

Parameter Estimation in Reservoir Engineering Models via Data Assimilation Techniques

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Introduction to Reservoir Engineering

Two-Phase Water-Oil Fluid Flow Model

Kalman Filtering Techniques

Ensemble Kalman Filter (EnKF)

Iterative Ensemble Kalman Filter (IEnKF)

Case Study

State Vector Feasibility

Re-scaling state vector

Experimental Setup

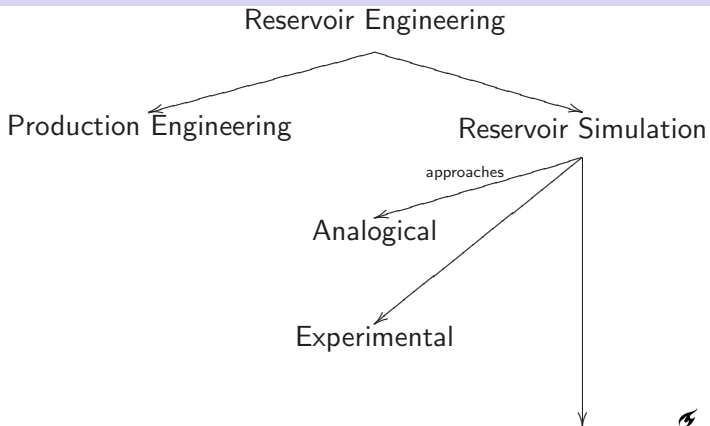
Results

EnKF

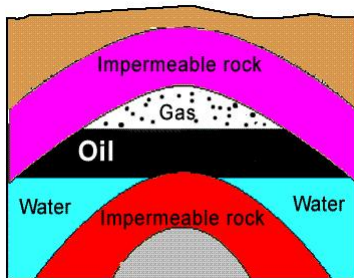
IEnKF

Conclusion

Structure of Reservoir Engineering



A Reservoir



General information

- > 40,000 oil fields in the world
- 300 *m* to 10 *km* below the surface
- 2 – 500 *million* years old

Ghawar oil field

- the biggest among discovered
- Location: Saudi Arabia
- Recovery: since 1951
- Size: 280 × 30 *km*
- Age: 320 *million* years old
- Production: 5 *million* barrels (800,000 *m*³) of oil per day

Oil Recovery

* TERTIARY RECOVERY



- ▶ Primary
20% extracted
- ▶ Secondary (water flooding)
25% to 35% extracted
- ▶ Tertiary
50% left

Reservoir Properties

- ▶ Rock properties
 - ▶ Porosity
 - ▶ (Absolute) permeability
 - ▶ Rock compressibility

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 - ▶ Relative permeability (Corey-type model)

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Two-Phase Water-Oil Fluid Flow Model

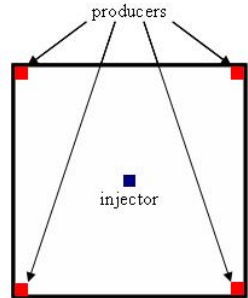
- ▶ Mass balance equation for each phase
- ▶ Darcy's law for each phase
- ▶ Capillary pressure equation
- ▶ Relative permeability equations
(Corey-type model)
- ▶ Equations of state

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- ▶ Well model



Model Discretization

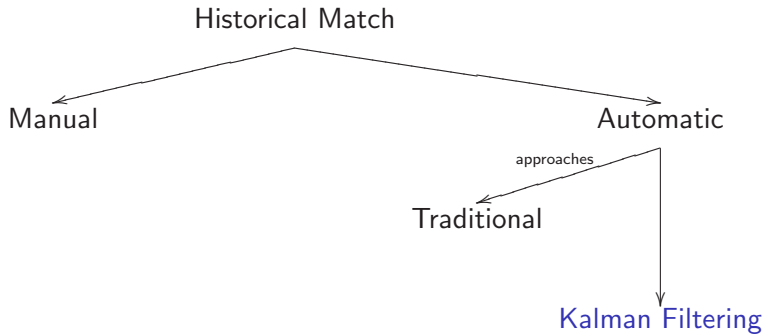
$$\hat{\mathbf{E}}(\mathbf{X}) \quad \dot{\mathbf{X}} \quad - \quad \hat{\mathbf{A}}(\mathbf{X}) \quad \mathbf{X} \quad - \quad \hat{\mathbf{B}}(\mathbf{X}) \quad \mathbf{U} \quad = \quad \mathbf{0}$$

↑ ↑ ↑ ↑ ↑
 accumulation system state input input
 matrix matrix vector matrix vector



$$\mathbf{X} = \begin{bmatrix} \mathbf{P} \\ \mathbf{S} \end{bmatrix}$$

History Matching Process



Data Assimilation Problem Statement

► System

$$\begin{aligned}\mathbf{X}_{k+1} &= \mathbf{F}(\mathbf{X}_k, \mathbf{U}_k, \mathbf{m}) + \mathbf{W}_k, \\ \mathbf{Z}_{k+1} &= \mathbf{M}\mathbf{X}_k + \mathbf{V}_k\end{aligned}$$

► Uncertainties

$$\begin{aligned}\mathbf{X}_0 &\sim \mathcal{N}(\mathbf{X}_0, \mathbf{P}_0) \text{ – uncertain initial state,} \\ \mathbf{W}_k &\sim \mathcal{N}(\mathbf{0}, \mathbf{Q}) \text{ – model noise,} \\ \mathbf{V}_k &\sim \mathcal{N}(\mathbf{0}, \mathbf{R}) \text{ – measurement noise,}\end{aligned}$$

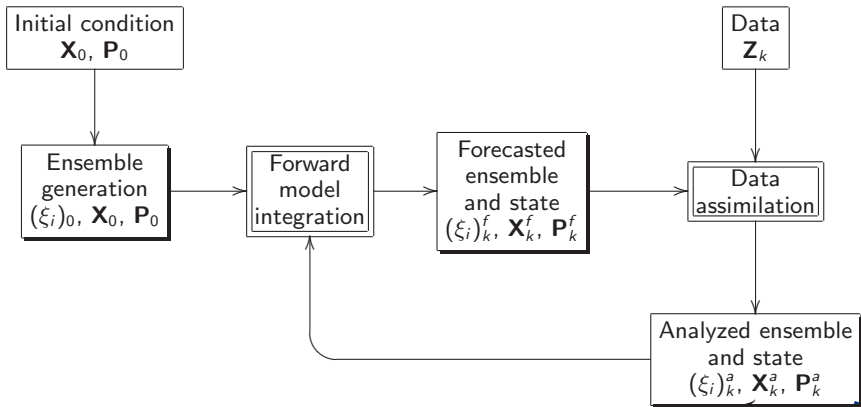
► Independency assumption

$$\mathbf{X}_0 \perp \mathbf{W}_k \perp \mathbf{V}_k$$

► State conditional pdf

$$(\mathbf{X}_k | \mathbf{Z}_1, \dots, \mathbf{Z}_l) \sim \mathcal{N}(\text{mean, cov})$$

Ensemble Kalman Filter (EnKF)

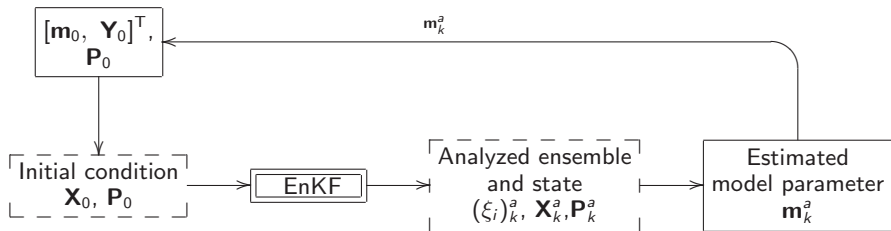


Parameter Estimation via EnKF

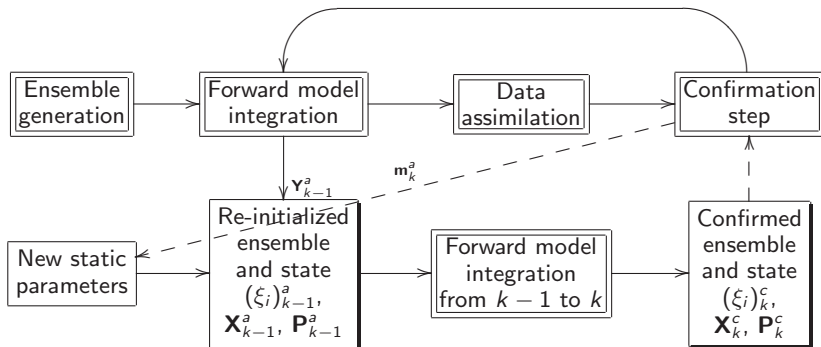
Augmented state vector

$$\mathbf{X} = \begin{bmatrix} \mathbf{p} \\ \mathbf{S} \end{bmatrix} \Rightarrow \mathbf{X} = \begin{bmatrix} \log \mathbf{k} \\ \mathbf{p} \\ \mathbf{S} \\ \mathbf{d} \end{bmatrix} = \begin{bmatrix} \mathbf{m} \\ \mathbf{Y} \end{bmatrix}$$

Iterative Ensemble Kalman Filter (IEnKF)



State Vector Feasibility



Re-scaling state vector

$$\mathbf{X} = \begin{bmatrix} \log k \\ \mathbf{P} \\ \mathbf{S} \\ \mathbf{Y} \end{bmatrix},$$

$$\begin{matrix} \mathbf{A} \\ \mathbf{B} \end{matrix} = \begin{bmatrix} 10^{-7} & | & & | \\ \hline & 10 & & \\ \hline & & 10^{-7} & \\ \hline & & & 10^3 \\ \hline \end{bmatrix} \Rightarrow \begin{matrix} \mathbf{AML} \\ \mathbf{BL} \end{matrix}$$

Re-scaling state vector

Kalman gain

$$\mathbf{K} = \frac{1}{N-1}$$

$$\mathbf{L}\mathbf{L}^T\mathbf{M}^T$$

$$\left(\frac{1}{N-1} \mathbf{M}\mathbf{L}\mathbf{L}^T\mathbf{M}^T + \mathbf{R} \right)^{-1}$$

Re-scaling state vector

Kalman gain

$$\mathbf{K} = \frac{1}{N-1} (\mathbf{B}^{-1}\mathbf{B}) \mathbf{L}\mathbf{L}^T\mathbf{M}^T (\mathbf{A}\mathbf{A}^{-1}) \left(\frac{1}{N-1} \mathbf{M}\mathbf{L}\mathbf{L}^T\mathbf{M}^T + \mathbf{R} \right)^{-1} (\mathbf{A}^{-1}\mathbf{A})$$

Re-scaling state vector

Kalman gain

$$\begin{aligned}
 \mathbf{K} &= \frac{1}{N-1} (\mathbf{B}^{-1}\mathbf{B}) \mathbf{L}\mathbf{L}^T\mathbf{M}^T (\mathbf{A}\mathbf{A}^{-1}) \left(\frac{1}{N-1} \mathbf{M}\mathbf{L}\mathbf{L}^T\mathbf{M}^T + \mathbf{R} \right)^{-1} (\mathbf{A}^{-1}\mathbf{A}) \\
 &= \mathbf{B}^{-1} \underbrace{\frac{1}{N-1} (\mathbf{B}\mathbf{L}) (\mathbf{A}\mathbf{M}\mathbf{L})^T \left(\frac{1}{N-1} \mathbf{A}\mathbf{M}\mathbf{L} (\mathbf{A}\mathbf{M}\mathbf{L})^T + \mathbf{A}\mathbf{R}\mathbf{A} \right)^{-1}}_{\mathbf{K}_1} \mathbf{A}
 \end{aligned}$$

Re-scaling state vector

Kalman gain

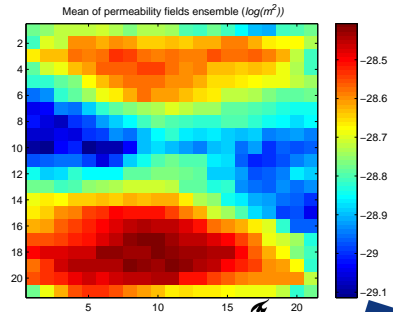
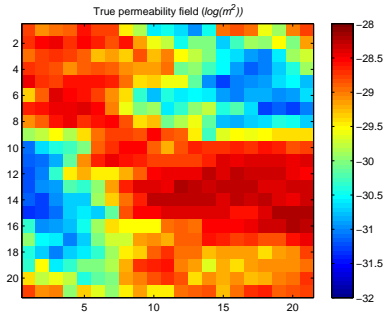
$$\begin{aligned} \mathbf{K} &= \frac{1}{N-1} (\mathbf{B}^{-1}\mathbf{B}) \mathbf{L}\mathbf{L}^T\mathbf{M}^T (\mathbf{A}\mathbf{A}^{-1}) \left(\frac{1}{N-1} \mathbf{M}\mathbf{L}\mathbf{L}^T\mathbf{M}^T + \mathbf{R} \right)^{-1} (\mathbf{A}^{-1}\mathbf{A}) \\ &= \mathbf{B}^{-1} \underbrace{\frac{1}{N-1} (\mathbf{B}\mathbf{L}) (\mathbf{A}\mathbf{M}\mathbf{L})^T \left(\frac{1}{N-1} \mathbf{A}\mathbf{M}\mathbf{L} (\mathbf{A}\mathbf{M}\mathbf{L})^T + \mathbf{A}\mathbf{R}\mathbf{A} \right)^{-1}}_{\mathbf{K}_1} \mathbf{A} \end{aligned}$$

Ensemble update

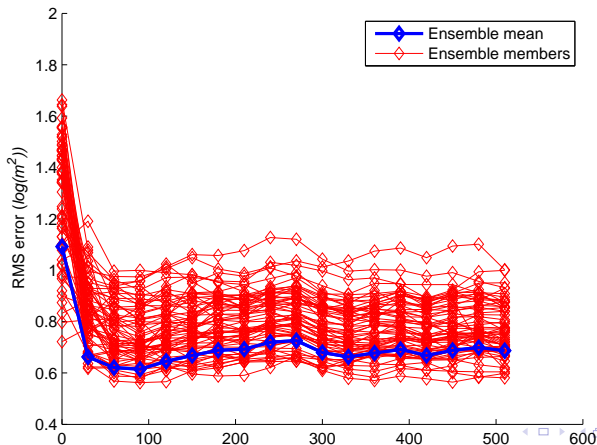
$$\begin{aligned} (\xi_i)_k^a &= (\xi_i)_k^f + \mathbf{K} (\mathbf{Z} - \mathbf{M}(\xi_i)_k^f + \mathbf{V}^i) \\ &= (\xi_i)_k^f + \mathbf{B}^{-1}\mathbf{K}_1\mathbf{A} (\mathbf{Z} - \mathbf{M}(\xi_i)_k^f + \mathbf{V}^i) \\ &= (\xi_i)_k^f + \mathbf{B}^{-1} (\mathbf{K}_1 (\mathbf{A}\mathbf{Z} - \mathbf{A}\mathbf{M}(\xi_i)_k^f + \mathbf{A}\mathbf{V}^i)) \end{aligned}$$

Experimental setup

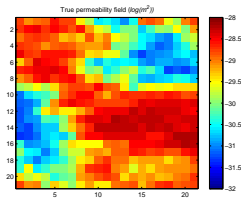
Twin experiment Initialization



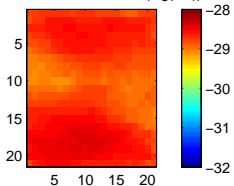
RMS Error in Model Parameter



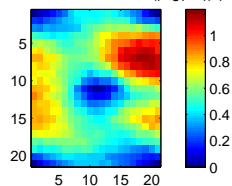
Estimated Permeability Field



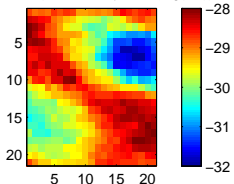
Mean of initial ensemble ($\log(m^2)$)



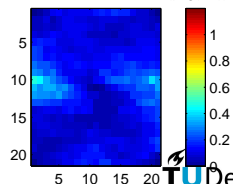
Variance of initial ensemble ($(\log(m^2))^2$)



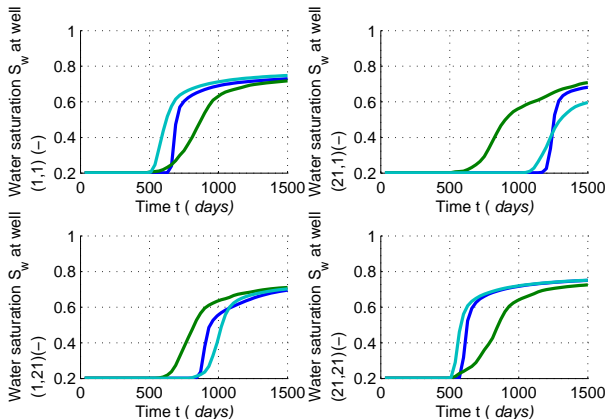
Estimated permeability field ($\log(m^2)$)



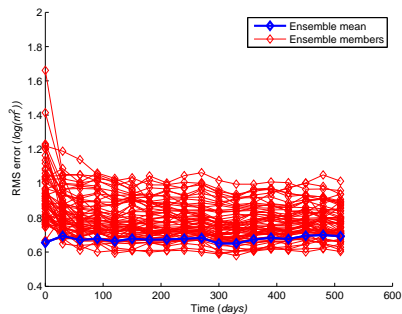
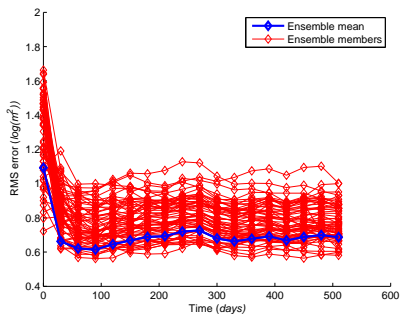
Variance of estimated ensemble ($(\log(m^2))^2$)



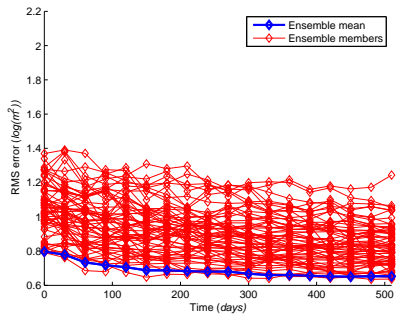
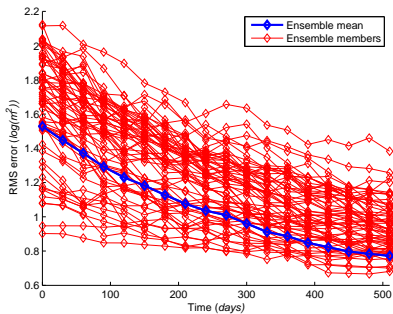
Forecasted Reservoir Performance



RMS Error in Model Parameter

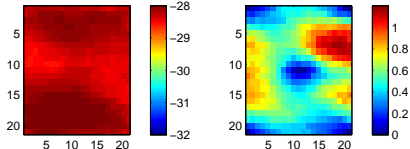


RMS Error in Model Parameter

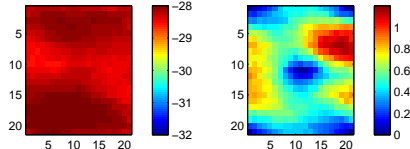


Estimated Permeability Field

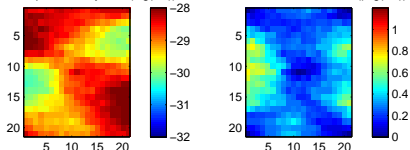
Mean of initial ensemble ($\log(m^2)$) Variance of initial ensemble ($(\log(m^2))^2$)



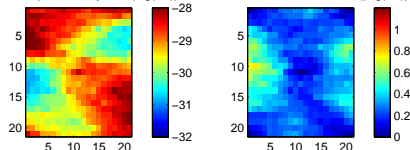
Mean of initial ensemble ($\log(m^2)$) Variance of initial ensemble ($(\log(m^2))^2$)



Estimated permeability field ($\log(m^2)$) Variance of estimated ensemble ($(\log(m^2))^2$)



Estimated permeability field ($\log(m^2)$) Variance of estimated ensemble ($(\log(m^2))^2$)



Conclusion

- ▶ Model calibration is essential
- ▶ EnKF provides reasonable parameter estimation
- ▶ There are cases at which IEnKF is superior to EnKF
- ▶ Further investigations on IEnKF sensitivities are required

- Outline
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- Case Study
- Results
- Conclusion
- Questions

Questions

