A Hybrid Ensemble Kalman Filter with Coarse Scale Constraint for Nonlinear Dynamics

Shingo Watanabe, Akhil Datta-Gupta, Yalchin Efendiev, Texas A&M University

Deepak Devegowda, University of Oklahoma

ABSTRACT

The recent interest in Ensemble Kalman Filters (EnKF) in the Petroleum Industry is driven to a large extent by the need for continuous reservoir model updating and uncertainty assessments based on dynamic data. The EnKF approach relies on sample-based statistics derived from an ensemble of reservoir model realizations. Sampling error in these statistics, particularly with the use of modest ensemble sizes, can severely degrade EnKF performance leading to parameter overshoots and filter divergence. However, for computational efficiency, the ensemble size needs to be kept small resulting in spurious sample correlations and loss of geologic realism during model updating. Moreover, facies-based non-Gaussian geologic models and the non-linearity of multiphase flow problems pose significant additional challenges for the EnKF. The EnKF updates are designed to be optimal only for Gaussian priors and linear model dynamics. For multiphase history matching, the posterior distribution will be non-Gaussian and the ensemble mean is not a good representation of the central tendency. As a result the EnKF can result in a poor match to the data or unrealistic model updates. The hybrid multiscale EnKF proposed here provides an improved approach to operational data assimilation problems and tends to overcome many of the limitations associated with the classical EnKF implementation. Our approach combines non-linear inversion with the EnKF to account for the inherent non-linearities of multiphase inverse problems. Specifically, we update the ensemble mean in a conventional EnKF through a non-linear inversion at selected time intervals and replace the ensemble mean with the 'posterior mode' from the inversion. This explicitly recognizes the fact that for non-Gaussian distributions, the posterior mode is a better representation of the central tendency compared to the ensemble mean. Furthermore, the inversion results are imposed on the individual ensemble members via a coarse-scale constraint using a sequential second stage updating in the conventional EnKF and a flow-based upscaling. Our approach ensures that the ensemble members in the conventional EnKF will follow the trajectory of the non-linear inversion within a specified degree of tolerance. This not only allows us to account for non-linearities in the model updates but also prevents filter divergence arising from the use of limited ensemble size. We first illustrate the advantage of the hybrid approach using a synthetic example and present a detailed validation of our results. Next, the approach is applied to a west Texas carbonate reservoir to demonstrate its power and utility for practical field problems.

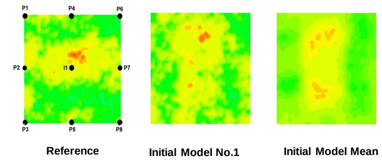
OBJECTIVES AND MOTIVATION

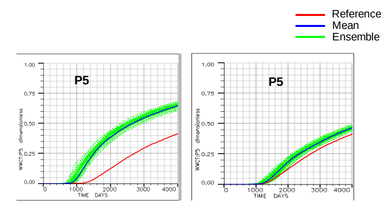
- **Combines EnKF With Non-Linear Inversion**
  Probabilistic Framework of EnKF + Deterministic Inversion On Ensemble Mean
- **Accounts For Non-Linearity Through The Inversion**
  Sequential Data Assimilation EnKF + Simultaneous Data Integration From Inversion
- **Coarse Scale Constraint From Inversion**
  Ensemble Members Are Driven Towards The Posterior Mode

EnKF LIMITATIONS

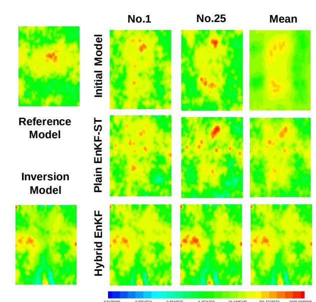
- **Updates Are A Linear/Weakly Non-linear Combination Of The Ensemble Members (Without Localization)**
- **Update Equations Are Optimal Only For Linear Dynamics And Gaussian Priors**
- **For Multiphase History Matching, Posterior PDF Is Likely To Be Non-Gaussian**
  Ensemble Mean Is Not A Good Representation Of Central Tendency

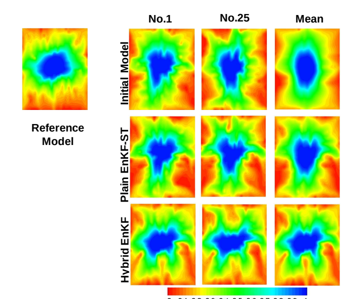
SYNTHETIC EXAMPLE: RESULTS





Plain-EnKF Hybrid EnKF





FORMULATIONS

1st Assimilation (Ordinary EnKF Updating)

$$\mathbf{y}_k^a = \mathbf{y}_k^p + \mathbf{K}_k(\mathbf{d}_{obs} + \boldsymbol{\varepsilon} - \mathbf{H}\mathbf{y}_k^p)$$

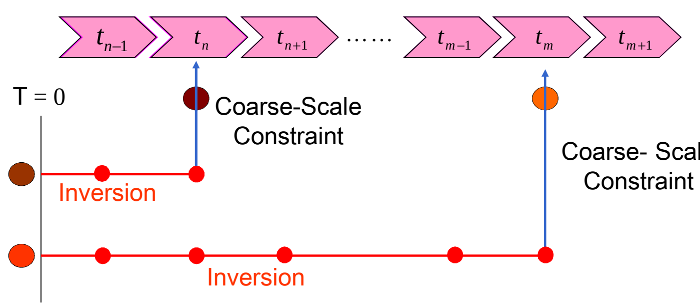
2nd Assimilation (Coarse Scale Constraint)

$$\hat{\mathbf{y}}_k^a = \mathbf{y}_k^a + \tilde{\mathbf{K}}(\underbrace{\mathbf{d}_{\ln k,c}}_{} + \boldsymbol{\varepsilon}_{\ln k} - \underbrace{\mathbf{U}\mathbf{y}_k^p}_{})$$

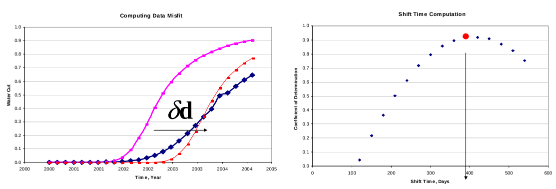
Coarse-cale permeability from inversion $\mathbf{d}_{\ln k,c} = \mathbf{U}\mathbf{y}_{mode}$

Ensemble upscaled permeability

EnKF Assimilation



Streamline Based Generalize Travel Time Inversion



The optimal shift time is calculated in order to maximize the correlation coefficient between the observed and calculated water cut

Deterministic Inversion

Minimizes objective function: $\|\delta\mathbf{d} - \mathbf{S}\delta\mathbf{R}\| + \|\delta\mathbf{R}\| + \|\mathbf{L}\delta\mathbf{R}\| \xrightarrow{\text{LSQR}}$ Mode estimate

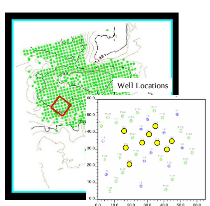
- Gaussianity / Prior Covariance are not assumed during inversion

Flow Based Upscaling used to derive coarse-scale constraint from fine-scale inversion

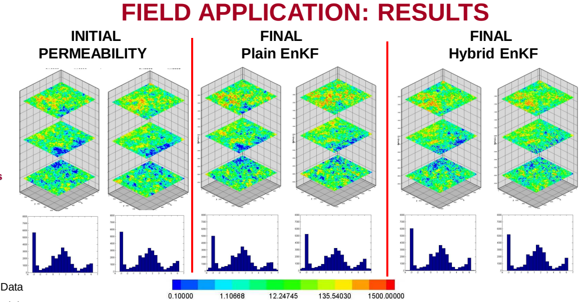
- Coarsening imposes large-scale spatial trends
- Avoids over-constraining the ensemble

FIELD APPLICATION: RESULTS

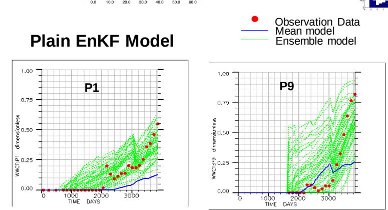
Field Application
The Goldsmith Case



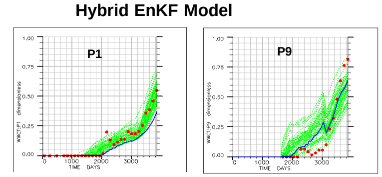
- 58x53x10 gridblocks
- 9 Production Wells
- WWCT Assimilated
- Unconditioned EnKF Uses 100 Realizations
- Conditioned EnKF Uses 50 Realizations
- Better Performance in Half the Time and Computational Effort



Plain EnKF Model



Hybrid EnKF Model



CONCLUSIONS

- **The Hybrid EnKF appears to be a promising approach**
- **Couples the conventional EnKF with non-linear inversion**
- **Inversion is carried out only on the ensemble mean. Low Computational overhead.**
- **Ensemble members seem to capture the flow dynamics**
- **The power and utility of the method has been demonstrated using synthetic and field examples.**