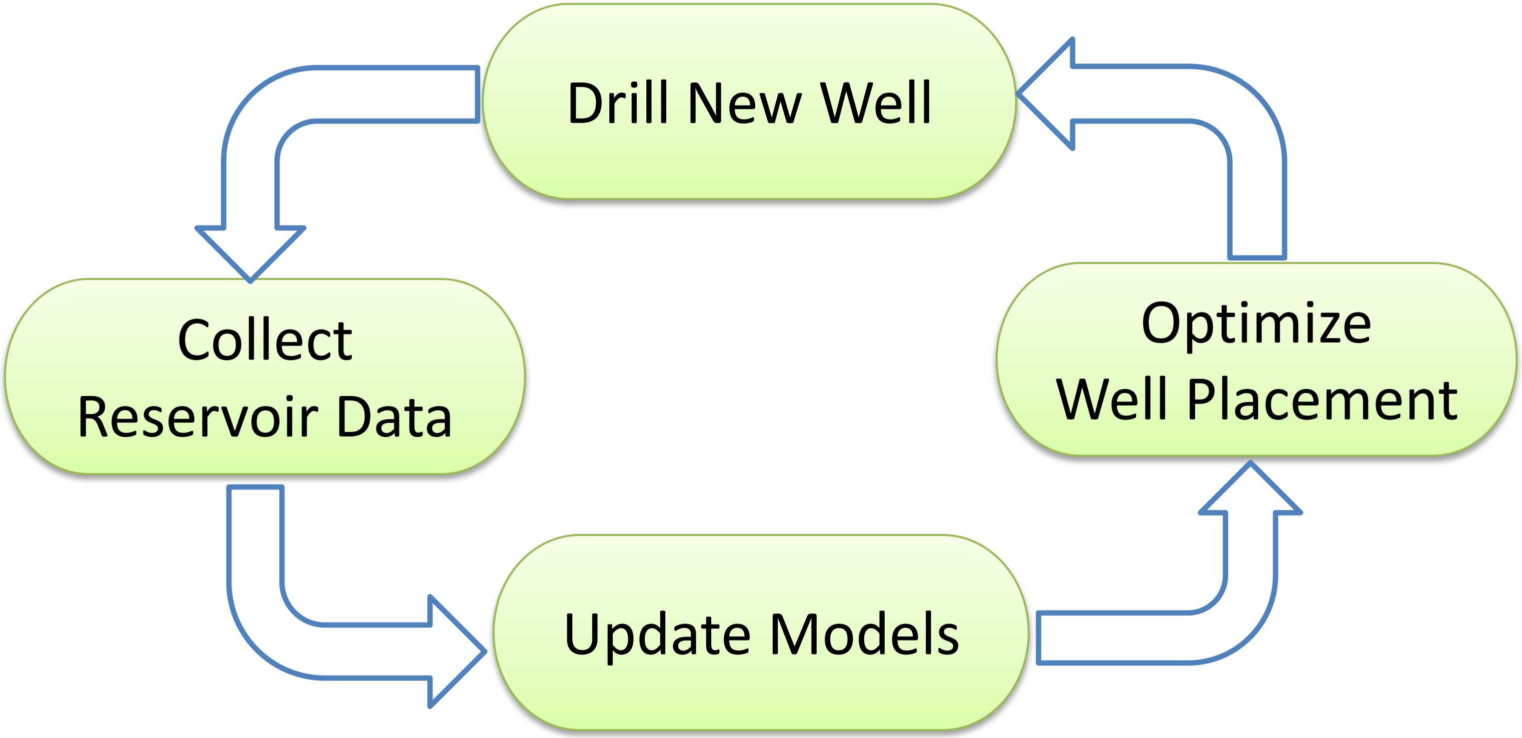
23–25 February 2015
HOUSTON, TEXAS, USA
Royal Sonesta Hotel

SPE-173219-MS
Closed-loop Field Development Optimization under Uncertainty

Mehrdad G. Shirangi Louis J. Durlofsky
Stanford University

Society of Petroleum Engineers

Closed-loop Field Development Optimization

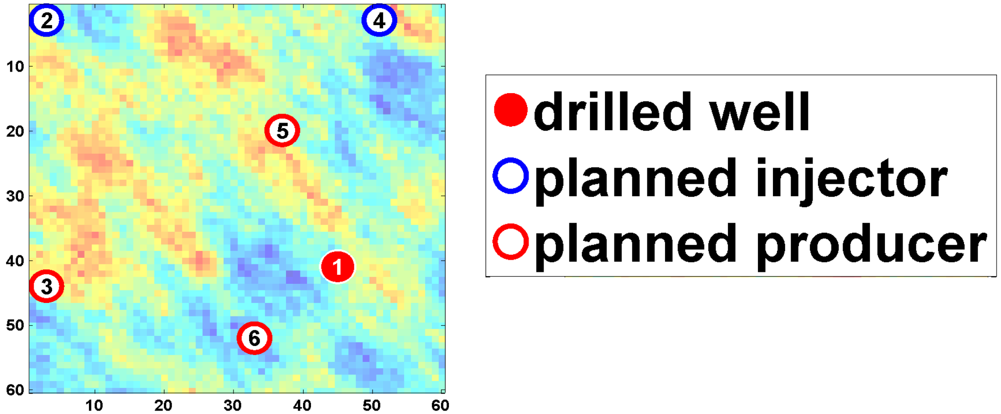


- Each new well is optimized with knowledge that it is one well in a sequence

Closed-loop Field Development Optimization

t_1

Optimization

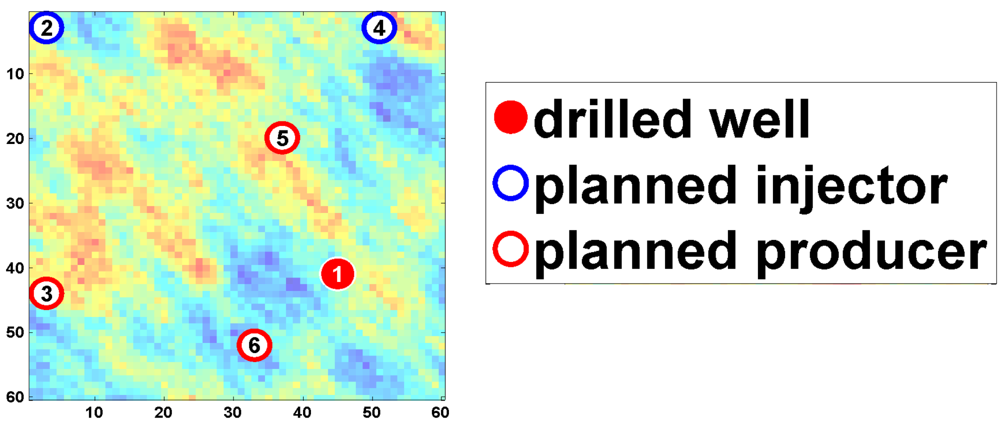


Closed-loop Field Development Optimization

t_1 → t_2

Production from Well 1

Optimization

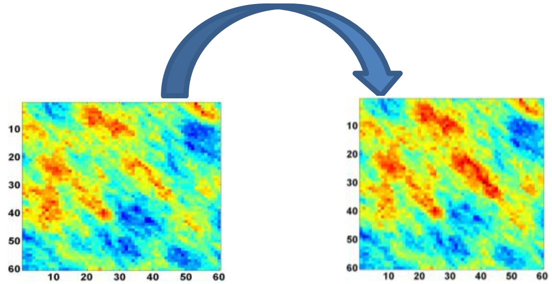


Closed-loop Field Development Optimization

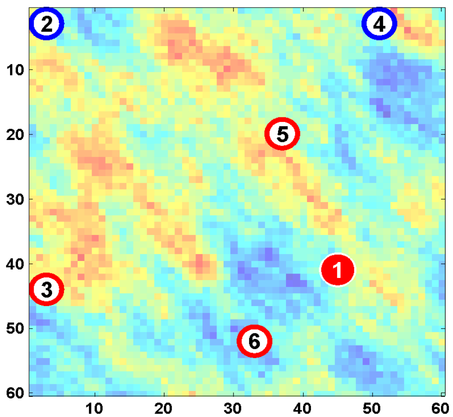
t_1 → t_2

*Production from Well **1***

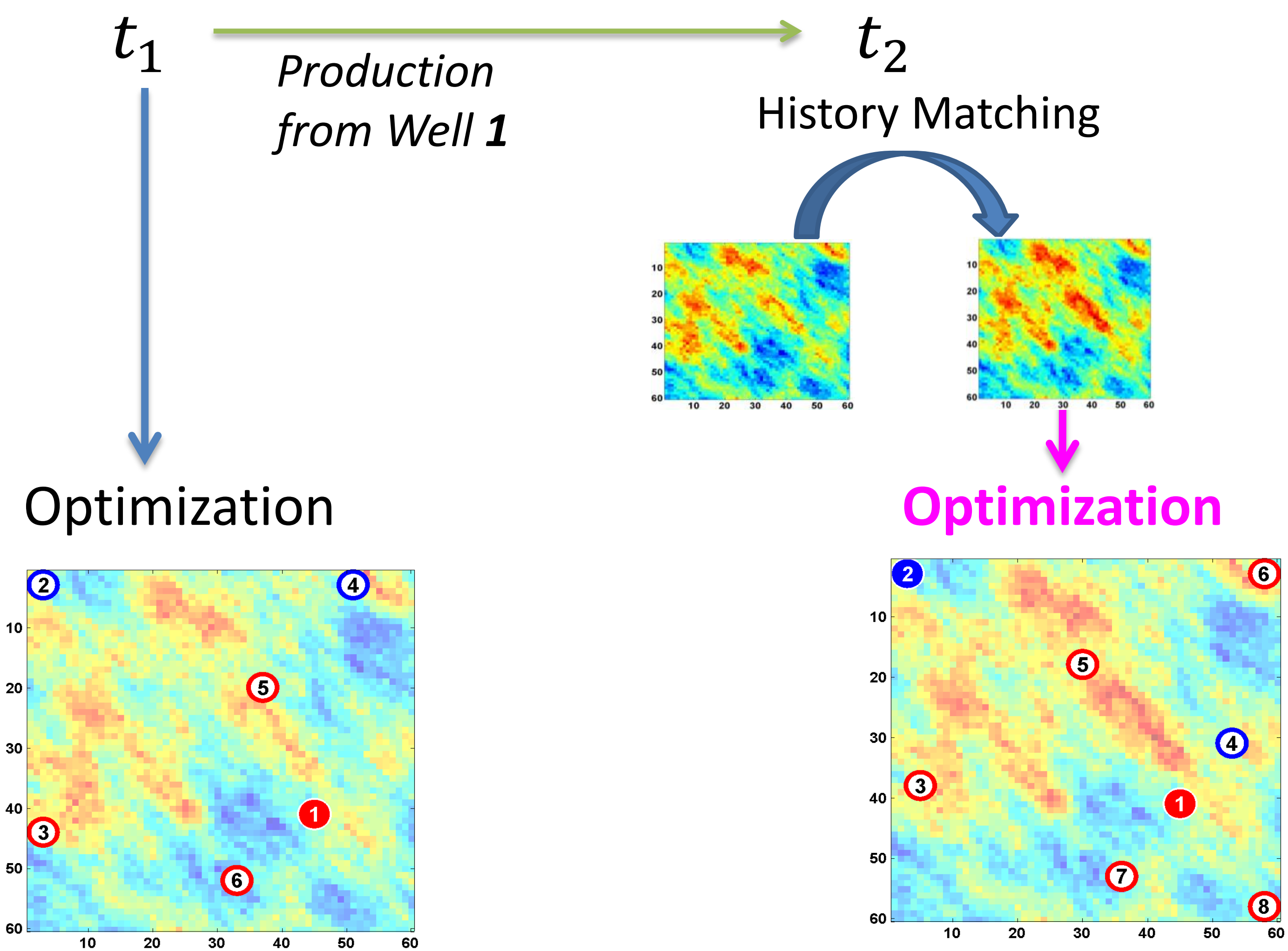
History Matching



Optimization



Closed-loop Field Development Optimization



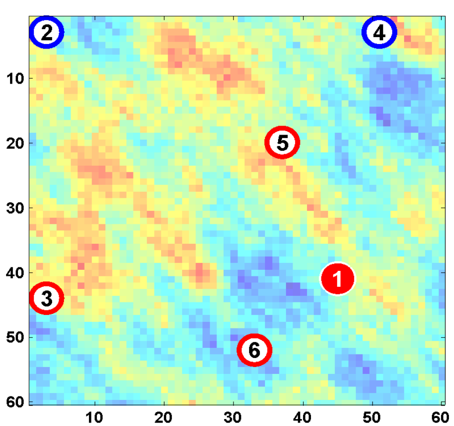
Closed-loop Field Development Optimization

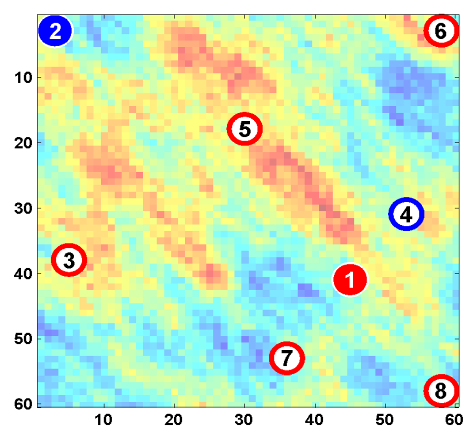
t_1 → *Production from Well **1*** → t_2 → ***Prod / Inj from Wells 1 & 2*** → t_3

History Matching

Optimization

Optimization





Closed-loop Field Development Optimization

t_1

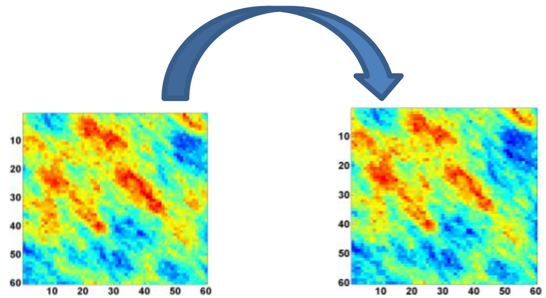
*Production from Well **1***

t_2

Prod / Inj from Wells 1 & 2

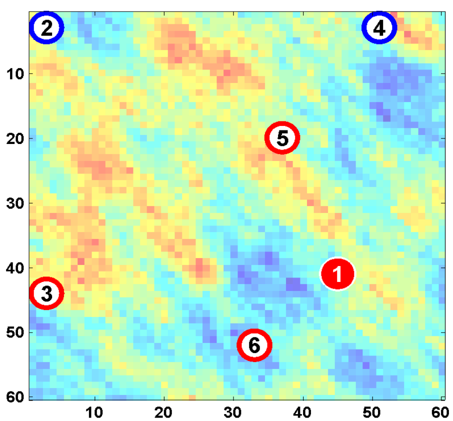
t_3

History Matching

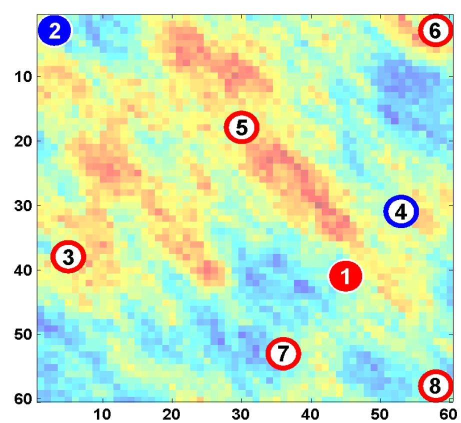


History Matching

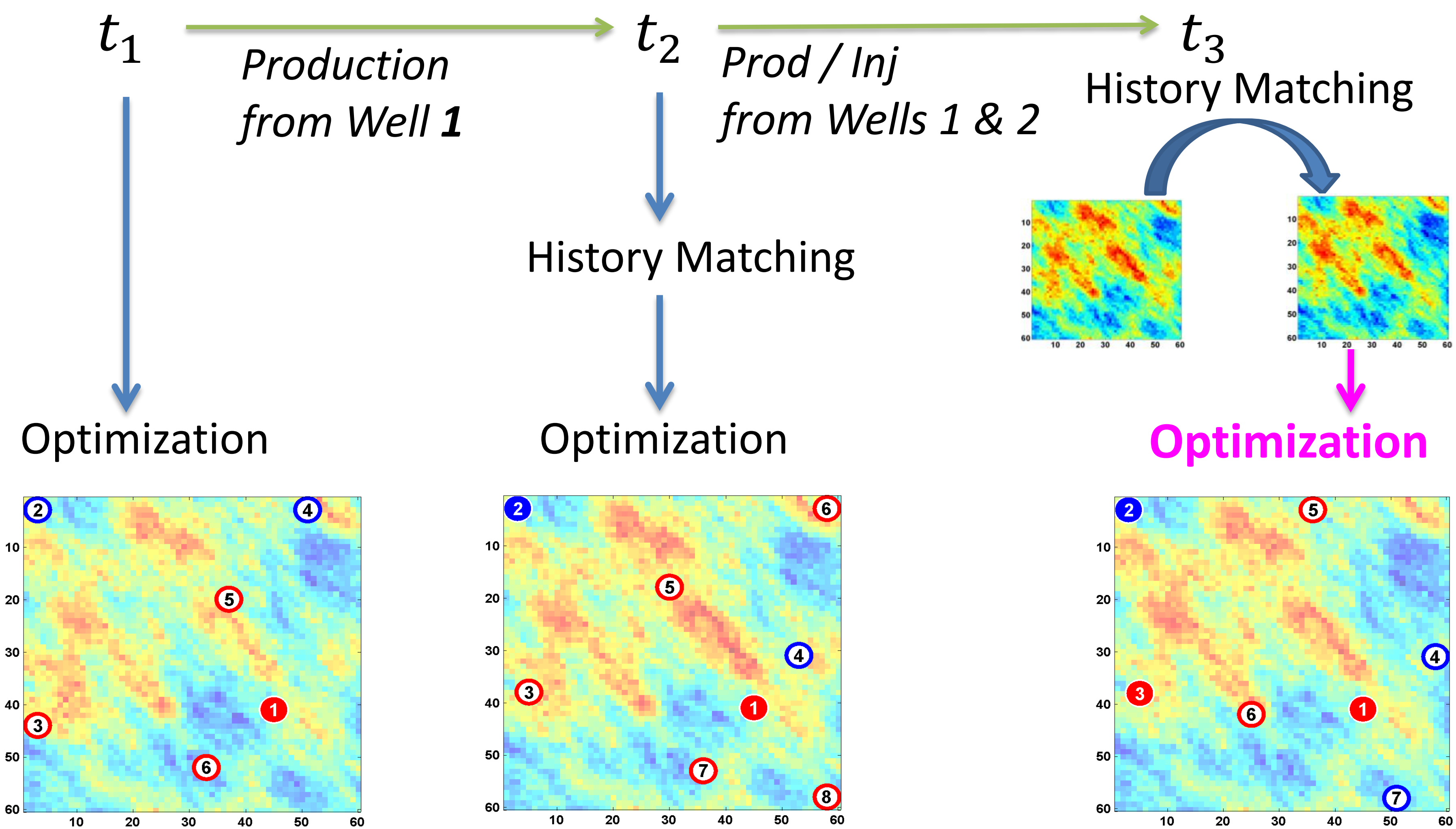
Optimization



Optimization



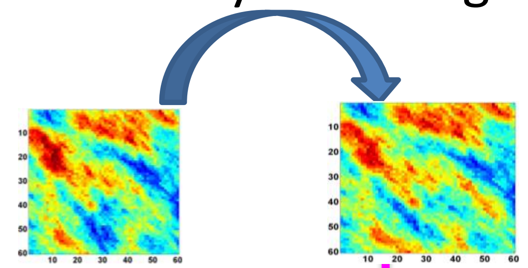
Closed-loop Field Development Optimization



Closed-loop Field Development Optimization

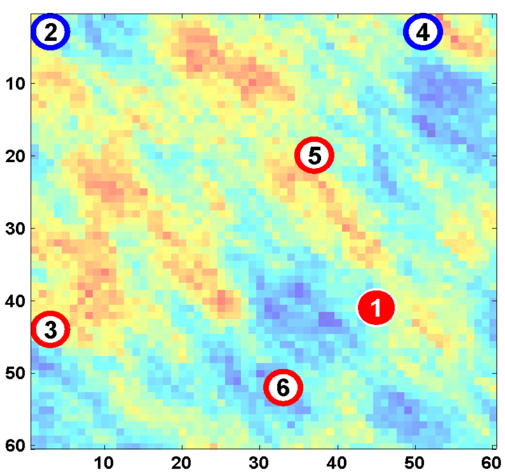
t_1 → $t_2 \ldots t_6$ → t_7

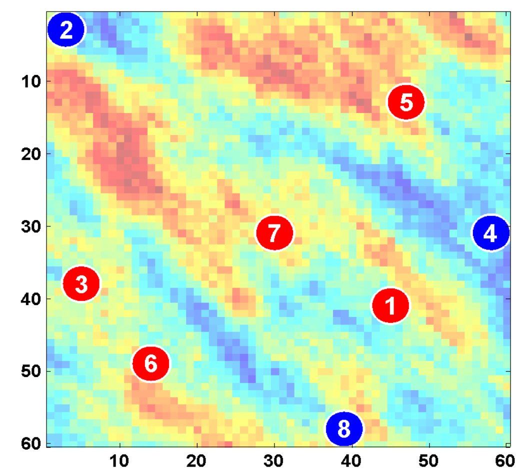
History Matching



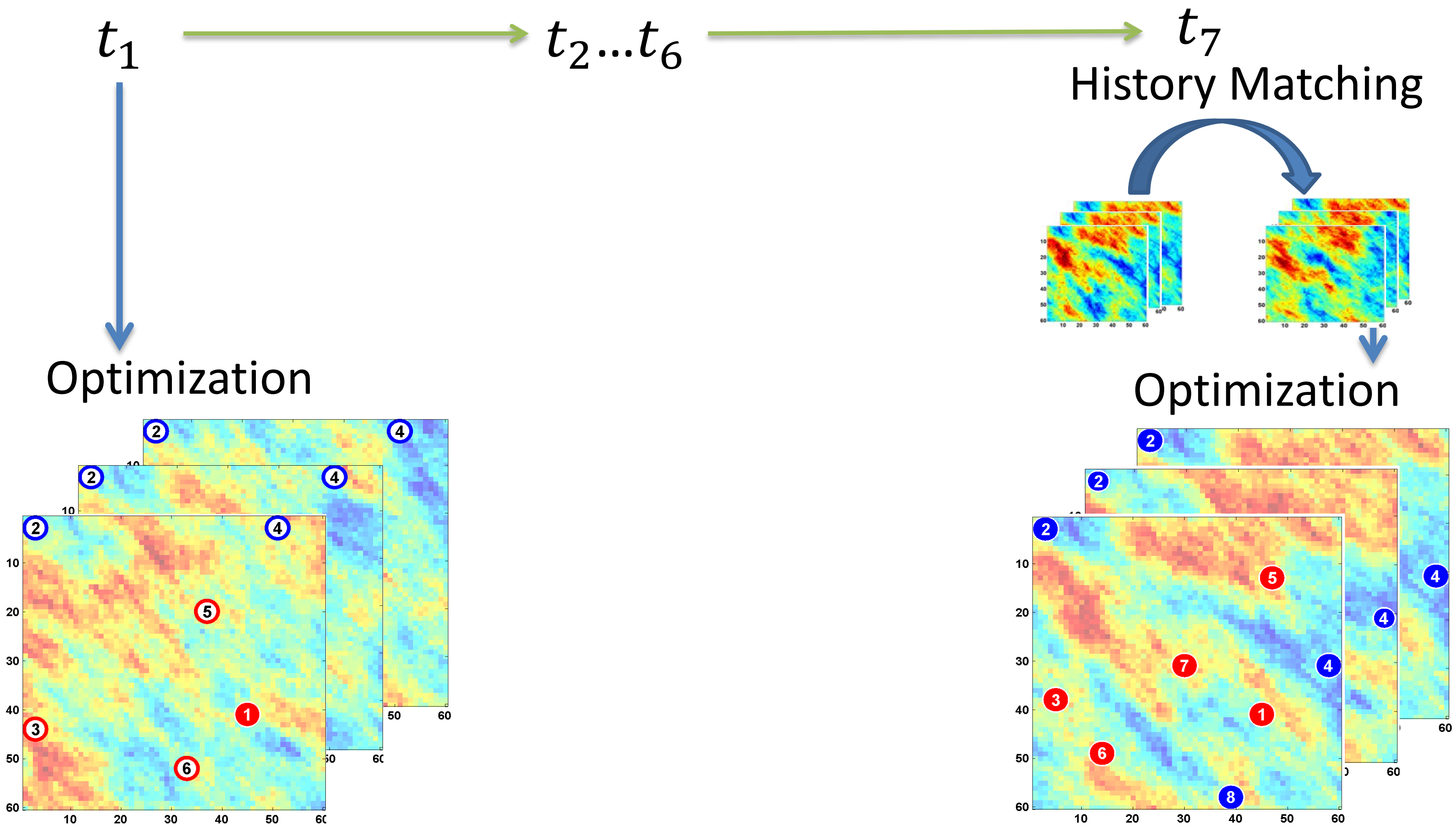
Optimization

Optimization





CLFD with Multiple Realizations



Optimization Problem in CLFD

- NPV objective for field development optimization:

$$J(\mathbf{x}, \mathbf{m}) = p_o Q_o - c_{wp} Q_{wp} - c_{wi} Q_{wi} - \sum c_{well}$$

- $\mathbf{x}$: vector of decision parameters (number of wells, well types, locations, controls, drilling sequence)

- $\mathbf{m}$: a “current” (updated) realization at time t_i

- Maximize expected NPV:

$$\bar{J}(\mathbf{x}) = \frac{1}{N} \sum_{j=1}^{N} J(\mathbf{x}, \mathbf{m}_j)$$

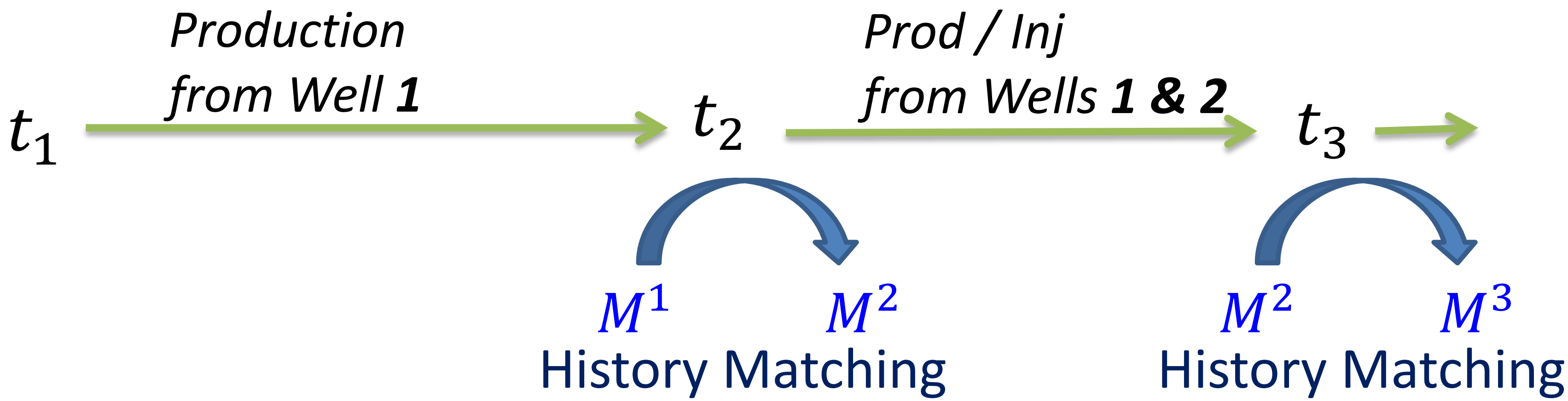
Optimization Problem in CLFD

- $\boldsymbol{M^i} = [\mathbf{m}_1^i, \mathbf{m}_2^i \ldots \mathbf{m}_N^i]$: set of current realizations (updated at t_i)

$$\bar{J} = \frac{1}{N} \sum_{j=1}^{N} J\left(\mathrm{x}, m_j^i\right), \qquad \bar{J} = \bar{J}(\mathrm{x}, \boldsymbol{M^i})$$

- Optimal solution (at t_i) : $\mathbf{x}^{\mathbf{i}} = \mathrm{argmax}x \; \bar{J}\left(\mathrm{x}, M^i\right)$, using PSO-MADS (Isebor et al. 2014 a, b)

Evolution of Solution in CLFD



$\bar{J}(\mathrm{x}^0, M^1)$ ⇩ Optimization $\bar{J}(\mathrm{x}^1, M^1)$

$\bar{J}(\mathrm{x}^1, M^2)$ ⇩ Optimization $\bar{J}(\mathrm{x}^2, M^2)$

$\bar{J}(\mathrm{x}^2, M^3)$ ⇩ $\bar{J}(\mathrm{x}^3, M^3)$

Evolution of Solution in CLFD

$t_1 \longrightarrow t_2 \longrightarrow t_3 \longrightarrow$

Optimal solution: x^1 Optimal solution: x^2 Optimal solution: x^3

$\bar{J}(\mathrm{x}^1, M^1)$ $\bar{J}(\mathrm{x}^2, M^2)$ $\bar{J}(\mathrm{x}^3, M^3)$

$J(\mathrm{x}^1, m_{\mathrm{true}}) \longrightarrow J(\mathrm{x}^2, m_{\mathrm{true}}) \longrightarrow J(\mathrm{x}^3, m_{\mathrm{true}})$

- Our interest is to investigate how "NPV for the true model" changes with update steps of CLFD

Randomized Maximum Likelihood (RML) for Generating Multiple History Matched Models

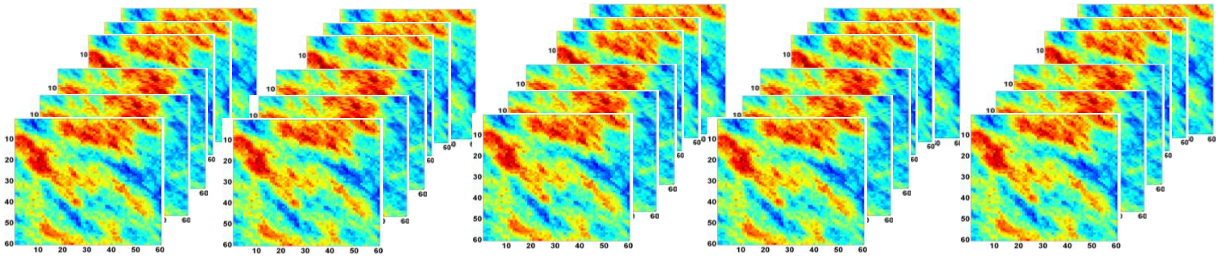
- History matching in CLFD is based on RML (Oliver et al. 1996)
- Minimize $\boldsymbol{N_R}$ objective functions to generate $\boldsymbol{N_R}$ posterior samples using L-BFGS

$$S(\mathbf{m}) = S_m(\mathbf{m}, \boldsymbol{m_{uc}}) \quad \leftarrow \text{Model mismatch term}$$
$$+ \; S_d(\mathbf{m}, \mathbf{d}_{\boldsymbol{uc}}) \quad \leftarrow \text{Data mismatch term}$$

- $\mathbf{d}_{\boldsymbol{uc}}$: perturbed observation sample
- $\mathbf{m}_{\boldsymbol{uc}}$: an unconditional realization of log-permeability field

Optimization under Geological Uncertainty

- A large number of realizations ($\boldsymbol{N_R}$) are used to capture uncertainty



- How many realizations should we use in optimization?
- Sample validation: optimize for $\boldsymbol{N} \ll \boldsymbol{N_R}$ representative realizations, then **validate** representivity

Optimization with Sample Validation (OSV)

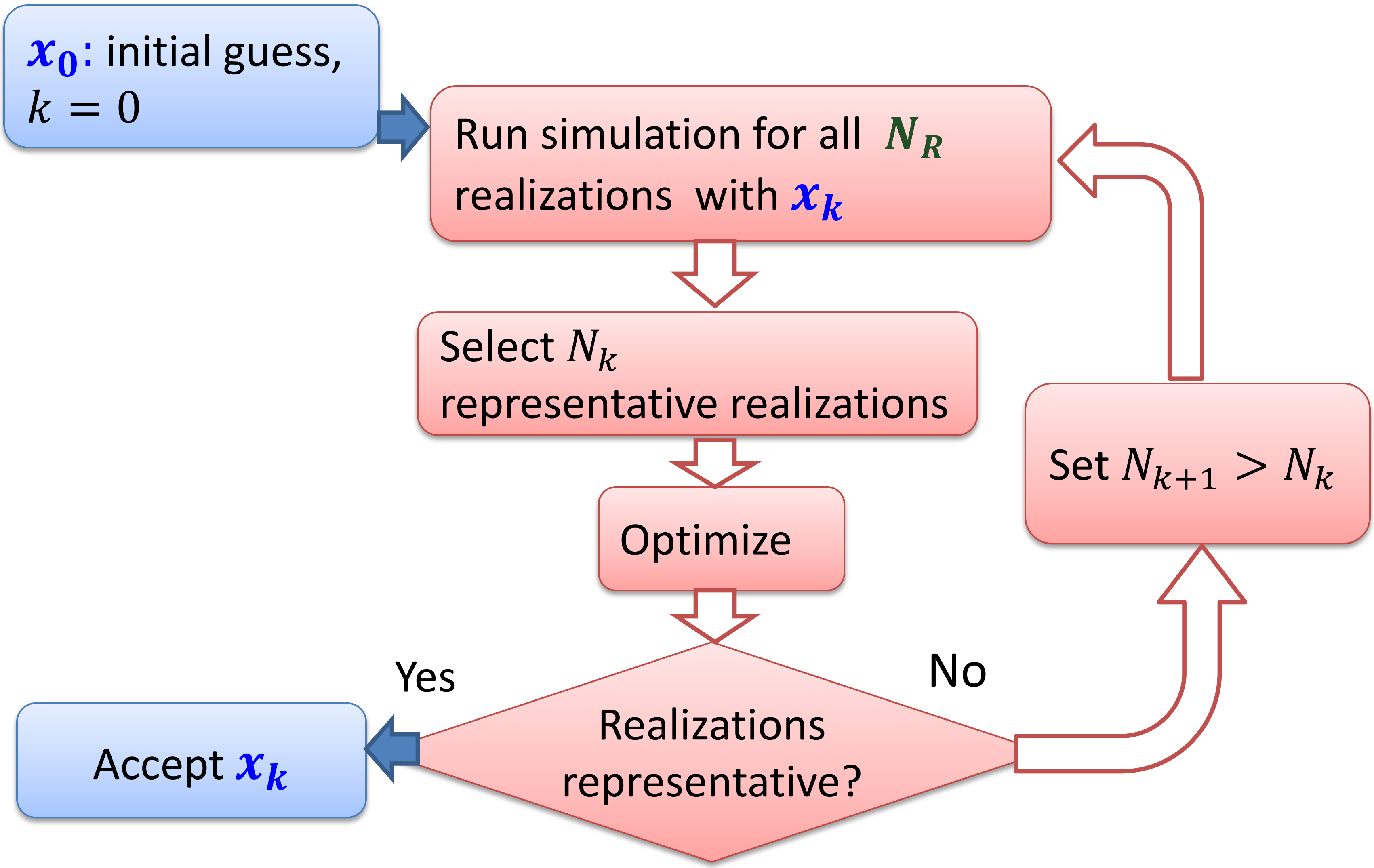
- Compute Relative Improvement ($\boldsymbol{RI}$): ratio of improvement for the entire set ($\boldsymbol{M}$) over that for the representative set ($\boldsymbol{M_{rep}}$):

$$\boldsymbol{RI} = \frac{\bar{J}\left(\mathrm{x}_{opt}, \boldsymbol{M}\right) - \bar{J}(\mathrm{x}_{init}, \boldsymbol{M})}{\bar{J}\left(\mathrm{x}_{opt}, \boldsymbol{M_{rep}}\right) - \bar{J}(\mathrm{x}_{init}, \boldsymbol{M_{rep}})}$$

  - $\boldsymbol{M}$: set of all realizations of size $\boldsymbol{N_R}$
  - $\boldsymbol{M_{rep}}$: representative set of size $\boldsymbol{N}$

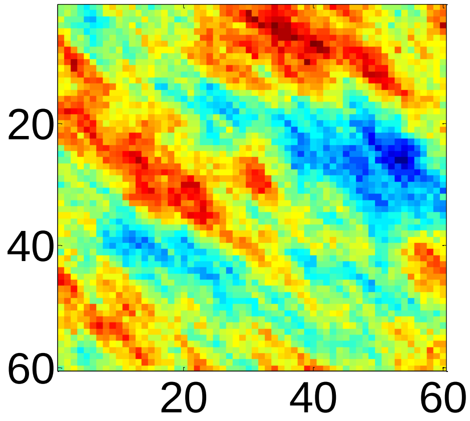
- We require $\boldsymbol{RI} \geq 0.5$ to accept x_{opt} as optimal solution

Optimization with Sample Validation (OSV)



Simultaneous versus Well-by-Well Optimization

- Deterministic reservoir description
- Simultaneous optimization: optimize the locations, controls and types of 4 wells drilled at 210 day intervals
- Well by well: optimize Well 1; then optimize Well 2 (drilled at 210 days), etc.

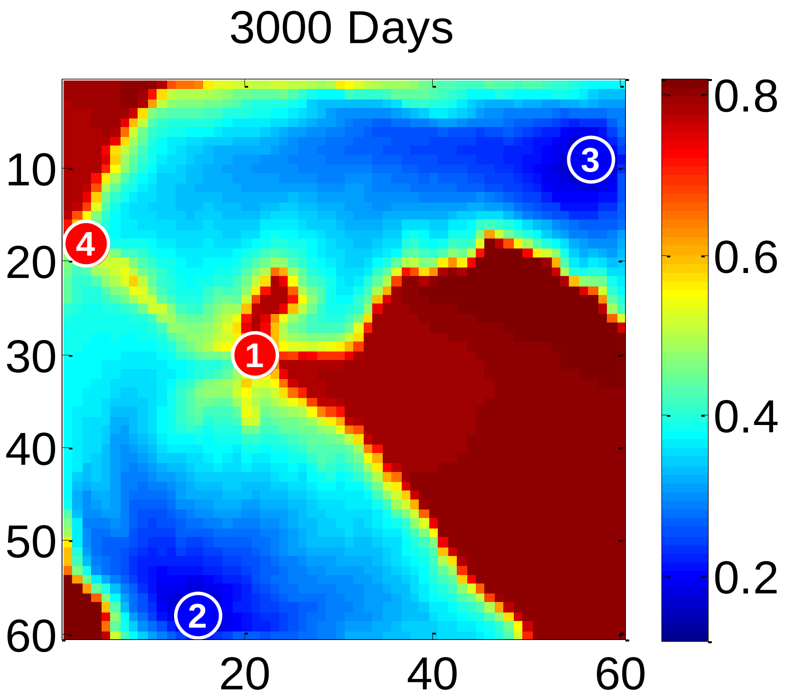


log-permeability

parameter	value
well cost	$ 25 MM
oil price	$ 90 / bbl
produced water	$ 10 / bbl
injected water	$ 10 / bbl
reservoir life	3000 days
Porosity	0.2

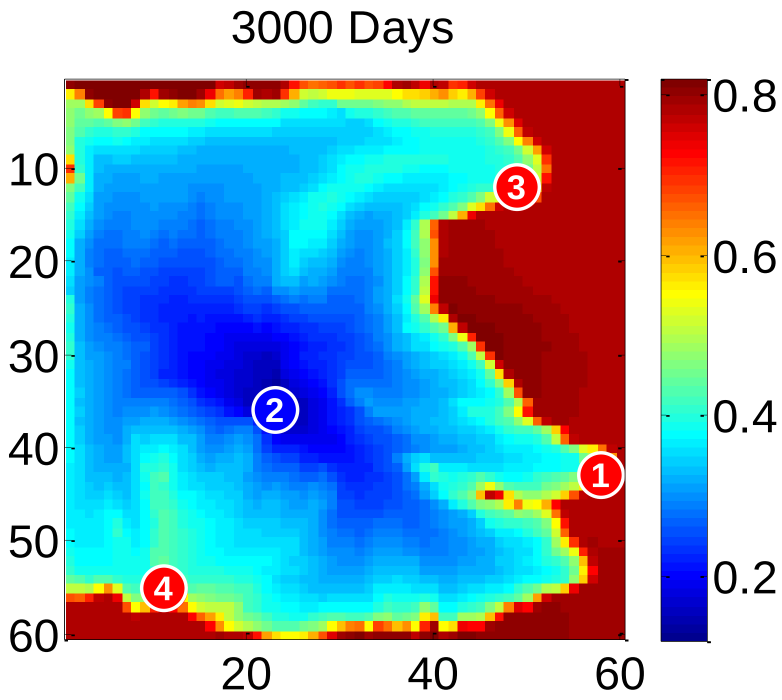
Final Saturation from Optimal Solutions

Well-by-Well



NPV = $**625** MM

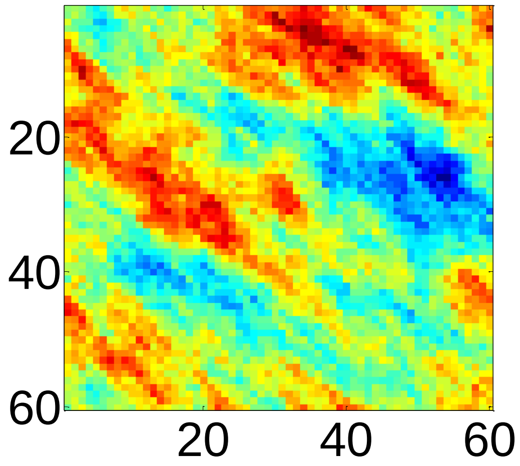
Simultaneous



NPV = $**708** MM

CLFD for a 2D Reservoir (60×60)

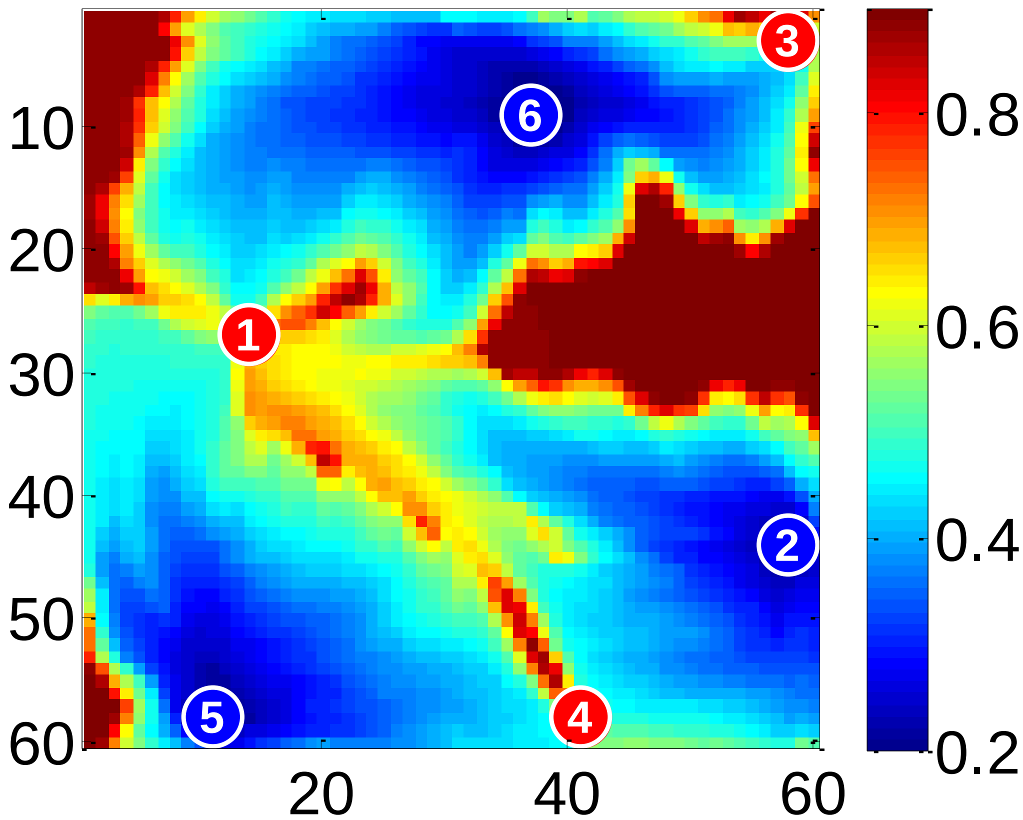
- Uncertain permeability field
- Budget to drill maximum **8** wells at 210 day intervals
- Case 1: $\boldsymbol{N = 3}$
- Case 2: $\boldsymbol{N = 10}$
- Case 3: $\boldsymbol{N}$ **determined from OSV**



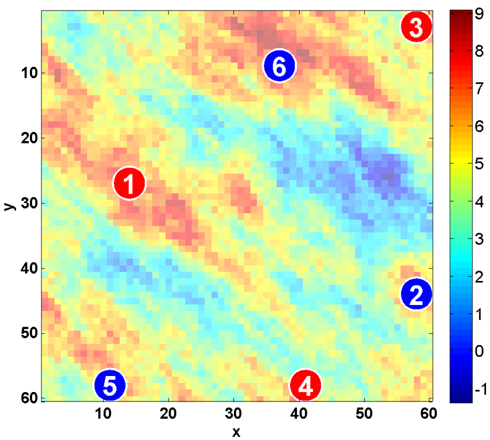
True log-permeability
(produces synthetic observed data)

parameter	value
well cost	\$ 25 MM
oil price	\$ 90 / bbl
Produced-injected water	\$ 10 / bbl
reservoir life	3000 days
Porosity	0.2
$\boldsymbol{N_R}$	**50**

Optimization on “True” Model (Deterministic)

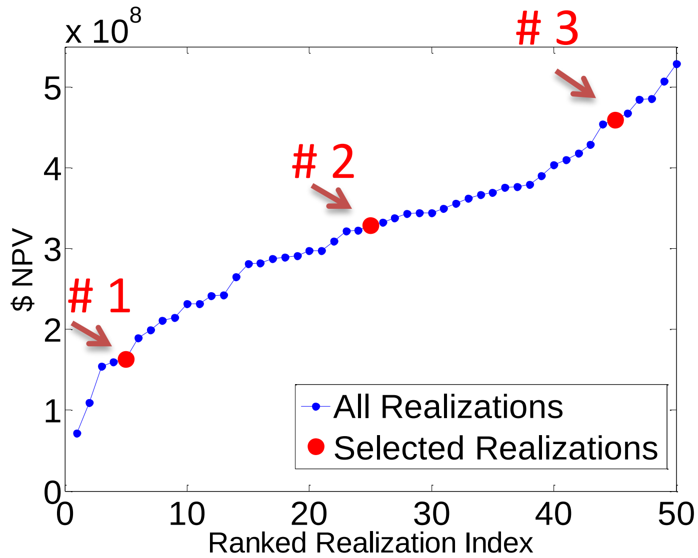


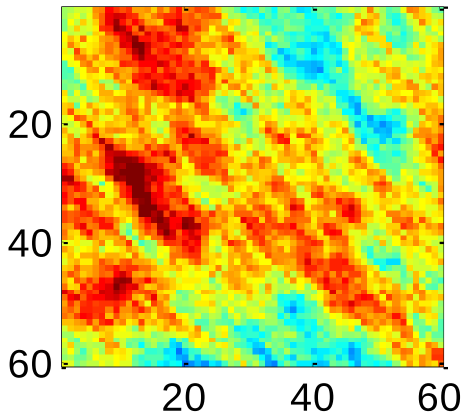
S_w distribution at 3000 days (NPV = $ 730 MM)



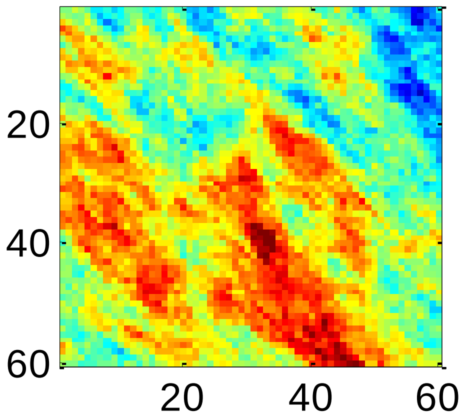
Optimal well
Configuration on truth

Selection of Realizations ($N = 3$)

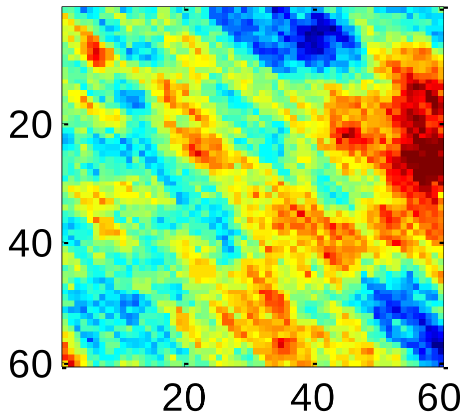




Real 1

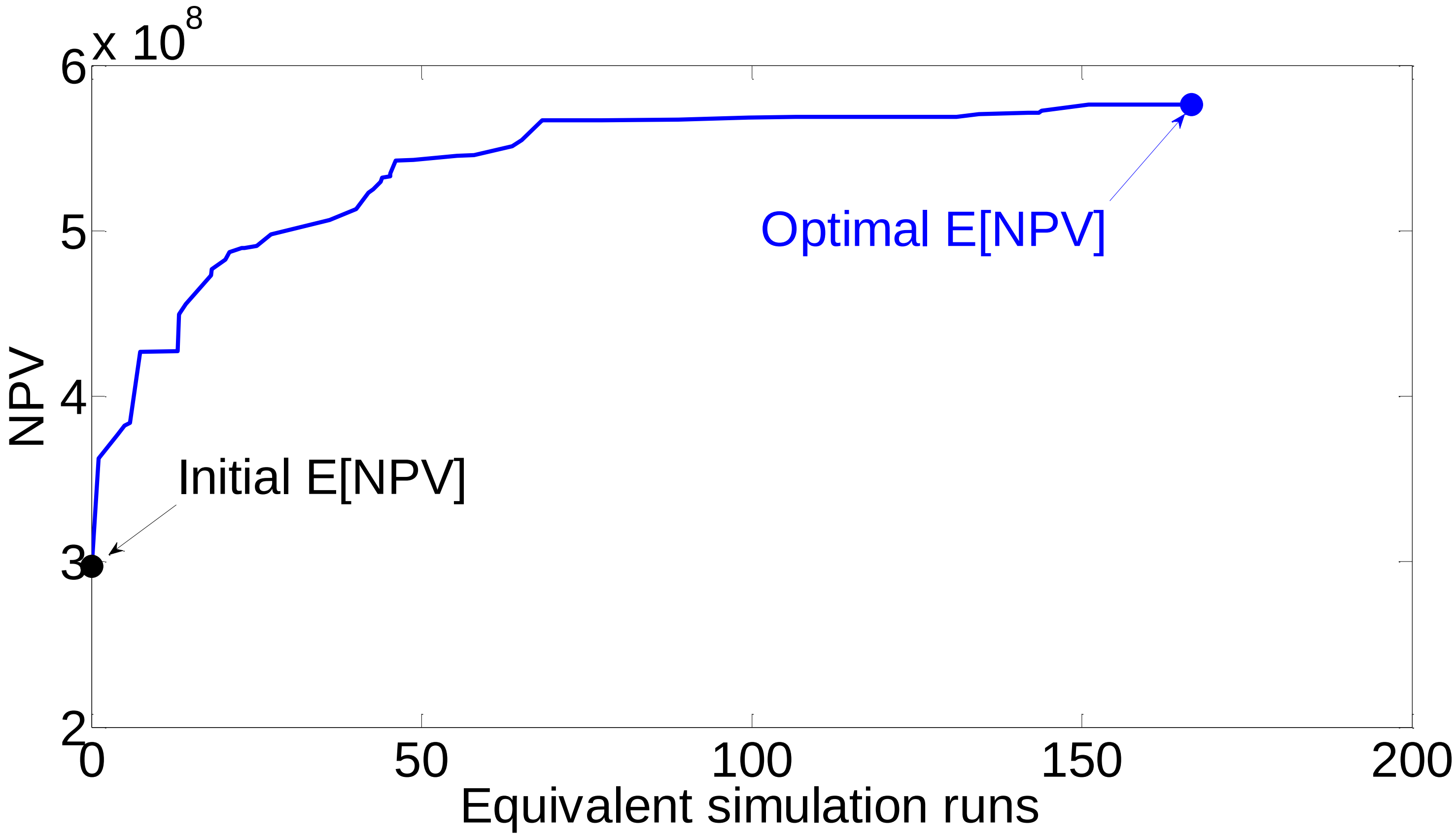


Real 2

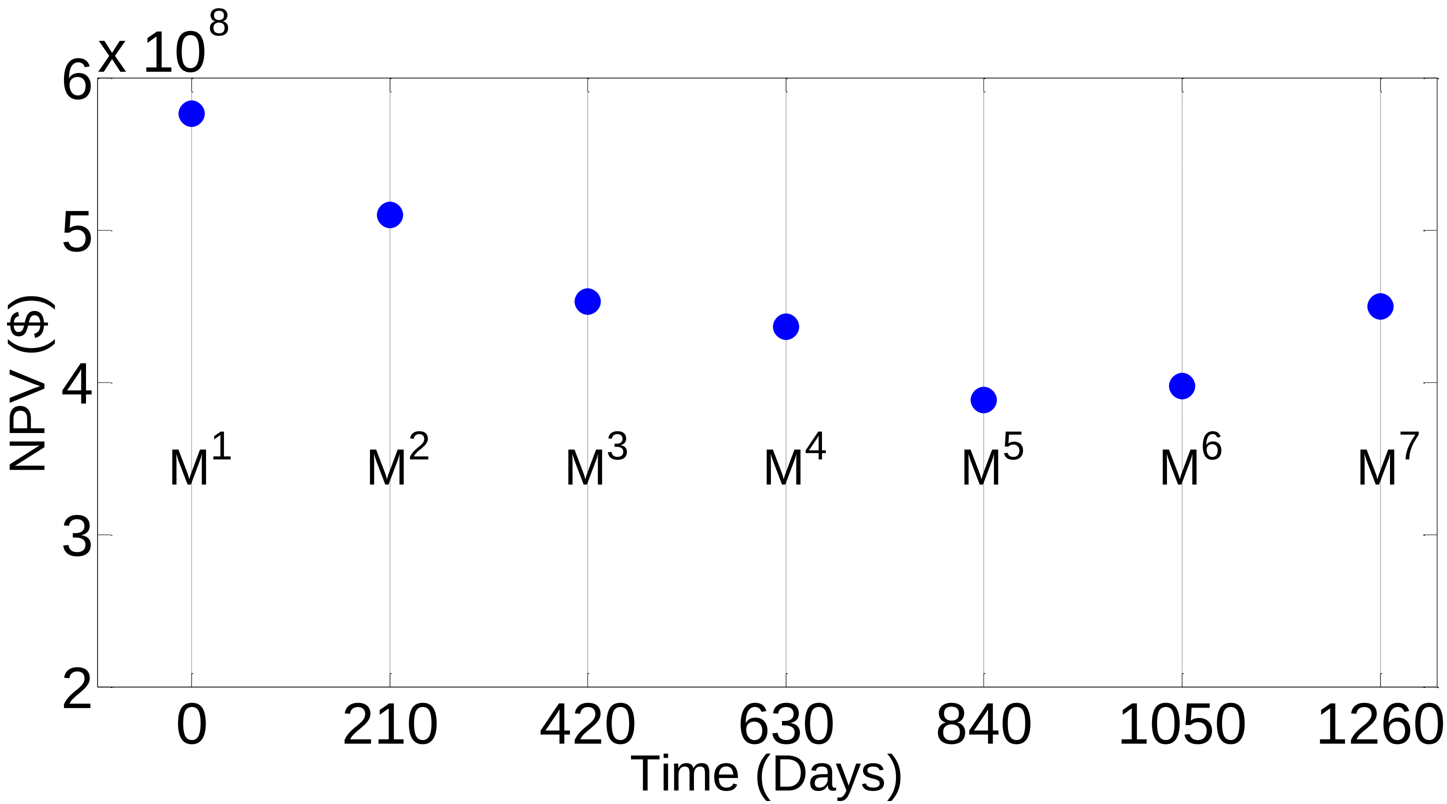


Real 3

Optimization over 3 Prior Realizations (1st Optimization Step of CLFD)

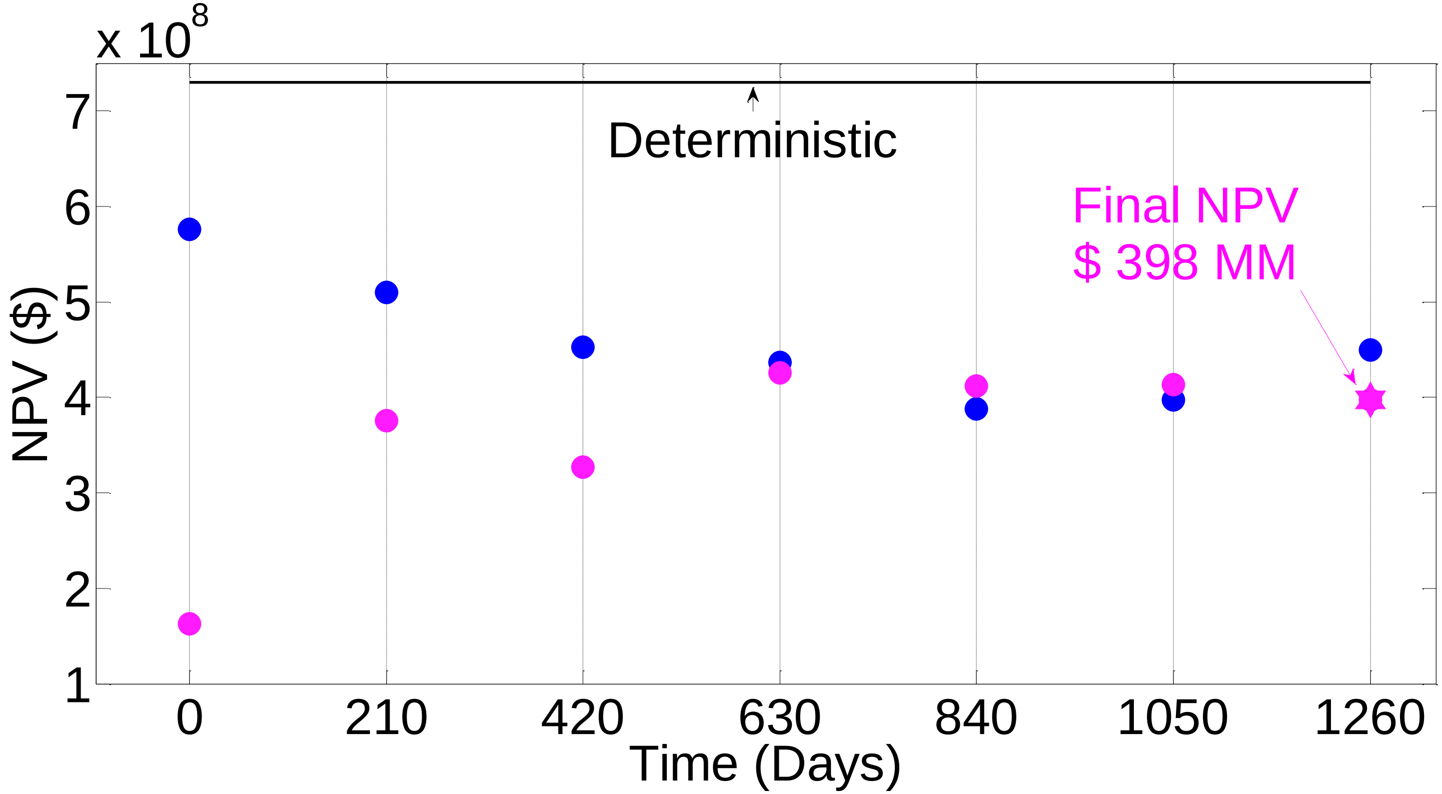


Optimal E[NPV] for CLFD ($\boldsymbol{N = 3}$)



- $J\left(\mathrm{x}^{i}, M_{rep}^{i}\right)$: **Optimal** E[NPV] at t_i

Optimal NPV versus CLFD Steps ($\boldsymbol{N = 3}$)



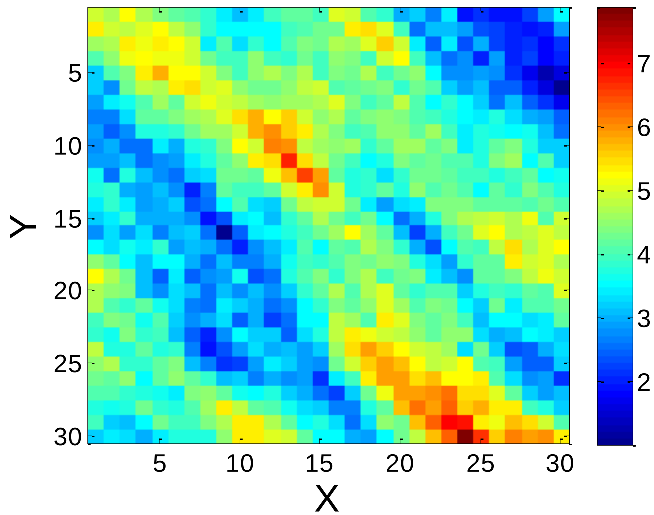
- $J(\mathrm{x}^i, M^i_{rep})$: Optimal E[NPV] updated at t_i
- $J(\mathrm{x}^i, m_{true})$: NPV for the true model

Summary of Optimization Results

Optimization cases	***True NPV*** *$ MM*
Deterministic (known geology)	**730**
50 Prior Reals	**350**
CLFD with 3 Reals	398
CLFD with 10 Reals	**599**
CLFD with OSV	**586**

CLFD for a 3D Reservoir $(\mathbf{30} \times \mathbf{30} \times \mathbf{5})$

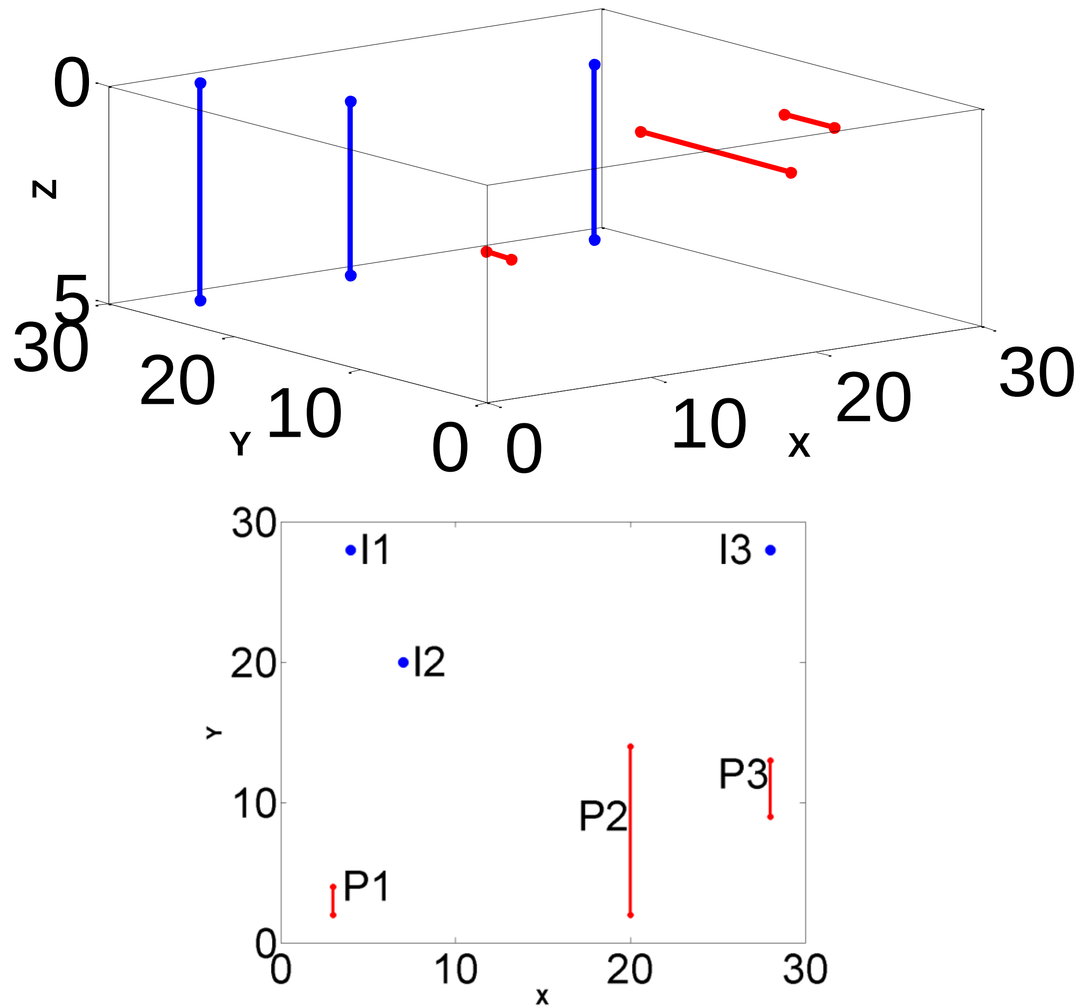
- Wells operated on BHP with maximum rate constraint
- Drill **6** wells: 3 horizontal producers, 3 vertical injectors
- Apply CLFD Optimization with Sample Validation (OSV)



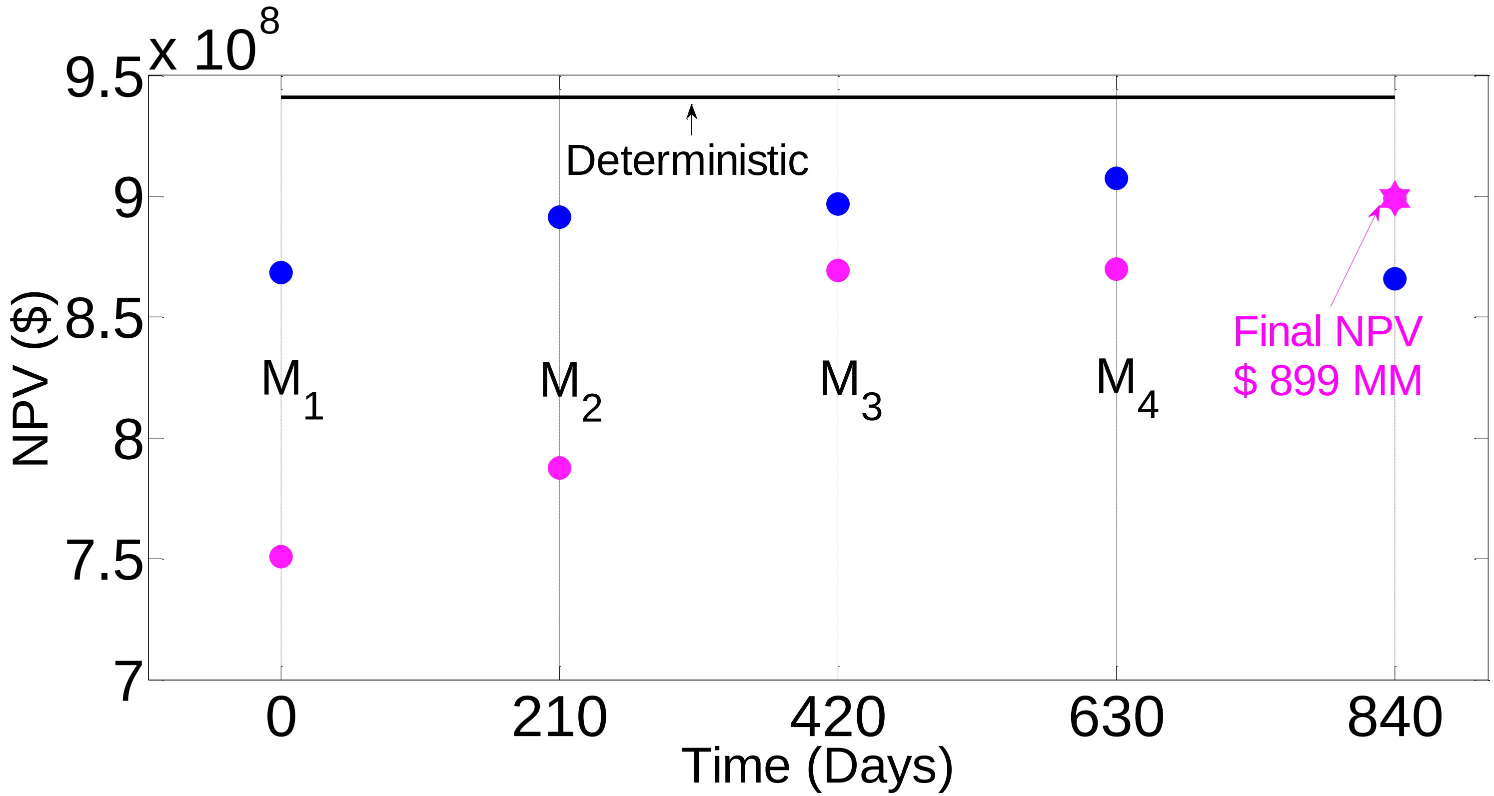
True log-perm (Layer 1)

parameter	value
well cost	$ 25 MM
oil price	$ 90 / bbl
Produced-injected water	$ 10 / bbl
drilling lag-time	210 days
reservoir life	2000 days
perforation cost	$ 2 MM /blk

Optimization on True Model



Optimal NPV versus CLFD Steps



- $J(x^i, M^i)$: Optimal E[NPV] updated at t_i
- $J(x^i, m_{true})$: NPV for the true model

Summary

- Implemented a framework for closed-loop field development (**CLFD**) optimization under uncertainty
- Results show that the use of too few realizations leads to lower NPV values for “true” model
- Optimization with sample validation (**OSV**) developed and tested for optimization under geological uncertainty
- Use of **CLFD** with **OSV** represents a robust and efficient overall methodology

Acknowledgements

- Stanford Smart Fields Consortium
- Oleg Volkov
- Obiajulu Isebor (now with BP)
- Stanford Center for Computational Earth & Environmental Science (CEES)

SPE-173219-MS
Closed-loop Field Development Optimization under Uncertainty

Mehrdad G. Shirangi   Louis J. Durlofsky
Stanford University

DOI: http://dx.doi.org/10.2118/173219-MS